Report Introduction

Using the the office of advancement's dataset we found data to back up insights that relate to categorizing distinct groups within the various donators. We further narrowed our scope to specifically discover which variables Blackbaud used to create their persona categories. To do this, we first cleaned the dataset after EDA to only include variables necessary to our statistical modeling. After this, we used various clustering and random forest methods to distinguish the groups in the dataset. By cross-referencing our results with Blackbaud's placement for datapoints into specific persona categories, we were able to provide numerical evidence for each persona's placement which can be used in further research to back up the current qualitative descriptions that were provided.

Loading Data, Libraries, and Functions

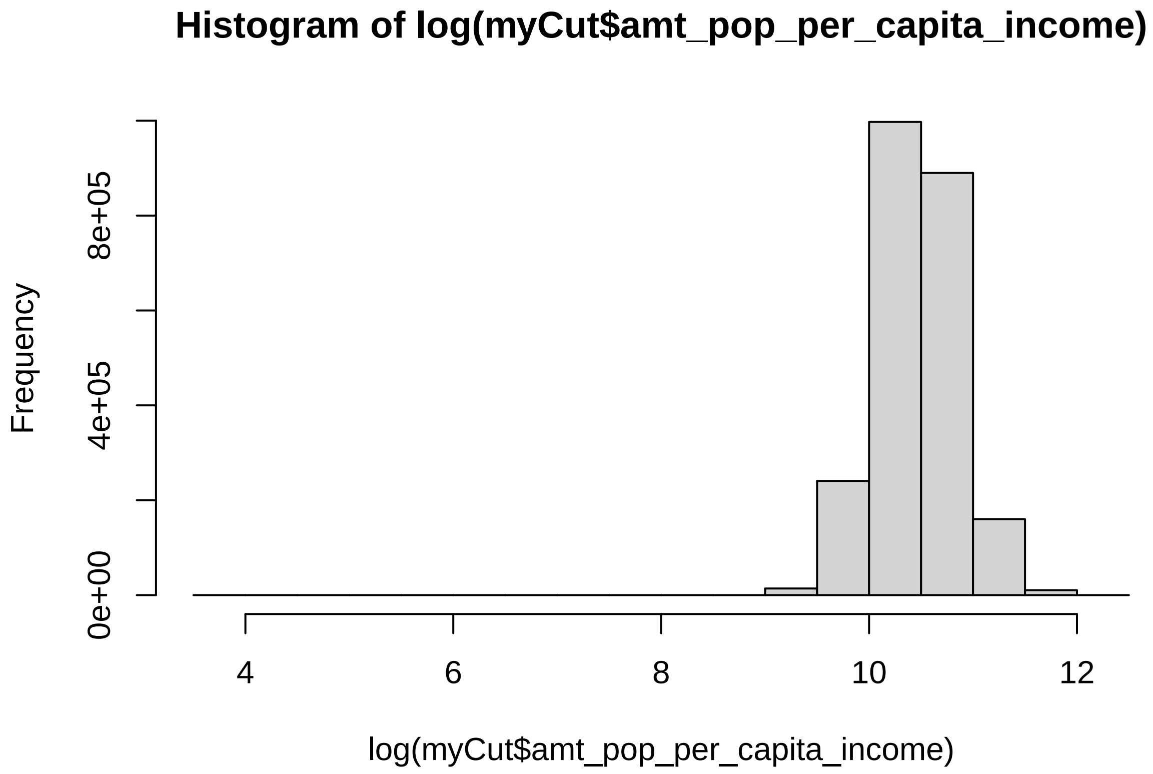
Initial EDA

I start by replacing all "null"s with NAs. Next, I removed the variables that don't make sense to use, such as name – which is completely random, address – which should be unique, TAS_ID – which is all the same value, etc.

```
sub = adv
for (i in 1:ncol(adv)) {
  if (is.character(adv[, i]))
    sub[, i] = nullToNA(adv[, i])
}

subRelRmv = sub %>% select(
  -c(
    "Not_in_use",
    "TAS_ID",
    "UniqueID",
    "SubmitDate",
    "Source",
    "_rescued_data",
    "HomeAddressStreet1",
    "HomeAddressStreet2",
    "HomeAddressSystemID",
    "FirstName",
    "MiddleName",
    "LastName",
    "HomeCity",
    "HomePostCode",
    "n_tran_credit_card_purchase"
  )
)
```

Here I modify the types of the classes from character to their correct type, either numeric, factor, or character.

```
nNames = names(subRelRmv %>% select(starts_with("n")))
catNames = names(subRelRmv %>% select(starts_with("cat")))
valNames = names(subRelRmv %>% select(starts_with("val") &
                                        !ends_with("map")))
mapNames = names(subRelRmv %>% select(ends_with("map")))
```



```
# Probably a good index of general income -- could be correlated with location
```

I am going to remove the next set of variables because they are all duplicates with variables that either are also in the set or that my group members have.

```
myCut2 = myCut %>% select(
  -c(
    "cat_score_donor_persona_map",
    "val_score_direct_marketing_score_map",
    "val_score_telemarketing_score_map",
    "val_score_online_score_map",
    "val_score_sustainer_score_map",
    "val_score_giving_tuesday_score_map",
    "val_score_end_of_year_score_map",
    "val_score_p2p_event_score_map",
    "val_score_p2p_diy_score_map",
    "cat_score_p2p_persona",
    "cat_demo_gender_map",
    "cat_demo_marital_status_map",
    "cat_demo_person_type_map",
    "cat_demo_dwelling_size_map",
    "cat_financial_mortgage_remainder_amount_map",
    "cat_financial_estimated_income_range_map",
    "cat_demo_occupation_map",
    "cat_demo_education_map",
    "cat_calc_political_persona_map",
    "cat_calc_social_score_map",
    "cat_ta_total_identified_assets_map",
    "cat_ta_wealth_segments_map",
    "cat_demo_dual_income_map",
    "val_score_philanthropic_score_map"
  )
)
```

Checking Correlations

```
corr_simple(myCut2, 0.8)
```

```
##                                    Var1                               Var2
## 301      val_score_philanthropic_score        val_score_end_of_year_score
## 66  val_pop_family_income_state_decile  val_pop_family_income_cbsa_decile
## 110     val_pop_home_value_state_index      val_pop_home_value_cbsa_index
## 22           amt_pop_per_capita_income                val_pop_ispsa_index
## 85           amt_pop_per_capita_income     val_pop_home_value_state_index
## 44                 val_pop_ispsa_index val_pop_family_income_state_decile
## 109  val_pop_family_income_cbsa_decile      val_pop_home_value_cbsa_index
##          Freq
## 301 0.9455868
## 66  0.9040495
## 110 0.8812910
## 22  0.8682611
## 85  0.8527969
## 44  0.8488959
## 109 0.8014389
```

```
# Philanthropic score correlated highly with end of year score and p2p event
# score.
# Going to get rid the other two, with the understanding that they are different
# and if phil score ends up being good, we can look deeper into those

myCut2 = myCut2 %>% select(-c("val_score_end_of_year_score",
                              "val_score_p2p_event_score"))

# Per capita income, ispsa index, home value cbsa/state, and income cbsa/state
# decile are in a fully connected correlation graph. We should only keep one,
# and we're going to choose family income cbsa decile. We think this is best
# because it is the most direct measure of wealth, is comparative to where they
# live, and it is a real value as opposed to an estimated/predicted value.

myCut2 = myCut2 %>% select(-c("val_pop_family_income_state_decile",
"val_pop_ispsa_index", "val_pop_home_value_cbsa_index",
"val_pop_home_value_state_index", "amt_pop_per_capita_income"))

corr_simple(myCut2, 0.8)
```

```
## [1] Var1 Var2 Freq
## <0 rows> (or 0-length row.names)
```

```
corr_simple(myCut2, 0.7)
```

```
##                               Var1                           Var2       Freq
## 120     val_score_sustainer_score val_score_giving_tuesday_score  0.7682351
## 118 val_score_telemarketing_score val_score_giving_tuesday_score  0.7618559
## 87        cat_score_donor_persona         val_score_online_score -0.7611372
## 104 val_score_telemarketing_score      val_score_sustainer_score  0.7373731
```

```
# We now see no more correlation at the 0.8 level, but we see a couple at the
# 0.7 level. We think it is fair to also remove giving Tuesday score since it
# logically should be very similar to the other many scores and is only one day,
# but the correlation between donor persona and online score is actually
# interesting; we won't remove that because we might look into why that occurs.

myCut2 = myCut2 %>% select(-"val_score_giving_tuesday_score")
```

Combining Our Sections Back Together

Now I am going to combine each of our datasets to get one standard one to use. This will reflect my work, so I will exclude some variables that my partners started with but had removed by the time I received their variables.

```
# Putting things together
# ----------------------------------------------------------------------------
# Chris Data

chrisNames = c(
  "val_donor_education_charities",
  "val_donor_private_foundation",
  "amt_ta_income",
  "amt_ta_discretionaryspending",
  "amt_ta_discretionaryspending_philanthropy",
  "amt_ta_networth",
  "amt_ta_investments_savings",
  "amt_ta_investments_savings_bonds",
  "pct_pop_some_college" ,
  "pct_pop_associate_degree",
  "pct_pop_bachelor_degree",
  "pct_pop_graduate_degree",
  "pct_pop_in_preschool",
  "Ppct_pop_in_elementary",
  "pct_pop_in_high_school",
  "pct_pop_in_college",
  "pct_pop_in_grad_school",
  "pct_pop_in_public_school",
  "pct_pop_in_private_school",
  "amt_tran_total_dollars_purchase",
  "amt_tran_avg_dollar_purchase",
  "cat_demo_political_affiliation",
  "cat_calc_social_score",
  "amt_financial_assessed_home_value",
  "n_demo_length_of_residence",
```

```r
  "amt_financial_estimated_monthly_mortgage"
)

# Not including networth, it will need to be dealt with separately
logFix = c(
  "amt_ta_income",
  "amt_ta_discretionaryspending",
  "amt_ta_discretionaryspending_philanthropy",
  "pct_pop_in_college",
  "pct_pop_in_grad_school",
  "pct_pop_in_private_school",
  "amt_tran_total_dollars_purchase",
  "amt_tran_avg_dollar_purchase",
  "amt_financial_assessed_home_value",
  "n_demo_length_of_residence",
  "amt_financial_estimated_monthly_mortgage"
)

chrisCut = subRelRmv %>% select(all_of(chrisNames))

# Doing transformations

# Have to take out net worth for a sec because there are negatives
chrisCut = chrisCut %>% mutate(across(all_of(logFix), function(x)
  log(x + 1)))

# This has several hundred large amounts in the negatives, so I'm going to use
# z-scores and then do a log transform
worthMean = mean(chrisCut$amt_ta_networth, na.rm = T)
worthSd = sd(chrisCut$amt_ta_networth, na.rm = T)
#hist(log((chrisCut$amt_ta_networth - worthMean)/worthSd+1))
chrisCut$amt_ta_networth = log((chrisCut$amt_ta_networth - worthMean) /
                                 worthSd + 1)

# Additional change that needs to be done
chrisCut$amt_ta_investments_savings_bonds =
  as.factor(chrisCut$amt_ta_investments_savings_bonds)

logFix[12] = "amt_ta_income"
for (col in logFix) {
  col_index <- which(colnames(chrisCut) == col)
  colnames(chrisCut)[col_index] <- paste(col, "log", sep = "_")
}
# Chris data is transformed
# -----------------------------------------------------------------------------


# -----------------------------------------------------------------------------
# Irfan Data


irNamesNotToInclude = c(
  "cat_demo_date_of_birth",
  "cat_demo_marital_status",
  "cat_demo_person_type",
  "cat_financial_mortgage_remainder_amount",
  "cat_demo_occupation",
  "ind_lifestyle_cont_animal",
  "ind_lifestyle_cont_child_welfare",
  "ind_lifestyle_cont_conspoli",
  "ind_lifestyle_cont_culture",
  "ind_lifestyle_cont_environment",
  "ind_lifestyle_cont_health",
  "ind_lifestyle_cont_libpol",
  "ind_lifestyle_cont_political",
  "ind_lifestyle_cont_religion",
  "ind_lifestyle_cont_social_services",
  "ind_lifestyle_cause_volunteer",
  "n_demo_length_of_residence",
  "amt_financial_estimated_monthly_mortgage",
  "amt_financial_assessed_home_value"
)

irCut = subRelRmv[1:50] %>% select(-all_of(irNamesNotToInclude))

# I looked at the distributions here -- commenting out for space
# for (i in 1:ncol(irCut)) {
#   if (class(irCut[,i]) == "factor") {
#     barplot(table(irCut[,i]), main=paste('Feature', i))
#   } else {
#     hist(irCut[,i], main=paste('Feature', i))
#   }
# }

# I think we should also remove: dwelling size

# Indicator variables with x% of data in a single category (x >= 95). I feel like
# it's hard to make the case for including them.

# 98% money market, real estate, libpoli
# 97% for iras
# 96% priv comp, conspoli, mail response, multi buyer
# 95% humanitarian

# Looking at plots, they're not correlated much at all with ltg, nor are they
# distributed in an interesting way. I think we take them out, with the
# understanding that if some type of "assets" or politics variable is important,
# we could potentially use these to differentiate more.

irCut = irCut %>% select(
  -c(
    "cat_demo_dwelling_size",
    "ind_investments_money_market",
    "ind_investments_real_estate",
    "ind_lifestyle_cause_libpoli",
    "ind_investments_iras",
    "ind_demo_private_company_ownership",
    "ind_lifestyle_cause_conspoli",
    "ind_purchase_mail_responsive_buyer",
    "ind_purchase_dm_multi_buyer",
    "ind_lifestyle_cont_humanitarian"
  )
)

# Irfan data done
# ----------------------------------------------------------------------------



# ----------------------------------------------------------------------------
# Add together

subTrim = cbind(myCut2, chrisCut, irCut)

# We can see there are only 4 correlated above 0.9, that's not that bad actually.
# We're comfortable keeping both degree variables.
corr_simple(subTrim, 0.8)
```

```
##                                     Var1
## 1037    amt_ta_discretionaryspending_log
## 1159                     amt_ta_networth
## 2013 amt_tran_total_dollars_purchase_log
## 1464             pct_pop_bachelor_degree
##                                               Var2      Freq
## 1037 amt_ta_discretionaryspending_philanthropy_log 0.9940208
## 1159                    amt_ta_investments_savings 0.9194206
## 2013              amt_tran_avg_dollar_purchase_log 0.9005213
## 1464                       pct_pop_graduate_degree 0.8373588
```

```
subTrim = subTrim %>% select(
  -c(
    "amt_ta_discretionaryspending_log",
    "amt_ta_investments_savings",
    "amt_tran_avg_dollar_purchase_log"
  )
)

# Combining Done
# ----------------------------------------------------------------------------
```

Libraries

```
library(dplyr)
library(ggplot2)
library(ggcorrplot)
library(factoextra)
library(randomForest)
library(gridExtra)
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=60),tidy=TRUE)
```

Functions

```
# just converts 'null' to NA
nullToNA <- function(dataName) {
    return(replace(dataName, dataName == "null", NA))
}

# turns numbers as strings into numbers
factorize <- function(dataName) {
    return(as.numeric(as.character(dataName)))
}

tester = function(data, title = "data") {
    data = factorize(data)
    hist(data, main = c("Histogram of", title))
}
```

Initial Data Loading

```
load("C:/Users/chris/OneDrive/Desktop/Capstone/OOA_Proj/subset_adv_ltg_environment.RData")
```

Initial EDA

```
sub2 = adv_sub_ltg
for (i in 1:ncol(adv_sub_ltg)) {
    if (is.character(adv_sub_ltg[, i])) {
        sub2[, i] = nullToNA(adv_sub_ltg[, i])
    }
}
# columns with NA > 0
sum(colMeans(is.na(sub2)) > 0)
```

```
## [1] 143
```

```
# removing very high NA columns
sub3 <- sub2 %>%
    select(-c("Not_in_use", "TAS_ID", "UniqueID", "SubmitDate",
        "Source", "_rescued_data", "HomeAddressStreet1", "HomeAddressStreet2",
        "HomeAddressSystemID", "FirstName", "MiddleName", "LastName",
        "HomeCity"))
```

From the beginning we saw variables that did not seem useful so we removed them first. Our reasoning consisted of two ideas; NA rates that were too high or too general of information. Attributes like TAS_ID, UniqueID, and Address are unique to each individual so they wouldn't be much help for model building.

Checking Distributions

```
# some variables needed factorized
tester(sub3$cat_calc_social_score, "social score")
```

```
tester(sub3$amt_pop_per_capita_income, "percap income")
```

```
tester(sub3$val_donor_private_foundation, "private dno")
```

```
tester(sub3$val_donor_education_charities, "edu charities")
```

```
tester(sub3$ind_life_new_mover_12mos, "newmover12")
```

```
tester(sub3$ind_life_new_homeowner_12mos, "newhome12")
```

```
tester(sub3$cat_demo_dual_income, "dual income")
```

```
tester(sub3$ind_purchase_dm_multi_buyer, "multi buyer")
```

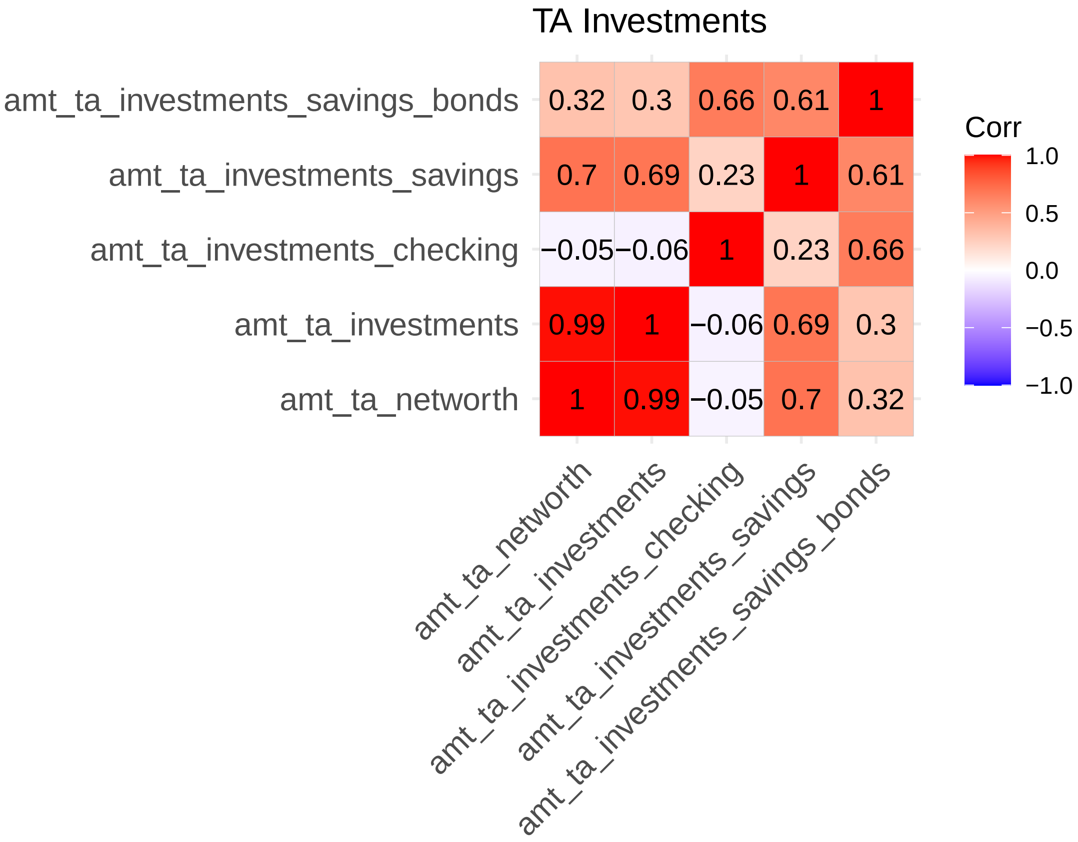
```
tester(sub3$n_purchase_mail_upscale_buyer, "upscale mail")
```

```
tester(sub3$cat_calc_political_persona, "politics")
tester(sub3$val_life_grandchildren, "grandchildren")
```

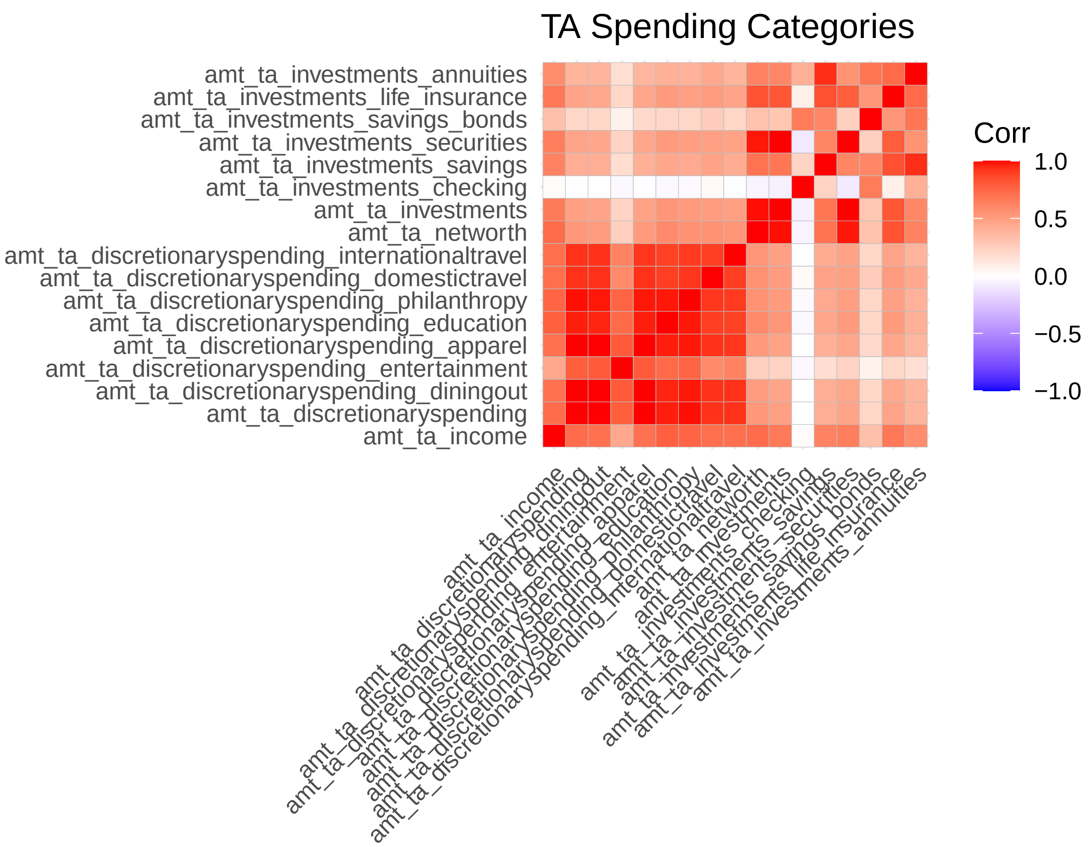
Checking the distributions for variables with consistent trends. Lots of variables have imbalanced class problem where most of the data is in one category. This won't be very helpful when building models, so they should potentially be removed. Examples of 'good' trends exist in variables like Social Score or Per Capita Income.

Checking Correlations and doing PCA on my section of intial data

```
sub4 = sub3[, c(50:98, 105)]
char_cols = sapply(sub4, is.character)
char_cols[c("cat_ta_total_identified_assets", "cat_demo_political_affiliation")] = FALSE
sub4[, char_cols] = as.data.frame(apply(sub4[, char_cols], 2,
    as.numeric))
bigcor = cor(na.omit(sub4[, c(23:26, 28)]))
ggcorrplot(bigcor, hc.order = FALSE, type = "full", lab = TRUE,
    title = "TA Investments")
```



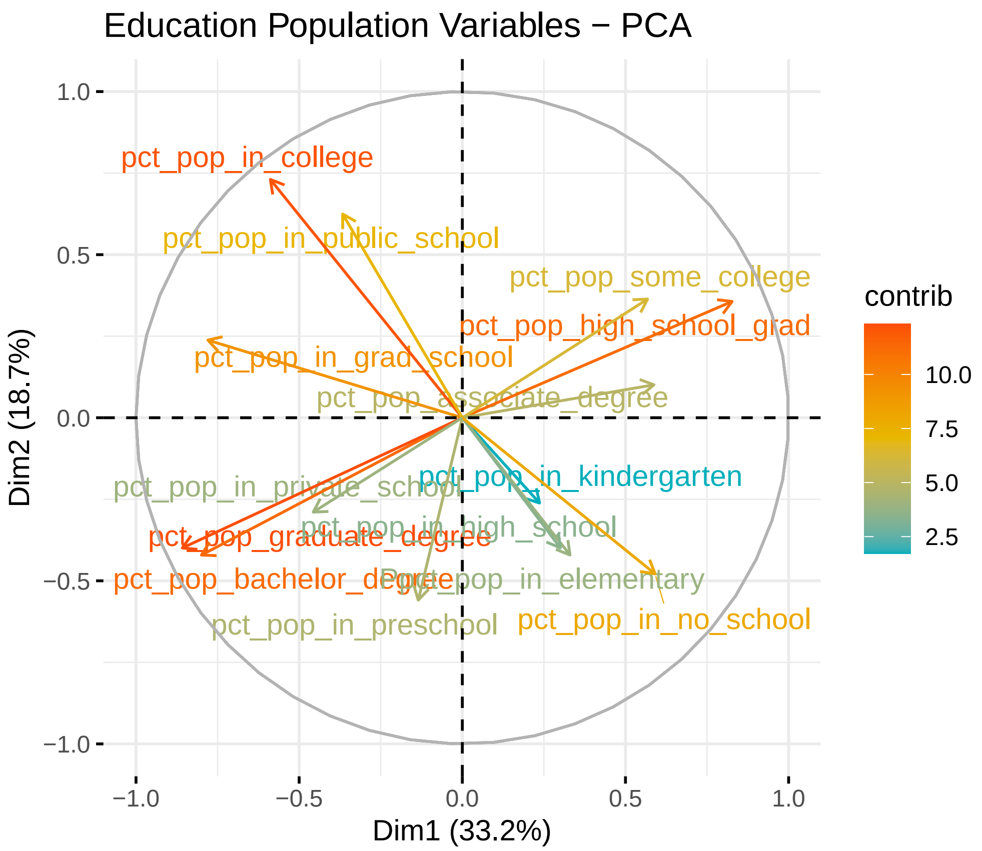
```
sub4_cor = na.omit(sub4[, 14:30])
corData = cor(sub4_cor)

ggcorrplot(corData, title = "TA Spending Categories", tl.cex = 9)
```



From correlations, we can see that we have a major multicollinearity problem. Lots of these variables from Target Analytics have very high correlations with each other. This means they encode similar information which can harm a model's ability to fit to the data accurately. We decided to remove the discretionary spending related variables except philanthropic spending. Also, we removed all investments related variables except investments in savings bonds because it had the least correlation with the other investments variables.

```
finance_pca = prcomp(na.omit(sub4[,23:30]), scale =TRUE)
#Scree Plot to determine number of PCs needed
#fviz_eig(finance_pca)

#fviz_pca_var(finance_pca,
#             col.var = "contrib", # Color by contributions to the PC
 #            gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
  #           repel = TRUE,     # Avoid text overlapping
   #          title='Finance Variables - PCA'
#)

#rotation matrix
#finance_pca$rotation

#checking seems least impactful (not by much, no major finding)

#on population dist
pop_pca = prcomp(na.omit(sub4[,36:49]), scale =TRUE)
#took more PC to explain substantial variance
#Scree Plot to determine number of PCs needed
#fviz_eig(pop_pca)
```

```
fviz_pca_var(pop_pca,
             col.var = "contrib", # Color by contributions to the PC
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE,      # Avoid text overlapping
             title='Education Population Variables - PCA'
)
```



```
#rotation matrix
#pop_pca$rotation
#kindergarten has lower contribution than the rest, maybe remove

par(mfrow=c(1,1))
```

PCA was used to understand how much dimension reduction was possible. For variables related to individuals finances, we saw that only 2 principle components was able to explain ~95% of the variation. As for the population education variables, it took almost all of the components to reach 95% of the variation. So most of these variable hold predictive power and should be used in the model. Specifically, variables such as Percent of Population in Kindergarten and Estimated Checking Account balance show low contribution to the principle components so they will be removed.

Loading in new dataset after removing vars from all of groups EDA

```
load("C:/Users/chris/OneDrive/Desktop/Capstone/OOA_Proj/projEnv.RData")
```

Renaming distributions with log transformations

```
logFix = c("amt_ta_income", "amt_ta_discretionaryspending_philanthropy",
    "pct_pop_in_college", "pct_pop_in_grad_school", "pct_pop_in_private_school",
    "amt_tran_total_dollars_purchase", "n_tran_credit_card_purchase",
    "amt_financial_assessed_home_value", "n_demo_length_of_residence",
    "amt_financial_estimated_available_equity", "amt_financial_estimated_monthly_mortgage")

for (col in logFix) {
    col_index <- which(colnames(subTrim) == col)  # Get the index of the column to modify
    colnames(subTrim)[col_index] <- paste(col, "log", sep = "_")  # Modify the column name
}
```

```
# cleaning data for random forest some variables log
# transformed weird so fixing -Inf values
subTrim = subTrim %>%
    select(c(-"n_tran_credit_card_purchase_log"))

subTrimRF = subTrim %>%
    select(-c("HomeState", "HomePostCode", "amt_financial_estimated_available_equity_log"))

subTrimRF$n_demo_length_of_residence_log[subTrimRF$n_demo_length_of_residence_log <
    0] <- 0

subTrimRF$amt_financial_assessed_home_value_log[subTrimRF$amt_financial_assessed_home_value_log <
    0] <- 0

subTrimRF$amt_financial_estimated_monthly_mortgage_log[subTrimRF$amt_financial_estimated_monthly_mortgag
    0] <- 0


# drops from 250000 to 95762 :/
subTrimRF = na.omit(subTrimRF)
```

Running Random Forest

```
# persona response
rf <- randomForest(cat_score_p2p_persona_map ~ ., data = subTrimRF,
    importance = T, ntree = 25, maxnodes = 50)
z = importance(rf)
head(z[order(z[, 2], decreasing = T), ], n = 3)
```

```
##                               1 Go Getters 2 Caring Contributors
## val_score_p2p_diy_score           4.073514              4.990280
## val_score_philanthropic_score     1.104172              4.621531
## val_score_telemarketing_score     3.518039              4.557508
##                                 3 Casual Contributors 4 Do Gooders
## val_score_p2p_diy_score                     3.554379   -0.7372299
## val_score_philanthropic_score             -1.436200    2.6740680
## val_score_telemarketing_score             -2.052927    2.5207076
##                                 5 Generous Joes 6 Over Achievers
## val_score_p2p_diy_score             1.5432142        0.7774499
## val_score_philanthropic_score      -0.3173565        2.8945071
## val_score_telemarketing_score       8.1993047       -0.5850514
##                                 7 Cause Enthusiasts 8 Thrill Seekers Average Joes
## val_score_p2p_diy_score                   -1.706693         2.903424     3.628204
## val_score_philanthropic_score              3.586202         4.544039     2.353092
## val_score_telemarketing_score              5.602689         7.934448     5.155071
##                                 MeanDecreaseAccuracy MeanDecreaseGini
## val_score_p2p_diy_score                     5.375455        1655.9365
## val_score_philanthropic_score               7.792200         732.0599
## val_score_telemarketing_score               9.215079        2241.0205
```

```
subTrimRF2 = subTrimRF %>%
    select(-c("cat_score_p2p_persona_map"))

# LTG response
rf2 <- randomForest(amt_lifetime_giving_log ~ ., data = subTrimRF2,
    importance = T, ntree = 25, maxnodes = 50)

z2 = importance(rf2)
head(z2[order(z2[, 2], decreasing = T), ], n = 5)
```

```
##                                   %IncMSE IncNodePurity
## val_score_telemarketing_score 12.026332     31267.922
## val_score_sustainer_score      7.590231     20673.938
## val_demo_age                  20.297923     14846.984
## val_score_p2p_diy_score        7.118600     12037.643
## val_score_philanthropic_score  8.909524      9374.465
```

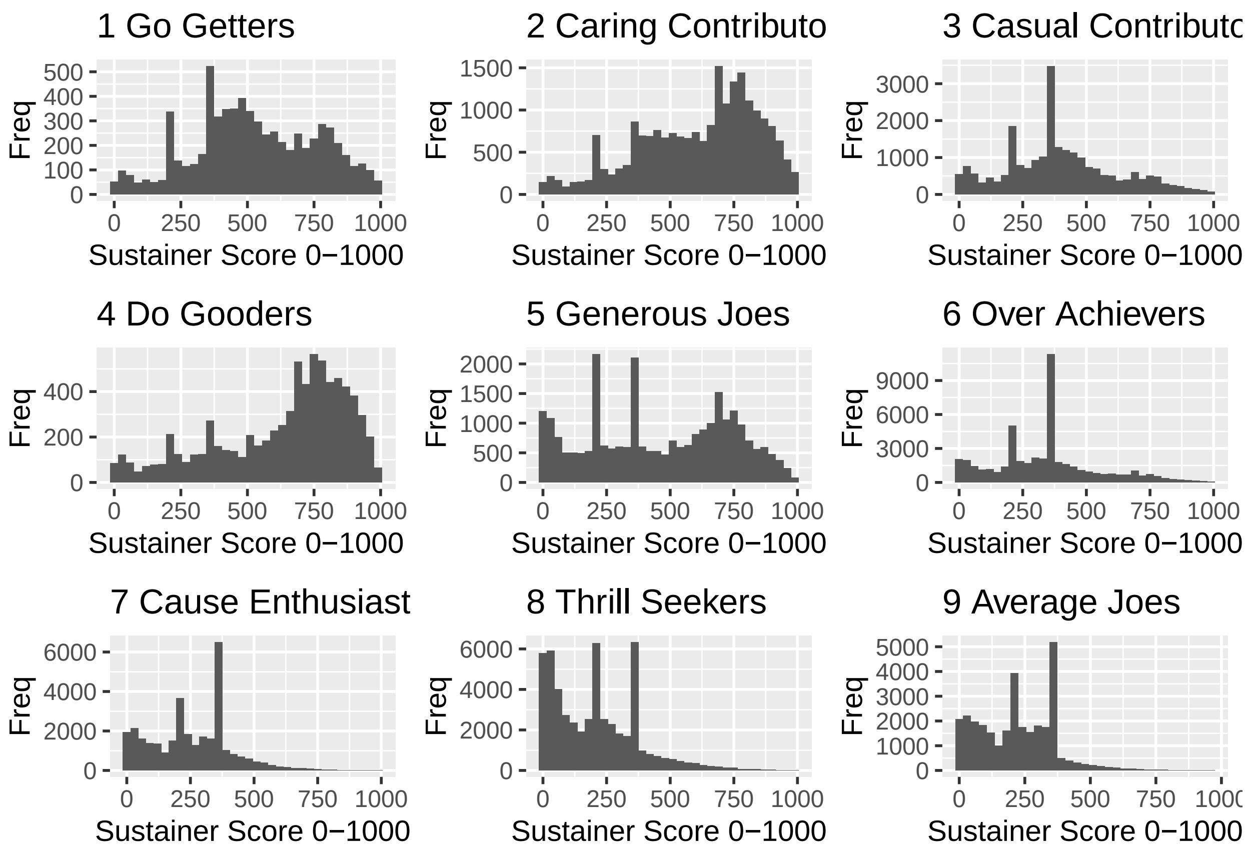
Ran the random forest with two response variables. The first model predicted the individual's lifetime giving total and the second predicted their p2p persona generated by Blackbaud. Both showed the Philantropic score, Telemarketing score, and Sustainer score were useful for predicting both responses.

Checking Trends with personas among important vars from RF

Sustainer Score

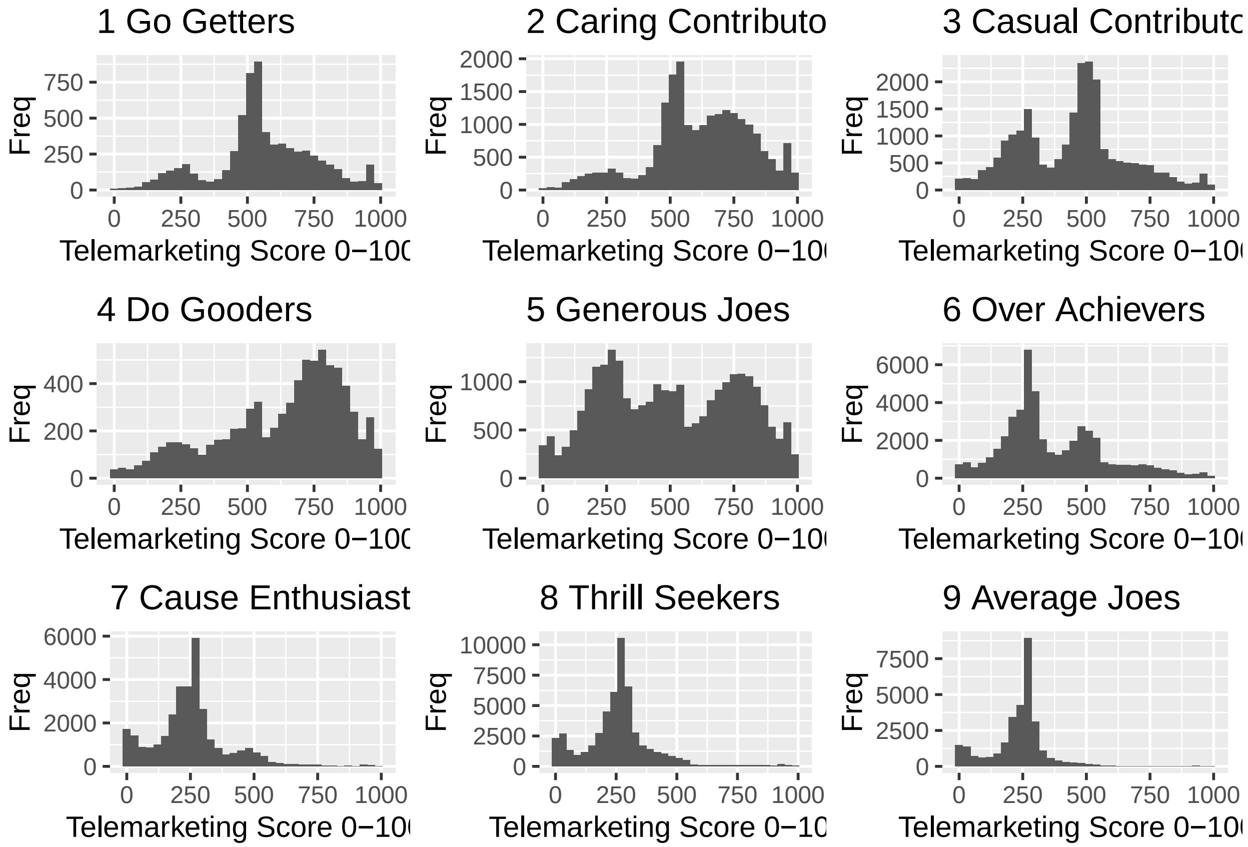
```
# fixing average joes to match formatting of other personas
levels(subTrim$cat_score_p2p_persona_map)[levels(subTrim$cat_score_p2p_persona_map) ==
    "Average Joes"] <- "9 Average Joes"
# vector to loop over all personas
personas = c("1 Go Getters", "2 Caring Contributors", "3 Casual Contributors",
    "4 Do Gooders", "5 Generous Joes", "6 Over Achievers", "7 Cause Enthusiasts",
    "8 Thrill Seekers", "9 Average Joes")
```

```
susPlots <- list()
for (i in 1:10) {
    susPlots[[i]] = ggplot(subTrim[subTrim$cat_score_p2p_persona_map ==
        personas[i], ], aes(x = val_score_sustainer_score)) +
        geom_histogram(binwidth = 30) + xlab("Sustainer Score 0-1000") +
        ggtitle(paste(substring(personas[i], 1, nchar(personas[i])))) +
        ylab("Freq")
}
grid.arrange(susPlots[[1]], susPlots[[2]], susPlots[[3]], susPlots[[4]],
    susPlots[[5]], susPlots[[6]], susPlots[[7]], susPlots[[8]],
    susPlots[[9]], ncol = 3)
```



Sustainer score was important according to our random forest models. Its distribution across the personas generally follows a constant decrease except for personas 2 and 4. Especially group 4, the Do Gooders, stand out as a group with a high frequency of individuals with high propensity to be a sustained donor.

```
telePlots <- list()
for (i in 1:10) {
    telePlots[[i]] = ggplot(subTrim[subTrim$cat_score_p2p_persona_map ==
        personas[i], ], aes(x = val_score_telemarketing_score)) +
        geom_histogram(binwidth = 30) + xlab("Telemarketing Score 0-1000") +
        ggtitle(paste(substring(personas[i], 1, nchar(personas[i])))) +
        ylab("Freq")

}
grid.arrange(telePlots[[1]], telePlots[[2]], telePlots[[3]],
    telePlots[[4]], telePlots[[5]], telePlots[[6]], telePlots[[7]],
    telePlots[[8]], telePlots[[9]], ncol = 3)
```



Here we show another important variable, Telemarketing score, across all the p2p personas. The same constant decrease trend is still shown as we move down the personas. However, here groups 2 and 4 stand out quite a bit. These two groups have much higher frequencies of individuals with a high propensity to make a telemarketing gift.

```
# subTrimRF$cat_score_p2p_persona_map

ggplot(subTrimRF, aes(y = amt_financial_assessed_home_value_log,
    x = cat_score_p2p_persona_map)) + geom_boxplot(outlier.shape = NA,
    lwd = 0.8) + theme(axis.text.x = element_text(angle = 300,
    vjust = 1, hjust = 0), plot.title = element_text(size = 20),
    axis.title = (element_text(size = 15))) + xlab("Persona") +
    ylab("Log Estimated Home Value") + ggtitle("Home Value by Persona") +
    ylim(11, 15.5)
```

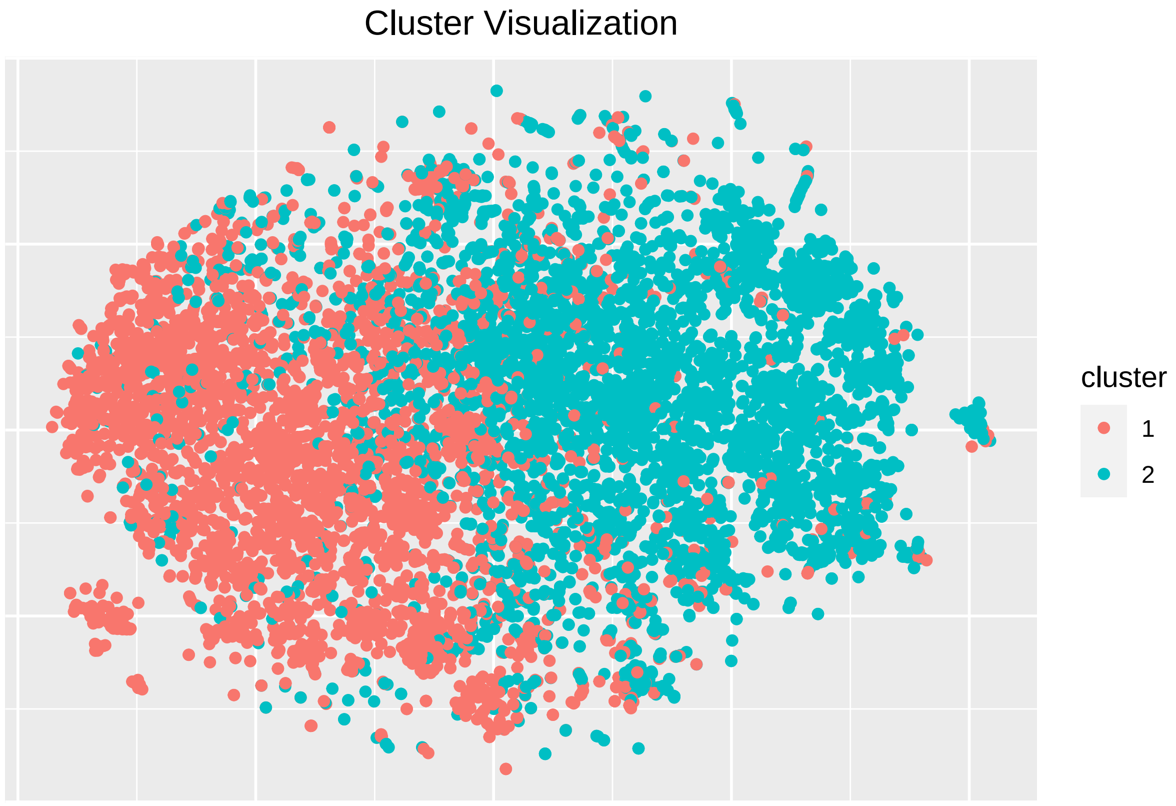
Clustering

K-Medoids With Gower Distance and PAM

We are only able to do this with a subset of the data because of hardware ability. Based on our results though, we don't feel like this is something worth pursuing.

Visualization With T-SNE

```
tsne_obj <- Rtsne(gowerDist, is_distance = TRUE)

tsne_data <- tsne_obj$Y %>%
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_fit$clustering))

ggplot(aes(x = X, y = Y), data = tsne_data) +
  geom_point(aes(color = cluster)) + theme(axis.ticks.x=element_blank(),
                                                  axis.text.x=element_blank(),
                                                  axis.ticks.y=element_blank(),
                                                  axis.text.y=element_blank(),
                                           plot.title=element_text(hjust=0.5)) +
  ylab("") + xlab("") + ggtitle("Cluster Visualization")
```



When we look at these clusters, there are some positives and negatives. The positives are that we achieved some fairly clear splits with fairly even clusters (4500 in 1 and 5500 in 2). It's obvious that cluster 1 tends to be less educated, less wealthy, and less likely to donate, while cluster 2 is the opposite. The negatives are that this doesn't segment our population much — we already expected that more educated/wealthy people would donate more.

However, our metrics give us 2 clusters as the ideal number. This is likely because the data just isn't distributed well to make nice clusters, so more clusters just makes more overlap/noise within clusters. We should zoom out.

Chris has done interesting work with random forests and we've reached a new goal: leverage Blackbaud's clusters to try to figure out what variables they used, rather than creating our own clusters from scratch.

I wanted to work on this as well, and I started very similarly to Chris, by trying our main, cleaned dataset in a random forest with the p2p personas as a response variable.

Random Forest

Forest 1 — Fully Cleaned Dataset

First I have to clean the data a little more to make random forest work:

```r
levels(subTrim$HomeState)[levels(subTrim$HomeState) %in% c("AA", "AE", "AP")] =
  "Armed Forces"
levels(subTrim$HomeState)[levels(subTrim$HomeState) %in%
                             c("PR", "GU", "MP", "VI")] = "Territory"
levels(subTrim$cat_score_p2p_persona_map)[levels(subTrim$cat_score_p2p_persona_map)
                                          == "Average Joes"] = "9 Average Joes"

subTrim$HomeState = droplevels(subTrim$HomeState, exclude = "AB")


# Also going to remove the other persona var because there's no point
subTrimRF = subTrim %>% select(-"cat_score_donor_persona")

# To use random forest, we also can only use complete observations. We still have
# over half a million observations though.
subTrimRF = na.omit(subTrimRF)
```

Modeling

```r
################################################################################
#RF MODELING

rf <- randomForest(cat_score_p2p_persona_map ~ .,
                   data=subTrimRF, importance=T,
                   ntree=30, maxnodes=50)

rf$err.rate[30,]
```

```
##                   OOB          1 Go Getters 2 Caring Contributors
##             0.5748244             0.6828401             0.3319883
## 3 Casual Contributors          4 Do Gooders       5 Generous Joes
##             0.6539625             0.9791023             0.6277522
##      6 Over Achievers   7 Cause Enthusiasts      8 Thrill Seekers
##             0.4340194             0.9696176             0.2455008
##        9 Average Joes
##             0.9825052
```

```
# We can see that predictions are pretty good for some categories (2 and 8),
# decent for some (1, 5, 6, and 7, as well as overall), while three categories
# had horrible error rates (4, 7, and 9)
```

It seems unlikely that Blackbaud would have some top secret data that completely predicts these very poor categories — more likely, some of the variables that we removed during data cleaning were important to distinguish these categories. We want to retry using random forests, but this time include all of the reasonable variables: under 50% NA. Other variables were removed either for multicolinearity or by intuition, but random forests shouldn't be susceptible to multicolinearity issues, and all we care about now is prediction accuracy.

Forest 2 — Expanded Data Set

```
badNames = names((sort(colSums(is.na(subRelRmv))/nrow(subRelRmv) >
                         0.5))[(sort(colSums(is.na(subRelRmv))/nrow(subRelRmv) > 0.5))])
subTrimRF2 = (subRelRmv %>% select(-all_of(badNames)))

# Too many levels
subTrimRF2 = subTrimRF2 %>% select(-"cat_calc_mosaic")

# Fix date of birth
subTrimRF2$cat_demo_date_of_birth = as.numeric(substr(
  as.numeric(as.character(subTrimRF2$cat_demo_date_of_birth)), 1, 4))
# Get rid of maps, they're duplicates
subTrimRF2 = subTrimRF2 %>% select(
  -c(
    "cat_score_donor_persona_map",
    "val_score_direct_marketing_score_map",
    "val_score_telemarketing_score_map",
    "val_score_online_score_map",
    "val_score_sustainer_score_map",
    "val_score_giving_tuesday_score_map",
    "val_score_end_of_year_score_map",
    "val_score_p2p_event_score_map",
    "val_score_p2p_diy_score_map",
    "cat_demo_gender_map",
    "cat_demo_marital_status_map",
    "cat_demo_person_type_map",
    "cat_demo_dwelling_size_map",
    "cat_financial_mortgage_remainder_amount_map",
    "cat_financial_estimated_income_range_map",
    "cat_demo_occupation_map",
    "cat_demo_education_map",
    "cat_calc_political_persona_map",
    "cat_ta_total_identified_assets_map",
    "cat_ta_wealth_segments_map",
    "val_score_philanthropic_score_map"
  )
)

levels(subTrimRF2$HomeState)[levels(subTrimRF2$HomeState) %in% c("AA", "AE", "AP")] =
  "Armed Forces"
levels(subTrimRF2$HomeState)[levels(subTrimRF2$HomeState) %in%
                            c("PR", "GU", "MP", "VI")] = "Territory"
levels(subTrimRF2$cat_score_p2p_persona_map)[levels(subTrimRF2$cat_score_p2p_persona_map)
                                          == "Average Joes"] = "9 Average Joes"

subTrimRF2$HomeState = droplevels(subTrimRF2$HomeState, exclude = "AB")


# Also going to remove the other persona var because there's no point and the
# non-map p2p persona because it will just predict everything perfectly
subTrimRF2 = subTrimRF2 %>% select(-"cat_score_donor_persona")
subTrimRF2 = subTrimRF2 %>% select(-"cat_score_p2p_persona")

subTrimRF2 = na.omit(subTrimRF2) # Still over 400,000 observations!

# Some further cleaning is done but not included, because it is a repeat of the log transformations fro
```

```
################################################################################
#RF MODELING 2

rf2 <- randomForest(cat_score_p2p_persona_map ~ .,
                   data=subTrimRF2, importance=T,
                   ntree=50)

rf2$err.rate[50,]
```

```
##                   OOB          1 Go Getters 2 Caring Contributors
##             0.3375637             0.3015864             0.2153877
## 3 Casual Contributors          4 Do Gooders       5 Generous Joes
##             0.3425329             0.4052257             0.3820683
##      6 Over Achievers   7 Cause Enthusiasts      8 Thrill Seekers
##             0.3311334             0.4752826             0.2311188
##        9 Average Joes
##             0.5407473
```

I would like to note that despite using a seed, the forest I get when knitting is different from the one when running for analysis. However, the end error is very similar, so I think it won't affect much.

We can see that the overall error is much improved (~24%), and we see huge improvements in the error rate of the three worst personas, 4, 7, and 9.

Here you can see the top 5 most important variables for each persona, as well as the 5 best for overall accuracy/impurity.

```
z2 = importance(rf2)
data.frame(Go_Getters_1 = names(head(sort(abs(z2[,1]), decreasing=T), 5)),
           Caring_Contributors_2 = names(head(sort(abs(z2[,2]), decreasing=T), 5)),
           Casual_Contributors_3 = names(head(sort(abs(z2[,3]), decreasing=T), 5)),
           Do_Gooders_4 = names(head(sort(abs(z2[,4]), decreasing=T), 5)),
           Generous_Joes_5 = names(head(sort(abs(z2[,5]), decreasing=T), 5)),
           Over_Achievers_6 = names(head(sort(abs(z2[,6]), decreasing=T), 5)),
           Cause_Enthusiasts_7 = names(head(sort(abs(z2[,7]), decreasing=T), 5)),
           Thrill_Seekers_8 = names(head(sort(abs(z2[,8]), decreasing=T), 5)),
           Average_Joes_9 = names(head(sort(abs(z2[,9]), decreasing=T), 5)),
           Overall_Accuracy = names(head(sort(abs(z2[,10]), decreasing=T), 5)),
           Overall_Gini = names(head(sort(abs(z2[,11]), decreasing=T), 5)))
```

```
##                               Go_Getters_1
## 1 cat_financial_mortgage_remainder_amount
## 2          n_demo_length_of_residence_log
## 3                               HomeState
## 4        val_score_direct_marketing_score
## 5                 val_score_p2p_diy_score
##                      Caring_Contributors_2
## 1 cat_financial_mortgage_remainder_amount
## 2                  pct_pop_in_college_log
## 3           pct_pop_in_private_school_log
## 4                pct_pop_in_public_school
## 5          n_demo_length_of_residence_log
##                           Casual_Contributors_3
## 1      cat_financial_mortgage_remainder_amount
## 2               n_demo_length_of_residence_log
## 3                                    HomeState
## 4                       pct_pop_in_college_log
## 5 amt_financial_estimated_available_equity_log
##                                      Do_Gooders_4
## 1        cat_financial_mortgage_remainder_amount
## 2                         Ppct_pop_in_elementary
## 3                         pct_pop_in_college_log
## 4 amt_ta_discretionaryspending_entertainment_log
## 5                       pct_pop_in_public_school
##                            Generous_Joes_5
## 1 cat_financial_mortgage_remainder_amount
## 2                  pct_pop_in_high_school
## 3                               HomeState
## 4                    pct_pop_in_preschool
## 5                  pct_pop_in_college_log
##                                       Over_Achievers_6
## 1              cat_financial_mortgage_remainder_amount
## 2                       n_demo_length_of_residence_log
## 3 amt_ta_discretionaryspending_internationaltravel_log
## 4                               pct_pop_in_high_school
## 5                            val_demo_number_of_adults
##                            Cause_Enthusiasts_7
## 1      cat_financial_mortgage_remainder_amount
## 2                                    HomeState
## 3                   cat_calc_political_persona
## 4               n_demo_length_of_residence_log
## 5 amt_financial_estimated_available_equity_log
##                                       Thrill_Seekers_8
## 1 amt_ta_discretionaryspending_internationaltravel_log
## 2                              val_score_p2p_diy_score
## 3         amt_financial_estimated_available_equity_log
## 4              cat_financial_mortgage_remainder_amount
## 5                               pct_pop_in_high_school
##                            Average_Joes_9                        Overall_Accuracy
## 1              val_score_p2p_diy_score cat_financial_mortgage_remainder_amount
## 2                            HomeState               val_demo_number_of_adults
## 3       n_demo_length_of_residence_log                pct_pop_in_public_school
## 4  amt_tran_total_dollars_purchase_log                    pct_pop_in_preschool
## 5 cat_financial_estimated_income_range          n_demo_length_of_residence_log
##                     Overall_Gini
## 1 val_score_giving_tuesday_score
## 2  val_score_telemarketing_score
## 3        val_score_p2p_diy_score
## 4      val_score_p2p_event_score
## 5         val_score_online_score
```

Analysis

Common Top Variables

All of the conclusions were drawn either from looking at graphs with the variable of interest as a response variable and the personas as the dependent variable (for numerical vars) or by filtering a single persona and looking at that against the variable of interest, and repeating for each persona (for categorical variables). As you may imagine, this resulted in many, many graphs. I will include one example of each type in the code for future use, but remove the rest for space.

```
################################################################################
# Looking at vars

# Variables to look at:

# For education in general, it follows as such: Personas 1-3 live in particularly
# educated areas; 4, 5, and 8 live in particularly uneducated areas; and 6, 7,
# and 9 are somewhat in the middle.

# For all score variables in general, 3 tends to underperform while 2 and 4
# overperform.

# For all money/wealth variables there is a general downwards trend, with the
# notable exception being that persona 2 is lower than 3.

# private school - Higher rates for category 1.

# number of adults in household - This has a median of 3 adults for every single
# persona except 1, which has a median of 4 adults in the household.

# length of residence - 7 and 9 have a shorter median length of residence, while
# 4 and 5 have noticeably longer residences.
# telemarketing - Particularly low for 7 and 9. Also, while it isn't very low
# for persona 1, it is uncharacteristically low. This is a weak spot for
# targeting them.

# homestate - Hard to find much with or even look at homestate. Our guess
# though is that it it just helps overall accuracy a lot because it has so
# many splits to offer at lower depths. But there probably isn't a clear
# pattern to find.

# age - Persona 5 has a median age about 3 years older than the overall median,
# while personas 7 and 9 are both 4 years younger than the overall median age.

# p2p diy events and online donation score - persona 4 scores particularly bad
# in these, despite overperforming in all of the others.



# Example of code used:
# boxplot(subTrimRF2$amt_financial_assessed_home_value~
#           subTrimRF2$cat_score_p2p_persona_map, outline=F,notch=T)
#
# barplot(table(subTrimRF2 %>% filter(cat_calc_political_persona == "03") %>%
# select(cat_score_p2p_persona_map))/table(subTrimRF2$cat_score_p2p_persona_map))
```

While most personas did not have politics as a top 5 important variable, multiple had it in their top 10s, and we thought it would be an interesting variable to analyze.

```
# Political tendancies by p2p category

# (x% higher) for y politics means that if the proportion of people in the dataset as a whole in politi

# Cat 1:
#   Are: On-the-fence-liberals (mean 10% higher), Mild republicans (8% higher)
#     super democrats (4% higher),
#   Not: Ultraconservative (13% lower), conservative democrats (6% lower)

# Cat 2:
#   Are: mild republicans  (9% higher)
#   Not: Ultraconservative (5% lower)

# Cat 3:
#   Are: Mild republicans (11% higher)
#   Not: Ultraconservatives (8% lower), conservative democrats (4% lower)

# Cat 4:
#   Are: Ultraconservatives (6% higher)

# Cat 5:
#   Are: Ultraconservatives (11% higher)
#   Not: Mild Republicans (8% lower)

# Cat 6: Completely even split
# Cat 7:
#   Not: Ultraconservatives (6% lower)

# Cat 8:
#   Are: Conservative democrats (6% higher) and ultraconservatives (10% higher)
#   Not: Mild Republicans (14% lower)

# Cat 9:
#   Are: Left out democrats (5% higher) and conservative democrats (5% higher)
#   Not: Mild republicans (10% lower)




# Example of code used:
# for (ind in c("1 Go Getters", "2 Caring Contributors", "3 Casual Contributors", "4 Do Gooders", 5 Gen
# "9 Average Joes")) {
#   print(paste("Table", ind))
#   print((table(subTrimRF2 %>% filter(cat_score_p2p_persona_map == ind) %>%
#         select(cat_calc_political_persona))/sum(table(subTrimRF2 %>%
#                                           filter(cat_score_p2p_persona_map == ind) %>%
#                                           select(cat_calc_political_persona))) -
#     table(subTrimRF2$cat_calc_political_persona) / nrow(subTrimRF2)) * 100)
# }
```

Using the full random forest, we see similar general trends as before. The most important variables overall are wealth, education, and the donation scores. However, we were able to much better divide the personas into four larger categories using these:

Personas 1, 2, and 3 — Highly educated, wealthy, and moderate in politics

Personas 4, 5, and 8 — Lower education and wealth, and conservative politics

Personas 7 and 9 — Average wealth, young, shorter length of residence, and respond poorly to donation messages, especially via telemarketing

Persona 6 — Average on all accounts

Moreover, we found ways to distinguish between the personas in each grouping if need be:

People with persona 1 attend private school in higher rates and have more adults in the household. They unfortunately respond poorly to telemarketing though, so they are best reached through other means.

Persona 2s oddly have less wealth than their persona 3 counterparts.

Persona 4s tend to have a longer length of residence. They have very high donation scores for their wealth, however not in p2p diy events or online donations. These people are worth targeting despite their wealth, but you really have to go out to get them – they won't come to you on their own.

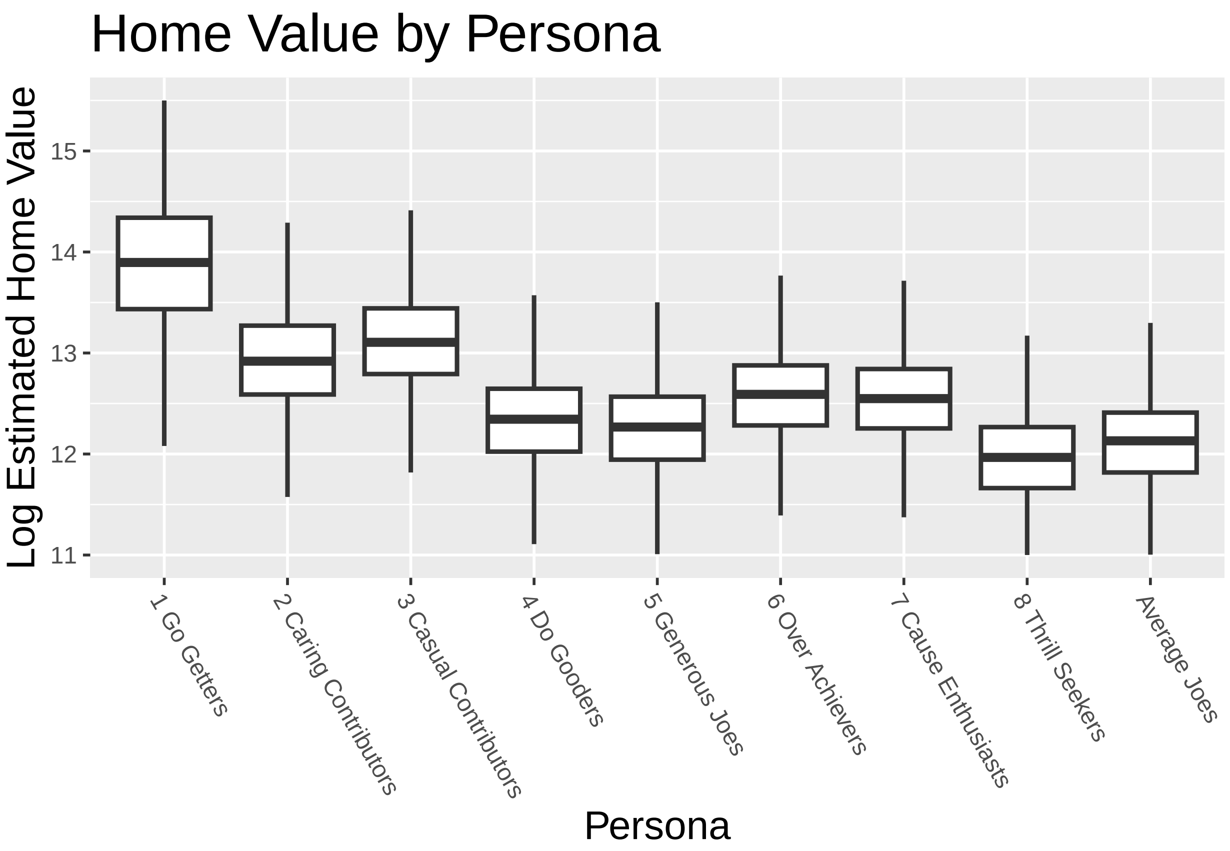
People with persona 5 tend to be older and have longer lengths of residence.

Once again, persona 6s are your real average Joes.

People with persona 7 live in slightly higher educated areas, and while they don't fall under a single political ideology, they are not "superconservatives"

Persona 8s are all around unlikely to donate. Combined with their grouping of low wealth, these people should not be prioritized for donations.

People with persona 9 tend to live in slightly lower educated areas and are politically democrat.



This plot sums up the overall trend of the financial variables that were found important by the random forest. The top three personas (groups 1-3) always were more well off than the rest of the bunch. However, within those three persona 2 typically ranked the lowest. This does not match the usual constantly decreasing trend seen in most financial variables.

Takeaways

After modeling with the random forest the main takeaways are the discoveries around personas 2 and 4. Persona 4, the Do Gooders, show high propensity to be sustained donors and to make telemarketing gifts. In the future, they could be good candidates for a phone campaign or a even a long term annual donation plan. Similarly, it seems that persona two, the Caring Contributors had propensity to given even though their financial standing was lower than expected. This could be interpreted as the persona describes people who give more than typical for their financial bracket. Further analysis could be done on these two groups to try to figure out attributes that link strongly with propensity to give.

In conclusion, our findings from this project allow us to create new groupings for the persona categories that match better with their original descriptions and also allow for further research to be done using these persona categories knowing the numerical values which dictate each variable in the dataset that bins each datapoint into their specific persona group.