Predicting personality based on smartphone usage

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THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE IN DATA SCIENCE & SOCIETY
DEPARTMENT OF COGNITIVE SCIENCE & ARTIFICIAL INTELLIGENCE
SCHOOL OF HUMANITIES AND DIGITAL SCIENCES
TILBURG UNIVERSITY

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Tilburg, The Netherlands
May 2021

Preface

Since I see that smartphones have so much influence on all my friends and family around me, including myself. I was interested in the comparison to the online and offline personalities. With the possibility of using the smartphone data collection I got the opportunity to investigate this topic and to see whether it is possible to use smartphone data to predict someone's personality.

I would like to express my appreciation to everyone that helped me during the process of writing my thesis. Firstly, I would like to thank my supervisor Drew Hendrickson for his guidance during the weekly meetings along the thesis process and George Aalbers for providing the smartphone usage data collection. Secondly, my housemates for all the support and encouragements, especially Kirill Sadovnikov and Charlotte Kerkhof. Thirdly, my parents for listening to some of my frustrations and helping me to cheer up when I was struggling. Lastly, I want to thank Frederique Romeyn for our daily walks to take a break and clear my head when needed.

Abstract

Large amounts of data are being collected everyday with the usage of smartphones. The passive collection of smartphone leads to new opportunities in research in human behavior, where the active participation of humans is not required. Prior research has stated the importance of the big five personalities in several research fields, however little research was done on objectively quantifiable behavior of individuals. In this research will be investigated to what extent the big five personalities can be predicted based on smartphone usage. Prior research found several features that could be of influence on predicting the five personalities. In this research these features are combined with several extracted features sets when predicting personality. The dataset that has been used for this research contains data on 221 participants including their personality scores and extracted features from their phone usage in a period of five months. The features that have been extracted from the raw data set were combinations of mainly: spatial features, communication application features, features from categorized applications, and features on notifications, time of smartphone usage and battery percentage. Random forest, logistic regression and support vector machine models have been tested on the combination of these feature sets. The best performing machine learning models per personality slightly outperformed their baseline model. The best performing model for the personalities that could be predicted above baseline was the random forest model. The best predicted personality in comparison to the baseline was openness. Also, agreeableness, conscientiousness and neuroticism outperformed their baseline models. Feature importances were extracted to create more explainability and interpretability in models that were used for this research. Actual correlations of the important features could not be found in this research.

Keywords: Big five personalities, feature importance, smartphone usage data, classification machine learning techniques

Contents

1. Introduction

The world is changing rapidly and smartphones are becoming a large part of human life (Harari, Gosling, Wang & Campbell, 2015). The features that smartphones have to offer go beyond simply calling and messaging (Concone, Gaglio, RE & Morana, 2017). With large-scale smartphone usage, large amount of data is created which could be collected and used for several purposes (Harari et al., 2015). For example, these data could provide insights that could be used for research in human behavior.

Therefore, these data could be beneficial in predicting the big five personalities (Mollgaard, Lehmann & Mathiessen, 2017; Harari, Lane, Wang, Crosier, Campbell & Gosling, 2016; Felix, Castro, Rodriguez & Banos, 2019). Software on smartphone measurement creates opportunities to collect large amounts of data on mobile media and application usage (Bouwman, de Reuver, Heerschap & Verkasalo, 2013). It allows for passive collection of data which can be beneficial in predicting personality (Harari, Gosling, Wang & Campbell, 2015). Collecting data in a passive way means that there is no requirement of active participation of the participants involved in the data collection and data can be autonomously collected (Torous & Powell, 2015). In other words, when using passive data on predicting the big five personalities, taking the big five personality questionnaire is not required anymore. The use of social media applications could provide data on communication and social behavior (Settanni, Azucar & Marengo, 2018). Application usage and smartphone usage in general could show patterns of behavior of individuals (Stalch, 2020). Location data derived from smartphones by using GPS space-time stamps could provide insights into the mobility of individuals (Ai, Liu & Zhao, 2019; Barbosa et al., 2018). Also, day- and night-time activity can be distinguished by analyzing smartphone usage data (Stalch et al., 2020). This thesis has researched whether the big five personalities could be predicted based on smartphone usage. Therefore, the following research question is formulated:

"To what extent can the big five personalities be predicted based on smartphone usage?"

Over the past few years, a lot of research was conducted on the behavior of individuals and the relation to the big five personality traits. However, little research has been done on objectively quantifiable behavior of individuals (Stachl et al., 2020). Only a few studies have been conducted on predicting personality based on smartphone usage, specified on the big five personality traits (Stalch et al., 2020; Ai et al., 2019; Mønsted, Mollgaard, & Mathiesen, 2018; Peltonen et al., 2020). However, all studies claim for limitation in generalizability, due to small sample sets, lack of cross-validation and the participants not being randomly chosen. Therefore, these studies differ in success of prediction of the five independent personalities and their results might be hard to compare. Previous studies on this topic have been conducted on students from China (Ai, Liu & Zhao, 2019), Germany (Stalch et al., 2020) and Denmark (Mønsted, Mollgaard, & Mathiesen, 2018), but also on people from different age categories and countries (Peltonen et al., 2020). Samples from different countries could lead to other characteristics. Cultural differences could influence the prediction because of different behavior found in phone usage (Harari, 2020). This kind of research, in predicting personality traits based on smartphone usage, has not been done among students in The Netherlands before, so there is still a novelty.

The big five personalities, also known as the OCEAN model, is largely known among researchers in psychological science (De Raad, 2000). This factor analysis shows five relatively independent dimensions that include: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (McCrae & John, 1992). These personality trait dimensions show differences in the way individuals think, feel and behave (Wang W., Harari, Wang R., Müller, Masaba & Campbell, 2018).

Insights in human personality are widely used in different kind of fields. Personality could help to understand the behavior of people in political environments (Gerber, Huber, Doherty & Dowling, 2011). Knowledge of the personalities of certain people could provide insights in people's concern of the environment (Milfont & Sibley, 2012). It could provide indications of academic performance (O'Connor & Paunonen, 2007). Also, knowledge of personality could be beneficial for job performance, for example in hiring processes (Moy & Lam, 2004; Stoughton, Thompson & Meade, 2013), where the personality scores might say something about the decision making of people (Byrne, Silasi-Mansat & Worthy, 2015) or work engagement (Zaidi N. R., Wajid, Zaidi F. B., Zaidi G. B. & Zaidi M. T., 2013).

Machine learning techniques can be used to predict personality. However, machine learning models are often seen as black-box models (Rudin, 2019; Pargent & Albert-vond der Gönna, 2018; Yarkoni & Westfall, 2017), which means that there are no insights in how the output is conducted from the model. These models can be more explainable and interpretable by creating insights into feature importance (Fisher, Rudin & Dominici, 2018; Gregorutti, Michel & Saint-Pierre, 2015), which could be beneficial in using the best performing models on new data collections in the future.

For this research, the following sub-questions are formulated to provide an answer to the main research question.

1. *"Which features can be extracted from the phone usage data to predict the big five personalities?"*
2. *"Which classification machine learning techniques predict each independent personality most accurately?"*
3. *"Which features are most important in predicting personality?"*

A collection of raw phone usage data has been used to provide answers to the research questions. As raw phone usage data has been used for this thesis, features have been extracted before making predictions. The features that have been extracted from the raw data set were combinations of mainly: spatial features, communication application features, features from categorized applications, and features on notifications, time of smartphone usage and battery percentage. The personality scores were divided into classes and several classification models were tested to predict the personalities most accurately. The random forest classification model was the best performing model for most of the personalities, even though the model performances were slightly above baseline. Openness was the personality that had the highest accuracy score, in comparison to the baseline model. Extraversion was the only personality that could not be predicted above baseline, the best performing model had an accuracy score equal to the baseline score. The most important features retrieved from the best performing models per personality indicate which features had the most influence on predicting the personality. However, actual correlations of the important features on the personality were not shown in the correlation plot, since the best performing models were non-linear and there might be intercorrelations between the features.

2. Related Work

In this section, a few relevant studies that are similar to this research have been highlighted. In previous research, some studies have been focusing on predicting personality traits in relation to smartphone usage in general (Stalch et al., 2020; Mønsted et al., 2018; Peltonen et al., 2020). A few studies zoomed in on predicting personality based on specific applications usage, for example, YouTube (Klobas, McGill, Moghavvemi & Paramanathan, 2018), Facebook (Ross, Orr, Sisic, Arseneault, Simmering & Orr, 2009), and WhatsApp (Montag et al., 2015). There have also been studies focusing on response behavior of individuals on notifications to predict personality (Mehrotra, Pejovic, Vermeulen, Hendley & Musolesi, 2016). Other studies used spatial information to predict personality (Alessandretti, Lehmann & Baronchelli, 2018; Ai et al., 2019; Barbosa et al., 2020). The main results of the studies will be compared per personality.

2.1 The OCEAN-model

Before diving into the results of previous studies, the big five personalities will be defined. Openness or Open-Mindedness can be described as people that tend to long for variety, new (intellectual) experiences, have a creative imagination, and a curious attitude for new things. Conscientious people are known to be self-disciplined, focused on achievements, organized, responsible, productive, and methodical. Facets that are typical for Agreeableness are compassion, respectfulness, trustworthiness, kindness, and friendliness. Extraversion can be described by facets of sociability, assertiveness, and energy. Neuroticism, or in some articles referred to as Emotional Stability, could be described as experiencing sadness, embarrassment, distrust, (social) anxiety, and spending time alone (McCrae & John, 1992; Soto & John, 2017; Peltonen et al., 2020).

These five personalities are claimed to be independent of one another (McCrae & John, 1992). In other words, score high on one of the five personalities, does not exclude a high score on the other four personalities. However, other research shows that are some intercorrelations between the five personalities. In a meta-analysis of the big five intercorrelations by van der Linden, te Nijenhuis & Bakker (2010) was shown that between conscientiousness and neuroticism was a slightly negative correlation. Between extraversion and neuroticism and agreeableness and neuroticism there was also a small negative correlation shown, and conscientiousness and agreeableness were positively correlated. In the study by Mønsted et al. (2018) on predicting personality based on smartphone usage an intercorrelation matrix of the personalities was conducted. This matrix showed that extraversion was the most correlated to the other personalities, the highest correlations were between extraversion and neuroticism and extraversion and agreeableness.

2.2 Prediction of the big five personalities

In this paragraph, the results of predictions on the five personalities will be outlined on each personality individually. The five personalities are sorted by the success of the prediction of the findings in the literature.

2.2.1 Extraversion

The most successfully predicted personality trait, in the majority of the studies on predicting personality based on phone usage, is extraversion (Mønsted et al., 2018; Alessandretti et al., 2018; Harari et al., 2019; Peltonen et al., 2020; Ai et al., 2019). In one of the studies, this personality was the only one predicted significantly better than the null model (Mønsted et al., 2018). This is because these studies had their focus mainly on communication behavior which is positively related to the frequency of communication via calling, texting, and the use of communication applications, for example WhatsApp (Montag et al., 2015). Mehrotra et al. (2016) showed in their research that the viewing time and decision time on smartphone notifications are also of significant influence for this personality. Chittaranjan et al. (2013) found that extraversion was found positively correlated with office-related applications, but negatively correlated with gaming, web-browsing, and camera usage. Zooming in on spatial data, extroverted people are expected to have a higher variety in the places they visit. This is expected because they are characterized by exploring different places, and seeking exciting, novel, and risk-taking activities (Ai et al., 2019; Alessandretti et al., 2018).

2.2.2 Openness

Stalch et al. (2020) found openness as the most successfully predictable personality in their study. These predictions were also related to communication and social behavior, but also to camera usage and the usage of music applications. The personality trait was negatively related to the use of sports applications. Montag et al. (2015) could not show significant results in WhatsApp usage and openness. Alessandretti et al. (2018) and Chorley et al. (2015) showed a correlation of openness with long-distance movements and visiting faraway places, and these individuals would have a tendency of changing their routine over time. However, the results of the study of Ai et al. (2019) did not show any spatial correlation to openness.

2.2.3 Agreeableness

In the study by Peltonen et al. (2020), agreeableness was positively correlated to communication applications. Klobas et al. (2018) showed in their results that the personality trait agreeableness was correlated with less use of YouTube. The results of the study of Ai et al. (2019) showed that people who score highly on agreeableness have a larger range of movement. It is expected that this is because these people are more likely to go out for social activities. Montag et al. (2015) did not succeed in showing significant results in predicting this personality trait, and also Stalch et al. (2020) did not succeed in predicting agreeableness.

2.2.4 Conscientiousness

The most important variables found by Stalch et al. (2020), when successfully predicting conscientiousness, were mainly in the phone activity, the frequency of unique applications used and there was a correlation between the battery level and the personality. Conscientious people tend to use their phones the most out of all personalities during the early and late phases of the day. Research by Peltonen et al. (2020) showed a correlation between the conscientiousness personality trait and the use of casino games. Montag et al. (2015) showed an inverse correlation with the length of daily WhatsApp usage and conscientiousness. Klobas et al. (2018) showed that people with this personality tend to make less use of the YouTube application. Viewing time when receiving notifications on a smartphone also has a significant influence on conscientiousness, showed the results of the study by Mehrotra et al. (2016). Zooming in on spatial data, conscientious people are expected to visit places at regular times and not visit many different places, as their personality indicates that these individuals prefer regular lifestyles (Ai et al., 2019).

2.2.5 Neuroticism

Just like conscientiousness, the use of casino games positively related to neuroticism, but neuroticism negatively related to communication applications in the study of Peltonen et al. (2020). However, Montag et al. (2015) showed a positive correlation between neuroticism and daily WhatsApp usage. Also, the usage of social media YouTube was positively correlated with this personality trait, which was shown in the study of Klobas et al. (2018). The viewing time and decision time of notifications are of significant influence in predicting the personality trait (Mehrotra et al., 2016). It is expected that people with this personality would not move as much as people with one of the other personalities. People with neuroticism would lack social competence, like to spend time alone, and may have social anxiety (Ai et al., 2019). Although, Alessandretti et al. (2018) found that neuroticism correlates with the tendency to change routines over time. Stalch et al. (2020) did not succeed in predicting this personality.

2.3 Feature extraction

There are differences in the results of these researches mentioned above, but also similarities were found. This was, for example, the case for openness where Alessandretti et al. (2018) and Chorley et al. (2015) found a correlation between long-distance movements and visiting far places on the personality, but Ai et al. (2019) did not find any correlations between spatial features and the personality. As mentioned, the results of these studies could not be generalized, which could explain the differences in results. However, the results provide an indication of the features that could be of influence when predicting personality, which was useful in feature extraction. For example, there has not been done research before on the combination of spatial features and communication features, so this will be a novelty. In previous research, the main focus was on specific features, while in this research several features are combined to predict personality based on the findings above.

2.4 Classification models

The models that were used in similar studies were mainly Random Forests (Stalch et al, 2020; Peletonen et al. 2020; Alessandretti et al., 2018), Support Vector Machines (Montjoye et al., 2013; Gao et al, 2019; Peletonen et al., 2020; Oliveira, Karatzoglou, Concejero, Armenta & Oliver, 2011; Mønsted et al., 2018) and Logistic Regression (Peltonen et al., 2020; Mehrotra et al., 2016; Stalch et al., 2020; Alessandretti et al., 2018). These models could also be used for retrieving feature importance (Horel & Giesecke, 2019). More on this can be found in the methods and experimental setup section.

3. Methods

There were multiple feature sets extracted during the research process. Along this research process, the three sub-questions have been answered using several methods. In total three feature sets have been extracted from the raw data. Therefore, the research process has been repeated three times to aim for better results when adding new features when repeating the research process. Figure 1 shows a flow chart of the application of the methods step-by-step.

First, features have been extracted from the raw smartphone usage data collection. On these extracted features, a feature selection was applied based on the model that was fitted in the following step. Leave-one-out cross-validation was used to split the data and to prevent the models from overfitting. Then three classification machine learning models were fitted to the selected features. The predictions were retrieved from the models and the evaluation metrics were computed to evaluate the performance of the models. Together with the predictions, the feature importances were retrieved from the models which would indicate which features would have the most influence on the predictions of the prediction model per personality. The information on the feature importance was used to visualize correlations of the important features to the personalities.

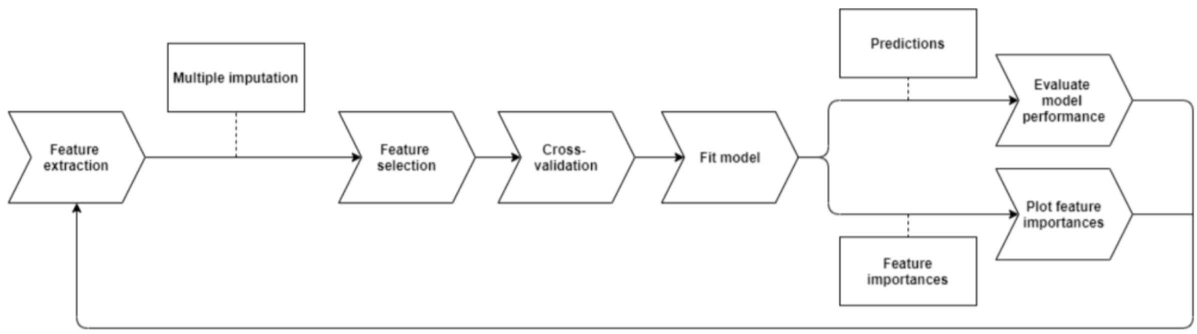


Fig. 1. Flow chart of the research process

Three feature sets were extracted in total to improve the performance of the model and get higher scores on the evaluation metrics computed from the predictions. The second feature set was added to the results of the modeling process applied on the first feature set. In other words, the features extracted in the second feature set were added to the selection of the first feature set and then the modeling process was repeated on the newly created combination of the feature sets. The third feature set was added to the selection of the first and second feature set and the modeling process was repeated again.

Not all features were complete in the feature sets. In some part of the data collection the longitude and latitude coordinates were missing for some of the participants. To counter this problem, multiple imputation has been applied. The modeling process has been applied on the complete feature sets and the imputed feature set to see if multiple imputation would improve the performance of the models.

The five personalities were modeled individually since these five personalities are independent of one another. Three different models were fitted to the combined feature sets with imputations and with only the complete instances. In total 90 models were tested to find the model with the highest score per personality.

4. Experimental Setup

The dataset, that has been used to answer the research questions, exists of a combination of multiple raw datasets on questionnaire data and phone usage data. The data has been collected from students from Tilburg University in the period from February 2020 till the end of May 2020. In total 274 participants were involved in this data collection. The data consists of two parts, the self-report, which the participants had to fill out before and during the data collection, and the phone usage data that has been tracked on the background of the participants. Not all data has been collected on all participants, and the number of days that the data has been collected is not equal for all participants. For 221 participants both the self-report data and the phone usage data have been collected for at least seven days. This is the selection of the raw data collection that is used in this research. The self-report dataset consists of answers to daily surveys and the onboarding survey that contains, among other information, the answers to the big five personalities questionnaire. In the collection of the phone usage data, information has been collected on application usage, time, and date of the usage, location data, notification data, and the battery percentage has been collected.

The shorter version of the big five personalities by Soto & John (2017) was questioned in the self-report, and the responses were used to compute the personality score. In total, each personality score has a maximum score of 30 points. For every participant, the five independent personality scores were derived by computing the proportion of their score to the maximum score possible, which resulted in a score between 0 and 1 for every personality, see formula 1.

$$personality\ score = \frac{score\ per\ personality}{total\ personality\ score} \tag{1}$$

As mentioned by Mønsted et al. (2018), in this case predicting personality would make more sense with classification models than with regression models. The reason for this is that there is no precise interpretation difference in a continuous score for personality (e.g., a difference of 0.04 does not say much about the accuracy of the prediction). Each personality is divided into three classes: 0, 1, and 2 which stands for “low”, “medium” and “high”. The classes have been computed relative to the range of the personalities, see table 1. This means that for each personality the range of all scores has been computed and divided by three so that all personalities would have three classes, see formula 2.

$$personality\ class = \frac{(\max personality\ score - \min personality\ score)}{3} \tag{2}$$

Table 1. Range of personality score per personality

Personality	Range
Openness	0.4 – 1.0
Conscientiousness	0.23 – 0.97
Extraversion	0.2 – 0.97
Agreeableness	0.37 – 0.97
Neuroticism	0.2 – 0.97

Even though the computation of the classes is relative to the range of the classes, the classes are still imbalanced which means the frequency of the classes per personality is not equal (see figure 2).

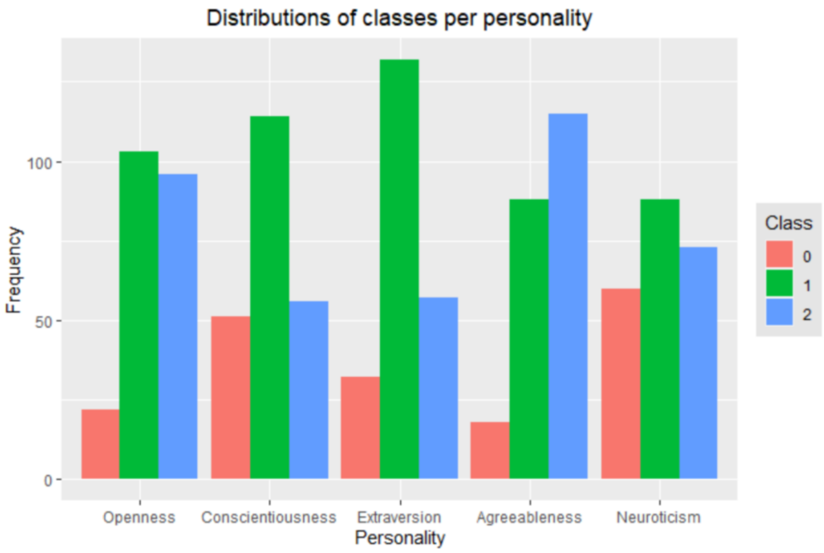


Fig. 2. A figure of the distribution of classes per personality

4.1 Feature extraction

For some participants, the data has not been collected during the whole period the data collection had taken place. The range of collection is between 7 and 148 days, as can be seen in the distribution presented in figure 3. To counter this problem, the majority of the features that have been extracted from the phone usage data collection were averaged per participant per day. Below the three feature sets will be further explained.

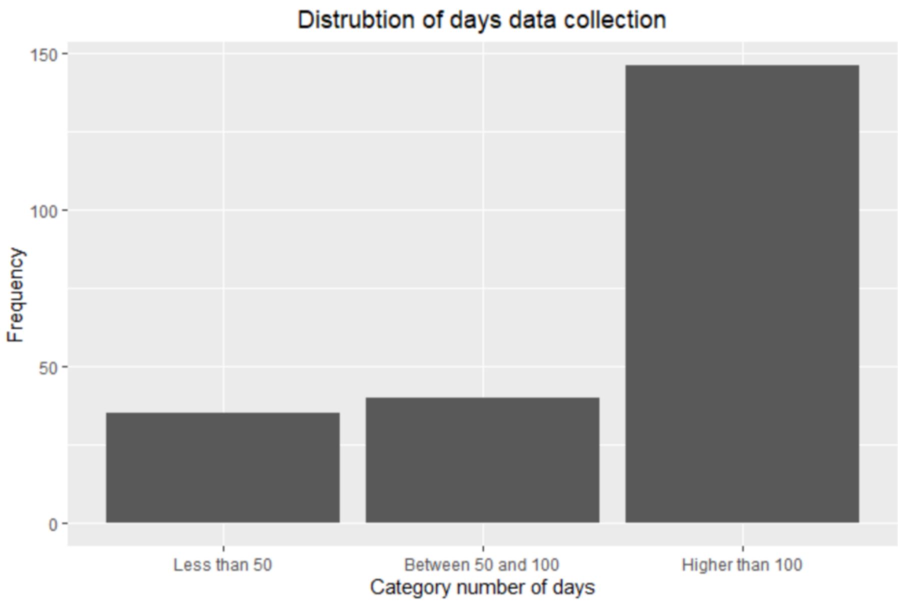


Fig. 3. Distribution of the number of days of data collection

4.1.1 First feature set

As mentioned in the method section, along the way of the modeling process, new feature sets were extracted from the raw data collection. The first feature set contains spatial features and the frequency of the use of communication applications per participant per day. The combination of spatial features and features on application usage on predicting personality has not been researched before, but have found successful separately in predicting personalities. Therefore, these are both included in the first extracted feature set.

Previous studies have shown that communication applications could significantly influence the prediction of personality, for instance, social media applications as YouTube (Klobas et al., 2018), Facebook (Ross et al., 2009), and WhatApp (Montag et al., 2015). In this research, the mean frequency of the use of communication applications per day was extracted. The communication applications that were used are WhatsApp, Facebook, Instagram, Snapchat, YouTube, Twitter, LinkedIn, text message, and phone.

The spatial features were extracted based on the longitude and latitude coordinates in the raw datasets. Since these data are privacy sensitive the features were extracted in a way that the actual location was not traceable. The distance was computed between the coordinates, which was used to extract the frequency of movements between places per participant per day. Also, the mean distance that participants traveled per day was extracted, and the maximum radius that the participant traveled during the data collection was extracted. The fourth spatial feature that was extracted was the number of unique locations that the participants visited per day. Which resulted in thirteen features for the first feature set.

4.1.2 Second feature set

For the second feature set, all applications not related to communication have been categorized and features on the frequency of use per participant per day have been extracted. There are a large number of different applications which are used for the same purpose. Since the categorization of the Google Play store was not specific enough for the purpose of all the applications, the categorization has been done manually.

There were more than 1000 unique applications used by all the participants. The applications with a frequency of use of less than 300 were filtered out of the categorization. And only the applications that served the purpose of the selected categories for this research were included in the categorization. following categories had been defined for the second feature extraction: transportation, music, video streaming, weather, shopping, photos and videos, dating, browsing, email, planning, food ordering, and news. The overview of the specific application names and the category they belong to can be found in appendix A. The category for games was also considered since this could be of influence as well according to Peltonen et al. (2020). However, since there is a large number of games and they might differ in purpose, this category was left out of the feature extraction. This was also the case for office-related applications, which could be of influence according to Chittaranjan et al. (2013) and sport related applications (Stalch et al., 2020).

4.1.3 Third feature set

The third feature set consists of features on notifications, battery percentage, unique application usage, and day- and evening-time activity. The selection was based on the previous studies mentioned in the related work section. The number of unique notifications per day per participant was extracted along with the mean priority of all the notifications per day. Also, the number of unique applications that the participants use per day was extracted. To see if the time of phone usage has an influence on personality, the phone usage was split into the morning (before noon) and the evening (after noon) and extracted as features per participant per day. Lastly, the mean battery percentage per participant per day was extracted.

The overview of all extracted features and the detailed description is included in appendix B.

4.2 Modeling

In this section the modeling process is described in detail.

4.2.1 Multiple imputation

For 45 out of 221 participants, which is around 20% of the dataset, less than seven days of spatial information was collected or none at all. The easiest way to deal with this problem is to delete the instances with missing data and to only use the complete data. However, this could lead to bias results and inefficiency (Chhabra, Vashisht & Ranjan, 2017). Also, the dataset with the extracted features is already small, using only the complete cases would make it even smaller and it could influence the performance of the prediction models for the personalities.

There are several ways to deal with missing values, for example computing the mean, the mode, or applying regression models (Chhabra, Vashisht & Ranjan, 2017). However, these methods could lead to biased estimation and inference (Deng, Chang, Ido & Long, 2016). A better way of imputing values to replace the missing values is multiple imputation (MI) because it produces unbiased parameter estimates and predictions. It produces standard deviations that are a little larger than the observed data which could be accounted for additional uncertainty that is introduced by having the missing data (Slade & Naylor, 2020). When applying MI, each missing datapoint will be replaced with a set of M plausible estimates. The downside of MI could be that it is a computationally expensive method (Huque, Carlin, Simpson & Lee, 2018), but since the dataset with the extracted features is not very large the application of MI is not that computationally expensive.

The MI model, that has been applied to the dataset with the extracted features, is the mice forest function in Python, which is similar to the mice package in R. This type of multiple imputation uses random forest techniques to impute new data where the missing values are (Chhabra et al., 2017). The following parameters were defined when applying the mice forest function: 20 datasets were imputed and the algorithm was running for 10 iterations. Figure 4 shows the density plots of the distribution of the multiple imputation on the four spatial features.

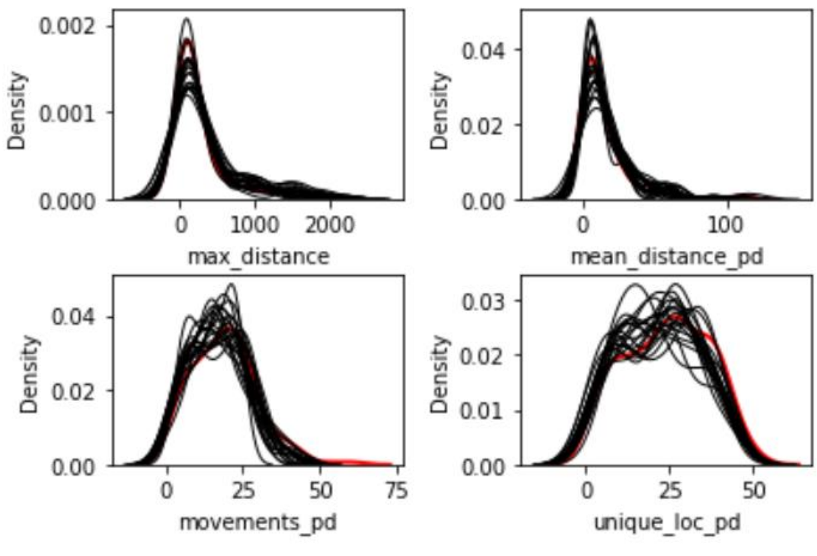


Fig. 4. Density plot of distributions of multiple imputed datasets

It is not clear what the type of missing data is. In the ideal situation, the missing data would be missing completely at random (MCAR) which would lead to the least bias since it is not related to the data collection. However, since it is location data, it is assumable that the data are missing at random (MAR) or not missing at random (NMAR). This would mean that the reason that the data is missing is related to the data collection (Bennet, 2001). The reason why the location data of some participants is not collected is not clear. For example, the GPS signal could have been turned off on purpose. Therefore, the data could be MAR or NMAR. This could influence the MI, especially if the data are NMAR it could still lead to bias parameter estimates (Madley-Dowd, Hughes, Tilling & Heron, 2019). Due to this risk, the classification models were trained on both the complete data and the data with imputations. The predictions and the importances of the features were only retrieved from complete cases. So, the evaluation metrics of the models were only computed on the complete cases. The reason for this is because the imputed data should not have too much influence on the predictions and feature importance since this is not the true data.

4.2.2 Feature selection, cross-validation and model fitting

For this thesis three, classification machine learning models were selected; the non-linear model Random Forest (RF), and the linear models Logistic Regression (LR) and Support Vector machines (SVM) using the linear kernel. To get higher performance on the classification models, feature selection was applied. These feature selection models would result in a selection of features that have the most influence on predicting personality, which makes the other features redundant. The feature selection has been applied before fitting the models. There were three types of feature selections dependent on the three different classification models.

The three classification models that were selected for this research were based on results from previous studies (see the related work section). Since one of the main goals of this research is to create explainable and interpretable machine learning models, the models were also selected based on the possibility of retrieving feature importances from the models. For the models, the default parameters of the python functions have been used since it was too computationally expensive to run grid search on 90 models. Since the values in the feature sets are not on the same scale, normalization was applied to change the numeric values to a common scale (Gonzalez-Abril, Velasco, Angulo & Ortega, 2013). The normalized feature sets were only required when fitting the SVM model (Hearst, Dumais, Osuna, Platt & Scholkopf, 1998). This was not necessary for the RF and the LR models.

When fitting the models, leave-one-out (LOO) cross-validation was used to estimate the performance of the classification models. Cross-validation would increase the accuracy reliability of the predictions. LOO is a special kind of k-fold cross-validation, in which the number of folds is equal the number of observations, in this case, 221 or 175. This type of cross-validation is specially designed for small datasets to reduce the chance of overfitting, that is the reason why this type of cross-validations was selected (Wong, 2015).

4.2.3 Evaluation

To evaluate the performance of the model, three metrics were computed using the predictions and the true values from the models; the accuracy rate, a poor classification ratio, and the F1-score. The accuracy rate was measured by computing the proportion of the correctly predicted classes from the total predicted classes, see formula 3.

$$accuracy = \frac{correctly\ predicted\ classes}{total\ predicted\ classes} \tag{3}$$

The personality scores were labeled in three classes, which means that the difference between the lowest and the highest class is higher than with the medium class. In other words, predicting the low class when the true label is high or the opposite is worse than predicting the medium class. Therefore, another metric is computed to evaluate this type of occurrence specifically. The metric would show the proportion of the poor classification compared to the total of misclassified target values, see formula 4.

$$poor\ classification\ ratio = \frac{poorly\ predicted\ classes}{total\ miss\ classifications} \tag{4}$$

Also, the F1-score is computed when evaluating the models. The classes of the personalities are imbalanced, which means that they are not equally divided. Therefore, the F1-score is also computed as a reference for the accuracy score, see formula 5. This F1-score is specially designed to deal with imbalanced classes (Scikit-learn developers, 2020a).

$$F1score = 2 * \frac{precision * recall}{precision + recall} \tag{5}$$

4.3 Feature importance

For all models, the importance of the features was retrieved from the models along with the predictions. Feature importance would give an indication on which features from the feature selection would have the most influence on predicting the target value (Horel & Giesecke, 2019), in this case, the personality class. For RF models the feature importance is measured using the prediction accuracy. It measures the decrease in prediction accuracy when a covariate is permuted (Fisher, Rudin & Dominici, 2018; Breiman, 2001). For LR and SVM models, the feature importance is measured by the coefficients. For the LR model, the coefficients for the target feature would indicate the effect of one unit change in the target feature. This coefficient could be either positive or negative. If it is negative, it would indicate that the event is less likely at the predictor level than at the reference level (Menard, 200). Coefficients of the SVM model are weights that represent the vector coordinates that are orthogonal to the hyperplane which separates the classes as best as possible to get predictions. These coefficients were obtained to measure the feature importance of the features that have been fitted to the SVM model (Guenther & Schonlau, 2016). There are different kernels considered for this research that can be used for SVM models, the linear kernel, and the non-linear kernels the polynomial function (RBF), and radial basis function (Patle & Chouchan, 2013). However, the coefficients can only be retrieved from the SVM model with the linear kernel. In the RBF and polynomial kernels, the separating plane exists in another space, which means that in the model there is a transformation of the original space and therefore the coefficients are not directly related to the features that are inputted in the SVM model (Wu, Tang & Wu, 2012). Therefore, only the linear kernel of the SVM model is applied in this research.

The feature importances retrieved from the models do not give an indication of how they are actually correlated to the target value. Therefore, the most important features from the best performing models per personality were plotted separately with the target value, the personality scores.

4.1 Software

The software that has been used was the programming language Python, mainly for feature extraction and modeling. This language was coded in Jupyter-lab. Visualizations on correlations and other figures were mainly coded in R, using the Rstudio software.

4.1.1 Python

The feature extraction, cross-validation, and the models were coded in Python, version 3.7.8 via Jupyter-lab. The random state of 2407 was added in certain functions if necessary, to make the research replicable. For the feature extraction the “numpy” (Python Software Foundation, 2021a), “pandas” (Python Software Foundation, 2021b), and “math” (Python Software Foundation, 2021c) packages were used. The “groupby” function from the pandas package was especially important for feature extraction to compute the mean per participant per day, to overcome the imbalanced number of days of collection from the participants (Pandas, 2021). From the math package the functions “radians”, “cos”, “sin”, “asin”, and “sqrt” were imported to compute the distance for the extraction of the spatial features (Python Software Foundation, 2021c).

For the MI of the missing values of the spatial features, the package “miceforest” was loaded, and the functions “MulitpleImputedKernel”, “mice”, and “complete_data” were applied to run the multiple imputations on the datasets. The plot functions from this package were used to visualize the performance of the MI (Wilson, 2021).

For the feature selection, cross-validation, model fitting, and evaluation the functions were imported from the "sklearn" package. The functions imported for feature selection were "SelectFromModel", "LinearSVC", "ExtraTreesClassifier", and "LogisticRegression". For cross-validation, the function "LeaveOneOut" was imported. The functions that were used to fit the three different models were "RandomForestClassifier", "LogisticRegression" and "svm". When evaluating the model metrics "f1_score", and "accuracy_score" were imported (Scikit-learn developers, 2020b).

The feature importance from the models was extracted from the Sklearn package using the "feature_importances_" function for the RF models (Scikit-learn developers, 2020c) and the "coef_" function for the LR and SVM models. The "Seaborn" (Python Software Foundation, 2021d) and "Matplotlib" (Python Software Foundation, 2021e) packages were used to visualize the results of the feature importance from the models.

4.1.4 R

R was the programming language that was mainly used for creating correlation plots or bar plots to visualize the results of this research. For visualizing the "ggplot2" package was used (tidyverse, 2021a), the "geom_jitter", "geom_point", and "geom_bar" plots were mainly used from this package. Adjustments in cleaning the data before visualization were made using the packages "dplyr" (tidyverse, 2021b), and "caret" (RDocumentation, 2021).

5 Results

In this section the results of all models are presented, including correlation plots.

5.1 Results of the best models

In total 90 models were fitted on the several combinations of feature sets, the scores of all evaluation metrics on the models are shown in appendix C and all feature importances are shown in appendix D. Table 2 shows the accuracy score of the best performing models per personality in comparison to the baseline accuracy scores. The best performing models were chosen for data with imputations and the complete data. The highest scoring model was on predicting the personality extraversion. However, this score did not exceed the score of the baseline model for this personality. The best performing models on the other personalities show a higher accuracy score than the baseline models. Except for the best scoring model on the conscientiousness personality with imputations, the accuracy score was below baseline. In most cases, the RF model shows the highest accuracy and is marked as the best performing model. This could indicate that there is a non-linear relationship of the features to the personalities since the RF model is a non-linear model and the SVM and LR models are linear models. Below the results per personality are outlined, sorted by performance.

Table 2. Accuracy scores of best performing models per personality

Personality	Dataset	Baseline	Results	Difference	Model
Openness	Complete	0.46	0.55	0.09	RF
	Imputed	0.47	0.51	0.04	RF, LR and SVM
Conscientiousness	Complete	0.5	0.55	0.05	RF
	Imputed	0.52	0.5	-0.02	RF, LR and SVM
Extraversion	Complete	0.57	0.57	0.00	RF and SVM
	Imputed	0.6	0.6	0.00	SVM
Agreeableness	Complete	0.5	0.56	0.06	RF
	Imputed	0.52	0.54	0.02	RF
Neuroticism	Complete	0.39	0.42	0.03	RF
	Imputed	0.4	0.46	0.06	RF

5.1.4 Openness

The personality with the highest accuracy score compared to the baseline model is openness. The results are from the RF model fitted on the complete data, 175 instances, with the selection of the most important features from all three feature sets. The accuracy score of this model was 9% higher than baseline. From the misclassifications, only 8% were badly classified. The F1-score was used as a reference to check whether the imbalanced classes would influence the scores (Scikit-learn developers, 2020a). The result was 0.52 which is close to the accuracy score of the model and indicates that the imbalanced classes did have a major influence on the performance of the model. In figure 5 the most important features of this model are shown.

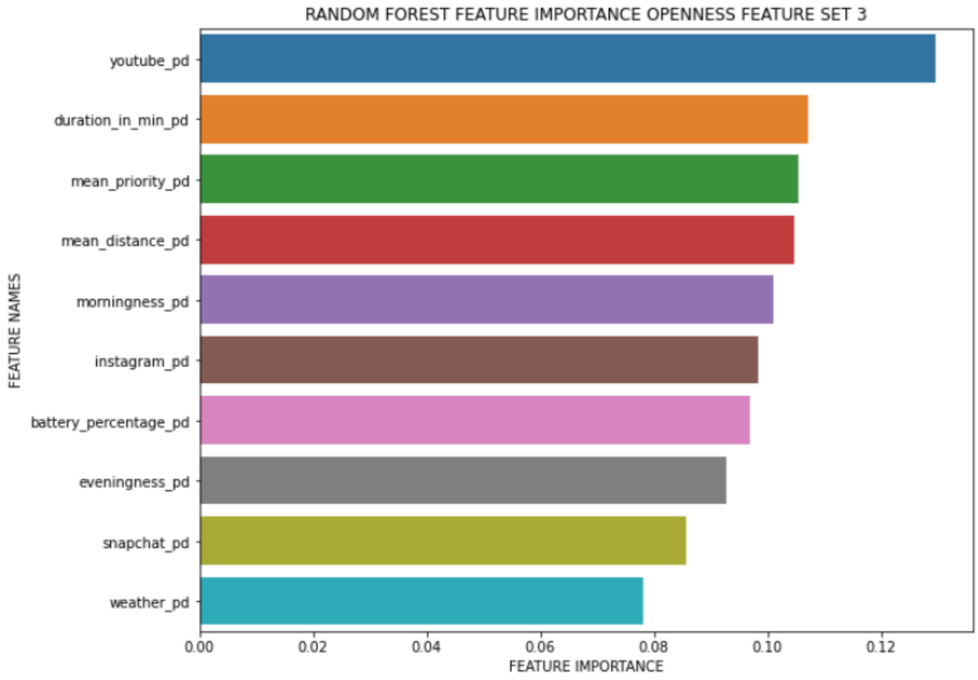


Fig. 5. Most important feature for the best performing model for openness (sorted by importance)

The frequency of use of YouTube is the most important feature in the best performing model for openness. Since the retrieved importances from the model do not indicate the actual relationship of the feature with the personality class, the most important features are plotted against the discrete class labels of the personality to visualize correlations. Figure 6 shows the relationship between openness and the frequency of use of the YouTube application. The correlation plot does not show a correlation between the two variables. The reason for this could be that the predictions were retrieved from a RF model, which is a non-linear model, therefore there would be no linear correlations. Another explanation could be that the importance is based on intercorrelations with other features in the model. Figure 6 shows a correlation plot between openness and the frequency use of YouTube, in appendix E.1 other similar plots on the important features are shown.

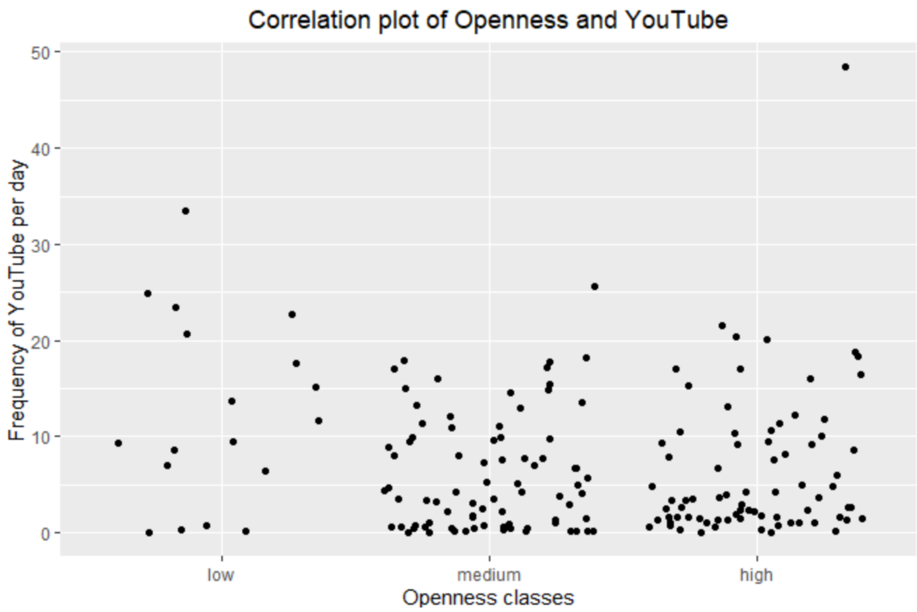


Fig. 6. Correlation plot of openness and the frequency of use of YouTube

5.1.5 Agreeableness

Also, for agreeableness, the RF model on the complete data from the feature selection of the three feature sets was found to be the model with the highest accuracy score. The RF model scored 6% higher on accuracy than the baseline model. The F1-score for this model was 0.53 which is close to the accuracy score. Only 4% of the misclassifications were poorly classified. The most important features for this model are visualized in figure 7. Also, for these features, the correlations of the features with the highest importance were plotted against the personality classes of agreeableness.

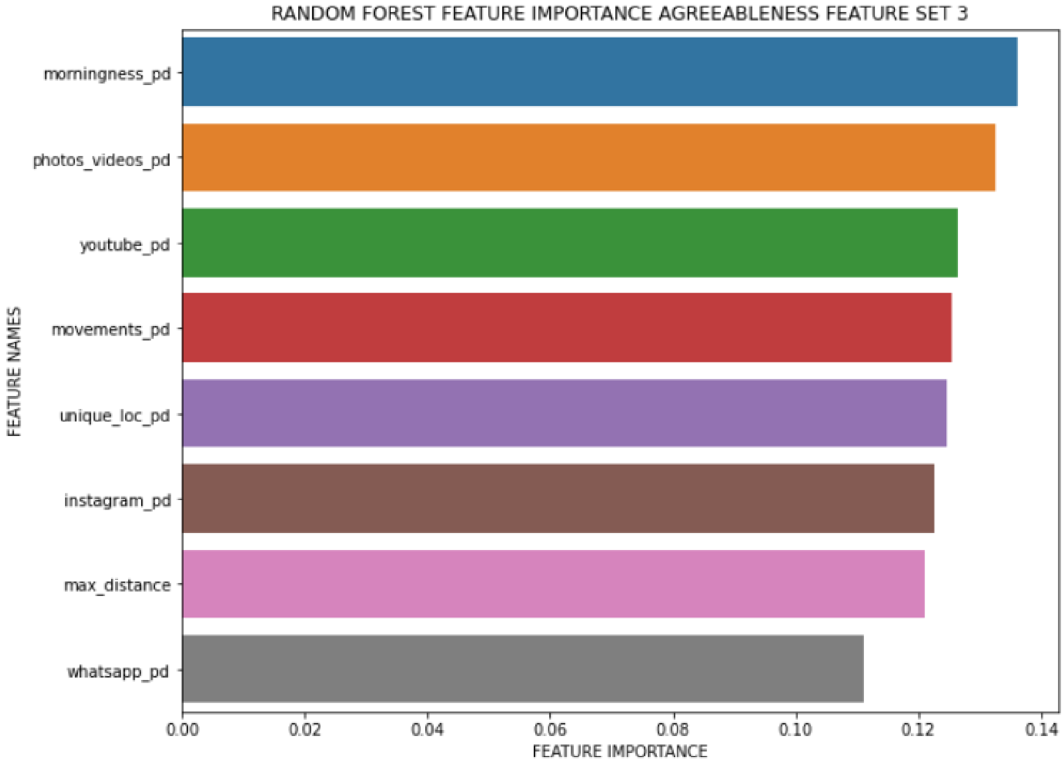


Fig. 7. Most important feature for the best performing model for agreeableness (sorted by importance)

When plotting the most important features of the model with the agreeableness classes, similar results as for the openness personality were shown. In figure 8 the correlation plot is shown and in appendix E.2 are the three other most important features of this personality included, with similar results.

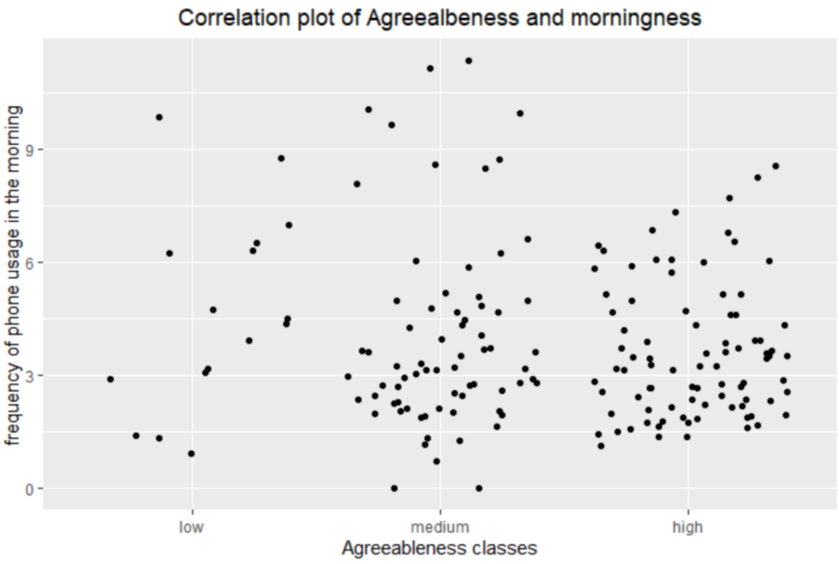


Fig. 8. Correlation plot of openness and the frequency of phone usage in the morning

5.1.6 Neuroticism

For neuroticism, the highest accuracy score was found on combination of feature set one and two with imputations. The accuracy score for the best performing model was 46% which was 6% higher than baseline. The F1-score metric was 0.44, which was close to the accuracy score. However, on the poor classification ratio, the model did not perform well. The ratio was 0.22, which indicates that 22% of the misclassifications were poorly classified.

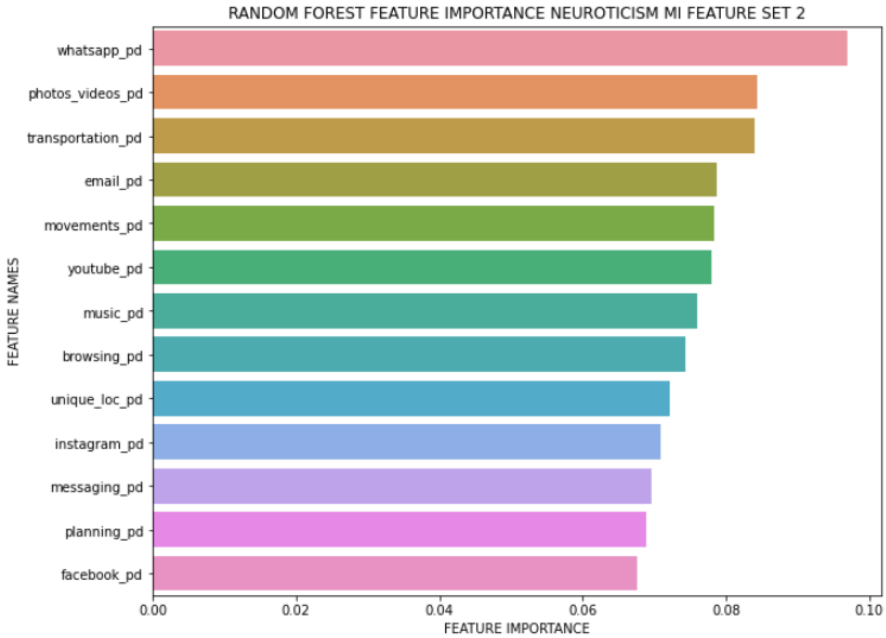


Fig. 9. Most important feature for the best performing model for neuroticism (sorted by importance)

Also, for neuroticism, there was no linear correlation shown when plotting the most important features against the personality classes. Figure 10 shows the correlation between neuroticism and the frequency of WhatsApp usage, other correlation plots are included in appendix E.3.

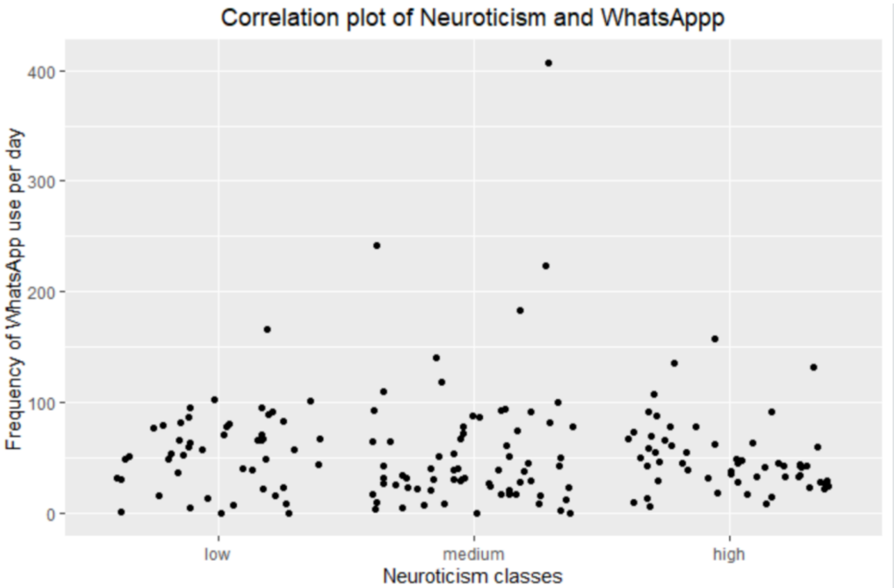


Fig. 10. Correlation plot of neuroticism and the frequency of WhatsApp use

5.1.7 Conscientiousness

Conscientiousness was also predicted above baseline, with a small difference of 3%. However, none of the imputed datasets scored above baseline. The F1-score for this model was 0.53, which was close to the accuracy score of the model. The classification ratio for this model was 0.11, which means that 11% of the misclassifications were poorly classified. The best performing model on imputed datasets showed an accuracy score of 0.5 which is 2% lower than the baseline model. The most important features for the best performing model are visualized in figure 11.

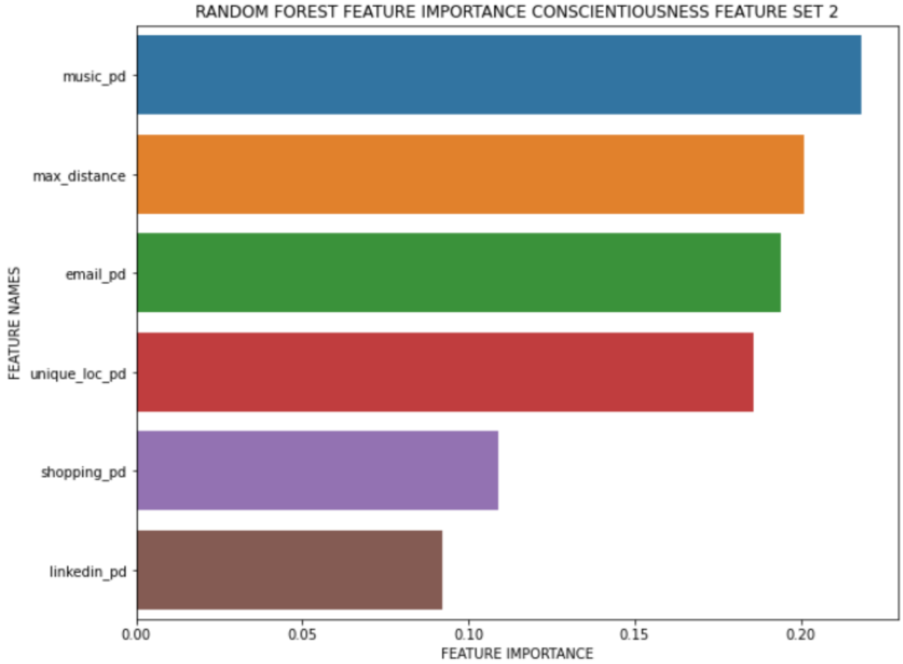


Fig. 11. Most important feature for the best performing model for conscientiousness (sorted by importance)

Similar to the previously shown correlation plots this personality also does not show any linear correlations with the most important features. In figure 12 the correlations between conscientiousness and the frequency of use of music applications is shows and in appendix E.4 the other correlation plots are shown.

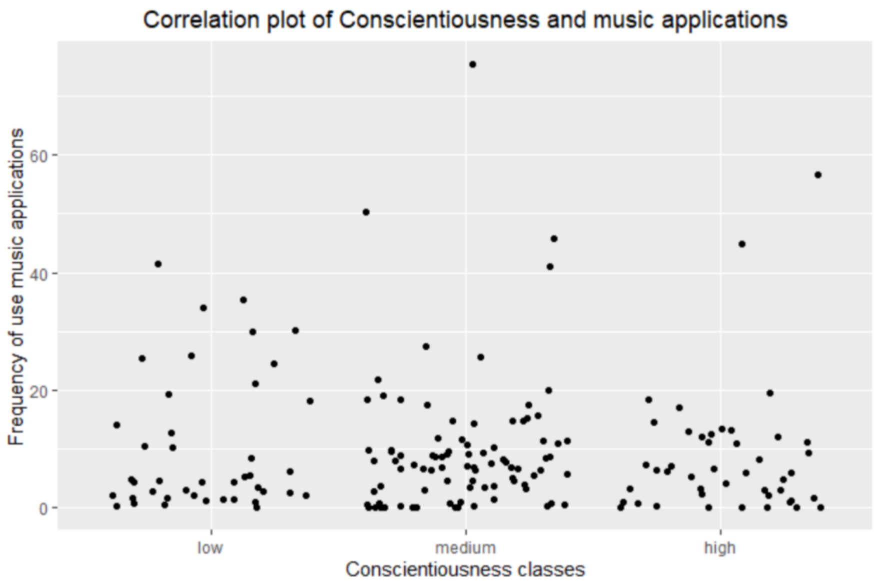


Fig. 12. Correlation plot of conscientiousness and the frequency of music application use

5.1.8 Extraversion

Extraversion was the only personality that could not be predicted above baseline. The scores of the best performing models were equal to the baseline scores. The complete feature sets and the feature sets with imputations could not be predicted above baseline, therefore the feature importances of both models are shown. Figure 13 shows the most important features for the RF model on the complete datasets and figure 14 on the imputed dataset. The results of the feature importance are different, which is expected since the SVM model is a linear model and the RF model is a non-linear model.

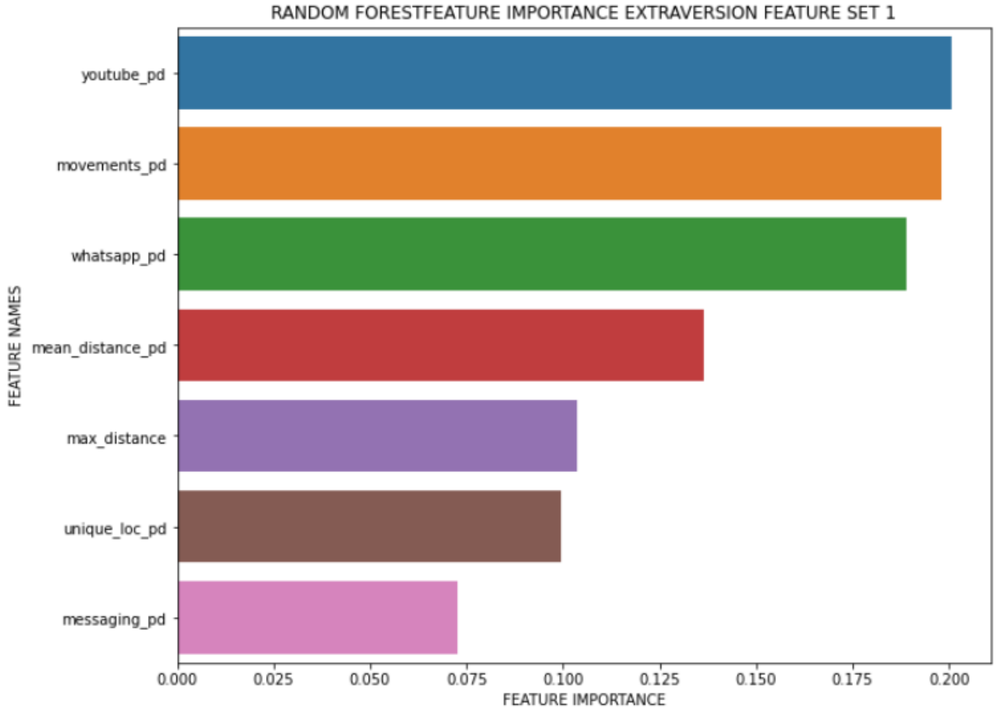


Fig. 13. Most important feature for the best performing model for extraversion (sorted by importance)

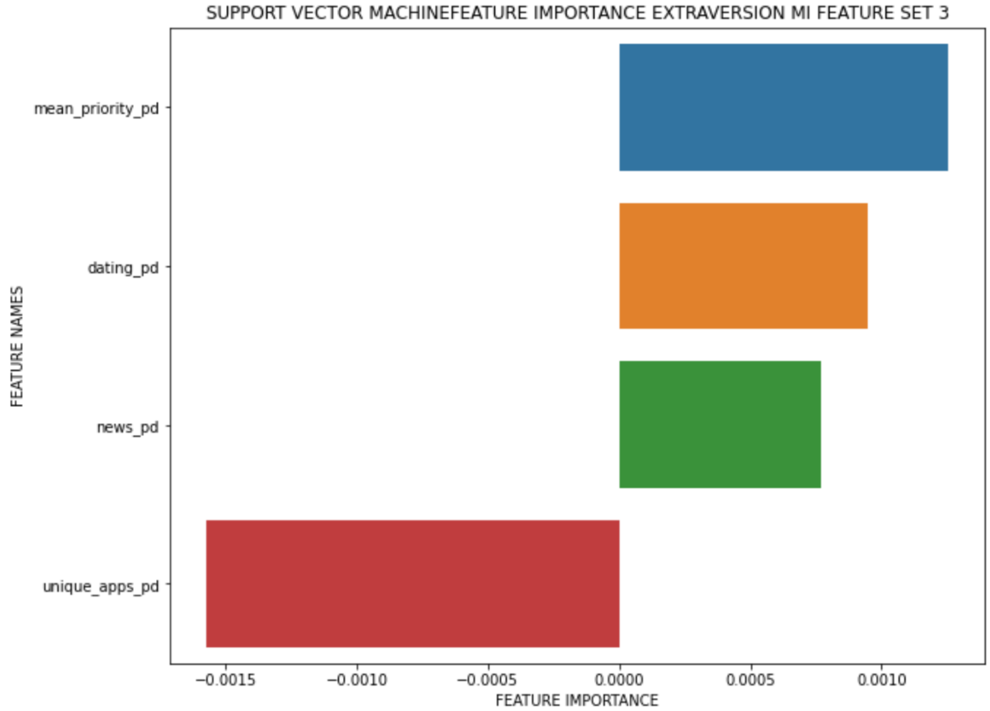


Fig. 14. Most important feature for the best performing model for extraversion (sorted by importance)

Since the SVM model is a linear model, a linear correlation was expected on the feature importance and the personality classes. However, figure 15 does not show any correlations, but this could also be because the coefficient for the frequency of unique locations is very small so the linear correlation could not be visible in the plot. Also, figure 16 does not indicate any linear correlations on the frequency of use of YouTube and extraversion. Other plots on the importances of these models are included in appendix E.5.

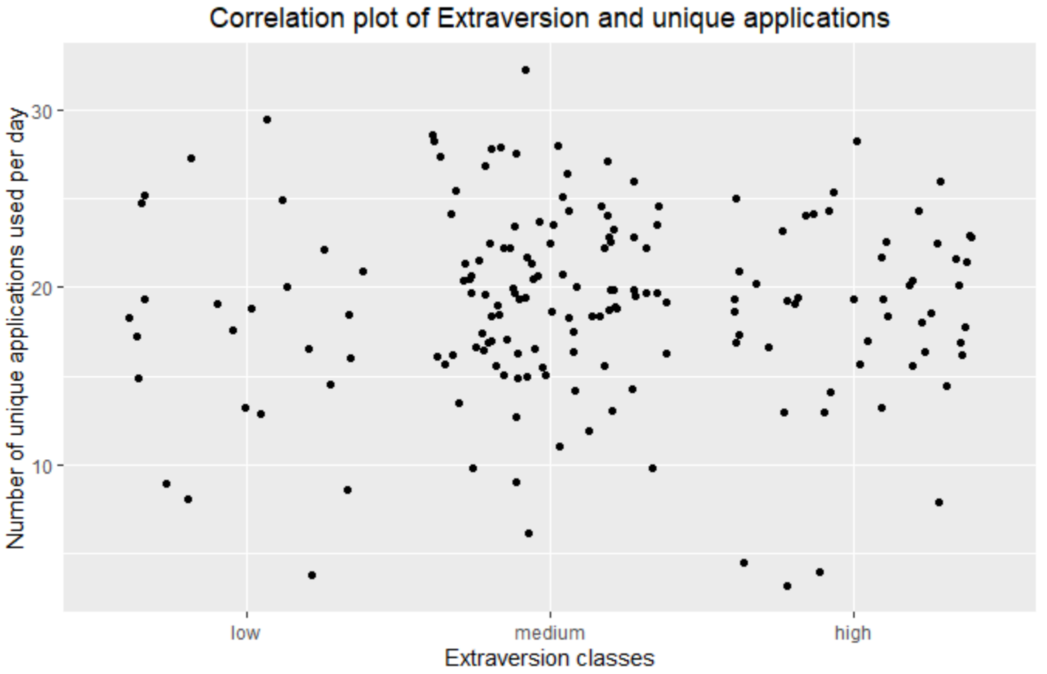


Fig. 15. Correlation plot of extraversion and the number of unique applications

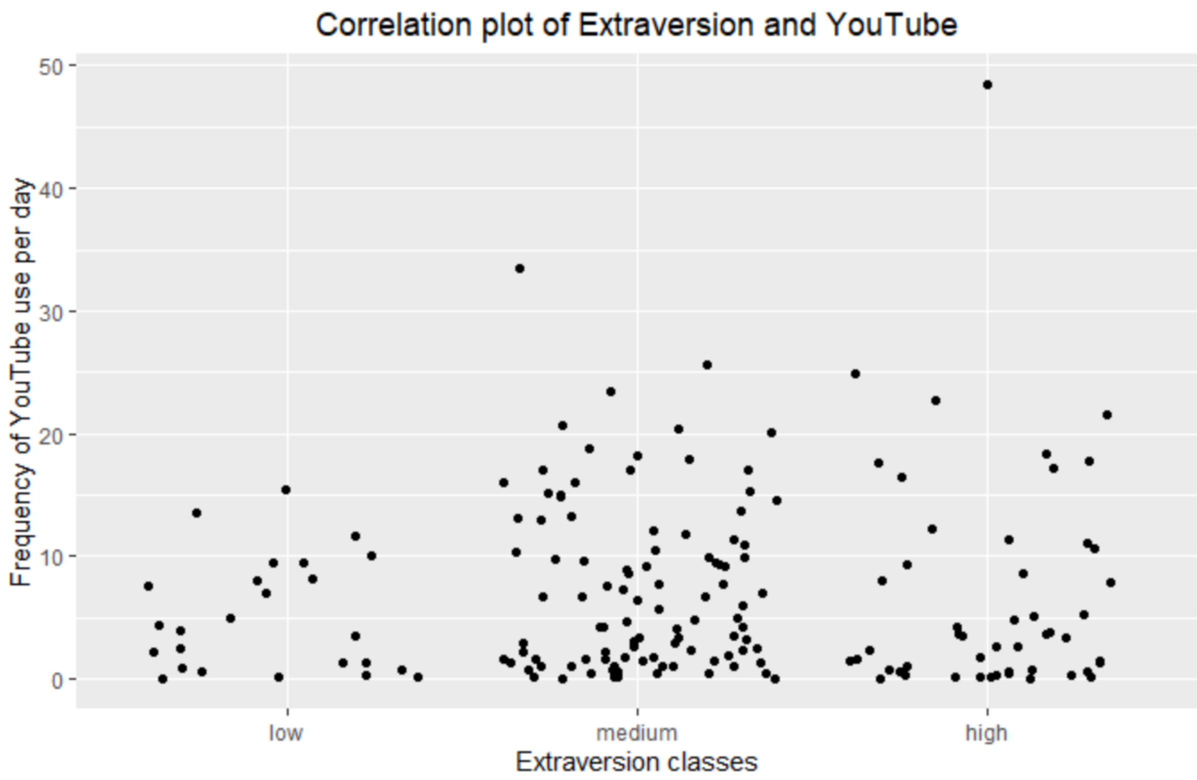


Fig. 16. Correlation plot of extraversion and the frequency of use of the YouTube application

5.2 Intercorrelations on all extracted features

As stated in the results above, there were no linear correlations shown between the personalities and the most important features. However, there could also be intercorrelations between the features when predicting the personalities. A full correlation heatmap on all features is included in appendix F.1.

From the results of the heatmap the correlations lower than 0.5 were filtered out to show the actual correlations of the highly correlated features. The following features, extracted by mean per day, were plotted: frequency of use of YouTube, unique application use, number of notifications, mean time spent on the phone, number of movements, unique locations visited, and evening and morning phone usage. One of the correlation plots is shown in figure 17. It shows a linear correlation between the frequency of use of the YouTube application and the mean time spend on the phone. When the frequency increases the mean time spend on the phone increases as well. In appendix F.2 the correlations between all these highly correlated features are shown.

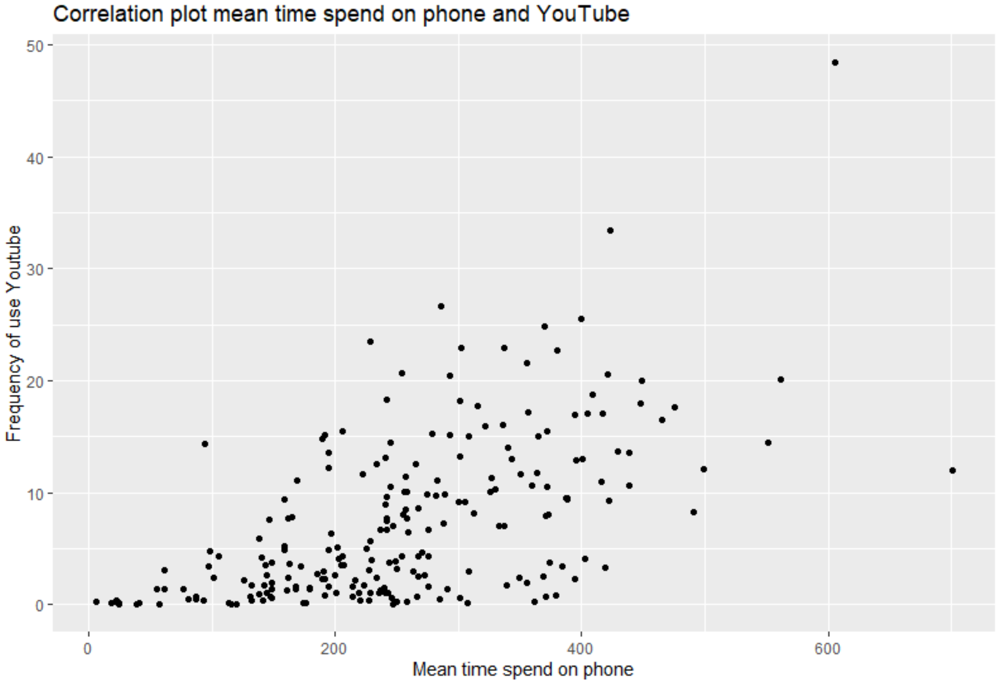
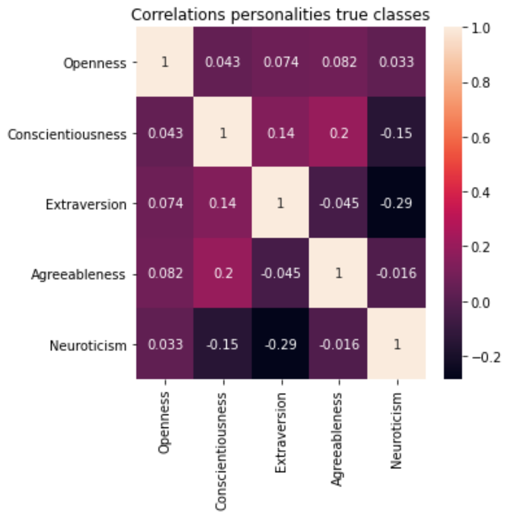


Fig. 17. Correlation plot of the extracted features mean time spend on phone and the frequency of use of YouTube

5.3 Intercorrelations on personalities

To see if there are intercorrelations between the personalities in the dataset being used for this thesis, two correlation heatmaps were created. Figure 18 shows the correlations between personalities with the true classes and figure 19 shows the correlation between the predicted classes. The heatmap for the true classes shows that the majority of the personalities are not correlated to each other. Extraversion and neuroticism are slightly correlated with a negative correlation of -0.29. The correlation heatmap on the predicted classes shows lower correlations between the personalities. The negative correlation between extraversion and neuroticism is smaller in the plot on the predicted classes than for the true values. However, this heatmaps shows a small negative correlation between openness and extraversion, which was not shown in the heatmap for the true correlations.



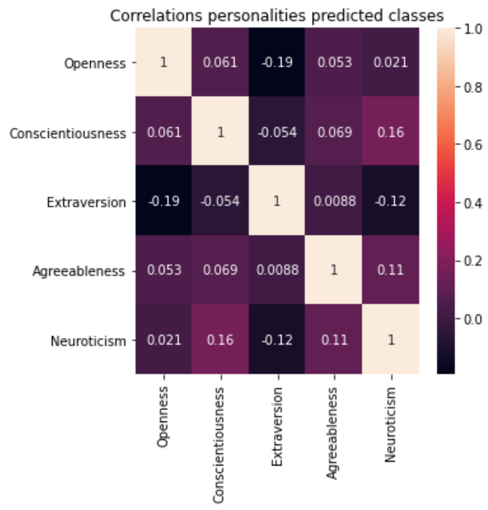


Fig. 18. Heatmap of correlations true personality classes

Fig. 19. heatmap of correlations predicted personality classes

All five personality scores were predicted for the participants from whom the data was collected. In other words, five predictions were made by five different models on every participant. This could mean that some personalities were predictable for participants and some were not. In figure 20 is the frequency visualized on how many personalities were correctly predicted on all participants. The results of the combination of best performing models on every personality were used to create this plot. For most of the participants, two or three out of the five personalities were correctly predicted. For just a few participants all personalities or none of the personalities were correctly predicted.

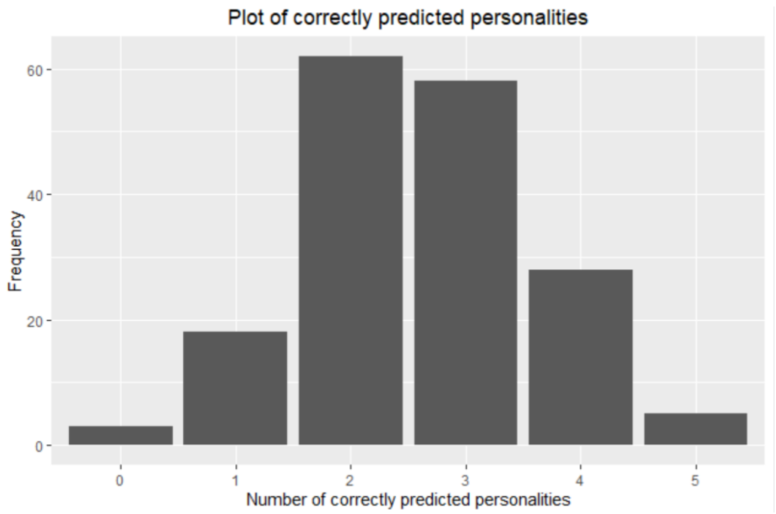


Fig. 20. Plot of the correctly predicted personalities of all participants

6 Discussion

The goal of this study was to predict the big five personalities based on features extracted from phone usage data. Along the process of aiming at the highest accuracy score, several feature sets were extracted and different models were fitted to combined feature sets. Also, the feature importance was retrieved from the models and correlation plots were created to visualize possible correlations between the most important features of the best scoring models and the personality the model belonged to. Besides, the intercorrelations of only the features and only the personalities have been looked into. The feature extraction of this study is based on several features of previous studies that have been successfully predicting personality and combined all together in several feature sets. Below the results per model, the results of the intercorrelations on the features, and the personalities will be compared to the results of previous studies mentioned in the related work section.

6.1 Discussion per personality

In the paragraph below the results and comparison to related work will be discussed separately.

6.1.4 Openness

The best predicting model, compared to the baseline results, was the RF model with the feature selection of feature set one, two, and three combined for the personality openness. In the literature, communication applications, camera usage, music applications and distance information were mentioned as the most influential (Stalch et al., 2020). The most important feature in the model of this study was YouTube, which could be listed as a communication application since this is a social media application (Klobas et al., 2018). However, this application serves several purposes and the data collection in this research could not show any context of the application use of the participants. The other application that could be categorized as a communication application would be Instagram, which was ranked sixth most important feature in this model. Spatial features as long-distance movements and visiting far places were also found influential by Alessandretti et al. (2018) and Chorley et al. (2015). In the best performing model for openness, the only spatial feature that was found important was the mean distance feature, which was ranked as the fourth most important in the model. McCrae & John (1992) described the facets for openness as people that tend to long for variety and experiences. These facets could be related tot traveling, and so this could explain the importance of the mean distance feature. However, since actual correlations are not visible in the correlation plots its is not possible to make any statements about this. The other three spatial features were not of influence on the performance of the model. Also, photo and video related applications and music applications were not of influence in the prediction of openness.

6.1.5 Agreeableness

Also, for agreeableness, the communication applications were found influential on this personality. The best performing model for agreeableness was found using the RF model with the combination of feature sets one, two, and three. The usage of the YouTube application, similar to what was found in the literature (Klobas et al., 2018), was found influential on the predictions of this personality. However, just as mentioned for openness there was not enough context on this application and the correlation plot did not show a particular correlation between this feature and the personality classes. Peltonen et al. (2020) found that agreeableness was correlated with communication applications. The results of the model for this personality also showed the importances of communication features, which were WhatsApp and Instagram. Prior research on the influence of spatial data on agreeableness showed that this personality was positively correlated to a large range of movements (Ai et al., 2019). The results of the model showed that the maximum distance feature was found important in predicting personality. The actual correlation between this feature and the personality was not visible in the plot.

6.1.6 Neuroticism

For neuroticism the best performing model was trained on the combined feature sets 1 and 2 with imputations. The most important feature that was retrieved from this model was the frequency of

WhatsApp usage. In research by Montag et al (2015) WhatsApp was also found influential on this personality. The frequency of use of YouTube was shown as important in the results of the best performing model for neuroticism, this was also shown in the study conducted by Klobas et al. (2018). Moreover, communication applications, in general, were found negatively correlated in the literature (Peltonen et al., 2019). The importance was also shown in this research, but also for neuroticism it was not possible to find actual correlations between the applications and the personality classes. Lastly, notification features were mentioned as an influence on this personality (Mehrotra et al, 2016), but the results of the model did not show any importance of notification features.

6.1.7 Conscientiousness

For conscientiousness, the RF model of the combination of the feature sets one and two were found the most accurate compared to the baseline model. In the literature, many features were mentioned as influential on this personality, such as time spent on phone, unique application frequency, battery level (Stalch et al., 2020), WhatsApp usage (Montag et al., 2015), and YouTube usage (Klobas et al., 2018), and notifications (Mehrotra et al., 2016). However, none of the features mentioned in the literature were retrieved as important from the best performing model on conscientiousness.

6.1.8 Extraversion

The accuracy scores for extraversion were not as high as expected. However, for the personality's openness, agreeableness, neuroticism, and conscientiousness, the accuracy scores of their best performing models were higher than their baseline models. This means that the models would predict the personality better than if the most frequent class of the personality was predicted. Surprisingly, the personality extraversion was the only personality that was found not predictable in this study, despite that the majority of previous research found this personality most predictable and therefore most of the extracted features were based on this success (Alessandretti et al., 2018; Harari et al., 2019; Peltonen et al., 2020; Ai et al., 2019).

Montag et al. (2015) found WhatsApp influential in predicting extraversion, this was also shown in the results of the best performing model for extraversion. This could also be linked to the facets mentioned by McCrae & John (1992) who name social as a characteristic of the personality and WhatsApp is mainly used to stay in touch with others. Another similarity with the results of Ai et al. (2019) and Alessandretti et al. (2018) that was found in this research was the influence of spatial features on the prediction of extraversion.

6.2 Intercorrelations all features

The results on the intercorrelation between all features that have been extracted, showed that some features were highly correlated. However, since no actual correlation between the feature importances and the personality classes can be shown, it is hard to make any statements about these intercorrelations.

6.3 Intercorrelations personalities

In the literature is stated that the five personalities are independent (McCrae & John, 1992). Meta-analysis on intercorrelations between the personalities showed some negative correlations between conscientiousness and neuroticism, extraversion and neuroticism, and agreeableness and neuroticism (van der Linden et al., 2010). Also, Mønsted et al. (2018) found the negative correlation between neuroticism and extraversion. The results of the intercorrelation heatmap on the true classes showed also a small negative correlation between extraversion and neuroticism. However, in their study, an intercorrelation of the same size was also shown between agreeableness and extraversion. This was not shown in the results of this research, also the other correlations of van der Linden (2010) were not shown in the results of this research. On the predicted classes the intercorrelations were smaller than on the true classes. However, in this heatmap, there is a small negative intercorrelation shown for the personality's extraversion and openness.

6.4 Limitations

From the comparisons between previous studies and this study can be seen that there are a lot of differences in the findings. One of the main reasons for this could be that the previous studies were not generalizable and the participants were from another country, which could indicate cultural differences that lead to different results in the personalities (Harari, 2020). So, applying similar models with similar feature sets could still output different results due to different participants.

Another limitation that could be mentioned is that the phone usage data for this research did not have any context on the application specific. For example, there was no actual data on what videos were watched when using the YouTube application or what messages were send with the WhatsApp applications. In researches by Montag et al. (2015) and Klobas et al. (2018), there was more information on these application use. However, this could lead to privacy concerns since collecting more data and more specific data would be privacy sensitive and should be according to the GDPR regulation (Harari, 2020). Besides, the data collection used for this research exists of 221 participants, which means that the data set that the models were fitted to contained 221 instances. If more there were more people participating there would be more data to fit the models too, which could have led to better model performance (Mønsted et al., 2018).

Due to time limitations, not all possible features were extracted from the raw data collection, grid search was not applied to the tested models and not all possible models have been tested. Based on findings from previous studies features were extracted for this study. However, there are more features that could be extracted from this data set. For example, the duration that applications have been used by the participants could be extracted or there could be more categories selected for feature extraction, such as gaming applications or sport related applications. Grid search could have been applied for parameter tuning to all models that have been tested, which could lead to higher model performances and prevents models from overfitting (Lameski, Zdravevski, Mingov & Kulakov, 2015). This study only focused on three models, which were selected based on the possibility of explainability and interpretability. However, different models could have been tested and could have led to different results.

7 Conclusion

The personalities openness, conscientiousness, agreeableness, and neuroticism can be predicted above baseline based on smartphone usage, where openness was the best predictable personality. This means that the predictions from the machine learning models would provide higher accuracy than when the majority class per personality would be predicted. Despite the findings from the literature, in this research extraversion was not predictable above baseline.

To provide an answer to the main research questions the three sub-questions were answered. The first sub-question was formulated as follows: “Which features can be extracted from the phone usage data to predict the big five personalities?”. From the raw phone usage data collection features on spatial information, frequency of use of communication applications, frequency of use of other applications categorized by purpose, notifications, battery percentage, phone usage of different phases of the day, and the mean time spent on the phone, have been extracted.

These features were used to answer the second sub-question: “Which classification machine learning techniques predict each independent personality most accurately?”. For all four successfully predicted personalities the random forest model was the model with the highest accuracy. For extraversion, the highest accuracy score was found using the support vector machine model on the linear kernel.

The third sub-question is the following: “Which features are most important in predicting personality?”. In appendix D a full overview is shown of the most important features per personality. These importances would indicate which data should be collected when predicting a certain personality using the same model on new data. The actual correlations could not be shown in the correlation plots since there was no linear correlation between the features and the personality.

Even though most of the personalities were predicted above baseline, the predictions on the personalities are still considered to be poor. It would not be advised to use these models on predicting personality, since the models outperformed the baseline with a minor difference. Also, the dataset used for this research is small, which does not make this research generalizable. Suggestions for further research on the same data collection could be extraction of more features, applying grid search on the models for parameter tuning, and fitting other classification models than used in this research. Another possibility would be fitting regression machine learning models to the data to try to get more accurate predictions. However, it would be hard to compare the results of regression models with the results of classification models, since these models would have other evaluation metrics.

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Appendices and Supplementary Materials

Appendix A – Categorized applications

Table 3. Table on categorization of the applications

Category	Application name
Transportation	google.apps.maps
	negentwee
	ns
	mapswithme.maps.pro
	flitsmeister
	ubercab
	hafas.db
	flixbus
music	spotify.music
	music
	soundcloud
	google.music
	shazam
	spotify.musid
	apple.music
	e247.radio538
	musicplayer.playermusic
	musicplayer.musicapps.music.mp3player
	musicfx
	nakko.radio538
	download.music.musicmp3pro
video_streaming	netflix
	rtl.videoland
	disneyplus
	uitzendinggemist
	dumpert
	lgi.ziggotv
weather	net.weather
	xs2theworld.weeronline
	weather
	totemweatherapp
	weather2
	org.yoki.buienalarm
	totemweather
	supportware.Buienradar
shopping	marktplaats
	unitedwardrobe
	asos
	amazon.mShop.shopping
	zalando.mobile
	hm.goe

	zalando.lounge
	ebay.mobile
	fr.vinted
	bol.shop
	hema.hey
	wehkamp.shop
	inditex.pullandbear
	ingka.ikea
	hema.mobiel
	alibaba.aliexpresshd
photos and videos	camera
	google.apps.photos
	gallery3d
	video
	gallery
	videoplayer
	google.GoogleCamera
	camera2
	mediacenter
	mimage.photoretouching
	smartcapture
	sonyericsson.album
browsing	browser
	sbrowser
	brave.browser
	chrome
	google.googlequicksearchbox
	org.mozilla.firefox
	ecosia
dating	tinder
	bumble
	badoo.mobile
	muzmatch.muzmatchapp
	ftw_and_co.happn
	grindrapp
email	email.provider
	email
	google.gm
	microsoft.office.outlook
	web.mobile.mail
	yahoo.mobile.client.mail
planning	calendar
	memo
	voicenote
	reminder
	clockpackage

	google.calendar
	example.notepad
	note
	coloros.alarmclock
	simplemobiletools.calendar
	alarmclock.xtreme.free
	microsoft.todos
	ibridge.planning
	worldclock
	deskclock
	notes
	google.deskclock
	socialnmobile.dictapps.notepad.color.note
	clock
	stayfocused
	apalon.myclockfree
	ztnstudio.notepad
	cc.forestapp
	google.keep
	works.jubilee.timetree
food_ordering	ubercab.eats
	takeaway
	deliveroo.orderapp
	mcdonalds.mobileapp
News	nos
	rtl.rtlnieuws
	bbc.mobile.news.ww
	sanomamedia.nu
	be.persgroep.news.mobilead

Appendix B - Extracted features

Table 4. Table of all extracted features, their description and the number of the feature set

Note: p.d. = per day. The mean has been computed over the number of days phone usage data has collected per participant.

Sort		Feature	description	Featureset
Spatial	1.	Movements p.d.	Frequency of participants moving from one place to another per day	F1
	2.	Mean distance p.d.	Computation of the distance participants travel per day	F1
	3.	Unique locations p.d.	Frequency of unique locations participants visited per day	F1
	4.	Maximum distance travelled	Maximum distance the participants travelled over the time of data collection	F1
Communication applications	5.	WhatsApp frequency p.d.	Frequency of WhatsApp use per day	F1
	6.	Facebook frequency p.d.	Frequency of Facebook use per day	F1
	7.	Instagram frequency p.d.	Frequency of Instagram use per day	F1
	8.	Snapchat frequency p.d.	Frequency of Snapchat use per day	F1
	9.	YouTube frequency p.d.	Frequency of YouTube use per day	F1
	10.	Twitter frequency p.d.	Frequency of Twitter use per day	F1
	11.	LinkedIn frequency p.d.	Frequency of LinkedIn use per day	F1
	12.	Messaging frequency p.d.	Frequency of Messaging application use per day	F1
	13.	Calling frequency p.d.	Frequency of calling per day	F1
Applications (categorised)	14.	Transportation p.d.	Frequency of transportation applications use per day	F2
	15.	Music p.d.	Frequency of music applications use per day	F2
	16.	Video streaming p.d.	Frequency of video streaming applications use per day	F2
	17.	Weather p.d.	Frequency of weather applications use per day	F2
	18.	Shopping p.d.	Frequency of shopping applications use per day	F2
	19.	Photos and videos p.d.	Frequency of photo and video related applications use per day	F2
	20.	Dating p.d.	Frequency of dating applications use per day	F2
	21.	Browsing p.d.	Frequency of browsing applications use per day	F2
	22.	Email p.d.	Frequency of email applications use per day	F2
	23.	Planning p.d.	Frequency of planning applications use per day	F2
	24.	Food ordering p.d.	Frequency of food ordering applications use per day	F2
	25.	News p.d.	Frequency of news applications use per day	F2

Notifications	26.	Notifications p.d.	Frequency of received notifications per day	F3
	27.	Priority p.d.	Sum of priority of received notifications per day	F3
Other	28.	Number of unique apps p.d.	Frequency of all unique application use per day	F3
	29.	Duration p.d.	Total time spend on smartphone per day	F3
	30.	Morningness p.d.	Frequency of application use in the morning per day	F3
	31.	Eveningness p.d.	Frequency of application use in the evening per day	F3
	32.	Battery percentage p.d.	Mean battery percentage per day	F3

Appendix C – Evaluation metrics of all classification models

Tabel 5. Evaltuation metrics of all classification models

O	C	E	A	N	Model	dataset	feature set	metric
0.46	0.53	0.57	0.5	0.39	RF	complete	1	accuracy
0.08	0.11	0	0.15	0.21	RF	complete	1	miss classification rate
0.44	0.49	0.41	0.42	0.38	RF	complete	1	weighted F1 score
0.41	0.49	0.55	0.49	0.34	LR	complete	1	accuracy
0.12	0.03	0.01	0.14	0.15	LR	complete	1	miss classification rate
0.39	0.38	0.46	0.44	0.32	LR	complete	1	weighted F1 score
0.47	0.5	0.57	0.5	0.4	SVM	complete	1	accuracy
0.03	0	0	0.18	0	SVM	complete	1	miss classification rate
0.37	0.34	0.41	0.34	0.24	SVM	complete	1	weighted F1 score
0.45	0.46	0.53	0.5	0.39	RF	imputed	1	accuracy
0.09	0.07	0.07	0.09	0.25	RF	imputed	1	miss classification rate
0.43	0.41	0.46	0.47	0.39	RF	imputed	1	weighted F1 score
0.43	0.5	0.57	0.52	0.37	LR	imputed	1	accuracy
0.05	0.05	0	0.18	0.12	LR	imputed	1	miss classification rate
0.38	0.37	0.41	0.45	0.33	LR	imputed	1	weighted F1 score
0.51	0.5	0.6	0.49	0.39	SVM	imputed	1	accuracy
0.07	0	0	0.15	0.03	SVM	imputed	1	miss classification rate
0.46	0.33	0.45	0.32	0.22	SVM	imputed	1	weighted F1 score
0.45	0.55	0.54	0.51	0.42	RF	complete	2	accuracy
0.07	0.11	0.07	0.08	0.24	RF	complete	2	miss classification rate
0.43	0.53	0.48	0.48	0.4	RF	complete	2	weighted F1 score
0.46	0.49	0.55	0.54	0.41	LR	complete	2	accuracy
0.11	0.04	0.03	0.11	0.16	LR	complete	2	miss classification rate
0.45	0.41	0.44	0.49	0.4	LR	complete	2	weighted F1 score
0.43	0.5	0.57	0.5	0.39	SVM	complete	2	accuracy
0.06	0	0	0.18	0	SVM	complete	2	miss classification rate
0.4	0.34	0.41	0.34	0.24	SVM	complete	2	weighted F1 score
0.4	0.47	0.54	0.5	0.46	RF	imputed	2	accuracy
0.1	0.08	0.04	0.07	0.22	RF	imputed	2	miss classification rate
0.38	0.41	0.48	0.47	0.44	RF	imputed	2	weighted F1 score
0.51	0.5	0.56	0.5	0.37	LR	imputed	2	accuracy
0.06	0.03	0.03	0.12	0.14	LR	imputed	2	miss classification rate
0.48	0.4	0.45	0.39	0.31	LR	imputed	2	weighted F1 score
0.5	0.5	0.6	0.49	0.39	SVM	imputed	2	accuracy
0.07	0	0	0.15	0.02	SVM	imputed	2	miss classification rate
0.46	0.33	0.45	0.32	0.23	SVM	imputed	2	weighted F1 score
0.55	0.52	0.55	0.56	0.38	RF	complete	3	accuracy
0.09	0.13	0.08	0.04	0.27	RF	complete	3	miss classification rate
0.52	0.49	0.49	0.53	0.37	RF	complete	3	weighted F1 score
0.46	0.46	0.55	0.52	0.37	LR	complete	3	accuracy
0.11	0.06	0.04	0.13	0.12	LR	complete	3	miss classification rate
0.45	0.39	0.46	0.49	0.33	LR	complete	3	weighted F1 score

0.46	0.5	0.57	0.5	0.39	SVM	complete	3	accuracy
0	0	0	0.18	0	SVM	complete	3	miss classification rate
0.29	0.34	0.41	0.34	0.24	SVM	complete	3	weighted F1 score
0.51	0.5	0.57	0.54	0.39	RF	imputed	3	accuracy
0.09	0.08	0.05	0.09	0.24	RF	imputed	3	miss classification rate
0.5	0.46	0.52	0.51	0.39	RF	imputed	3	weighted F1 score
0.42	0.5	0.55	0.53	0.37	LR	imputed	3	accuracy
0.14	0.03	0.03	0.13	0.16	LR	imputed	3	miss classification rate
0.4	0.39	0.44	0.47	0.33	LR	imputed	3	weighted F1 score
0.45	0.5	0.6	0.49	0.39	SVM	imputed	3	accuracy
0	0	0	0.15	0	SVM	imputed	3	miss classification rate
0.27	0.33	0.45	0.32	0.22	SVM	imputed	3	weighted F1 score

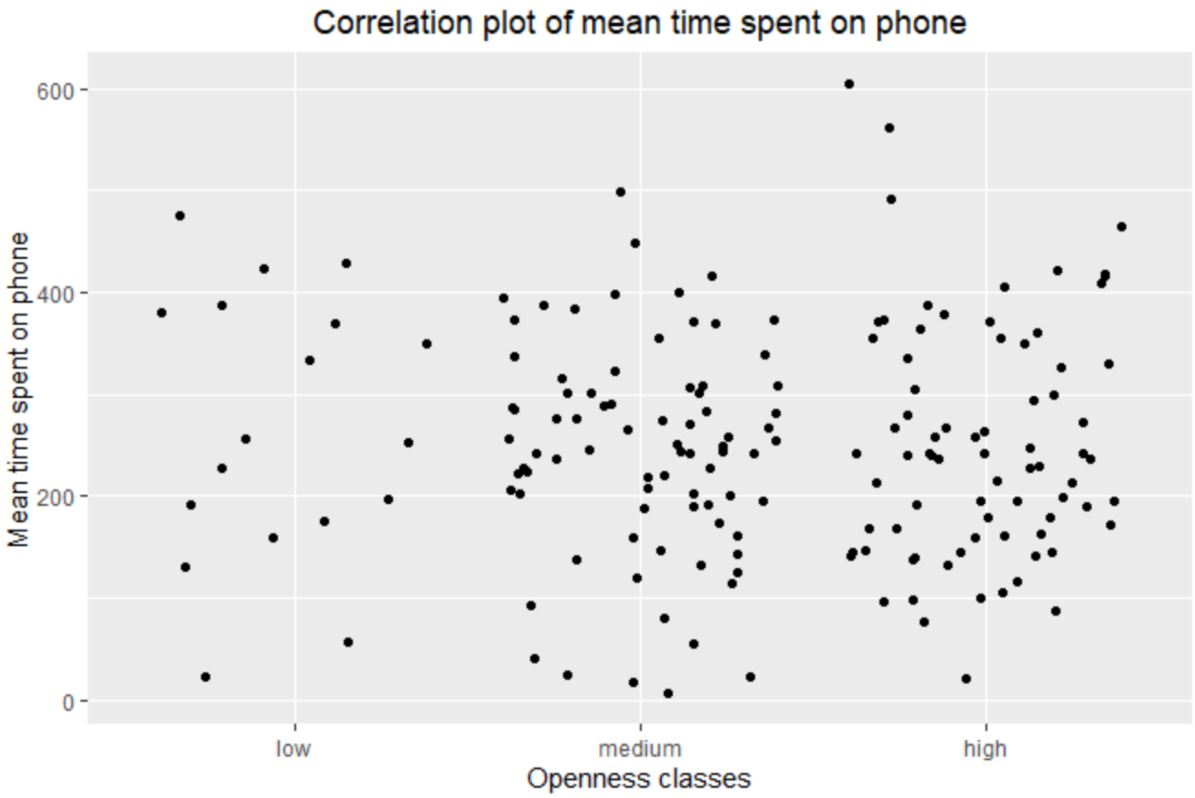
Appendix D – Feature importances per personality

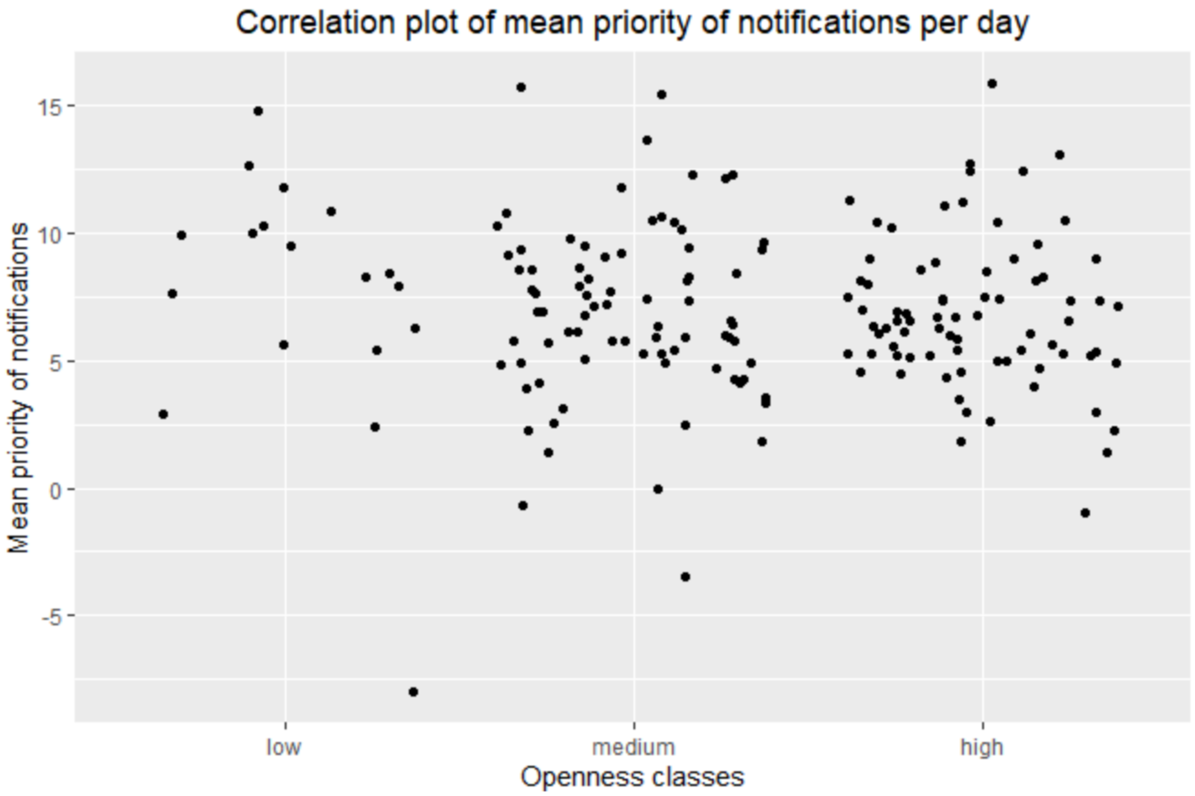
Table 6. All features and the importances per personality

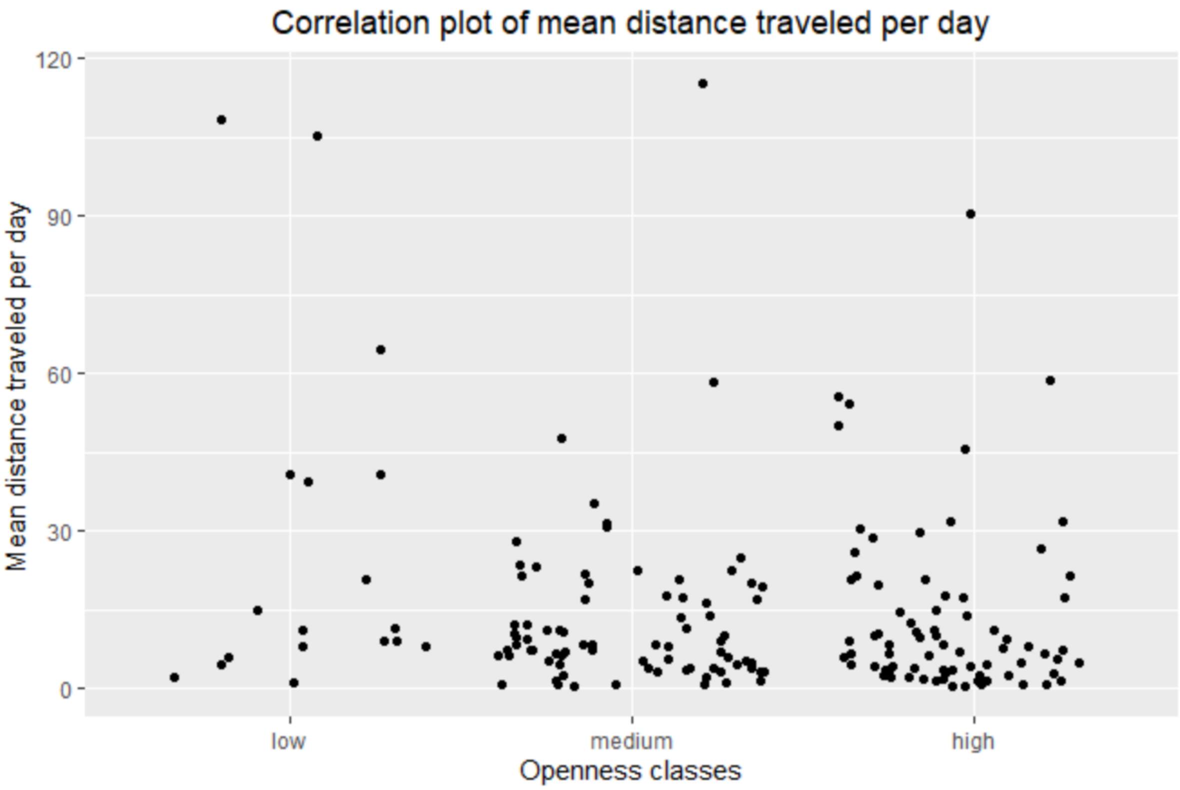
Feature	O	C	E	A	N
Movements p.d.			X	X	X
Mean distance p.d.	X		X		
Unique locations p.d.		x	X	X	X
Maximum distance travelled		X	X	X	
WhatsApp frequency p.d.			X	X	X
Facebook frequency p.d.					X
Instagram frequency p.d.	X			X	X
Snapchat frequency p.d.	X				
YouTube frequency p.d.	X		X	X	X
Twitter frequency p.d.					
LinkedIn frequency p.d.		X			
Messaging frequency p.d.			X		X
Calling frequency p.d.					
Transportation p.d.					X
Music p.d.		X			X
Video streaming p.d.					
Weather p.d.	X				
Shopping p.d.		X			
Photos and videos p.d.				X	X
Dating p.d.					
Browsing p.d.					X
Email p.d.		X			X
Planning p.d.					X
Food ordering p.d.					
News p.d.					
Notifications p.d.					
Mean priority p.d.	X				
Number of unique apps p.d.					
Duration p.d.	X				
Morningness p.d.	X			X	
Eveningness p.d.	X				
Battery percentage p.d.	X				

Appendix E - Correlation plots of feature importance personalities

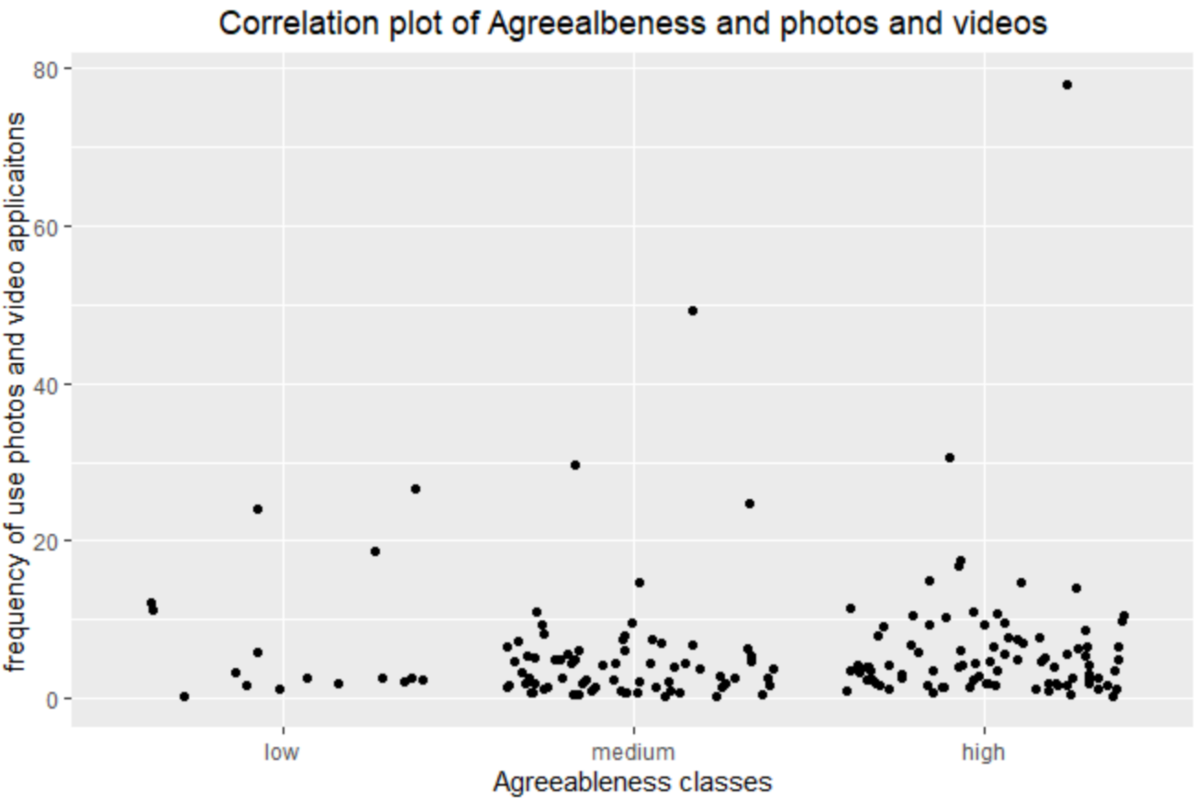
E.1 Openness

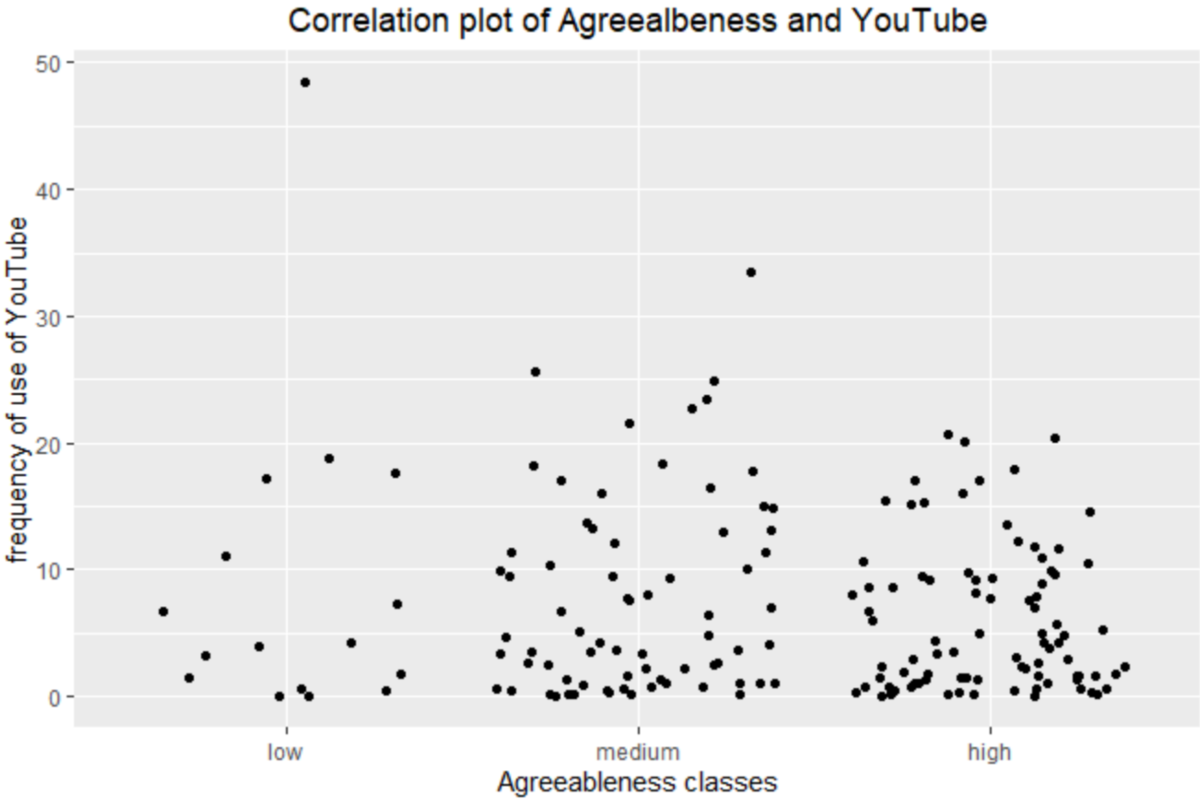


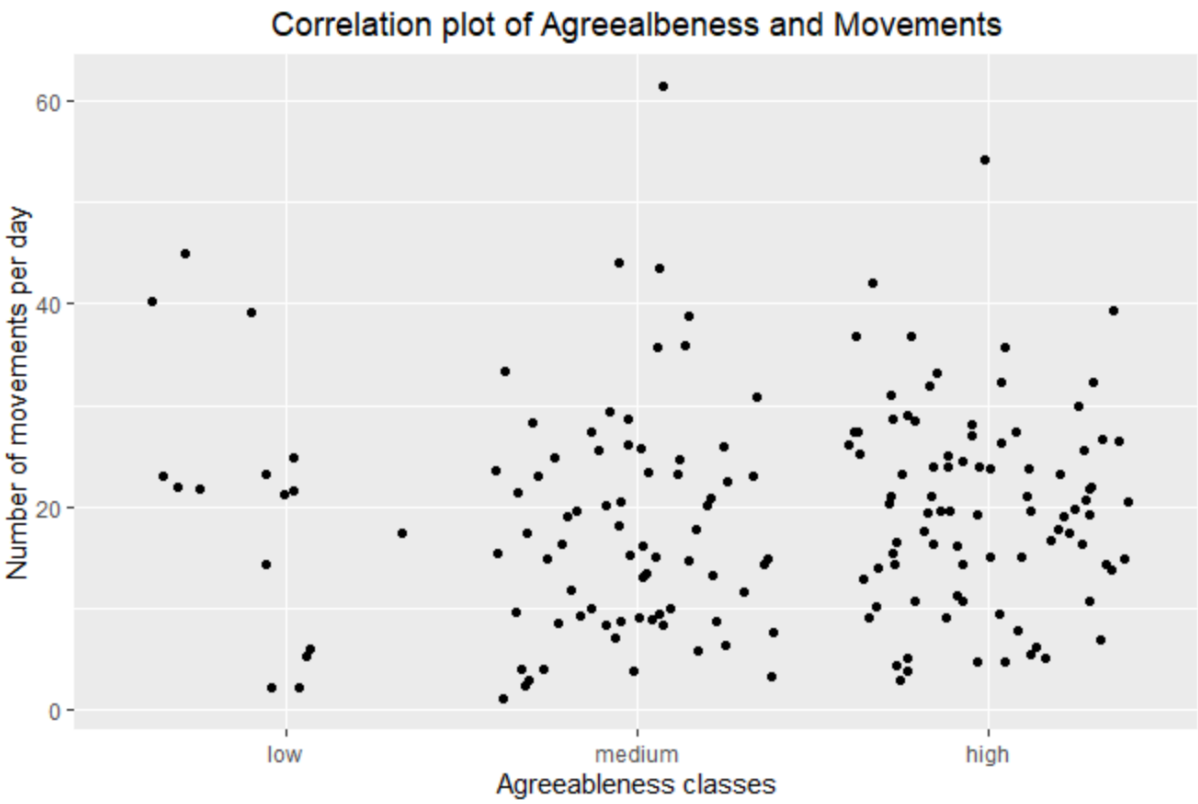




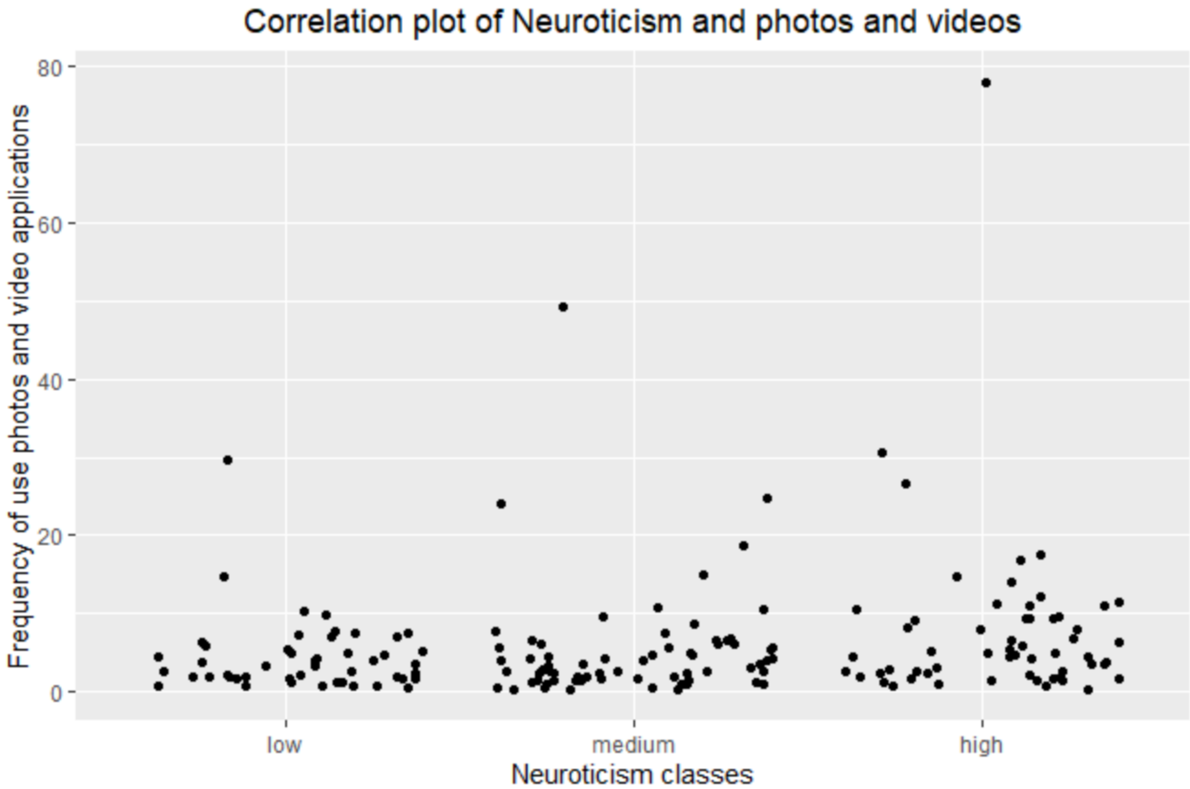
E.2 Agreeableness

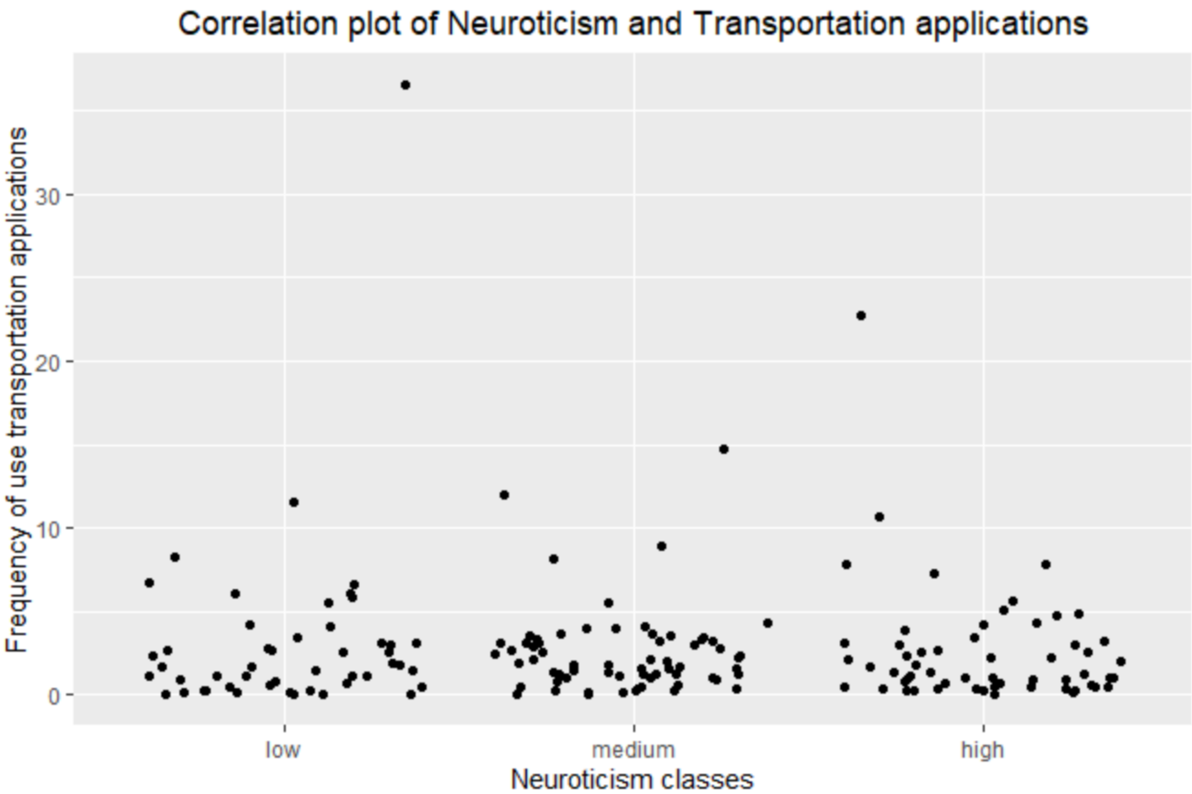


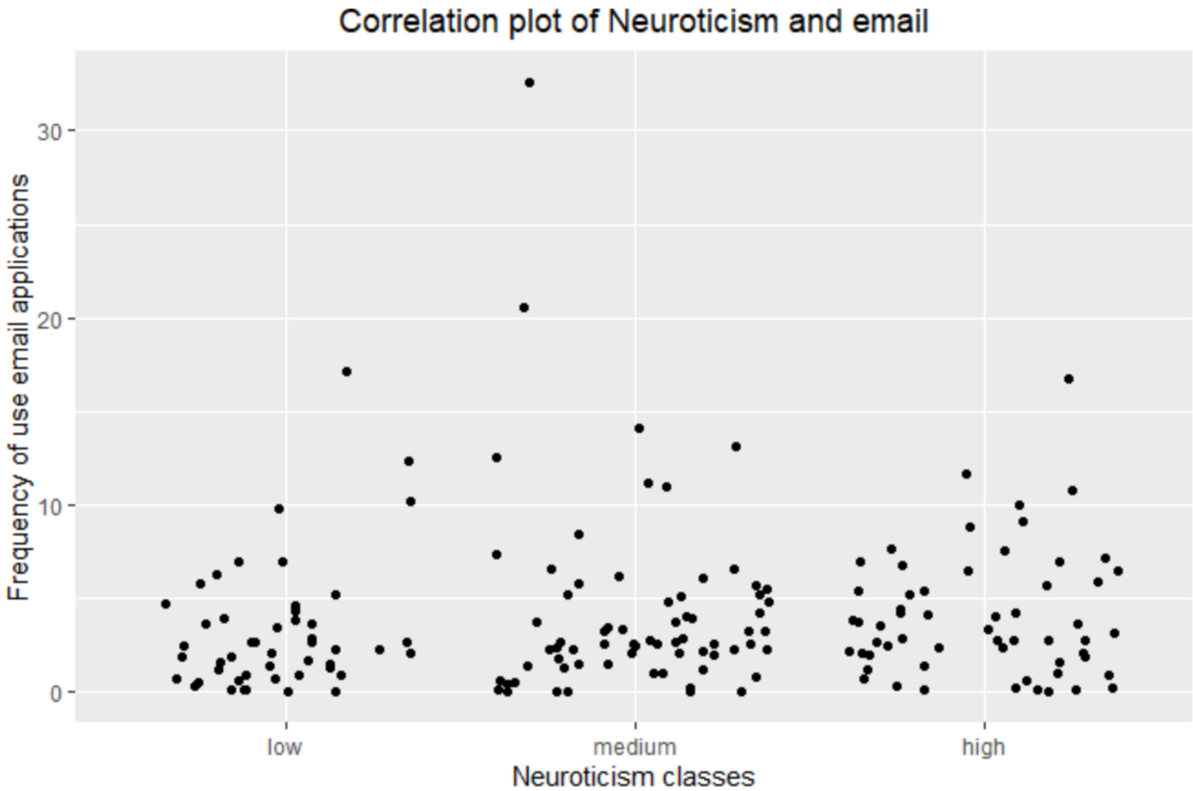

Correlation plot of Agreealbeness and YouTube
frequency of use of YouTube
0
10
20
30
40
50
low
medium
high
Agreeableness classes


Correlation plot of Agreealbeness and Movements
Number of movements per day
0
20
40
60
low
medium
high
Agreeableness classes

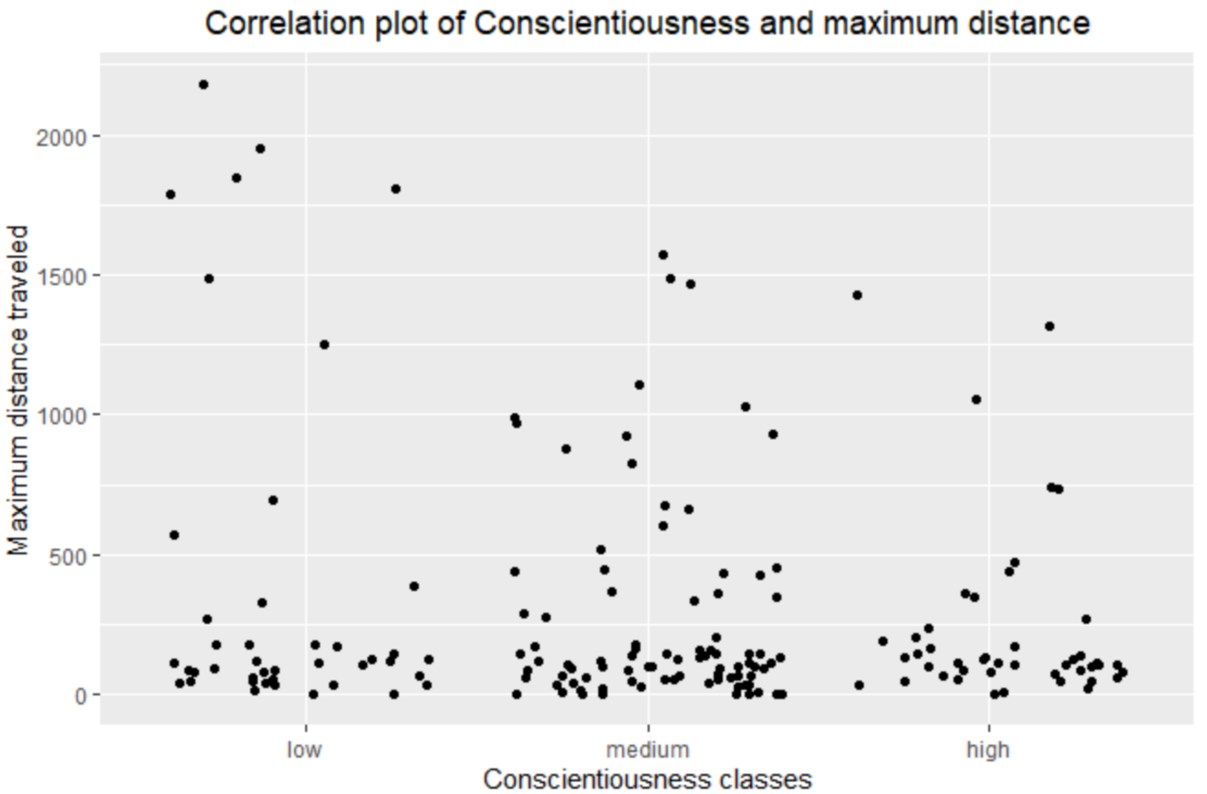
E.3 Neuroticism

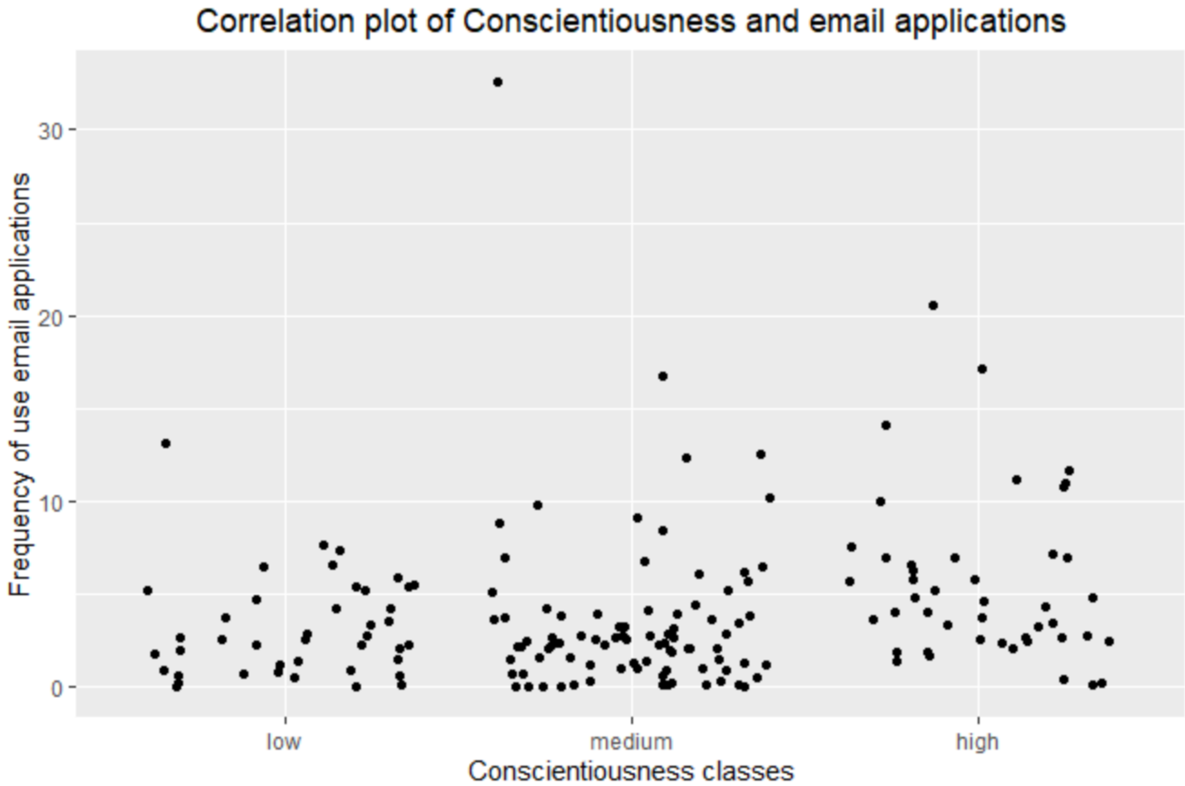


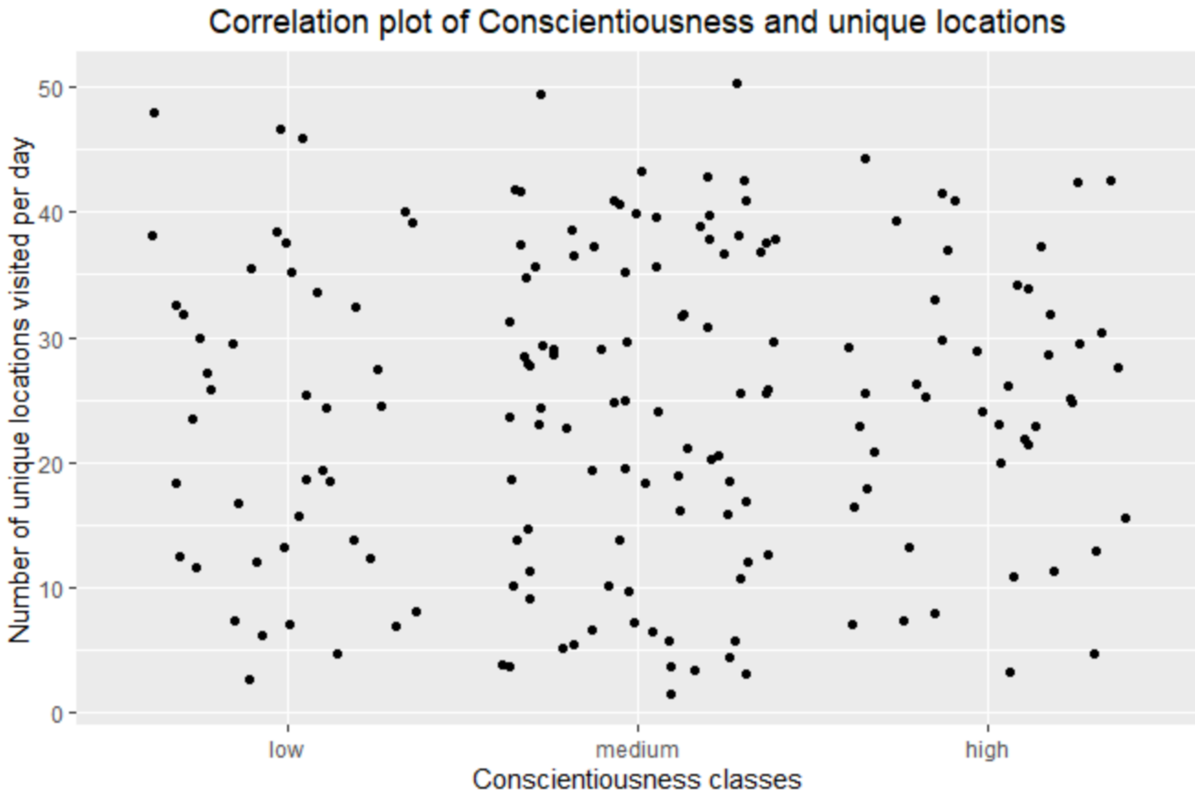




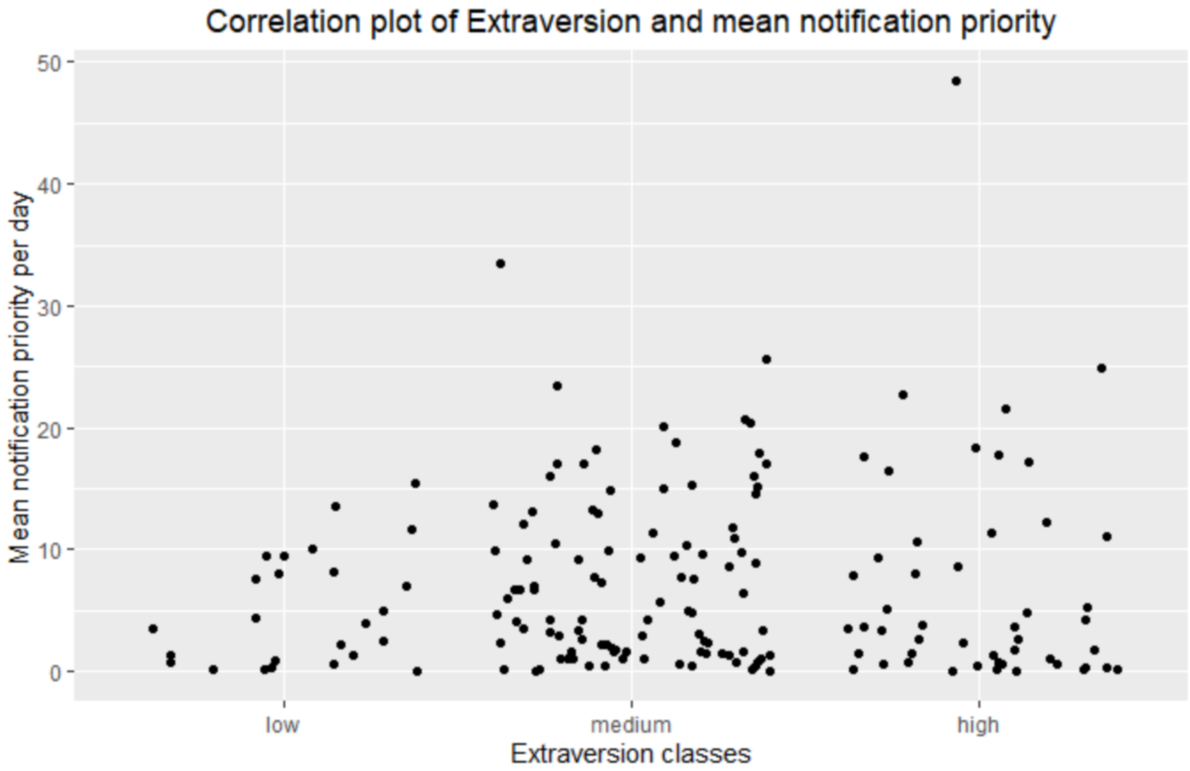
E.4 Conscientiousness

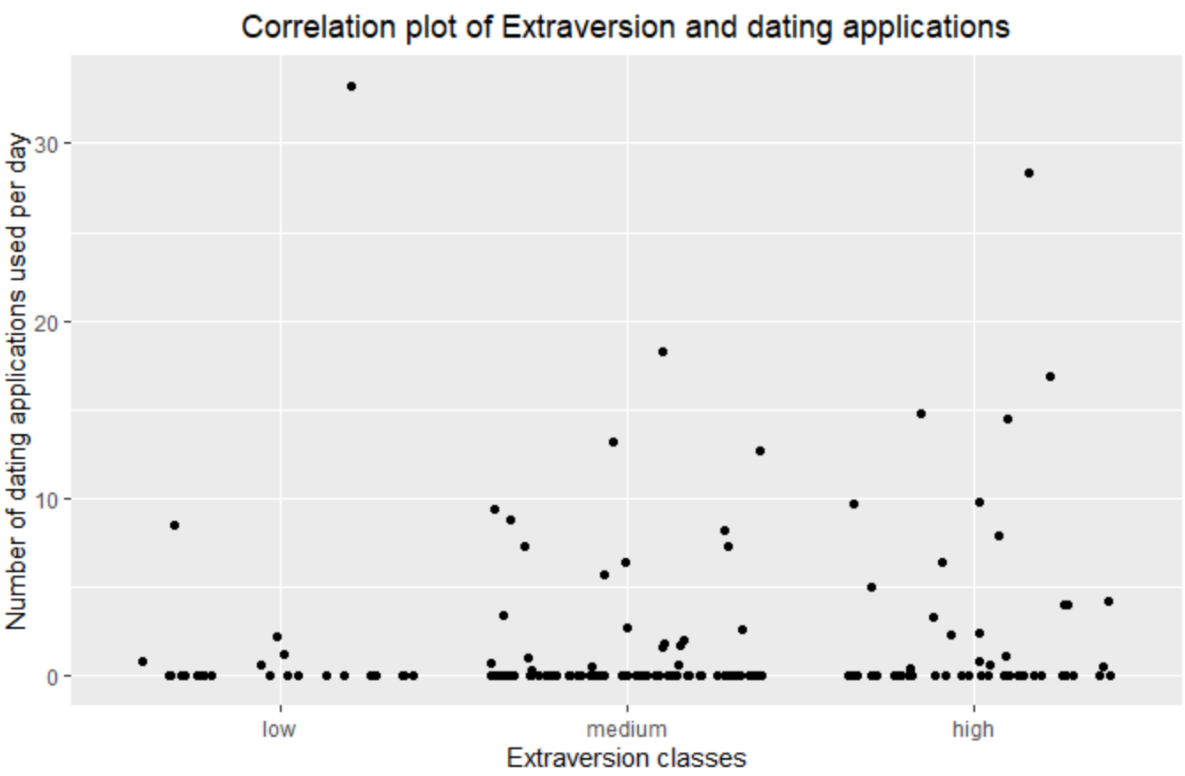


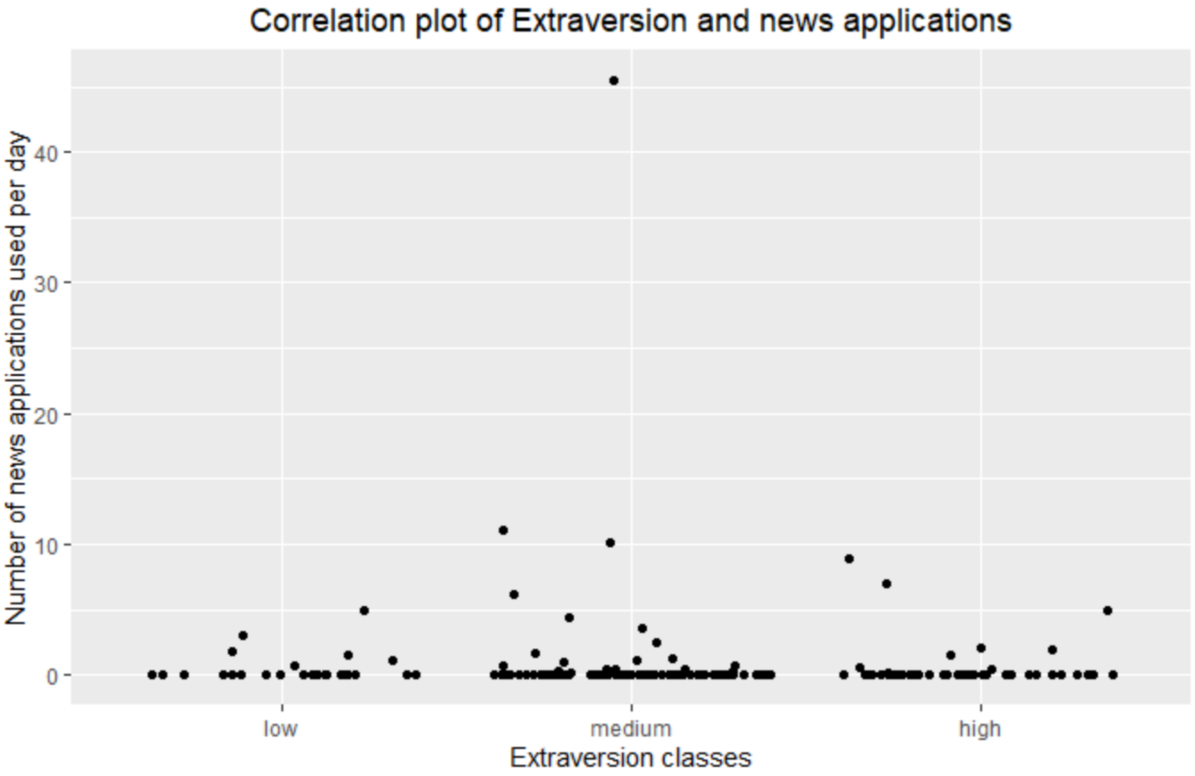

Correlation plot of Conscientiousness and email applications
Frequency of use email applications
0
10
20
30
low
medium
high
Conscientiousness classes

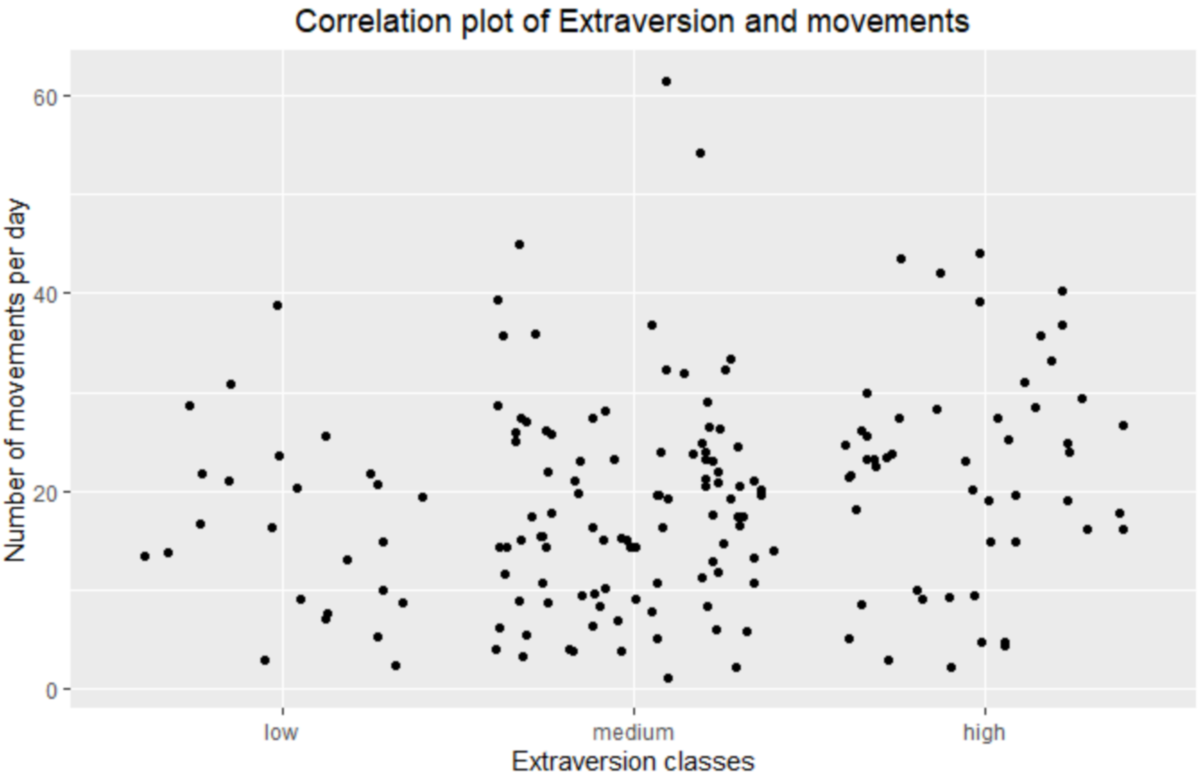

Correlation plot of Conscientiousness and unique locations
Number of unique locations visited per day
0
10
20
30
40
50
low
medium
high
Conscientiousness classes

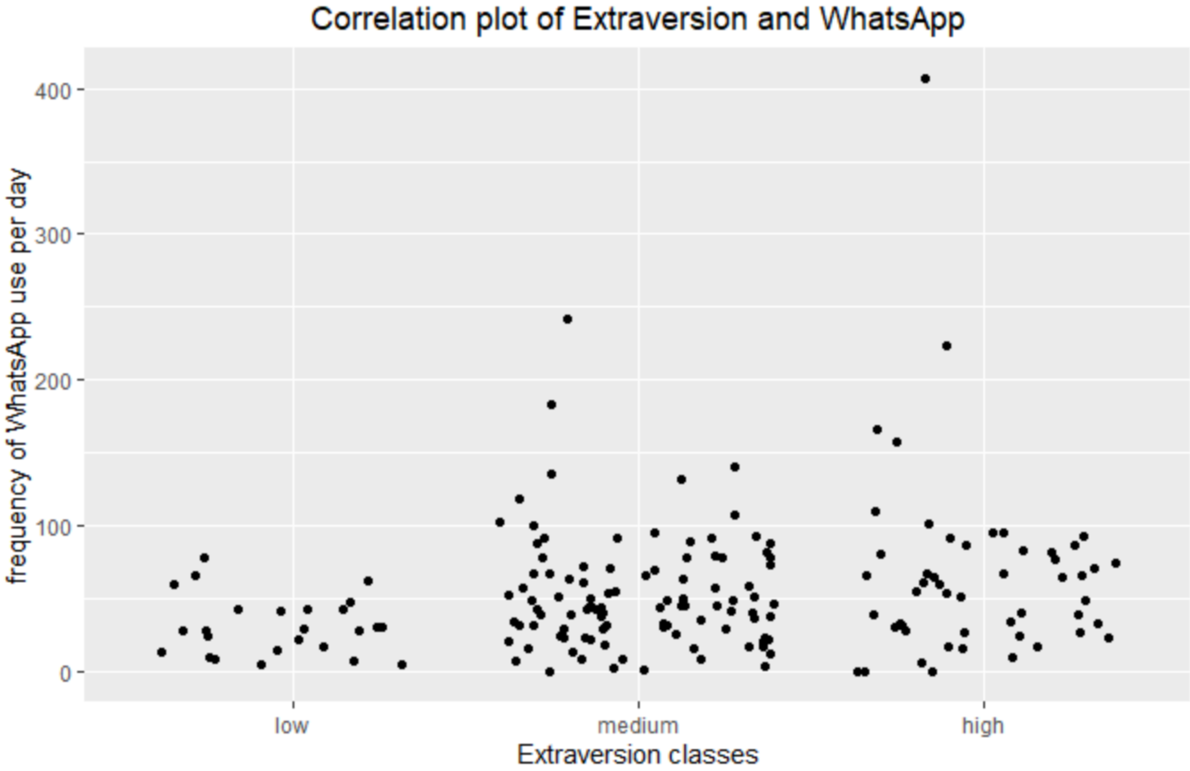
E.5 Extraversion

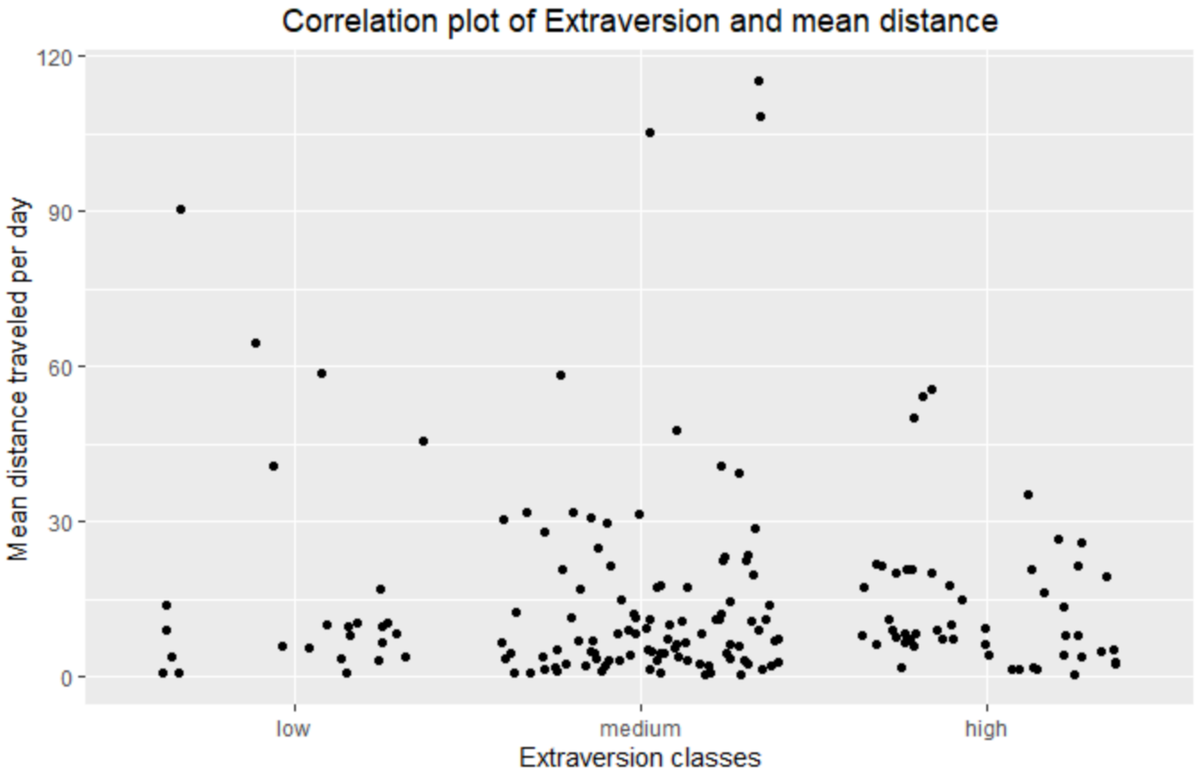





Correlation plot of Extraversion and news applications
Number of news applications used per day
0
10
20
30
40
low
medium
high
Extraversion classes

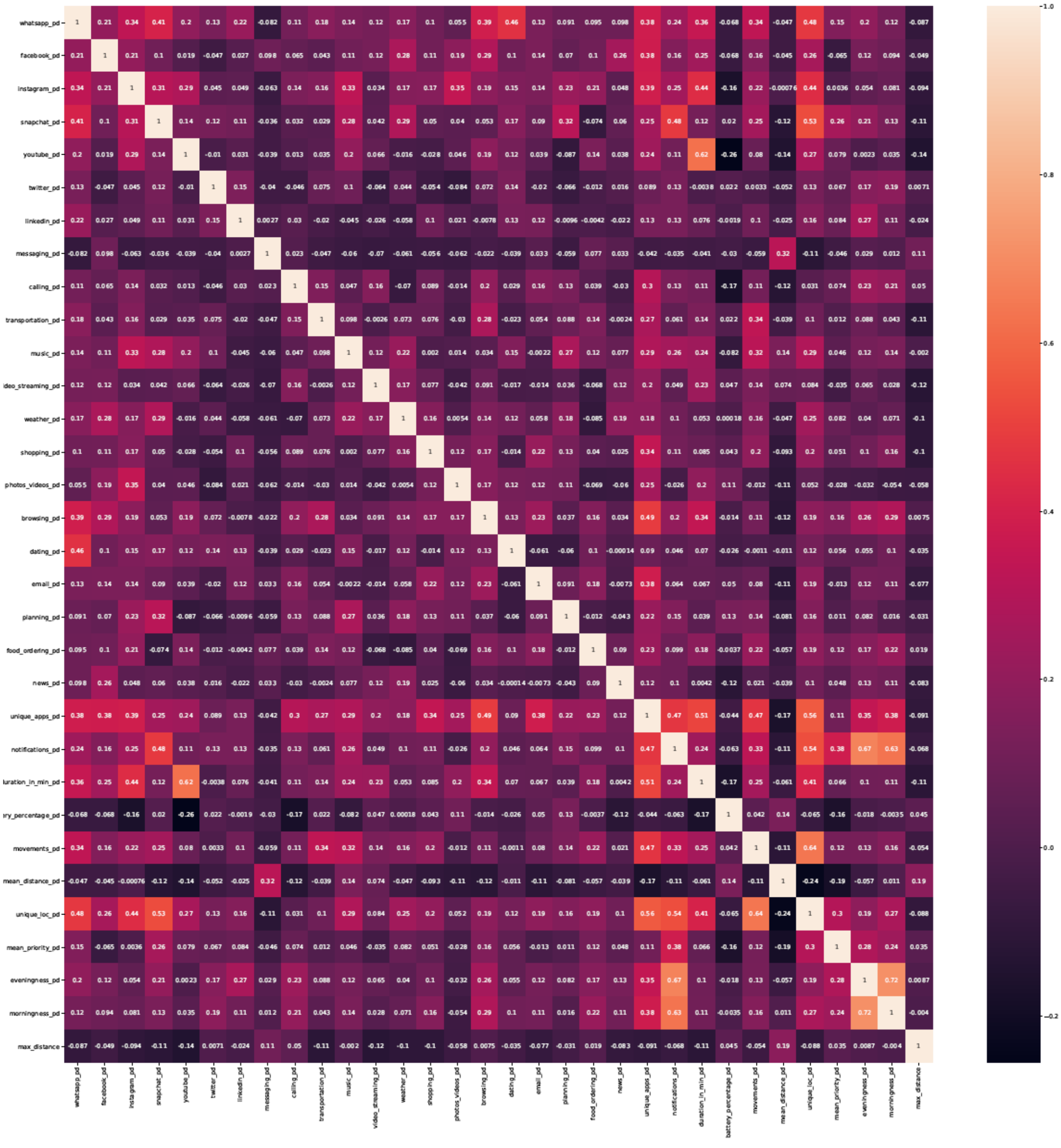

Correlation plot of Extraversion and movements
Number of movements per day
0
20
40
60
low
medium
high
Extraversion classes


Correlation plot of Extraversion and WhatsApp
frequency of WhatsApp use per day
0
100
200
300
400
low
medium
high
Extraversion classes


Correlation plot of Extraversion and mean distance
Mean distance traveled per day
0
30
60
90
120
low
medium
high
Extraversion classes

Appendix F - Correlation plots all features

F.1 Correlation heat all features



F.2 Correlation plots most correlated features