

# Bank EDA

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```
library(readr)
library(tidyverse)

## -- Attaching packages ----- tidyverse
## v ggplot2 3.2.1      v purrr  0.3.2
## v tibble  2.1.3      v dplyr  0.8.3
## v tidyr   1.0.2      v stringr 1.4.0
## v ggplot2 3.2.1      v forcats 0.4.0

## -- Conflicts ----- tidyverse
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()

library(MASS)

##
## Attaching package: 'MASS'

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

library(ggplot2)
library(dplyr)
library(here)

## here() starts at /Users/zmartygirl/data/MSDSR/Stats 6372 Project Two /Stats-6372-Project-Two
root = here()

bank_20 = read.csv(paste(root, "/data/bank-additional/bank-additional-full.csv", sep = ""), sep=";")
bank_17 = read.csv(paste(root, "/data/bank/bank-full.csv", sep = ""), sep = ";")
```

## Summary

Unknown whether we should work with both data sets or if Dr. Turner is good with us choosing one. My vote is for bank\_20 if we can choose.

Variable Notes: -Duration is a variable not known until Y is determined, duration is the duration of the call when attempting to sell the term deposit package.

- No NAs, uses unknown in places otherwise -Campaign is # of contacts, minimum 1 b/c it includes this contact in the data, even if the contact was unsuccessful -pdays needs to be potentially cleaned where 999 should equal NA or potentially switched to a categorical variable -Do not understand some of the later variables, seem to be more socially based.

```
#Dr Turner is heavily requesting summary stats
summary(bank_20)
```

```

##      age      job      marital
## Min.   :17.00  admin.   :10422  divorced: 4612
## 1st Qu.:32.00  blue-collar: 9254  married :24928
## Median :38.00  technician : 6743  single  :11568
## Mean   :40.02  services   : 3969  unknown : 80
## 3rd Qu.:47.00  management : 2924
## Max.    :98.00  retired    : 1720
##          (Other) : 6156
##      education      default      housing
## university.degree :12168  no      :32588  no      :18622
## high.school        : 9515  unknown: 8597  unknown: 990
## basic.9y           : 6045  yes      : 3    yes      :21576
## professional.course: 5243
## basic.4y           : 4176
## basic.6y           : 2292
## (Other)            : 1749
##      loan      contact      month      day_of_week
## no      :33950  cellular :26144  may      :13769  fri:7827
## unknown: 990  telephone:15044  jul      : 7174  mon:8514
## yes      : 6248  aug      : 6178  thu:8623
##          jun      : 5318  tue:8090
##          nov      : 4101  wed:8134
##          apr      : 2632
##          (Other): 2016
##      duration      campaign      pdays      previous
## Min.   : 0.0  Min.   : 1.000  Min.   : 0.0  Min.   :0.000
## 1st Qu.:102.0  1st Qu.: 1.000  1st Qu.:999.0  1st Qu.:0.000
## Median :180.0  Median : 2.000  Median :999.0  Median :0.000
## Mean   :258.3  Mean   : 2.568  Mean   :962.5  Mean   :0.173
## 3rd Qu.:319.0  3rd Qu.: 3.000  3rd Qu.:999.0  3rd Qu.:0.000
## Max.   :4918.0  Max.   :56.000  Max.   :999.0  Max.   :7.000
##
##      poutcome      emp.var.rate      cons.price.idx      cons.conf.idx
## failure   : 4252  Min.   : -3.40000  Min.   :92.20  Min.   : -50.8
## nonexistent:35563  1st Qu.: -1.80000  1st Qu.:93.08  1st Qu.: -42.7
## success    : 1373  Median : 1.10000  Median :93.75  Median : -41.8
##          Mean   : 0.08189  Mean   :93.58  Mean   : -40.5
##          3rd Qu.: 1.40000  3rd Qu.:93.99  3rd Qu.: -36.4
##          Max.   : 1.40000  Max.   :94.77  Max.   : -26.9
##
##      euribor3m      nr.employed      y
## Min.   :0.634  Min.   :4964  no :36548
## 1st Qu.:1.344  1st Qu.:5099  yes: 4640
## Median :4.857  Median :5191
## Mean   :3.621  Mean   :5167
## 3rd Qu.:4.961  3rd Qu.:5228
## Max.   :5.045  Max.   :5228
##

```

```

#Does not look like any NAs in either data set
sapply(bank_20, function(x) sum(is.na(x)))

```

```

##      age      job      marital      education      default
##      0      0      0      0      0
##      housing      loan      contact      month      day_of_week

```

```
##          0          0          0          0          0
##      duration      campaign      pdays      previous      poutcome
##          0          0          0          0          0
##  emp.var.rate cons.price.idx cons.conf.idx      euribor3m  nr.employed
##          0          0          0          0          0
##          y
##          0
```

```
supply(bank_17, function(x) sum(is.na(x)))
```

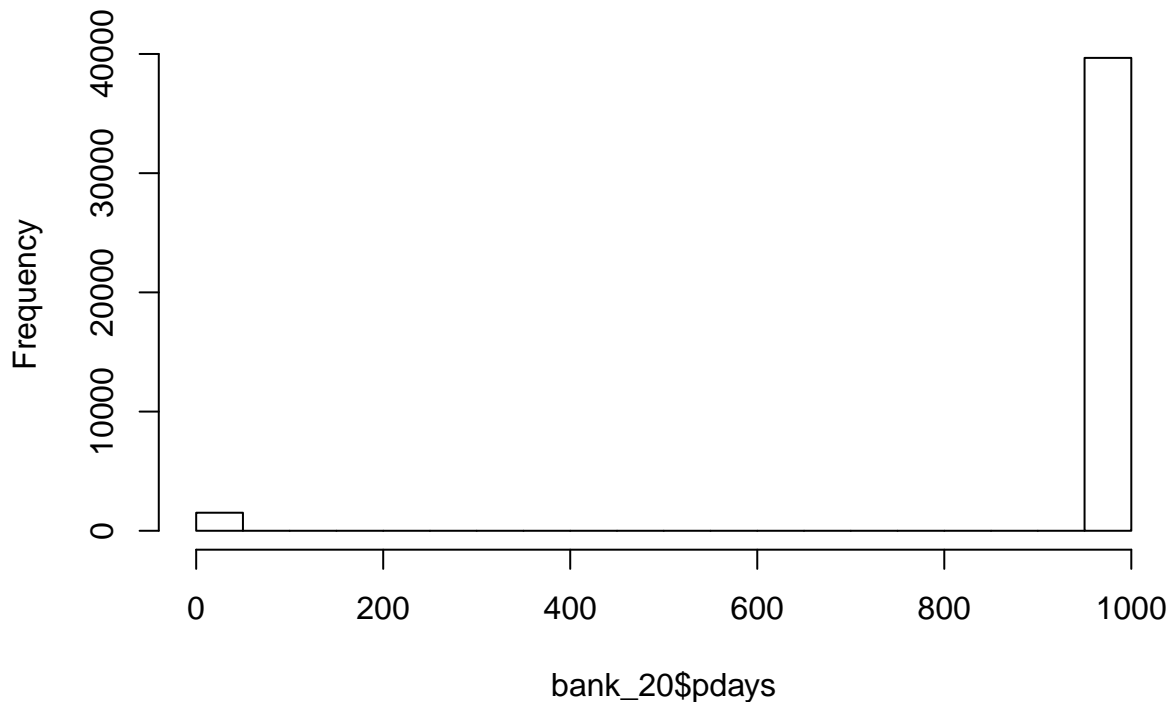
```
##      age      job  marital education  default  balance  housing
##      0      0      0          0          0      0      0
##      loan  contact      day      month  duration  campaign  pdays
##      0      0      0          0          0      0      0
##  previous  poutcome      y
##      0      0      0
```

```
#Set any predictions without using Duration or Y
```

```
#pdays- about 40k of the 41k are at level 999, no previous contact
#could bin this data
```

```
hist(bank_20$pdays)
```

## Histogram of bank\_20\$pdays

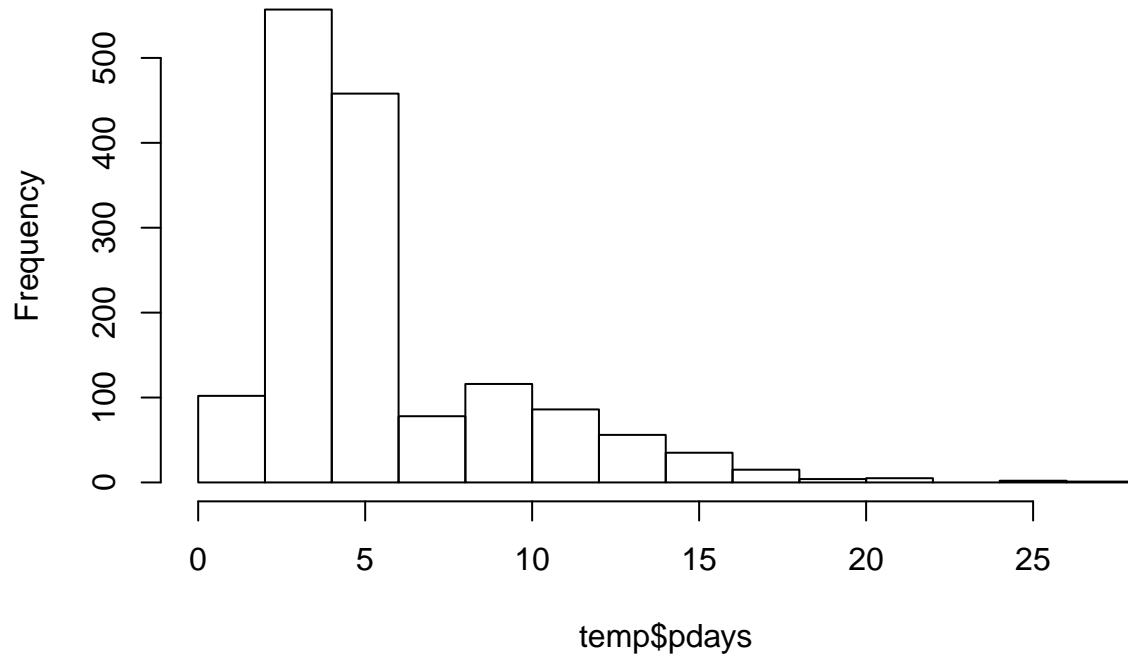


```
temp = bank_20 %>% filter(pdays != 999)
dim(temp)
```

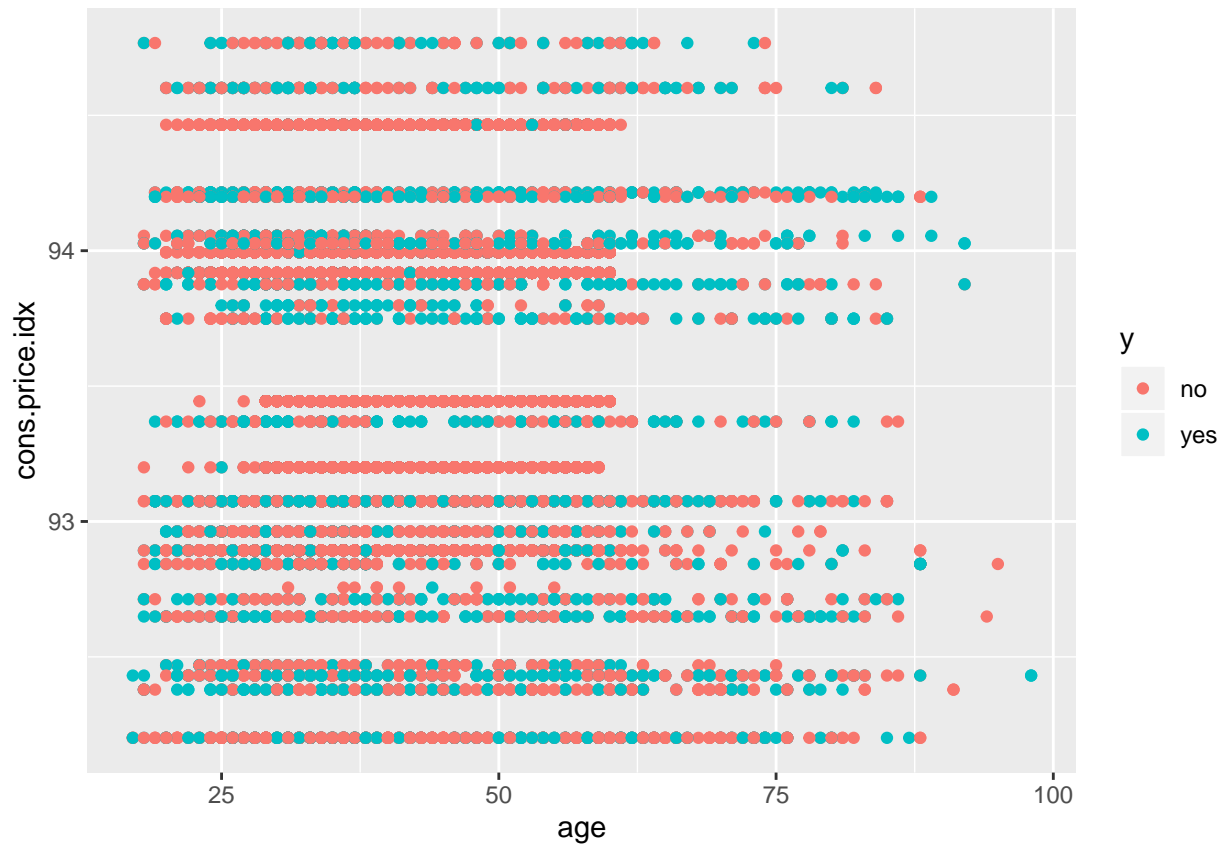
```
## [1] 1515  21
```

```
hist(temp$pdays)
```

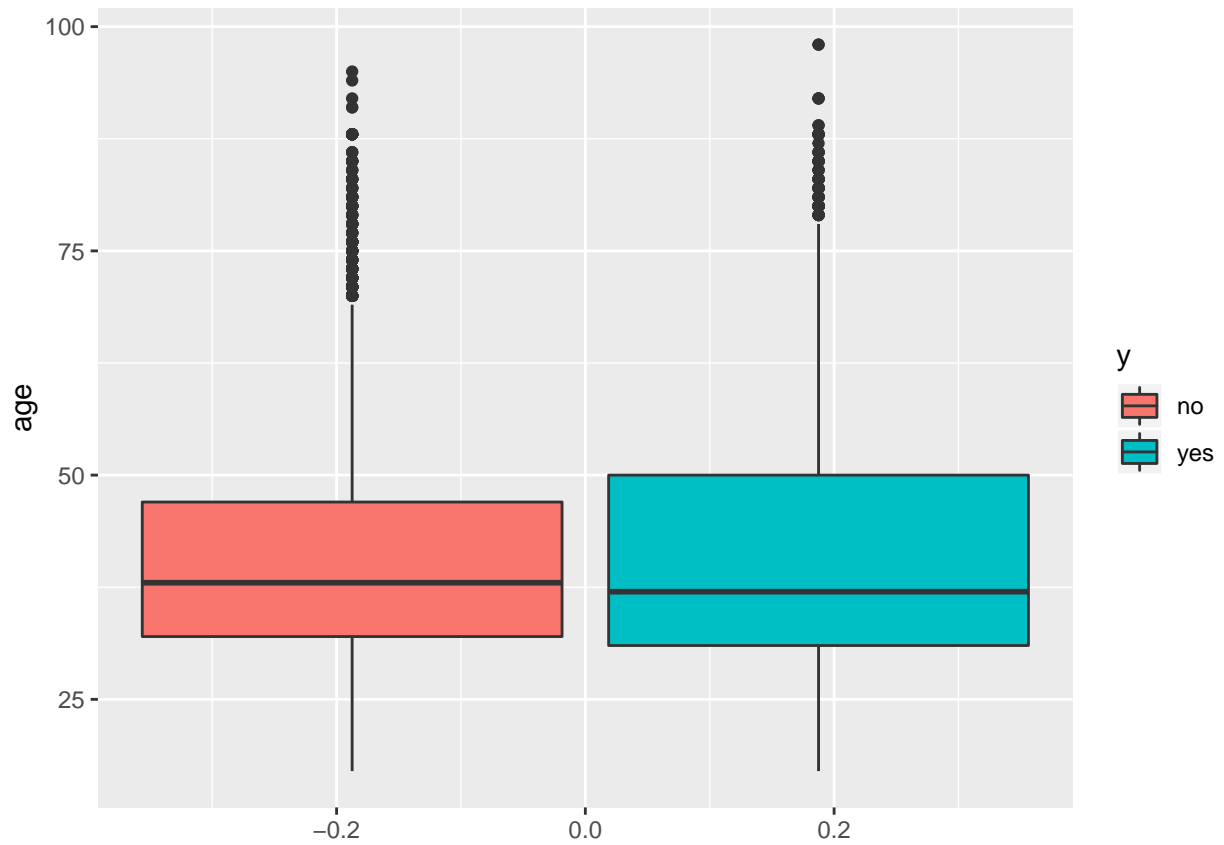
**Histogram of temp\$pdays**



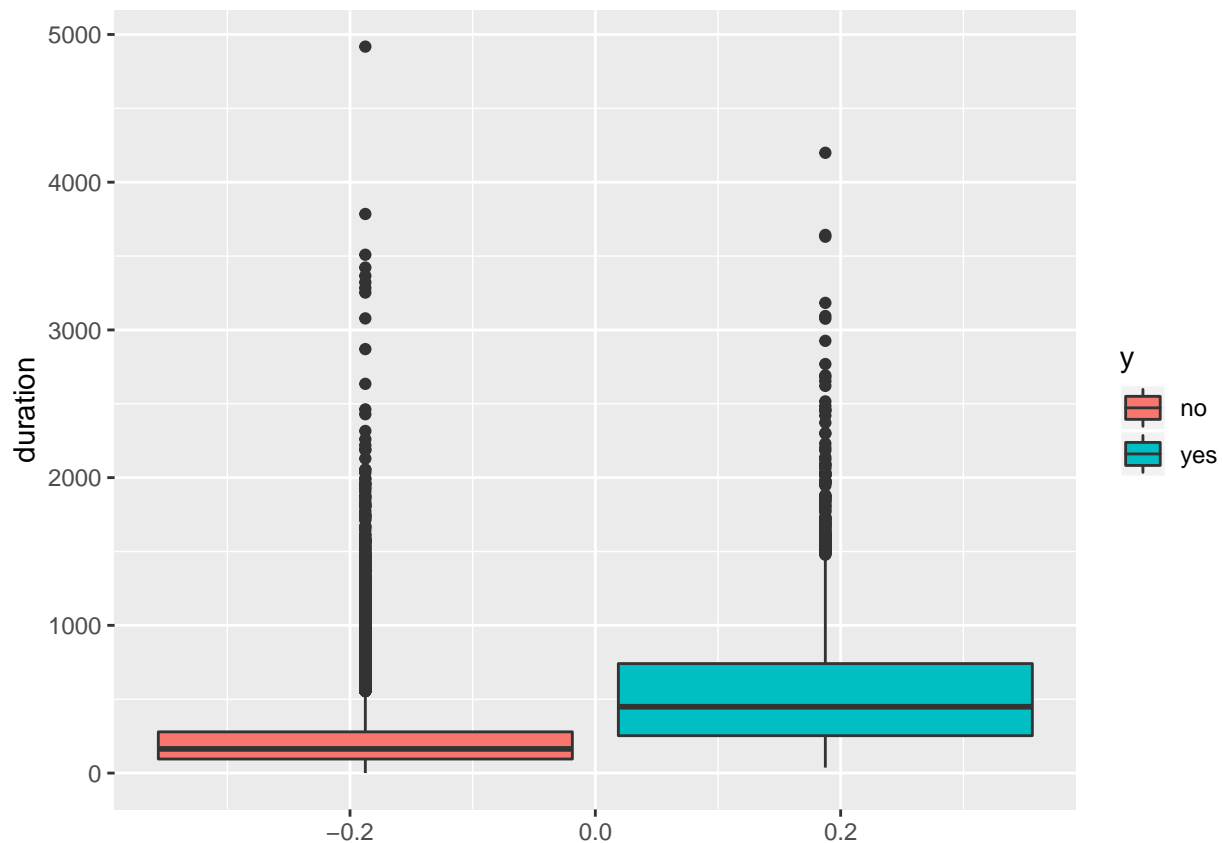
```
bank_20 %>% ggplot(aes(x = age, y = cons.price.idx, color = y)) + geom_point()
```



```
bank_20 %>% ggplot(aes(y = age, fill = y)) + geom_boxplot()
```



```
bank_20 %>% ggplot(aes(y = duration, fill = y)) + geom_boxplot()
```



## Predicting Duration, in order to predict calls.

Basically if we know there is a relationship between duration and the result we are predicting, we can use information that explains duration to therefore explain response.

```
duration_model = lm(duration ~ ., data = bank_20)
```

## Uneven Split in outcomes

Yes happens about 10% of the time, where no is the response 90% of the time. This unbalance makes it difficult to predict. - Can balance the train/test split, what else have we learned about predicting unbalanced outcomes?

```
yes_answer = bank_20 %>% filter(y == "yes")

no_answer_all = bank_20 %>% filter(y == "no")
no_indices = sample(dim(no_answer_all)[1], dim(yes_answer)[1])
no_answer = no_answer_all[no_indices,]

balanced_bank_20 = data.frame(yes_answer, no_answer)
balanced_indices = sample(dim(balanced_bank_20)[1], round(dim(balanced_bank_20)[1] * .1))
balanced_test = balanced_bank_20[balanced_indices,]
balanced_train = balanced_bank_20[-balanced_indices,]
```