Final Project - Bank Dataset

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Youtube Link: https://youtu.be/oeHvLTXBvNQ?si=Wxctb9p1mOr-wJOV

EDA

The first thing that is done when you get a dataset is to peform an Exploratory Data Anslysis, to see what characteristics the data has. The variable we are trying to predict is the y column whic represents if the client has subscribed to a term deposit. The possible values are "yes" or "no".

Create training and test set

Going forward, we will use the training set for all analysis and model building. The test set will be used at the end to get metrics for the various models we create.

```
# Pull in data
data<-read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/bank-additional-full.csv',stringsAsFactors = T, sep=";")

# Set levels to use for later
data$y <- relevel(data$y, ref="yes")
data$month <- factor(data$month,
levels=c('mar','apr','may','jun','jul','aug','sep','oct','nov','dec'))
data$day_of_week <- factor(data$day_of_week,
levels=c('mon','tue','wed','thu','fri'))

# Duration was removed since the dataset explanation file said that it was created after y variable was known, so shouldn't be used for prediction.
data$duration <- c()

# Create the train and test split
train_perc <- .8
set.seed(1234)
train_indices <- sample(nrow(data), floor(train_perc * nrow(data)))
train_data <- data[train_indices, ]
nrow(train_data)

## [1] 32950

test_data <- data[-train_indices, ]
nrow(test_data)
```

```
## [1] 8238
```

Look at summary statistics for numeric variables

There are several numeric variables where we can look at the min/max, quartiles, median, and mean.

```r
summary(train_data$age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   32.00   38.00   40.07   47.00   98.00

summary(train_data$campaign)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   2.561   3.000  56.000

summary(train_data$pdays)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0   999.0   999.0   962.8   999.0   999.0

summary(train_data$previous)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1733  0.0000  7.0000

summary(train_data$emp.var.rate)

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -3.40000 -1.80000  1.10000  0.07483  1.40000  1.40000

summary(train_data$cons.price.idx)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   92.20   93.08   93.75   93.57   93.99   94.77

summary(train_data$cons.conf.idx)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -50.80  -42.70  -41.80  -40.51  -36.40  -26.90

summary(train_data$euribor3m)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.634   1.344   4.857   3.614   4.961   5.045

summary(train_data$nr.employed)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    4964    5099    5191    5167    5228    5228
```

Look at summary statistics for categorical variables

There are several categorical variables. Summary statistics don't make as much sense for them, but you can look at the distribution of values in the different categories.

```
summary(train_data$job)

##        admin.   blue-collar  entrepreneur     housemaid    management
##          8283          7426          1189           836          2355
##       retired self-employed      services       student    technician
##          1391          1130          3185           712          5359
##    unemployed       unknown
##           827           257

summary(summary(train_data$job))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   257.0   833.8  1290.0  2745.8  3728.5  8283.0

length(summary(train_data$job))

## [1] 12

summary(train_data$marital)

## divorced  married   single  unknown
##     3699    19937     9248       66

summary(summary(train_data$marital))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      66    2791    6474    8238   11920   19937

length(summary(train_data$marital))

## [1] 4

summary(train_data$education)

##            basic.4y            basic.6y            basic.9y
high.school
##                3345                1859                4803
7646
##          illiterate professional.course   university.degree
unknown
##                  16                4172                9738
1371

summary(summary(train_data$education))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      16    1737    3758    4119    5514    9738
```

```r
length(summary(train_data$education))

## [1] 8

summary(train_data$default)

##      no unknown     yes 
##   26060    6888       2

summary(summary(train_data$default))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##       2    3445    6888   10983   16474   26060

length(summary(train_data$default))

## [1] 3

summary(train_data$housing)

##      no unknown     yes 
##   14918     794   17238

summary(summary(train_data$housing))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     794    7856   14918   10983   16078   17238

length(summary(train_data$housing))

## [1] 3

summary(train_data$loan)

##      no unknown     yes 
##   27197     794    4959

summary(summary(train_data$loan))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##     794    2876    4959   10983   16078   27197

length(summary(train_data$loan))

## [1] 3

summary(train_data$contact)

##  cellular telephone 
##     20989     11961

summary(summary(train_data$contact))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
##   11961   14218   16475   16475   18732   20989
```

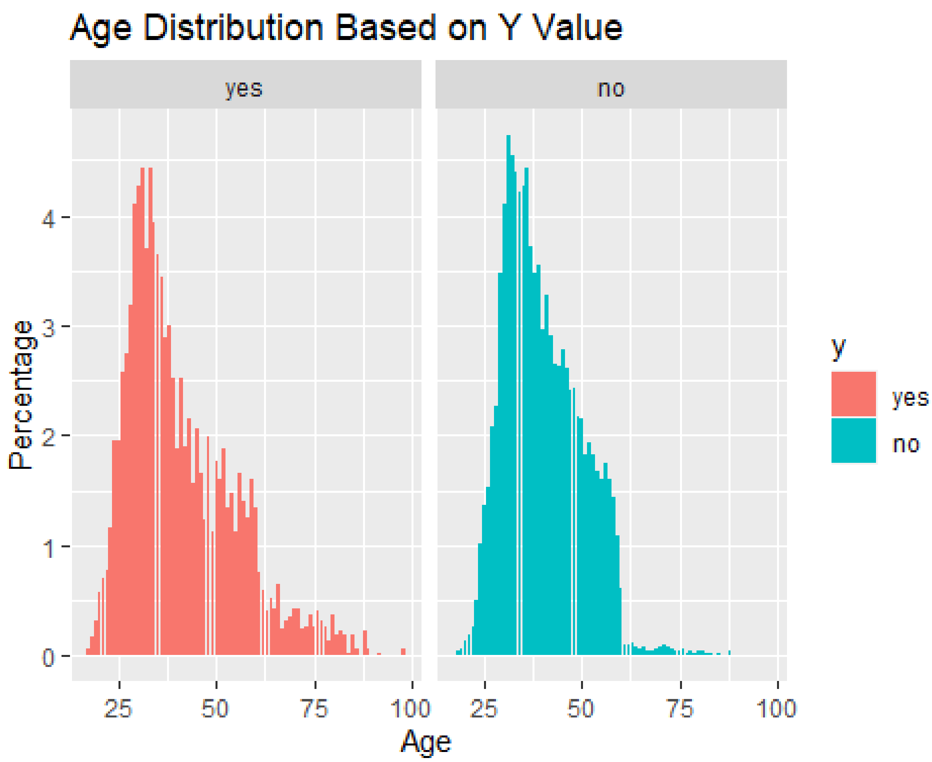
```
length(summary(train_data$contact))

## [1] 2

summary(train_data$month)

##   mar   apr   may   jun   jul   aug   sep   oct   nov   dec
##   440  2098 11023  4233  5760  4931   450   572  3305   138

summary(summary(train_data$month))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   138.0   480.5  2701.5  3295.0  4756.5 11023.0

length(summary(train_data$month))

## [1] 10

summary(train_data$day_of_week)

##  mon  tue  wed  thu  fri
## 6772 6513 6506 6874 6285

summary(summary(train_data$day_of_week))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    6285    6506    6513    6590    6772    6874

length(summary(train_data$day_of_week))

## [1] 5

summary(train_data$poutcome)

##     failure nonexistent     success
##        3438       28425        1087

summary(summary(train_data$poutcome))

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1087    2262    3438   10983   15932   28425

length(summary(train_data$poutcome))

## [1] 3
```

Examine bank client data

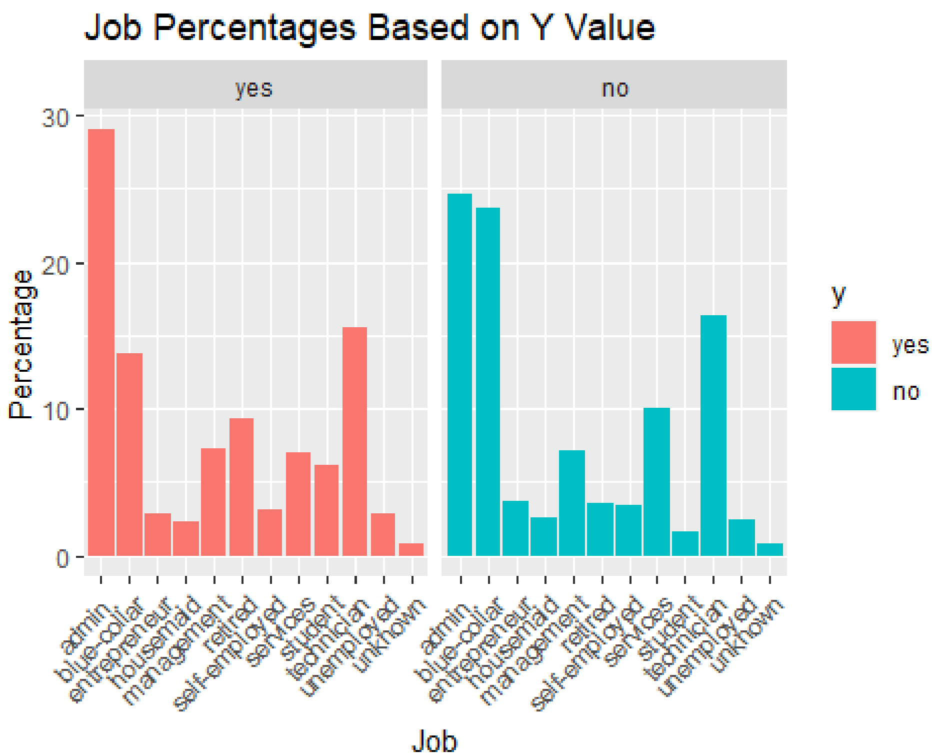
The dataset includes age, job, marital, education, default, housing, and loan columns, which were identified as client data.

```
library(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────── tidyverse
2.0.0 ──
```

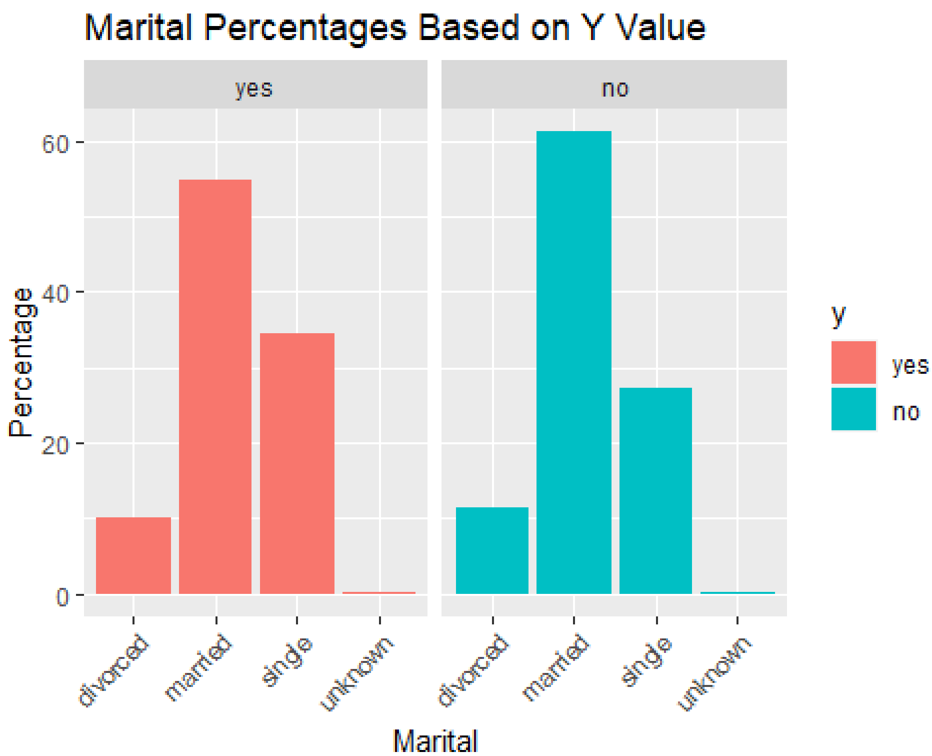
```
## ✓ dplyr     1.1.1     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.0
## ✓ ggplot2   3.4.1     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.0
## ✓ purrr     1.0.1
## ── Conflicts ──────────────────────────────────────────
tidyverse_conflicts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the ]8;;http://conflicted.r-lib.org/conflicted package]8;; to force
all conflicts to become errors

# Plot age
summary <- train_data %>%
  group_by(age,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'age'. You can override using the
`.groups`
## argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=age,y=perc,fill=y)) + geom_bar(stat="identity") +
facet_wrap(~y) +
  ylab('Percentage') + xlab('Age') + ggtitle('Age Distribution Based on Y
Value')
```



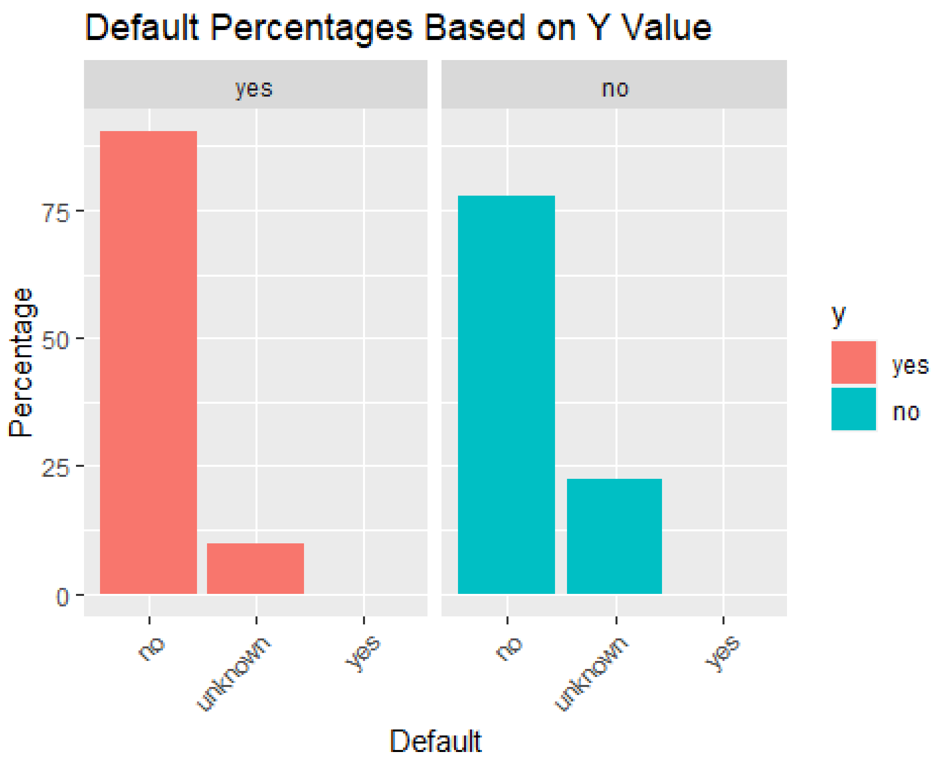

```
# Plot job
summary <- train_data %>%
  group_by(job,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'job'. You can override using the
`.groups`
## argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=job,y=perc,fill=y)) + geom_bar(stat="identity") +
facet_wrap(~y) +
  ylab('Percentage') + xlab('Job') + ggtitle('Job Percentages Based on Y
Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



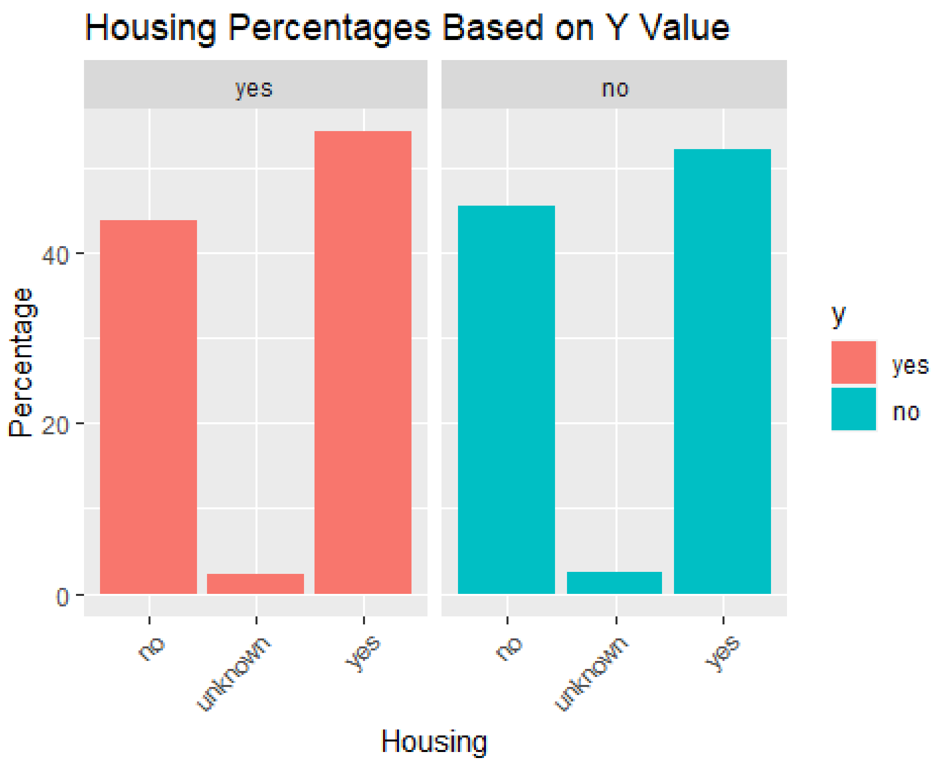

```r
# Plot marital
summary <- train_data %>%
  group_by(marital,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'marital'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=marital,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
  ylab('Percentage') + xlab('Marital') + ggtitle('Marital Percentages Based
on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




```
# Plot default
summary <- train_data %>%
  group_by(default,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'default'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=default,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
  ylab('Percentage') + xlab('Default') + ggtitle('Default Percentages Based
on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




```
# Plot housing
summary <- train_data %>%
  group_by(housing,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'housing'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=housing,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
  ylab('Percentage') + xlab('Housing') + ggtitle('Housing Percentages Based
on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

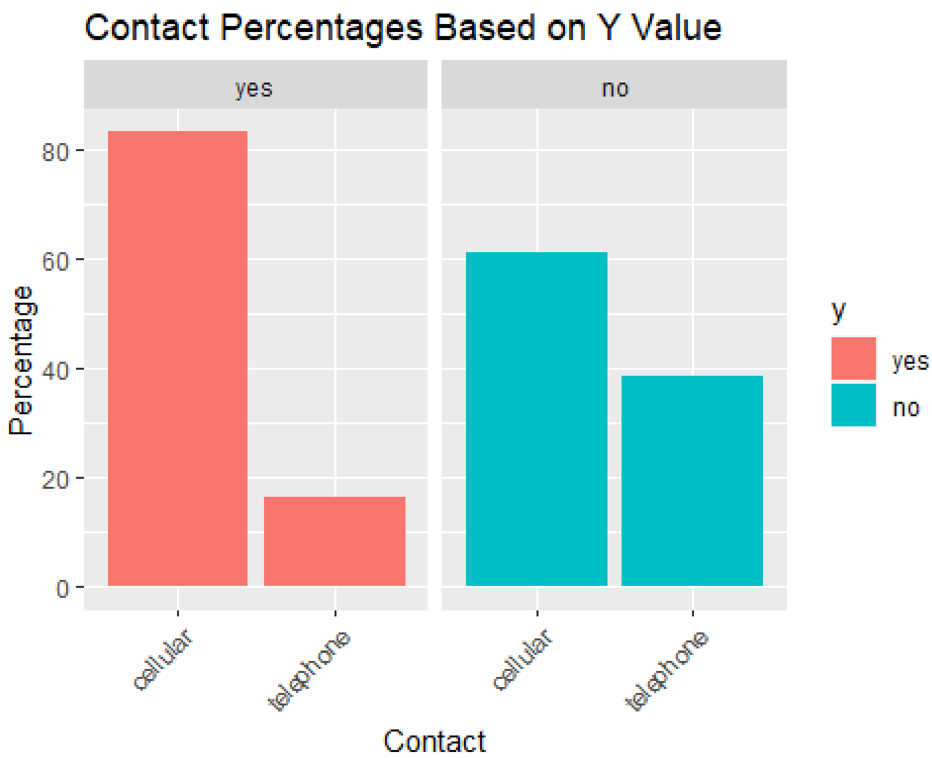


None of these variables appear to show any strong indicator for yes or no. It looks like higher ages tend to lean more towards yes, and certain jobs (Ex: admin) lean more towards yes. When Y = no, there are more than about double the unknown values, but still far under 50%.

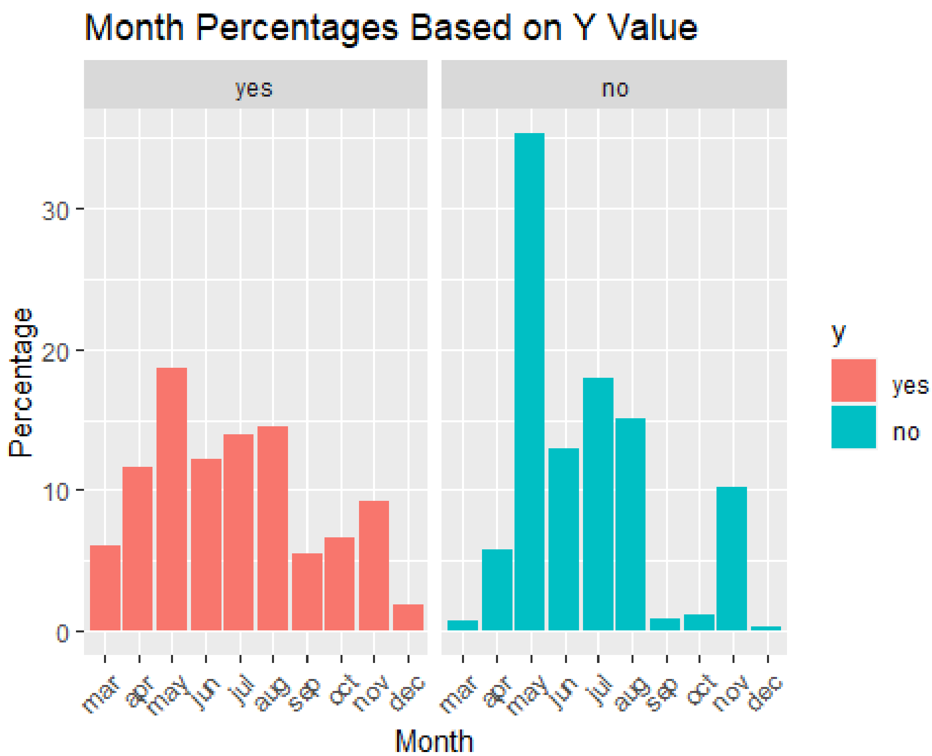
Examine data related with the last contact of the current campaign

The dataset includes contact communication type, month of contact, and day of week of contac, for the last contact of the current campaign to sell term deposits.

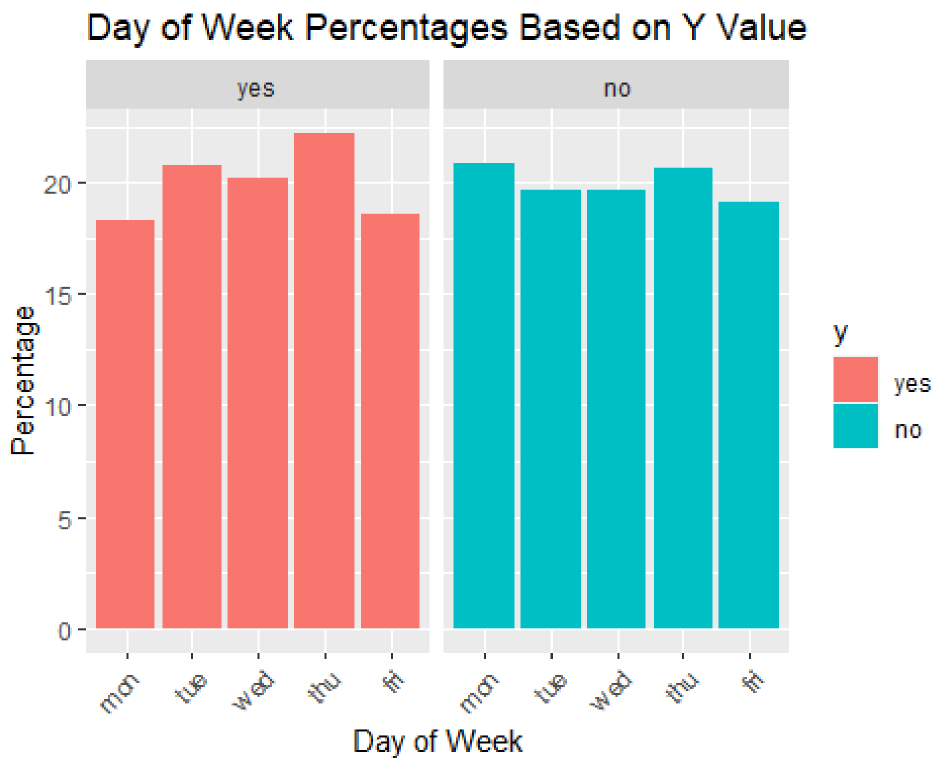
```
# Plot contact
summary <- train_data %>%
  group_by(contact,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'contact'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=contact,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
  ylab('Percentage') + xlab('Contact') + ggtitle('Contact Percentages Based
on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




```
# Plot month
summary <- train_data %>%
  group_by(month,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'month'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=month,y=perc,fill=y)) + geom_bar(stat="identity") +
facet_wrap(~y) +
  ylab('Percentage') + xlab('Month') + ggtitle('Month Percentages Based on Y
Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




```
# Plot day of week
summary <- train_data %>%
  group_by(day_of_week,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'day_of_week'. You can override using
the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=day_of_week,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Day of Week') + ggtitle('Day of Week Percentages
Based on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



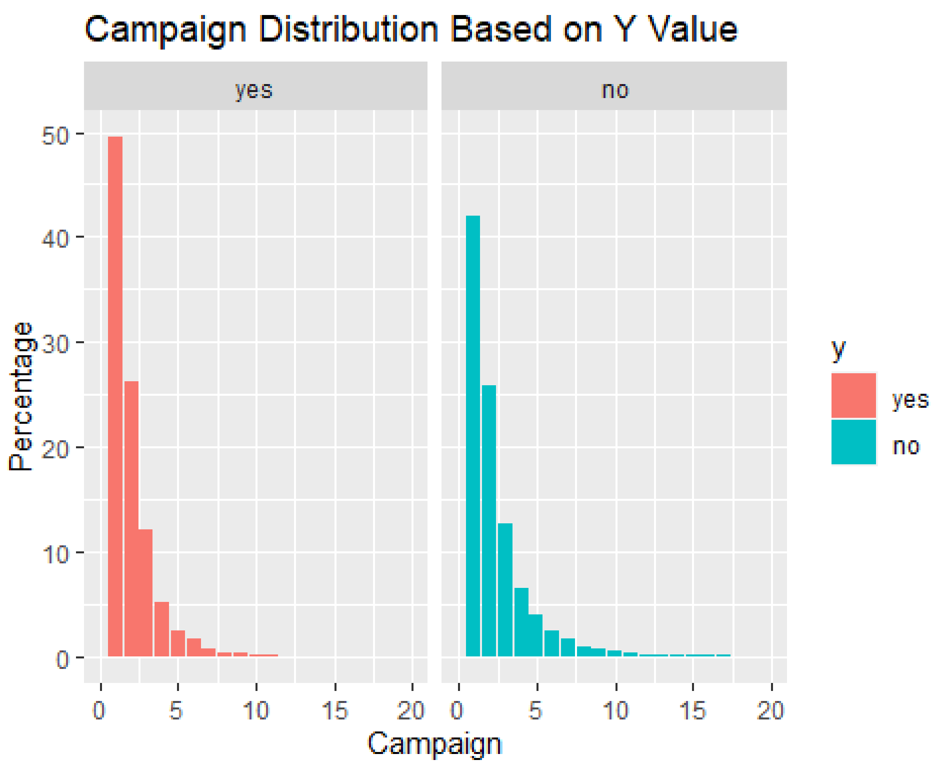
If y is Yes, there are ~20% more likely to be contacted on your cell phone than on landline. There are certain months that also seem to have more term deposit sales in them. Day of week looks to not have much change.

Examine other data related with the current campaign or previous campaigns

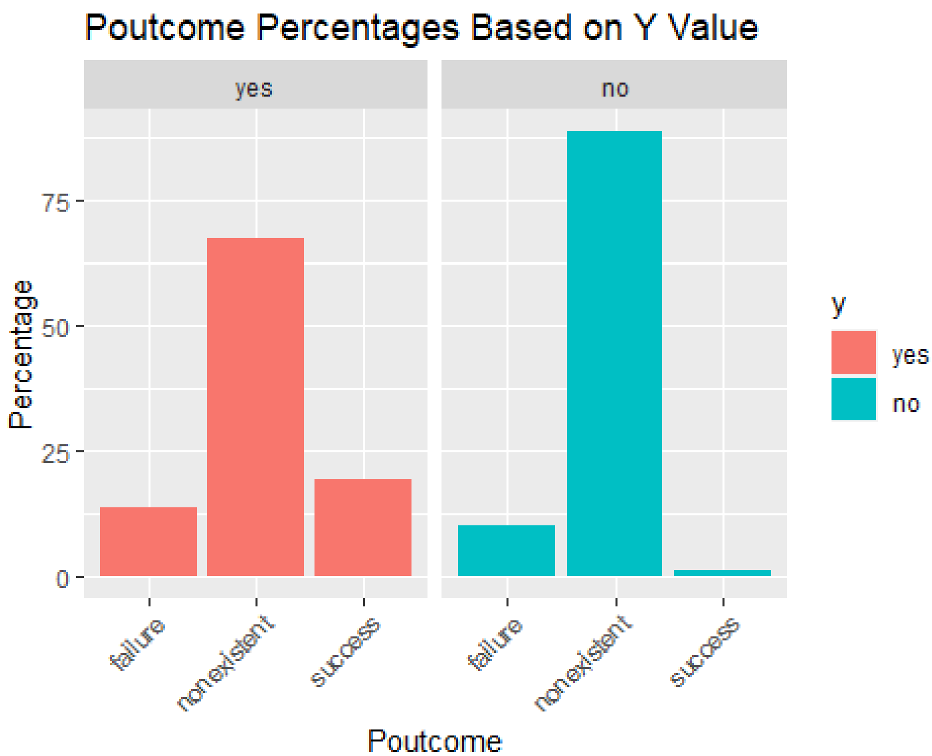
There are variables for number of contacts performed during this campaign and for this client (campaign), number of days that passed by after the client was last contacted from a previous campaign (pdays), number of contacts performed before this campaign and for this client (previous), and outcome of the previous marketing campaign (poutcome).

```
# Plot campaign
summary <- train_data %>%
  group_by(campaign,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'campaign'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=campaign,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
```

```
  ylab('Percentage') + xlab('Campaign') + ggtitle('Campaign Distribution
Based on Y Value') + xlim(c(0,20))

## Warning: Removed 23 rows containing missing values (`position_stack()`).

## Warning: Removed 1 rows containing missing values (`geom_bar()`).
```




```
# Plot poutcome
summary <- train_data %>%
  group_by(poutcome,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'poutcome'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=poutcome,y=perc,fill=y)) + geom_bar(stat="identity")
+ facet_wrap(~y) +
  ylab('Percentage') + xlab('Poutcome') + ggtitle('Poutcome Percentages Based
on Y Value') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



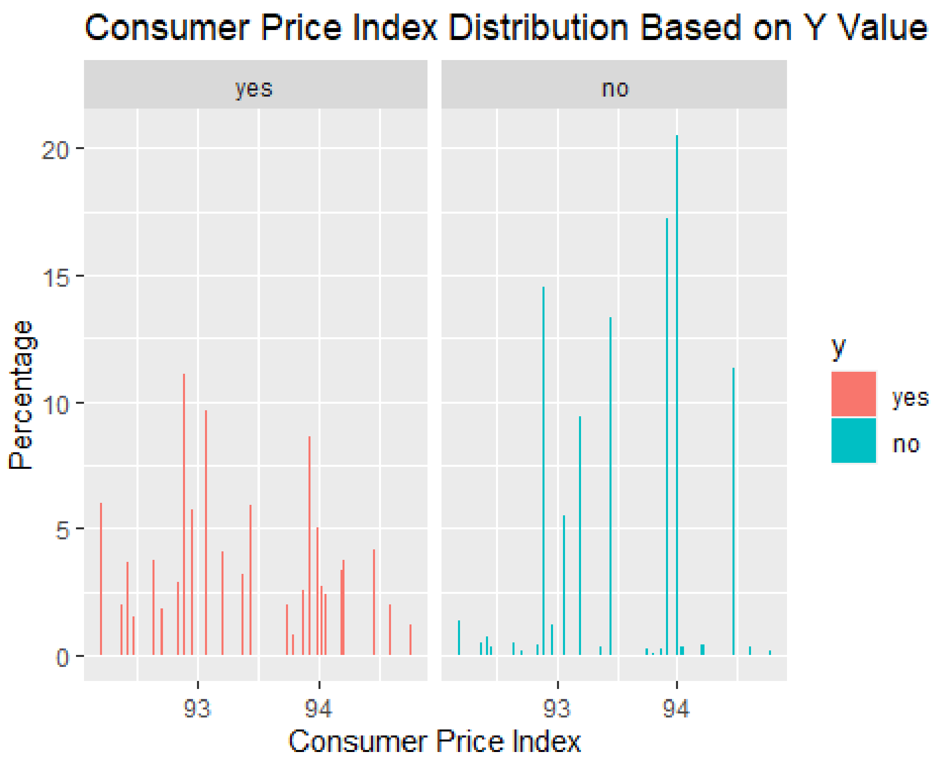
Campaign distributions seem pretty similar between Yes and No. For Poutcome, success is more common for the yes than for no.

Examine socio-economic data

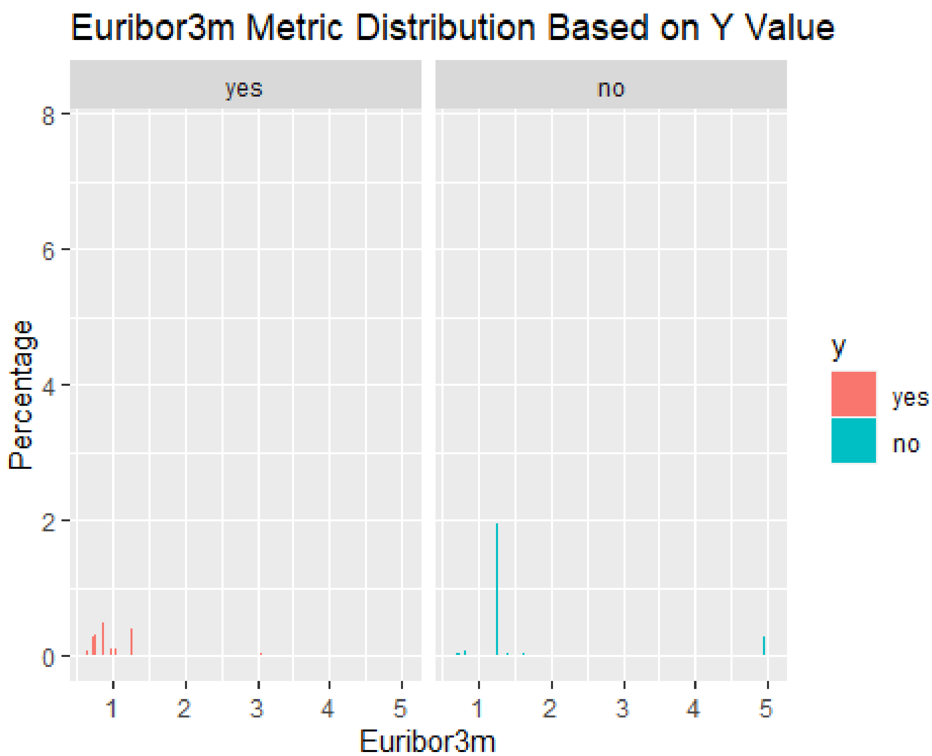
There are variables for socio economic data for Employement Variation Rate, Consumer Price Index, Consumer Confidence Index, Euribor 3 month rate, and Numer of Employees.

```
# Plot emp.var.rate
summary <- train_data %>%
  group_by(emp.var.rate,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'emp.var.rate'. You can override using
the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=emp.var.rate,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Employment Variation Rate') +
ggtitle('Employment Variation Rate Distribution Based on Y Value')
```

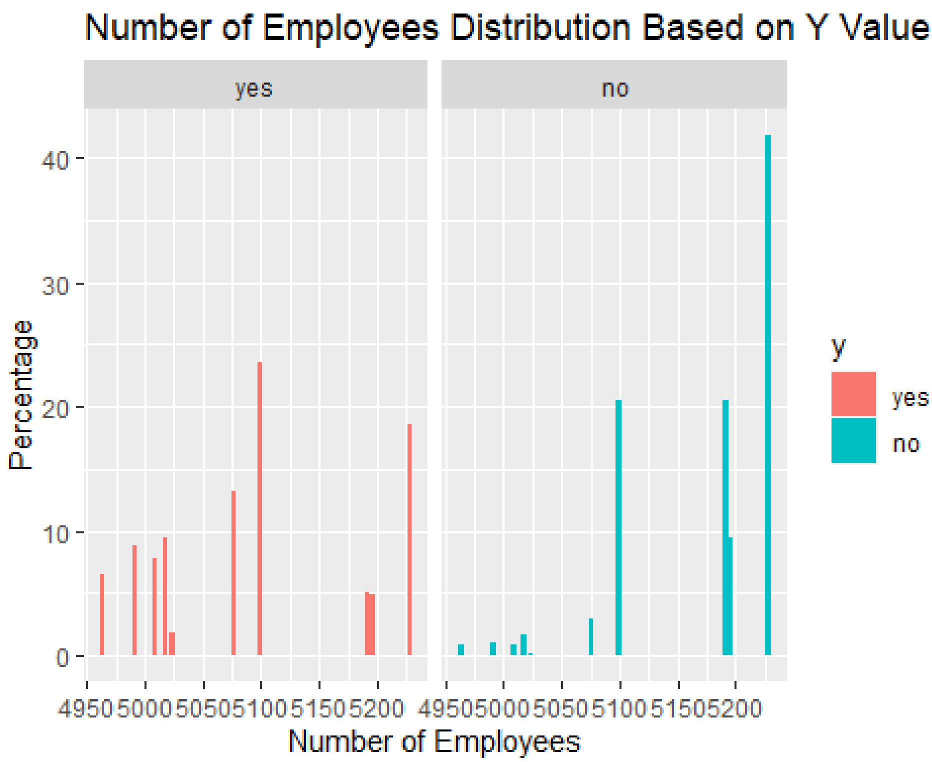

```
# Plot cons.price.idx
summary <- train_data %>%
  group_by(cons.price.idx,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'cons.price.idx'. You can override
using
## the `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=cons.price.idx,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Consumer Price Index') + ggtitle('Consumer Price
Index Distribution Based on Y Value')
```



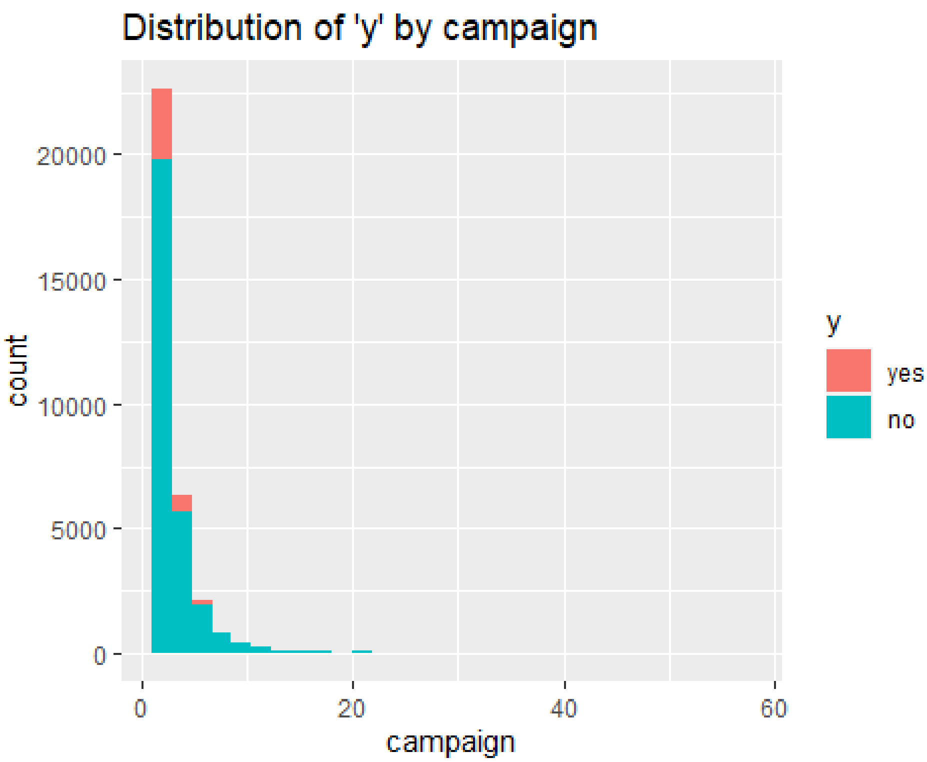

```
# Plot euribor3m
summary <- train_data %>%
  group_by(euribor3m,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'euribor3m'. You can override using
the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=euribor3m,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Euribor3m') + ggtitle('Euribor3m Metric
Distribution Based on Y Value')
```



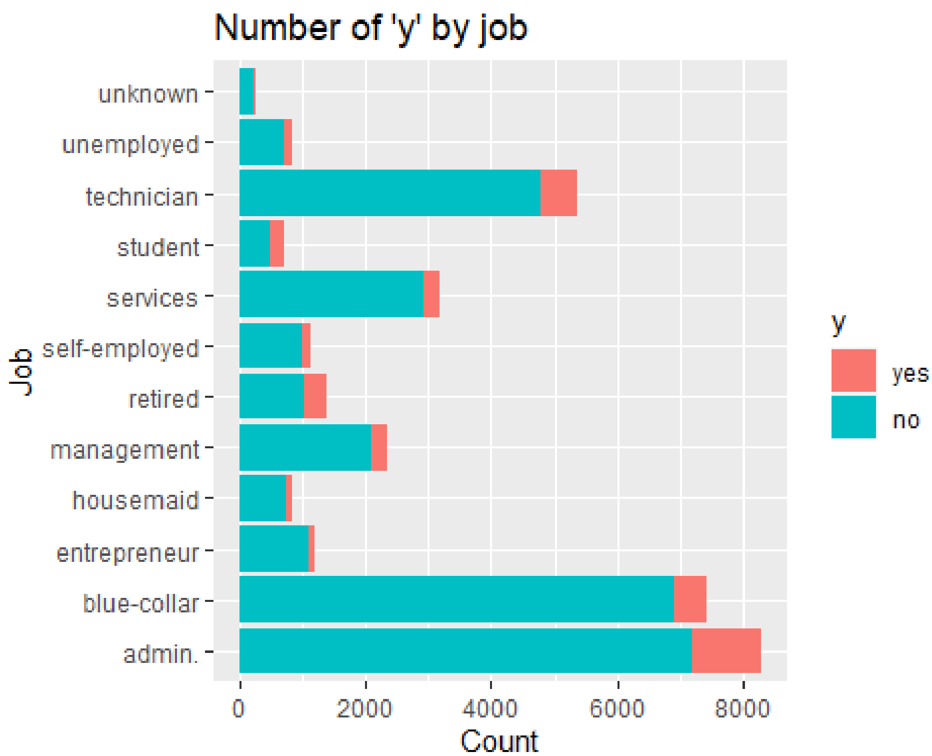

```r
# Plot nr.employed
summary <- train_data %>%
  group_by(nr.employed,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'nr.employed'. You can override using
the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=nr.employed,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Number of Employees') + ggtitle('Number of
Employees Distribution Based on Y Value')
```




```
### Analyzing campaign

ggplot(train_data) +
  geom_histogram(mapping = aes(x=campaign, fill=y)) +
  ggtitle("Distribution of 'y' by campaign")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

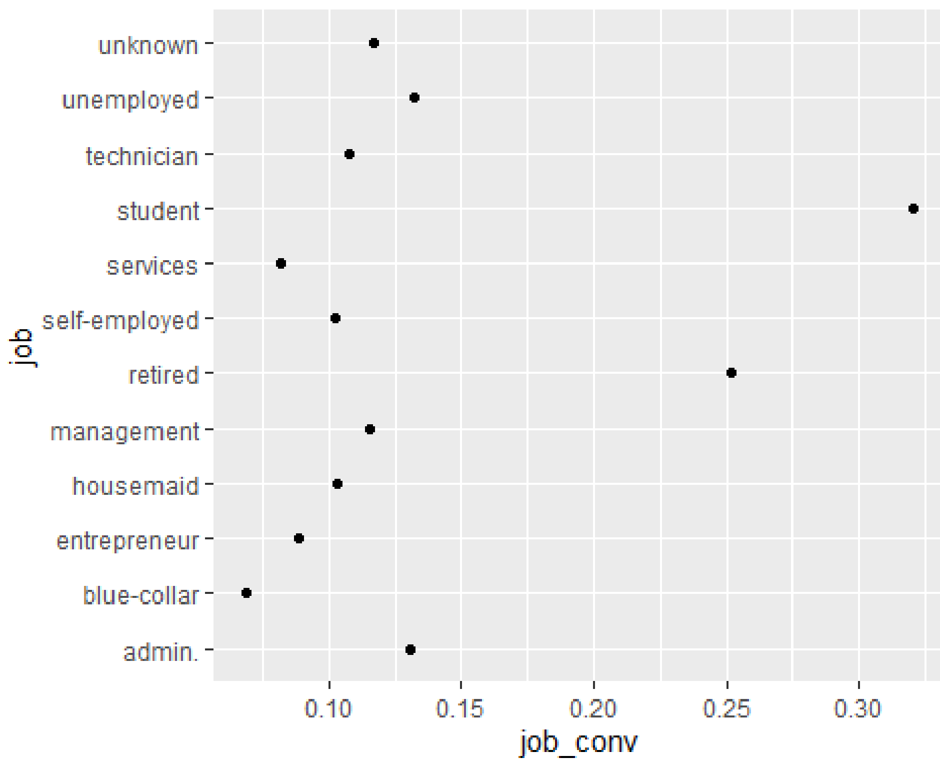



```
### Analyzing JOB

ggplot(train_data) +
  geom_bar(mapping = aes(x=job, fill = y)) +
  coord_flip() +      #Added coord flip here to make it more readable
  ggtitle("Number of 'y' by job") +
  ylab("Count") +
  xlab("Job")
```



Admin, technician and blue collar jobs are the top 3 subscribers by volume

```
df2 <- train_data %>%
  group_by(job) %>%
  count(y) %>%
  mutate(job_conv = n/sum(n)) %>%
  filter(y == "yes")

ggplot(df2, aes(x=job, y=job_conv)) +
  geom_point() +
  coord_flip()
```

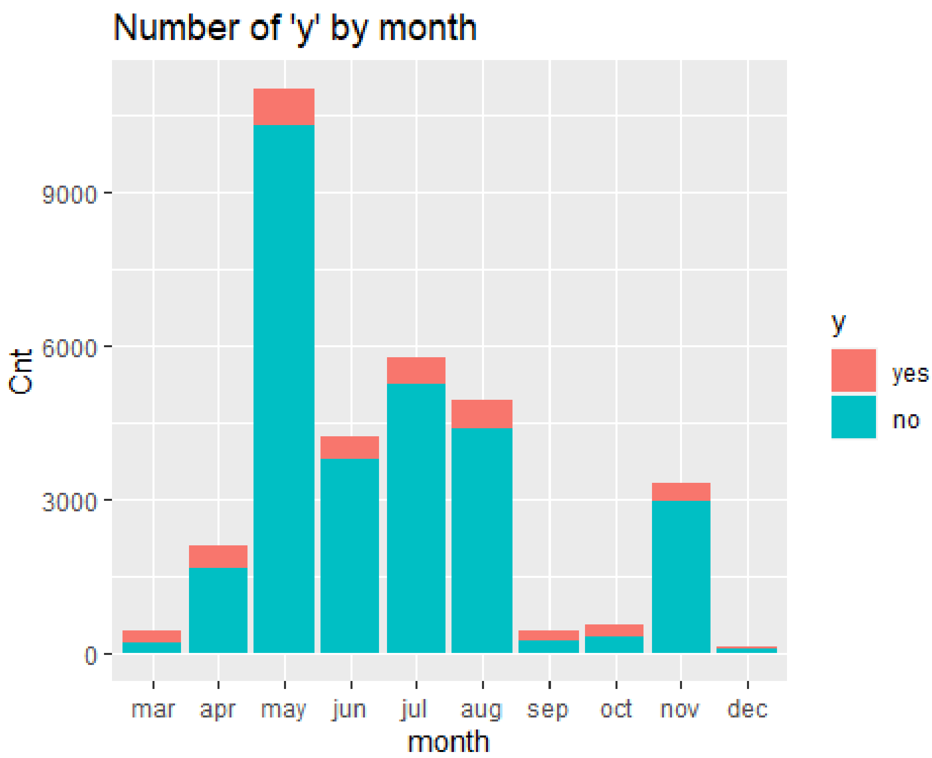


Above, I looked at the ratio of “yes” vs “no” and see that students and retired persons convert at much higher rates than those of other professions. And ‘blue collar’ has the lowest conversion rate

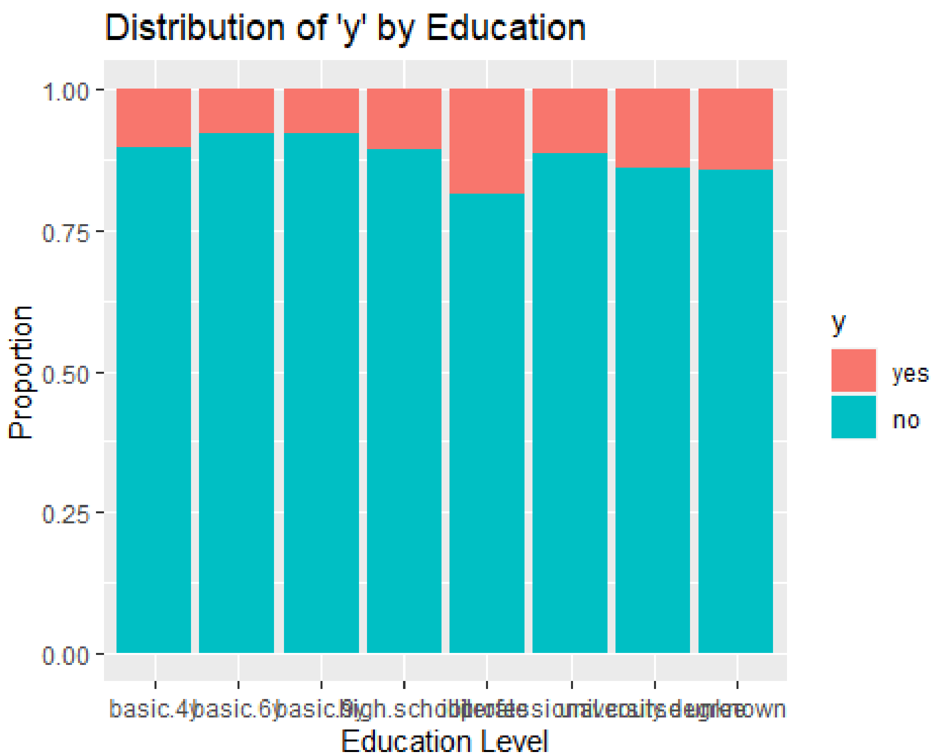
So, if they were to want to improve the cost effectiveness of their campaigns they might want to target more ‘students’ and ‘retirees’

Analyzing By Month

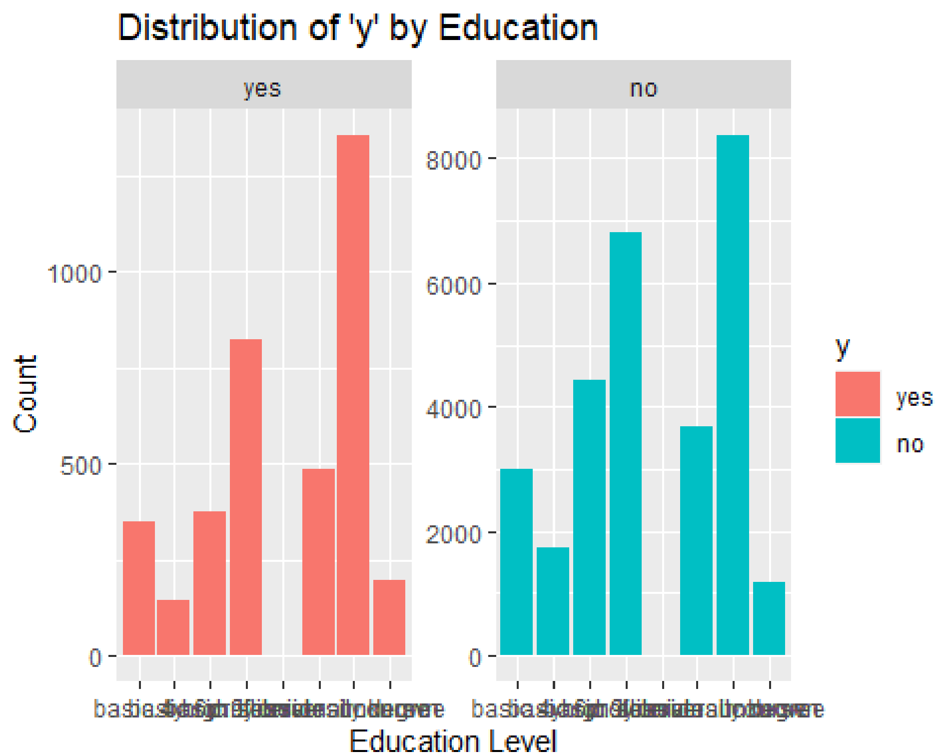
```
ggplot(train_data) +
  geom_bar(mapping = aes(x=month, fill = y)) +
  ggtitle("Number of 'y' by month") +
  ylab("Cnt") + xlab("month")
```



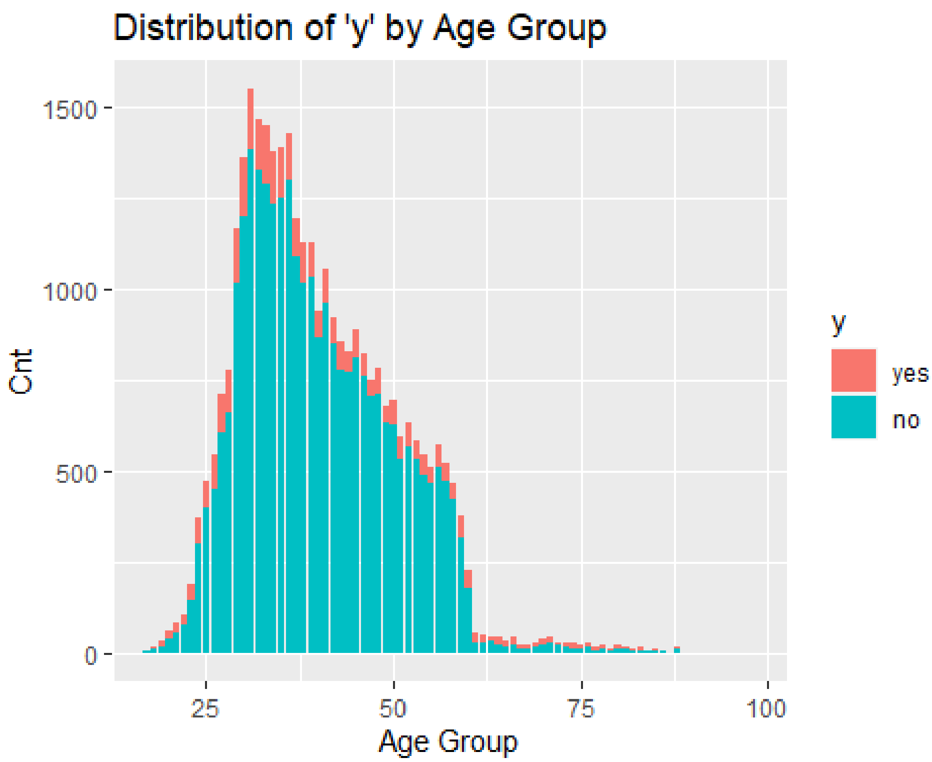

```r
#Education
ggplot(train_data, aes(x = education, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Distribution of 'y' by Education") +
  ylab("Proportion") +
  xlab("Education Level")
```



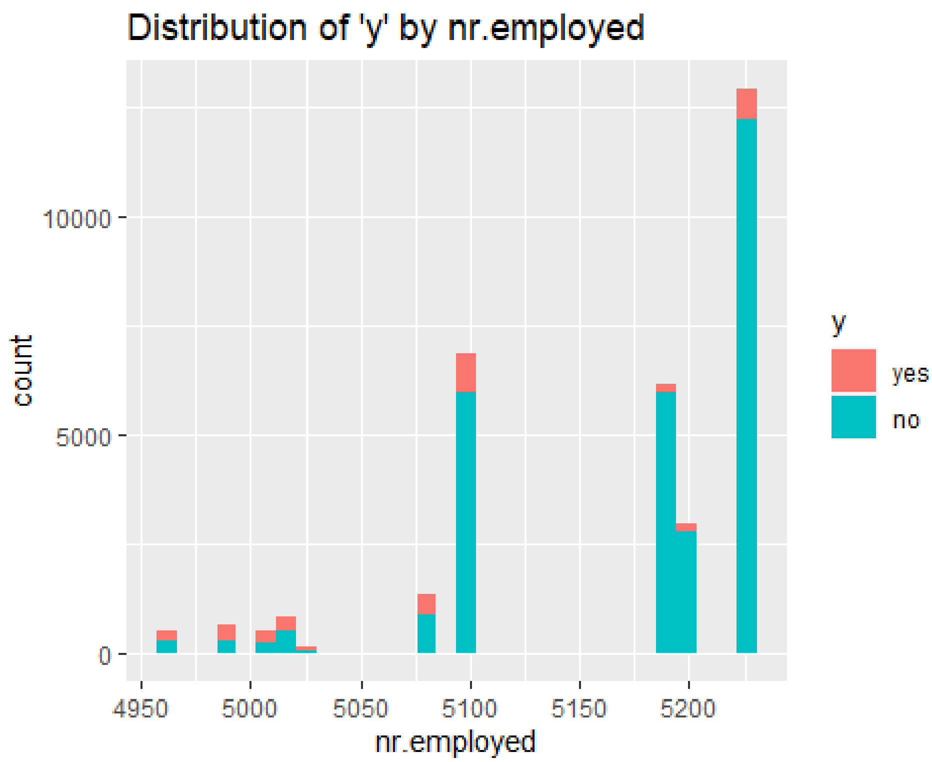

```r
ggplot(train_data, aes(x = education, fill = y)) +
  geom_bar() +
  facet_wrap(~ y, scales = "free_y") +
  ggtitle("Distribution of 'y' by Education") +
  ylab("Count") +
  xlab("Education Level")
```



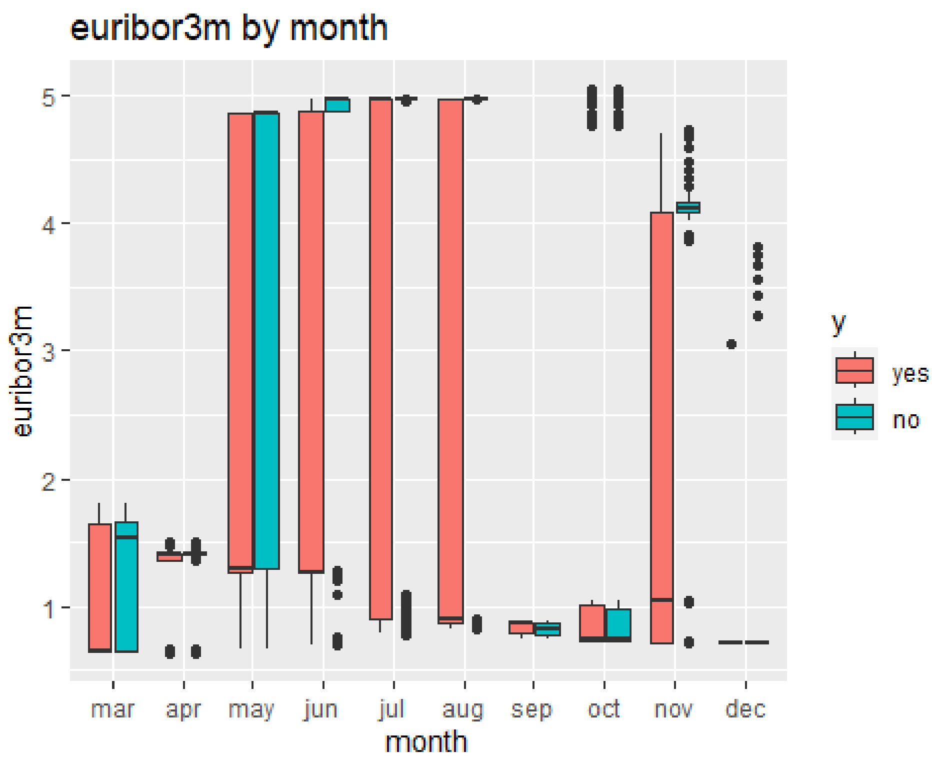

```r
#Age
ggplot(train_data) +
  geom_bar(mapping = aes(x=age, fill = y)) +
  ggtitle("Distribution of 'y' by Age Group") +
  ylab("Cnt") +
  xlab("Age Group")
```



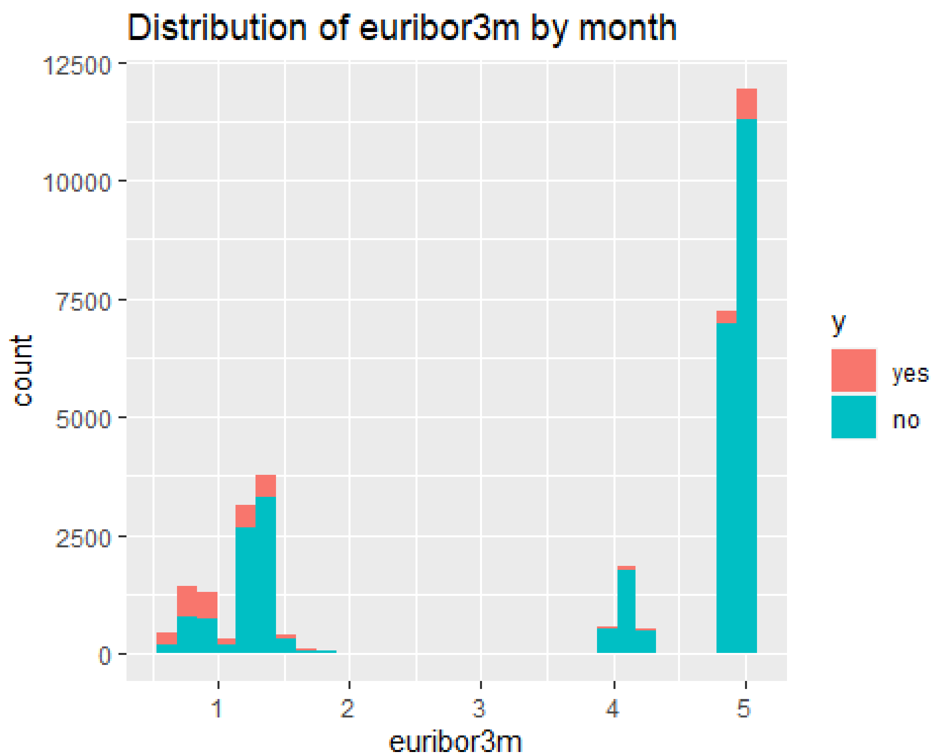

```
# by nr.employed
ggplot(train_data) + geom_histogram(mapping = aes(x = nr.employed, fill = y))
+
  ggtitle("Distribution of 'y' by nr.employed")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
# Euribor 3 month rate
ggplot(train_data, aes(x = month , y = euribor3m, fill = y)) +
  geom_boxplot() +
  ggtitle("euribor3m by month")
```




```
ggplot(train_data) + geom_histogram(mapping = aes(x = euribor3m, fill = y)) +
  ggtitle("Distribution of euribor3m by month")

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
# Correlations of socio-economic variables
library(GGally)

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2

ggpairs(train_data[,c('emp.var.rate','cons.price.idx','nr.employed','euribor3
m')],aes(color = train_data$y))
```

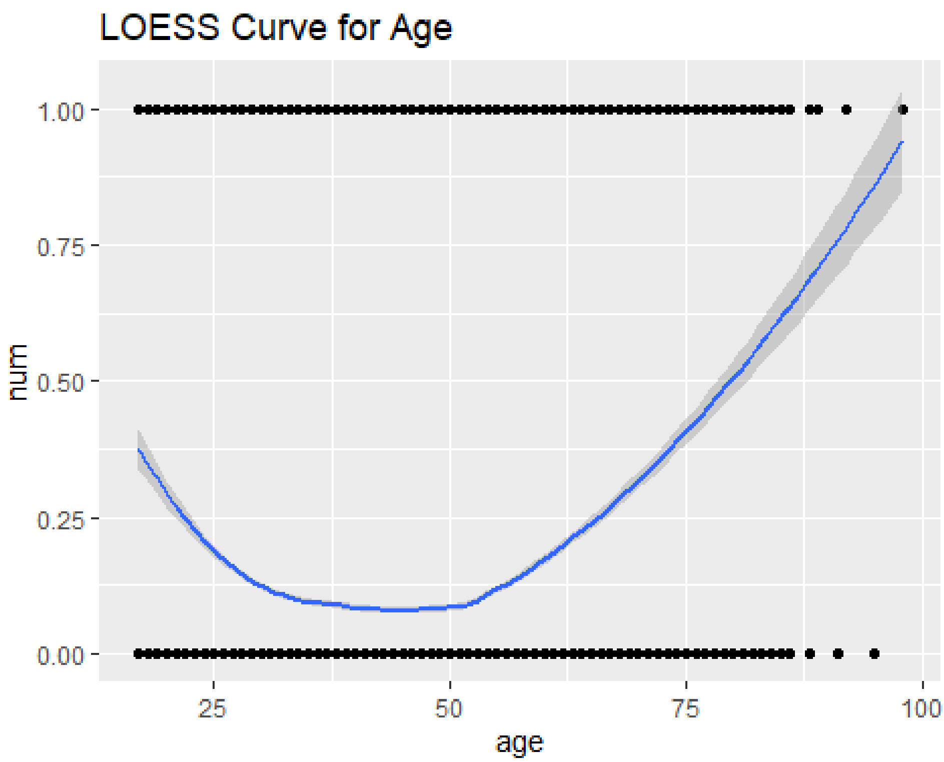
The Consumer Price Index data seems to have more of a flat distribution for those with a term deposit. Employment Variation Rate, Euribor3m, and Number Employed all seem to have similar distributions where there is a higher percentage without term deposits for higher values of the index.

Looking at the paired correlations between out of the socio economic variables, we can see that Employment Variation Rate, Euribor3m, and Number Employed are highly correlated.

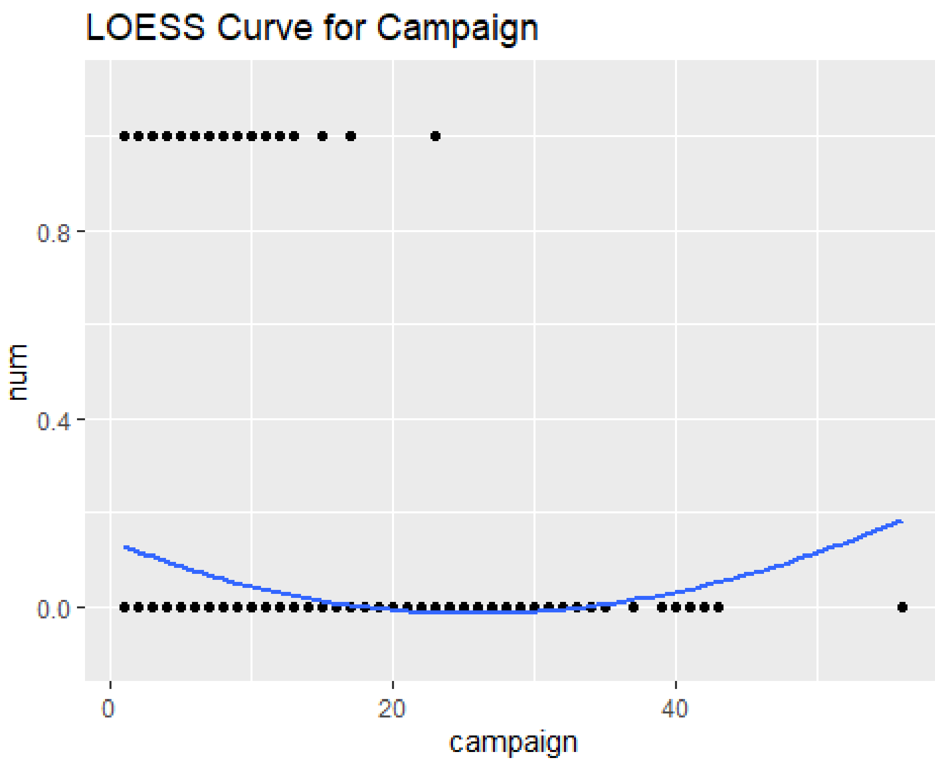
LOESS Curves

LOESS curves can be useful to plot for numeric variables. They show if there is a general trend to higher or lower probabilities if the numeric variable increases. If they increase and then decrease, or vice-versa, this shows that the relationship between the two variables isn't quite as simple.

```
# LOESS for Age
train_data$num <- ifelse(train_data$y=="yes",1,0)
train_data %>% ggplot(aes(x=age,y=num)) +
  geom_point() + geom_smooth(method="loess") +
  ggtitle('LOESS Curve for Age')

## `geom_smooth()` using formula = 'y ~ x'
```

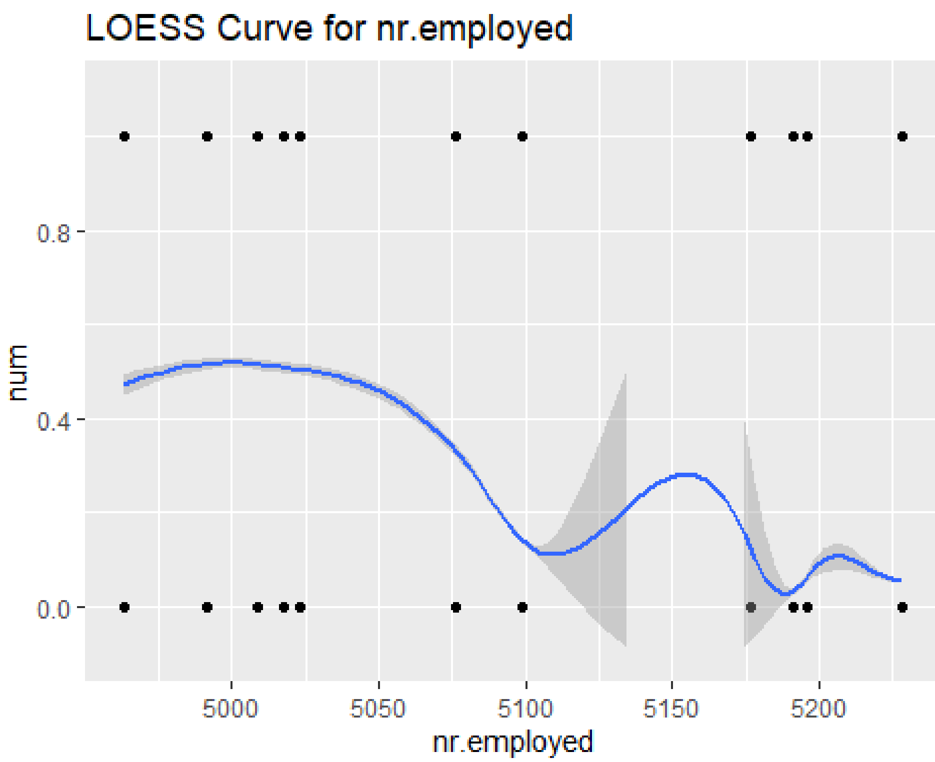



```
# LOESS for Campaign
train_data$num <- ifelse(train_data$y=="yes",1,0)
train_data %>% ggplot(aes(x=campaign,y=num)) +
  geom_point() + geom_smooth(method="loess", size = 1, span = 2, se = FALSE)
+
  ggtitle('LOESS Curve for Campaign') + ylim(c(-.1,1.1))

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

## `geom_smooth()` using formula = 'y ~ x'
```




```
# LOESS for nr.employed
train_data %>% ggplot(aes(x=nr.employed,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for nr.employed')  +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 5228.1

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 37.1

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 1.4919e-14

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 5228.1
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 37.1

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 1.4919e-14
```




```
# LOESS for emp.var.rate
train_data %>% ggplot(aes(x=emp.var.rate,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for emp.var.rate')

## `geom_smooth()` using formula = 'y ~ x'

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 1.424

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 0.324
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 1.0203e-26
```

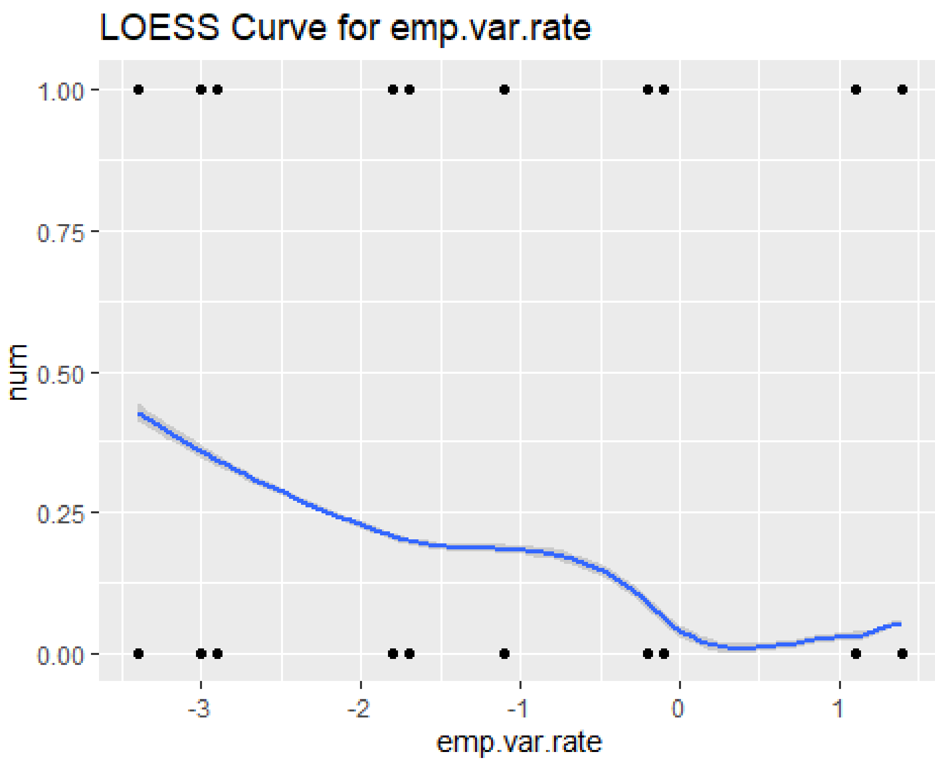
```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : There are other near singularities as well. 0.09
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 1.424
```

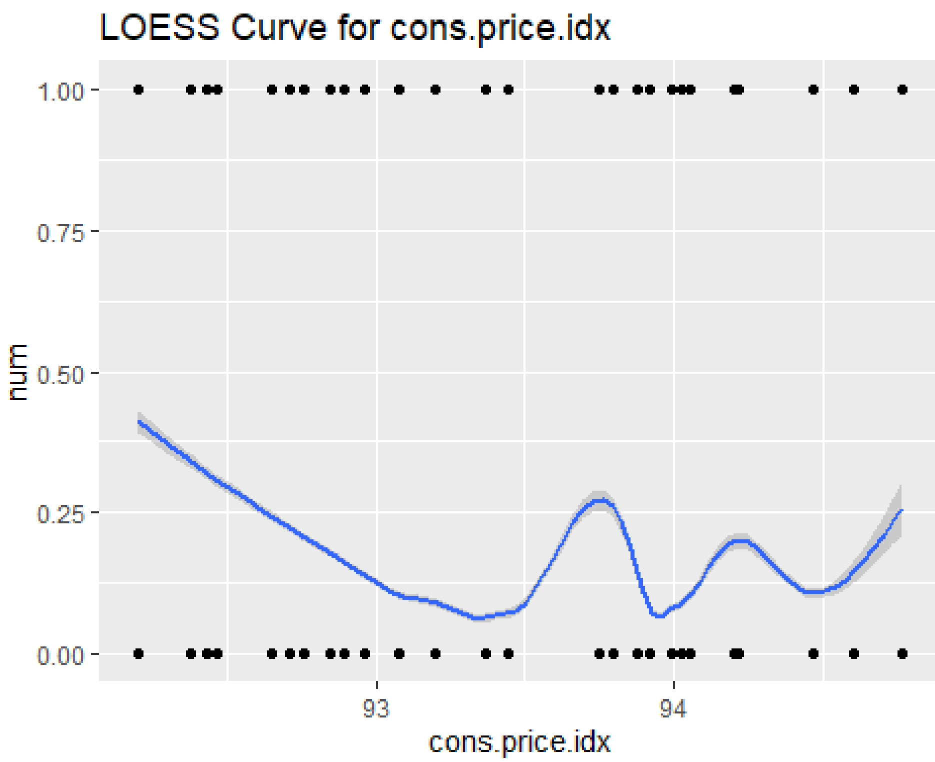
```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 0.324
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 1.0203e-26
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
near
## singularities as well. 0.09
```




```
# LOESS for cons.price.idx
train_data %>% ggplot(aes(x=cons.price.idx,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for cons.price.idx')

## `geom_smooth()` using formula = 'y ~ x'
```



The LOESS plots for Age and Campaign show that No becomes more likely as Age and Campaign increase, and then less likely. However, the LOESS plots for nr.employed, emp.var.rate, and cons.price.idx show a general downward trend toward a higher likelihood of No as those values increase.

```
# LOESS for nr.employed by Month
train_data %>% ggplot(aes(x=nr.employed,y=num,color = month)) +
  geom_point() + geom_smooth(method="loess", size = 1, span=1.1) +
  ggtitle('LOESS Curve for nr.employed by Month') +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 5008.2

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 95.286

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 2.775e-15

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : There are other near singularities as well. 9079.5
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 5008.2

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 95.286

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 2.775e-15

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
near
## singularities as well. 9079.5

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 5008.2

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 95.286

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 5.8467e-15

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : There are other near singularities as well. 9079.5

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 5008.2
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 95.286

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 5.8467e-15

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
near
## singularities as well. 9079.5

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 4963.3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 56.813

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 3.1301e-15

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : There are other near singularities as well. 3227.8

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 4963.3
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 56.813

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 3.1301e-15

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
near
## singularities as well. 3227.8

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : Chernobyl! trL<k 3

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 5022.7

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 161.06

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 0
```

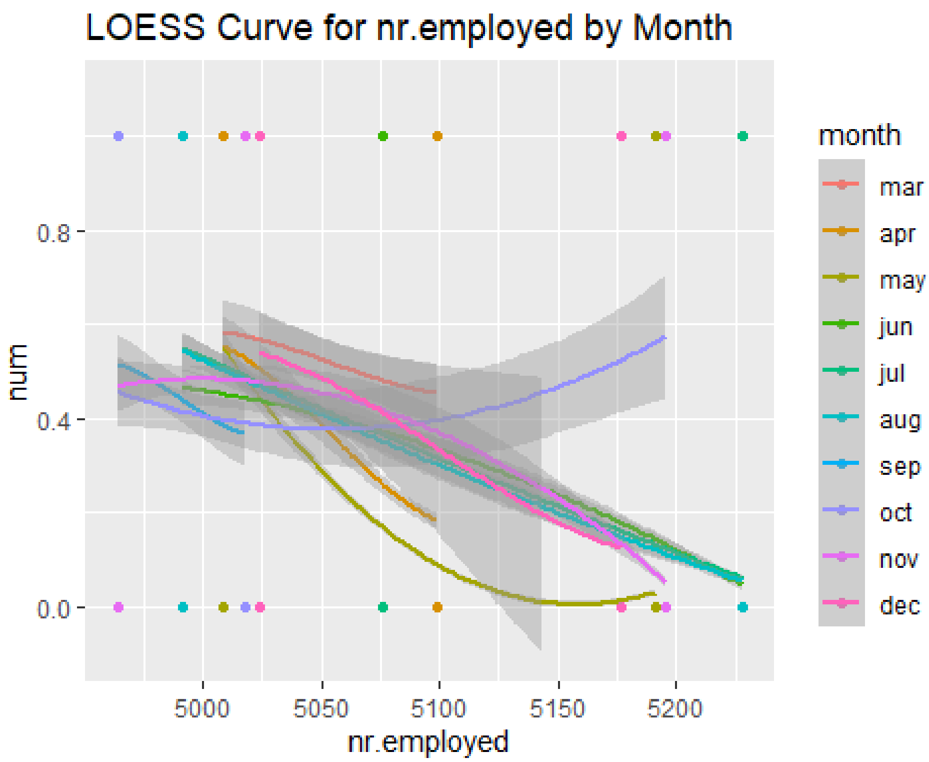
```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : There are other near singularities as well. 25940
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
at
## 5022.7
```

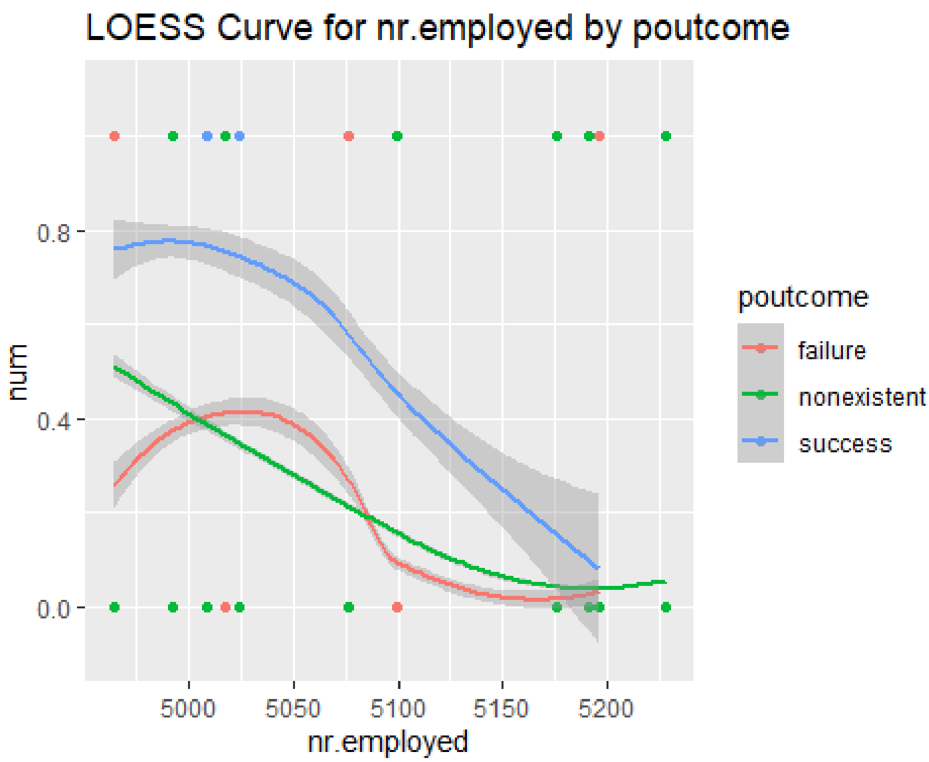
```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 161.06
```

```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 0
```

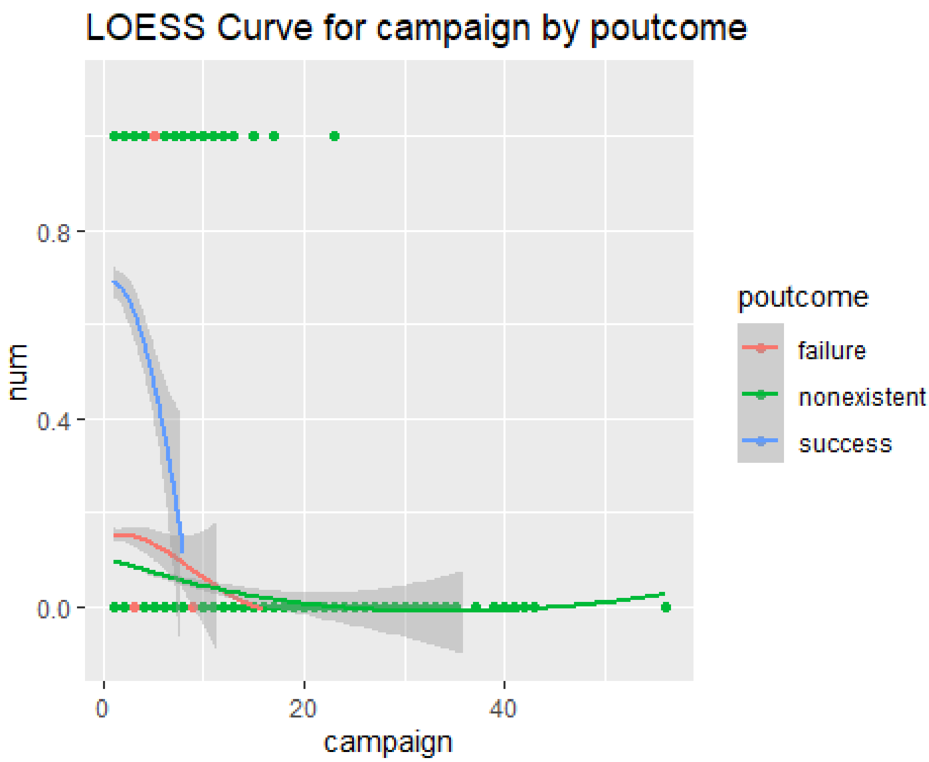
```
## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
near
## singularities as well. 25940
```




```r
# LOESS for nr.employed by poutcome
train_data %>% ggplot(aes(x=nr.employed,y=num,color = poutcome)) +
  geom_point() + geom_smooth(method="loess", size = 1, span = 1) +
  ggtitle('LOESS Curve for nr.employed by poutcome') +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'
```



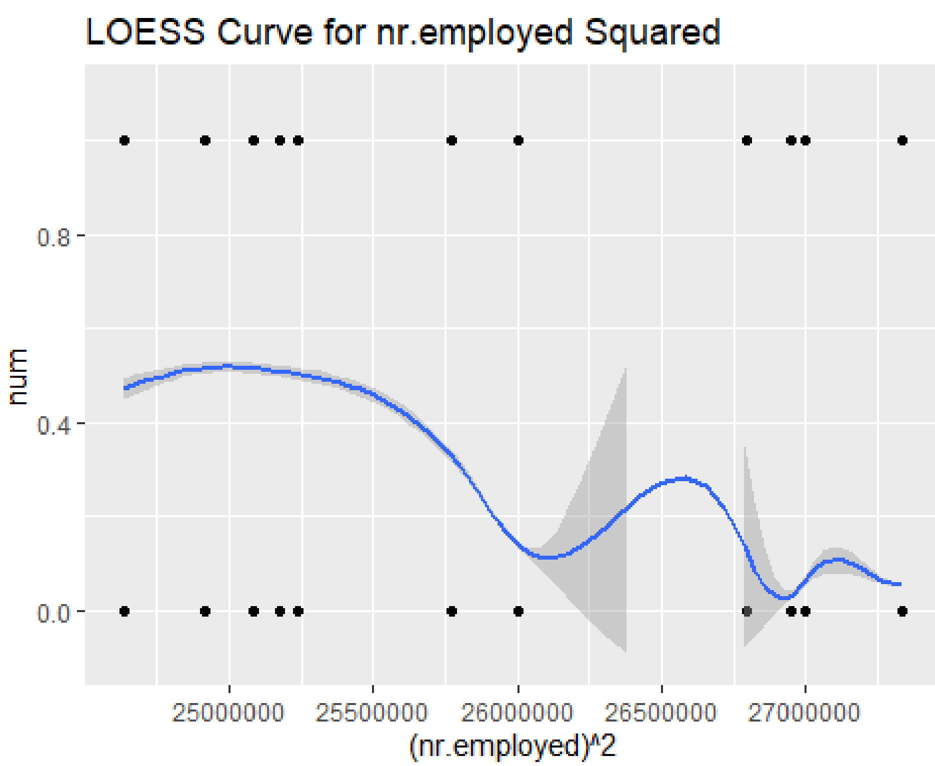

```
# LOESS for campaign by poutcome
train_data %>% ggplot(aes(x=campaign,y=num,color = poutcome)) +
  geom_point() + geom_smooth(method="loess", size = 1, span = 1.1) +
  ggtitle('LOESS Curve for campaign by poutcome') +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'
```



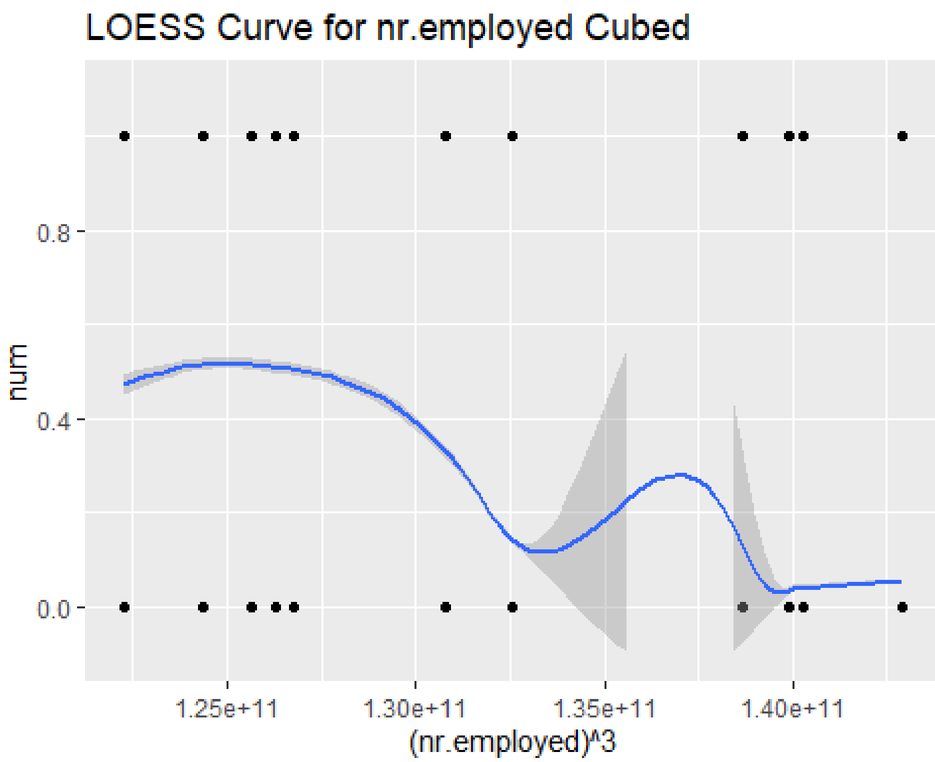
The LOESS curves for these variable combinations show that using these variables in the same model or even as an interaction between these two variables could be useful.

```
# LOESS for nr.employed squared
train_data %>% ggplot(aes(x=(nr.employed)^2,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for nr.employed Squared')  +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : pseudoinverse used at 2.7333e+07

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : neighborhood radius 3.8655e+05

## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
parametric,
## : reciprocal condition number 2.0272e-14

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
```

```
at
## 2.7333e+07

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood
radius
## 3.8655e+05

## Warning in predLoess(object$y, object$x, newx = if (is.null(newdata))
object$x
## else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
condition
## number 2.0272e-14
```

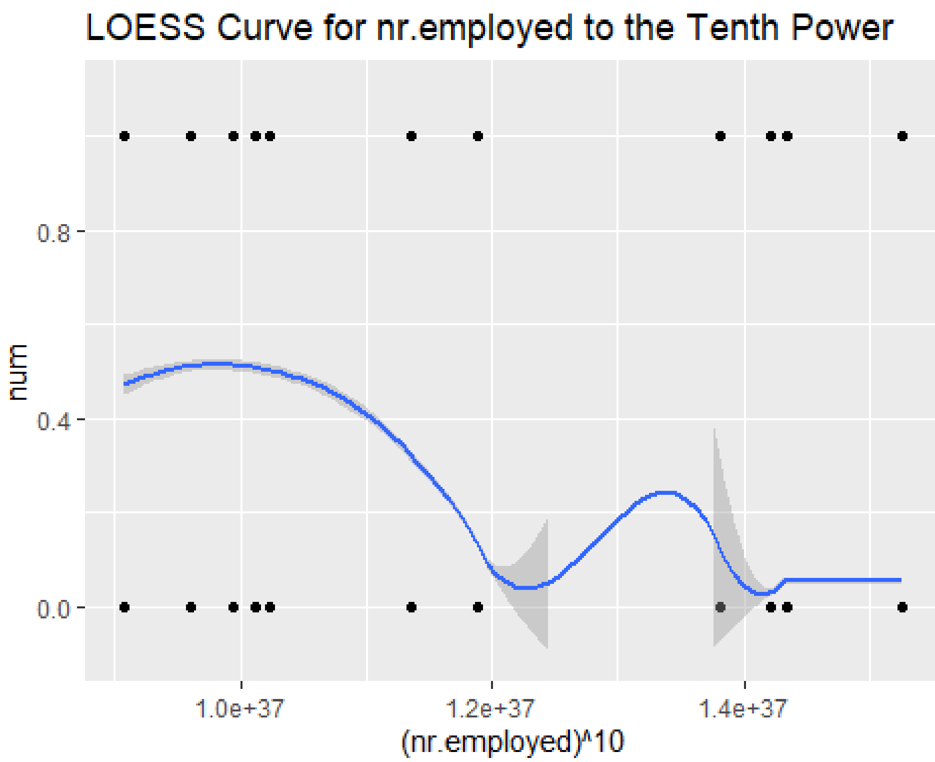



```
# LOESS for nr.employed cubed
train_data %>% ggplot(aes(x=(nr.employed)^3,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for nr.employed Cubed') +
  ylim(c(-.1,1.1))

## `geom_smooth()` using formula = 'y ~ x'

## Warning: Removed 10 rows containing missing values (`geom_smooth()`).
```




```r
# LOESS for nr.employed tenth power
train_data %>% ggplot(aes(x=(nr.employed)^10,y=num)) +
  geom_point() + geom_smooth(method="loess",span=.5) +
  ggtitle('LOESS Curve for nr.employed to the Tenth Power') +
  ylim(c(-.1,1.1))
```

```
## `geom_smooth()` using formula = 'y ~ x'

## Warning: Removed 11 rows containing missing values (`geom_smooth()`).
```

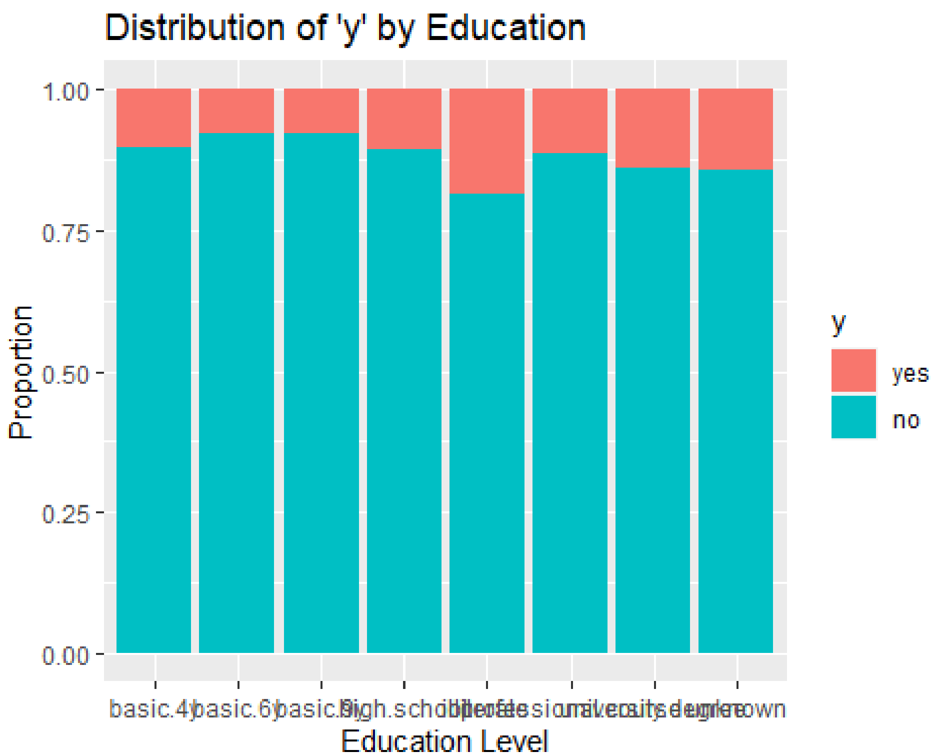


The LOESS curves for powers of nr.employed (particularly comparing the tenth power to the first or second power) seem to improve as the power increases. This points to adding polynomial complexity terms to the model could be useful.

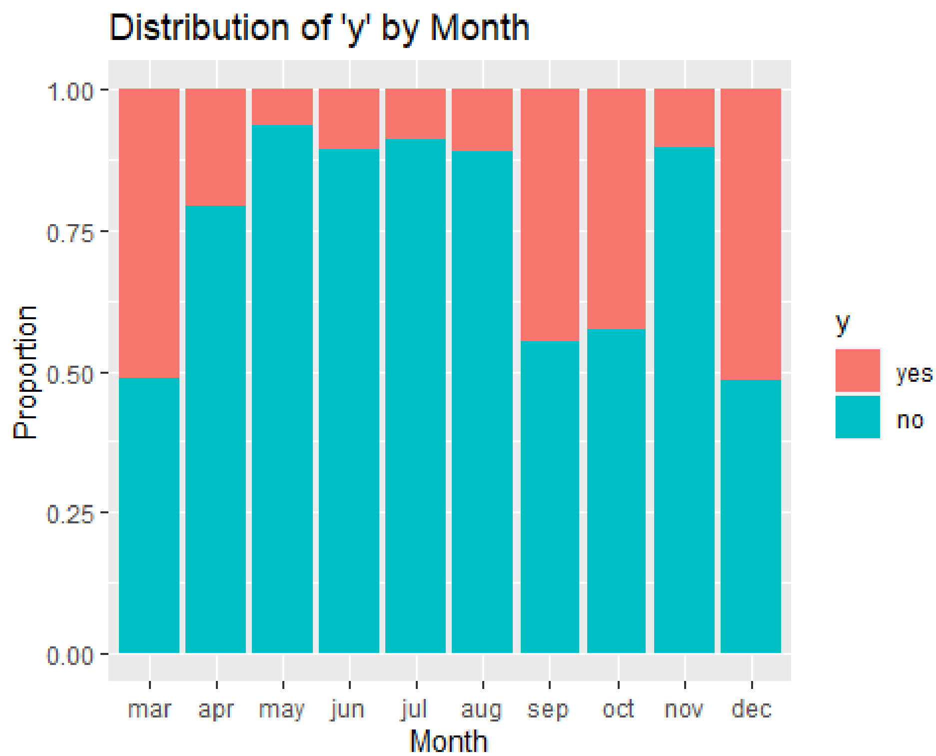
Percentage Plots

It can be helpful to look at plots that sum up to 100% for Yes and No results for categorical variables. This can show that certain values have a higher or lower percentage of Yes results.

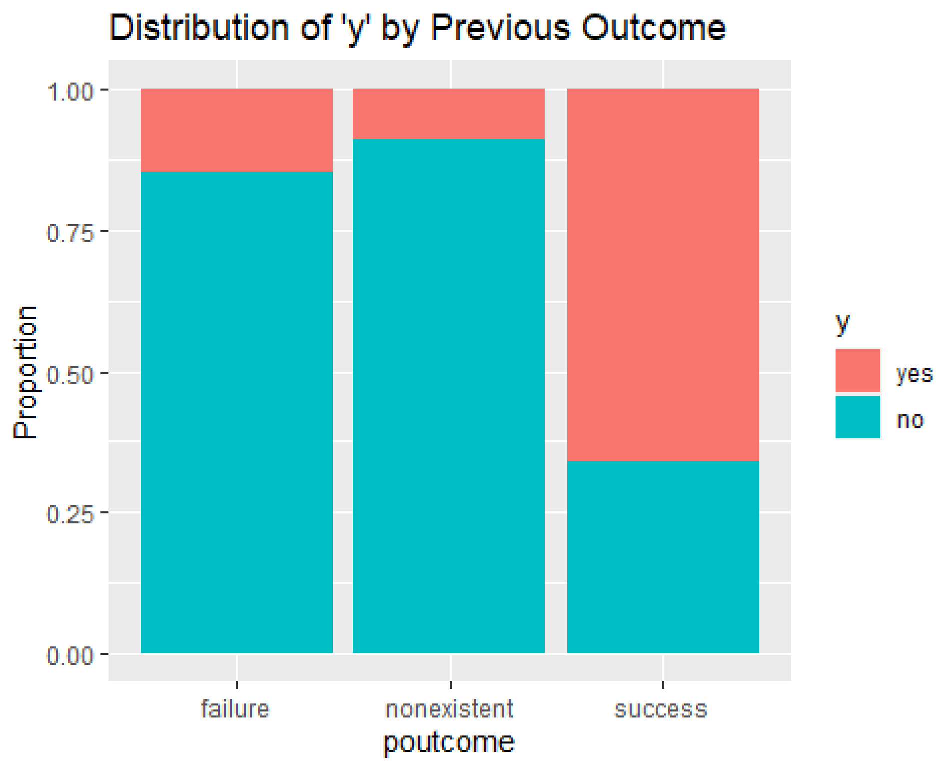
```
# Percentage plot for education
ggplot(train_data, aes(x = education, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Distribution of 'y' by Education") +
  ylab("Proportion") +
  xlab("Education Level")
```



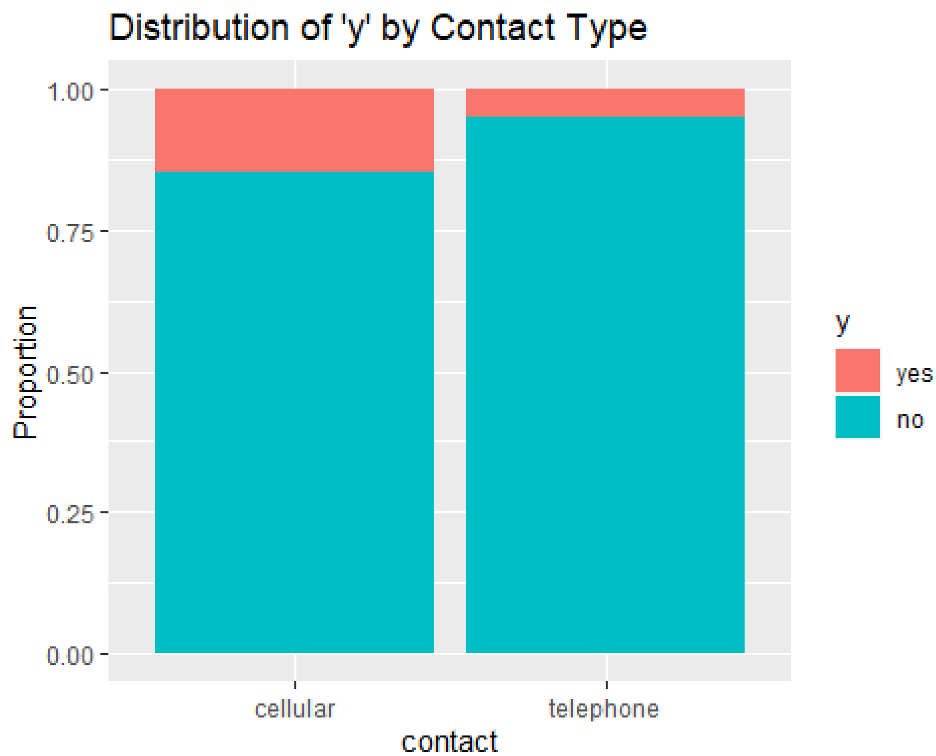

```r
# Percentage plot for month
ggplot(train_data, aes(x = month, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Distribution of 'y' by Month") +
  ylab("Proportion") +
  xlab("Month")
```




```r
# Percentage plot for poutcome
ggplot(train_data, aes(x = poutcome, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Distribution of 'y' by Previous Outcome") +
  ylab("Proportion") +
  xlab("poutcome")
```




```r
# Percentage plot for contact
ggplot(train_data, aes(x = contact, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Distribution of 'y' by Contact Type") +
  ylab("Proportion") +
  xlab("contact")
```



Education shows very similar Yes/No percentages across the different Education Types, which indicates that it won't be a useful variable for model building. Month and poutcome have 1 or more values with very high values of yes, which could be useful for model building. Contact seems to have one category with roughly double the number of yes, so it might be slightltly useful in model building.

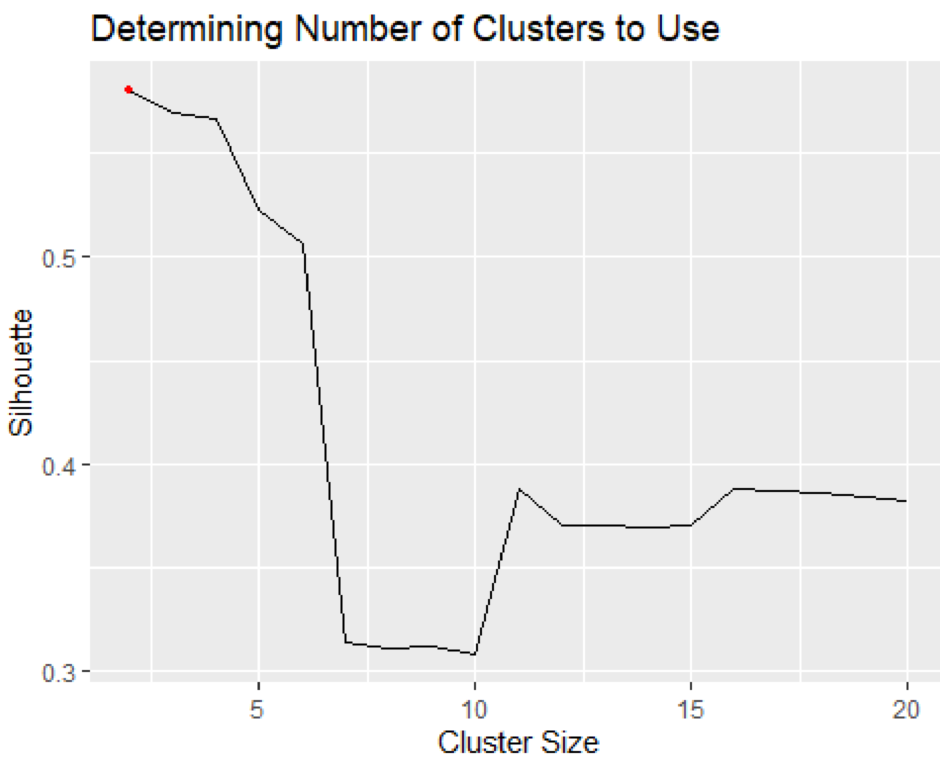
Clustering

We wanted to see if a clustering analysis of the data would be useful. We only looked at the numeric variables. The purpose of a clustering analysis is to see if splitting the data into clusters allows for additional insight, particularly into classification.

First, we will try to determine the number of clusters to use. The metric we used for comparing cluster sizes is the Silhoutte Statistic. Below is the code I ran, but it has trouble knitting. The heat maps are in the PPT though.

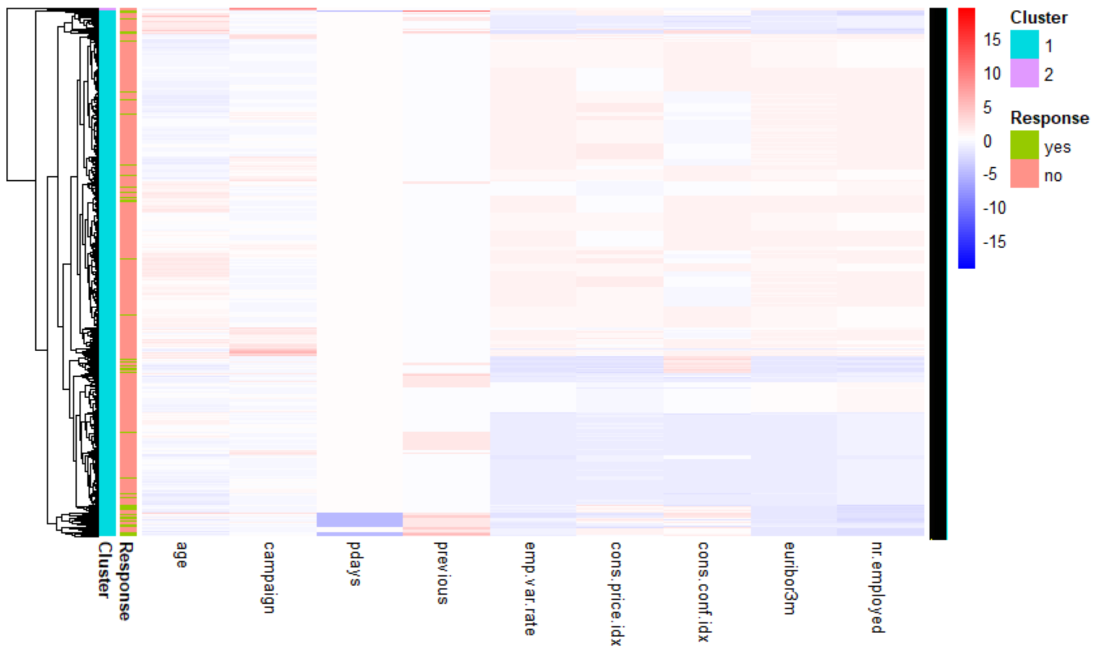
```
library(RColorBrewer)
library(pheatmap)
library(cluster)
df.numeric <- train_data[ , sapply(train_data, is.numeric)]
center.scale=scale(df.numeric)
mydist<-dist(center.scale)
sim.clust<-hclust(mydist,method="complete")
max_clusters <- 20
my.sil<-c()
for (i in 2:max_clusters){
  print(i)
```

```
  sil.result<-silhouette(cutree(sim.clust,i),mydist)
  my.sil[i-1]<-summary(sil.result)$avg.width
}

max_clusters <- 20
my.sil <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/my_sil.csv')
my.sil <- my.sil$x
ggplot(data = data.frame(x=2:max_clusters, y=my.sil),aes(x=x,y=y)) + geom_line() +
  ylab('Silhouette') + xlab('Cluster Size') + ggtitle('Determining Number of Clusters to Use') +
  geom_point(data = data.frame(x = 2, y = my.sil[1]), aes(x = x, y = y), size = 1, color = "red", fill = "red", shape = 21)
```



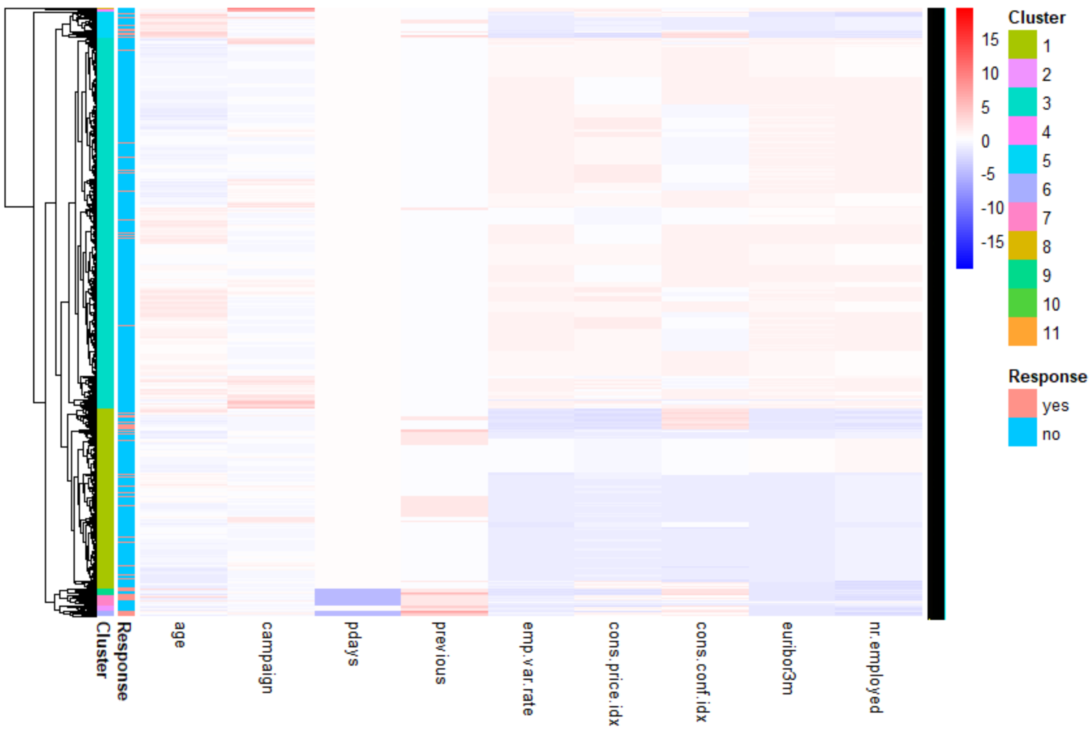
It looks like 2 clusters is the highest, so we will try that.

```
num_clusters <- 2
rownames(df.numeric)<-paste("R",1:nrow(df.numeric),sep="")
annotation_row<-data.frame(Response=factor(train_data$y),Cluster=factor(cutree(sim.clust,num_clusters)))
rownames(annotation_row)<-rownames(df.numeric)
pheatmap(df.numeric,annotation_row=annotation_row,cluster_cols=F,scale="column",fontsize_row=3,legend=T
         ,color=colorRampPalette(c("blue","white", "red"), space = "rgb")(100))
```



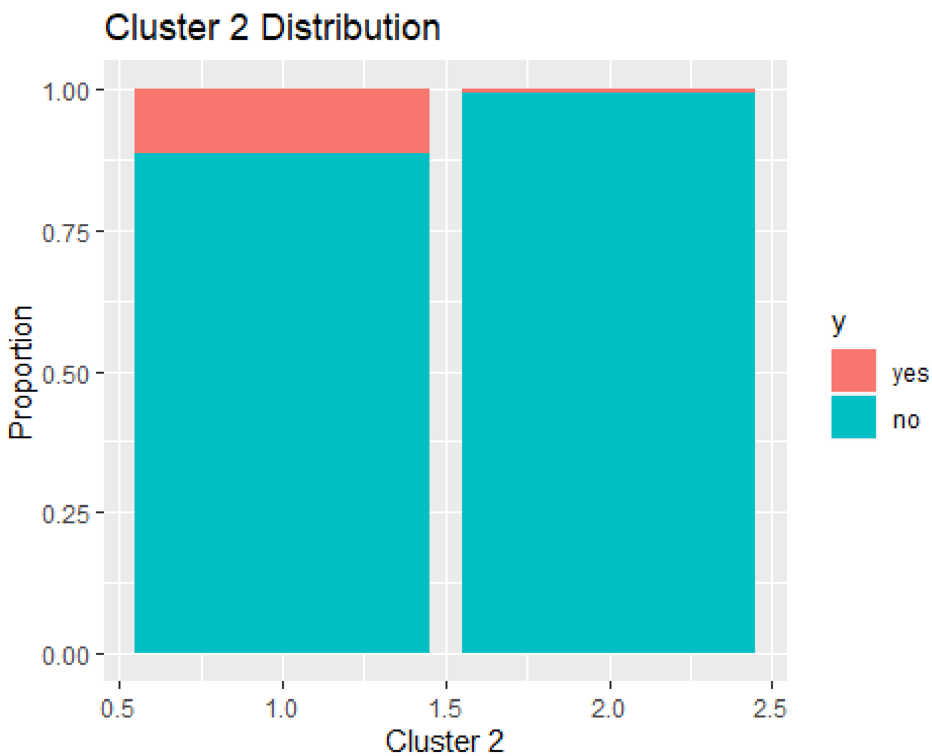
One of the clusters is huge and the other is tiny. Let's try with 11 clusters.

```
num_clusters <- 11
rownames(df.numeric)<-paste("R",1:nrow(df.numeric),sep="")
annotation_row<-
data.frame(Response=factor(train_data$y),Cluster=factor(cutree(sim.clust,num_
clusters)))
rownames(annotation_row)<-rownames(df.numeric)
pheatmap(df.numeric,annotation_row=annotation_row,cluster_cols=F,scale="colum
n",fontsize_row=3,legend=T
         ,color=colorRampPalette(c("blue","white", "red"), space =
"rgb")(100))
```



This is a little bit more interesting. Some clusters had a lot of 'yes' results. Others seem to be the same distribution as before.

```
cluster2 <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/cluster2.csv')
cluster11 <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/cluster11.csv')
train_data$cluster2 <- cluster2$x
train_data$cluster11 <- cluster11$x

ggplot(train_data, aes(x = cluster2, fill = y)) +
    geom_bar(position = "fill") +
    ggtitle("Cluster 2 Distribution") +
    ylab("Proportion") +
    xlab("Cluster 2")
```



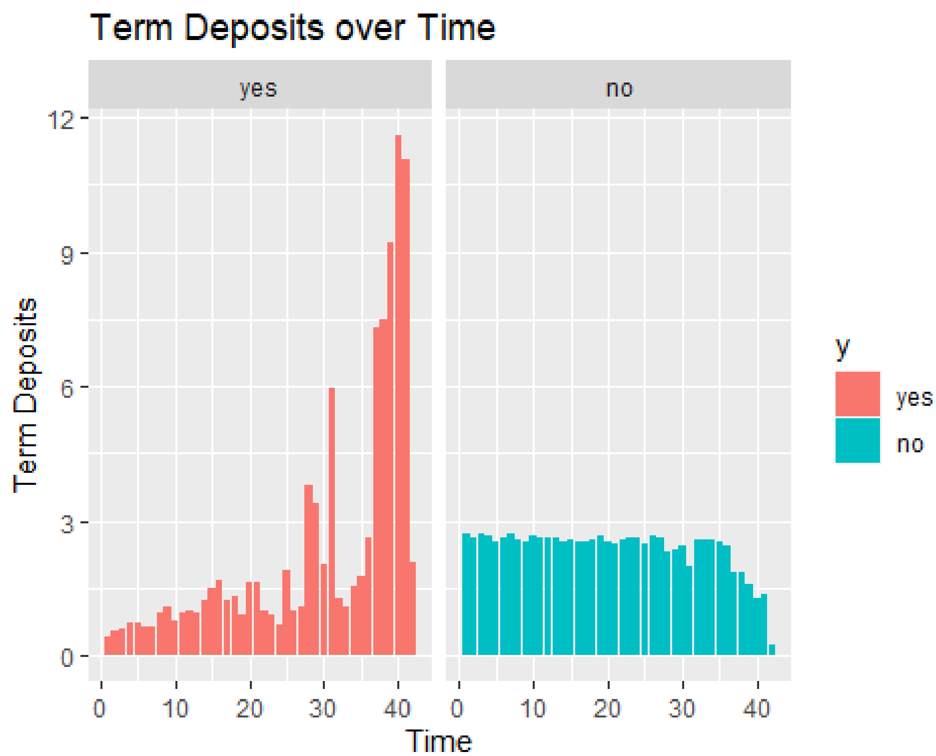

```r
ggplot(train_data, aes(x = cluster11, fill = y)) +
  geom_bar(position = "fill") +
  ggtitle("Cluster 11 Distribution") +
  ylab("Proportion") +
  xlab("Cluster 11")
```

The 11 cluster example does seem like it does a reasonable job of picking out clusters with

Variables over time

We want to see if there was any variation in term deposits over time. The file explaining the dataset mentioned that the data was in order of date.

```
# Sorting data by row number
train_data_sorted <- train_data
train_data_sorted$num <- as.numeric(rownames(train_data_sorted))
train_data_sorted$group <- ceiling(train_data_sorted$num / 1000)
summary <- train_data_sorted %>%
  group_by(group,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'group'. You can override using the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data_sorted[train_data_sorted$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data_sorted[train_data_sorted$y == 'yes',]) * 100

# Term deposit over time
summary %>% ggplot(aes(x=group,y=perc,fill=y)) + geom_bar(stat="identity") +
facet_wrap(~y) +
  ylab('Term Deposits') + xlab('Time') + ggtitle('Term Deposits over Time')
```




```r
# Month over time
train_data_sorted %>% ggplot(aes(x=num, y=month, color=y)) + geom_jitter() +
  xlab('Time') + ylab('Month') + ggtitle('Last Contact Month over Time')
```

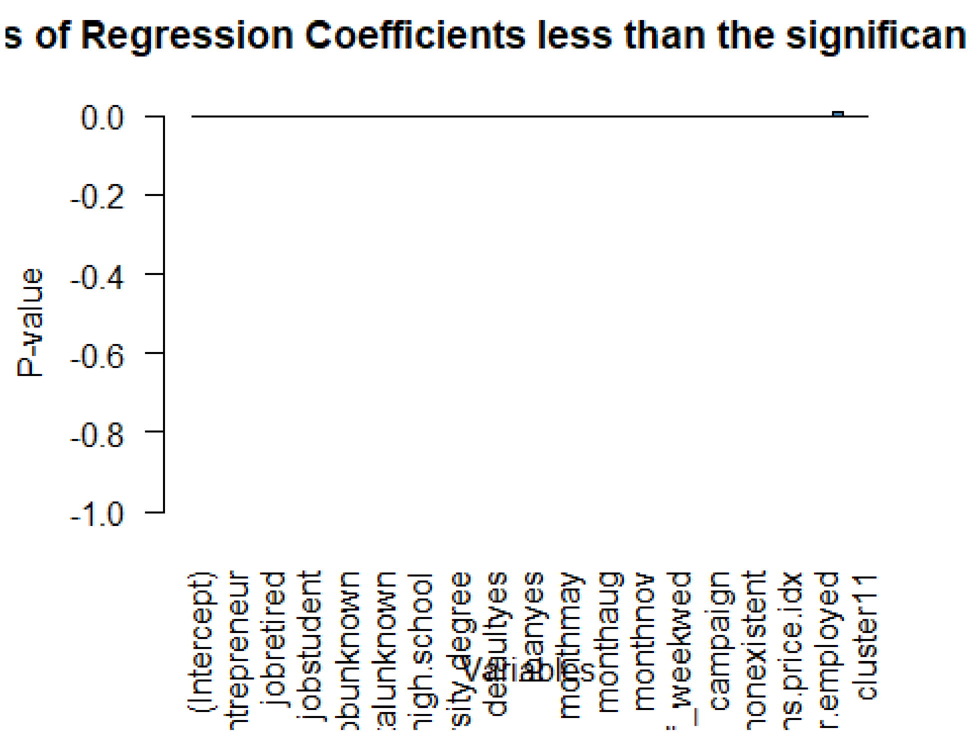
```r
# Employment Variation Rate over time
train_data_sorted %>% ggplot(aes(x=num, y=emp.var.rate, color=y)) +
geom_jitter() +
  xlab('Time') + ylab('Month') + ggtitle('Employment Variation Rate over
Time')
```

LOOKING AT THE PVALUE DISTRIBUTIONS

Looking at how each variable in the model, significantly impacts our response variable

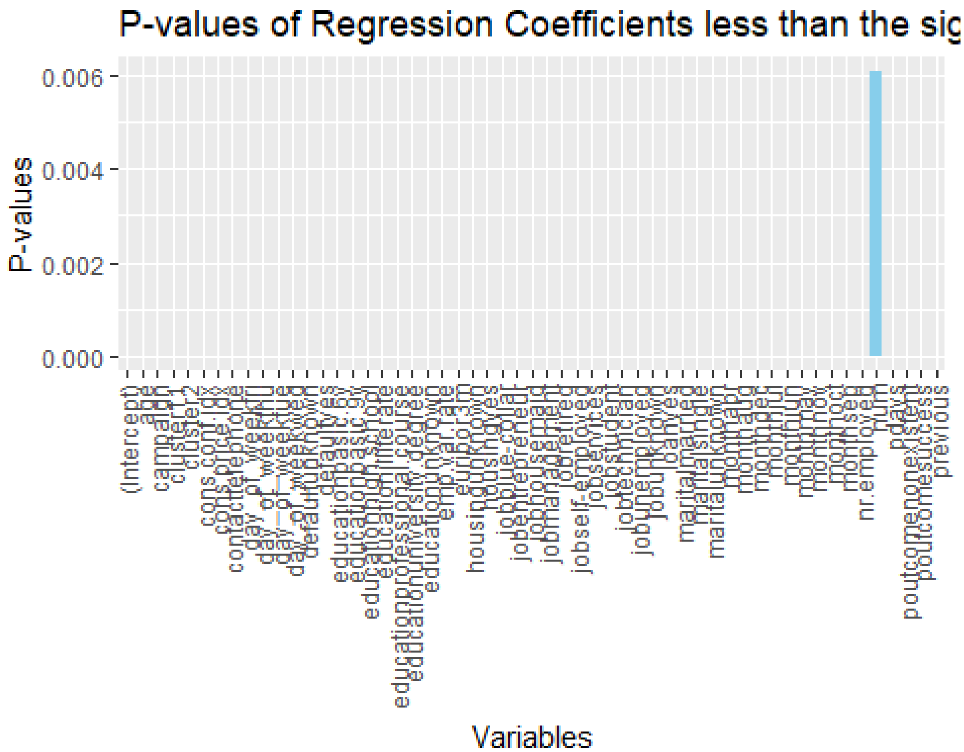
```r
log.model <-glm(y ~ . ,data = train_data,family="binomial")

## Warning: glm.fit: algorithm did not converge

# Extract variable names
variable_names <- rownames(summary(log.model)$coefficients)

# Setting the levels back
data$y <- relevel(data$y, ref="yes")

# getting the  p-values from the model3
p_values <- summary(log.model)$coefficients[, 4]  # Assuming p-values are in
the 4th column of the summary table
p_values <- data.frame(p_values)$p_values

df <- data.frame(variable_names, p_values) #combining the pvalues and
variable names into a dataframe
```

```
df <- df[!df$p_value == 0 , ] #removing varaiables with pvalue = 0
df$p_values <- log(df$p_values)  * -1

barplot(df$p_values,
        main = "P-values of Regression Coefficients less than the
significance level 0.05",
        xlab = "Variables",
        ylab = "P-value",
        names.arg = df$variable_names,
        las = 2,  # Rotate x-axis labels vertically for better readability
        col = "steelblue",  # Set color of bars
        ylim = c(exp(0.05) * -1, max(df$p_values) * 1.2)  # Set ylim from the
significance level to the max p-values

)
```




```
library(ggplot2)
ggplot(df,aes(variable_names,p_values, fill = ifelse(p_values > (exp(0.05) *
-1), "Positive", "Negative"))) + #filtering just the highly significant p-
values
  geom_bar(stat="identity", fill = "skyblue") +
  #geom_text(aes(label = variable_names), vjust = -0.5) +  # Add text labels
on top of bars
  scale_fill_manual(values = c("Positive" = "skyblue", "Negative" =
"salmon")) +
```

```r
  labs(x = "Variables", y = "P-values", title = "P-values of Regression Coefficients less than the significance level 0.05") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))  # Rotate x-axis labels for better readability
```



From the plot above, we can see that the top 5 highly significant values with respoct to the response variable y are months(most of them), poutcome, emp.var.rate, contact, cons.price.idx, which are similar to our selected simple logistic model

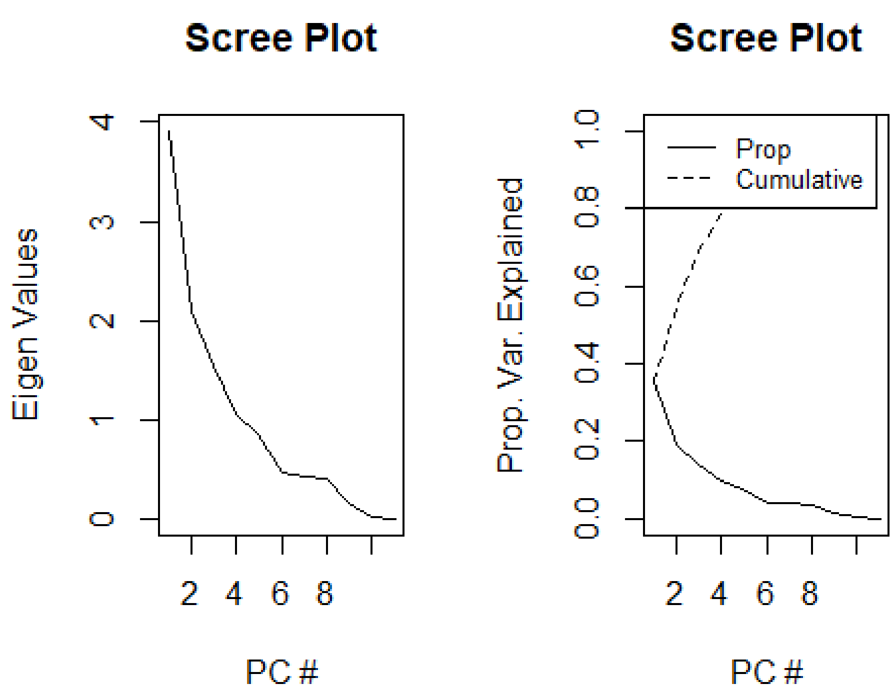
PCA models

```r
#make sure "success" level is defined as "yes"
str(train_data$y)

##  Factor w/ 2 levels "yes","no": 1 2 2 2 2 2 1 2 2 2 ...

train_data$num <- c()


#PCA
df.numericPC <- train_data[ , sapply(train_data, is.numeric)]
pc.result<-prcomp(df.numericPC,scale.=TRUE)
pc.scores<-pc.result$x
pc.scores<-data.frame(pc.scores)
pc.scores$y<-train_data$y
```

```r
#Eignenvector Matrix
View(pc.result$rotation)

#Scree plot
eigenvals<-(pc.result$sdev)^2
eigenvals
```

```
##  [1] 3.90935320 2.10748012 1.55067031 1.06927372 0.86991295 0.46536151
##  [7] 0.42482392 0.40536507 0.16265162 0.02466925 0.01043832
```

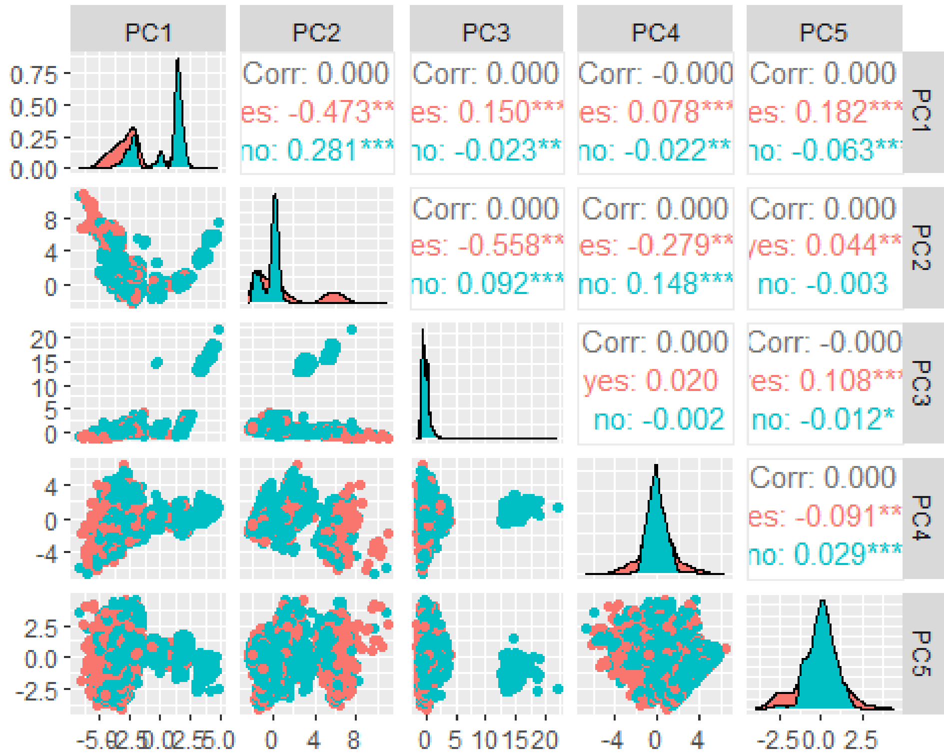
```r
par(mfrow=c(1,2))
plot(eigenvals,type="l",main="Scree Plot",ylab="Eigen Values",xlab="PC #")
plot(eigenvals/sum(eigenvals),type="l",main="Scree Plot",ylab="Prop. Var.
Explained",xlab="PC #",ylim=c(0,1))
cumulative.prop<-cumsum(eigenvals/sum(eigenvals))
lines(cumulative.prop,lty=2)
legend("topleft", legend=c("Prop","Cumulative"),
       lty=1:2, cex=0.8)
```



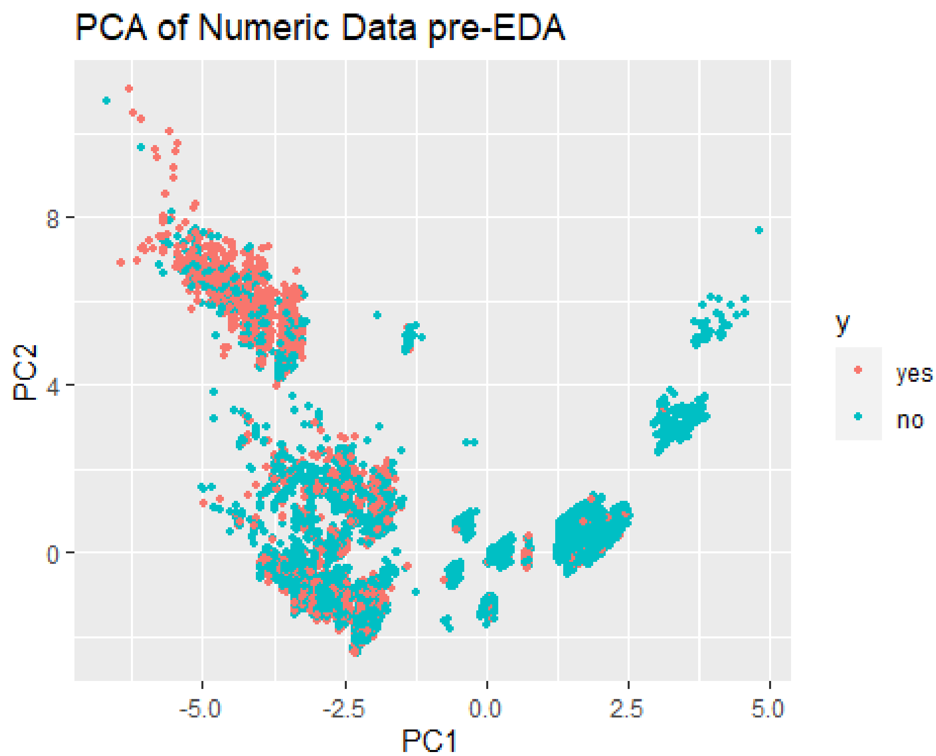

```r
data.frame(PC=1:length(eigenvals),Prop=eigenvals/sum(eigenvals),Cumulative=cu
mulative.prop)
```

```
##    PC         Prop Cumulative
## 1   1 0.3553957456  0.3553957
## 2   2 0.1915891022  0.5469848
## 3   3 0.1409700280  0.6879549
```

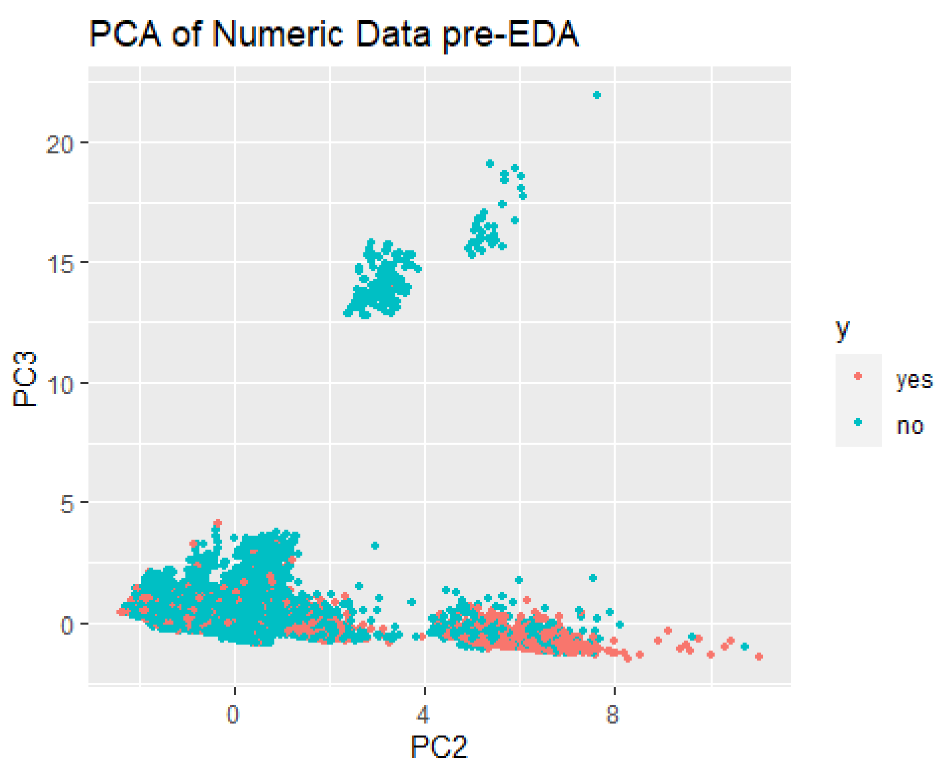
```
## 4   4 0.0972067021  0.7851616
## 5   5 0.0790829955  0.8642446
## 6   6 0.0423055922  0.9065502
## 7   7 0.0386203567  0.9451705
## 8   8 0.0368513697  0.9820219
## 9   9 0.0147865105  0.9968084
## 10 10 0.0022426592  0.9990511
## 11 11 0.0009489382  1.0000000

# Calculate the variance explained by each principal component
var_explained <- pc.result$sdev^2 / sum(pc.result$sdev^2)
cum_var_explained <- cumsum(var_explained)

# Find the number of components that explain at least 90% of the variance
num_comp_90 <- which(cum_var_explained >= 0.9)[1]

# Print the number of components
print(num_comp_90) #We would need 5 to retain approximately 90%

## [1] 6

#Plotting PCA variables with the two colors:


pc.result<-prcomp(df.numericPC,scale.=TRUE)
PC <- data.frame(diagnosis = train_data$y)
PC$PC1 <- pc.result$x[,1]
PC$PC2 <- pc.result$x[,2]
PC$PC3 <- pc.result$x[,3]
PC$PC4 <- pc.result$x[,4]
PC$PC5 <- pc.result$x[,5]
ggpairs(PC[,-1],aes(color=PC[,1]))
```



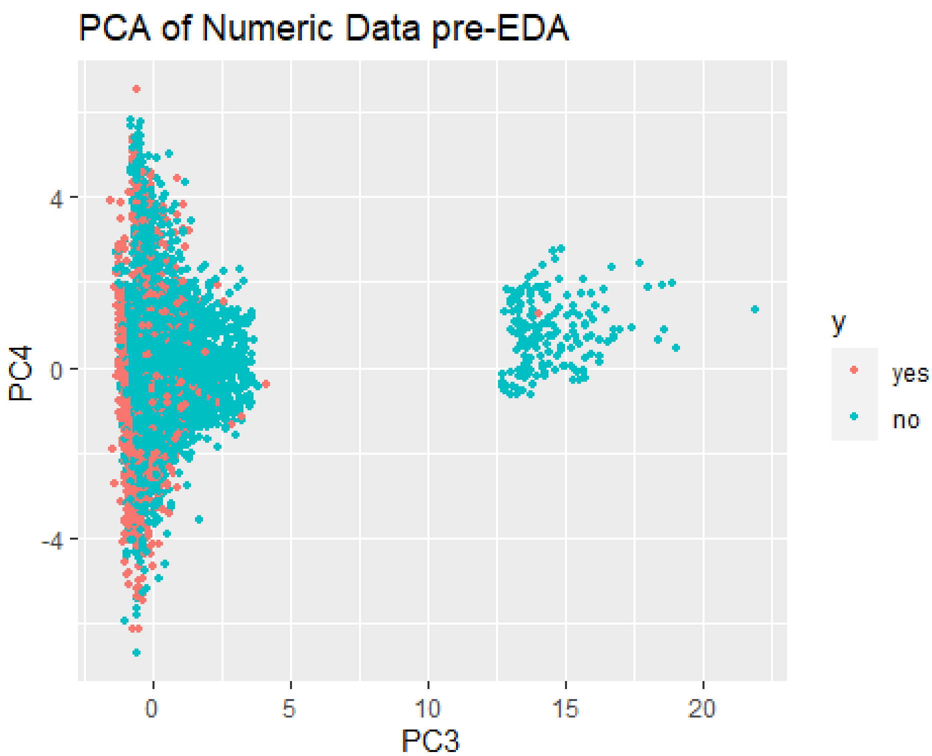

```
#Use ggplot2 to plot the first few pc's
ggplot(data = pc.scores, aes(x = PC1, y = PC2)) +
  geom_point(aes(col=y), size=1)+
  ggtitle("PCA of Numeric Data pre-EDA")
```



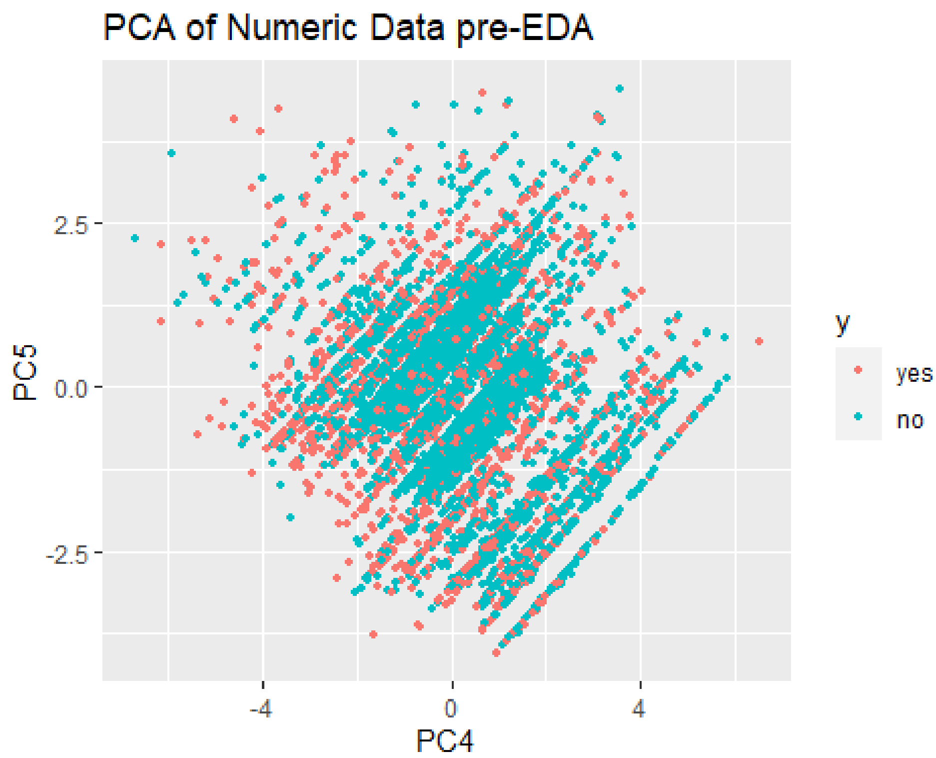

```r
ggplot(data = pc.scores, aes(x = PC2, y = PC3)) +
  geom_point(aes(col=y), size=1)+
  ggtitle("PCA of Numeric Data pre-EDA")
```



```r
ggplot(data = pc.scores, aes(x = PC3, y = PC4)) +
  geom_point(aes(col=y), size=1)+
  ggtitle("PCA of Numeric Data pre-EDA")
```

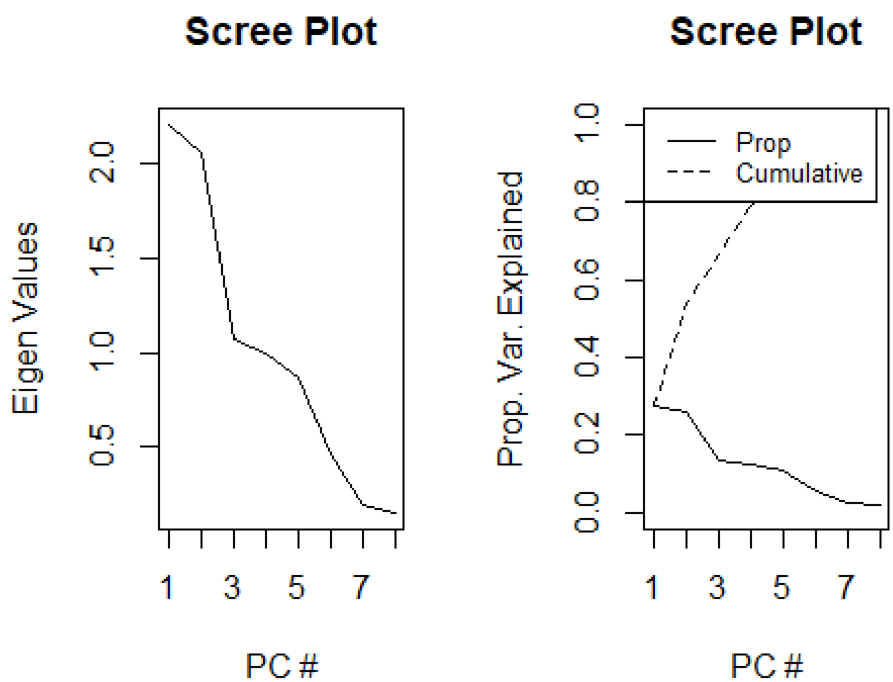



```r
ggplot(data = pc.scores, aes(x = PC4, y = PC5)) +
  geom_point(aes(col=y), size=1)+
  ggtitle("PCA of Numeric Data pre-EDA")
```



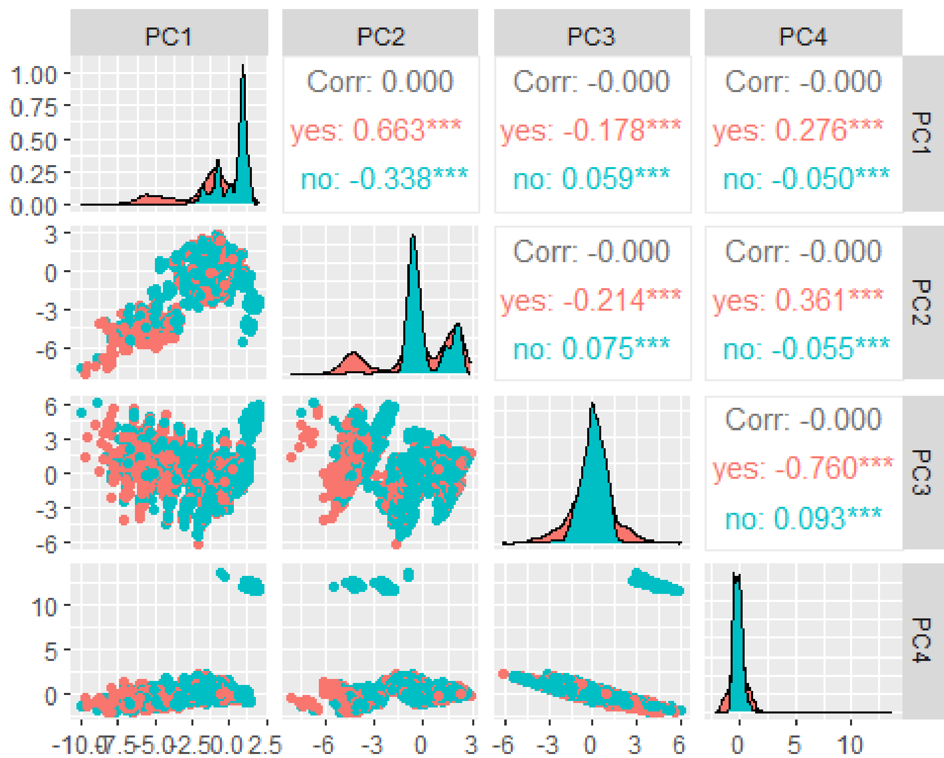

```
# PCA without campaign, euribor3m,and nr.employed as they are more like
factors and not continuous


#Performing PCA on predictors

df.numeric2 <- df.numericPC[,-c(2,8,9)]
pc.result2<-prcomp(df.numeric2,scale.=TRUE)
pc.scores2<-pc.result2$x
pc.scores2<-data.frame(pc.scores2)
pc.scores2$y<-train_data$y
#pc.scores2


#Eignenvector Matrix
View(pc.result2$rotation)

#Scree plot
eigenvals2<-(pc.result2$sdev)^2
eigenvals2

## [1] 2.2091986 2.0617699 1.0752687 0.9925676 0.8622411 0.4611968 0.1881167
## [8] 0.1496406

par(mfrow=c(1,2))
plot(eigenvals2,type="l",main="Scree Plot",ylab="Eigen Values",xlab="PC #")
```

```
plot(eigenvals2/sum(eigenvals2),type="l",main="Scree Plot",ylab="Prop. Var.
Explained",xlab="PC #",ylim=c(0,1))
cumulative.prop<-cumsum(eigenvals2/sum(eigenvals2))
lines(cumulative.prop,lty=2)
legend("topleft", legend=c("Prop","Cumulative"),
       lty=1:2, cex=0.8)
```




```
data.frame(PC=1:length(eigenvals2),Prop=eigenvals2/sum(eigenvals2),Cumulative
=cumulative.prop)

##   PC       Prop Cumulative
## 1  1 0.27614982  0.2761498
## 2  2 0.25772124  0.5338711
## 3  3 0.13440859  0.6682796
## 4  4 0.12407095  0.7923506
## 5  5 0.10778013  0.9001307
## 6  6 0.05764961  0.9577803
## 7  7 0.02351459  0.9812949
## 8  8 0.01870507  1.0000000

# Calculate the variance explained by each principal component
var_explained <- pc.result2$sdev^2 / sum(pc.result2$sdev^2)
cum_var_explained <- cumsum(var_explained)

# Find the number of components that explain at least 90% of the variance
num_comp_90 <- which(cum_var_explained >= 0.9)[1]
```

```r
# Print the number of components
print(num_comp_90) #We would need 4 to retain approximately 90%

## [1] 5

#Plotting PCA variables with the two colors:

pc.result<-prcomp(df.numeric2[,-c(2,8,9)],scale.=TRUE)
PC <- data.frame(diagnosis = train_data$y)
PC$PC1 <- pc.result2$x[,1]
PC$PC2 <- pc.result2$x[,2]
PC$PC3 <- pc.result2$x[,3]
PC$PC4 <- pc.result2$x[,4]
ggpairs(PC[,-1],aes(color=PC[,1]))
```



Final Project - Bank Dataset

Aaron Abromowitz, Stephanie Duarte, Dammy Owolabi

2024-04-20

Before Part 2

```
library(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.1     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.0
## ✓ ggplot2   3.4.1     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.0
## ✓ purrr     1.0.1
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()    masks stats::lag()
## ℹ Use the ]8;;http://conflicted.r-lib.org/conflicted package]8;; to force all conflicts to become errors

# Pull in data
data<-read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/bank-additional-full.csv',stringsAsFactors = T, sep=";")

# Set levels to use for later
data$y <- relevel(data$y, ref="yes")
data$month <- factor(data$month,
levels=c('mar','apr','may','jun','jul','aug','sep','oct','nov','dec'))
data$day_of_week <- factor(data$day_of_week,
levels=c('mon','tue','wed','thu','fri'))

# Duration was removed since the dataset explanation file said that it was created after y variable was known, so shouldn't be used for prediction.
data$duration <- c()
data$default <- c()

# Create the train and test split
train_perc <- .8
set.seed(1234)
train_indices <- sample(nrow(data), floor(train_perc * nrow(data)))
train_data <- data[train_indices, ]
nrow(train_data)

## [1] 32950
```

```
test_data <- data[-train_indices, ]
nrow(test_data)

## [1] 8238
```

#GLMNET Model

```
library(readr)
library(GGally)

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2

library(caret)

## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift

library(ggcorrplot)
# Prepare the matrix of predictors
x <- model.matrix(~ . - 1 - y, data = train_data) # Excludes the intercept
and the response variable

# Define the trainControl with classProbs enabled
fitControl <- trainControl(method = "cv",
                           number = 10,
                           classProbs = TRUE, # Enable class probability
predictions
                           summaryFunction = twoClassSummary) # Use a summary
function for classification

# Run the glmnet model
set.seed(1234) # for reproducibility
glmnet_fit <- train(x, y = train_data$y,
                    method = "glmnet",
                    trControl = fitControl,
                    tuneLength = 10, # Number of lambda values to test
                    metric = "ROC") # Optimize the model based on ROC curve

# View the best model's lambda value and corresponding coefficients
best_lambda <- glmnet_fit$bestTune$lambda
coef(glmnet_fit$finalModel, s = best_lambda)

## 52 x 1 sparse Matrix of class "dgCMatrix"
##                                          s1
```

```
## (Intercept)                    1.271357e+02
## age                            6.288258e-04
## jobadmin.                     -5.537285e-02
## jobblue-collar                 1.042755e-01
## jobentrepreneur               -3.234962e-03
## jobhousemaid                  -1.306103e-02
## jobmanagement                  .
## jobretired                    -3.078555e-01
## jobself-employed               3.618493e-02
## jobservices                    5.156474e-02
## jobstudent                    -2.873845e-01
## jobtechnician                  .
## jobunemployed                  5.206854e-02
## jobunknown                     7.563443e-02
## maritalmarried                -2.397840e-02
## maritalsingle                 -2.912019e-02
## maritalunknown                -4.058666e-01
## educationbasic.6y              .
## educationbasic.9y              2.706680e-02
## educationhigh.school          -1.043184e-02
## educationilliterate           -3.876507e-01
## educationprofessional.course -6.937688e-02
## educationuniversity.degree    -1.123063e-01
## educationunknown              -6.533999e-02
## housingunknown                 8.105645e-02
## housingyes                     3.384646e-02
## loanunknown                    1.362202e-02
## loanyes                        4.709627e-02
## contacttelephone               6.154443e-01
## monthapr                       1.206473e+00
## monthmay                       1.744218e+00
## monthjun                       1.548731e+00
## monthjul                       1.116250e+00
## monthaug                       8.789533e-01
## monthsep                       1.219657e+00
## monthoct                       1.305819e+00
## monthnov                       1.619636e+00
## monthdec                       7.376210e-01
## day_of_weektue                -2.501461e-01
## day_of_weekwed                -3.222477e-01
## day_of_weekthu                -2.604626e-01
## day_of_weekfri                -2.037529e-01
## campaign                       4.271160e-02
## pdays                          9.320162e-04
## previous                       6.642481e-02
## poutcomenonexistent           -3.905654e-01
## poutcomesuccess               -9.262589e-01
## emp.var.rate                   1.023679e+00
## cons.price.idx                -1.356221e+00
## cons.conf.idx                 -2.066279e-02
```

```
## euribor3m                          -1.918785e-01
## nr.employed                          .
```

There definitely is a change in the data over time. We may re-visit this later on.

Objective 1: Simple Logistic Regerssion Model

We used a combination of forward and backward selection to determine a simple logistic regression model that performed well on the data. We did this by adding each variable to a model, and then doing Cross Validation to test the out of sample data on AUROC (Area under the ROC curve). We used 10 folds.   After we chose the first variable, we then did this to add more variables to see if those increased the AUROC. We also tried removing variables (once we got three of them) to see if that improved the score. Below, I included example code for this logic. It takes several minutes to run though, so it is not set to evaluate the code.   One caveat is that since the Default variable only has 2 Yes values, it can cause errors sometimes during the cross validation. This happens when the training data (a randomly chosen 90%) doesn't have either of those values, and the test data (the other 10%) has both of them. This only happens 1% of the time, but when you are running 100s of tests, this happens regularly. And since Default didn't increase the AUROC much anyways, we decided to drop the variable.

```r
train_data$default <- c()

# Forward Selection Example
set.seed(21)
vars <- names(train_data)
vars <- vars[vars!="y"]
num_vars <- length(vars)
var_aucs <- data.frame("vars" = vars)
num_folds <- 10
for (j in 1:num_vars) {
  var <- vars[j]
  print(var)
  folds <- createFolds(train_data$y, k = num_folds)
  auc_scores <- numeric(num_folds)
  for (i in 1:num_folds) {
    train_indices <- unlist(folds[-i])
    test_indices <- unlist(folds[i])
    train <- train_data[train_indices, ]
    test <- train_data[test_indices, ]
    form <- as.formula(paste("y ~ ",var,sep=""))
    model <- glm(form, data = train, family = "binomial")
    predictions <- predict(model, newdata = test, type = "response")
    roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
    auc_scores[i] <- auc(roc)
  }
  var_aucs$auc[var_aucs$var == var] <- mean(auc_scores)
```

```
}

# Backward selection example
set.seed(24)
start_form_str <- 'y ~ nr.employed + month + poutcome'
vars <- c('nr.employed','month','poutcome')
num_vars <- length(vars)
var_aucs <- data.frame("vars" = vars)
num_folds <- 10
for (j in 1:num_vars) {
  var <- vars[j]
  print(var)
  folds <- createFolds(train_data$y, k = num_folds)
  auc_scores <- numeric(num_folds)
  for (i in 1:num_folds) {
    train_indices <- unlist(folds[-i])
    test_indices <- unlist(folds[i])
    train <- train_data[train_indices, ]
    test <- train_data[test_indices, ]
    form <- as.formula(paste(start_form_str," -",var,sep=""))
    model <- glm(form, data = train, family = "binomial")
    predictions <- predict(model, newdata = test, type = "response")
    roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
    auc_scores[i] <- auc(roc)
  }
  var_aucs$auc[var_aucs$var == var] <- mean(auc_scores)
}
```

After we did this until the AUROC didn't increase any more, the resulting model was y ~ month + poutcome + emp.var.rate + euribor3m + contact + cons.price.idx. We then checked the p values and VIR to see if it made sense to keep all of those variables.

```
library(car)

## Loading required package: carData

##
## Attaching package: 'car'

## The following object is masked from 'package:dplyr':
##
##     recode

## The following object is masked from 'package:purrr':
##
##     some

model <- glm(y ~ month + poutcome + emp.var.rate + euribor3m + contact +
cons.price.idx, data = train_data, family = "binomial")
summary(model)
```

```
##
## Call:
## glm(formula = y ~ month + poutcome + emp.var.rate + euribor3m +
##     contact + cons.price.idx, family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7180   0.2565   0.3225   0.3652   2.0610
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)         165.34420    9.72777  16.997  < 2e-16 ***
## monthapr              1.48149    0.11493  12.891  < 2e-16 ***
## monthmay              1.95366    0.10893  17.936  < 2e-16 ***
## monthjun              1.99307    0.13976  14.261  < 2e-16 ***
## monthjul              1.34672    0.12631  10.662  < 2e-16 ***
## monthaug              0.77035    0.11695   6.587 4.48e-11 ***
## monthsep              1.23224    0.14671   8.399  < 2e-16 ***
## monthoct              1.48029    0.15076   9.819  < 2e-16 ***
## monthnov              1.93888    0.13899  13.950  < 2e-16 ***
## monthdec              0.88523    0.21637   4.091 4.29e-05 ***
## poutcomenonexistent  -0.41002    0.06036  -6.793 1.10e-11 ***
## poutcomesuccess      -1.81692    0.08686 -20.919  < 2e-16 ***
## emp.var.rate          1.50678    0.10080  14.948  < 2e-16 ***
## euribor3m            -0.53296    0.07687  -6.933 4.12e-12 ***
## contacttelephone      0.63484    0.06856   9.260  < 2e-16 ***
## cons.price.idx       -1.73621    0.10191 -17.037  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 18332  on 32934  degrees of freedom
## AIC: 18364
##
## Number of Fisher Scoring iterations: 6
```

```
vif(model)
```

```
##                     GVIF Df GVIF^(1/(2*Df))
## month           6.253389  9        1.107207
## poutcome        1.288981  2        1.065520
## emp.var.rate   76.465448  1        8.744452
## euribor3m      51.138803  1        7.151140
## contact         1.990009  1        1.410677
## cons.price.idx 11.218806  1        3.349449
```

The p values were all significant at the 0.05 level, but there was a high amount of correlation between emp.var.rate and euribor3m. So we removed euribor3m to see if that didn't make the model too much worse.

```
library(caret)
library(pROC)

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

set.seed(80)
form <- as.formula('y ~ month + poutcome + emp.var.rate + contact +
cons.price.idx')
num_folds <- 10
folds <- createFolds(train_data$y, k = num_folds)
accuracy_scores <- numeric(num_folds)
auc_scores <- numeric(num_folds)
for (i in 1:num_folds) {
  train_indices <- unlist(folds[-i])
  test_indices <- unlist(folds[i])
  train <- train_data[train_indices, ]
  test <- train_data[test_indices, ]
  model <- glm(form, data = train, family = "binomial")
  predictions <- predict(model, newdata = test, type = "response")
  roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
  auc_scores[i] <- auc(roc)
}
mean(auc_scores)

## [1] 0.7917643
```

It wasn't too much worse. And removing the correlation between those two variables makes the model easier to interpret.

```
model <- glm(y ~ month + poutcome + emp.var.rate + contact + cons.price.idx,
data = train_data, family = "binomial")
summary(model)

##
## Call:
## glm(formula = y ~ month + poutcome + emp.var.rate + contact +
##     cons.price.idx, family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -2.7139   0.2257   0.3265   0.3616   1.9460
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)         108.53001    5.14668  21.087  < 2e-16 ***
## monthapr              1.36684    0.11411  11.979  < 2e-16 ***
## monthmay              1.88593    0.10846  17.388  < 2e-16 ***
## monthjun              1.47245    0.11859  12.416  < 2e-16 ***
## monthjul              1.02367    0.11750   8.712  < 2e-16 ***
## monthaug              0.69115    0.11645   5.935 2.94e-09 ***
## monthsep              1.01545    0.14351   7.076 1.49e-12 ***
## monthoct              1.03319    0.13677   7.554 4.21e-14 ***
## monthnov              1.44456    0.11940  12.098  < 2e-16 ***
## monthdec              0.55440    0.21012   2.638  0.00833 **
## poutcomenonexistent  -0.43221    0.05976  -7.232 4.75e-13 ***
## poutcomesuccess      -1.81937    0.08629 -21.083  < 2e-16 ***
## emp.var.rate          0.82587    0.02213  37.325  < 2e-16 ***
## contacttelephone      0.43524    0.06009   7.244 4.37e-13 ***
## cons.price.idx       -1.14550    0.05491 -20.863  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 18379  on 32935  degrees of freedom
## AIC: 18409
##
## Number of Fisher Scoring iterations: 6
```

```r
vif(model)
```

```
##                    GVIF Df GVIF^(1/(2*Df))
## month          2.394736  9        1.049711
## poutcome       1.274785  2        1.062574
## emp.var.rate   3.656646  1        1.912236
## contact        1.506607  1        1.227439
## cons.price.idx 3.284604  1        1.812348
```

Now the VIFs are much more resonable without euribor3m. So we chose the simpler model for our Simple Logistic Regression Model.

Now that we have a model, we look at the model coefficients for interpretations.

```r
train_data$y <- relevel(train_data$y, ref="no")
mod <- glm(y ~ month + poutcome + emp.var.rate + contact + cons.price.idx,
data = train_data, family = "binomial")
summary(mod)
```

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

```
## glm(formula = y ~ month + poutcome + emp.var.rate + contact +
##     cons.price.idx, family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9460  -0.3616  -0.3265  -0.2257   2.7139
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -108.53001    5.14668 -21.087  < 2e-16 ***
## monthapr              -1.36684    0.11411 -11.979  < 2e-16 ***
## monthmay              -1.88593    0.10846 -17.388  < 2e-16 ***
## monthjun              -1.47245    0.11859 -12.416  < 2e-16 ***
## monthjul              -1.02367    0.11750  -8.712  < 2e-16 ***
## monthaug              -0.69115    0.11645  -5.935 2.94e-09 ***
## monthsep              -1.01545    0.14351  -7.076 1.49e-12 ***
## monthoct              -1.03319    0.13677  -7.554 4.21e-14 ***
## monthnov              -1.44456    0.11940 -12.098  < 2e-16 ***
## monthdec              -0.55440    0.21012  -2.638  0.00833 **
## poutcomenonexistent    0.43221    0.05976   7.232 4.75e-13 ***
## poutcomesuccess        1.81937    0.08629  21.083  < 2e-16 ***
## emp.var.rate          -0.82587    0.02213 -37.325  < 2e-16 ***
## contacttelephone      -0.43524    0.06009  -7.244 4.37e-13 ***
## cons.price.idx         1.14550    0.05491  20.863  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 18379  on 32935  degrees of freedom
## AIC: 18409
##
## Number of Fisher Scoring iterations: 6
```

```
odds_ratio <- exp(mod$coefficients)
confident_interval <- exp(confint(mod))
```

```
## Waiting for profiling to be done...
```

```
train_data$y <- relevel(train_data$y, ref="yes")
```

Interpretations (interpreting individually):

Monthapr The odds of getting the clients subscribing to a term deposit in the month of April is 0.255 times lower than that of subscribing in the month of March with a CI of (0.204, 0.319)

Monthmay The odds of getting the clients subscribing to a term deposit in the month of May is 0.152 times lower than that of subscribing in the month of March with a CI of (0.123, 0.188)

Monthjun The odds of getting the clients subscribing to a term deposit in the month of June is 0.229 times lower than that of subscribing in the month of March with a CI of (0.182, 0.289).

Monthjul The odds of getting the clients subscribing to a term deposit in the month of July is 0.359 times lower than that of subscribing in the month of March with a CI of (0.285, 0.452).

Monthaug The odds of getting the clients subscribing to a term deposit in the month of August is 0.500 times lower than that of subscribing in the month of March with a CI of (0.399, 0.629)

Monthsep The odds of getting the clients subscribing to a term deposit in the month of September is 0.362 times lower than that of subscribing in the month of March with a CI of (0.273, 0.479)

Monthoct The odds of getting the clients subscribing to a term deposit in the month of October is 0.356 times lower than that of subscribing in the month of March with a CI of (0.272, 0.465)

Monthnov The odds of getting the clients subscribing to a term deposit in the month of November is 0.236 times lower than that of subscribing in the month of March with a CI of (0.187, 0.298)

Monthdec The odds of getting the clients subscribing to a term deposit in the month of December is 0.574 times lower than that of subscribing in the month of March with a CI of (0.380, 0.868)

poutcomenonexistent The odds of getting the clients subscribing to a term deposit based on a nonexistent outcome of the previous campaign is 1.54 times higher than that of a failed outcome with a CI of (1.37, 1.73)

poutcomesuccess The odds of getting the clients subscribing to a term deposit based on a succesful outcome of the previous campaign is 6.17 times higher than that of a failed outcome with a CI of (5.21, 7.31)

emp.var.rate For every 1 unit increase in customer subscription to a term deposit, the odds of the customer subscribing based on the employment variation rate decreases by 56.2% with a CI of (58.1%, 54.3%)

contacttelephone The odds of getting the clients subscribing to a term deposit based on the contact communication type is 0.647 times lower than that of subscribing by cell phone with a CI of (0.575, 0.728)

cons,price.idx For every 1 unit increase in customer subscription to a term deposit, the odds of the customer subscribing based on the consumers price index increases by a factor of 3.14 with a CI of (2.82, 3.50)

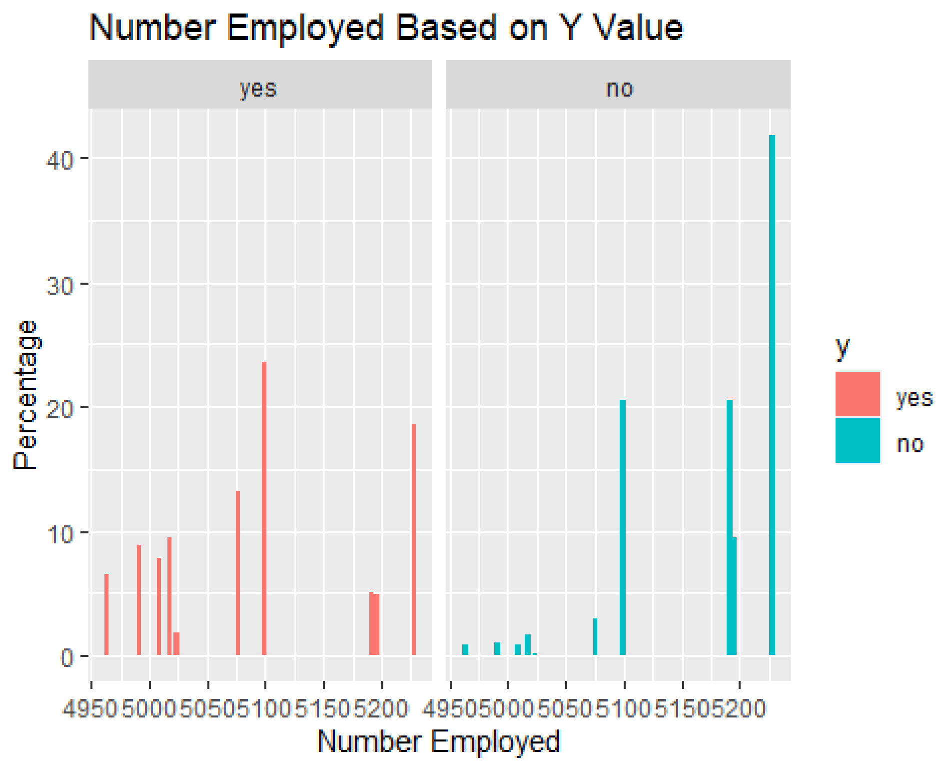
Objective 2: Complex Logistic Regerssion Model

For the second model, we looked into adding polynomial terms and/or interaction terms to the regression model.

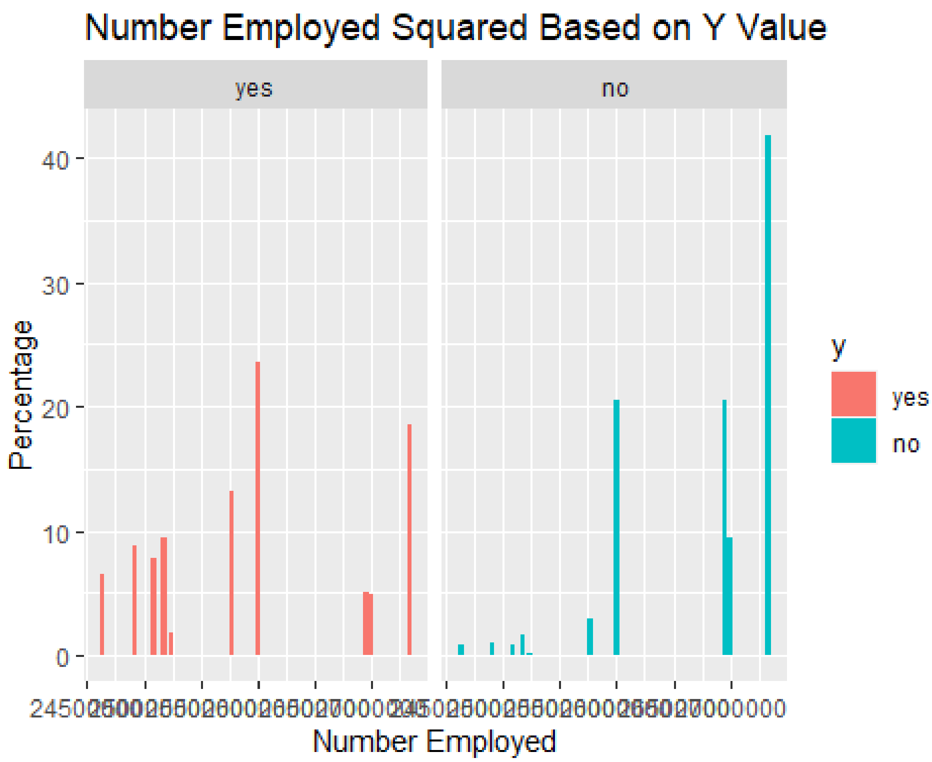
Polynomial Terms

To see if it made sense to add some polynomial terms we looked at what happened with adding those for Number of Employees, since that was the first variable added during Forward Selection (although it got removed later).

```
library(tidyverse)

# Make a nr.employed^2 variable
train_data$ne2 = (train_data$nr.employed)^2

# Plot nr.employed
summary <- train_data %>%
  group_by(nr.employed,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'nr.employed'. You can override using
the
## `.groups` argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=nr.employed,y=perc,fill=y)) +
geom_bar(stat="identity") + facet_wrap(~y) +
  ylab('Percentage') + xlab('Number Employed') + ggtitle('Number Employed
Based on Y Value')
```




```
# Plot nr.employed^2
summary <- train_data %>%
  group_by(ne2,y) %>%
  summarize(count=n())

## `summarise()` has grouped output by 'ne2'. You can override using the
`.groups`
## argument.

summary$perc <- 0
summary$perc[summary$y == 'no'] <- summary$count[summary$y == 'no'] /
nrow(train_data[train_data$y == 'no',]) * 100
summary$perc[summary$y == 'yes'] <- summary$count[summary$y == 'yes'] /
nrow(train_data[train_data$y == 'yes',]) * 100
summary %>% ggplot(aes(x=ne2,y=perc,fill=y)) + geom_bar(stat="identity") +
facet_wrap(~y) +
  ylab('Percentage') + xlab('Number Employed') + ggtitle('Number Employed
Squared Based on Y Value')
```



These plots look very hard to distinguish. So instead of plotting polynomial terms, we tried creating simple models and then calculating out of sample AUC. If this increases as polynomial degree increases, then it could make sense to include polynomial terms.

```
# Maybe just plot the improvement of out of sample AUC
set.seed(120)
vars <- 'nr.employed'
allVars <- vars
num_poly <- 10
for (i in 1:length(vars)){
  for (j in 2:num_poly){
    if (class(train_data[,vars[i]]) != "factor") {
      allVars <- c(allVars,paste('poly(',vars[i],',',j,')',sep=""))
    }
  }
}
num_vars <- length(allVars)
var_aucs <- data.frame("vars" = allVars)
num_folds <- 10
for (j in 1:num_vars) {
  var <- allVars[j]
  print(var)
  folds <- createFolds(train_data$y, k = num_folds)
  auc_scores <- numeric(num_folds)
  for (i in 1:num_folds) {
    train_indices <- unlist(folds[-i])
    test_indices <- unlist(folds[i])
```

```
    train <- train_data[train_indices, ]
    test <- train_data[test_indices, ]
    form <- as.formula(paste("y ~ ",var,sep=""))
    model <- glm(form, data = train, family = "binomial")
    predictions <- predict(model, newdata = test, type = "response")
    roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
    auc_scores[i] <- auc(roc)
  }
  var_aucs$auc[var_aucs$var == var] <- mean(auc_scores)
}
```

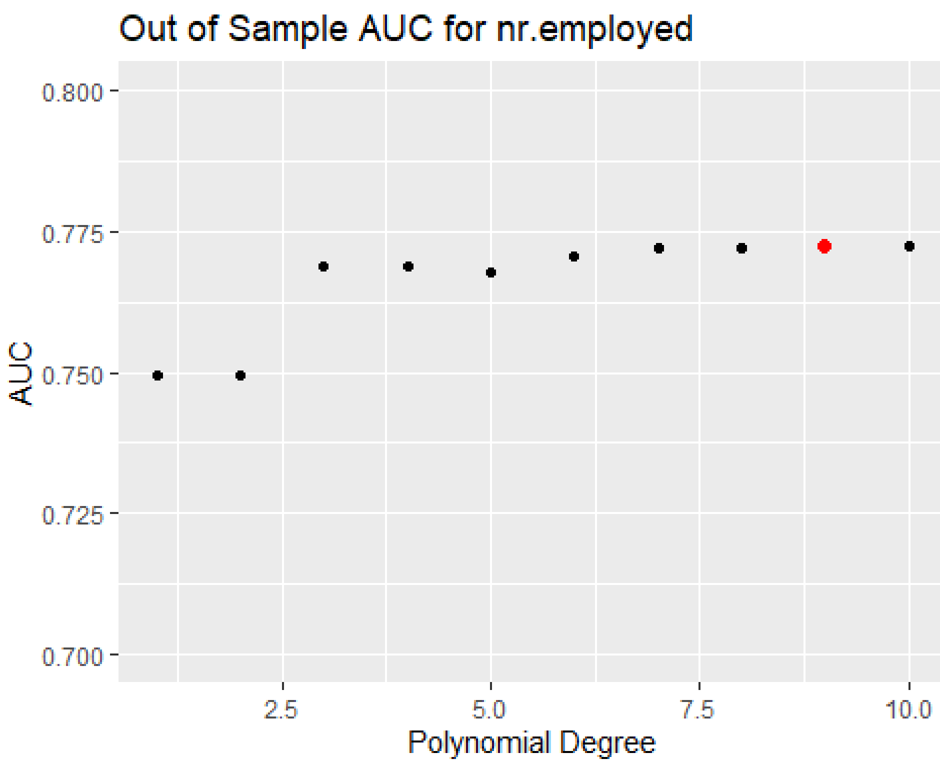
```
## [1] "nr.employed"
## [1] "poly(nr.employed,2)"
## [1] "poly(nr.employed,3)"
## [1] "poly(nr.employed,4)"
## [1] "poly(nr.employed,5)"
## [1] "poly(nr.employed,6)"
## [1] "poly(nr.employed,7)"
## [1] "poly(nr.employed,8)"
## [1] "poly(nr.employed,9)"
## [1] "poly(nr.employed,10)"
```

```
# Get max val
maxAUC <- max(var_aucs$auc, na.rm = TRUE)
maxDeg <- which.max(var_aucs$auc)

# Looking at the p values for the highest degree model
model <- glm(form, data = train_data, family = "binomial")
summary(model)
```

```
##
## Call:
## glm(formula = form, family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6432   0.2485   0.3321   0.3578   1.2860
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)                2.44760    0.02338 104.676  < 2e-16 ***
## poly(nr.employed, 10)1   156.34441    3.19323  48.961  < 2e-16 ***
## poly(nr.employed, 10)2   -44.45416    3.14126 -14.152  < 2e-16 ***
## poly(nr.employed, 10)3   -51.90203    4.32051 -12.013  < 2e-16 ***
## poly(nr.employed, 10)4     4.92844    2.83743   1.737 0.082398 .
## poly(nr.employed, 10)5    26.51619    2.34879  11.289  < 2e-16 ***
## poly(nr.employed, 10)6    30.20002    3.42973   8.805  < 2e-16 ***
## poly(nr.employed, 10)7     8.50557    3.68814   2.306 0.021100 *
## poly(nr.employed, 10)8    -2.79958    2.14882  -1.303 0.192628
```

```
## poly(nr.employed, 10)9   11.69125    3.00755   3.887 0.000101 ***
## poly(nr.employed, 10)10  -7.20951    2.02859  -3.554 0.000379 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 19131  on 32939  degrees of freedom
## AIC: 19153
##
## Number of Fisher Scoring iterations: 6
```

```
# Plot the AUC improving
var_aucs %>% ggplot(aes(x=1:10, y=auc)) + geom_point() + ylim(c(0.7,0.8)) +
  ylab('AUC') + xlab('Polynomial Degree') + ggtitle('Out of Sample AUC for
nr.employed') +
  geom_point(data = data.frame(x = maxDeg, y = maxAUC),
             aes(x = x, y = y), size = 2, color = "red", fill = "red", shape
= 21)
```



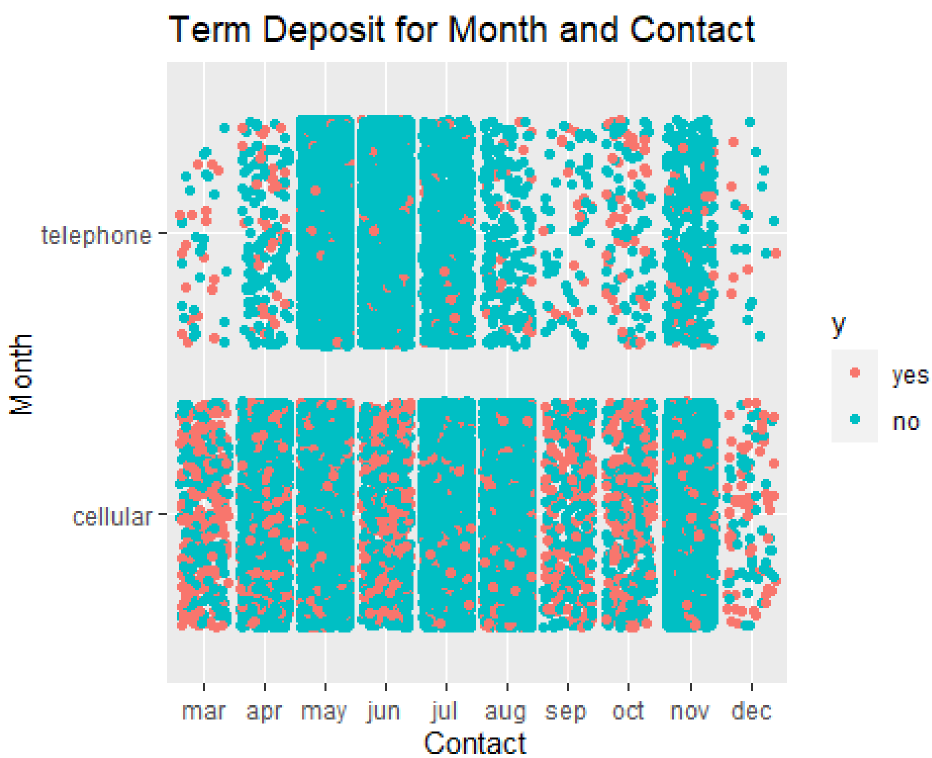
You can see from the plot that there is a pretty substantial increase in performance after 4 polynomial terms. It levels off after that, but the maximum AUC is technically at n = 9. And even the model for n = 10 shows that many of the higher degree terms are statistically significant, including the 10th term.

We will proceed with trying forward selection using polynomial terms. Using up to the 10th degree term seems like it should be sufficient.

Variable Interactions

Variable interactions are often present that affect numeric response variables. Usually to show that, you can plot. To see if there are possible interactions, let's try with a coloring a couple of interactions.

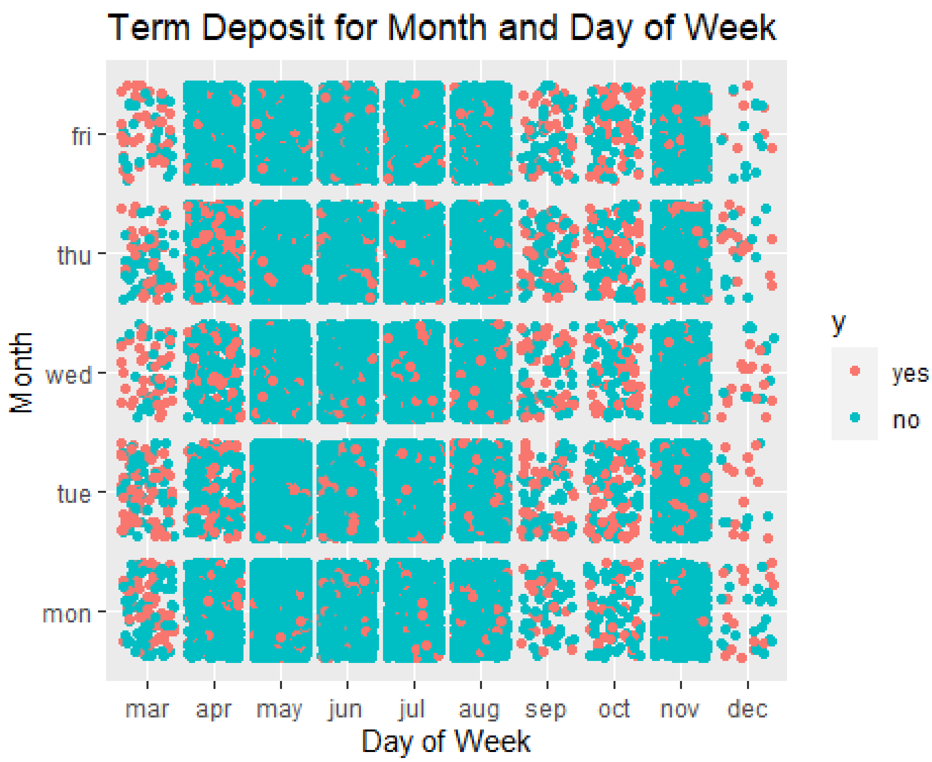
```
# Try plotting month by contact
train_data %>% ggplot(aes(x=month,y=contact,color=y)) + geom_jitter() +
  ylab('Month') + xlab('Contact') + ggtitle('Term Deposit for Month and
Contact')
```




```
# Looking at model
model <- glm('y ~ month*contact', data = train_data, family = "binomial")
summary(model)

##
## Call:
## glm(formula = "y ~ month*contact", family = "binomial", data = train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6172   0.2573   0.4524   0.4794   1.2668
##
## Coefficients:
```

```
##                              Estimate Std. Error z value Pr(>|z|)    
## (Intercept)                  -0.09097    0.10061  -0.904  0.36588    
## monthapr                      1.44852    0.11528  12.565  < 2e-16 ***
## monthmay                      2.19672    0.11155  19.692  < 2e-16 ***
## monthjun                      0.37338    0.12758   2.927  0.00343 ** 
## monthjul                      2.31893    0.11155  20.788  < 2e-16 ***
## monthaug                      2.19520    0.11095  19.786  < 2e-16 ***
## monthsep                      0.16392    0.14336   1.143  0.25287    
## monthoct                      0.31811    0.13822   2.301  0.02137 *  
## monthnov                      2.27145    0.11756  19.322  < 2e-16 ***
## monthdec                     -0.11667    0.21208  -0.550  0.58224    
## contacttelephone              0.36541    0.32055   1.140  0.25431    
## monthapr:contacttelephone    -0.57305    0.37493  -1.528  0.12640    
## monthmay:contacttelephone     0.92049    0.33152   2.777  0.00549 ** 
## monthjun:contacttelephone     2.34176    0.33919   6.904 5.06e-12 ***
## monthjul:contacttelephone     0.39625    0.36151   1.096  0.27305    
## monthaug:contacttelephone    -0.59236    0.38226  -1.550  0.12123    
## monthsep:contacttelephone     0.70108    0.44236   1.585  0.11300    
## monthoct:contacttelephone    -0.03293    0.38399  -0.086  0.93166    
## monthnov:contacttelephone    -0.50233    0.36799  -1.365  0.17223    
## monthdec:contacttelephone     0.60437    0.58918   1.026  0.30499    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 20600  on 32930  degrees of freedom
## AIC: 20640
## 
## Number of Fisher Scoring iterations: 6
```

```
# Try plotting month by day of week
train_data %>% ggplot(aes(x=month,y=day_of_week,color=y)) + geom_jitter() +
  ylab('Month') + xlab('Day of Week') + ggtitle('Term Deposit for Month and
Day of Week')
```




```r
# Looking at model
model <- glm('y ~ month*day_of_week', data = train_data, family = "binomial")
summary(model)

##
## Call:
## glm(formula = "y ~ month*day_of_week", family = "binomial", data =
train_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4220   0.3623   0.4223   0.4727   1.4132
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 0.312872   0.187972   1.664 0.096020 .
## monthapr                    1.827194   0.233674   7.819 5.31e-15 ***
## monthmay                    2.278239   0.206389  11.039  < 2e-16 ***
## monthjun                    1.730202   0.213119   8.118 4.72e-16 ***
## monthjul                    2.162129   0.216775   9.974  < 2e-16 ***
## monthaug                    1.979662   0.218099   9.077  < 2e-16 ***
## monthsep                    0.337715   0.314228   1.075 0.282489
## monthoct                    0.435845   0.278242   1.566 0.117249
## monthnov                    1.977134   0.234519   8.431  < 2e-16 ***
## monthdec                   -0.158722   0.372167  -0.426 0.669758
## day_of_weektue             -0.696831   0.266651  -2.613 0.008968 **
## day_of_weekwed             -0.772405   0.321428  -2.403 0.016259 *
```

```
## day_of_weekthu          -0.055043   0.295758  -0.186 0.852359
## day_of_weekfri          -0.430655   0.307183  -1.402 0.160930
## monthapr:day_of_weektue -0.659116   0.336886  -1.956 0.050407 .
## monthmay:day_of_weektue  0.983982   0.295241   3.333 0.000860 ***
## monthjun:day_of_weektue  0.506141   0.303830   1.666 0.095739 .
## monthjul:day_of_weektue  0.521733   0.304277   1.715 0.086407 .
## monthaug:day_of_weektue  0.427297   0.304207   1.405 0.160132
## monthsep:day_of_weektue  0.112202   0.422507   0.266 0.790577
## monthoct:day_of_weektue  0.148785   0.383220   0.388 0.697832
## monthnov:day_of_weektue  0.496488   0.325825   1.524 0.127562
## monthdec:day_of_weektue  0.003684   0.632825   0.006 0.995355
## monthapr:day_of_weekwed -0.514429   0.377348  -1.363 0.172796
## monthmay:day_of_weekwed  0.872195   0.343141   2.542 0.011028 *
## monthjun:day_of_weekwed  0.797344   0.355250   2.244 0.024803 *
## monthjul:day_of_weekwed  0.608365   0.353901   1.719 0.085610 .
## monthaug:day_of_weekwed  0.493582   0.354500   1.392 0.163821
## monthsep:day_of_weekwed  0.041774   0.454737   0.092 0.926805
## monthoct:day_of_weekwed  0.233983   0.428858   0.546 0.585344
## monthnov:day_of_weekwed  0.670189   0.372352   1.800 0.071879 .
## monthdec:day_of_weekwed  0.243561   0.599916   0.406 0.684749
## monthapr:day_of_weekthu -1.284675   0.338186  -3.799 0.000145 ***
## monthmay:day_of_weekthu  0.193431   0.321553   0.602 0.547473
## monthjun:day_of_weekthu  0.282541   0.335666   0.842 0.399938
## monthjul:day_of_weekthu -0.028636   0.330096  -0.087 0.930869
## monthaug:day_of_weekthu -0.018694   0.331765  -0.056 0.955064
## monthsep:day_of_weekthu -0.470381   0.438986  -1.072 0.283936
## monthoct:day_of_weekthu -0.442359   0.401626  -1.101 0.270714
## monthnov:day_of_weekthu -0.033120   0.350090  -0.095 0.924630
## monthdec:day_of_weekthu -0.159732   0.558543  -0.286 0.774894
## monthapr:day_of_weekfri  0.426120   0.367607   1.159 0.246385
## monthmay:day_of_weekfri  0.449520   0.329336   1.365 0.172275
## monthjun:day_of_weekfri  0.759834   0.343928   2.209 0.027155 *
## monthjul:day_of_weekfri -0.007922   0.343393  -0.023 0.981596
## monthaug:day_of_weekfri  0.061498   0.342213   0.180 0.857382
## monthsep:day_of_weekfri  0.239600   0.450654   0.532 0.594953
## monthoct:day_of_weekfri -0.208862   0.415835  -0.502 0.615476
## monthnov:day_of_weekfri  0.209000   0.361374   0.578 0.563030
## monthdec:day_of_weekfri  0.681970   0.637079   1.070 0.284411
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 23269  on 32949  degrees of freedom
## Residual deviance: 21314  on 32900  degrees of freedom
## AIC: 21414
##
## Number of Fisher Scoring iterations: 5
```

It looks like there is some promise for variable interactions. When looking at Month vs Day of Week, certain months have days that have a different distribution of yes and no. And certain days have months that have a different distribution. Some of the interaction terms also have significant p values. We will also include interaction terms in the Forward Selection, along with the polynomial terms. Below is some example code (not being evaluate, because it takes over an hour to finish) of adding all the single variables, polynomial variables, and interaction terms to the model.

```
set.seed(70)
vars <- colnames(train_data)
vars <- vars[vars!="y"]
allVars <- vars
num_poly <- 10
for (i in 1:length(vars)){
  for (j in 2:num_poly){
    if (class(train_data[,vars[i]]) != "factor") {
      allVars <- c(allVars,paste('poly(',vars[i],',',j,')',sep=""))
    }
  }
}
for (i in 1:length(vars)){
  for (j in 1:i){
    if(vars[i]!=vars[j]) {
      allVars <- c(allVars,paste(vars[i],'*',vars[j],sep=''))
    }
  }
}
# These variables need to be removed so the code doesn't error out
allVars <- allVars[allVars!="poly(pdays,6)"]
allVars <- allVars[allVars!="poly(pdays,7)"]
allVars <- allVars[allVars!="poly(pdays,8)"]
allVars <- allVars[allVars!="poly(pdays,9)"]
allVars <- allVars[allVars!="poly(pdays,10)"]
allVars <- allVars[allVars!="poly(previous,7)"]
allVars <- allVars[allVars!="poly(previous,8)"]
allVars <- allVars[allVars!="poly(previous,9)"]
allVars <- allVars[allVars!="poly(previous,10)"]
allVars <- allVars[allVars!="poly(emp.var.rate,10)"]
var_aucs <- data.frame("vars" = allVars)
num_vars <- length(allVars)
num_folds <- 10
start_num <- 124
for (j in start_num:num_vars) {
  var <- allVars[j]
  print(paste(j,'/',num_vars,': ',var,sep=''))
  folds <- createFolds(train_data$y, k = num_folds)
  auc_scores <- numeric(num_folds)
  for (i in 1:num_folds) {
    train_indices <- unlist(folds[-i])
```

```
    test_indices <- unlist(folds[i])
    train <- train_data[train_indices, ]
    test <- train_data[test_indices, ]
    form <- as.formula(paste("y ~ ",var,sep=""))
    model <- glm(form, data = train, family = "binomial")
    predictions <- predict(model, newdata = test, type = "response")
    roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
    auc_scores[i] <- auc(roc)
  }
  var_aucs$auc[var_aucs$var == var] <- mean(auc_scores)
}
```

After several iterations of this (plus Backwards Selection), we arrived at the final model: y ~ poly(cons.conf.idx,10) + pdays + day_of_week * month + month * contact + cons.conf.idx * housing + poutcome * previous + poly(campaign,5) + poly(euribor3m,8) + campaign * month + cons.conf.idx * age + poly(previous,6) + campaign * contact + poly(age,3).

Adding PCA

Since our earlier PCA analysis looked promising, I tried adding PC1 to the model.

```
# PCA
df.numeric <- train_data[ , sapply(train_data, is.numeric)]
pc.result<-prcomp(df.numeric,scale.=TRUE)
pc.scores<-pc.result$x
pc.scores<-data.frame(pc.scores)

# Trying out adding PC1
train_data$PC1 <- pc.scores$PC1
set.seed(134)
form <- as.formula('y ~ PC1 + poly(cons.conf.idx,10) + pdays +
day_of_week*month + month*contact + cons.conf.idx*housing + poutcome*previous
+ poly(campaign,5) + poly(euribor3m,8)  + campaign*month + cons.conf.idx*age
+ poly(previous,6) + campaign*contact + poly(age,3)')
num_folds <- 10
folds <- createFolds(train_data$y, k = num_folds)
accuracy_scores <- numeric(num_folds)
auc_scores <- numeric(num_folds)
for (i in 1:num_folds) {
  train_indices <- unlist(folds[-i])
  test_indices <- unlist(folds[i])
  train <- train_data[train_indices, ]
  test <- train_data[test_indices, ]
  model <- glm(form, data = train, family = "binomial")
  predictions <- predict(model, newdata = test, type = "response")
  roc <- roc(response=test$y,predictor=predictions,levels=c("no",
"yes"),direction = ">")
  auc_scores[i] <- auc(roc)
```

```
}
mean(auc_scores)

## [1] 0.8026035
```

The AUC value was slightly worse than it was when PC1 wasn't there. So we'll just use the formula derived above.

Support Vector Machine (SVM)

For a non-parametric model, we tried Support Vector Machines (SVM). These are a type of non-parametric model that try to form a line, plane, hyper-plan between datapoints.

They had three important hyper parameters: the kernal, gamma, and the cost. The kernal would be the type of fit. Possible values are linear, polynomial, radial, etc. Gamma sets the curvature of the separating hyper-plane. A higher Gamma values means more curvature. The Cost parameter sets how much error points it wants to classify on. The higher the Cost, the worse it predicts on the training set errors (and hope isn't overfitting).

Here is some example code for training the SVM. It takes over half an hour to train even fairly simple models, so it isn't set to execute.

```
form <- as.formula("y ~ euribor3m + month + poutcome + contact +
cons.conf.idx + campaign + previous + age + housing + day_of_week")
svm_model <- svm(form, data = train_data, kernel = "radial", gamma = 1, cost
= 1, probability = TRUE, decision.values = TRUE)
predictions <- predict(svm_model, newdata = train_data, probability = TRUE,
decision.values = TRUE)
probs <- attr(predictions,"probabilities")[,'yes']
predicted_classes <- ifelse(probs > .083, 'yes','no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))
confusion_matrix # PPV = 0.69, Sens = 0.62
confusion_matrix$byClass['F1'] # 0.65
roc <- roc(response=train_data$y,predictor=probs,levels=c("yes",
"no"),direction = ">")
auc(roc) # 0.8513
plot(roc,print.thres="best",col="red")
title(main = 'ROC Curve for SVM', line = 3)
```

And here is the sample code for testing.

```
predictions <- predict(svm_model, newdata = test_data, probability = TRUE)
probs <- attr(predictions,"probabilities")[,'yes']
predicted_classes <- ifelse(probs > .083, 'yes','no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
confusion_matrix # Sensitivity = 0.5236, Specificity = 0.8705, PPV = 0.3345,
NPV = 0.9363
confusion_matrix$byClass['F1'] # 0.4082157
roc <- roc(response=test_data$y,predictor=probs,levels=c("yes",
```

```
"no"),direction = ">")
auc(roc) # 0.6979
```

Calculating Metrics

We are calculating Sensitivity (Correctly Predicted Positive / All Positive), Specificity (Correctly Predicted Negative / All Negative), Prevalence (All Positive / All Observations), PPV (Correctly Predicted Positive / Predicted Positive), NPV (Correctly Predicted Negative / Predicted Negative), and AUROC (Area under the ROC Curve).

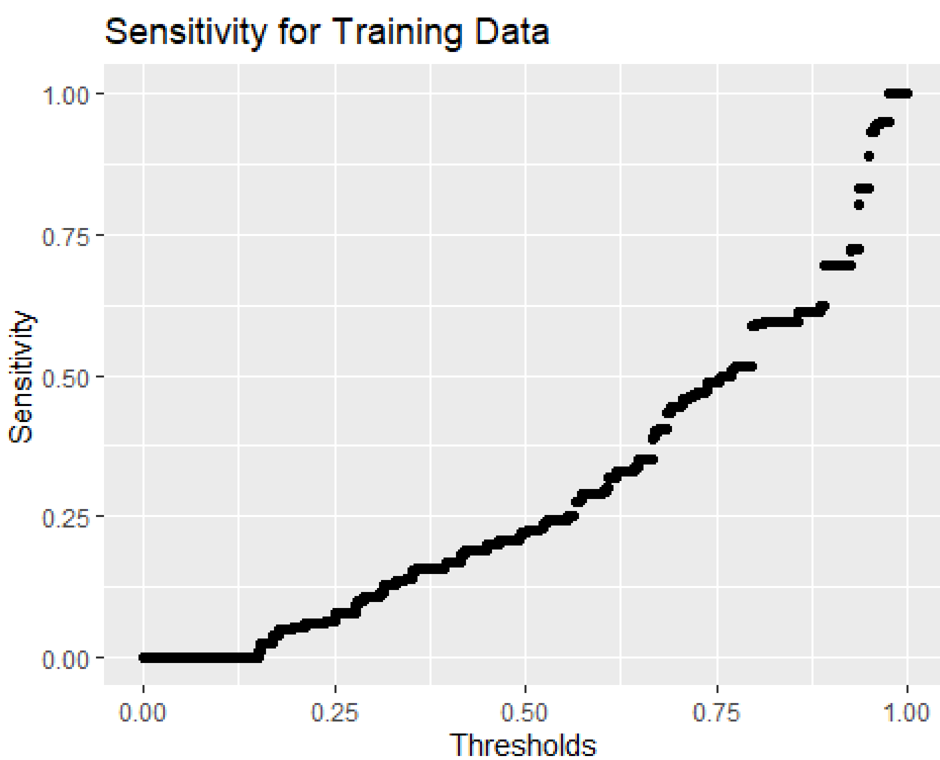
In addition, we are also calculating the F1 score. This is equal to 2 * Sensitivity * PPV / (Sensitivity + PPV). Since it is more important that we do a good job of predicting whether people will get a term deposit, and the F1 score is a nice metric to make sure that there is a good balance between Sensitivity and PPV, we decided to track this metric as well.

Simple Logisitc Regression Model

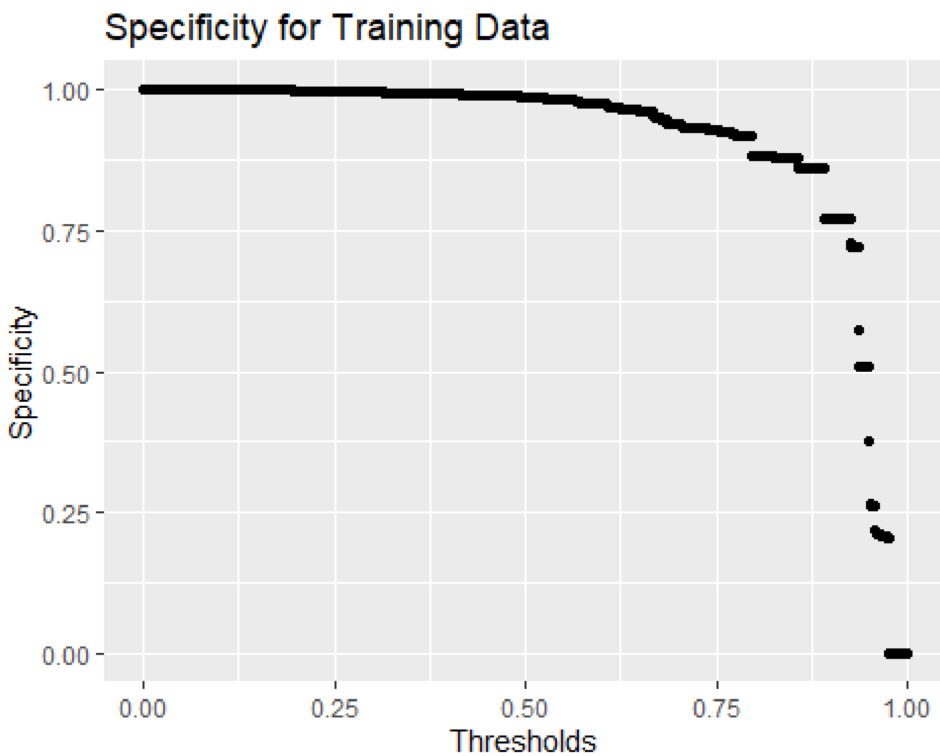
First we determined the threshold to use for the Simple Logistic Regression Model in order to maximize the F1 metric.

```
# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 0
metrics$specificity <- 0
metrics$ppv <- 0
metrics$npv <- 0
metrics$accuracy <- 0
metrics$f1 <- 0
form <- as.formula(y ~ month + poutcome + emp.var.rate + contact +
cons.price.idx)
model <- glm(form, data = train_data, family = "binomial")
predicted <- predict(model, newdata = train_data, type = "response")

for (i in 1:num_thresh){

  # Confusion Matrix
  predicted_classes <- ifelse(predicted > metrics$thresh[i], 'no','yes')
  confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))

  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
```

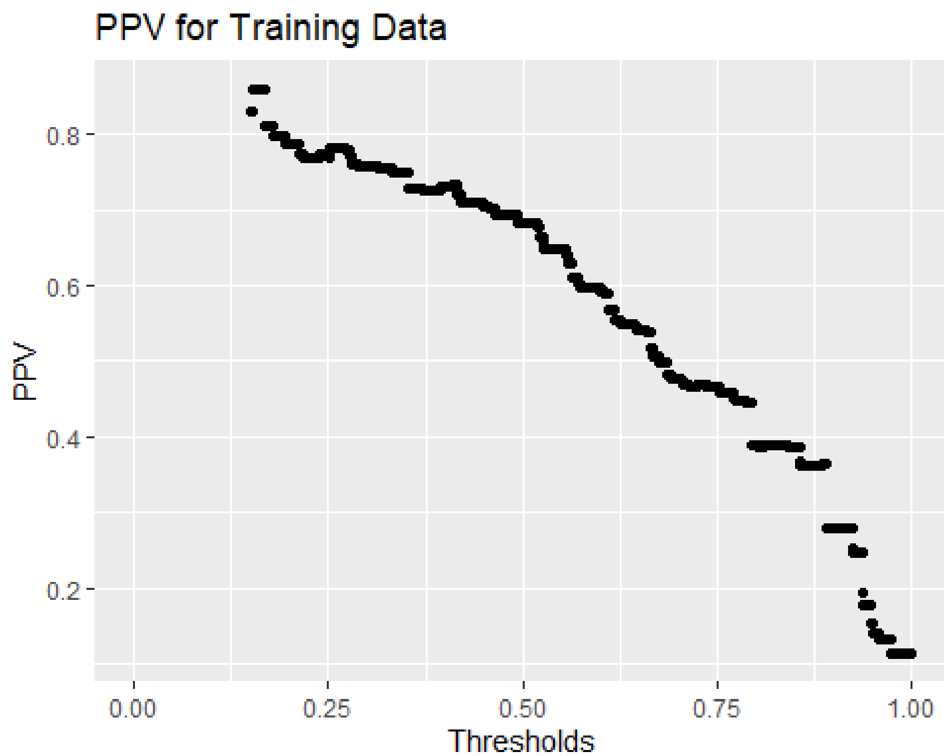
```
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}

# Get threshold value that maximizes F1
metrics <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/metrics_simple.csv')
maxF1 <- max(metrics$f1, na.rm = TRUE)
maxF1

## [1] 0.4798184

theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1

## [1] 0.7703

# Plots
metrics %>% ggplot(aes(x = thresh, y = sensitivity)) + geom_point() +
  ylab('Sensitivity') + xlab('Thresholds') + ggtitle('Sensitivity for Training Data')
```



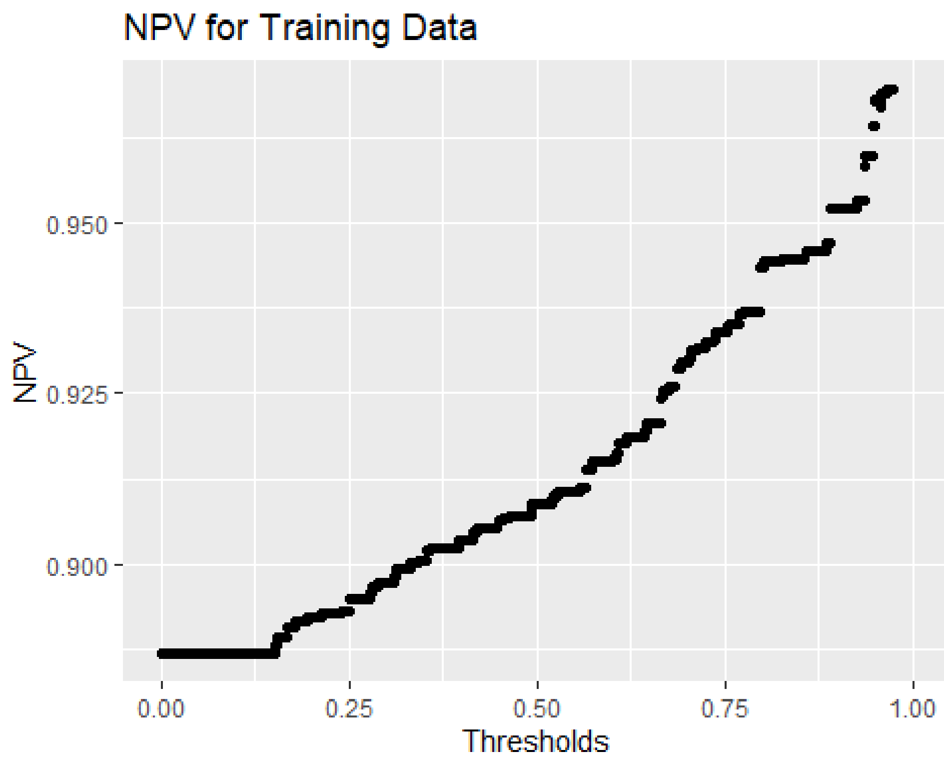

```
metrics %>% ggplot(aes(x = thresh, y = specificity)) + geom_point() +
  ylab('Specificity') + xlab('Thresholds') + ggtitle('Specificity for Training Data')
```




```
metrics %>% ggplot(aes(x = thresh, y = ppv)) + geom_point() +
  ylab('PPV') + xlab('Thresholds') + ggtitle('PPV for Training Data')

## Warning: Removed 1506 rows containing missing values (`geom_point()`).
```

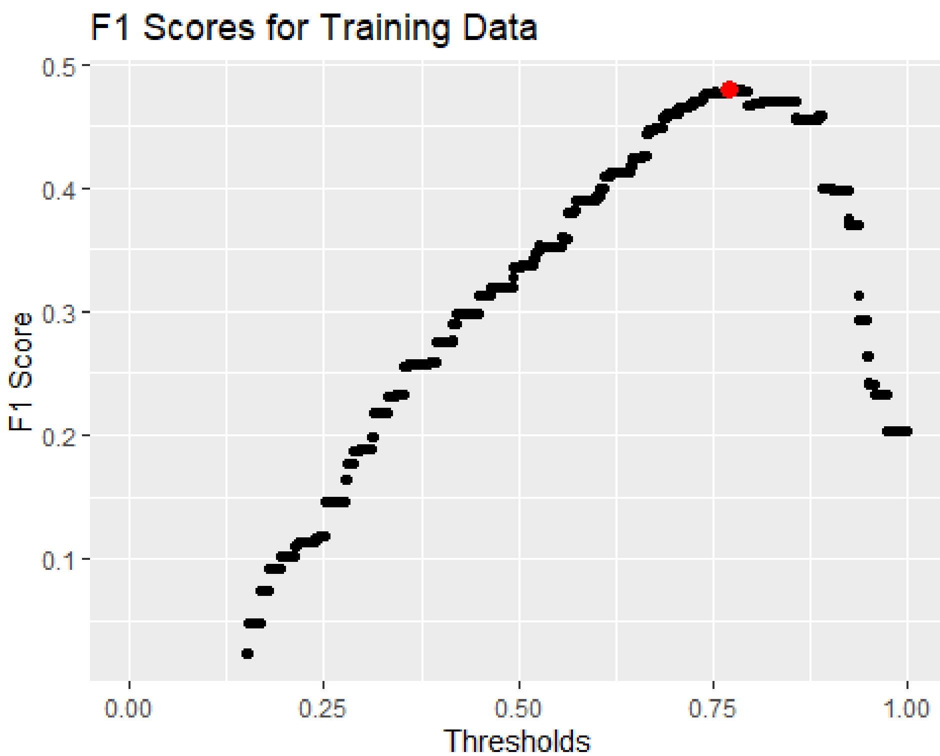



```
metrics %>% ggplot(aes(x = thresh, y = npv)) + geom_point() +
  ylab('NPV') + xlab('Thresholds') + ggtitle('NPV for Training Data')

## Warning: Removed 252 rows containing missing values (`geom_point()`).
```




```r
metrics %>% ggplot(aes(x = thresh, y = f1)) + geom_point() +
  ylab('F1 Score') + xlab('Thresholds') + ggtitle('F1 Scores for Training
Data') +
  geom_point(data = data.frame(x = theshF1, y = maxF1), aes(x = x, y = y),
size = 3, color = "red", fill = "red", shape = 21)
```

```
## Warning: Removed 1506 rows containing missing values (`geom_point()`).
```




```
# Get Confusion Matrix for threshold value
predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(train_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.

confusion_matrix

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   yes    no
##        yes  1902  2297
##        no   1827 26924
##
##                Accuracy : 0.8748
##                  95% CI : (0.8712, 0.8784)
##     No Information Rate : 0.8868
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.409
##
##  Mcnemar's Test P-Value : 2.81e-13
```

```
##
##             Sensitivity : 0.51006
##             Specificity : 0.92139
##          Pos Pred Value : 0.45296
##          Neg Pred Value : 0.93645
##              Prevalence : 0.11317
##          Detection Rate : 0.05772
##    Detection Prevalence : 0.12744
##       Balanced Accuracy : 0.71572
##
##        'Positive' Class : yes
##
```

```r
confusion_matrix$byClass['F1']
```

```
##        F1
## 0.4798184
```

After we got the thresholds to use, then we calculated the metrics on the test dataset.

```r
# Test data
predicted <- predict(model, newdata = test_data, type = "response")
predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```r
confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  449  571
##        no   462 6756
##
##                Accuracy : 0.8746
##                  95% CI : (0.8673, 0.8817)
##     No Information Rate : 0.8894
##     P-Value [Acc > NIR] : 0.9999882
##
##                   Kappa : 0.3943
##
##  Mcnemar's Test P-Value : 0.0007787
##
##             Sensitivity : 0.4929
##             Specificity : 0.9221
```

```
##          Pos Pred Value : 0.4402
##          Neg Pred Value : 0.9360
##              Prevalence : 0.1106
##          Detection Rate : 0.0545
##    Detection Prevalence : 0.1238
##       Balanced Accuracy : 0.7075
##
##        'Positive' Class : yes
##
```

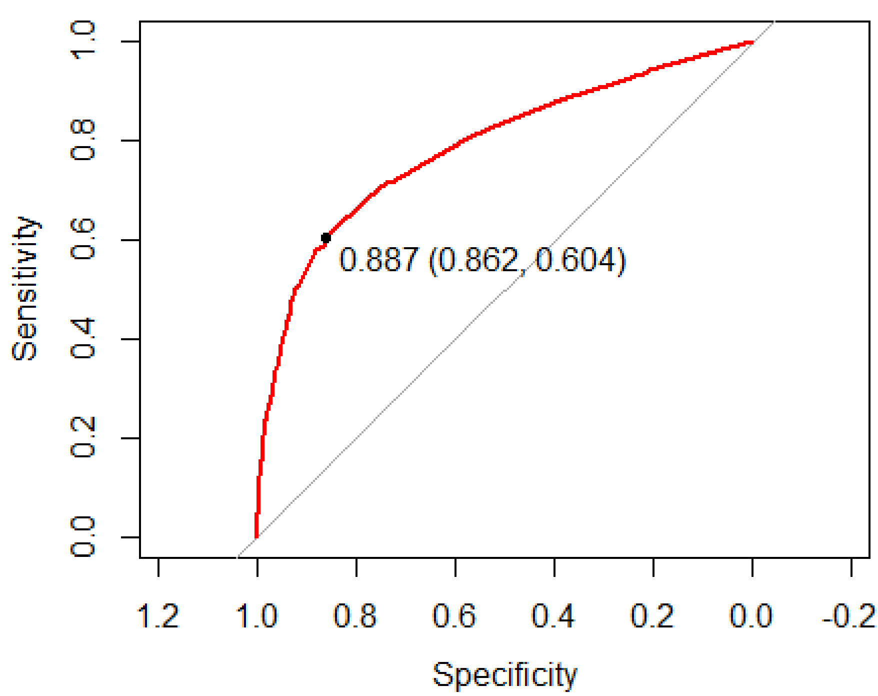
```
confusion_matrix$byClass['F1']
```

```
##       F1
## 0.465044
```

```
# AUC
roc <- roc(response=test_data$y,predictor=predicted,levels=c("no",
"yes"),direction = ">")
auc(roc)
```

```
## Area under the curve: 0.7868
```

```
plot(roc,print.thres="best",col="red")
```



This code takes a while to run, so we won't include the code to maximize the threshold value going forward. Given the thresholds though, here is the code to get the metrics for the complicated logistic regression model.

Complex Logistic Regression

```
# Get threshold value that maximizes F1
metrics <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/metrics_complex_logistic.csv')
maxF1 <- max(metrics$f1, na.rm = TRUE)
maxF1

## [1] 0.5073269

theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1

## [1] 0.7354

# Get Confusion Matrix for threshold value
form <- as.formula(y ~ poly(cons.conf.idx,10) + pdays + day_of_week*month +
month*contact + cons.conf.idx*housing + poutcome*previous + poly(campaign,5)
+ poly(euribor3m,8)  + campaign*month + cons.conf.idx*age + poly(previous,6)
+ campaign*contact + poly(age,3))
model <- glm(form, data = train_data, family = "binomial")
predicted <- predict(model, newdata = train_data, type = "response")

## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type
== :
## prediction from a rank-deficient fit may be misleading

predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(train_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.

confusion_matrix

## Confusion Matrix and Statistics
##
##             Reference
## Prediction   yes    no
##        yes  2008  2179
##        no   1721 27042
##
##                Accuracy : 0.8816
##                  95% CI : (0.8781, 0.8851)
##     No Information Rate : 0.8868
##     P-Value [Acc > NIR] : 0.9985
##
##                   Kappa : 0.4403
##
```

```
##  Mcnemar's Test P-Value : 2.52e-13
##
##             Sensitivity : 0.53848
##             Specificity : 0.92543
##          Pos Pred Value : 0.47958
##          Neg Pred Value : 0.94017
##              Prevalence : 0.11317
##          Detection Rate : 0.06094
##    Detection Prevalence : 0.12707
##       Balanced Accuracy : 0.73196
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1']
```

```
##        F1
## 0.5073269
```

```
# Test data
predicted <- predict(model, newdata = test_data, type = "response")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type
== :
## prediction from a rank-deficient fit may be misleading
```

```
predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  481  550
##        no   430 6777
##
##                Accuracy : 0.881
##                  95% CI : (0.8739, 0.888)
##     No Information Rate : 0.8894
##     P-Value [Acc > NIR] : 0.9922347
##
##                   Kappa : 0.4282
##
##  Mcnemar's Test P-Value : 0.0001439
```

```
##
##             Sensitivity : 0.52799
##             Specificity : 0.92494
##          Pos Pred Value : 0.46654
##          Neg Pred Value : 0.94034
##              Prevalence : 0.11059
##          Detection Rate : 0.05839
##    Detection Prevalence : 0.12515
##       Balanced Accuracy : 0.72646
##
##        'Positive' Class : yes
##
```

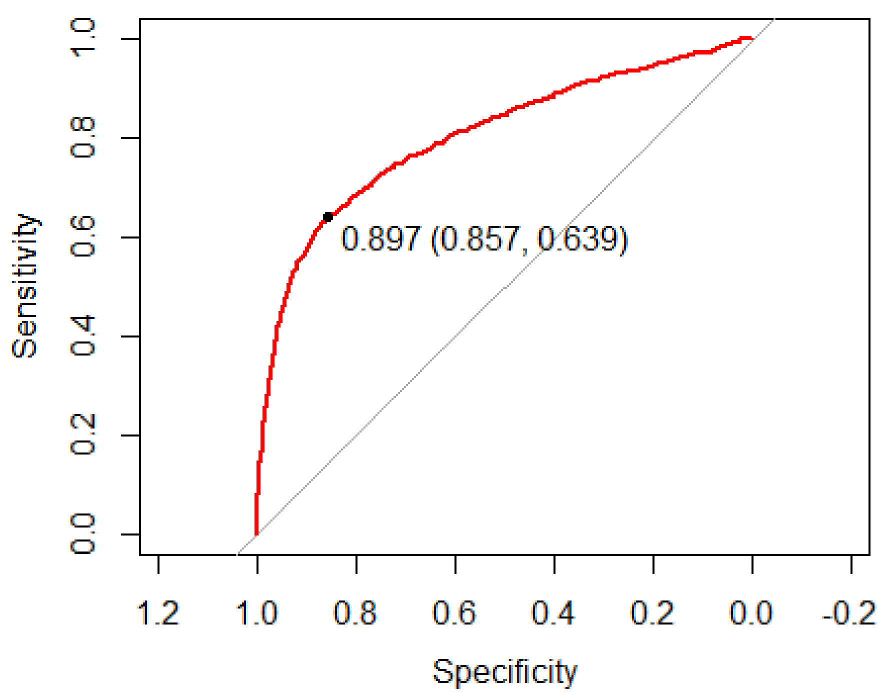
```
confusion_matrix$byClass['F1']
```

```
##        F1
## 0.4953656
```

```
# AUC
roc <- roc(response=test_data$y,predictor=predicted,levels=c("no",
"yes"),direction = ">")
auc(roc)
```

```
## Area under the curve: 0.8013
```

```
plot(roc,print.thres="best",col="red")
```



Comparing old vs new data

We noticed as part of EDA that the newer data (data was in order of when it was received) had a different Yes/No distribution than older data. We thought it would be interesting to see how training on old data and testing on newer data would perform.

```
# Simple logistic model
metrics <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-2/main/metrics_simple_date.csv')

# Train simple model
form <- as.formula(y ~ month + poutcome + emp.var.rate + contact + cons.price.idx)
model <- glm(form, data = train_data, family = "binomial")

# Get threshold value that maximizes F1
maxF1 <- max(metrics$f1, na.rm = TRUE)
maxF1 # 0.2623695

## [1] 0.2623695

theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.8486

## [1] 0.8486

# Try filtering data to get it to work
test_data <- test_data[test_data$month != "sep",]

# Get the confusion matrix
predicted <- predict(model, newdata = test_data, type = "response")
predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes), as.factor(test_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference and
## data. Refactoring data to match.

confusion_matrix # Sensitivity = 0.5661, Specificity = 0.7740, PPV = 0.5151, NPV = 0.8079, Prevalence = 0.2979

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  474  819
##        no   382 6443
##
##                Accuracy : 0.8521
```

```
##                  95% CI : (0.8441, 0.8597)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3599
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.55374
##             Specificity : 0.88722
##          Pos Pred Value : 0.36659
##          Neg Pred Value : 0.94403
##              Prevalence : 0.10544
##          Detection Rate : 0.05839
##    Detection Prevalence : 0.15928
##       Balanced Accuracy : 0.72048
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1'] # 0.5394243
```

```
##        F1
## 0.4411354
```

```
# AUC
roc <- roc(response=test_data$y,predictor=predicted,levels=c("no",
"yes"),direction = ">")
auc(roc) # 0.7095
```

```
## Area under the curve: 0.7788
```

```
# Complex model
metrics <- read.csv('https://raw.githubusercontent.com/stedua22/6372-Project-
2/main/metrics_complex_logistic_date.csv')

# Train simple model
form <- as.formula(y ~ poly(cons.conf.idx,10) + pdays + day_of_week*month +
month*contact + cons.conf.idx*housing + poutcome*previous + poly(campaign,5)
+ poly(euribor3m,8)  + campaign*month + cons.conf.idx*age + poly(previous,6)
+ campaign*contact + poly(age,3))
model <- glm(form, data = train_data, family = "binomial")

# Error about poly(cons.conf.idx,10) having too high of a degree
form <- as.formula(y ~ poly(cons.conf.idx,9) + pdays + day_of_week*month +
month*contact + cons.conf.idx*housing + poutcome*previous + poly(campaign,5)
+ poly(euribor3m,8)  + campaign*month + cons.conf.idx*age + poly(previous,3)
+ campaign*contact + poly(age,3))
model <- glm(form, data = train_data, family = "binomial")

# Get threshold value that maximizes F1
```

```r
maxF1 <- max(metrics$f1, na.rm = TRUE)
maxF1 # 0.2431846
```

```
## [1] 0.2431846
```

```r
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.7308
```

```
## [1] 0.7308
```

```r
# Try filtering data to get it to work
test_data <- test_data[test_data$month != "sep",]

# Get the confusion matrix
predicted <- predict(model, newdata = test_data, type = "response")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type
== :
## prediction from a rank-deficient fit may be misleading
```

```r
predicted_classes <- ifelse(predicted > theshF1, 'no','yes')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```r
confusion_matrix # Sensitivity = 0.6287, Specificity = 0.6716, PPV = 0.4482,
NPV = 0.8100, Prevalence = 0.2979
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  430  513
##        no   426 6749
##
##                Accuracy : 0.8843
##                  95% CI : (0.8772, 0.8912)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 0.998562
##
##                   Kappa : 0.4132
##
##  Mcnemar's Test P-Value : 0.005008
##
##             Sensitivity : 0.50234
##             Specificity : 0.92936
##          Pos Pred Value : 0.45599
##          Neg Pred Value : 0.94063
```

```
##               Prevalence : 0.10544
##           Detection Rate : 0.05297
##     Detection Prevalence : 0.11616
##        Balanced Accuracy : 0.71585
##
##         'Positive' Class : yes
##
```

```r
confusion_matrix$byClass['F1'] # 0.5233236
```

```
##        F1
## 0.4780434
```

```r
# AUC
roc <- roc(response=test_data$y,predictor=predicted,levels=c("no",
"yes"),direction = ">")
auc(roc) # 0.6502
```

```
## Area under the curve: 0.7936
```

We compared the simple model and complex model to how they did previously. To even be able to test against the newer data, we first had to filter out month = Sep, since that didn't exist in the training data. Also, we had to lower the order of some of the polynomials for the complex model.

The training metrics were poor, with an F1 score of around .25 for both models. However, the F1 scores for the test data were both above 0.5. The extra Yes results in the data seemed to help out. However, the AUC scores were worse, as well as the Specificity and NPV. This makes some sense, since there were less No results.

#QDA/LDA Model

```r
library(caret) # CreateFolds
library(pROC)
library(car) # VIF
library(tidyverse)


#LDA Model--- simple model month + poutcome + emp.var.rate + contact +
cons.price.idx

# Convert the binary outcome to a factor
train_data$y <- as.factor(train_data$y)


fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)
```

```
lda.fit<-train(y~ month + poutcome + emp.var.rate + contact + cons.price.idx,
               data=train_data,
               method="lda",
               trControl=fitControl,
               metric="logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(lda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}

## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
## [1] "900/10001"
```

```
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
## [1] "1700/10001"
## [1] "1800/10001"
## [1] "1900/10001"
## [1] "2000/10001"
## [1] "2100/10001"
## [1] "2200/10001"
## [1] "2300/10001"
## [1] "2400/10001"
## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
## [1] "3200/10001"
## [1] "3300/10001"
## [1] "3400/10001"
## [1] "3500/10001"
## [1] "3600/10001"
## [1] "3700/10001"
## [1] "3800/10001"
## [1] "3900/10001"
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
## [1] "4500/10001"
## [1] "4600/10001"
## [1] "4700/10001"
## [1] "4800/10001"
## [1] "4900/10001"
## [1] "5000/10001"
## [1] "5100/10001"
## [1] "5200/10001"
## [1] "5300/10001"
## [1] "5400/10001"
## [1] "5500/10001"
## [1] "5600/10001"
## [1] "5700/10001"
## [1] "5800/10001"
## [1] "5900/10001"
```

```
## [1] "6000/10001"
## [1] "6100/10001"
## [1] "6200/10001"
## [1] "6300/10001"
## [1] "6400/10001"
## [1] "6500/10001"
## [1] "6600/10001"
## [1] "6700/10001"
## [1] "6800/10001"
## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
## [1] "8200/10001"
## [1] "8300/10001"
## [1] "8400/10001"
## [1] "8500/10001"
## [1] "8600/10001"
## [1] "8700/10001"
## [1] "8800/10001"
## [1] "8900/10001"
## [1] "9000/10001"
## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1 # 0.4847
```

```
## [1] 0.4847892
```

```r
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.1313

## [1] 0.1313

# Test data
predicted <- predict(lda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.

confusion_matrix # Sensitivity = 0.5159, Specificity = 0.9179, PPV = 0.4388,
NPV = 0.9385, Prevalence = 0.11059

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  415  536
##        no   441 6726
##
##                Accuracy : 0.8797
##                  95% CI : (0.8724, 0.8867)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 0.999992
##
##                   Kappa : 0.3918
##
##  Mcnemar's Test P-Value : 0.002636
##
##             Sensitivity : 0.48481
##             Specificity : 0.92619
##          Pos Pred Value : 0.43638
##          Neg Pred Value : 0.93847
##              Prevalence : 0.10544
##          Detection Rate : 0.05112
##    Detection Prevalence : 0.11715
##       Balanced Accuracy : 0.70550
##
##        'Positive' Class : yes
##

confusion_matrix$byClass['F1'] # 0.4743

##        F1
## 0.4593248
```

```
#AUC


# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc <- roc(response = test_data$y,
                 predictor = as.numeric(as.character(predicted[, "yes"])),
                 levels = rev(levels(test_data$y)))  # Ensure correct
ordering of levels if needed

## Setting direction: controls < cases

# Print the AUROC
auc(roc) # 0.7846

## Area under the curve: 0.7768

#LDA Model--- using numeric variables only campaign + pdays + previous +
emp.var.rate + cons.price.idx + euribor3m + nr.employed



fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)


lda.fit<-train(y~ campaign + pdays + previous + emp.var.rate + cons.price.idx
+ euribor3m + nr.employed,
               data=train_data,
               method="lda",
               trControl=fitControl,
               metric="logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(lda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
```

```
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}
```

```
## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
## [1] "900/10001"
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
## [1] "1700/10001"
## [1] "1800/10001"
## [1] "1900/10001"
## [1] "2000/10001"
## [1] "2100/10001"
## [1] "2200/10001"
## [1] "2300/10001"
## [1] "2400/10001"
## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
## [1] "3200/10001"
```

```
## [1] "3300/10001"
## [1] "3400/10001"
## [1] "3500/10001"
## [1] "3600/10001"
## [1] "3700/10001"
## [1] "3800/10001"
## [1] "3900/10001"
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
## [1] "4500/10001"
## [1] "4600/10001"
## [1] "4700/10001"
## [1] "4800/10001"
## [1] "4900/10001"
## [1] "5000/10001"
## [1] "5100/10001"
## [1] "5200/10001"
## [1] "5300/10001"
## [1] "5400/10001"
## [1] "5500/10001"
## [1] "5600/10001"
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## [1] "6100/10001"
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## [1] "6600/10001"
## [1] "6700/10001"
## [1] "6800/10001"
## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
## [1] "8200/10001"
```

```
## [1] "8300/10001"
## [1] "8400/10001"
## [1] "8500/10001"
## [1] "8600/10001"
## [1] "8700/10001"
## [1] "8800/10001"
## [1] "8900/10001"
## [1] "9000/10001"
## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE)
maxF1 #
```

```
## [1] 0.4744277
```

```
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 #
```

```
## [1] 0.1082
```

```
# Test data
predicted <- predict(lda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  410  563
##        no   446 6699
##
##                Accuracy : 0.8757
```

```
##                  95% CI : (0.8683, 0.8828)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 1.0000000
##
##                   Kappa : 0.3786
##
##  Mcnemar's Test P-Value : 0.0002604
##
##             Sensitivity : 0.47897
##             Specificity : 0.92247
##          Pos Pred Value : 0.42138
##          Neg Pred Value : 0.93758
##              Prevalence : 0.10544
##          Detection Rate : 0.05051
##    Detection Prevalence : 0.11986
##       Balanced Accuracy : 0.70072
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1'] # 0.4640
```

```
##        F1
## 0.4483324
```

```
#AUC

# Assuming `predicted` contains the predicted probabilities for the 'yes' class
roc <- roc(response = test_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(test_data$y)))  # Ensure correct ordering of levels if needed
```

```
## Setting direction: controls < cases
```

```
# Print the AUROC
auc(roc)
```

```
## Area under the curve: 0.7502
```

```
#LDA Model--- using numeric variables  pdays + previous + emp.var.rate + cons.price.idx  + nr.employed

# Convert the binary outcome to a factor
train_data$y <- as.factor(train_data$y)


fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
```

```r
set.seed(1234)


lda.fit<-train(y~ pdays + previous + emp.var.rate + cons.price.idx +
nr.employed,
               data=train_data,
               method="lda",
               trControl=fitControl,
               metric="logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(lda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}
```

```
## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
```

```
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
## [1] "900/10001"
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
## [1] "1700/10001"
## [1] "1800/10001"
## [1] "1900/10001"
## [1] "2000/10001"
## [1] "2100/10001"
## [1] "2200/10001"
## [1] "2300/10001"
## [1] "2400/10001"
## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
## [1] "3200/10001"
## [1] "3300/10001"
## [1] "3400/10001"
## [1] "3500/10001"
## [1] "3600/10001"
## [1] "3700/10001"
## [1] "3800/10001"
## [1] "3900/10001"
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
## [1] "4500/10001"
## [1] "4600/10001"
## [1] "4700/10001"
## [1] "4800/10001"
## [1] "4900/10001"
## [1] "5000/10001"
## [1] "5100/10001"
## [1] "5200/10001"
## [1] "5300/10001"
## [1] "5400/10001"
## [1] "5500/10001"
```

```
## [1] "5600/10001"
## [1] "5700/10001"
## [1] "5800/10001"
## [1] "5900/10001"
## [1] "6000/10001"
## [1] "6100/10001"
## [1] "6200/10001"
## [1] "6300/10001"
## [1] "6400/10001"
## [1] "6500/10001"
## [1] "6600/10001"
## [1] "6700/10001"
## [1] "6800/10001"
## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
## [1] "8200/10001"
## [1] "8300/10001"
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## [1] "8500/10001"
## [1] "8600/10001"
## [1] "8700/10001"
## [1] "8800/10001"
## [1] "8900/10001"
## [1] "9000/10001"
## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```r
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1 #0.4744
```

```
## [1] 0.4647335
```

```
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.1082
```

```
## [1] 0.1254
```

```
# Test data
predicted <- predict(lda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix # Sensitivity = 0.51043, Specificity = 0.9143, PPV = 0.4254,
NPV = 0.9376, Prevalence = 0.1106
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  376  470
##        no   480 6792
##
##                Accuracy : 0.883
##                  95% CI : (0.8758, 0.8899)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 0.9996
##
##                   Kappa : 0.3765
##
##  Mcnemar's Test P-Value : 0.7703
##
##             Sensitivity : 0.43925
##             Specificity : 0.93528
##          Pos Pred Value : 0.44444
##          Neg Pred Value : 0.93399
##              Prevalence : 0.10544
##          Detection Rate : 0.04632
##    Detection Prevalence : 0.10421
##       Balanced Accuracy : 0.68727
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1'] # 0.4641
```

```
##        F1
## 0.4418331

#AUC

# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc <- roc(response = test_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(test_data$y)))  # Ensure correct ordering of
levels if needed

## Setting direction: controls < cases

# Print the AUROC
auc(roc) # 0.7599

## Area under the curve: 0.7439

#LDA Model--- using numeric variables  emp.var.rate + cons.price.idx +
euribor3m



fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)



lda.fit<-train(y~  emp.var.rate + cons.price.idx + euribor3m ,
               data=train_data,
               method="lda",
               trControl=fitControl,
               metric="logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(lda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }
```

```
  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}
```

```
## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
## [1] "900/10001"
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
## [1] "1700/10001"
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## [1] "2000/10001"
## [1] "2100/10001"
## [1] "2200/10001"
## [1] "2300/10001"
## [1] "2400/10001"
## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
```

```
## [1] "3200/10001"
## [1] "3300/10001"
## [1] "3400/10001"
## [1] "3500/10001"
## [1] "3600/10001"
## [1] "3700/10001"
## [1] "3800/10001"
## [1] "3900/10001"
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
## [1] "4500/10001"
## [1] "4600/10001"
## [1] "4700/10001"
## [1] "4800/10001"
## [1] "4900/10001"
## [1] "5000/10001"
## [1] "5100/10001"
## [1] "5200/10001"
## [1] "5300/10001"
## [1] "5400/10001"
## [1] "5500/10001"
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## [1] "5900/10001"
## [1] "6000/10001"
## [1] "6100/10001"
## [1] "6200/10001"
## [1] "6300/10001"
## [1] "6400/10001"
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## [1] "6800/10001"
## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
```

```
## [1] "8200/10001"
## [1] "8300/10001"
## [1] "8400/10001"
## [1] "8500/10001"
## [1] "8600/10001"
## [1] "8700/10001"
## [1] "8800/10001"
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## [1] "9000/10001"
## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  # 0.4561
```

```
## [1] 0.4560976
```

```
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.2306
```

```
## [1] 0.2306
```

```
# Test data
predicted <- predict(lda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

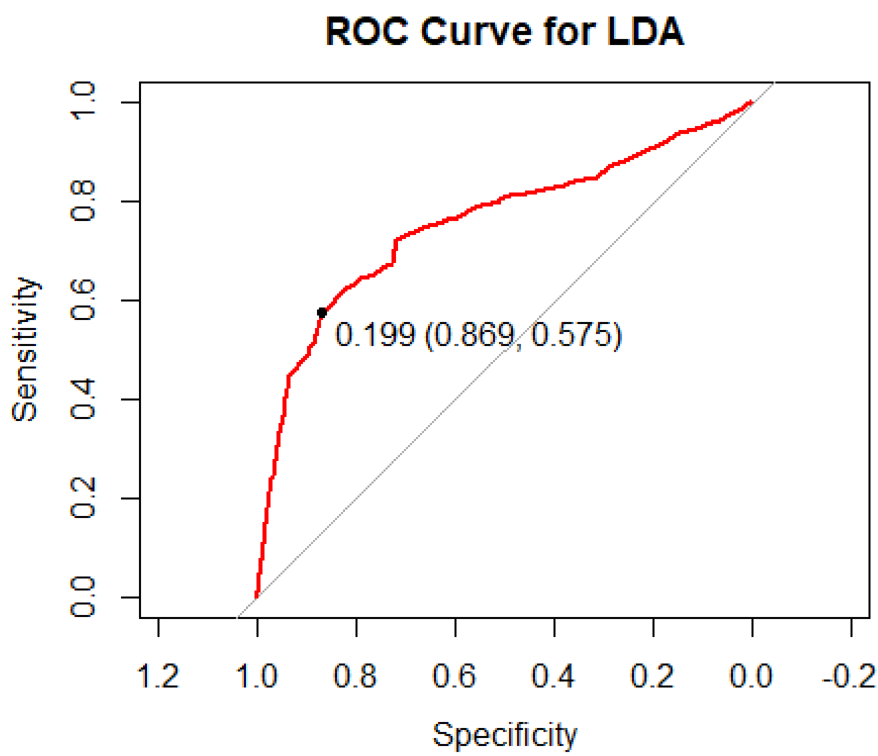
```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix  # Sensitivity = 0.4522, Specificity = 0.9335, PPV = 0.4583,
NPV = 0.9320, Prevalence = 0.1106
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  357  422
##        no   499 6840
```

```
##
##                Accuracy : 0.8865
##                  95% CI : (0.8794, 0.8934)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 0.99051
##
##                   Kappa : 0.3738
##
##  Mcnemar's Test P-Value : 0.01227
##
##             Sensitivity : 0.41706
##             Specificity : 0.94189
##          Pos Pred Value : 0.45828
##          Neg Pred Value : 0.93201
##              Prevalence : 0.10544
##          Detection Rate : 0.04398
##    Detection Prevalence : 0.09596
##       Balanced Accuracy : 0.67947
##
##        'Positive' Class : yes
##

confusion_matrix$byClass['F1'] # 0.4552

##        F1
## 0.4366972

# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc <- roc(response = test_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(test_data$y)))  # Ensure correct ordering of
levels if needed

## Setting direction: controls < cases

# Print the AUROC
auc(roc) # 0.7506

## Area under the curve: 0.7414

# Training data
predicted <- predict(lda.fit, newdata = train_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(train_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```r
confusion_matrix

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   yes    no
##        yes  1683  1968
##        no   2046 27253
##
##                Accuracy : 0.8782
##                  95% CI : (0.8746, 0.8817)
##     No Information Rate : 0.8868
##     P-Value [Acc > NIR] : 1.0000
##
##                   Kappa : 0.3875
##
##  Mcnemar's Test P-Value : 0.2242
##
##             Sensitivity : 0.45133
##             Specificity : 0.93265
##          Pos Pred Value : 0.46097
##          Neg Pred Value : 0.93017
##              Prevalence : 0.11317
##          Detection Rate : 0.05108
##    Detection Prevalence : 0.11080
##       Balanced Accuracy : 0.69199
##
##        'Positive' Class : yes
##

confusion_matrix$byClass['F1'] #0.4561

##        F1
## 0.4560976

# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc <- roc(response = train_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(train_data$y)))  # Ensure correct ordering of
levels if needed

## Setting direction: controls < cases

# Print the AUROC
auc(roc) # 0.7555

## Area under the curve: 0.7555

plot(roc,print.thres="best",col="red")
title(main = 'ROC Curve for LDA', line = 3)
```




```
# QDA Model--simple model

fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)

qda.fit <- train(y~ month + poutcome + emp.var.rate + contact +
cons.price.idx,
                 data = train_data,
                 method = "qda",
                 trControl = fitControl,
                 metric = "logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(qda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
```

```r
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}

## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
## [1] "900/10001"
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
## [1] "1700/10001"
## [1] "1800/10001"
## [1] "1900/10001"
## [1] "2000/10001"
## [1] "2100/10001"
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## [1] "2300/10001"
## [1] "2400/10001"
## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
```

```
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
## [1] "3200/10001"
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## [1] "3400/10001"
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## [1] "3800/10001"
## [1] "3900/10001"
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
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## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
```

```
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
## [1] "8200/10001"
## [1] "8300/10001"
## [1] "8400/10001"
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## [1] "8600/10001"
## [1] "8700/10001"
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## [1] "9200/10001"
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## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```r
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  # 0.4692
```

```
## [1] 0.4692364
```

```r
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.0227
```

```
## [1] 0.0227
```

```r
# Test data
predicted <- predict(qda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```r
confusion_matrix # Sensitivity = 0.5917, Specificity = 0.8781, PPV = 0.3764,
NPV = 0.9453, Prevalence =0.1106
```

```
## Confusion Matrix and Statistics
##
##             Reference
```

```
## Prediction  yes   no
##        yes  484  828
##        no   372 6434
##
##                Accuracy : 0.8522
##                  95% CI : (0.8443, 0.8598)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3655
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.56542
##             Specificity : 0.88598
##          Pos Pred Value : 0.36890
##          Neg Pred Value : 0.94534
##              Prevalence : 0.10544
##          Detection Rate : 0.05962
##    Detection Prevalence : 0.16162
##       Balanced Accuracy : 0.72570
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1'] # 0.4600
```

```
##        F1
## 0.4464945
```

```
# Assuming `predicted` contains the predicted probabilities for the 'yes' class
roc.qda <- roc(response = test_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(test_data$y)))  # Ensure correct ordering of levels if needed
```

```
## Setting direction: controls < cases
```

```
# Print the AUROC
auc(roc.qda) # 0.7811
```

```
## Area under the curve: 0.7741
```

```
# QDA --- using numeric variables  pdays + previous + emp.var.rate + cons.price.idx  + nr.employed

fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)
```

```
qda.fit <- train(y~ pdays + previous + emp.var.rate + cons.price.idx  +
nr.employed,
                 data = train_data,
                 method = "qda",
                 trControl = fitControl,
                 metric = "logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(qda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}
```

```
## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
## [1] "700/10001"
## [1] "800/10001"
```

```
## [1] "900/10001"
## [1] "1000/10001"
## [1] "1100/10001"
## [1] "1200/10001"
## [1] "1300/10001"
## [1] "1400/10001"
## [1] "1500/10001"
## [1] "1600/10001"
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## [1] "3000/10001"
## [1] "3100/10001"
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## [1] "3600/10001"
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## [1] "3800/10001"
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## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
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## [1] "4900/10001"
## [1] "5000/10001"
## [1] "5100/10001"
## [1] "5200/10001"
## [1] "5300/10001"
## [1] "5400/10001"
## [1] "5500/10001"
## [1] "5600/10001"
## [1] "5700/10001"
## [1] "5800/10001"
```

```
## [1] "5900/10001"
## [1] "6000/10001"
## [1] "6100/10001"
## [1] "6200/10001"
## [1] "6300/10001"
## [1] "6400/10001"
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## [1] "6900/10001"
## [1] "7000/10001"
## [1] "7100/10001"
## [1] "7200/10001"
## [1] "7300/10001"
## [1] "7400/10001"
## [1] "7500/10001"
## [1] "7600/10001"
## [1] "7700/10001"
## [1] "7800/10001"
## [1] "7900/10001"
## [1] "8000/10001"
## [1] "8100/10001"
## [1] "8200/10001"
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## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```r
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  # 0.4382
```

```
## [1] 0.4381683
```

```r
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.0635
```

```
## [1] 0.0635
```

```r
# Test data
predicted <- predict(qda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```r
confusion_matrix # accuracy = 0.8546, Sensitivity = 0.4951, Specificity =
0.8993, PPV = 0.3793, NPV = 0.9347, Prevalence =0.1106
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction  yes   no
##        yes  396  673
##        no   460 6589
##
##                Accuracy : 0.8604
##                  95% CI : (0.8527, 0.8679)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3334
##
##  Mcnemar's Test P-Value : 3.01e-10
##
##             Sensitivity : 0.46262
##             Specificity : 0.90733
##          Pos Pred Value : 0.37044
##          Neg Pred Value : 0.93474
##              Prevalence : 0.10544
##          Detection Rate : 0.04878
##    Detection Prevalence : 0.13168
##       Balanced Accuracy : 0.68497
##
##        'Positive' Class : yes
##
```

```r
confusion_matrix$byClass['F1'] # 0.4295
```

```
##        F1
## 0.4114286
```

```r
# Assuming `predicted` contains the predicted probabilities for the 'yes' class
roc.qda <- roc(response = test_data$y,
               predictor = as.numeric(as.character(predicted[, "yes"])),
               levels = rev(levels(test_data$y)))  # Ensure correct ordering of levels if needed

## Setting direction: controls < cases

# Print the AUROC
auc(roc.qda) # 0.7527

## Area under the curve: 0.7428

# QDA --- using numeric variables  emp.var.rate + cons.price.idx + euribor3m

fitControl<-
trainControl(method="repeatedcv",number=5,repeats=1,classProbs=TRUE,
summaryFunction=mnLogLoss)
set.seed(1234)

qda.fit <- train(y~ emp.var.rate + cons.price.idx + euribor3m,
                 data = train_data,
                 method = "qda",
                 trControl = fitControl,
                 metric = "logLoss")

# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 1
metrics$specificity <- 1
metrics$ppv <- 1
metrics$npv <- 1
metrics$accuracy <- 1
metrics$f1 <- 1
predicted <- predict(qda.fit, newdata = train_data, type = "prob")
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)
```

```
  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}
```

```
## [1] "100/10001"
## [1] "200/10001"
## [1] "300/10001"
## [1] "400/10001"
## [1] "500/10001"
## [1] "600/10001"
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## [1] "1100/10001"
## [1] "1200/10001"
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## [1] "2500/10001"
## [1] "2600/10001"
## [1] "2700/10001"
## [1] "2800/10001"
## [1] "2900/10001"
## [1] "3000/10001"
## [1] "3100/10001"
## [1] "3200/10001"
## [1] "3300/10001"
## [1] "3400/10001"
## [1] "3500/10001"
## [1] "3600/10001"
## [1] "3700/10001"
## [1] "3800/10001"
## [1] "3900/10001"
```

```
## [1] "4000/10001"
## [1] "4100/10001"
## [1] "4200/10001"
## [1] "4300/10001"
## [1] "4400/10001"
## [1] "4500/10001"
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## [1] "8500/10001"
## [1] "8600/10001"
## [1] "8700/10001"
## [1] "8800/10001"
## [1] "8900/10001"
```

```
## [1] "9000/10001"
## [1] "9100/10001"
## [1] "9200/10001"
## [1] "9300/10001"
## [1] "9400/10001"
## [1] "9500/10001"
## [1] "9600/10001"
## [1] "9700/10001"
## [1] "9800/10001"
## [1] "9900/10001"
## [1] "10000/10001"
```

```
# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  # 0.4681
```

```
## [1] 0.4680797
```

```
theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.1264
```

```
## [1] 0.1264
```

```
# Test data
predicted <- predict(qda.fit, newdata = test_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(test_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix # accuracy = 0.8765, Sensitivity = 0.4829, Specificity =
0.9255, PPV = 0.4463, NPV = 0.9351, Prevalence = 0.1106
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  385  481
##        no   471 6781
##
##                Accuracy : 0.8827
##                  95% CI : (0.8755, 0.8897)
##     No Information Rate : 0.8946
##     P-Value [Acc > NIR] : 0.9997
##
##                   Kappa : 0.3816
##
```

```
##  Mcnemar's Test P-Value : 0.7705
##
##             Sensitivity : 0.44977
##             Specificity : 0.93376
##          Pos Pred Value : 0.44457
##          Neg Pred Value : 0.93505
##              Prevalence : 0.10544
##          Detection Rate : 0.04743
##    Detection Prevalence : 0.10668
##       Balanced Accuracy : 0.69177
##
##        'Positive' Class : yes
##
```

```
confusion_matrix$byClass['F1'] # 0.4639
```

```
##        F1
## 0.4471545
```

```
# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc.qda <- roc(response = test_data$y,
               predictor = as.numeric(as.character(predicted[, "yes"])),
               levels = rev(levels(test_data$y)))  # Ensure correct ordering
of levels if needed
```

```
## Setting direction: controls < cases
```

```
# Print the AUROC
auc(roc.qda) # 0.7623
```

```
## Area under the curve: 0.754
```

```
# Training data
predicted <- predict(qda.fit, newdata = train_data, type = "prob")
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
confusion_matrix <- confusionMatrix(as.factor(predicted_classes),
as.factor(train_data$y))
```

```
## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(train_data$y)): Levels are not in the same order for reference
and
## data. Refactoring data to match.
```

```
confusion_matrix
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction    yes    no
##        yes   1833  2270
##        no    1896 26951
```

```
##
##                Accuracy : 0.8736
##                  95% CI : (0.8699, 0.8771)
##     No Information Rate : 0.8868
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.3965
##
##  Mcnemar's Test P-Value : 7.517e-09
##
##             Sensitivity : 0.49155
##             Specificity : 0.92232
##          Pos Pred Value : 0.44675
##          Neg Pred Value : 0.93427
##              Prevalence : 0.11317
##          Detection Rate : 0.05563
##    Detection Prevalence : 0.12452
##       Balanced Accuracy : 0.70693
##
##        'Positive' Class : yes
##
```

```r
confusion_matrix$byClass['F1'] #0.4681
```

```
##        F1
## 0.4680797
```

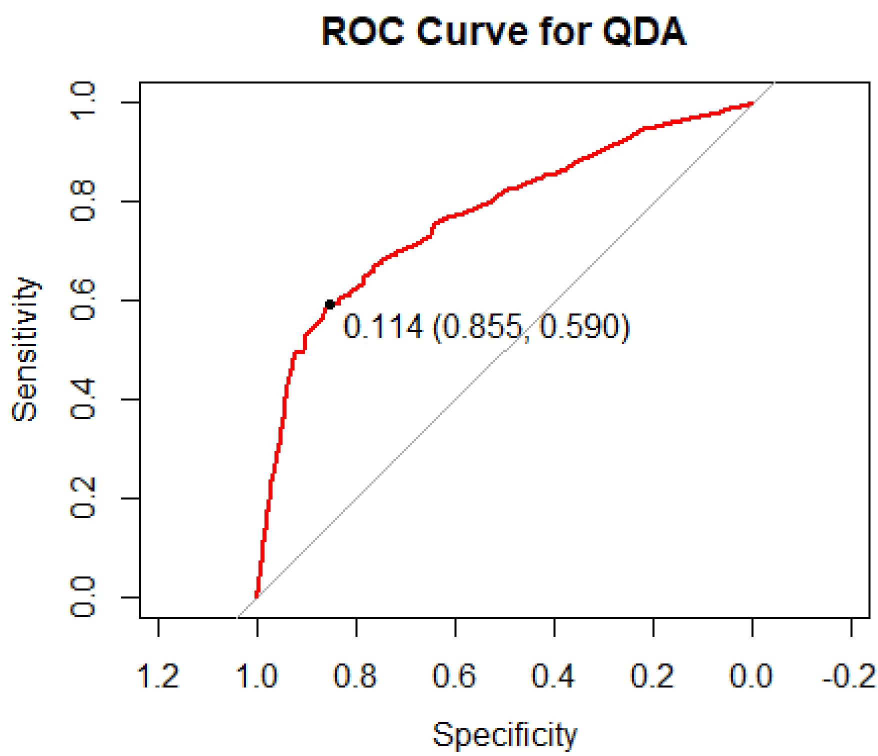
```r
# Assuming `predicted` contains the predicted probabilities for the 'yes'
class
roc <- roc(response = train_data$y,
           predictor = as.numeric(as.character(predicted[, "yes"])),
           levels = rev(levels(train_data$y)))  # Ensure correct ordering of
levels if needed
```

```
## Setting direction: controls < cases
```

```r
# Print the AUROC
auc(roc) # 0.7694
```

```
## Area under the curve: 0.7694
```

```r
plot(roc,print.thres="best",col="red")
title(main = 'ROC Curve for QDA', line = 3)
```



Clasification

Oluwadamilola Owolabi

2024-04-20

RANDOM FOREST MODEL 1: SIMPLE LOGISTIC MODEL

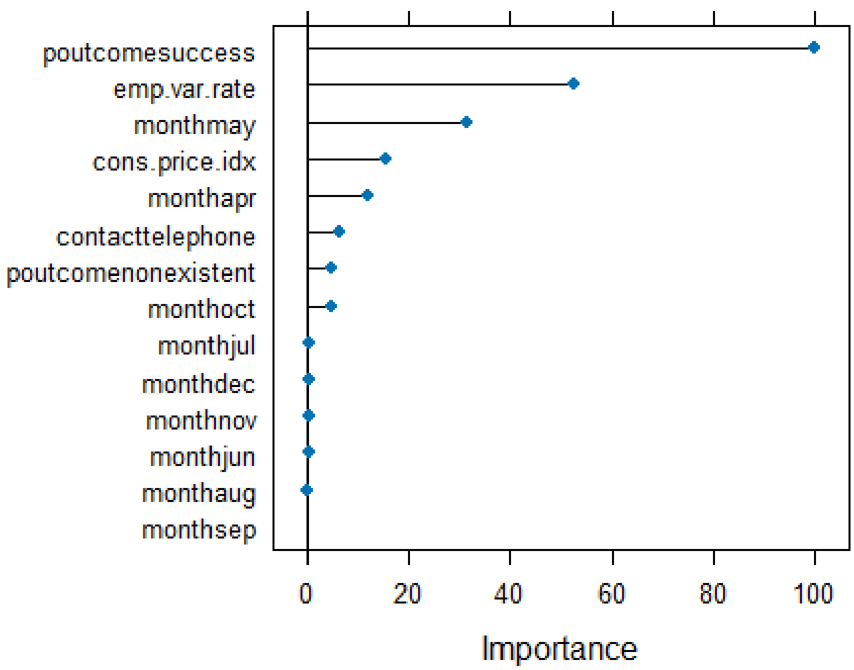
For our non-parametric model, we plan on using Random forest on our Simple Logistic Model. It is an ensemble learning method that combines the predictions of multiple individual decision trees to improve the overall performance and robustness of the model.

SLM : CARET PACKAGE

We plan on using the caret package, which iterates through different mtry and ntree values, to find the optimum one

```
set.seed(1234) #setting the seed
library(caret) # Loading the caret package

# Running Random Forest
# Specify the training control parameters
train_control <- trainControl(method = "cv",    # Cross-validation method
```

```r
                              number = 5,)       # Number of folds

# Define the random forest model
fitted_rf <- train(y ~ month + poutcome + emp.var.rate + contact + 
cons.price.idx, # formulae
                  data = train_data,            # Response variable
                  method = "rf",          # Random forest method
                  trControl = train_control) # Training control parameters

#fitted_rf

#plotting the importance plot
plot(varImp(fitted_rf, horizontal = TRUE))
```



From the plot above, we can see that the 3 most impactful variables in the SLM are poutcome, emp.var.rate and cons.price.idx.

Making predictions and getting the metrics

```r
# Getting the threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)

#initializing the new metrics to 0
metrics$sensitivity <- 0
metrics$specificity <- 0
metrics$ppv <- 0
metrics$npv <- 0
```

```r
metrics$accuracy <- 0
metrics$f1 <- 0
predicted <- predict(fitted_rf, newdata = train_data, type = "prob")['yes']
#Getting the threshold

#Running a for loop to find the optimum threshold
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    #print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes',
'no')
  predicted_classes_factor <- factor(predicted_classes, levels =
levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)


  # Metrics
  metrics$sensitivity[i] <-
as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <-
as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}

# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  # 0.4593

## [1] 0.9468008

theshF1 <- metrics$thresh[which.max(metrics$f1)]
theshF1 # 0.004

## [1] 0.534

# Test data
predicted <- predict(fitted_rf, newdata = test_data, type = "prob")['yes']
predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')
CM <- confusionMatrix(as.factor(predicted_classes), as.factor(test_data$y))

## Warning in confusionMatrix.default(as.factor(predicted_classes),
## as.factor(test_data$y)): Levels are not in the same order for reference
```

```
and
## data. Refactoring data to match.
```

```r
CM
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  yes   no
##        yes  215  125
##        no   696 7202
##
##                Accuracy : 0.9003
##                  95% CI : (0.8937, 0.9067)
##     No Information Rate : 0.8894
##     P-Value [Acc > NIR] : 0.0007196
##
##                   Kappa : 0.3018
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.23600
##             Specificity : 0.98294
##          Pos Pred Value : 0.63235
##          Neg Pred Value : 0.91188
##              Prevalence : 0.11059
##          Detection Rate : 0.02610
##    Detection Prevalence : 0.04127
##       Balanced Accuracy : 0.60947
##
##        'Positive' Class : yes
##
```

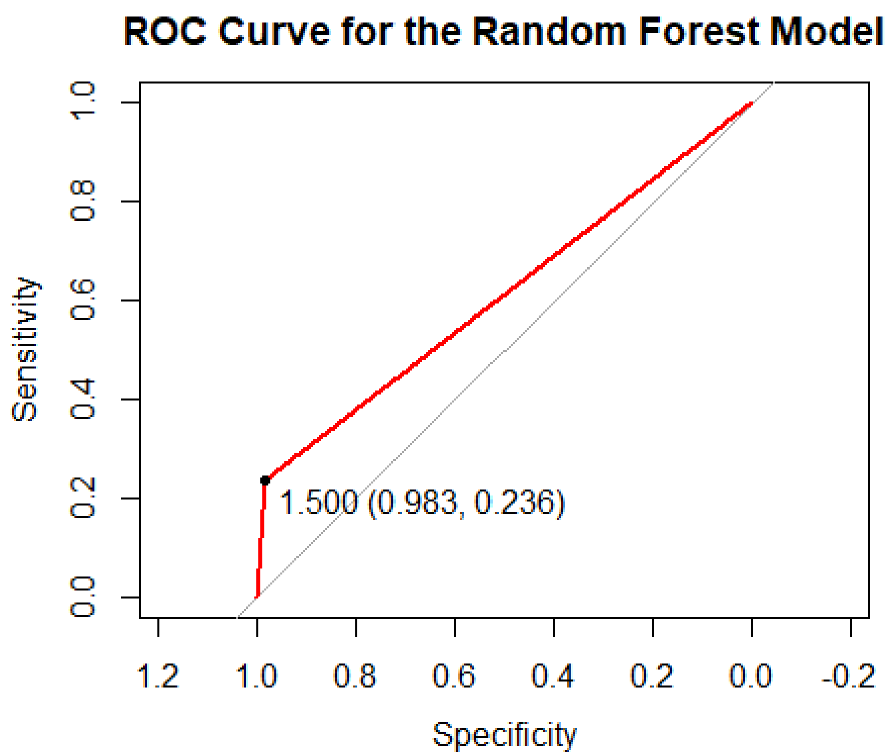
```r
#Printing out the metric
Sensitivity <- CM$byClass["Sensitivity"]
Specificity <- CM$byClass["Specificity"]
Prevalence <- CM$byClass["Prevalence"]
PPV <- CM$byClass["Pos Pred Value"]
NPV <- CM$byClass["Neg Pred Value"]
F1 <- (2 * Sensitivity * PPV)/(Sensitivity + PPV)

#AUROC
predicted_classes <- factor(predicted_classes, levels = c("yes", "no"))
roc_rf <- roc(response=test_data$y,predictor=
as.numeric(predicted_classes),levels=c("no","yes"),direction = ">")
auroc <- auc(roc_rf)

#printing merics
cat("F1: ", F1, "\n") # 0.4380
```

```
## F1:  0.343725
```

```r
cat("Sensitivity: ", Sensitivity, "\n") #0.3820

## Sensitivity:  0.2360044

cat("Specificity: ", Specificity, "\n") #0.9550

## Specificity:  0.9829398

cat("Prevalence: ", Prevalence, "\n") #0.1106

## Prevalence:  0.1105851

cat("PPV: ", PPV, "\n") #0.5133

## PPV:  0.6323529

cat("NPV: ", NPV, "\n") #0.9255

## NPV:  0.9118764

cat("AUROC: ", auroc, "\n") #0.6685

## AUROC:  0.6094721
```

GETTING THE ROC CURVE

```r
# Print the AUROC
auroc <- auc(roc_rf) # 0.6685

plot(roc_rf,print.thres="best",col="red")
title(main = 'ROC Curve for the Random Forest Model', line = 3)
```



The graphs looks different. It looks like the Random Forest model is confident of its predictions. Its most likely due to overfitting due to the high complexity of the Random Forest model.

SLM : RANDOM FOREST PACKAGE

Running the random forest again using the Random Forest Package this time. I am looking for the one to produce the best AUC value. For my hyperparameters, I chose mtry = 2 and ntree = 6000.We plan on using the caret package, which iterates through different mtry and ntree values, to find the optimum one

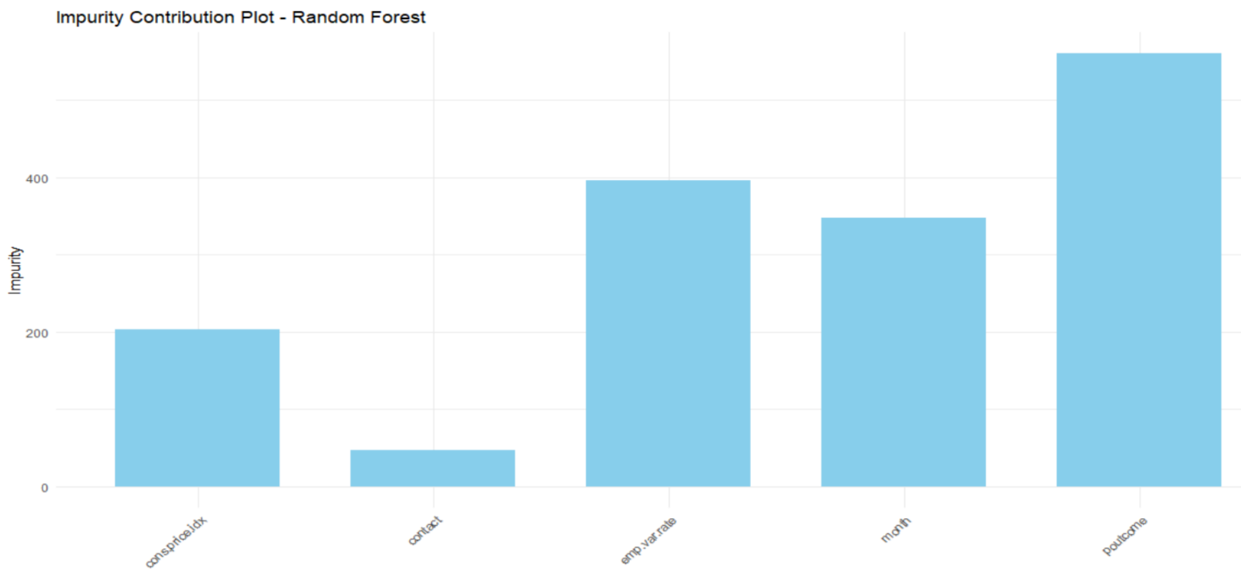
```
set.seed(1234) #setting the seed

# Convert the binary outcome to a factor
train_data$y <- as.factor(train_data$y)


# Define the random forest model
fitted_rf1.2 <-randomForest(y ~ month + poutcome + emp.var.rate + contact +
cons.price.idx, data=train_data, ntree=5000, importance = TRUE,
keep.forest=TRUE, mtry=3)
```

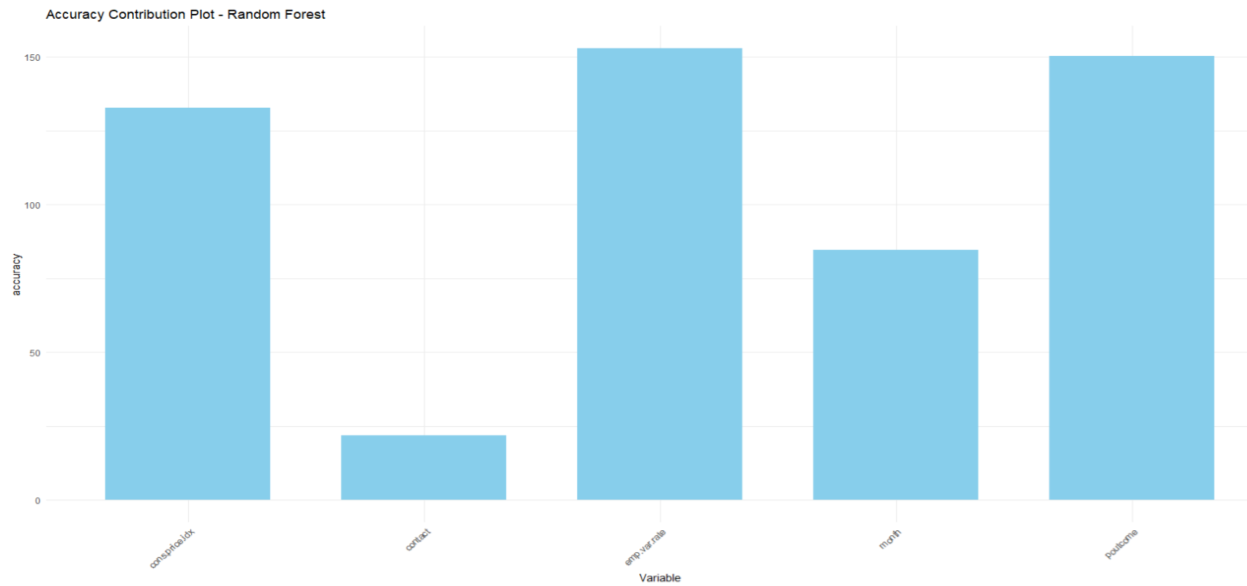
CONTRIBUTION PLOTS FROM THE RANDOM FOREST

Looking at the contribution plots of our RF results to visualize the data to see which variables contributed the most

```
importance_data <- as.data.frame(importance(fitted_rf1.2))


plot_data <- data.frame(
  Variable = row.names(importance_data),
  no = importance_data$no,
  yes = importance_data$yes,
  accuracy = importance_data$MeanDecreaseAccuracy, #impact of each variable on the overall accuracy of the model
  Impurity = importance_data$MeanDecreaseGini #  reduction in impurity (how well a variable separates the classes) achieved by each variable.
)



plot_data <- plot_data[order(plot_data$accuracy, decreasing = TRUE), ]


# Make a contribution plot



ggplot(plot_data, aes(x = Variable, y = accuracy)) +
  geom_bar(stat = "identity", fill = "skyblue", width = 0.7) +
  labs(title = "Accuracy Contribution Plot - Random Forest",
       x = "Variable",
       y = "accuracy") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```
ggplot(plot_data, aes(x = Variable, y = Impurity)) +
  geom_bar(stat = "identity", fill = "skyblue", width = 0.7) +
  labs(title = "Impurity Contribution Plot - Random Forest",
       x = "Variable",
       y = "Impurity") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```





Based on the contribution plot, there is evidence that the 3 most influential variables within the dataset are Poutcome, cons.price.idx & emp.var.rate, which is similar to the previous caret package.

MAKING PREDICTIOND AND GETTONG METRICS

```
# Get threshold
metrics = data.frame(thresh=seq(0, 1, by = 0.0001))
num_thresh <- nrow(metrics)
metrics$sensitivity <- 0
metrics$specificity <- 0
metrics$ppv <- 0
metrics$npv <- 0
metrics$accuracy <- 0
metrics$f1 <- 0
predicted <- data.frame(predict(fitted_rf1.2, newdata = train_data, type = "prob"))['yes']
#Getting the threshold
```

```
for (i in 1:num_thresh){
  if(i %% 100 == 0) {
    #print(paste(i,'/',num_thresh,sep=''))
  }

  # Confusion Matrix
  predicted_classes <- ifelse(predicted[, "yes"] > metrics$thresh[i], 'yes', 'no')
  predicted_classes_factor <- factor(predicted_classes, levels = levels(train_data$y))
  confusion_matrix <- confusionMatrix(predicted_classes_factor, train_data$y)



  # Metrics
  metrics$sensitivity[i] <- as.numeric(confusion_matrix$byClass['Sensitivity'])
  metrics$specificity[i] <- as.numeric(confusion_matrix$byClass['Specificity'])
  metrics$ppv[i] <- as.numeric(confusion_matrix$byClass['Pos Pred Value'])
  metrics$npv[i] <- as.numeric(confusion_matrix$byClass['Neg Pred Value'])
  metrics$accuracy[i] <- as.numeric(confusion_matrix$overall['Accuracy'])
  metrics$f1[i] <- as.numeric(confusion_matrix$byClass['F1'])
}

# Get threshold value that maximizes F1
# Get F1 thresholds
maxF1 <- max(metrics$f1, na.rm = TRUE) #
maxF1  #0.4605
```

```
[1] 0.4605124
```

```
theshF1 <- metrics$thresh[which.max(metrics$f1)]
```

```r
theshF1 # 0.0034
```

```
[1] 0.0034
```

```r
# Test data

predicted <- data.frame(predict(fitted_rf1.2, newdata = test_data, type = "prob"))['yes']

predicted_classes <- ifelse(predicted[, "yes"] >  theshF1, 'yes', 'no')

CM <- confusionMatrix(as.factor(predicted_classes), as.factor(test_data$y))

CM
```

```
          Reference
Prediction  yes   no
       yes  352  335
       no   559 6992
                                          
               Accuracy : 0.8915          
                 95% CI : (0.8846, 0.8981)
    No Information Rate : 0.8894          
    P-Value [Acc > NIR] : 0.2821          
                                          
                  Kappa : 0.3818          
                                          
 Mcnemar's Test P-Value : 8.769e-14       
                                          
            Sensitivity : 0.38639         
            Specificity : 0.95428         
         Pos Pred Value : 0.51237         
         Neg Pred Value : 0.92597         
             Prevalence : 0.11059         
         Detection Rate : 0.04273         
   Detection Prevalence : 0.08339         
      Balanced Accuracy : 0.67033         
                                          
       'Positive' Class : yes             
```

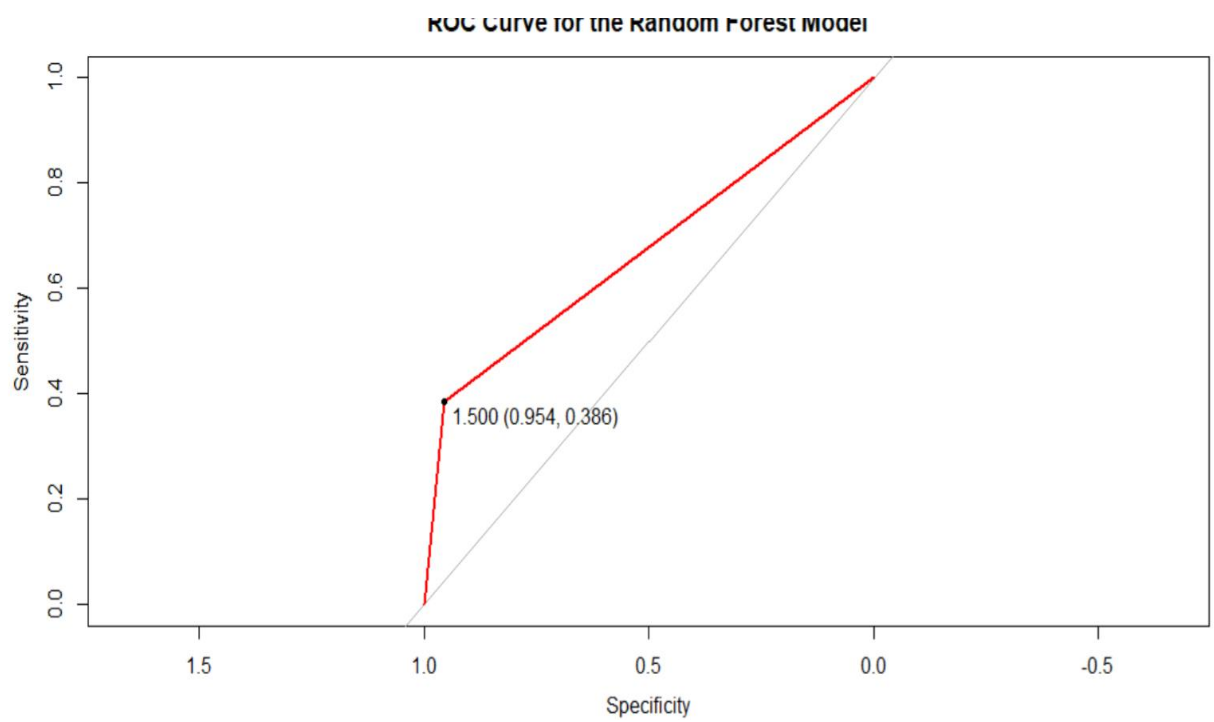
```r
#Printing out the metric

Sensitivity <- CM$byClass["Sensitivity"]

Specificity <- CM$byClass["Specificity"]

Prevalence <- CM$byClass["Prevalence"]

PPV <- CM$byClass["Pos Pred Value"]

NPV <- CM$byClass["Neg Pred Value"]

F1 <- (2 * Sensitivity * PPV)/(Sensitivity + PPV)



#AUROC
```

```
predicted_classes <- factor(predicted_classes, levels = c("yes", "no"))

roc_rf <- roc(response=test_data$y,predictor=
as.numeric(predicted_classes),levels=c("no","yes"),direction = ">")

auroc <- auc(roc_rf)



cat("F1: ", F1, "\n")

cat("Sensitivity: ", Sensitivity, "\n")

cat("Specificity: ", Specificity, "\n")

cat("Prevalence: ", Prevalence, "\n")

cat("PPV: ", PPV, "\n")

cat("NPV: ", NPV, "\n")

cat("AUROC: ", auroc, "\n")


# Results:

# F1:  0.4405507

# Sensitivity:  0.3863886

# Specificity:  0.9542787

# Prevalence:  0.1105851

# PPV:  0.5123726

# NPV:  0.9259701

# AUROC:  0.6703336
```

The RF model for the randomForest package is greater than the caret package by 0.5%. Hence i will go ahead with this model

GETTING THE ROC CURVE

```
# Print the AUROC

auroc <- auc(roc_rf) # 0.7044


plot(roc_rf,print.thres="best",col="red")

title(main = 'ROC Curve for the Random Forest Model', line = 3)
```



The ROC curve is is similar to the previous model. Hence i can infer that this is the roc curve of what a random forest model would predict. Most likely due to the complexity.