Predicting Loneliness from Social, Technology, and Demographic Factors

Jean Singer

9/4/2022

Contents

1. Introduction 2

1.1 Background 2

1.2 Project Objectives 2

1.3 Dataset and Variables 2

1.4 Key Steps Performed 4

2. Methods and Analysis 4

2.1 Exploratory Analysis and Variable Selection 4

2.1.1 Exploratory Analysis of Outcome Variable 6

2.1.2 Exploratory Analysis of Predictors and Variable Selection 8

2.2 Modeling Approaches 16

3. Models and Results 17

3.1 Linear Regression Model 18

3.2 XGBoost Model 19

3.3 Principal Components Regression Model (PCR) 22

3.4 Ensemble Model 24

3.5 Variable Importance 25

4. Conclusion 26

4.1 Discussion of Results and Potential Impact 26

4.2 Limitations 27

4.3 Future Work 27

Appendix A: AARP Variables 28

References 29

1. Introduction

1.1 Background

Loneliness has been described as "the newest epidemic in America" (Murphy 2020). In a 2020 study of more than 10,400 adults by the health insurer Cigna, roughly three in five Americans (61%) were classified as lonely (Coombs 2020). Compared to 2018, when the survey was first introduced, loneliness rates rose by roughly 7 percentage points. Studies using different methodologies show various rates of loneliness but confirm that a sizable proportion of the country suffers from this condition. The Covid-19 pandemic may also be playing a role in the rise of loneliness. In October 2020, Harvard University researchers found that 36% of Americans felt "serious loneliness" while two months prior, the proportion was 25% (Weissbourd et al., n.d.).

Social connection is a fundamental human need, akin to our needs for food and warmth (Lieberman 2013). When our social needs are insufficiently met by the quantity or especially the quality of our social relationships, we feel loneliness (L. Hawkley and Cacioppo 2010). Loneliness serves as a distress signal telling us that we need to improve social connection—and we suffer physical and emotional consequences if we don't. Chronic loneliness has been associated with increased risk for a host of physical and mental health issues, including a 26% increase in the risk for early mortality – putting loneliness in the same league as more commonly recognized health risks such as obesity, inactivity, and smoking (Holt-Lunstad, Smith, and Layton 2010a; Holt-Lunstad et al. 2015). Loneliness has also been associated with increased risks for coronary heart disease and stroke (Everson-Rose and Lewis 2005), impaired immune function (Cohen et al. 1997a), and cognitive decline and dementia (Cacioppo and Cacioppo 2014; Kim 2017). Given the reported rates of loneliness and the prospect that it may be further on the rise, we need to address loneliness as a serious public health concern.

Loneliness is a *measurable feeling* that may be influenced by a number of *objective factors*, such as the size or diversity of our social networks, the amount of time we spend alone, or the ways in which we use technology. If we can better understand the drivers behind loneliness and quantify their impact, we can more effectively target the factors that matter most. Machine learning models that predict loneliness from social, technology and demographic factors can help us to identify relevant factors to target.

1.2 Project Objectives

The objective of this project was to build a machine learning model to predict loneliness from a set of social, technology and demographic factors. The data I used was collected by AARP to study loneliness among people age 45 and above. AARP used the data to build a linear regression model and identify factors affecting loneliness.

In the current project, I sought to:

- Build a linear regression model with better predictive ability than the one built by AARP.
- Further optimize predictive ability with three additional machine learning models: XGBoost, PCR and an ensemble.
- Use machine learning models to identify the social, technology and demographic features most important to predicting loneliness.

1.3 Dataset and Variables

In 2018, AARP conducted a study of loneliness and how it relates to social connections, life experiences, health, and technology among adults age 45 and over. They contacted a nationally-representative sample of 6343 people for participation in a web-based survey, and obtained a response rate of 50.8%, or 3223 people. I removed from the dataset 20 people (0.6%) who did not complete the key outcome measure (UCLA Loneliness Index.) The final dataset consisted of 3203 observations.

The main outcome variable was loneliness, measured by the UCLA Loneliness Scale (Russell 1996), a validated and widely-used index of 20 items measuring dimensions of loneliness on a 4-point scale from "never" to "always." The index is created by summing the responses. The possible range of responses is 20 (least lonely) to 80 (most lonely), and AARP classifies a score of 44 or higher as "lonely."

The AARP dataset I started with contained 67 predictor variables. The variables included measures of social connection, technology use, life events such as moving or death of someone close, activities such as volunteering and belonging to groups, attitudes regarding the internet, health, and demographics. A list of the variables is provided in Appendix A: AARP Variables.

The AARP variables did not include a measure of complex social integration (CSI), which is an indicator of the extent to which an individual participates in a wide range of social activities and relationships (Brissette, Cohen, and Seeman 2000). CSI has frequently been associated with increased risk of mortality (Holt-Lunstad, Smith, and Layton 2010b; L. F. Berkman and Syme 1979a; Lisa F. Berkman et al. 2004) and morbidity (Cohen et al. 1997b; Coyle and Dugan 2012), and is a commonly-used measure in studies of social connection and isolation. I created an index of CSI using the variable DiversitySupportive (a measure of the diversity of people who have been supportive of you in the last year, across friends, spouse, children, parents, other relatives, neighbors, co-workers, and others) and adding points for being married or living with a partner, being employed, volunteering, membership in groups. This approach is similar to those used by researchers to create other established indexes such as the Berkman-Syme Social Network Index (L. F. Berkman and Syme 1979b) and the Cohen Social Network Index (Cohen et al. 1997c).

Here I load the dataset and add the CSI variable.

```r
#Install any required packages
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
if(!require(DescTools)) install.packages("DescTools", repos = "http://cran.us.r-project.org")
if(!require(Hmisc)) install.packages("Hmisc", repos = "http://cran.us.r-project.org")
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")
if(!require(xgboost)) install.packages("xgboost", repos = "http://cran.us.r-project.org")
if(!require(pls)) install.packages("pls", repos = "http://cran.us.r-project.org")

library(tidyverse)

# Read in the data from the Github repository
df <- read.csv("https://raw.githubusercontent.com/JeanSinger/Capstone-CYO-Predicting-Loneliness/master/

#-------------------------------------------------------------------
#Create the variable for Complex Social Integration (CSI)
#-------------------------------------------------------------------
#CSI starts with the value for DiversitySupportive and adds points for marital satisfaction, employment

#Create variable with points to be added for marital: marital satisfaction
#greater than 3 gets a point.
df <- df %>% mutate(CSImarital = ifelse(Q22_marital_satn>3, 1, 0))

#Create variable with points to be added for employed: 1 or 2 gets a point
df <- df %>% mutate(CSIemployed = ifelse(employ==1 |employ==2, 1, 0))

#Create variable with points to be added for volunteer: 1 gets a point
df <- df %>% mutate(CSIvolunteer = ifelse(Q48_volunteer==1, 1, 0))

#Create variable with points to be added for groups: 2 or more (meaning 1-3 groups)gets a point
```

```
df <- df %>% mutate(CSIgroups = ifelse(Q50_groups > 1, 1, 0))

#Creat the index by adding the variables above to DiversitySupportive
df$DiversitySupportive <- as.numeric(df$DiversitySupportive)
df <- df %>% mutate(CSI = rowSums(across(c(DiversitySupportive,CSImarital, CSIemployed,CSIvolunteer, CS

#convert 0s to NAs
df$CSI[df$CSI==0] <- NA

#remove the point calculations so they don't show up as variables
df <- df %>% select (-c(CSImarital, CSIemployed, CSIvolunteer, CSIgroups))
```

1.4 Key Steps Performed

I started by exploring the data and selecting the variables that were most likely to be predictive in my models. Using those variables, I built three machine learning models: linear regression, Extreme Gradient Boosting (XGBoost), and principal components regression (PCR.) I evaluated my linear regression model against AARP's linear regression model using R^2 as my performance measure. I also evaluated each of my models against each other using RMSE. (AARP did not report RMSE for their model.) I combined the three models into an ensemble and compared RMSE to the individual models.

I used the linear regression and XGBoost models to generate measures of variable importance. (PCR and the ensemble do not provide variable importance metrics.) I then examined the top five most important variables in each model to see where the two models identified similar variables.

2. Methods and Analysis

2.1 Exploratory Analysis and Variable Selection

First, I examined the structure of the data. The dataset contains 3203 rows and 69 variables: 67 predictor variables, one outcome variable and the respondent number. All variables appeared as numeric, although some should have be characterized as factor type. I will convert them later on.

```
str(df)
```

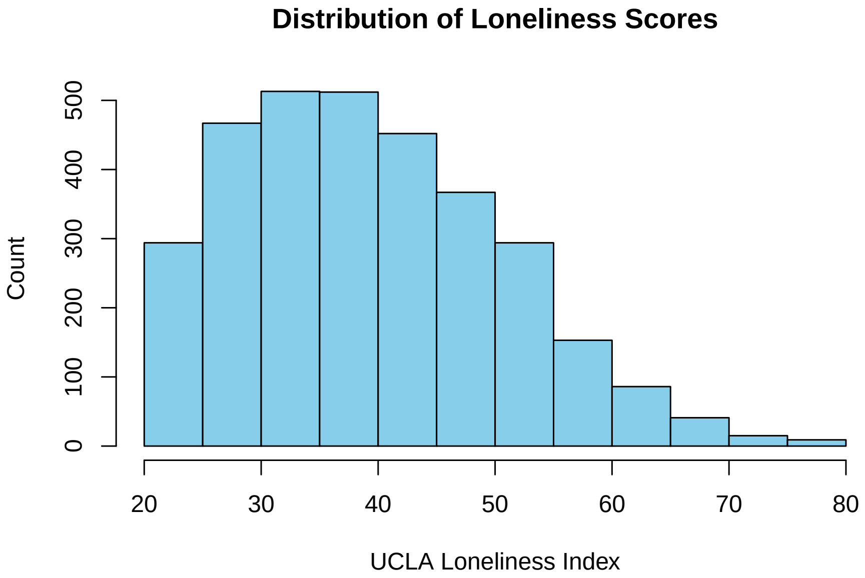
```
## 'data.frame':    3203 obs. of  69 variables:
##  $ respondent                    : int  3 4 5 6 7 8 9 10 11 12 ...
##  $ UCLA_index                    : num  29 23 51 31 48 28 36 32 37 39 ...
##  $ Q8_disability                 : int  0 0 0 0 1 0 0 1 0 1 ...
##  $ NeighborIndex                 : num  0.0871 2.2295 2.0115 -0.3488 2.2295 ...
##  $ DiversityDiscussImportant     : int  3 2 1 5 NA 4 4 1 3 3 ...
##  $ DiversitySupportive           : num  5 4 1 6 NA 3 2 1 2 4 ...
##  $ Q22_marital_satn              : int  5 5 5 5 3 5 2 5 1 0 ...
##  $ Q46_attend_religious          : int  6 6 6 2 1 1 3 2 2 3 ...
##  $ Q39_caregiver                 : int  0 0 1 0 0 0 0 0 0 0 ...
##  $ Q30_supportive_num            : int  100 12 5 8 0 5 2 20 2 25 ...
##  $ Q64_yrs_current_residence     : int  4 1 5 2 1 2 5 2 5 3 ...
##  $ Q65_relocate                  : int  0 1 0 3 1 2 0 1 0 1 ...
##  $ ethnic                        : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ gender                        : int  2 1 1 1 1 2 1 1 1 2 ...
##  $ household_size                : int  4 2 1 4 3 1 2 2 2 1 ...
##  $ income                           : int  14 19 21 9 16 9 21 17 21 6 ...
##  $ employ                           : int  7 5 1 1 5 5 2 2 5 5 ...
##  $ age_group                        : int  5 7 7 5 6 7 7 7 7 7 ...
##  $ Q2_health_overall                : int  5 4 5 2 2 5 3 2 4 4 ...
##  $ Q27_11_parents_inperson          : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_12_parents_email             : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_13_parents_phone             : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_14_parents_letters           : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_15_parents_text              : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_16_parents_online            : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_17_parents_SN                : int  NA NA NA NA NA NA NA NA NA NA ...
##  $ Q27_21_child_inperson            : int  5 3 5 5 5 4 5 5 4 NA ...
##  $ Q27_22_child_email               : int  1 4 5 4 1 1 5 5 5 NA ...
##  $ Q27_23_child_phone               : int  5 4 5 5 5 5 4 5 5 NA ...
##  $ Q27_24_child_letters             : int  1 1 2 1 1 1 2 3 2 NA ...
##  $ Q27_25_child_text                : int  5 5 5 5 5 5 5 5 5 NA ...
##  $ Q27_26_child_online              : int  1 5 5 4 1 1 1 1 5 NA ...
##  $ Q27_27_child_SN                  : int  1 4 5 5 1 5 4 1 4 NA ...
##  $ Q27_31_sibling_inperson          : int  5 2 4 4 2 4 4 3 4 4 ...
##  $ Q27_32_sibling_email             : int  1 3 4 3 1 1 4 4 5 5 ...
##  $ Q27_33_sibling_phone             : int  5 3 4 3 2 5 3 4 3 4 ...
##  $ Q27_34_sibling_letters           : int  1 1 2 1 1 1 2 1 2 4 ...
##  $ Q27_35_sibling_text              : int  5 4 4 4 1 5 2 4 5 5 ...
##  $ Q27_36_sibling_online            : int  1 4 4 1 1 1 1 1 3 1 ...
##  $ Q27_37_sibling_SN                : int  1 1 4 5 1 4 3 1 5 1 ...
##  $ Q27_41_friend_inperson           : int  4 5 5 5 3 4 5 5 4 5 ...
##  $ Q27_42_friend_email              : int  1 1 5 5 1 2 5 5 5 5 ...
##  $ Q27_43_friend_phone              : int  4 1 5 5 3 5 2 4 5 5 ...
##  $ Q27_44_friend_letters            : int  2 1 5 1 1 1 2 1 2 4 ...
##  $ Q27_45_friend_text               : int  5 5 5 5 1 4 2 4 5 4 ...
##  $ Q27_46_friend_online             : int  1 5 5 1 1 1 1 1 2 2 ...
##  $ Q27_47_friend_SN                 : int  1 1 1 2 5 2 5 5 1 5 ...
##  $ Q28_discuss_important_matters_num: int  3 2 1 5 0 4 6 1 2 5 ...
##  $ passaway_index                   : int  1 0 1 1 NA 0 0 2 0 2 ...
##  $ moveaway_index                   : int  0 0 1 0 0 1 0 NA 1 1 ...
##  $ Q38_more_less_friends            : int  2 3 2 3 2 2 3 2 2 2 ...
##  $ Q48_volunteer                    : int  1 1 0 0 0 0 1 0 1 1 ...
##  $ Q50_groups                       : int  1 3 1 1 1 1 1 2 2 3 ...
##  $ Q53_hobbies                      : int  5 2 3 2 4 2 2 2 5 5 ...
##  $ Q77_hrs_alone                    : int  2 1 1 1 3 1 3 1 1 4 ...
##  $ Q89_1_internet_sentiment         : num  1 2 5 4 1 5 4 2 4 3 ...
##  $ Q89_2_internet_sentiment         : num  1 2 5 4 1 4 3 3 1 1 ...
##  $ Q89_3_internet_sentiment         : num  4 1 1 3 5 1 2 2 2 1 ...
##  $ Q89_4_internet_sentiment         : int  5 4 5 5 1 5 4 1 3 2 ...
##  $ Q89_5_internet_sentiment         : int  5 5 3 3 5 5 4 5 3 3 ...
##  $ Q89_6_internet_sentiment         : num  5 4 3 5 1 5 3 1 3 3 ...
##  $ Q89_7_internet_sentiment         : num  4 5 3 3 5 4 3 4 3 5 ...
##  $ Q89_8_internet_sentiment         : num  5 1 3 5 1 3 3 2 3 3 ...
##  $ Q89_9_internet_sentiment         : num  4 5 3 2 5 4 4 3 4 4 ...
##  $ Q89_10_internet_sentiment        : num  5 5 3 4 3 3 5 2 1 3 ...
##  $ internet_sentiment_index         : num  39 34 34 38 28 39 35 25 27 28 ...
##  $ Q90_tradeoffs_family             : int  2 2 1 1 2 2 2 2 2 2 ...
##  $ Q91_tradeoffs_intimate_convo     : int  2 2 1 1 2 2 2 2 2 1 ...
##  $ CSI                              : num  7 7 3 8 NA 4 4 4 4 6 ...
```

2.1.1 Exploratory Analysis of Outcome Variable

I examined the distribution of the outcome variable, loneliness, examined descriptive statistics, and generated a plot of loneliness by age.

Here is the histogram:

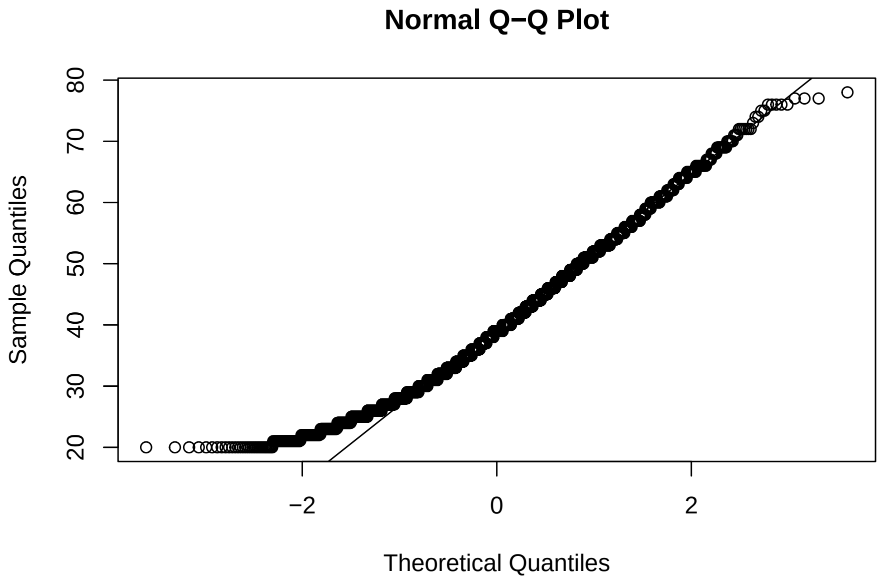
```
#create a histogram of the loneliness variable
hist(df$UCLA_index, main = "Distribution of Loneliness Scores",
     xlab = "UCLA Loneliness Index", ylab = "Count", col = "sky blue", border = "black")
```



The loneliness histogram is skewed right. A relatively large number of respondents have low levels of loneliness compared to those at the highest end of the scale.

This deviation from the normal distribution can also be seen in the Q-Q plot. The distribution follows the Q-Q line fairly well except for the lowest values.

```
#create a Q-Q plot of loneliness
qqnorm(df$UCLA_index)
qqline(df$UCLA_index)
```



The chart below shows the mean, standard deviation, median and mode values for the loneliness variable. The mean is higher than the median, as would be expected in a right-skewed distribution.

```
#compute the mean, sd, median and mode for loneliness
mean_loneliness <- mean(df$UCLA_index)
sd_loneliness <- sd(df$UCLA_index)
median_loneliess <- median(df$UCLA_index)
library(DescTools)
mode_loneliness <- Mode(df$UCLA_index)

#place the stats in a table
descriptive_stats <- tibble(Statistic = c("Mean", "SD", "Median", "Mode"),
                            Value = c(mean_loneliness, sd_loneliness,
                                      median_loneliess,mode_loneliness))
descriptive_stats %>% knitr::kable()
```

Statistic	Value
Mean	39.80182
SD	11.34231
Median	39.00000
Mode	39.00000

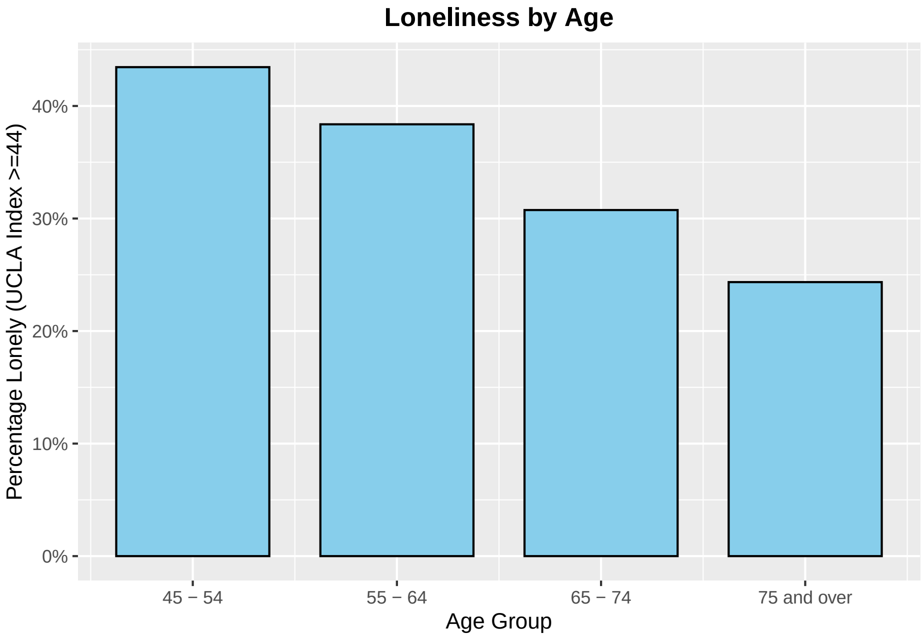
Using the AARP cutoff of 44 and above to define “lonely”, I found that a little over a third (35.6%) of the sample would be considered lonely.

```
#compute the percentage of people who would be considered lonely (UCLA index >=44)
mean(df$UCLA_index >=44)
```

```
## [1] 0.3562285
```

A plot of average loneliness by age group shows that loneliness declines with age. This finding is consistent with other studies indicating that loneliness is highest among young people (around age 16 – 24) and declines after middle age, although some studies show loneliness increasing at age 75 and above (L. C. Hawkley et al. 2019; "Community Life Survey 2018-19," n.d.).

```
#Percentage of people classified as "lonely" by age
df %>% group_by(age_group) %>%
  summarise(Percentage_lonely = mean(UCLA_index >= 44)) %>%
  ggplot(aes(age_group, Percentage_lonely)) + geom_bar(stat = "identity",
                                                       col = "black", fill = "sky blue", width = 0.75) +
  xlab("Age Group") + ylab("Percentage Lonely (UCLA Index >=44)") +
  labs(title = "Loneliness by Age") + theme(plot.title = element_text(hjust = 0.5, face = "bold"))+
  scale_y_continuous(labels = scales::percent_format(accuracy=1)) +
  scale_x_continuous(breaks = 5:8, labels = c("45 - 54", "55 - 64", "65 - 74", "75 and over"))
```



2.1.2 Exploratory Analysis of Predictors and Variable Selection

To identify the variables that would be most useful in predicting loneliness, I conducted three types of analyses: correlation with loneliness, ANOVA, and t-tests.

Correlation with loneliness. I treated ordinal variables with 5 or more response options and any variables created by summing multiple items into an index variables as "pseudo-continuous", and generated Pearson's correlation coefficients for them. I selected all variables with correlations of greater than .20 or less than -.20, and p<.05 for use in my machine learning models. Out of 55 variables, only 13 met this fairly low hurdle, indicating that individually, the variables were not very strong predictors. All p-values, however, were significant (p<.001). The variables that met these criteria are shown in the table below.

Below is the code for running the correlations and selecting the variables that meet my criteria.

```
#Create a correlation matrix for the variables of interest, which are
#those that are indexes or ordinal with 5 or more response options
variables <- df %>% select(-c(respondent, ethnic,
                          Q22_marital_satn, Q38_more_less_friends,
                          Q50_groups,
                         Q90_tradeoffs_family, Q91_tradeoffs_intimate_convo,
                        age_group, employ, gender,
                        Q39_caregiver, Q48_volunteer, Q8_disability))

#Generate the correlation matrix and p values
library(Hmisc)
cor_variables <- rcorr(as.matrix(variables))
cor_variables_r <- round(cor_variables[["r"]],2)
cor_variables_p <- round(cor_variables[["P"]],3)

#In the r-value matrix, select the variables with correlations >.20 or <-0.2
new_variables <- as.data.frame(cor_variables_r) %>%
  filter(UCLA_index>0.2 | UCLA_index<(-.2)) %>%
  select(UCLA_index)

#create a column with the names of all the variables
new_variables$variable_names <- row.names(new_variables)

#remove the first row that contains UCLA_index as a variable
new_variables <- new_variables[-1, ]

#Now take a look at the p-values
#In the p-value matrix, add variable names as a column
new_variables_p <- as.data.frame(cor_variables_p)
new_variables_p$variable_names <- row.names(new_variables_p)

#select the relevant variables from the p-value matrix
relevant_variables <- c("NeighborIndex", "DiversityDiscussImportant",
                        "DiversitySupportive", "Q30_supportive_num",
                        "income", "Q2_health_overall",
                        "Q27_41_friend_inperson",
                        "Q27_43_friend_phone",
                        "Q28_discuss_important_matters_num",
                        "Q77_hrs_alone", "Q89_5_internet_sentiment",
                        "Q89_7_internet_sentiment", "CSI")

new_variables_p <- new_variables_p %>% filter(variable_names %in% relevant_variables) %>%
  select(UCLA_index, variable_names)

#add three decimal places to the p-value
new_variables_p[,'UCLA_index']=format(round(new_variables_p[,'UCLA_index'],3),nsmall=3)

#create a table with the variables, correlations and p-values for all variables
# with r>0.20
correlation_table <- tibble(Variable_name = new_variables$variable_names,
                            Pearsons_r = new_variables$UCLA_index,
                            p_value = new_variables_p$UCLA_index)
#sort the table
correlation_table <- correlation_table %>% arrange(desc(Pearsons_r))

#format the table
```

```r
correlation_table %>% knitr::kable()
```

Variable_name	Pearsons_r	p_value
Q77_hrs_alone	0.33	0.000
Q27_43_friend_phone	-0.21	0.000
income	-0.22	0.000
Q30_supportive_num	-0.23	0.000
DiversityDiscussImportant	-0.24	0.000
Q89_7_internet_sentiment	-0.24	0.000
Q89_5_internet_sentiment	-0.26	0.000
Q28_discuss_important_matters_num	-0.27	0.000
Q2_health_overall	-0.28	0.000
Q27_41_friend_inperson	-0.29	0.000
NeighborIndex	-0.32	0.000
DiversitySupportive	-0.33	0.000
CSI	-0.37	0.000

We can see from the table above that the only predictor positively associated with loneliness is number of hours spent alone (Q77_hrs_alone.) The positive relationship implies that the more hours we spend physically alone, the lonelier we feel. The strongest predictor overall (although still not a "strong" correlation) is complex social integration (CSI), which is negatively associated with loneliness. The negative relationship implies that the more we participate in a wide range of social activities and relationships, the less lonely we are.

I generated scatterplots of the 13 variables but because the correlations were low, the scatterplots were not informative. (Plots not shown.)

ANOVA. For variables that were nominal or that were ordinal with fewer than 5 responses, I ran ANOVAs to determine whether there was a statistically significant (p<.05) difference in mean loneliness across levels. The 7 relevant variables were:

- ethnic (ethnicity)
- Q22_marital_satn (marital satisfaction)
- Q38_more_less_friends (increase or decrease in number of friends over the past five years)
- Q50_groups (number of groups you belong to)
- Q90_tradeoffs_family (whether you spend more/less/same time with family as a result of the internet)
- Q91_tradeoffs_intimate_convo (whether you spend more/less/same time in intimate conversations as a result of the internet)
- age_group.

All seven variables showed significant differences in mean loneliness across their levels (p<.01 or lower.) I therefore included all of them in my models. Below is the code for running the seven ANOVAs.

```r
#Convert all the variables to factor
df$Q22_marital_satn <- as.factor(df$Q22_marital_satn)
df$age_group <- as.factor(df$age_group)
df$Q38_more_less_friends <- as.factor(df$Q38_more_less_friends)
df$Q90_tradeoffs_family <- as.factor(df$Q90_tradeoffs_family)
```

```
df$Q91_tradeoffs_intimate_convo <- as.factor(df$Q91_tradeoffs_intimate_convo)
df$Q50_groups <- as.factor(df$Q50_groups)
df$ethnic <- as.factor(df$ethnic)

#ANOVA of Q22_marital_satn vs loneliness
df_marital_satn <- df %>%
  filter(Q22_marital_satn != "NA" & UCLA_index != "NA")
ANOVA_marital_satn_loneliness <- aov(UCLA_index ~ Q22_marital_satn,
                                     data = df_marital_satn)
summary(ANOVA_marital_satn_loneliness)
```

```
##                     Df Sum Sq Mean Sq F value Pr(>F)    
## Q22_marital_satn    5  43169    8634   74.85 <2e-16 ***
## Residuals        3197 368762     115                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of ethnicity vs loneliness
df_ethnic <- df %>%
  filter(ethnic != "NA" & UCLA_index != "NA")
ANOVA_ethnic <- aov(UCLA_index ~ ethnic,
                    data = df_ethnic)
summary(ANOVA_ethnic)
```

```
##                Df Sum Sq Mean Sq F value  Pr(>F)   
## ethnic          4   1766   441.6   3.443 0.00815 **
## Residuals    3198 410165   128.3                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of age group vs loneliness
df_agegroup <- df %>%
  filter(age_group != "NA" & UCLA_index != "NA")
ANOVA_agegroup_loneliness <- aov(UCLA_index ~ age_group,
                                 data = df_agegroup)
summary(ANOVA_agegroup_loneliness)
```

```
##                Df Sum Sq Mean Sq F value Pr(>F)    
## age_group       3  11562    3854   30.79 <2e-16 ***
## Residuals    3199 400369     125                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of Q38_more_less_friends (changes in number of friends
#over the last 5 years) vs loneliness
df_friends <- df %>%
  filter(Q38_more_less_friends != "NA" & UCLA_index != "NA")
ANOVA_friends_loneliness <- aov(UCLA_index ~ age_group,
                                data = df_friends)
summary(ANOVA_friends_loneliness)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)    
## age_group      3  11561    3854    30.8 <2e-16 ***
## Residuals   3192 399309     125                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of Q90_tradeoffs_family (as a result of technology, spending
#less, same or more time with family) vs loneliness
df_tradeoffsfam <- df %>%
  filter(Q90_tradeoffs_family != "NA" & UCLA_index != "NA")
ANOVA_tradeoffsfam_loneliness <- aov(UCLA_index ~ Q90_tradeoffs_family,
                                     data = df_tradeoffsfam)
summary(ANOVA_tradeoffsfam_loneliness)
```

```
##                         Df Sum Sq Mean Sq F value Pr(>F)    
## Q90_tradeoffs_family    2  18026    9013   73.19 <2e-16 ***
## Residuals            3185 392214     123                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of Q91_tradeoffs_intimate_convo (as a result of technology, spending
#less, same or more time in intimate conversations) vs loneliness
df_tradeoffsint <- df %>%
  filter(Q91_tradeoffs_intimate_convo != "NA" & UCLA_index != "NA")
ANOVA_tradeoffsint_loneliness <- aov(UCLA_index ~ Q91_tradeoffs_intimate_convo,
                                     data = df_tradeoffsint)
summary(ANOVA_tradeoffsint_loneliness)
```

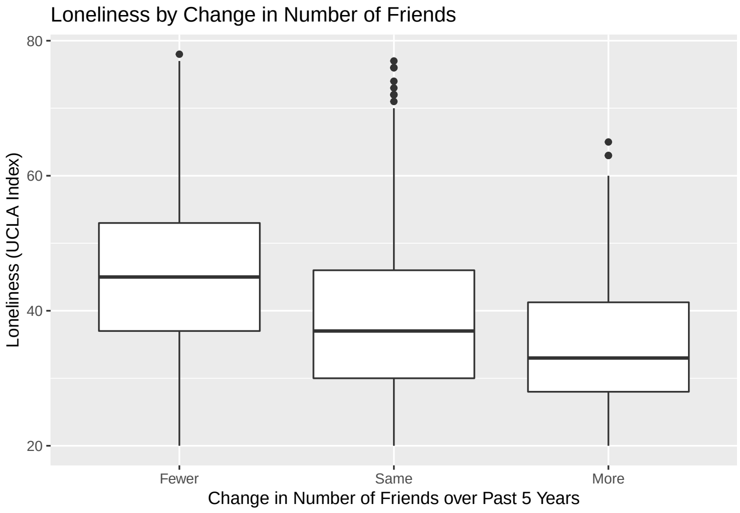
```
##                                 Df Sum Sq Mean Sq F value Pr(>F)    
## Q91_tradeoffs_intimate_convo    2  19442    9721   79.61 <2e-16 ***
## Residuals                    3119 380876     122                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

```
#ANOVA of Q50_groups (number of groups you belong to with
#1=0, 2=1, 3=2, 4=3 or more) vs loneliness
df_groups <- df %>%
  filter(Q50_groups != "NA" & UCLA_index != "NA")
ANOVA_groups_loneliness <- aov(UCLA_index ~ Q50_groups,
                               data = df_groups)
summary(ANOVA_groups_loneliness)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)    
## Q50_groups     3  11117    3706   29.52 <2e-16 ***
## Residuals   3187 400136     126                   
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

I generated boxplots for all seven variables. Below I show a sample boxplot showing how loneliness varies with change in the number of friends over the last five years. Average loneliness is highest when the number of friends has declined, and lowest when the number of friends has increased. (The other six boxplots are not shown.)

```
df %>% filter(Q38_more_less_friends != "NA") %>%
  ggplot(aes(as.factor(Q38_more_less_friends), UCLA_index)) + geom_boxplot() +
  xlab("Change in Number of Friends over Past 5 Years") + ylab("Loneliness (UCLA Index)") +
  labs(title = "Loneliness by Change in Number of Friends")+
  scale_x_discrete(breaks = c("1", "2", "3"),
                   labels = c("Fewer", "Same", "More"))
```



T-tests. For binary variables, I conducted t-tests and selected those variables whose levels show significant (p<.05) differences in mean level of loneliness. Three variables showed significant differences and I included them in the models:

- Q48_volunteer (whether you have volunteered in the last 12 months), p<.001
- Q8_disability (whether you have a disability or chronic disease that keeps you from participating fully in work, school, household, or other activities), p<.001
- Q39_caregiver (whether you are providing unpaid care or assistance to an adult who needs assistance due to aging, a disability, or a health-related issue), p<.01

Two variables did not show significant differences between levels and were removed. These were gender (p = 0.17) and employed (p = .06).

Below is the code for running the five t-tests.

```
#t-test on mean loneliness for Q48_volunteer (whether or not you have
#in the last 12 months.)
df_volunteer <- df %>%
  filter(Q48_volunteer != "NA" & UCLA_index != "NA")
t.test(UCLA_index ~ Q48_volunteer, data = df_volunteer)
```

```
##
##  Welch Two Sample t-test
##
## data:  UCLA_index by Q48_volunteer
## t = 8.4587, df = 3029.2, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  2.564041 4.111443
## sample estimates:
## mean in group 0 mean in group 1
##        41.17371        37.83597
```

```
#t-test on mean loneliness for Q8_disabled (whether or not you are disabled)
df_disabled <- df %>%
  filter(Q8_disability != "NA" & UCLA_index != "NA")
t.test(UCLA_index ~ Q8_disability, data = df_disabled)
```

```
##
##  Welch Two Sample t-test
##
## data:  UCLA_index by Q8_disability
## t = -9.2856, df = 932.58, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -6.00009 -3.90637
## sample estimates:
## mean in group 0 mean in group 1
##        38.77344        43.72667
```

```
#t-test on mean loneliness for Q39_caregiver (whether or not you are
#providing unpaid care to an adult)
df_caregiver <- df %>%
  filter(Q39_caregiver != "NA" & UCLA_index != "NA")
t.test(UCLA_index ~ Q39_caregiver, data = df_caregiver)
```

```
##
##  Welch Two Sample t-test
##
## data:  UCLA_index by Q39_caregiver
## t = -3.2898, df = 623.35, p-value = 0.001059
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -2.9645117 -0.7482516
## sample estimates:
## mean in group 0 mean in group 1
##        39.52254        41.37892
```

```
#t-test on mean loneliness for gender
df_gender <- df %>%
  filter(gender != "NA" & UCLA_index != "NA")
t.test(UCLA_index ~ gender, data = df_gender)
```

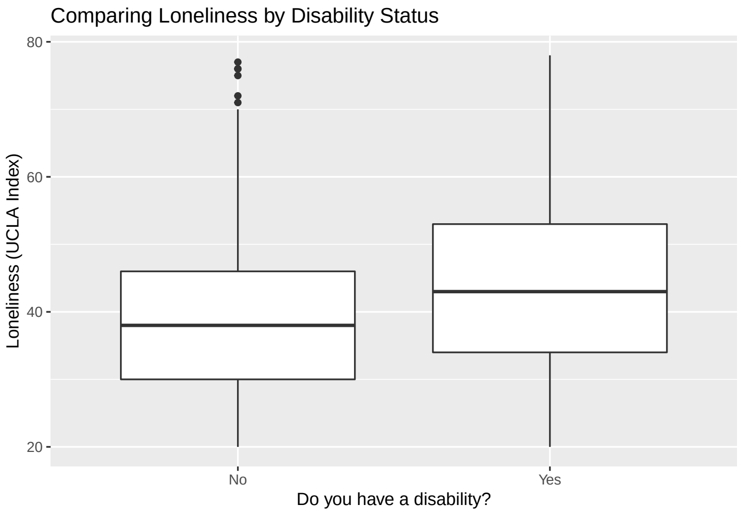
```
##
##  Welch Two Sample t-test
##
## data:  UCLA_index by gender
## t = 1.3622, df = 3194.3, p-value = 0.1732
## alternative hypothesis: true difference in means between group 1 and group 2 is not equal to 0
## 95 percent confidence interval:
##  -0.2398954  1.3317958
## sample estimates:
## mean in group 1 mean in group 2
##        40.07522        39.52927
```

```
#t-test on mean loneliness for whether or not you're employed
df_employed <- df %>% mutate(CSIemployed = ifelse(employ==1 |employ==2, 1, 0))%>%
  filter(CSIemployed != "NA" & UCLA_index != "NA")
t.test(UCLA_index ~ CSIemployed, data = df_employed)
```

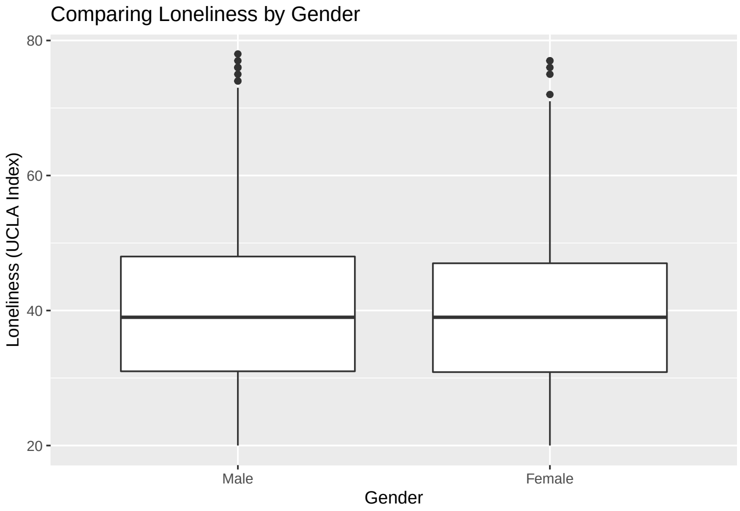
```
##
##  Welch Two Sample t-test
##
## data:  UCLA_index by CSIemployed
## t = -1.9196, df = 3133.6, p-value = 0.05499
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -1.55883759  0.01650072
## sample estimates:
## mean in group 0 mean in group 1
##        39.40697        40.17813
```

I generated boxplots on all five variables. Below I show examples for Q8_disability, in which the means are significantly different, and gender, where they are not.

```
#boxplot showing higher level of loneliness when you have a disability
df %>% filter(Q8_disability != "NA") %>%
  ggplot(aes(as.factor(Q8_disability), UCLA_index)) + geom_boxplot() +
  xlab("Do you have a disability?") + ylab("Loneliness (UCLA Index)") +
  labs(title = "Comparing Loneliness by Disability Status") +
  scale_x_discrete(breaks = c("0", "1"),
                   labels = c("No", "Yes"))
```



```
#boxplot showing no significant difference in loneliness between genders.
df %>% filter(gender != "NA") %>%
  ggplot(aes(as.factor(gender), UCLA_index)) + geom_boxplot() +
  xlab("Gender") + ylab("Loneliness (UCLA Index)") +
  labs(title = "Comparing Loneliness by Gender") +
  scale_x_discrete(breaks = c("1", "2"),
                   labels = c("Male", "Female"))
```



My final dataset consisted of 23 predictors, each of which had either a Pearson's correlation coefficient with loneliness of greater than |0.20|, significance (p<.01) in ANOVA, or significance (p<.05) in the t-test.

2.2 Modeling Approaches

I started with a linear regression model to see if the 23 variables I selected could out-perform the AARP linear regression model on the basis of R^2.

I then created an XGBoost model with the same variables. I chose XGBoost because I wanted to see if a tree-based model would be more accurate than a linear model, given that most of the linear relationships as measured by Pearson's correlation coefficient were weak, and some of my variables were categorical. I chose XGBoost rather than Random Forest because it is more efficient and accurate. Unlike Random Forest, which creates decision trees in parallel and averages them (for regression), XGBoost uses a *gradient boosting* technique in which decision trees are created sequentially. It increases the weights of variables that were predicted wrong by one tree prior to feeding it into the next tree. The result is often a more accurate model.

Although I reduced the number of predictors from 67 to 23, I still had a large number of variables. I therefore thought a dimension reduction approach would be helpful, and tried principal components regression (PCR.) PCR regresses the principal components of the predictors against the outcome variable rather than using predictors themselves. It can lower the number of parameters in the model. However, because the outcomes are described in terms of principal components rather than variables, it can be more difficult to interpret.

Finally, I created an ensemble as a way to combine multiple weaker models into a stronger model. I computed the ensemble prediction by taking the average of the predictions for the linear regression, XGBoost and PCR models.

I evaluated the relative performance of the linear regression, XGBoost, PCR and ensemble models on the basis of RMSE.

I identified the the variables that were most important to predicting loneliness in the linear regression and XGBoost models. In the regression model, I used the absolute value of the t-score as my indicator of variable importance. The rationale for using t-scores (rather than normalized coefficients) is that it gives us the variables that most certainly have non-zero effects and takes into account the uncertainty in the regression coefficients (Haman 2020). In the XGBoost model, I used the Gain metric generated by the xgb.importance function. Gain represents the fractional improvement in accuracy that a predictor brings to the branch that it is on. A higher percentage Gain indicates a more important predictor (Abu-Rmileh 2021).

I examined the top five most important variables in each model to see where they had commonalities.

3. Models and Results

Before building the models, I split the data 80/20 into training and test sets. All models were built on the training data and RMSE computed in the test set.

```
#Create the relevant data frame with 23 predictor variables and the loneliness variable
variables <- df %>% select(UCLA_index, Q77_hrs_alone, Q27_43_friend_phone,
                           income, Q30_supportive_num, DiversityDiscussImportant,
                           Q89_7_internet_sentiment, Q89_5_internet_sentiment,
                           Q28_discuss_important_matters_num,Q2_health_overall,
                           Q27_41_friend_inperson, NeighborIndex, DiversitySupportive,
                           CSI,
                           ethnic, Q22_marital_satn, Q38_more_less_friends,
                           Q50_groups, Q90_tradeoffs_family,
                           Q91_tradeoffs_intimate_convo, age_group,
                           Q48_volunteer, Q8_disability,
                           Q39_caregiver)

#convert binary and nominal variables to factor class
variables$ethnic <- as.factor(variables$ethnic)
variables$Q22_marital_satn <- as.factor(variables$Q22_marital_satn)
variables$Q38_more_less_friends <- as.factor(variables$Q38_more_less_friends)
variables$Q50_groups <- as.factor(variables$Q50_groups)
variables$Q90_tradeoffs_family <- as.factor(variables$Q90_tradeoffs_family)
variables$Q91_tradeoffs_intimate_convo <- as.factor(variables$Q91_tradeoffs_intimate_convo)
variables$age_group <- as.factor(variables$age_group)
variables$Q48_volunteer <- as.factor(variables$Q48_volunteer)
variables$Q8_disability <- as.factor(variables$Q8_disability)
variables$Q39_caregiver <- as.factor(variables$Q39_caregiver)

#Make sure the outcome variable is in the last column
variables <- variables %>% select(-UCLA_index, UCLA_index)

#convert to a data frame
variables <- as.data.frame(variables)

#Split the data 80/20 into training and test sets.
library(caret)
set.seed(2, sample.kind="Rounding")
train_index <- createDataPartition(variables$UCLA_index, times = 1, p=.8, list = FALSE)
train <- variables[train_index, ]
test <- variables[-train_index, ]
```

3.1 Linear Regression Model

Below is the code for building the linear regression model, printing the summary with significance levels and R^2, and computing RMSE in the test set.

```r
#Create the linear regression model using the training set
LM <- lm(UCLA_index ~ ., data = train)

#print out the summary of the model
LMsummary <- summary(LM)
LMsummary
```

```
## 
## Call:
## lm(formula = UCLA_index ~ ., data = train)
## 
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -26.6392  -5.6650  -0.0972   5.5826  27.6253 
## 
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                       64.51084    1.56427  41.240  < 2e-16 ***
## Q77_hrs_alone                      1.58246    0.14865  10.645  < 2e-16 ***
## Q27_43_friend_phone               -0.37826    0.18983  -1.993 0.046426 *  
## income                            -0.13048    0.04673  -2.792 0.005279 ** 
## Q30_supportive_num                -0.03546    0.01851  -1.915 0.055564 .  
## DiversityDiscussImportant         -0.21159    0.22024  -0.961 0.336791    
## Q89_7_internet_sentiment          -0.65160    0.17933  -3.633 0.000286 ***
## Q89_5_internet_sentiment          -1.22255    0.17804  -6.867 8.51e-12 ***
## Q28_discuss_important_matters_num -0.19065    0.08953  -2.129 0.033334 *  
## Q2_health_overall                 -1.14349    0.22736  -5.029 5.32e-07 ***
## Q27_41_friend_inperson            -1.09548    0.21660  -5.058 4.59e-07 ***
## NeighborIndex                     -0.52039    0.07956  -6.541 7.59e-11 ***
## DiversitySupportive               -2.09363    0.46888  -4.465 8.40e-06 ***
## CSI                                1.19288    0.43206   2.761 0.005811 ** 
## ethnic2                           -1.32315    0.63419  -2.086 0.037060 *  
## ethnic3                           -1.45903    1.11687  -1.306 0.191567    
## ethnic4                           -1.68767    0.60967  -2.768 0.005684 ** 
## ethnic5                           -0.09572    1.13228  -0.085 0.932640    
## Q22_marital_satn1                  0.13354    0.89637   0.149 0.881583    
## Q22_marital_satn2                  4.44113    1.12080   3.962 7.65e-05 ***
## Q22_marital_satn3                  3.64916    0.95843   3.807 0.000144 ***
## Q22_marital_satn4                  0.63838    0.75040   0.851 0.395021    
## Q22_marital_satn5                 -2.64805    0.63557  -4.166 3.21e-05 ***
## Q38_more_less_friends2            -3.01616    0.44657  -6.754 1.83e-11 ***
## Q38_more_less_friends3            -3.79740    0.61532  -6.171 8.03e-10 ***
## Q50_groups2                       -1.34922    0.66258  -2.036 0.041839 *  
## Q50_groups3                       -2.05813    0.82671  -2.490 0.012863 *  
## Q50_groups4                       -2.46220    1.03116  -2.388 0.017033 *  
## Q90_tradeoffs_family2             -1.06453    0.58237  -1.828 0.067695 .  
## Q90_tradeoffs_family3             -2.58870    0.81387  -3.181 0.001489 ** 
## Q91_tradeoffs_intimate_convo2     -2.56839    0.52375  -4.904 1.01e-06 ***
## Q91_tradeoffs_intimate_convo3     -1.70151    0.83620  -2.035 0.041988 *  
## age_group6                         -0.85156    0.47152  -1.806 0.071057 .
## age_group7                         -2.15896    0.54856  -3.936 8.55e-05 ***
## age_group8                         -4.40931    0.70868  -6.222 5.86e-10 ***
## Q48_volunteer1                     -1.19895    0.61312  -1.955 0.050651 .
## Q8_disability1                      1.42819    0.50773   2.813 0.004953 **
## Q39_caregiver1                      1.92942    0.50750   3.802 0.000148 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.325 on 2211 degrees of freedom
##   (315 observations deleted due to missingness)
## Multiple R-squared:  0.4249, Adjusted R-squared:  0.4153
## F-statistic: 44.15 on 37 and 2211 DF,  p-value: < 2.2e-16
```

```
#Create a function to compute RMSE
RMSE <- function(actual_ratings, predicted_ratings){
  sqrt(mean((actual_ratings - predicted_ratings)^2, na.rm = TRUE))
}

#generate predictions on the test set
predict_LM <- predict(LM, newdata = test)

#compute RMSE for the linear regression model
RMSE_LM <- RMSE(test$UCLA_index, predict_LM)
RMSE_LM
```

```
## [1] 7.94992
```

The linear regression model produces an adjusted R^2 of 41.5% and an RMSE in the test set of 7.950. The table below compares these results with the AARP linear regression. The AARP model, which contained over 50 variables produced an R^2 of 21.3%. My linear regression model explained almost twice as much of the variance in the outcome variable.

```
#Store the linear regression results in a table and compare
#to the AARP performance
model_results <- tibble(Model = c("AARP", "Linear Regression"),
                        Adjusted_R2 = c(.213, LMsummary$adj.r.squared),
                        RMSE = c(NA, RMSE_LM))
model_results %>% knitr::kable()
```

Model	Adjusted_R2	RMSE
AARP	0.2130000	NA
Linear Regression	0.4152828	7.94992

3.2 XGBoost Model

Below is the code for fitting and tuning the XGBoost model.

```
#load the xgboost package
library(xgboost)
```

```r
#Create separate objects for the predictor and outcome variables in the training set
train_x <- data.matrix(train[ ,-ncol(train)])
train_y <- train[ , ncol(train)]

#Create separate objects for the predictor and response variables in the test set
test_x <- data.matrix(test[ ,-ncol(test)])
test_y <- test[ , ncol(test)]

#Define the final training and testing sets.
xgb_train = xgb.DMatrix(data = train_x, label = train_y)
xgb_test = xgb.DMatrix(data = test_x, label = test_y)

#Fit and tune the model. First define the watchlist
watchlist = list(train=xgb_train, test=xgb_test)

#Fit the XGBoost model and display the training and testing data at each round
set.seed(2, sample.kind="Rounding")
model_XG = xgb.train(data = xgb_train, max.depth = 3, watchlist=watchlist, nrounds = 70)
```

```
## [1]  train-rmse:29.486989    test-rmse:29.578601
## [2]  train-rmse:21.730417    test-rmse:21.851331
## [3]  train-rmse:16.577929    test-rmse:16.742274
## [4]  train-rmse:13.250493    test-rmse:13.434962
## [5]  train-rmse:11.197256    test-rmse:11.446410
## [6]  train-rmse:9.962569 test-rmse:10.298171
## [7]  train-rmse:9.226861 test-rmse:9.621707
## [8]  train-rmse:8.794883 test-rmse:9.223249
## [9]  train-rmse:8.531663 test-rmse:8.996041
## [10] train-rmse:8.348206 test-rmse:8.837393
## [11] train-rmse:8.241927 test-rmse:8.760532
## [12] train-rmse:8.152464 test-rmse:8.660068
## [13] train-rmse:8.087599 test-rmse:8.630103
## [14] train-rmse:8.036833 test-rmse:8.603567
## [15] train-rmse:7.996164 test-rmse:8.553246
## [16] train-rmse:7.948341 test-rmse:8.523716
## [17] train-rmse:7.907028 test-rmse:8.497382
## [18] train-rmse:7.859900 test-rmse:8.484594
## [19] train-rmse:7.815695 test-rmse:8.457700
## [20] train-rmse:7.784342 test-rmse:8.448484
## [21] train-rmse:7.755187 test-rmse:8.414996
## [22] train-rmse:7.729497 test-rmse:8.409334
## [23] train-rmse:7.698795 test-rmse:8.396251
## [24] train-rmse:7.675488 test-rmse:8.384122
## [25] train-rmse:7.665717 test-rmse:8.384767
## [26] train-rmse:7.637970 test-rmse:8.385073
## [27] train-rmse:7.611871 test-rmse:8.382819
## [28] train-rmse:7.593398 test-rmse:8.366231
## [29] train-rmse:7.567768 test-rmse:8.363145
## [30] train-rmse:7.547800 test-rmse:8.374626
## [31] train-rmse:7.536046 test-rmse:8.373139
## [32] train-rmse:7.525187 test-rmse:8.370241
## [33] train-rmse:7.513220 test-rmse:8.354466
## [34] train-rmse:7.479812 test-rmse:8.341227
## [35] train-rmse:7.462732 test-rmse:8.346497
## [36] train-rmse:7.441799 test-rmse:8.346922
## [37] train-rmse:7.433281 test-rmse:8.338707
## [38] train-rmse:7.412193 test-rmse:8.343437
## [39] train-rmse:7.395950 test-rmse:8.352533
## [40] train-rmse:7.375471 test-rmse:8.363573
## [41] train-rmse:7.357914 test-rmse:8.359103
## [42] train-rmse:7.345241 test-rmse:8.352324
## [43] train-rmse:7.329830 test-rmse:8.361366
## [44] train-rmse:7.312186 test-rmse:8.348143
## [45] train-rmse:7.293408 test-rmse:8.316597
## [46] train-rmse:7.278738 test-rmse:8.314274
## [47] train-rmse:7.262073 test-rmse:8.308970
## [48] train-rmse:7.244770 test-rmse:8.297479
## [49] train-rmse:7.233773 test-rmse:8.302850
## [50] train-rmse:7.217058 test-rmse:8.295362
## [51] train-rmse:7.200347 test-rmse:8.290831
## [52] train-rmse:7.186363 test-rmse:8.305541
## [53] train-rmse:7.171670 test-rmse:8.302815
## [54] train-rmse:7.161494 test-rmse:8.303241
## [55] train-rmse:7.148002 test-rmse:8.313640
## [56] train-rmse:7.137662 test-rmse:8.311287
## [57] train-rmse:7.123148 test-rmse:8.318779
## [58] train-rmse:7.105134 test-rmse:8.326676
## [59] train-rmse:7.088669 test-rmse:8.335913
## [60] train-rmse:7.081620 test-rmse:8.339999
## [61] train-rmse:7.063128 test-rmse:8.342937
## [62] train-rmse:7.056711 test-rmse:8.342384
## [63] train-rmse:7.044755 test-rmse:8.350295
## [64] train-rmse:7.034615 test-rmse:8.353435
## [65] train-rmse:7.029626 test-rmse:8.356246
## [66] train-rmse:7.011212 test-rmse:8.350670
## [67] train-rmse:7.002024 test-rmse:8.361233
## [68] train-rmse:6.991727 test-rmse:8.365565
## [69] train-rmse:6.977224 test-rmse:8.355774
## [70] train-rmse:6.966176 test-rmse:8.355578
```

```r
#Find the lowest RMSE and insert in the code for nrounds.
set.seed(2, sample.kind="Rounding")
final_model = xgboost(data = xgb_train, max.depth = 3, nrounds = 51, verbose = 0)

#Make predictions on the test set and compute RMSE
predict_XG <- predict(final_model, newdata = xgb_test)
RMSE_XG <- caret::RMSE(test_y, predict_XG)
```

The table below compares the XGBoost model to the linear regression on the basis of RMSE. To my surprise, the XGBoost model, with an RMSE of 8.290, did not perform as well as the linear regression, with an RMSE of 7.950.

```r
#Add the XGBoost model to the table
model_results <- bind_rows(model_results,
                           tibble(Model = "XGBoost",
                                  Adjusted_R2 = NA,
                                  RMSE = RMSE_XG))
model_results %>% knitr::kable()
```

Model	Adjusted_R2	RMSE
AARP	0.2130000	NA
Linear Regression	0.4152828	7.949920
XGBoost	NA	8.290831

3.3 Principal Components Regression Model (PCR)

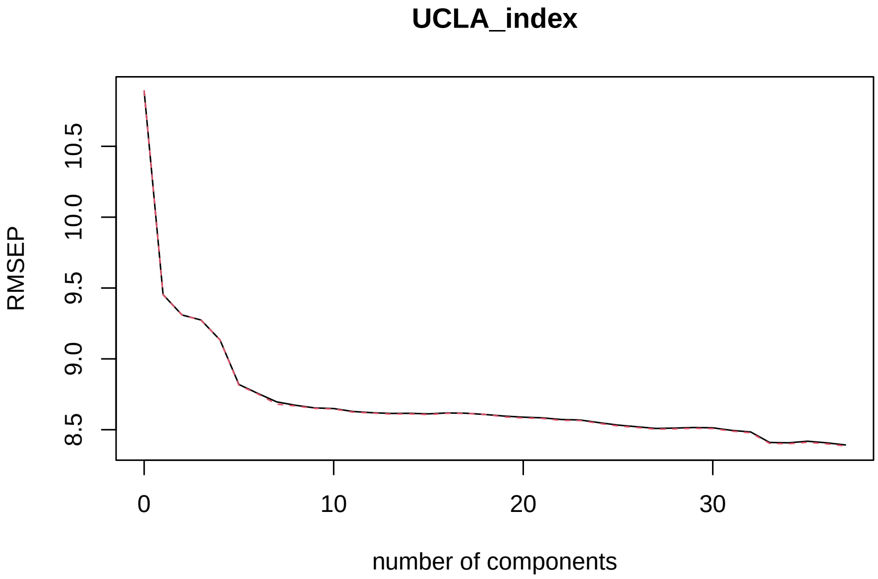
Below is the code for fitting and tuning the PCR model.

```
#Fit the PCR model
library(pls)
model_PCR <- pcr(UCLA_index ~., data = train, scale=TRUE, validation="CV")

#View a summary of the model fitting and select number of components that yields
#the lowest RMSE in cross-validation
summary(model_PCR)
```

```
## Data:    X dimension: 2249 37
##  Y dimension: 2249 1
## Fit method: svdpc
## Number of components considered: 37
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           10.89    9.453    9.310    9.274    9.134    8.819    8.756
## adjCV        10.89    9.452    9.309    9.273    9.134    8.814    8.752
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV       8.696    8.672    8.654     8.649     8.629     8.620     8.615
## adjCV    8.680    8.667    8.651     8.647     8.624     8.618     8.611
##        14 comps  15 comps  16 comps  17 comps  18 comps  19 comps  20 comps
## CV        8.616     8.612     8.618     8.616     8.607     8.596     8.589
## adjCV     8.612     8.607     8.616     8.615     8.608     8.591     8.583
##        21 comps  22 comps  23 comps  24 comps  25 comps  26 comps  27 comps
## CV        8.584     8.572     8.569     8.550     8.533     8.521     8.509
## adjCV     8.580     8.566     8.565     8.545     8.526     8.516     8.504
##        28 comps  29 comps  30 comps  31 comps  32 comps  33 comps  34 comps
## CV        8.512     8.516     8.513     8.495     8.484     8.410     8.408
## adjCV     8.506     8.510     8.508     8.490     8.478     8.404     8.401
##        35 comps  36 comps  37 comps
## CV        8.419     8.408     8.393
## adjCV     8.411     8.401     8.385
##
## TRAINING: % variance explained
##             1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
## X             10.52    17.28    22.41    26.81    30.98    34.87    38.54
## UCLA_index    24.62    26.94    27.59    29.84    34.85    35.68    36.80
##             8 comps  9 comps  10 comps  11 comps  12 comps  13 comps  14 comps
## X             42.12    45.61     48.85     51.98     55.04     58.03     60.88
## UCLA_index    37.06    37.30     37.37     37.74     37.91     38.03     38.04
##             15 comps  16 comps  17 comps  18 comps  19 comps  20 comps
## X              63.67     66.42     69.10     71.74     74.29     76.73
## UCLA_index     38.16     38.16     38.21     38.38     38.83     39.00
##             21 comps  22 comps  23 comps  24 comps  25 comps  26 comps
## X               79.1     81.33     83.47     85.48     87.25     88.93
## UCLA_index      39.0     39.29     39.34     39.66     39.91     40.09
##             27 comps  28 comps  29 comps  30 comps  31 comps  32 comps
## X              90.56     92.09     93.53     94.91     96.02     97.06
## UCLA_index     40.32     40.33     40.34     40.37     40.70     40.94
##             33 comps  34 comps  35 comps  36 comps  37 comps
## X              97.89     98.64     99.29     99.94    100.00
## UCLA_index     41.97     42.04     42.14     42.21     42.49
```

```
#view plot to confirm that 33 components gives the lowest RMSE
validationplot(model_PCR)
```



```
#Use the model to make predictions on the test set
predict_PCR <- predict(model_PCR, test, ncomp=33)

#Compute RMSE for PCR model in the test set
RMSE_PCR <- RMSE(test$UCLA_index, predict_PCR)
RMSE_PCR
```

```
## [1] 7.982405
```

The table below shows the PCR results compared to linear regression and XGBoost. The PCR model, with an RMSE of 7.982, performed better than the XGBoost but not as well as the linear regression. The linear regression model is still in the lead.

```
#Add the PCR results to the table
model_results <- bind_rows(model_results,
                           tibble(Model = "PCR",
                                  Adjusted_R2 = NA,
                                  RMSE = RMSE_PCR))
model_results %>% knitr::kable()
```

Model	Adjusted_R2	RMSE
AARP	0.2130000	NA
Linear Regression	0.4152828	7.949920
XGBoost	NA	8.290831
PCR	NA	7.982405

3.4 Ensemble Model

Below is the code for creating an ensemble from the average of the predictions of the linear regression, XGBoost and PCR models.

```
#Create a dataframe with the predictions from the LM, XGBoost and PCR models
ensemble_preds <- data.frame(LM_preds = predict_LM,
                             XG_preds = predict_XG,
                             PCR_preds = as.vector(predict_PCR),
                             Avg = as.vector((predict_LM + predict_XG +
                                                predict_PCR)/3))

#compute RMSE for the ensemble
RMSE_ensemble <- RMSE(test$UCLA_index, ensemble_preds$Avg)
RMSE_ensemble
```

```
## [1] 7.908848
```

As the table below shows, the ensemble, with an RMSE of 7.91, performed better than the other three models. As expected!

```
#Add the ensemble to the table
model_results <- bind_rows(model_results,
                           tibble(Model = "Ensemble",
                                  Adjusted_R2 = NA,
                                  RMSE = RMSE_ensemble))
model_results %>% knitr::kable()
```

Model	Adjusted_R2	RMSE
AARP	0.2130000	NA
Linear Regression	0.4152828	7.949920
XGBoost	NA	8.290831
PCR	NA	7.982405
Ensemble	NA	7.908848

3.5 Variable Importance

I used the linear regression and XGBoost models to rank the importance of each variable in predicting loneliness.

First, I generated the top five predictors from the linear regression based on absolute value of the t-values.

```r
#Extract the absolute value of the t-values from the linear regression model
#summary and convert to a data frame
LM_tvalues <- as.data.frame(LMsummary$coefficients[-1 ,3])
LM_tvalues <- data.frame(Variable = rownames(LM_tvalues), LM_tvalues)
rownames(LM_tvalues) <- NULL
names(LM_tvalues)[2] <- "t_values"

#Take the absolute value of the t-values and sort highest to lowest
LM_tvalues$t_values <- abs(LM_tvalues$t_values)
LM_tvalues <- arrange(LM_tvalues, desc(t_values))
#Extract the top five predictors fromthe linear regression model
top_five_LM <- head(LM_tvalues, 5)
top_five_LM
```

```
##                   Variable  t_values
## 1             Q77_hrs_alone 10.645220
## 2 Q89_5_internet_sentiment  6.866658
## 3   Q38_more_less_friends2  6.754008
## 4             NeighborIndex  6.540587
## 5                age_group8  6.221880
```

Then I generated the top five predictors from the XGBoost model based the Gain metric in the feature importance matrix.

```r
# Generate the feature importance matrix for the XGBoost model
XGimportance_matrix = xgb.importance(colnames(xgb_train), model = final_model)
XGimportance_matrix <- XGimportance_matrix[ , 1:2]

#The matrix is already sorted in descending order
#Extract the top five predictors from the XGBoost model
top_five_XG <- head(XGimportance_matrix, 5)
top_five_XG
```

```
##                      Feature       Gain
## 1:       Q30_supportive_num 0.16655884
## 2:            NeighborIndex 0.10297016
## 3:            Q77_hrs_alone 0.10080670
## 4: Q89_5_internet_sentiment 0.09071484
## 5:    Q38_more_less_friends 0.07136437
```

Comparing the two lists, we see they have four factors in common:

- Hours spent physically alone (Q77_hrs_alone)
- Relationships with neighbors (NeighborIndex)

- Agreement with the statement that "the more I use the internet as a replacement for other forms of communication, the lonelier I feel" (Q89_5_internet_sentiment)
- Change in numbers of friends over the last five years. (Q38_more_less_friends)

Thus, these four factors are consistently found to be top predictors of loneliness.

4. Conclusion

4.1 Discussion of Results and Potential Impact

For this project, I created four machine learning models to predict loneliness from a set of social, technology, and demographic factors. The goals were to (a) perform better than the AARP linear regression model on R^2 , (b) maximize accuracy in the test set on the basis of RMSE, and (c) identify the features most important to predicting loneliness.

My linear regression model substantially out-performed the AARP model. With an R^2 of 41.5%, my model explained almost double the variability in the loneliness measure as the AARP model, which had an R^2 of 21.3%. Although both of these values may appear low, it is not unusual in the social sciences to see R^2 values less than 50%. It was interesting to see that my model with 23 predictors did better than the AARP model with more than 50 predictors. Typically, adding more variables to a linear regression model increases R^2. Perhaps greater selectivity reduced redundancy (multicollinearity) or eliminated irrelevant variables, thereby improving the model.

Of the four machine learning models I evaluated on the basis of RMSE, the ensemble performed best. Ensemble methods typically perform better than their constituent models, so this was not surprising. The next best performing model was the linear regression. I had expected XGBoost to perform better than linear regression because it would do a better job of fitting categorical variables, but in the current project it did not offer any improvement. Nor did the PCR. It was notable in the PCR model that the optimal number of components was 33, indicating that it did not offer any dimension reduction.

I examined feature importance in the linear regression and XGBoost models. The top predictors were fairly consistent between them, with four of the top five the same:

- Hours spent physically alone
- Relationships with neighbors
- Agreement that using the internet as a replacement for other forms of communication leads to loneliness
- Change in number of friends over the past five years.

It is interesting to note that three of the top predictors have to do with *offline* interaction. Hours spent physically alone were positively associated with loneliness, suggesting that we need to engage face-to-face with others in order to avoid loneliness. The NeighborIndex variable includes questions about how often you speak to neighbors and how strong a relationship you have with them. More interaction with neighbors helps to minimize loneliness, and it is conceivable that because neighbors are physically proximate, more of these interactions would occur face-to-face. Again, support for the value of interacting offline. While the question asking respondents whether they agree that *using the internet as a replacement for other forms of communication leads to loneliness* didn't measure their actual behavior, it nonetheless suggests that people who recognize the value of offline communications tend to be less lonely. Together, these three factors suggest that time we spend with others offline is important to avoiding loneliness.

The current findings are consistent with prior research exploring how social technologies affect loneliness. According to a review by Nowland et al (Nowland, Necka, and Cacioppo 2017), digital social interaction can reduce loneliness when it is used as a way to enhance existing offline relationships or forge new relationships, but when social technologies are used to displace offline relationships and avoid the messy demands of face-to-face interaction, feelings of loneliness increase. Thus, maintaining an offline social network is necessary to avoid loneliness. Our offline networks may, however, be at risk. A study by Twenge et al (Twenge, Spitzberg, and Campbell 2019) showed that, at least in teen populations, offline interaction is being eroded by social technologies. Compared to previous generations, today's teens are spending less time with friends in activities such as hanging out at the mall, going to parties, dating, riding in cars for fun, or going to the movies, and these reductions correspond to escalating levels of loneliness. In 2017, 39% of 12th graders felt lonely, up from 26% in 2012, when the use of social technologies began to soar. Granted, the Twenge study was performed on teens and young adults, which is a very different population from the current study of middle aged and older adults. And the point is not that we should avoid online interaction entirely. Rather, studies such as these raise the question of how our diminishing face-to-face time affects feelings of loneliness, and suggest that we take care to maintain our offline networks as an essential foundation of healthy social relationships.

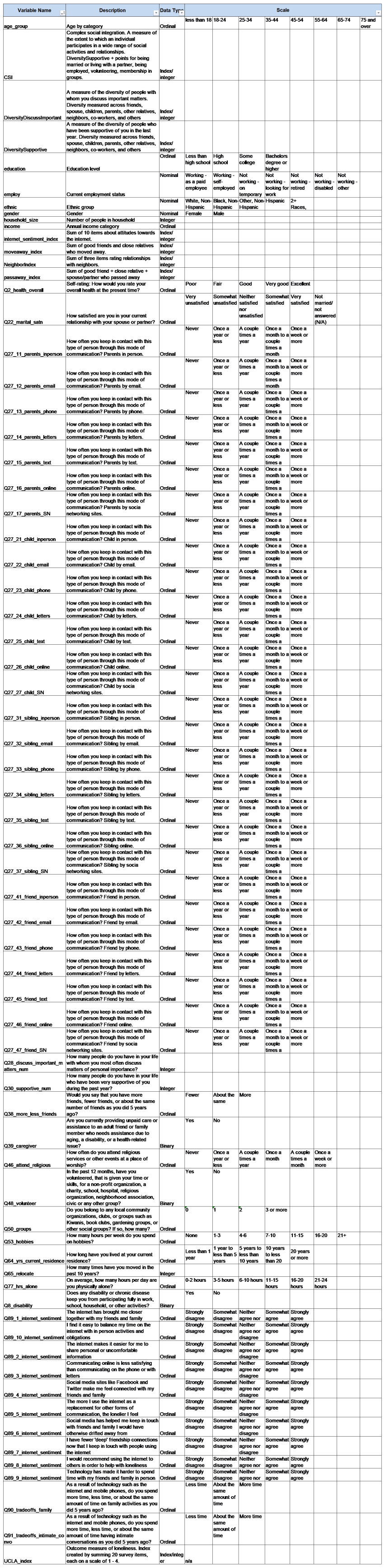
4.2 Limitations

- The AARP data were collected from a sample of respondents age 45 and above. We therefore need to be cautious about applying the findings to younger populations.
- The AARP survey was not hypothesis driven and because I didn't design the survey questions, I was unable to directly test hypotheses (e.g., about the relationship between social technology use and loneliness.)
- The AARP survey included ten questions about "internet sentiment", asking how strongly respondents agreed with a set of statements such as, "The more I use the internet as a replacement for other forms of communication, the lonelier I feel." These ten questions did not ask about actual behaviors, e.g., whether respondents have in fact used the internet as a replacement for other forms of communication. We are therefore limited in our ability to draw conclusions about the relationships between *behaviors* and loneliness from these ten questions, only about *attitudes* and loneliness.

4.3 Future Work

Additional hypothesis-driven studies should be conducted to better understand the relationships between online and offline interactions and loneliness. Further, because loneliness is most common among teens and young adults, future work should examine similar factors in this population. The existing literature does not often explore relationships with neighbors as a factor in reducing loneliness. Further research should be conducted to better understand the role and importance of neighborhood relationships.

Appendix A: AARP Variables



Variable Name	Description	Data Typ	Scale							
age_group	Age by category	Ordinal	less than 18	18-24	25-34	35-44	45-54	55-64	65-74	75 and over
CSI	Complex social integration. A measure of the extent to which an individual participates in a wide range of social activities and relationships. DiversitySupportive + points for being married or living with a partner, being employed, volunteering, membership in groups.	Index/ integer								
DiversityDiscussImportant	A measure of the diversity of people with whom you discuss important matters. Diversity measured across friends, spouse, children, parents, other relatives, neighbors, co-workers, and others	Index/ integer								
DiversitySupportive	A measure of the diversity of people who have been supportive of you in the last year. Diversity measured across friends, spouse, children, parents, other relatives, neighbors, co-workers, and others	Index/ integer								
education	Education level	Ordinal	Less than high school	High school	Some college	Bachelors degree or higher				
employ	Current employment status	Nominal	Working - as a paid employee	Working - self-employed	Not working - on temporary	Not working - looking for work	Not working - retired	Not working - disabled	Not working - other	
ethnic	Ethnic group	Nominal	White, Non-Hispanic	Black, Non-Hispanic	Other, Non-Hispanic	Hispanic	2+ Races,			
gender	Gender	Nominal	Female	Male						
household_size	Number of people in household	Integer								
income	Annual income category	Ordinal								
internet_sentiment_index	Sum of 10 items about attitudes towards the internet.	Index/ integer								
moveaway_index	Sum of good friends and close relatives who moved away.	Index/ integer								
NeighborIndex	Sum of three items rating relationships with neighbors.	Index/ integer								
passaway_index	Sum of good friend + close relative + spouse/partner who passed away	Index/ integer								
Q2_health_overall	Self-rating: How would you rate your overall health at the present time?	Ordinal	Poor	Fair	Good	Very good	Excellent			
Q22_marital_satn	How satisfied are you in your current relationship with your spouse or partner?	Ordinal	Very unsatisfied	Somewhat unsatisfied	Neither satisfied nor unsatisfied	Somewhat satisfied	Very satisfied	Not married/ not answered (N/A)		
Q27_11_parents_inperson	How often you keep in contact with this type of person through this mode of communication? Parents in person.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a month	Once a week or more			
Q27_12_parents_email	How often you keep in contact with this type of person through this mode of communication? Parents by email.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a month	Once a week or more			
Q27_13_parents_phone	How often you keep in contact with this type of person through this mode of communication? Parents by phone.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_14_parents_letters	How often you keep in contact with this type of person through this mode of communication? Parents by letters.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_15_parents_text	How often you keep in contact with this type of person through this mode of communication? Parents by text.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_16_parents_online	How often you keep in contact with this type of person through this mode of communication? Parents online.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_17_parents_SN	How often you keep in contact with this type of person through this mode of communication? Parents by socia networking sites.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_21_child_inperson	How often you keep in contact with this type of person through this mode of communication? Child in person.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_22_child_email	How often you keep in contact with this type of person through this mode of communication? Child by email.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_23_child_phone	How often you keep in contact with this type of person through this mode of communication? Child by phone.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_24_child_letters	How often you keep in contact with this type of person through this mode of communication? Child by letters.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_25_child_text	How often you keep in contact with this type of person through this mode of communication? Child by text.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_26_child_online	How often you keep in contact with this type of person through this mode of communication? Child online.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_27_child_SN	How often you keep in contact with this type of person through this mode of communication? Child by socia networking sites.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_31_sibling_inperson	How often you keep in contact with this type of person through this mode of communication? Sibling in person.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_32_sibling_email	How often you keep in contact with this type of person through this mode of communication? Sibling by email.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_33_sibling_phone	How often you keep in contact with this type of person through this mode of communication? Sibling by phone.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_34_sibling_letters	How often you keep in contact with this type of person through this mode of communication? Sibling by letters.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_35_sibling_text	How often you keep in contact with this type of person through this mode of communication? Sibling by text.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_36_sibling_online	How often you keep in contact with this type of person through this mode of communication? Sibling online.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_37_sibling_SN	How often you keep in contact with this type of person through this mode of communication? Sibling by socia networking sites.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_41_friend_inperson	How often you keep in contact with this type of person through this mode of communication? Friend in person.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_42_friend_email	How often you keep in contact with this type of person through this mode of communication? Friend by email.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_43_friend_phone	How often you keep in contact with this type of person through this mode of communication? Friend by phone.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_44_friend_letters	How often you keep in contact with this type of person through this mode of communication? Friend by letters.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_45_friend_text	How often you keep in contact with this type of person through this mode of communication? Friend by text.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_46_friend_online	How often you keep in contact with this type of person through this mode of communication? Friend online.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q27_47_friend_SN	How often you keep in contact with this type of person through this mode of communication? Friend by socia networking sites.	Ordinal	Never	Once a year or less	A couple times a year	Once a month to a couple times a	Once a week or more			
Q28_discuss_important_matters_num	How many people do you have in your life with whom you most often discuss matters of personal importance?	Integer								
Q30_supportive_num	How many people do you have in your life who have been very supportive of you during the past year?	Integer								
Q38_more_less_friends	Would you say that you have more friends, fewer friends, or about the same number of friends as you did 5 years ago?	Ordinal	Fewer	About the same	More					
Q39_caregiver	Are you currently providing unpaid care or assistance to an adult friend or family member who needs assistance due to aging, a disability, or a health-related issue?	Binary	Yes	No						
Q46_attend_religious	How often do you attend religious services or other events at a place of worship?	Ordinal	Never	Once a year or less	A couple times a year	Once a month	A couple times a month	Once a week or more		
Q48_volunteer	In the past 12 months, have you volunteered, that is given your time or skills, for a non-profit organization, a charity, school, hospital, religious organization, neighborhood association, civic or any other group?	Binary	Yes	No						
Q50_groups	Do you belong to any local community organizations, clubs, or groups such as Kiwanis, book clubs, gardening groups, or other social groups? If so, how many?	Ordinal	0	1	2	3 or more				
Q53_hobbies	How many hours per week do you spend on hobbies?	Ordinal	None	1-3	4-6	7-10	11-15	16-20	21+	
Q64_yrs_current_residence	How long have you lived at your current residence?	Ordinal	Less than 1 year	1 year to less than 5 years	5 years to less than 10 years	10 years to less than 20	20 years or more			
Q65_relocate	How many times have you moved in the past 10 years?	Integer								
Q77_hrs_alone	On average, how many hours per day are you physically alone?	Ordinal	0-2 hours	3-5 hours	6-10 hours	11-15 hours	16-20 hours	21-24 hours		
Q8_disability	Does any disability or chronic disease keep you from participating fully in work, school, household, or other activities?	Binary	Yes	No						
Q89_1_internet_sentiment	The internet has brought me closer together with my friends and family	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor	Somewhat agree	Strongly agree			
Q89_10_internet_sentiment	I find it easy to balance my time on the internet with in person activities and obligations	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_2_internet_sentiment	The internet makes it easier for me to share personal or uncomfortable information	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_3_internet_sentiment	Communicating online is less satisfying than communicating on the phone or with letters	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_4_internet_sentiment	Social media sites like Facebook and Twitter make me feel connected with my friends and family	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_5_internet_sentiment	The more I use the internet as a replacement for other forms of communication, the lonelier I feel	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_6_internet_sentiment	Social media has helped me keep in touch with friends and family I would have otherwise drifted away from	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_7_internet_sentiment	I have fewer 'deep' friendship connections now that I keep in touch with people using the internet	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree			
Q89_8_internet_sentiment	I would recommend using the internet to others in order to help with loneliness	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor	Somewhat agree	Strongly agree			
Q89_9_internet_sentiment	Technology has made it harder to spend time with my friends and family in person	Ordinal	Strongly disagree	Somewhat disagree	Neither agree nor	Somewhat agree	Strongly agree			
Q90_tradeoffs_family	As a result of technology such as the internet and mobile phones, do you spend more time, less time, or about the same amount of time on family activities as you did 5 years ago?	Ordinal	Less time	About the same amount of time	More time					
Q91_tradeoffs_intimate_convo	As a result of technology such as the internet and mobile phones, do you spend more time, less time, or about the same amount of time having intimate conversations as you did 5 years ago?	Ordinal	Less time	About the same amount of time	More time					
UCLA_index	Outcome measure of loneliness. Index created by summing 20 survey items, each on a scale of 1 - 4.	Index/integer	n/a							

References

Abu-Rmileh, Amjad. 2021. "Be Careful When Interpreting Your Features Importance in XGBoost!" https://towardsdatascience.com/be-careful-when-interpreting-your-features-importance-in-xgboost-6e16132588e7.

Berkman, L. F., and S. L. Syme. 1979a. "Social networks, host resistance, and mortality: a nine-year follow-up study of Alameda County residents." *American Journal of Epidemiology* 109 (2): 186–204. https://doi.org/10.1093/oxfordjournals.aje.a112674.

———. 1979b. "Social networks, host resistance, and mortality: a nine-year follow-up study of Alameda County residents." *American Journal of Epidemiology* 109 (2): 186–204. https://doi.org/10.1093/oxfordjournals.aje.a112674.

Berkman, Lisa F., Maria Melchior, Jean-François Chastang, Isabelle Niedhammer, Annette Leclerc, and Marcel Goldberg. 2004. "Social Integration and Mortality: A Prospective Study of French Employees of Electricity of France–Gas of FranceThe GAZEL Cohort." *American Journal of Epidemiology* 159 (2): 167–74. https://doi.org/10.1093/aje/kwh020.

Brissette, Ian, Sheldon Cohen, and Teresa E. Seeman. 2000. "Measuring Social Integration and Social Networks." In, 53–85. New York, NY, US: Oxford University Press. https://doi.org/10.1093/med:psych/9780195126709.003.0003.

Cacioppo, John T., and Stephanie Cacioppo. 2014. "Older Adults Reporting Social Isolation or Loneliness Show Poorer Cognitive Function 4 Years Later." *Evidence-Based Nursing* 17 (2): 59–60. https://doi.org/10.1136/eb-2013-101379.

Cohen, Sheldon, William J Doyle, David P Skoner, S Rabin, and Jack M Gwaltney. 1997a. "Social Ties and Susceptibility to the Common Cold" 277 (24): 5.

———. 1997b. "Social Ties and Susceptibility to the Common Cold" 277 (24): 5.

———. 1997c. "Social Ties and Susceptibility to the Common Cold." *JAMA* 277 (24): 5.

"Community Life Survey 2018-19." n.d. https://www.gov.uk/government/statistics/community-life-survey-2018-19.

Coombs, Bertha. 2020. "Loneliness Is on the Rise and Younger Workers and Social Media Users Feel It Most, Cigna Survey Finds." https://www.cnbc.com/2020/01/23/loneliness-is-rising-younger-workers-and-social-media-users-feel-it-most.html.

Coyle, Caitlin, and Elizabeth Dugan. 2012. "Social Isolation, Loneliness and Health Among Older Adults." *Journal of Aging and Health* 24 (December): 1346–63. https://doi.org/10.1177/0898264312460275.

Everson-Rose, Susan A., and Tené T. Lewis. 2005. "Psychosocial factors and cardiovascular diseases." *Annual Review of Public Health* 26: 469–500. https://doi.org/10.1146/annurev.publhealth.26.021304.144542.

Haman, John. 2020. "Variable Importance - Linear Regression | Random Effect." https://randomeffect.net/post/2020/11/01/variable-importance-linear-regression/.

Hawkley, Louise C., Kristen Wroblewski, Till Kaiser, Maike Luhmann, and L. Philip Schumm. 2019. "Are U.S. older adults getting lonelier? Age, period, and cohort differences." *Psychology and Aging* 34 (8): 1144–57. https://doi.org/10.1037/pag0000365.

Hawkley, Louise, and John Cacioppo. 2010. "Loneliness Matters: A Theoretical and Empirical Review of Consequences and Mechanisms." *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine* 40 (October): 218–27. https://doi.org/10.1007/s12160-010-9210-8.

Holt-Lunstad, Julianne, Timothy B. Smith, Mark Baker, Tyler Harris, and David Stephenson. 2015. "Loneliness and Social Isolation as Risk Factors for Mortality: A Meta-Analytic Review." *Perspectives on Psychological Science* 10 (2): 227–37. https://doi.org/10.1177/1745691614568352.

Holt-Lunstad, Julianne, Timothy B. Smith, and J. Bradley Layton. 2010a. "Social Relationships and Mortality Risk: A Meta-Analytic Review." *PLOS Medicine* 7 (7): e1000316. https://doi.org/10.1371/journal.pmed.1000316.

———. 2010b. "Social Relationships and Mortality Risk: A Meta-Analytic Review." *PLOS Medicine* 7 (7): e1000316. https://doi.org/10.1371/journal.pmed.1000316.

Kim, Eric. 2017. "The Brain and Social Connectedness: Global Council on Brain Health Recommendations on Social Engagement and Brain Health," January.

Lieberman, Matthew D. 2013. *Social: Why Our Brains Are Wired to Connect.* First Edition. New York:

Crown.

Murphy, John. 2020. “New Epidemic Affects Nearly Half of American Adults.” https://www.mdlinx.com/article/new-epidemic-affects-nearly-half-of-american-adults/lfc-3272.

Nowland, Rebecca, Elizabeth Necka, and John Cacioppo. 2017. “Loneliness and Social Internet Use: Pathways to Reconnection in a Digital World?” *Perspectives on Psychological Science* 13 (September): 174569161771305. https://doi.org/10.1177/1745691617713052.

Russell, Daniel W. 1996. “UCLA Loneliness Scale (Version 3): Reliability, Validity, and Factor Structure.” *Journal of Personality Assessment* 66 (1): 20–40. https://doi.org/10.1207/s15327752jpa6601_2.

Twenge, Jean M., Brian H. Spitzberg, and W. Keith Campbell. 2019. “Less in-Person Social Interaction with Peers Among U.S. Adolescents in the 21st Century and Links to Loneliness.” *Journal of Social and Personal Relationships* 36 (6): 1892–1913. https://doi.org/10.1177/0265407519836170.

Weissbourd, Richard, Milena Batanova, Virginia Lovison, and Eric Torres. n.d. “How the Pandemic Has Deepened an Epidemic of Loneliness and What We Can Do About It,” 13.