

W271 Section 3 Lab 2

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```
#knitr::opts_chunk$set(cache=TRUE)
library(knitr)
library(vcd)
```

```
## Loading required package: grid
opts_chunk$set(tidy.opts=list(width.cutoff=60),tidy=TRUE)
```

1 Introduction

An introduction to the project, which should include a concise summary of the key results as well as techniques you used in your final model.

2 Exploratory Data Analysis

```
library(Hmisc)
```

```
## Loading required package: lattice
## Loading required package: survival
## Loading required package: Formula
## Loading required package: ggplot2
##
## Attaching package: 'Hmisc'
## The following objects are masked from 'package:base':
##
##   format.pval, round.POSIXt, trunc.POSIXt, units
```

```
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:Hmisc':
##
##   combine, src, summarize
## The following objects are masked from 'package:stats':
##
##   filter, lag
## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```

library(GGally)

##
## Attaching package: 'GGally'
## The following object is masked from 'package:dplyr':
##
##      nasa

library(data.table)

##
## Attaching package: 'data.table'
## The following objects are masked from 'package:dplyr':
##
##      between, first, last

library(stargazer)

##
## Please cite as:
## Hlavac, Marek (2015). stargazer: Well-Formatted Regression and Summary Statistics Tables.
## R package version 5.2. http://CRAN.R-project.org/package=stargazer

library(tidyverse)

## Loading tidyverse: tibble
## Loading tidyverse: tidyr
## Loading tidyverse: readr
## Loading tidyverse: purrr

## Conflicts with tidy packages -----
## between():    dplyr, data.table
## combine():    dplyr, Hmisc
## filter():     dplyr, stats
## first():      dplyr, data.table
## lag():        dplyr, stats
## last():       dplyr, data.table
## src():        dplyr, Hmisc
## summarize():  dplyr, Hmisc
## transpose():  purrr, data.table

library(forcats)
library(scales)

##
## Attaching package: 'scales'

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

## The following object is masked from 'package:readr':
##
##      col_factor

```

```
library(gridExtra)

##
## Attaching package: 'gridExtra'

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

## The following object is masked from 'package:Hmisc':
##
##   combine

if (dir.exists("XXXX")) {
  ## For Kiersten
  setwd("XXXX")
} else if (dir.exists("YYY")) {
  ## For Jill
  setwd("YYY")
} else if (dir.exists("ZZZ")) {
  ## For Hoang
  setwd("ZZZ")
} else if (dir.exists("/Users/daghan/Hacking/Berkeley/W271/Labs/w271_lab2/")) {
  ## For Daghan home computer
  setwd("/Users/daghan/Hacking/Berkeley/W271/Labs/w271_lab2/")
}

givings = read.csv("./lab2data.csv")
describe(givings)
```

```
## givings
##
## 12 Variables      1000 Observations
## -----
## X
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    1000      0      1000      1      615.4      410.6      62.95      122.90
##      .25      .50      .75      .90      .95
##    308.75    613.00    917.25    1110.30    1174.05
##
## lowest :      1      2      3      4      5, highest: 1225 1226 1228 1229 1230
## -----
## Gender
##      n missing distinct
##    1000      0      2
##
## Value      F      M
## Frequency    505    495
## Proportion 0.505 0.495
## -----
## Class.Year
##      n missing distinct      Info      Mean      Gmd
##    1000      0      5      0.949      1996      15.07
##
## Value      1972    1982    1992    2002    2012
```

```

## Frequency    105    176    203    223    293
## Proportion 0.105 0.176 0.203 0.223 0.293
## -----
## Marital.Status
##      n missing distinct
##    1000      0      4
##
## Value      D      M      S      W
## Frequency    61    584    344    11
## Proportion 0.061 0.584 0.344 0.011
## -----
## Major
##      n missing distinct
##    1000      0      45
##
## lowest : American Studies      Anthropology      Art      Biology      Chemist:
## highest: Spanish      Speech (Drama, etc.) Speech Correction      Theatre      Zoology
## -----
## Next.Degree
##      n missing distinct
##    1000      0      47
##
## lowest : AA      BA      BAE      BD      BFA , highest: UBDS UDDS UMD      UMDS UNKD
## -----
## AttendanceEvent
##      n missing distinct      Info      Sum      Mean      Gmd
##    1000      0      2      0.717      605      0.605      0.4784
##
## -----
## FY12Giving
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    1000      0      66      0.826      186.9      345.5      0      0
##      .25      .50      .75      .90      .95
##      0      0      60      200      350
##
## lowest :      0.00      5.00      6.50      7.00      8.00
## highest: 10000.00 12000.00 16959.99 20000.00 21000.00
## -----
## FY13Giving
##      n missing distinct      Info      Mean      Gmd      .05      .10
##    1000      0      78      0.864      311.5      590.4      0.0      0.0
##      .25      .50      .75      .90      .95
##      0.0      0.0      75.0      210.5      400.0
##
## Value      0      500      1000      1500      2000      2500      3000      5000      5500
## Frequency    920      48      13      4      2      3      2      2      1
## Proportion 0.920 0.048 0.013 0.004 0.002 0.003 0.002 0.002 0.001
##
## Value      8000      12000      13000      14500      161500
## Frequency    1      1      1      1      1
## Proportion 0.001 0.001 0.001 0.001 0.001
## -----
## FY14Giving
##      n missing distinct      Info      Mean      Gmd      .05      .10

```

```
##      1000      0      80      0.83      142.6      255.5      0      0
##      .25      .50      .75      .90      .95
##      0      0      50      200      450
##
## lowest :      0.00      1.00      5.00      8.00      10.00
## highest: 5000.00 6000.00 8031.00 10000.00 11187.26
## -----
## FY15Giving
##      n missing distinct      Info      Mean      Gmd      .05      .10
##      1000      0      62      0.817      252.2      470.7      0.0      0.0
##      .25      .50      .75      .90      .95
##      0.0      0.0      75.0      200.0      538.3
##
## lowest :      0.0      5.0      10.0      13.0      15.0
## highest: 10000.0 14776.0 15634.5 26500.0 58785.5
## -----
## FY16Giving
##      n missing distinct      Info      Mean      Gmd      .05      .10
##      1000      0      71      0.798      170      308.2      0      0
##      .25      .50      .75      .90      .95
##      0      0      75      216      500
##
## lowest :      0.00      5.00      10.00      15.00      18.00
## highest: 5000.00 6500.00 11500.00 11505.84 14655.25
## -----
```

2.1 Observations

- There are no missing variables, which simplifies the data clean-up task.
- There are 1000 observations and twelve variables (five of them are donations in different years).
- FY2016 is the dependent variable that we'd like to predict. However, we are given FYGiving for years 2012 through 2016 as amount in dollars (a continuous variable).
- Maximum donation is \$161500 (in 2013)
- Gender is a binary variable.
- Marital status has four categories (D, M, S, W), which we interpret as divorced, married, single, widowed.
- Graduating class is strangely in five categories each ten years apart (1972, 1982, 1992, 2002, 2012).
- Donor's major is a categorical variable with 45 categories.
- Attendance of events is a binary category variable (0 for no, 1 for yes).
- Next degree is a categorical variable with 47 categories.

After i cleaned up the variables, i need to go back and describe each one (univariate analysis).

2.2 Data clean-up

First, we are going to clean-up the factor variables by providing explicit values for each level.

```
levels(givings$Gender) = c("Female", "Male")
givings$AttendanceEvent = factor(givings$AttendanceEvent, levels = c(0,
  1), labels = c("Didn't Attend", "Attended"))
levels(givings$Marital.Status) = c("Divorced", "Married", "Single",
  "Widowed")
givings$Class.Year = factor(givings$Class.Year)
```

```

givings$FY12Giving = as.numeric(givings$FY12Giving)
givings$FY13Giving = as.numeric(givings$FY13Giving)
givings$FY14Giving = as.numeric(givings$FY14Giving)
givings$FY15Giving = as.numeric(givings$FY15Giving)
givings$FY16Giving = as.numeric(givings$FY16Giving)

```

We are also going to group majors into main categories including Sciences, SocialScience, FineArts, ForeignLanguages, Education, PhilosophyReligion, Mathematics, MultidisciplinaryStudies, English_Literature, Business_Economics, and ComputerScience_Engineering.

```

givings$Grouped.Major <- fct_collapse(givings$Major, Sciences = c("Chemistry",
  "Physics", "Biology", "General Science-Chemistry", "General Science-Psycho",
  "General Science-Math", "Mathematics-Physics", "General Science-Biology",
  "Zoology", "General Science", "General Science-Physics"),
  SocialScience = c("Psychology", "Anthropology", "Sociology",
    "History", "Political Science", "Sociology-Anthropology",
    "Economics-Regional Stds.", "Pol. Sci.-Regional Stds."),
  FineArts = c("Theatre", "Music", "Art", "Speech (Drama, etc.)"),
  ForeignLanguages = c("Spanish", "German", "French", "Russian",
    "Chinese"), Education = c("Physical Education", "Education",
    "Speech Correction"), PhilosophyReligion = c("Religious Studies",
    "Philosophy", "Philosophy-Religion"), Mathematics = "Mathematics",
  MultidisciplinaryStudies = "Independent", English_Literature = c("English",
    "Classics", "American Studies", "Comparative Literature",
    "English-Journalism"), Business_Economics = c("Economics-Business",
    "Economics"), ComputerScience_Engineering = c("Computer Science",
    "Engineering"))

```

Lastly, we are going to create factor variables out of donations, since we are asked to group FY2016 donations to 5 buckets, we have decided to apply that same logic to all other years.

```

givings$FY12Giving.Grouped <- factor(cut(givings$FY12Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))
givings$FY13Giving.Grouped <- factor(cut(givings$FY13Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))
givings$FY14Giving.Grouped <- factor(cut(givings$FY14Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))
givings$FY15Giving.Grouped <- factor(cut(givings$FY15Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))
givings$FY16Giving.Grouped <- factor(cut(givings$FY16Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))

```

2.3 Univariate Data Analysis

We are going to conduct univariate data analysis for the following variables:

- Gender
- Class.Year
- Marital.Status
- Major and Grouped.Major
- Next.Degree
- AttendanceEvent
- FY12 though FY16 Giving (numerical, log transformed and Grouped)

2.3.1 Gender

```
row <- xtabs(~Gender, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Donor Count",
  "Ratio"))
```

```
##           Female      Male
## Donor Count 505.000 495.000
## Ratio      0.505   0.495
```

The dataset contains nearly identical amount of female vs. male donors. This result is mildly surprising but possible. According to the National Center for Education Statistics, the national average is 56% for female and 44% for male enrollment in college education (https://nces.ed.gov/programs/coe/indicator_cha.asp) in 2015. The data for graduation rates is similarly skewed towards women. However, the rates are more likely to be skewed toward men in earlier years. Also, there is a chance that this specific university bucks the national trends for a variety of reasons.

2.3.2 Class.Year

```
row <- xtabs(~Class.Year, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Class.Year Count",
  "Ratio"))
```

```
##           X1972   X1982   X1992   X2002   X2012
## Class.Year Count 105.000 176.000 203.000 223.000 293.000
## Ratio           0.105   0.176   0.203   0.223   0.293
```

This table is surprising. There are only 5 graduation years. The data is not a random subsample from the entire population but rather a subsample of 10-years (each data is 10 years apart). **It will be very difficult to argue that the results we infer from our model is applicable to all graduates of the university.**

2.3.4 Marital.Status

```
row <- xtabs(~Marital.Status, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Marital.Status Count",
  "Ratio"))
```

```
##           Divorced Married   Single Widowed
## Marital.Status Count   61.000 584.000 344.000  11.000
## Ratio                 0.061   0.584   0.344   0.011
```

Divorce to Marriage ratio is very low. According to Wikipedia (https://en.wikipedia.org/wiki/Divorce_demography), the expected ratio is around 44%. That said, the measurement methodology is slightly different and we expect rates to change with graduation years (divorce rates are more likely to increase with age). So we are going to assume that Marital.Status data is valid sample for the population.

2.3.5 Major and Grouped.Major

```
row <- xtabs(~Major, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Major Count",
  "Ratio"))
```

```
##           American.Studies Anthropology   Art Biology Chemistry Chinese
## Major Count          23.000         35.000 32.000  88.000   53.000   1.000
## Ratio           0.023         0.035 0.032  0.088   0.053   0.001
##           Classics Comparative.Literature Computer.Science Economics
## Major Count          5.000         2.000         4.000   78.000
## Ratio           0.005         0.002         0.004   0.078
##           Economics.Business Economics.Regional.Stds. Education
## Major Count          22.000         2.000         5.000
## Ratio           0.022         0.002         0.005
##           Engineering English English.Journalism French General.Science
## Major Count          1.000 101.000         1.000 22.000         2.000
## Ratio           0.001  0.101         0.001 0.022         0.002
##           General.Science.Biology General.Science.Chemistry
## Major Count          8.000         3.000
## Ratio           0.008         0.003
##           General.Science.Math General.Science.Physics
## Major Count          1.000         1.000
## Ratio           0.001         0.001
##           General.Science.Psycho German History Independent Mathematics
## Major Count          1.000 12.000 102.000         18.000         32.000
## Ratio           0.001  0.012  0.102         0.018         0.032
##           Mathematics.Physics Music Philosophy Philosophy.Religion
## Major Count          3.000 27.000         17.000         9.000
## Ratio           0.003  0.027         0.017         0.009
##           Physical.Education Physics Pol..Sci..Regional.Stds.
## Major Count          3.000 16.000         1.000
## Ratio           0.003  0.016         0.001
##           Political.Science Psychology Religious.Studies Russian
## Major Count          61.000  65.000         20.00 12.000
## Ratio           0.061  0.065         0.02  0.012
##           Sociology Sociology.Anthropology Spanish Speech..Drama..etc..
## Major Count          49.000         12.000 21.000         6.000
## Ratio           0.049         0.012  0.021         0.006
##           Speech.Correction Theatre Zoology
## Major Count          4.000 17.000  2.000
## Ratio           0.004  0.017  0.002
```

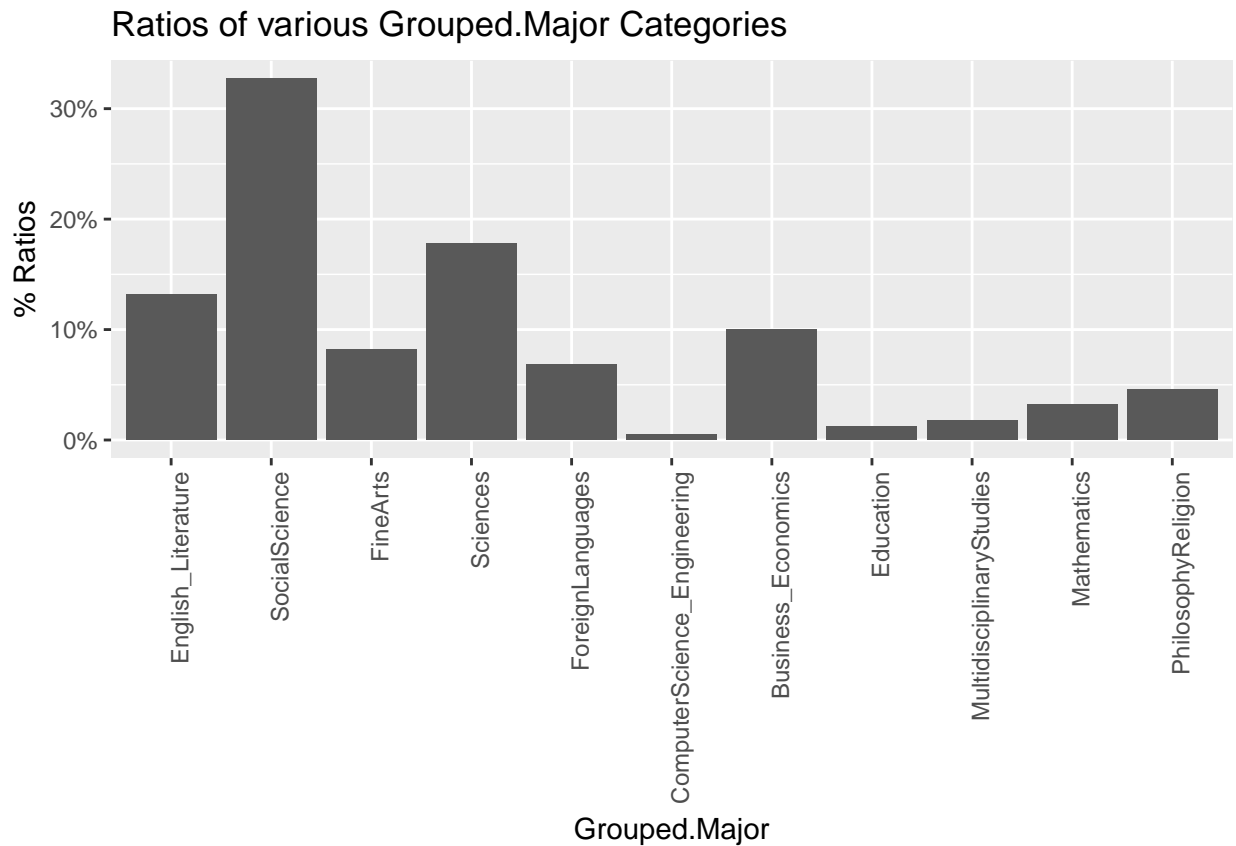
Many of these factors have very little representation (ex: Zoology, Political stuiies in regional studies) so it makes sense to group them into major categories

```
row <- xtabs(~Grouped.Major, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Grouped.Major Count",
  "Ratio"))
```



```
##           English_Literature SocialScience FineArts Sciences
## Grouped.Major Count          132.000        327.000    82.000  178.000
## Ratio           0.132          0.327     0.082    0.178
##           ForeignLanguages ComputerScience_Engineering
## Grouped.Major Count          68.000              5.000
## Ratio           0.068              0.005
##           Business_Economics Education MultidisciplinaryStudies
## Grouped.Major Count          100.0    12.000              18.000
## Ratio           0.1      0.012              0.018
##           Mathematics PhilosophyReligion
## Grouped.Major Count          32.000          46.000
## Ratio           0.032          0.046
```

```
ggplot(givings, aes(x = Grouped.Major)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  scale_y_continuous(labels = percent) + labs(y = "% Ratios",
  title = "Ratios of various Grouped.Major Categories")
```



2.3.6 Next.Degree

```
row <- xtabs(~Next.Degree, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("Next.Degree Count",
"Ratio"))
```

```
##           AA  BA  BAE  BD  BFA  BN  BS  BSN  DC
## Next.Degree Count 1.000 4.000 1.000 1.000 1.000 2.000 2.000 3.000 1.000
```

```
## Ratio          0.001 0.004 0.001 0.001 0.001 0.002 0.002 0.003 0.001
##              DDS   DMD   DO   DO2   DP   JD   LLB   LLD   MA
## Next.Degree Count 1.000 1.000 2.000 1.000 1.000 90.00 1.000 1.000 108.000
## Ratio          0.001 0.001 0.002 0.001 0.001 0.09 0.001 0.001 0.108
##              MA2   MAE   MALS   MAT   MBA   MCP   MD   MD2   ME
## Next.Degree Count 1.000 1.000 1.000 10.00 34.000 1.000 42.000 9.000 17.000
## Ratio          0.001 0.001 0.001 0.01 0.034 0.001 0.042 0.009 0.017
##              MFA   MHA   ML   MLS   MM   MPA   MPH   MS   MSM
## Next.Degree Count 14.000 1.000 1.000 9.000 1.000 6.000 4.000 53.000 1.000
## Ratio          0.014 0.001 0.001 0.009 0.001 0.006 0.004 0.053 0.001
##              MSW   NDA   NONE   PHD   STM   TC   UBDS   UDDS
## Next.Degree Count 11.000 58.000 378.000 78.000 1.000 22.000 6.000 4.000
## Ratio          0.011 0.058 0.378 0.078 0.001 0.022 0.006 0.004
##              UMD   UMDS   UNKD
## Next.Degree Count 6.000 2.000 6.000
## Ratio          0.006 0.002 0.006
```

The Next.Degree as a factor variable is too scathered. Many levels only have a single count (ex: MA2, MALS, MSM, BD, etc). We should either group these degrees into few major groups or perhaps create a new factor category for level of study (None, Bachelor, Master, PhD, Other).

2.3.7 AttendanceEvent

```
row <- xtabs(~AttendanceEvent, data = givings)
data.frame(rbind(row, row/dim(givings)[1]), row.names = c("AttendanceEvent Count",
  "Ratio"))
```

```
##              Didn.t.Attend Attended
## AttendanceEvent Count          395.000 605.000
## Ratio              0.395    0.605
```

40% of graduates have attended at least one Alumni event organized between 2012 and 2015. This is a very high ratio. Intuitively, we expect a high correlation between this variable and donatios so we'll include this variable in our analysis.

2.3.8 FY12 though FY16 Giving (numerical, log transformed and Grouped)

```
givings.tidy.donations <- givings[1:12] %>% gather("Giving.Year",
  "Donations", 8:12)
givings.tidy.donations$Giving.Grouped <- factor(cut(givings.tidy.donations$Donations,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
  "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  right = FALSE))
givings.tidy.donations.aggregate <- as.data.frame(xtabs(~Giving.Grouped +
  Giving.Year, data = givings.tidy.donations))
p1 <- ggplot(givings.tidy.donations, aes(x = Donations, colour = Giving.Year)) +
  geom_density(alpha = 0.3) + labs(title = "Density plot for contributions") +
  theme_bw()

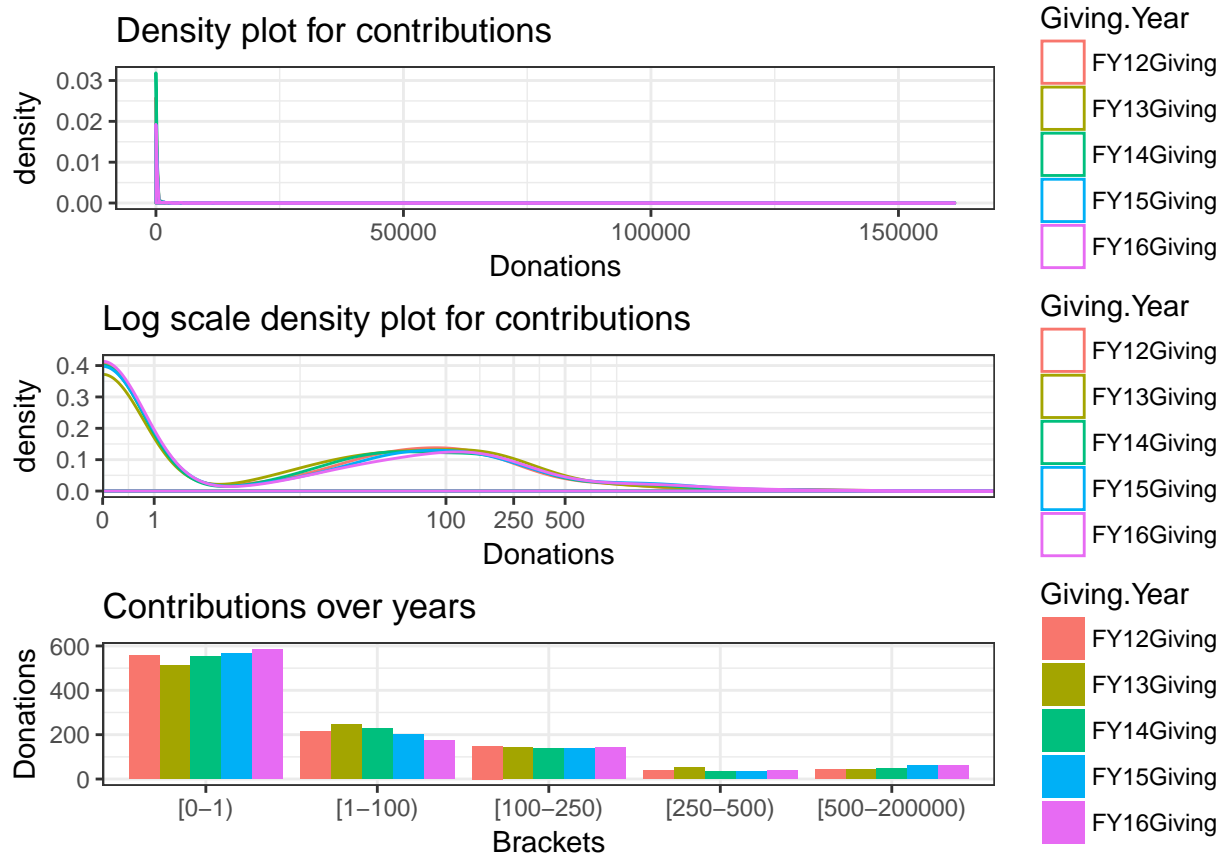
p2 <- ggplot(givings.tidy.donations, aes(x = Donations, colour = Giving.Year)) +
  geom_density(alpha = 0.3) + scale_x_continuous(breaks = c(0,
  1, 100, 250, 500, 2e+05), trans = "log1p", expand = c(0,
  0)) + labs(title = "Log scale density plot for contributions") +
```

```

scale_y_continuous() + theme_bw()

p3 <- ggplot(givings.tidy.donations.aggregate, aes(x = Giving.Grouped,
y = Freq)) + geom_bar(aes(fill = Giving.Year), stat = "identity",
position = "dodge") + theme(axis.text.x = element_text(angle = 90,
hjust = 1)) + labs(y = "Donations", x = "Brackets", title = "Contributions over years") +
theme_bw()
grid.arrange(p1, p2, p3, ncol = 1, nrow = 3)

```



We note that continuous scale values for the contributions have a very strong skew. At log scale, we have a bi-modal distribution, with most of the values centered around 0, and other around the \$100 range. What may be important, however, is to uniquely identify and model donors who are willing to make large contributions. We observe that most years follow a similar pattern. The donor behavior seems to be consistent over multiple years. We expect (and will confirm through bivariate analysis) to find a strong correlation between a donor's 2016 preference and his/her previous years' preferences.

2.4 Bivariate Data Analysis

We are going to look at the interaction between 2016 donations level and other variables.

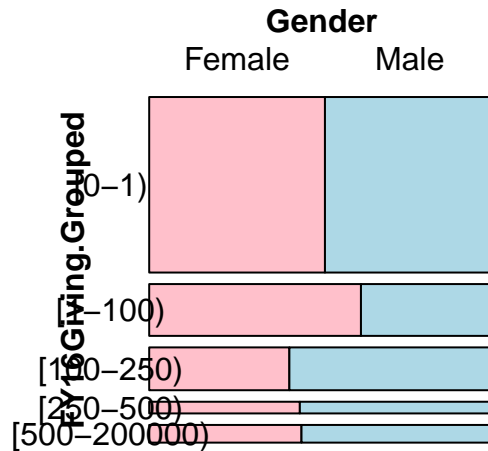
2.4.1 FY16Giving.Grouped vs. Gender

```

mosaic(~FY16Giving.Grouped + Gender, data = givings, highlighting = "Gender",
highlighting_fill = c("pink", "lightblue"), labeling = labeling_border(rot_labels = c(0,

```

```
0)))
```



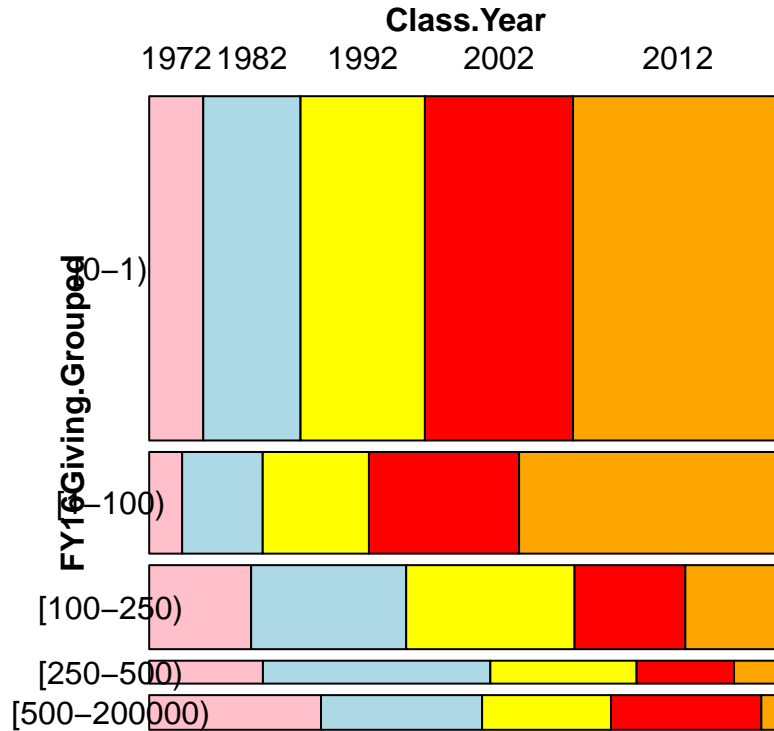
```
xtabs(~FY16Giving.Grouped + Gender, data = givings)
```

```
##           Gender
## FY16Giving.Grouped Female Male
##      [0-1)           298   288
##      [1-100)          106    67
##      [100-250)         58    85
##      [250-500)         17    22
##      [500-200000)       26    33
```

We note two interesting observations. There are more donations in the [\$500-\$200K) bracket than the [\$250-\$500) bracket. Also at \$100 or above, men consistently donate more than women. **Gender will be an important factor in our model selection.**

2.4.2 FY16Giving.Grouped vs. Class.Year

```
mosaic(~FY16Giving.Grouped + Class.Year, data = givings, highlighting = "Class.Year",
  highlighting_fill = c("pink", "lightblue", "yellow", "red",
    "orange"), labeling = labeling_border(rot_labels = c(0,
    0)))
```



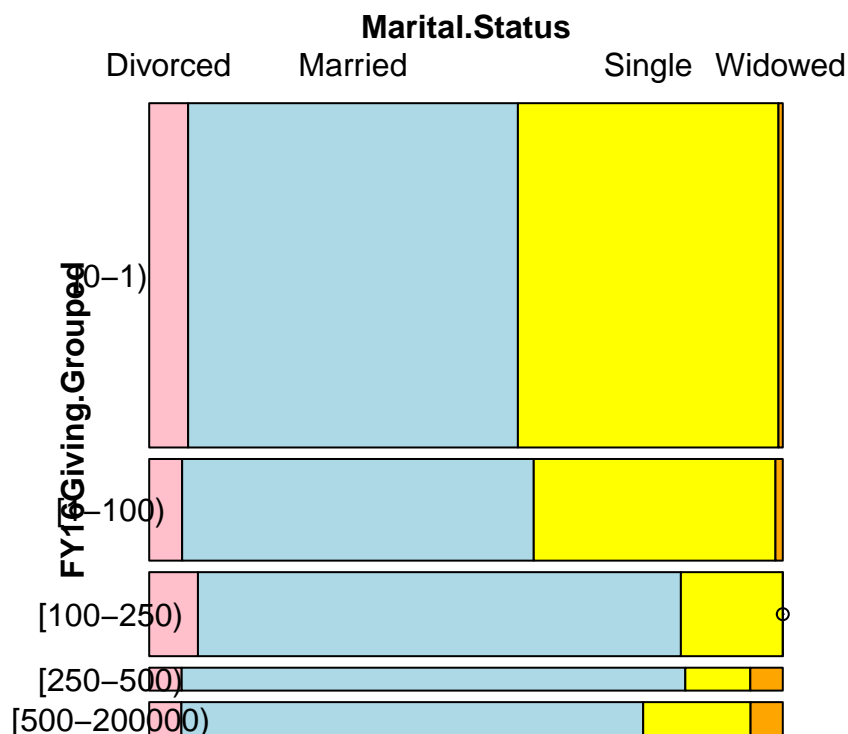
```
xtabs(~FY16Giving.Grouped + Class.Year, data = givings)
```

```
##           Class.Year
## FY16Giving.Grouped 1972 1982 1992 2002 2012
##           [0-1)      50   90  115  137  194
##           [1-100)     9   22   29   41   72
##           [100-250)   23   35   38   25   22
##           [250-500)    7   14    9    6    3
##           [500-200000) 16   15   12   14    2
```

We observe that older alumni make disproportionately bigger donations. What they lack in number (as expected due to age, mortality and other factors), they make up in generosity.

2.4.3 FY16Giving.Grouped vs. Marital.Status

```
mosaic(~FY16Giving.Grouped + Marital.Status, data = givings,
  highlighting = "Marital.Status", highlighting_fill = c("pink",
    "lightblue", "yellow", "orange"), labeling = labeling_border(rot_labels = c(0,
    0)))
```



```
xtabs(~FY16Giving.Grouped + Marital.Status, data = givings)
```

```
##           Marital.Status
## FY16Giving.Grouped Divorced Married Single Widowed
##      [0-1)           36      305    241      4
##      [1-100)          9       96     66      2
##      [100-250)        11      109     23      0
##      [250-500)         2       31      4      2
##      [500-200000)      3       43     10      3
```

The data is impressively clear. Married and single people are biggest source of donations. **We expect Marital.Status to be a significant explanatory variable in our final model.**

2.4.4 FY16Giving.Grouped vs. Major

```
top.majors <- spread(data.frame(xtabs(~Major + Giving.Year, data = subset(givings.tidy.donations,
  Giving.Grouped == "[500-200000)")), Giving.Year, Freq)

top.majors$Total <- rowSums(top.majors[-1])
colS = colSums(top.majors[-1])
top.majors1 = top.majors[top.majors$Total > 10, 1:6]
top.majors1$FY16Giving <- round(top.majors1$FY16Giving/colS[5],
  2)
top.majors1$FY15Giving <- round(top.majors1$FY15Giving/colS[4],
  2)
top.majors1$FY14Giving <- round(top.majors1$FY14Giving/colS[3],
```

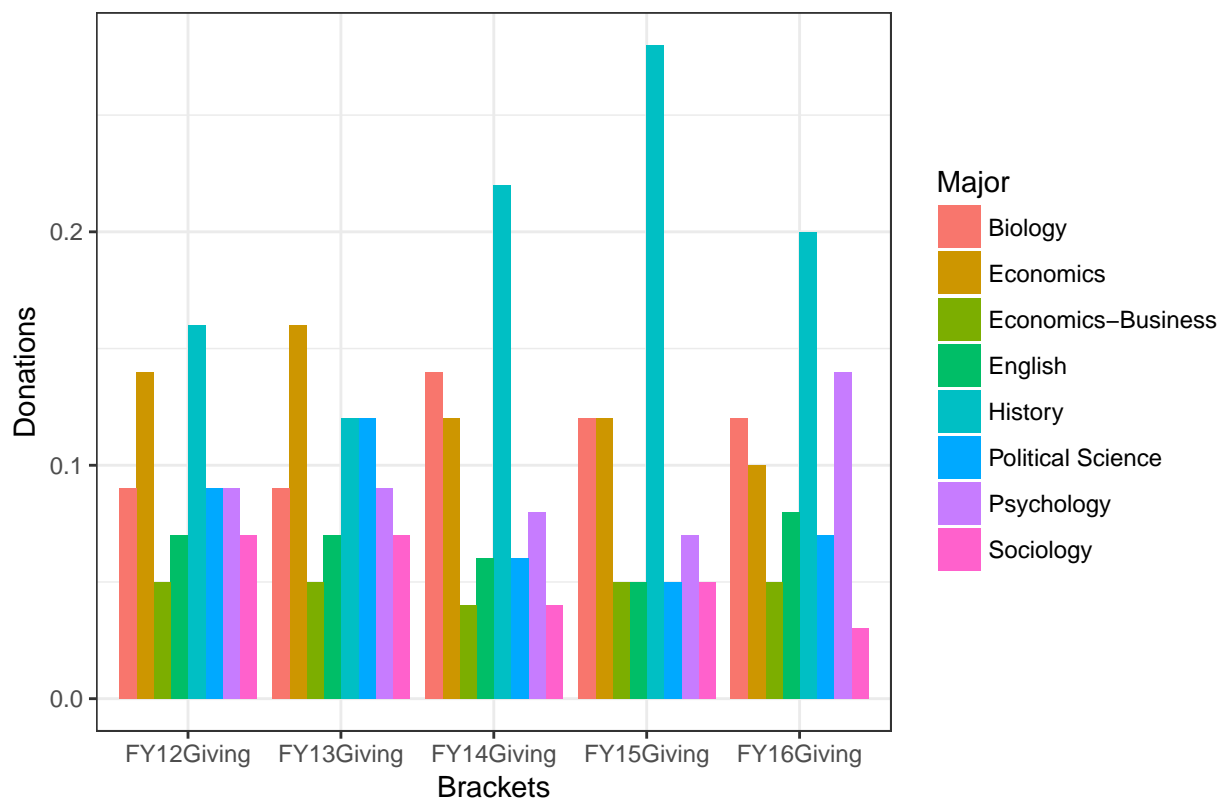
```

2)
top.majors1$FY13Giving <- round(top.majors1$FY13Giving/colS[2],
2)
top.majors1$FY12Giving <- round(top.majors1$FY12Giving/colS[1],
2)
top.majors2 <- top.majors1[1:6] %>% gather("Giving.Year", "Donations",
2:6)

ggplot(top.majors2, aes(x = Giving.Year, y = Donations)) + geom_bar(aes(fill = Major),
stat = "identity", position = "dodge") + theme(axis.text.x = element_text(angle = 90,
hjust = 1)) + labs(y = "Donations", x = "Brackets", title = "Contributions over years") +
theme_bw()

```

Contributions over years



```

(results <- top.majors1[top.majors1$Major %in% c("History", "Psychology",
"Biology", "Economics"), ])

```

```

##      Major FY12Giving FY13Giving FY14Giving FY15Giving FY16Giving
## 4    Biology      0.09      0.09      0.14      0.12      0.12
## 10  Economics      0.14      0.16      0.12      0.12      0.10
## 25   History      0.16      0.12      0.22      0.28      0.20
## 36  Psychology      0.09      0.09      0.08      0.07      0.14

```

```
colSums(results[-1])
```

```

## FY12Giving FY13Giving FY14Giving FY15Giving FY16Giving
##      0.48      0.46      0.56      0.59      0.56

```

```
givings$High.Donor.Major <- ifelse(givings$Major %in% c("History",
  "Psychology", "Biology", "Economics"), TRUE, FALSE)
```

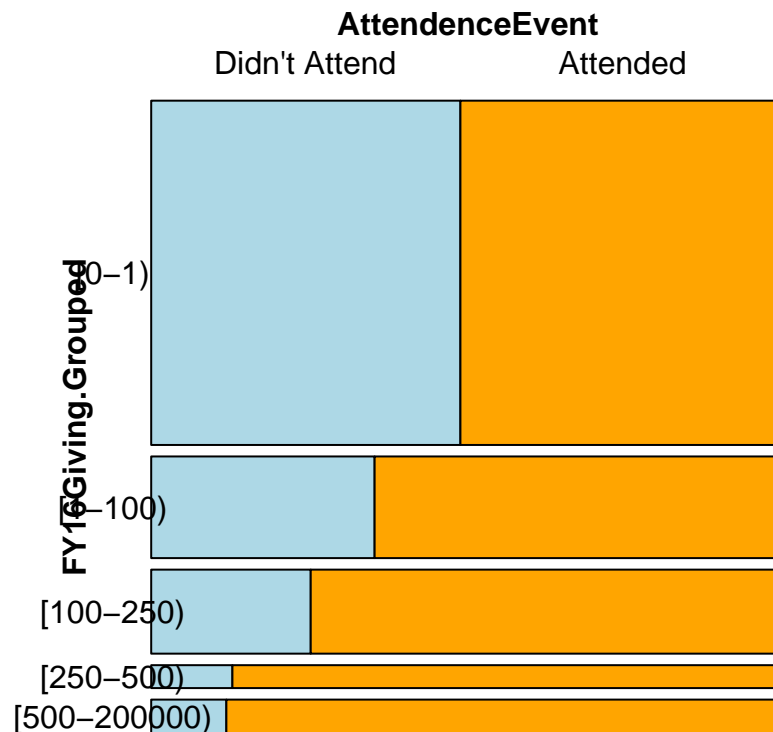
This data will change after Jill's update, skipping for now

2.4.5 FY16Giving.Grouped vs. Next.Degree

This data will change after Jill's update, skipping for now

2.4.6 FY16Giving.Grouped vs. AttendanceEvent

```
mosaic(~FY16Giving.Grouped + AttendanceEvent, data = givings,
  highlighting = "AttendanceEvent", highlighting_fill = c("lightblue",
    "orange"), labeling = labeling_border(rot_labels = c(0,
    0)))
```



```
xtabs(~FY16Giving.Grouped + AttendanceEvent, data = givings)
```

```
##           AttendanceEvent
## FY16Giving.Grouped Didn't Attend Attended
##      [0-1)             286      300
##      [1-100)           61      112
##      [100-250)         36      107
##      [250-500)          5       34
##      [500-200000)       7       52
```


The data is inline with our expectations. Among the people who donate, there is a strong correlation between attendance and donations. In fact, most of the top donors (85%) have attended an Alumni event. **We'll include AttendanceEvent in our model exploration.**

2.4.7 FY16Giving.Grouped vs. previous years' Donation levels

```
library(car)

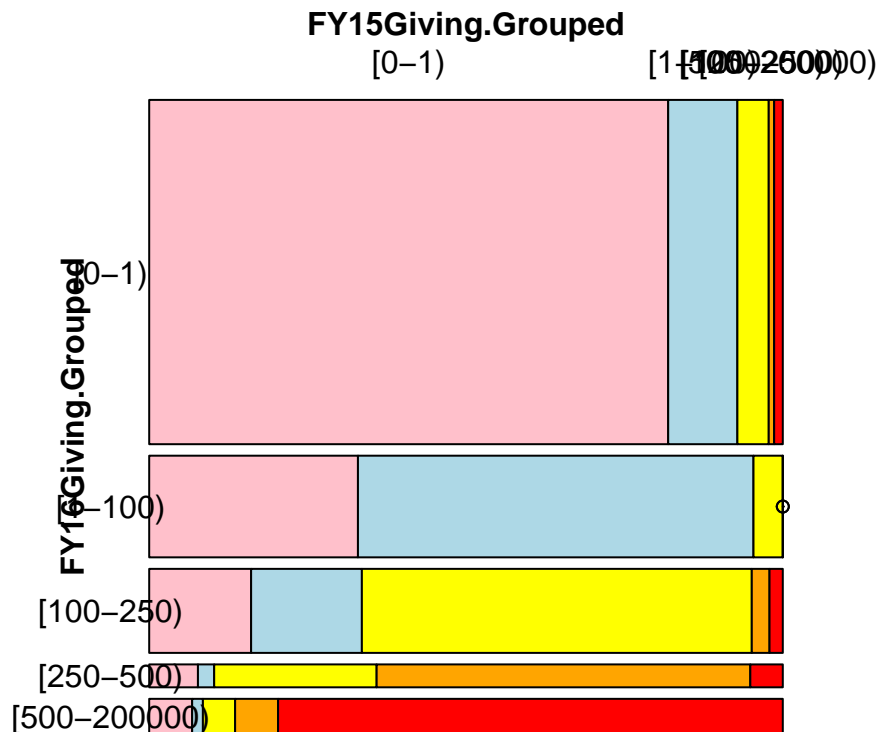
##
## Attaching package: 'car'
##
## The following object is masked from 'package:purrr':
##
##   some
##
## The following object is masked from 'package:dplyr':
##
##   recode
```

```
library(corrplot)
M = givings[c(8:12)]
M_corr = cor(M)
corrplot(M_corr, method = "circle", type = "upper")
```



```
mosaic(~FY16Giving.Grouped + FY15Giving.Grouped, data = givings,
  highlighting = "FY15Giving.Grouped", highlighting_fill = c("pink",
```

```
"lightblue", "yellow", "orange", "red"), labeling = labeling_border(rot_labels = c(0,
0)))
```



```
xtabs(~FY16Giving.Grouped + FY15Giving.Grouped, data = givings)
```

```
##              FY15Giving.Grouped
## FY16Giving.Grouped [0-1) [1-100) [100-250) [250-500) [500-200000)
##      [0-1)          480      64          29          5          8
##      [1-100)        57      108          8          0          0
##      [100-250)       23       25         88          4          3
##      [250-500)        3        1         10         23          2
##      [500-200000)    4        1          3          4         47
```

We notice that for any given donation bracket, most likely donation level for 2016 is the same level in 2015 (Ex: 40 out of 48 top donors in 2016 were also top donors in 2015). **So the prior year donation levels are a strong indicator for this year's donation levels.**

Note(Daghan): The above table is for 2016-2015 donations only. I'll add 2014 through 2012 later

2.5 Multivariate Data Analysis and Interactions

Here I am going to explore various combinations and possible interactions. (not done yet)

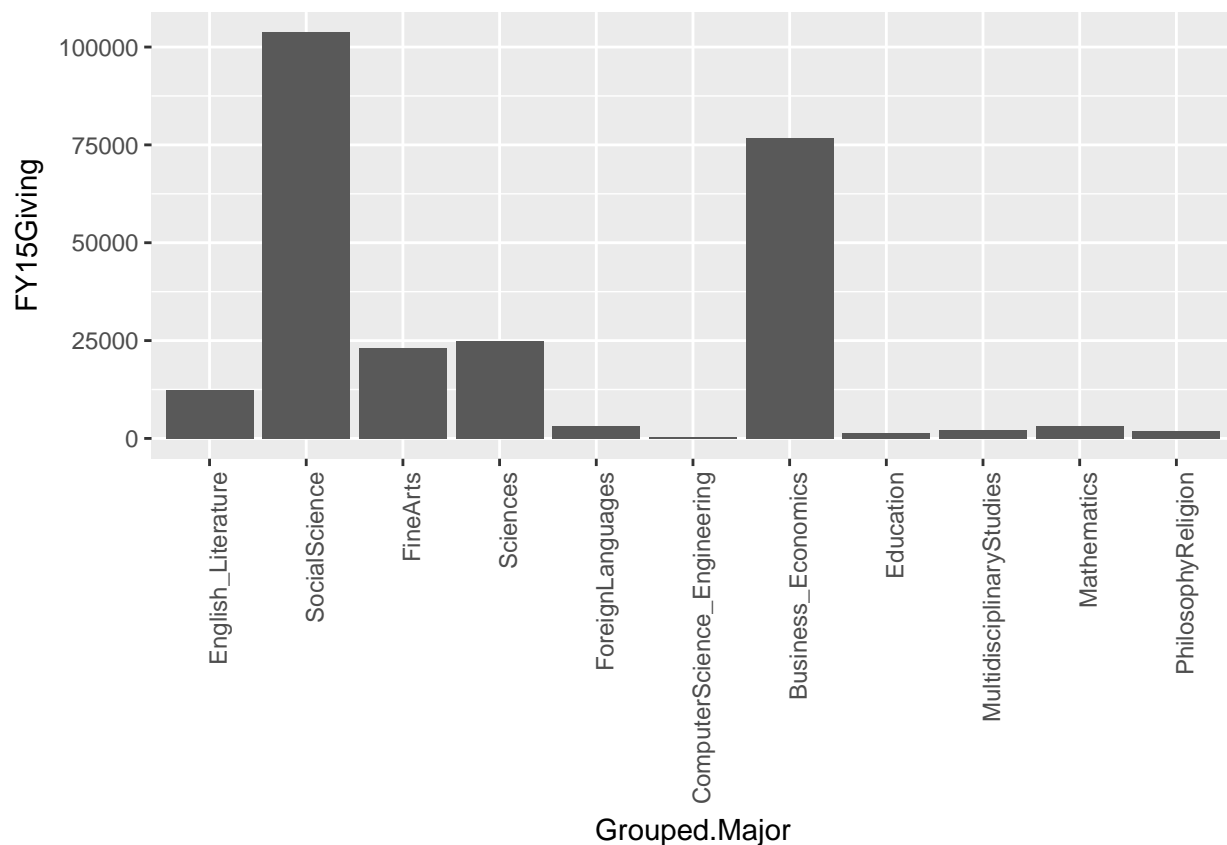
Note (Daghan): Didn't touch the stuff below so you can merge more easily

We need a total donation normalized by number of people (average - median maybe- donation). But considering the above and below charts, it is obvious that business/economics is overrepresented in terms of FY15 giving (consider doing this with averaged 2012, 2014 FY giving when predicting 2015 giving).

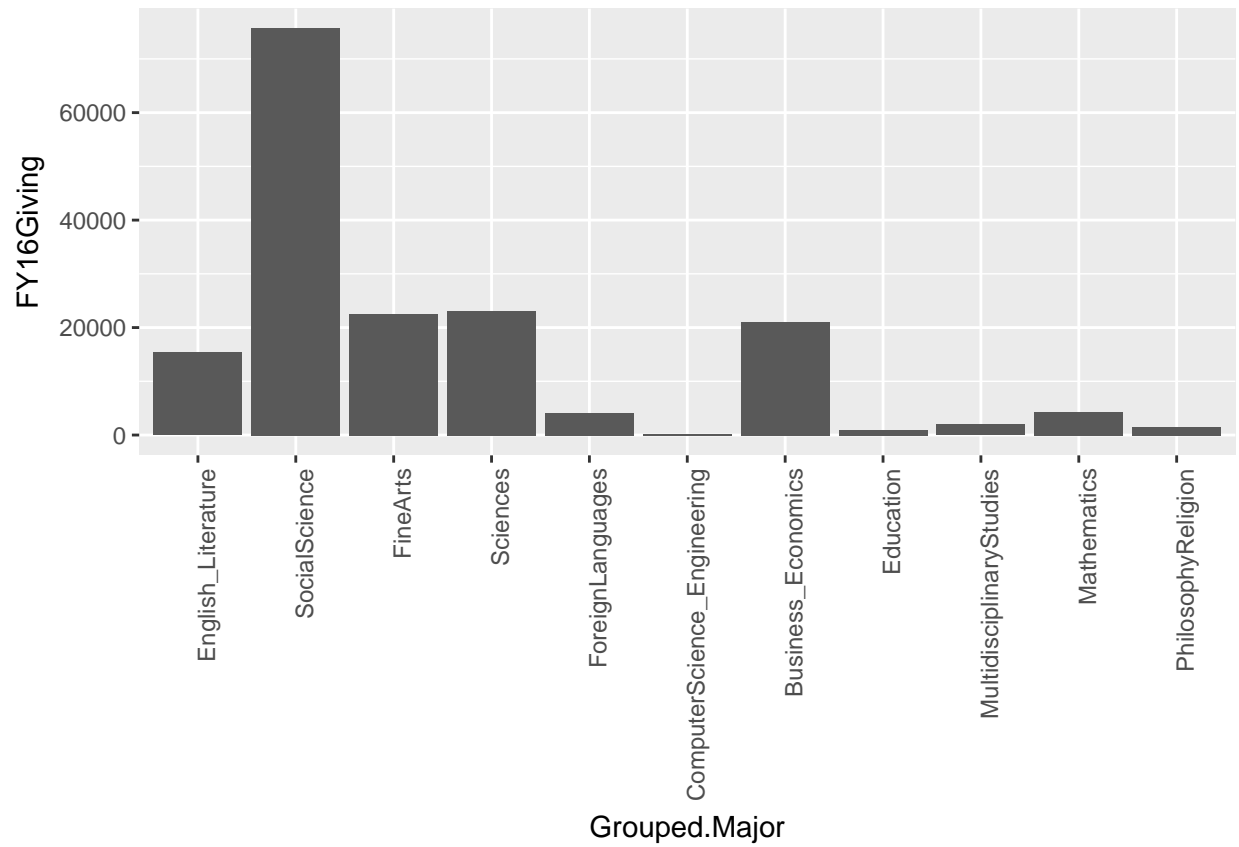
Wow! It seems that the very large donations throw everything off (like which major has higher donations every year fluctuates based on large donations that differ in major from year to year). It seems like FYGiving 2013 is very different from the others because there seems to be a very large donation of >\$150,000.

**should i do Median donation by person in each major in each year? need some kind of aggregation - instead maybe do more careful analysis categorical donation variable below.

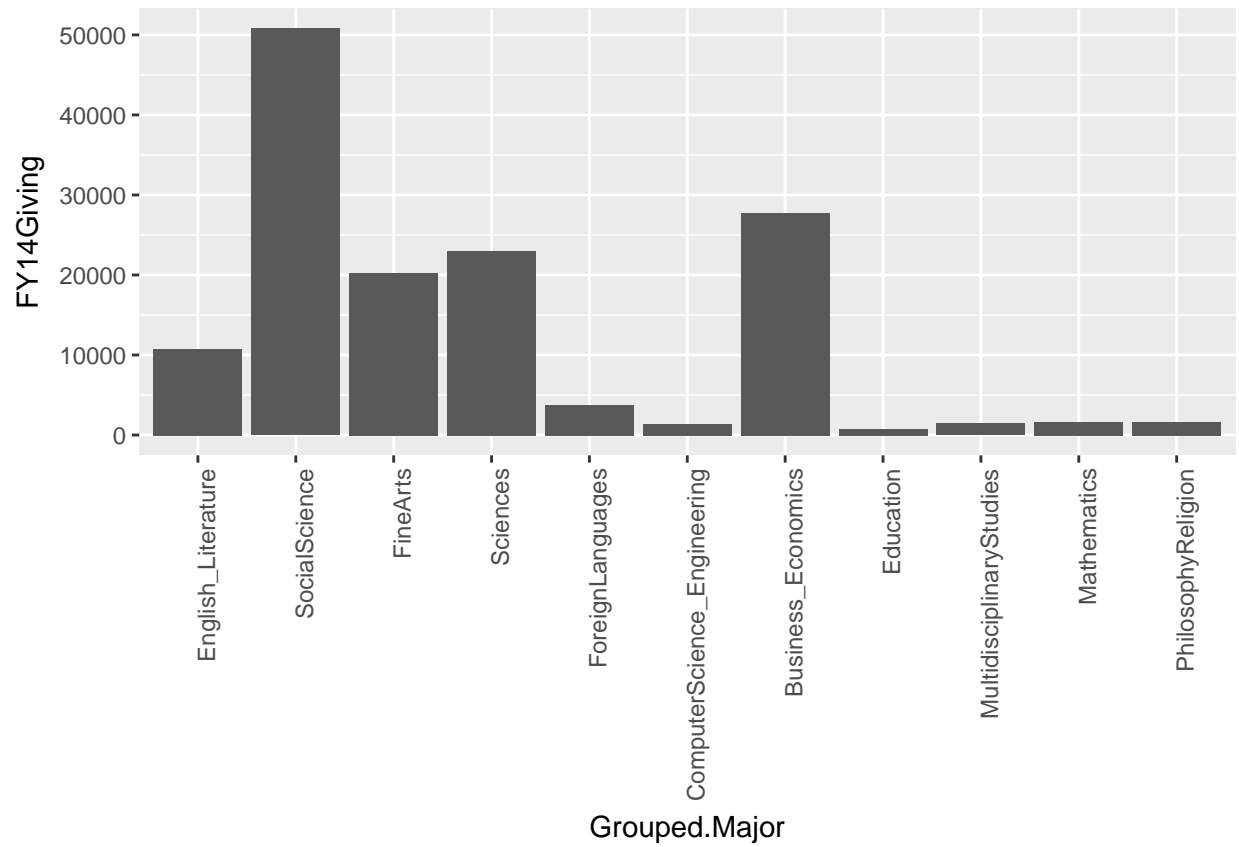
```
ggplot(givings, aes(Grouped.Major, FY15Giving)) + geom_bar(stat = "identity") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



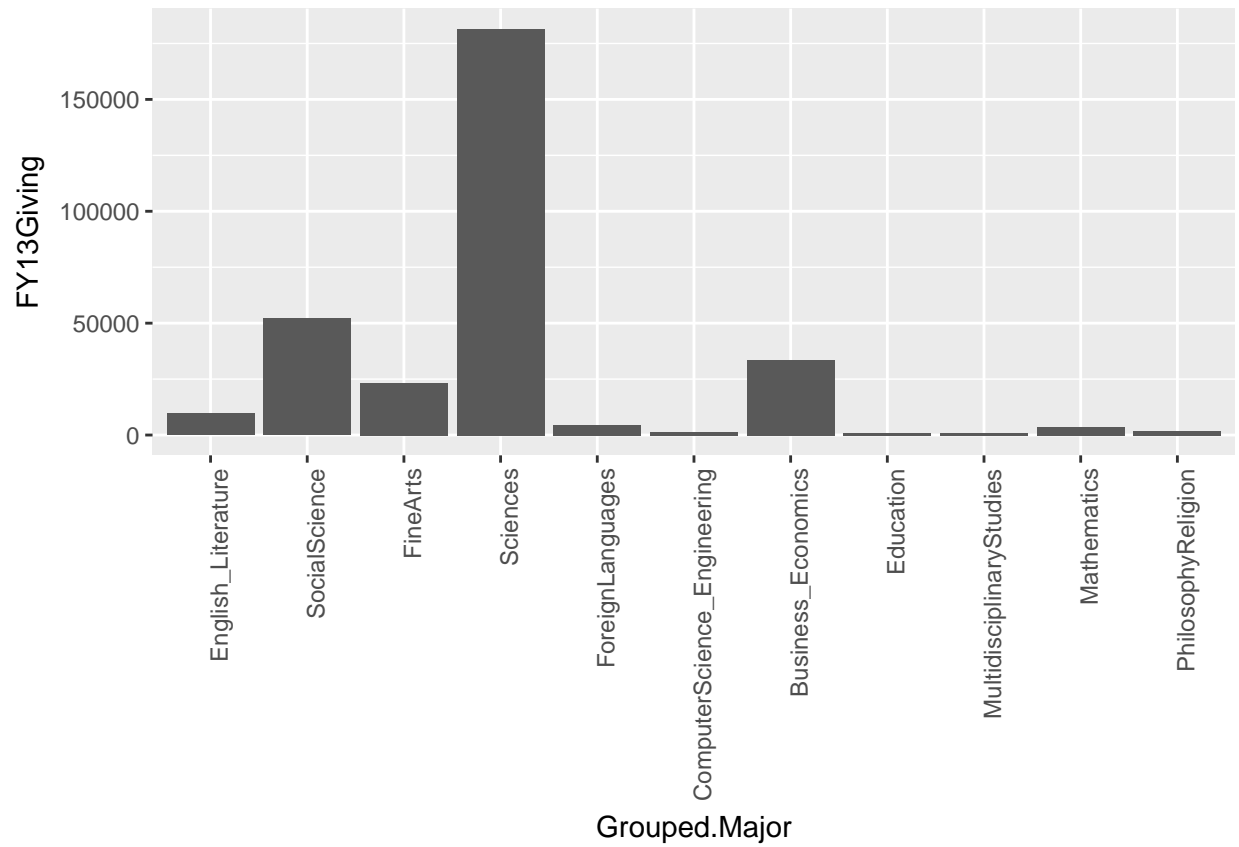
```
ggplot(givings, aes(Grouped.Major, FY16Giving)) + geom_bar(stat = "identity") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



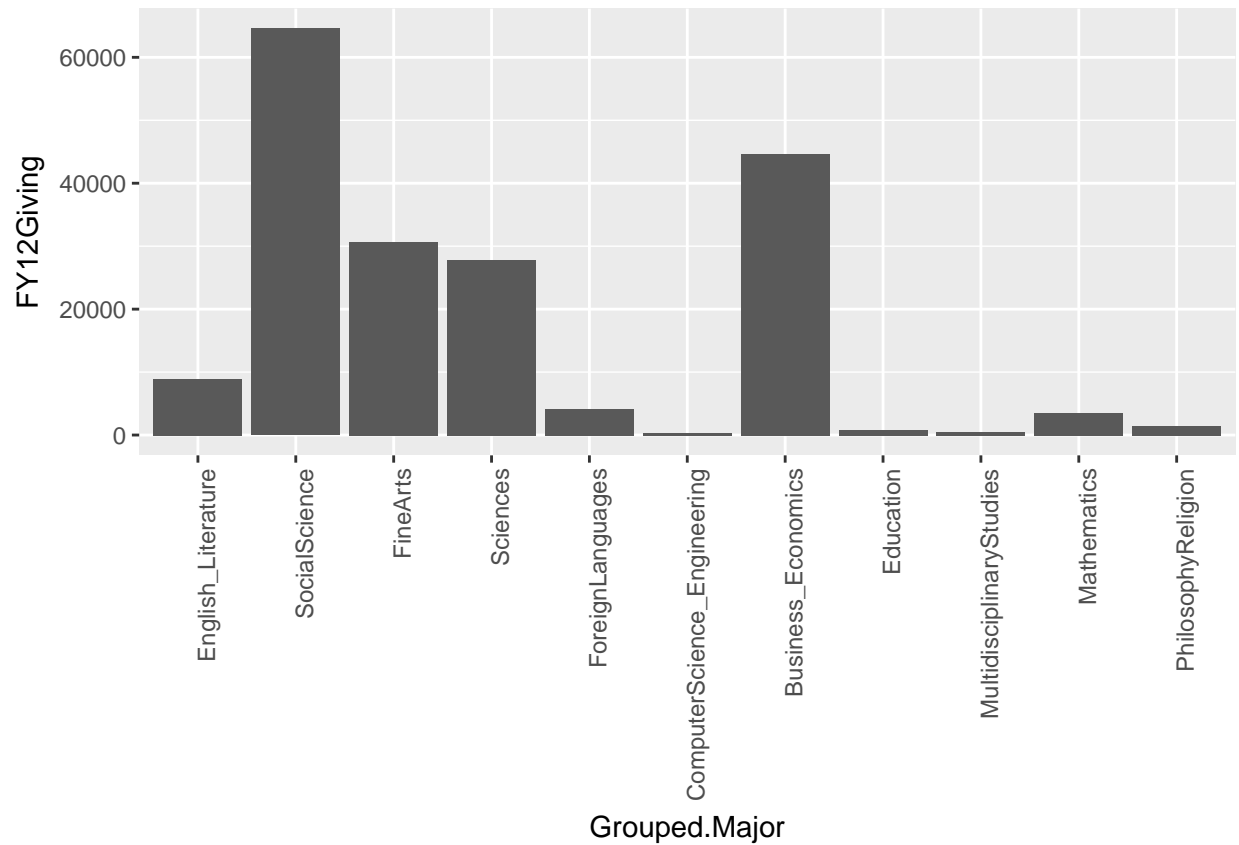
```
ggplot(givings, aes(Grouped.Major, FY14Giving)) + geom_bar(stat = "identity") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



```
ggplot(givings, aes(Grouped.Major, FY13Giving)) + geom_bar(stat = "identity") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

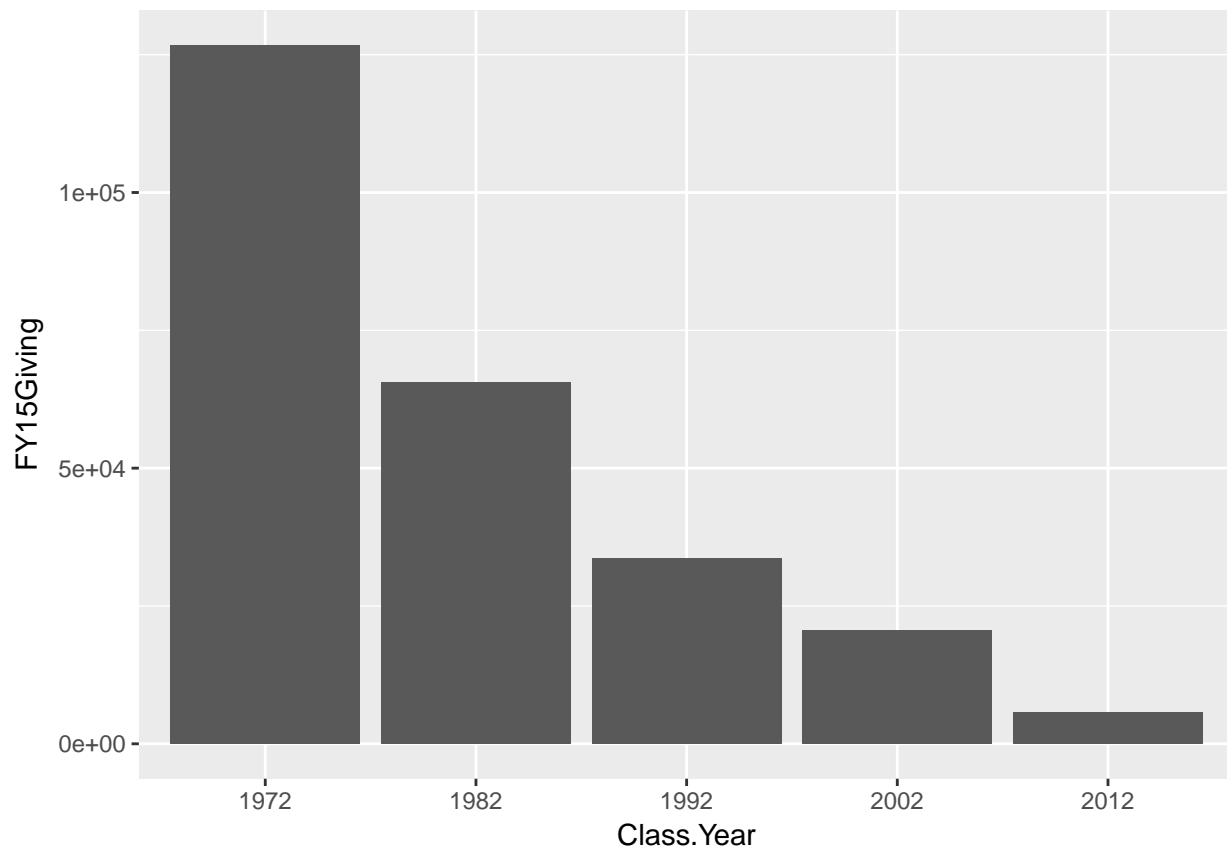


```
ggplot(givings, aes(Grouped.Major, FY12Giving)) + geom_bar(stat = "identity") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



Class year affects total donations. People who graduated longer ago are probably older and they seem to donate more total money. It seems like they make more larger donations, but there are fewer people in “older” class years. See contingency table below for grouped giving category observations.

```
ggplot(givings, aes(Class.Year, FY15Giving)) + geom_bar(stat = "identity")
```



There is a high correlation of the different fiscal years of giving with most other years (except fiscal year 2013). Maybe something went wrong with soliciting donations that year? NO - There was one very large donation by a former Science major that throws off correlations in 2013.

This is why it is good to use the grouped donation variable we are asked to create (done below).

Conclusion: Maybe should do some kind of grouping of years? But how - average continuous dollars for each year and then cut into groups? Or i guess we could just pick the most recent year (2014 for 2015 and 2015 for 2016). Below, there is a contingency table for categorical donation amount variables of 2015 and 2014 and it supports the idea of using the year before to model the current year.

```
library(car)
library(corrplot)
M = givings[-c(1:7, 13:17)]
head(M)
```

```
##   FY12Giving FY13Giving FY14Giving FY15Giving FY16Giving
## 1         50         51         51          0          0
## 2          0          0          0          0          0
## 3        100          0        100        100        100
## 4          0          0          0          0          0
## 5          0          0          0          0          0
## 6          0          0          0          0          0
##   FY16Giving.Grouped High.Donor.Major
## 1           [0-1)             FALSE
## 2           [0-1)             TRUE
## 3       [100-250)             TRUE
## 4           [0-1)             FALSE
```



```
## 5          [0-1)          FALSE
## 6          [0-1)          FALSE

# M_corr = cor(M) corrplot(M_corr, method='circle',
# type='upper')
```

Creating grouped (categorical) donation amount variables:

```
givings$FY12Giving.Grouped <- factor(cut(givings$FY12Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  include.lowest = TRUE))

givings$FY13Giving.Grouped <- factor(cut(givings$FY13Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  include.lowest = TRUE))

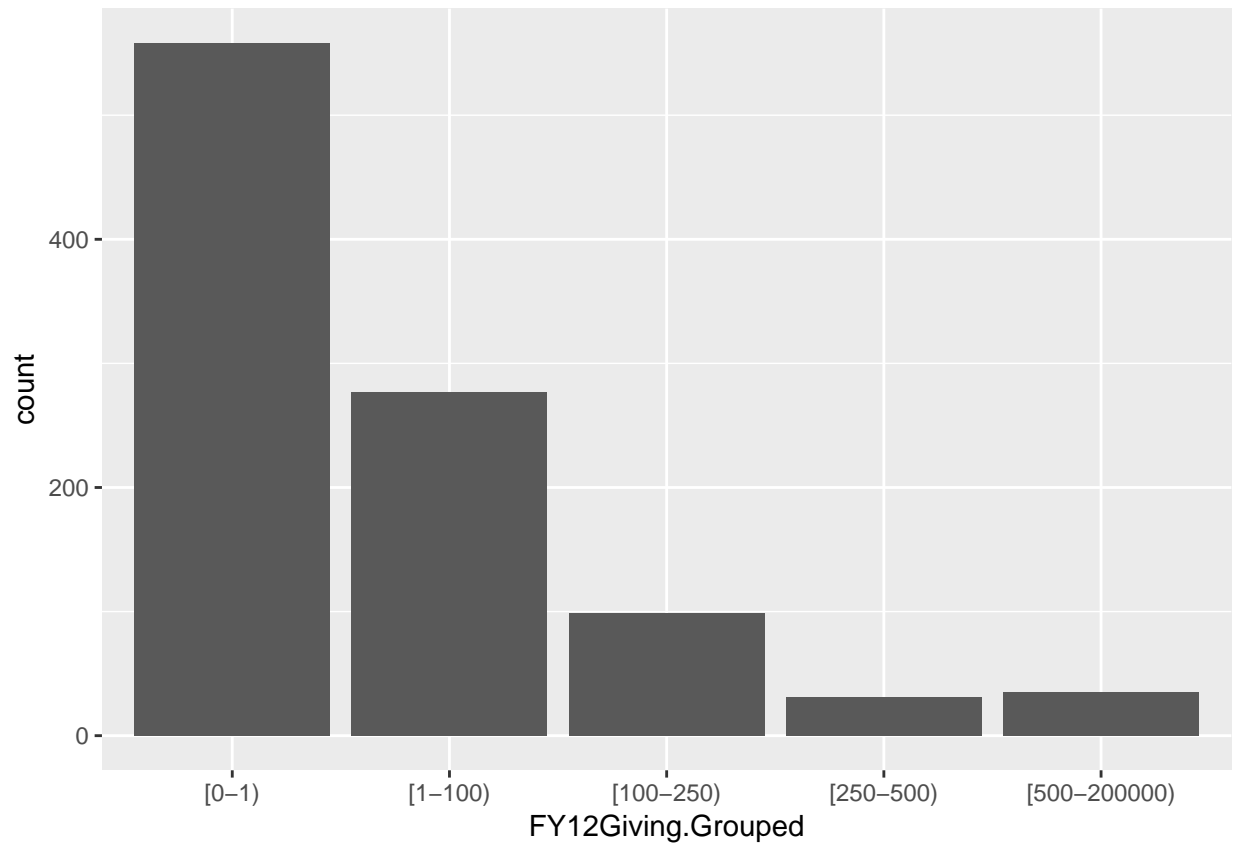
givings$FY14Giving.Grouped <- factor(cut(givings$FY14Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  include.lowest = TRUE))

givings$FY15Giving.Grouped <- factor(cut(givings$FY15Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  include.lowest = TRUE))

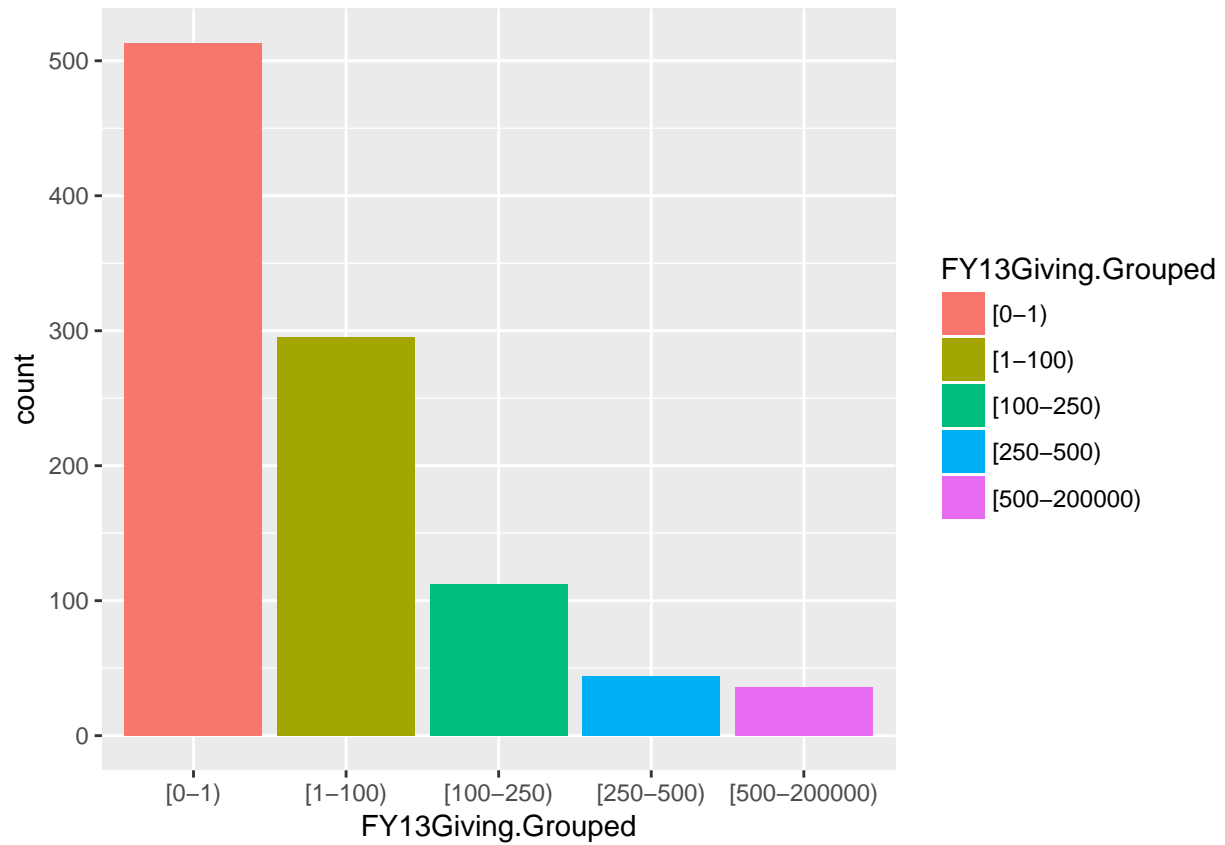
givings$FY16Giving.Grouped <- factor(cut(givings$FY16Giving,
  breaks = c(0, 1, 100, 250, 500, 2e+05), labels = c("[0-1)",
    "[1-100)", "[100-250)", "[250-500)", "[500-200000)"),
  include.lowest = TRUE))
```

In general (across years) half of people donate and half do not. Half of people who donate give under a hundred dollars. Around one fifth of people who donate (1/10 of all people) give between 100 and 250 dollars. There are usually less than 25 people every year who give 250-500 dollars or 500+ dollars. That could be problematic for accurately predicting who gives the highest donations.

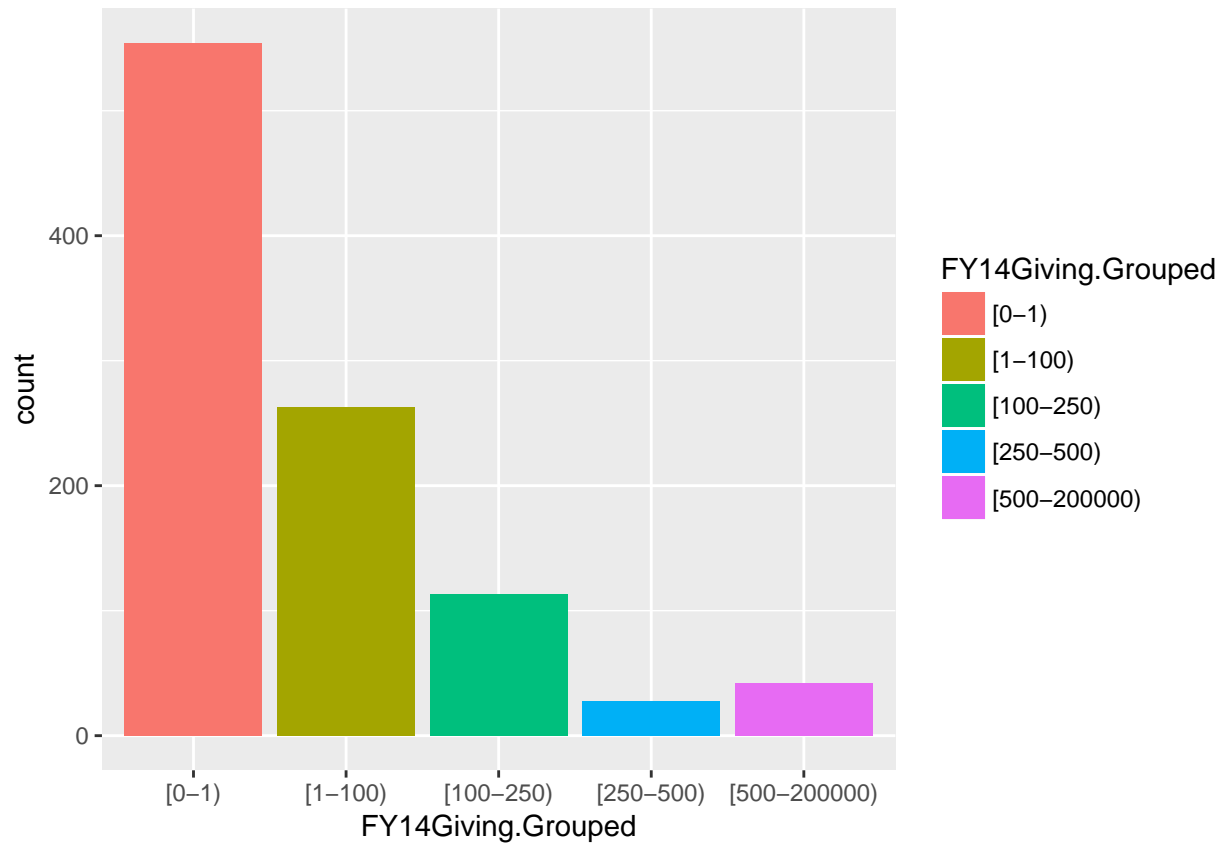
```
ggplot(givings, aes(FY12Giving.Grouped)) + geom_bar()
```



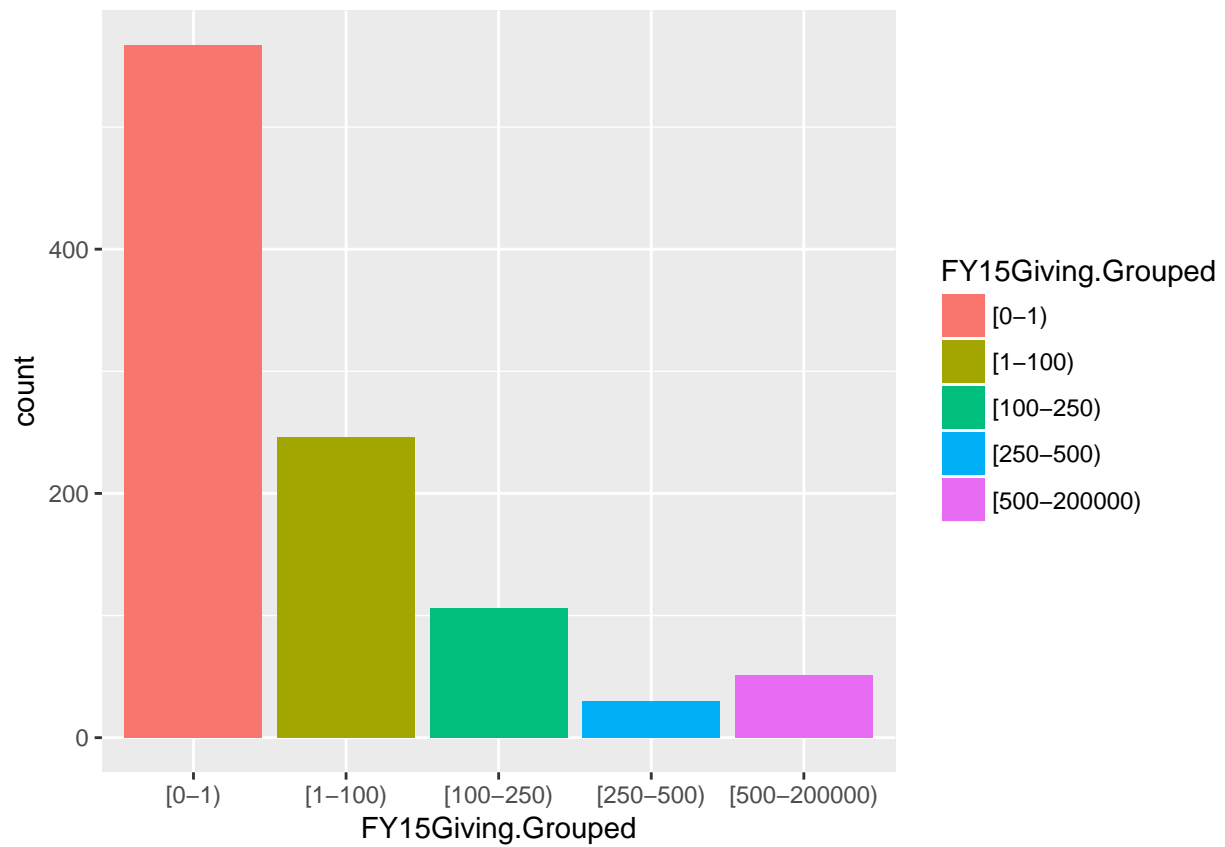
```
ggplot(givings, aes(FY13Giving.Grouped)) + geom_bar(aes(fill = FY13Giving.Grouped))
```



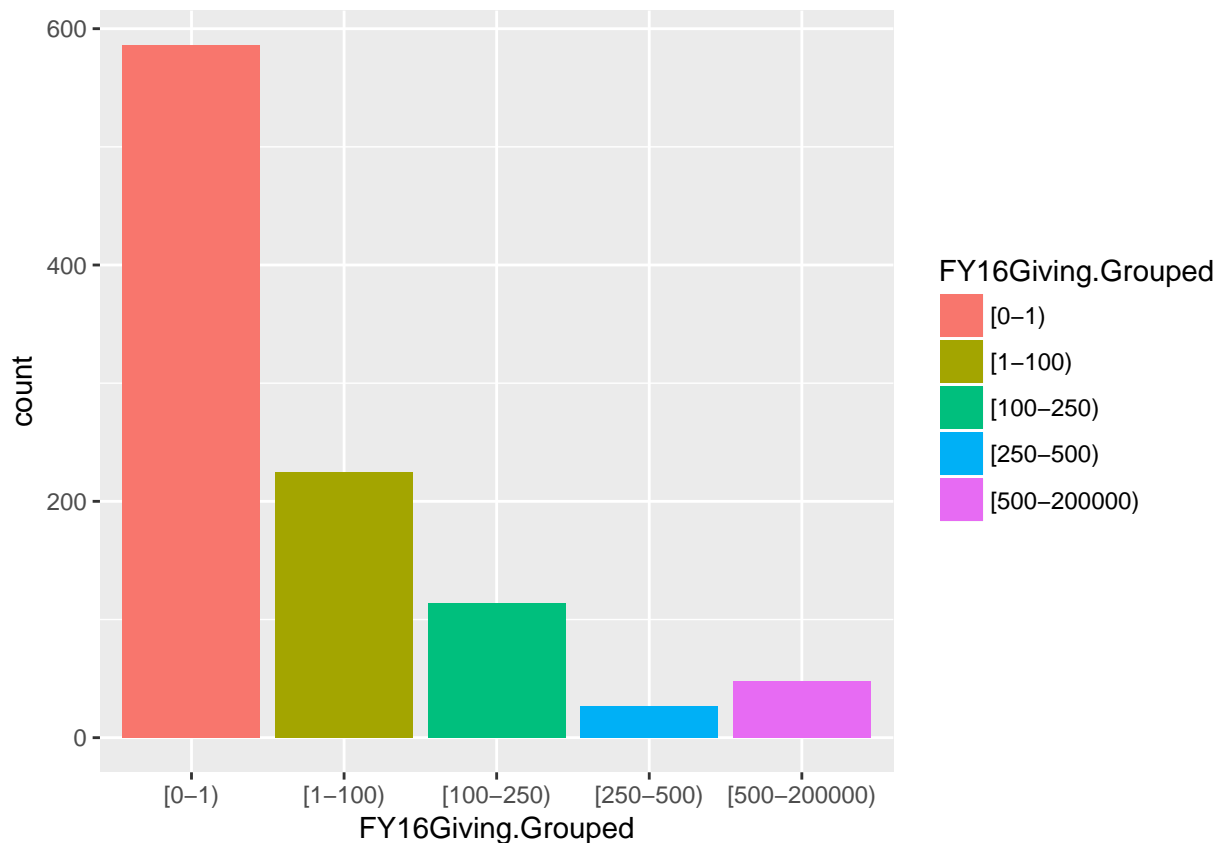
```
ggplot(givings, aes(FY14Giving.Grouped)) + geom_bar(aes(fill = FY14Giving.Grouped))
```



```
ggplot(givings, aes(FY15Giving.Grouped)) + geom_bar(aes(fill = FY15Giving.Grouped))
```



```
ggplot(givings, aes(FY16Giving.Grouped)) + geom_bar(aes(fill = FY16Giving.Grouped))
```

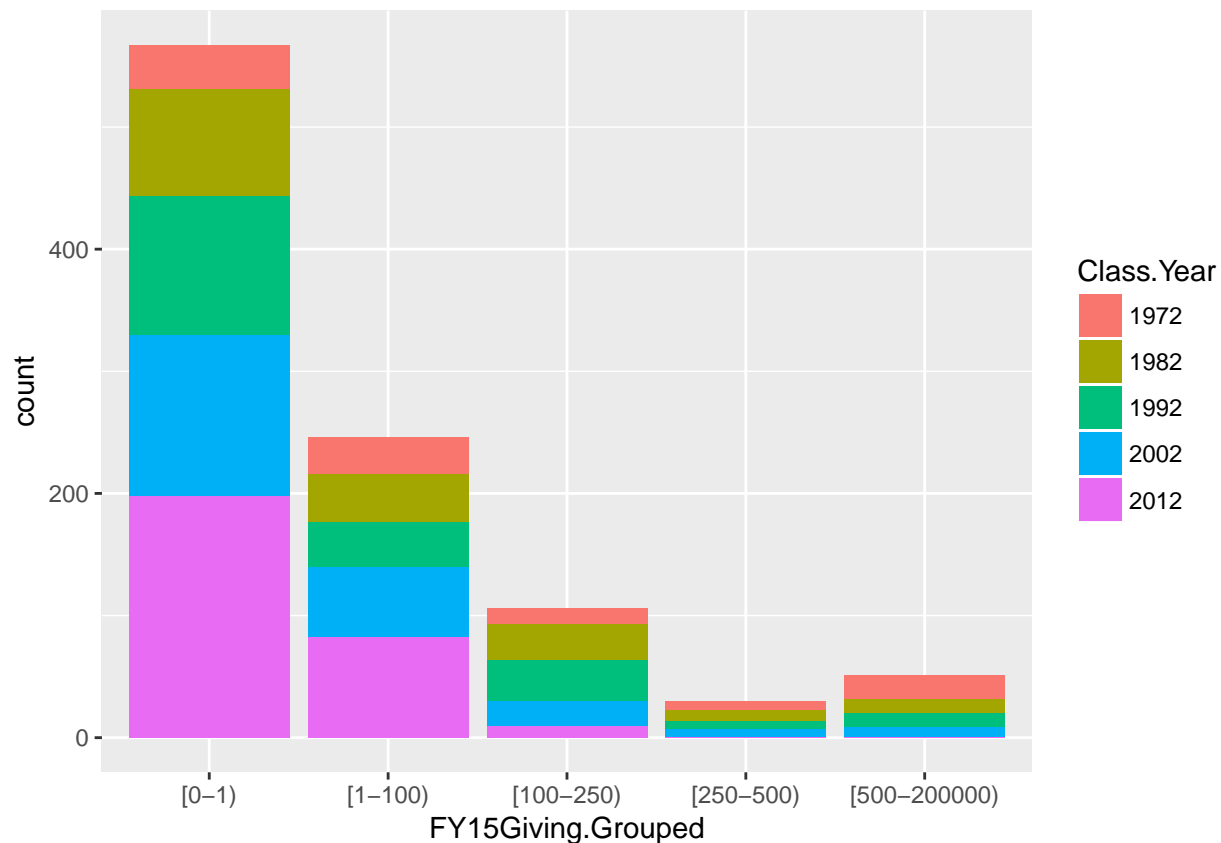


DONATION LEVEL VS. CLASS YEAR

!! Caveat: should make all the bar charts below percent of people in each category that give the particular donation amount - ie. percent of the class of 1972 that donate nothing, percent of the class of 1972 that donate 1-100 dollars. Right now the charts are counts of the categories in the legends and the number of people in each category is different (except for in the case of men and women).

More people from more recent classes do not donate. More people from recent classes donate in lower donation amounts. As graduation year is “older”, there are more larger value donations (remember, chart is not normalized to # of people in each category).

```
ggplot(givings, aes(FY15Giving.Grouped)) + geom_bar(aes(fill = Class.Year))
```



As seen in the contingency table below, class year does affect amount donated. The most recent graduates have the highest percent of people who do not donate. Whereas the “oldest” graduates have the highest amount of people who donate in the higher donation bracket.

The Pearson Chi Square and Likelihood Ratio Tests indicate that we should reject the null hypothesis that Class Year and Donation group are independent of each other (for FY15Giving.Grouped data).

```
Class.year.table <- xtabs(~Class.Year, data = givings)
prop.table(Class.year.table)
```

```
## Class.Year
## 1972 1982 1992 2002 2012
## 0.105 0.176 0.203 0.223 0.293
```

```
# t7 <-xtabs(~FY16Giving.Grouped+Class.Year, data=givings)
# round(t7/rowSums(t7),2)
```

```
# t8 <-xtabs(~FY12Giving.Grouped+Class.Year, data=givings)
# round(t8/rowSums(t8),2)
```

```
# t9 <-xtabs(~FY13Giving.Grouped+Class.Year, data=givings)
# round(t9/rowSums(t9),2)
```

```
# t10 <-xtabs(~FY14Giving.Grouped+Class.Year, data=givings)
# round(t10/rowSums(t10),2)
```

```
t11 <- xtabs(~FY15Giving.Grouped + Class.Year, data = givings)
round(t11/rowSums(t11), 2)
```

```
##              Class.Year
## FY15Giving.Grouped 1972 1982 1992 2002 2012
##      [0-1)         0.06 0.15 0.20 0.23 0.35
##      [1-100)        0.12 0.16 0.15 0.23 0.34
##      [100-250)       0.12 0.27 0.32 0.19 0.09
##      [250-500)       0.23 0.30 0.23 0.20 0.03
##      [500-200000)    0.37 0.24 0.22 0.16 0.02
```

```
assocstats(t11)
```

```
##              X^2 df P(> X^2)
## Likelihood Ratio 118.84 16      0
## Pearson          115.91 16      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.322
## Cramer's V        : 0.17
```

I created new binary variable to compare number of people who donate versus do not donate for fiscal year 2015.

```
givings$donatedFY15 <- fct_collapse(givings$FY15Giving.Grouped,
  Donated = c("(1-100)", "(100-250)", "(250-500)", "(500-200000)"),
  DidnotDonate = "(0-1)")
```

```
## Warning: Unknown levels in `f`: (1-100), (100-250), (250-500),
## (500-200000), (0-1)
```

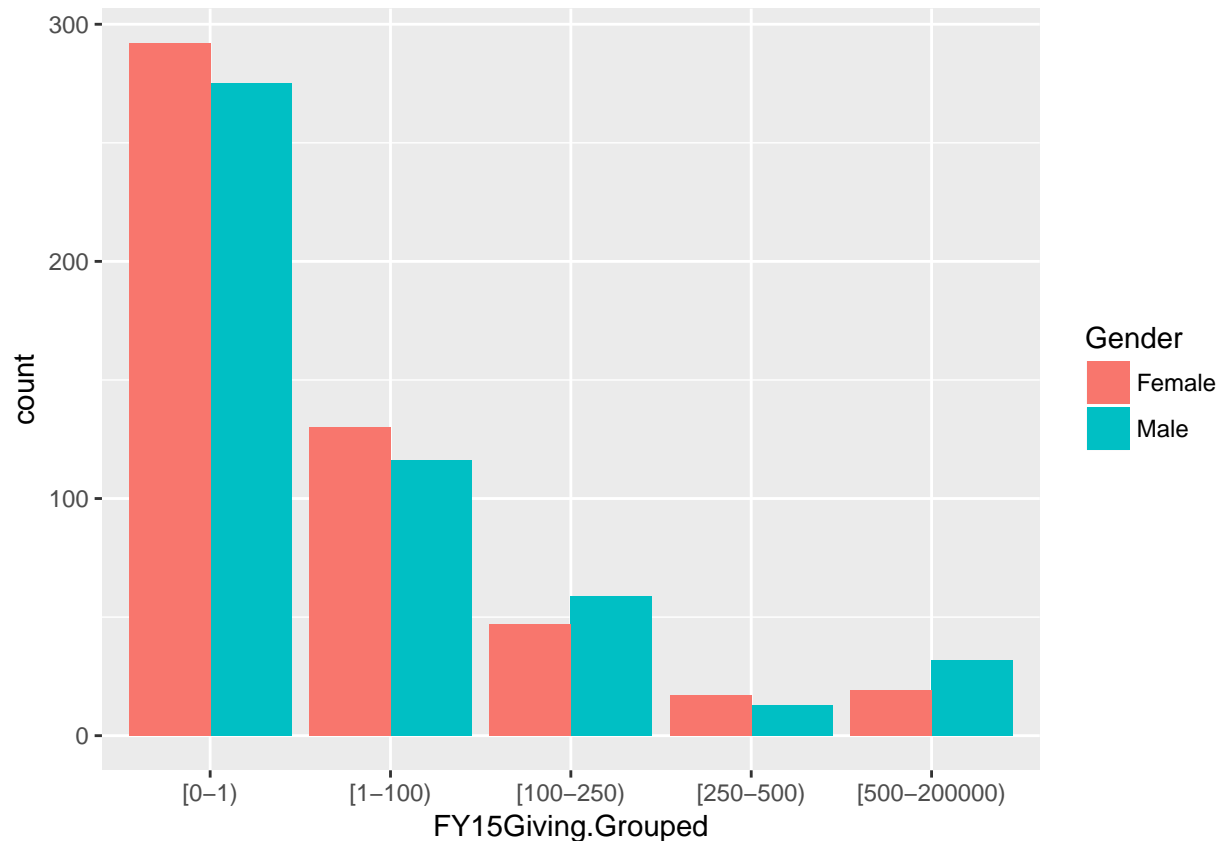
I wanted to conclusively see if the number of people who do and do not donate differ between class years. They do!

```
donated.classyearTable = xtabs(~donatedFY15 + Class.Year, data = givings)
donated.classyearTable
```

```
##              Class.Year
## donatedFY15  1972 1982 1992 2002 2012
##   [0-1)         36   87  114  132  198
##   [1-100)        30   39   37   57   83
##   [100-250)       13   29   34   20   10
##   [250-500)        7    9    7    6    1
##   [500-200000)   19   12   11    8    1
```

DONATION LEVEL VS. GENDER

```
ggplot(givings, aes(FY15Giving.Grouped)) + geom_bar(aes(fill = Gender),
  position = "dodge")
```

FY15 donations are independent of gender according to LR and Pearson Chi square tests. There are clear differences in donation patterns for larger donation categories, but there are few observations in these categories.

```
t1 <- xtabs(~FY15Giving.Grouped + Gender, data = givings)
round(t1/rowSums(t1), 2)
```

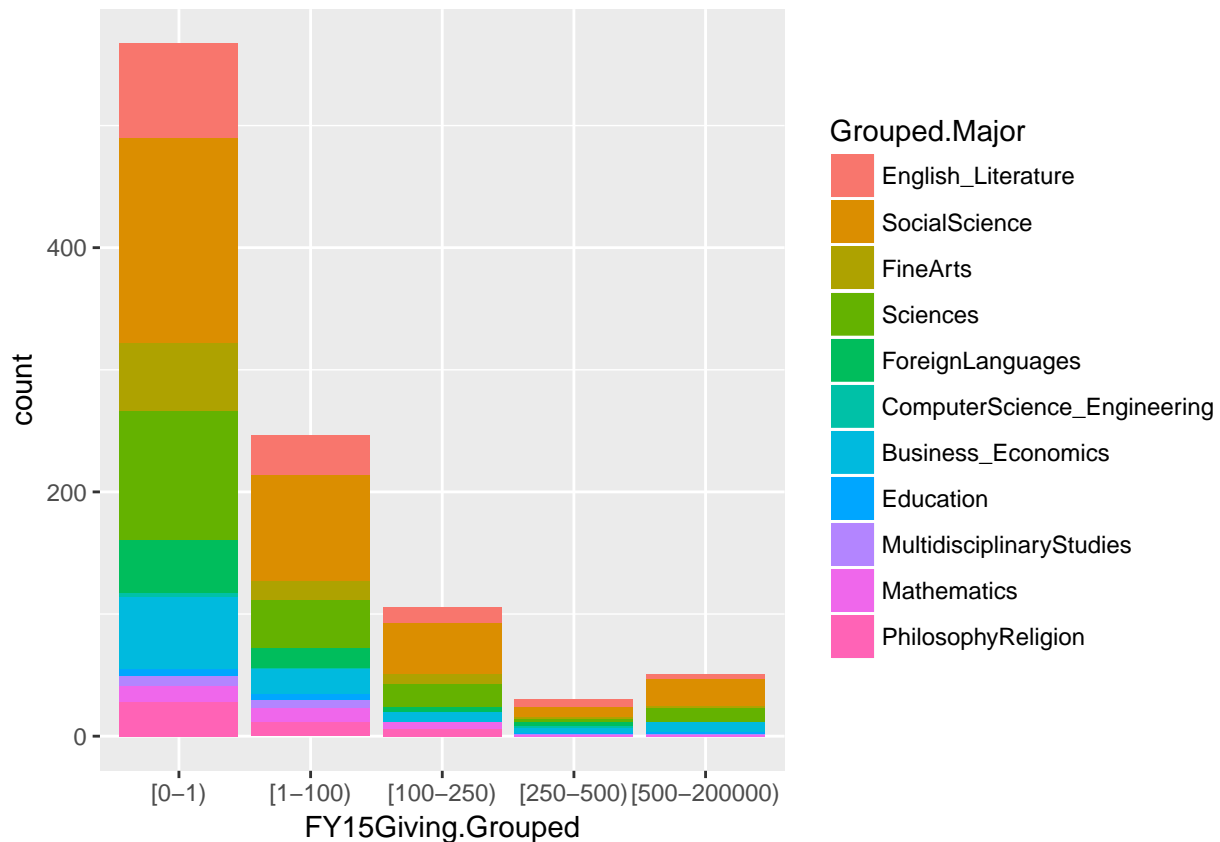
```
##           Gender
## FY15Giving.Grouped Female Male
##      [0-1)          0.51 0.49
##      [1-100)        0.53 0.47
##      [100-250)       0.44 0.56
##      [250-500)       0.57 0.43
##      [500-200000)    0.37 0.63
```

```
assocstats(t1)
```

```
##           X^2 df P(> X^2)
## Likelihood Ratio 6.4539 4 0.16772
## Pearson          6.4126 4 0.17038
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.08
## Cramer's V        : 0.08
```

DONATION LEVEL VS. MAJOR

```
ggplot(givings, aes(FY15Giving.Grouped)) + geom_bar(aes(fill = Grouped.Major))
```



Seems marginally significant by LR test that FY15 giving dependent on major. But not significant by Pearson Chi square test. I put it in first pass of models - not convincingly significant!

```
t17 <- xtabs(~FY15Giving.Grouped + Grouped.Major, data = givings)
round(t17/rowSums(t17), 2)
```

```
##                               Grouped.Major
## FY15Giving.Grouped English_Literature SocialScience FineArts Sciences
##      [0-1)                0.14          0.30       0.10      0.19
##      [1-100)              0.13          0.35       0.06      0.16
##      [100-250)            0.12          0.40       0.08      0.18
##      [250-500)            0.20          0.27       0.07      0.07
##      [500-200000)         0.08          0.43       0.04      0.22
##                               Grouped.Major
## FY15Giving.Grouped ForeignLanguages ComputerScience_Engineering
##      [0-1)                0.08                          0.01
##      [1-100)              0.07                          0.00
##      [100-250)            0.04                          0.00
##      [250-500)            0.13                          0.03
##      [500-200000)         0.00                          0.00
##                               Grouped.Major
## FY15Giving.Grouped Business_Economics Education MultidisciplinaryStudies
##      [0-1)                0.10          0.01                          0.02
```

```
##      [1-100)      0.08      0.02      0.03
##      [100-250)     0.08      0.00      0.00
##      [250-500)     0.13      0.03      0.03
##      [500-200000)  0.18      0.02      0.02
##                               Grouped.Major
## FY15Giving.Grouped Mathematics PhilosophyReligion
##      [0-1)      0.02      0.05
##      [1-100)     0.04      0.05
##      [100-250)    0.06      0.06
##      [250-500)    0.03      0.00
##      [500-200000) 0.02      0.00
```

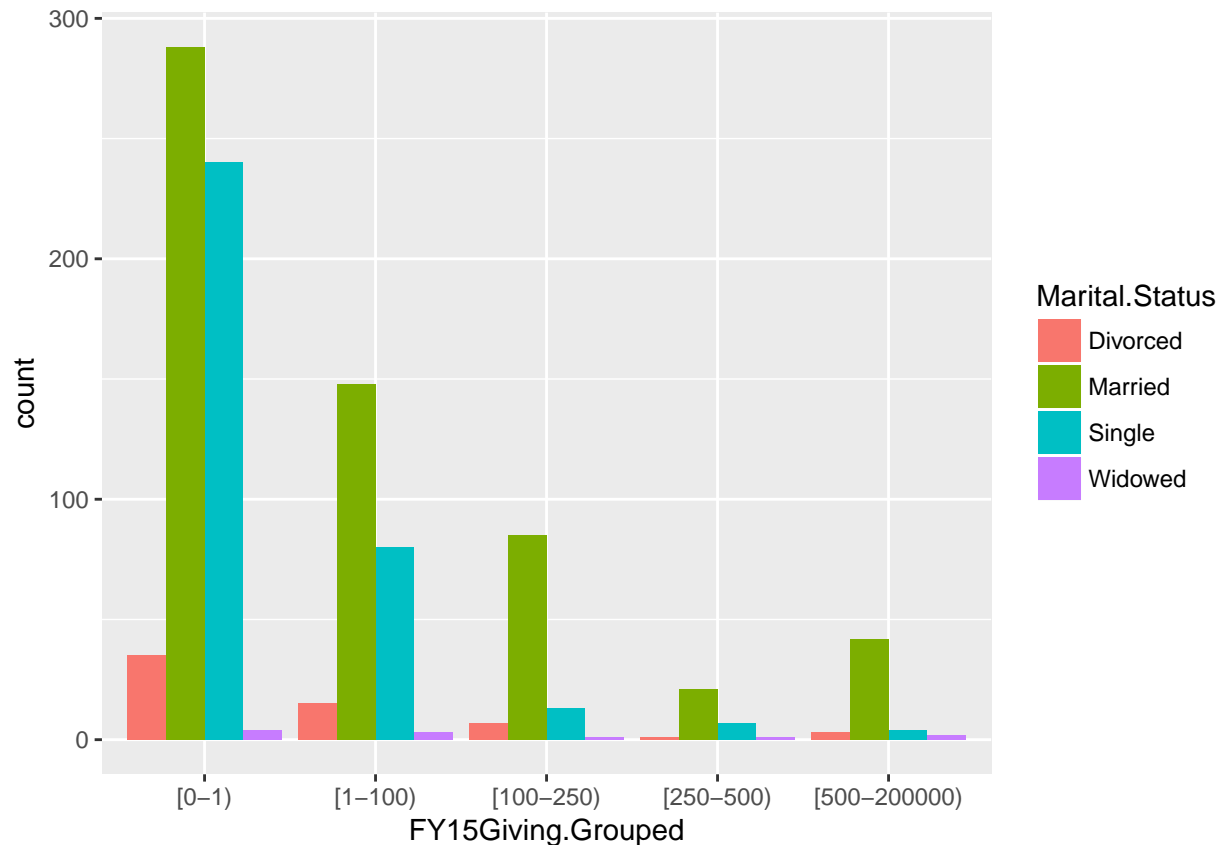
```
assocstats(t17)
```

```
##              X^2 df P(> X^2)
## Likelihood Ratio 58.422 40 0.030033
## Pearson          51.055 40 0.113015
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.22
## Cramer's V        : 0.113
```

DONATION LEVEL VS. MARITAL STATUS

Marital status seems to contribute to amount donated in all fiscal years. Married people give more than single people and larger amounts are disproportionately from married people. Divorced and widowed people tend to give less often

```
ggplot(givings) + geom_bar(mapping = aes(FY15Giving.Grouped,
    fill = Marital.Status), position = "dodge")
```



The Pearson Chi Square and LR tests indicate that we should reject the null hypothesis that marital status and donations in each category are independent of each other (for FY15Giving.Grouped data).

```
# t2 <-xtabs(~FY16Giving.Grouped+Marital.Status,
# data=givings) round(t2/rowSums(t2),2)

# t3 <-xtabs(~FY12Giving.Grouped+Marital.Status,
# data=givings) round(t3/rowSums(t3),2)

# t4 <-xtabs(~FY13Giving.Grouped+Marital.Status,
# data=givings) round(t4/rowSums(t4),2)

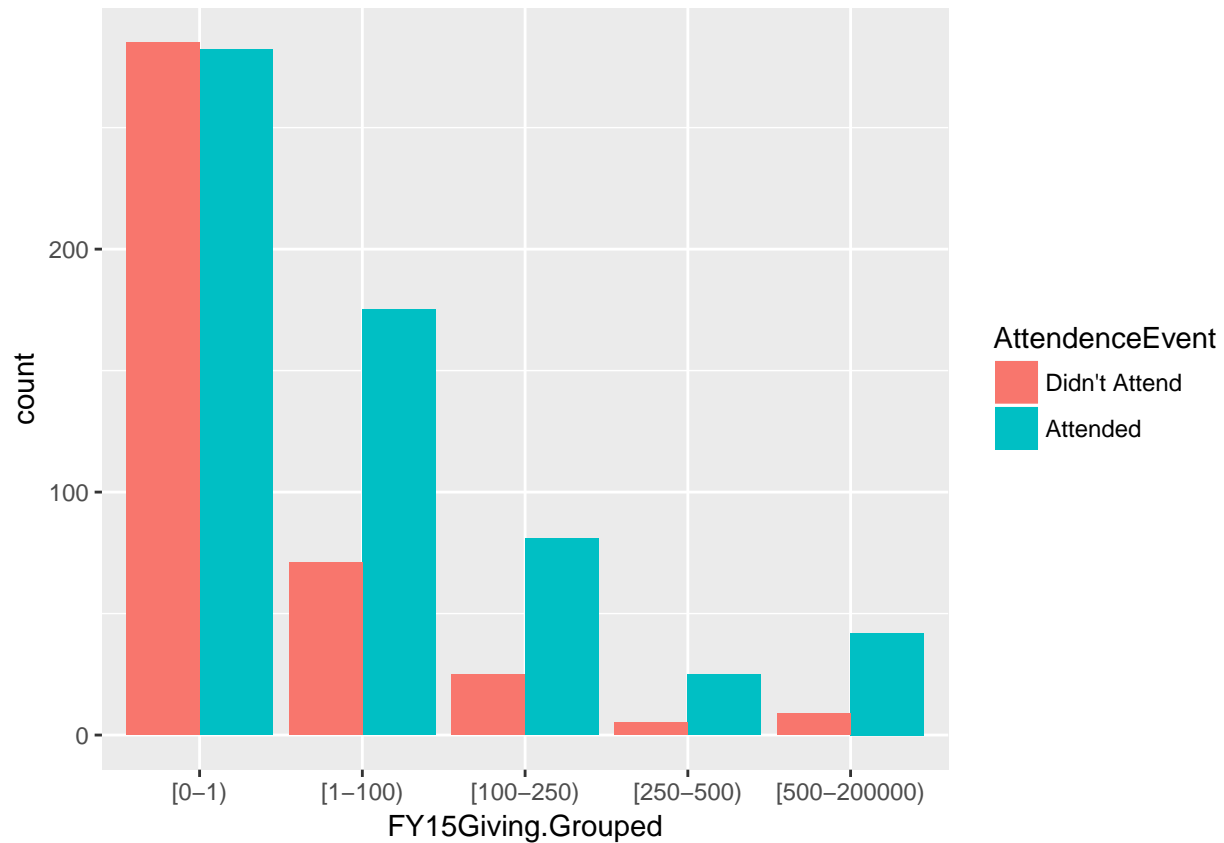
# t5 <-xtabs(~FY14Giving.Grouped+Marital.Status,
# data=givings) round(t5/rowSums(t5),2)

t6 <- xtabs(~FY15Giving.Grouped + Marital.Status, data = givings)
# round(t6/rowSums(t6),2)
assocstats(t6)
```

```
##                X^2 df    P(> X^2)
## Likelihood Ratio 69.849 12 3.4178e-10
## Pearson         63.641 12 4.8571e-09
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.245
## Cramer's V       : 0.146
```

DONATION LEVEL VS. ATTENDANCE EVENTS

```
ggplot(givings) + geom_bar(mapping = aes(FY15Giving.Grouped,
  fill = AttendanceEvent), position = "dodge")
```



People who attended events are more likely to give in every donation level category (FY15 dependent on attendance of events).

```
# t12 <-xtabs(~FY16Giving.Grouped+AttendanceEvent,
# data=givings) round(t12/rowSums(t12),2)

# t13 <-xtabs(~FY12Giving.Grouped+AttendanceEvent,
# data=givings) round(t13/rowSums(t13),2)

# t14 <-xtabs(~FY13Giving.Grouped+AttendanceEvent,
# data=givings) round(t14/rowSums(t14),2)

# t15 <-xtabs(~FY14Giving.Grouped+AttendanceEvent,
# data=givings) round(t15/rowSums(t15),2)

t16 <- xtabs(~FY15Giving.Grouped + AttendanceEvent, data = givings)
round(t16/rowSums(t16), 2)
```

```
##           AttendanceEvent
## FY15Giving.Grouped Didn't Attend Attended
##      [0-1)           0.50      0.50
##      [1-100)         0.29      0.71
```

```
##      [100-250)          0.24    0.76
##      [250-500)          0.17    0.83
##      [500-200000)       0.18    0.82
```

```
assocstats(t16)
```

```
##              X^2 df    P(> X^2)
## Likelihood Ratio 69.834  4 2.4647e-14
## Pearson          67.114  4 9.2260e-14
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.251
## Cramer's V        : 0.259
```

Wanted to check in general if attending events increased chance of donating (independent of size of donation). It does.

```
donated.attendanceTable = xtabs(~donatedFY15 + AttendanceEvent,
  data = givings)
donated.attendanceTable
```

```
##              AttendanceEvent
## donatedFY15  Didn't Attend Attended
## [0-1)                285      282
## [1-100)              71      175
## [100-250)            25      81
## [250-500)            5      25
## [500-200000)         9      42
```

```
prop.table(donated.attendanceTable)
```

```
##              AttendanceEvent
## donatedFY15  Didn't Attend Attended
## [0-1)                0.285    0.282
## [1-100)              0.071    0.175
## [100-250)            0.025    0.081
## [250-500)            0.005    0.025
## [500-200000)         0.009    0.042
```

DONATION LEVEL VS. DONATION LEVEL IN PREVIOUS YEAR

Fiscal year 2015 donation levels are very obviously not independent of 2014 giving levels.

```
t0 <- xtabs(~FY15Giving.Grouped + FY14Giving.Grouped, data = givings)
round(t0/rowSums(t0), 2)
```

```
##              FY14Giving.Grouped
## FY15Giving.Grouped [0-1) [1-100) [100-250) [250-500) [500-200000)
## [0-1)              0.80   0.15    0.04    0.01    0.00
## [1-100)            0.28   0.67    0.04    0.01    0.00
## [100-250)          0.18   0.11    0.67    0.02    0.02
## [250-500)          0.17   0.03    0.20    0.57    0.03
## [500-200000)       0.10   0.02    0.08    0.06    0.75
```

```
assocstats(t0)
```

```
##              X^2 df P(> X^2)
## Likelihood Ratio 839.59 16    0
```

```
## Pearson          1647.95 16      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.789
## Cramer's V        : 0.642
```

Preliminary Modeling

```
# i decided to estimate a model for FY15 categorical
# donations. Then we could use the model to evaluate how well
# we predicts FY16 donation patterns.
```

```
# i haven't looked at interaction terms yet! because i haven't
# done bivariate analysis between explanatory variables yet.
```

```
# Proportional Odds Model don't forget to switch the sign of
# the coefficients from the polr function remember that if
# the coefficient for the overall variable is not
# significant, cannot use the coefficients for each
# category.(like in this case Grouped.Major)
```

```
library(MASS)
```

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

```
modell1 <- polr(formula = FY15Giving.Grouped ~ Class.Year + Grouped.Major +
  Marital.Status + AttendanceEvent + FY14Giving.Grouped, data = givings,
  method = "logistic", Hess = TRUE)
```

```
summary(modell1)
```

```
## Call:
## polr(formula = FY15Giving.Grouped ~ Class.Year + Grouped.Major +
##      Marital.Status + AttendanceEvent + FY14Giving.Grouped, data = givings,
##      Hess = TRUE, method = "logistic")
##
## Coefficients:
##              Value Std. Error  t value
## Class.Year1982   -0.7093961    0.2707  -2.620370
## Class.Year1992   -0.9156060    0.2717  -3.369593
## Class.Year2002   -0.8331680    0.2736  -3.045228
## Class.Year2012   -0.9270929    0.2774  -3.342253
## Grouped.MajorSocialScience    0.3655454    0.2274   1.607315
## Grouped.MajorFineArts        -0.3304133    0.3300  -1.001388
## Grouped.MajorSciences        -0.1389501    0.2611  -0.532240
## Grouped.MajorForeignLanguages -0.2818735    0.3438  -0.819760
## Grouped.MajorComputerScience_Engineering  0.3430542    1.2490   0.274672
## Grouped.MajorBusiness_Economics -0.0006069    0.3047  -0.001992
```

```
## Grouped.MajorEducation          0.1460583      0.6529  0.223722
## Grouped.MajorMultidisciplinaryStudies 0.6734920      0.5213  1.292001
## Grouped.MajorMathematics         0.6725754      0.3932  1.710664
## Grouped.MajorPhilosophyReligion    0.2092423      0.3711  0.563894
## Marital.StatusMarried             0.2534578      0.3120  0.812313
## Marital.StatusSingle             -0.0472717      0.3407 -0.138756
## Marital.StatusWidowed            0.2101301      0.7123  0.294989
## AttendanceEventAttended           0.5235779      0.1581  3.312523
## FY14Giving.Grouped[1-100)         1.8172014      0.1651 11.007321
## FY14Giving.Grouped[100-250)       3.7885789      0.2560 14.797157
## FY14Giving.Grouped[250-500)       5.4430930      0.4474 12.165445
## FY14Giving.Grouped[500-200000)    8.8663695      0.6388 13.878800
##
## Intercepts:
##                               Value Std. Error t value
## [0-1) | [1-100)              1.2250  0.4086   2.9983
## [1-100) | [100-250)          3.3666  0.4266   7.8925
## [100-250) | [250-500)        5.4893  0.4680  11.7303
## [250-500) | [500-200000)     6.8422  0.5236  13.0675
##
## Residual Deviance: 1596.823
## AIC: 1648.823
```

```
Anova(model1)
```

```
## Analysis of Deviance Table (Type II tests)
```

```
##
```

```
## Response: FY15Giving.Grouped
```

```
##               LR Chisq Df Pr(>Chisq)
## Class.Year      13.42  4  0.0093964 **
## Grouped.Major   15.83 10  0.1046168
## Marital.Status   3.45  3  0.3268428
## AttendanceEvent  11.12  1  0.0008534 ***
## FY14Giving.Grouped 544.49 4 < 2.2e-16 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
model1b <- polr(formula = FY15Giving.Grouped ~ Class.Year + Marital.Status +
  AttendanceEvent + FY14Giving.Grouped, data = givings, method = "logistic",
  Hess = TRUE)
```

```
summary(model1b)
```

```
## Call:
```

```
## polr(formula = FY15Giving.Grouped ~ Class.Year + Marital.Status +
##   AttendanceEvent + FY14Giving.Grouped, data = givings, Hess = TRUE,
##   method = "logistic")
##
```

```
## Coefficients:
```

```
##                               Value Std. Error t value
## Class.Year1982                -0.69820      0.2607 -2.6779
## Class.Year1992                -0.95841      0.2594 -3.6944
## Class.Year2002                -0.89040      0.2597 -3.4289
## Class.Year2012                -0.99215      0.2652 -3.7414
## Marital.StatusMarried          0.35589      0.3123  1.1394
```



```
## Marital.StatusSingle      0.08707      0.3407  0.2556
## Marital.StatusWidowed     0.16109      0.6769  0.2380
## AttendanceEventAttended   0.57275      0.1567  3.6554
## FY14Giving.Grouped[1-100) 1.77963      0.1629 10.9269
## FY14Giving.Grouped[100-250) 3.71902      0.2533 14.6806
## FY14Giving.Grouped[250-500) 5.38642      0.4411 12.2106
## FY14Giving.Grouped[500-200000) 8.76459      0.6352 13.7990
##
## Intercepts:
##               Value Std. Error t value
## [0-1) | [1-100)    1.1989  0.3571   3.3574
## [1-100) | [100-250) 3.3073  0.3762   8.7905
## [100-250) | [250-500) 5.4125  0.4229  12.7993
## [250-500) | [500-200000) 6.7597  0.4832  13.9898
##
## Residual Deviance: 1612.653
## AIC: 1644.653
```

```
Anova(model1b)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: FY15Giving.Grouped
##               LR Chisq Df Pr(>Chisq)
## Class.Year      16.87  4  0.0020444 **
## Marital.Status    3.51  3  0.3195330
## AttendanceEvent   13.58  1  0.0002282 ***
## FY14Giving.Grouped 540.21  4  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# they kind of suggested we should compare against
# multinomial regression
```

```
library(nnet)
```

```
model2 <- multinom(formula = FY15Giving.Grouped ~ Class.Year +
  Grouped.Major + Marital.Status + AttendanceEvent + FY14Giving.Grouped,
  data = givings)
```

```
## # weights: 120 (92 variable)
## initial value 1609.437912
## iter 10 value 843.008425
## iter 20 value 693.932143
## iter 30 value 680.087189
## iter 40 value 679.049338
## iter 50 value 678.820096
## iter 60 value 678.734454
## iter 70 value 678.695055
## iter 80 value 678.687982
## iter 90 value 678.687439
## final value 678.687321
## converged
```

```
Anova(model2)
```

```
## Analysis of Deviance Table (Type II tests)
```

```
##
## Response: FY15Giving.Grouped
##           LR Chisq Df Pr(>Chisq)
## Class.Year      36.77 16  0.002262 **
## Grouped.Major    53.60 40  0.073699 .
## Marital.Status   12.11 12  0.436814
## AttendanceEvent   14.57  4  0.005685 **
## FY14Giving.Grouped 683.03 16 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

model2a <- multinom(formula = FY15Giving.Grouped ~ Class.Year +
  Marital.Status + AttendanceEvent + FY14Giving.Grouped, data = givings)
```

```
## # weights: 70 (52 variable)
## initial value 1609.437912
## iter 10 value 770.401719
## iter 20 value 711.289384
## iter 30 value 706.027509
## iter 40 value 705.510178
## iter 50 value 705.492502
## iter 60 value 705.488753
## final value 705.488020
## converged
```

```
Anova(model2a)
```

```
## Analysis of Deviance Table (Type II tests)
##
## Response: FY15Giving.Grouped
##           LR Chisq Df Pr(>Chisq)
## Class.Year      39.83 16  0.0008255 ***
## Marital.Status   12.51 12  0.4059224
## AttendanceEvent   17.55  4  0.0015091 **
## FY14Giving.Grouped 687.12 16 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We might want to switch base level of Class.Year to 2012 instead of 1972. As EDA suggests, Major doesn't seem significant in either model.

```
# here we predict estimated probability of being in a certain
# amount donated category based on values of explanatory
# variables we choose - can we feed in the FY15 dataframe to
# get out predictions for 2016?. Or should we just give
# specific combinations of variables that we think are the
# most interesting/enlightening?
```

```
# We probably compare and contrast predictions for
# multinomial regression vs ordinal regression like he did in
# the LiveSession04_v3_JY document.
```

Predictive problems:

-very few of some of majors, not good ability to predict how much people with those majors are likely to donate - this may not matter depending on whether major is significant in our final model.

Also, there very few large donations every year -usually less than 25 people who give 250-500 dollars and less

than 25 people who give 500+ dollars. It may be hard to predict who are the highest donors. For instance, it seems like men may make large donations more frequently than women, but the difference is not significantly different. Maybe if we had higher numbers, we would see a trend exists there?

I will create a "next degree" grouping (i didn't explore this variable yet): thinking of doing "bachelors", "graduate level degree", "none". Or should i make it more granular ie. split into MBA, MD, JD, etc ? Or try to guess which degrees are "professional degrees" - like MBA, MD, JD vs masters and PhD?