Lab 6

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#Visualization with the package ggplot2

I highly recommend using the [ggplot cheat sheet](https://rstudio.com/wp-content/uploads/2015/03/ggplot2

Load up the `GSSvocab` dataset in package `carData` as `X` and drop all observations with missing measurements.

```
#Turn off warnings
options(warn = -1)


pacman::p_load(carData)

data(GSSvocab)

GSSvocab = na.omit(GSSvocab)

?GSSvocab
```

```
## starting httpd help server ... done
```

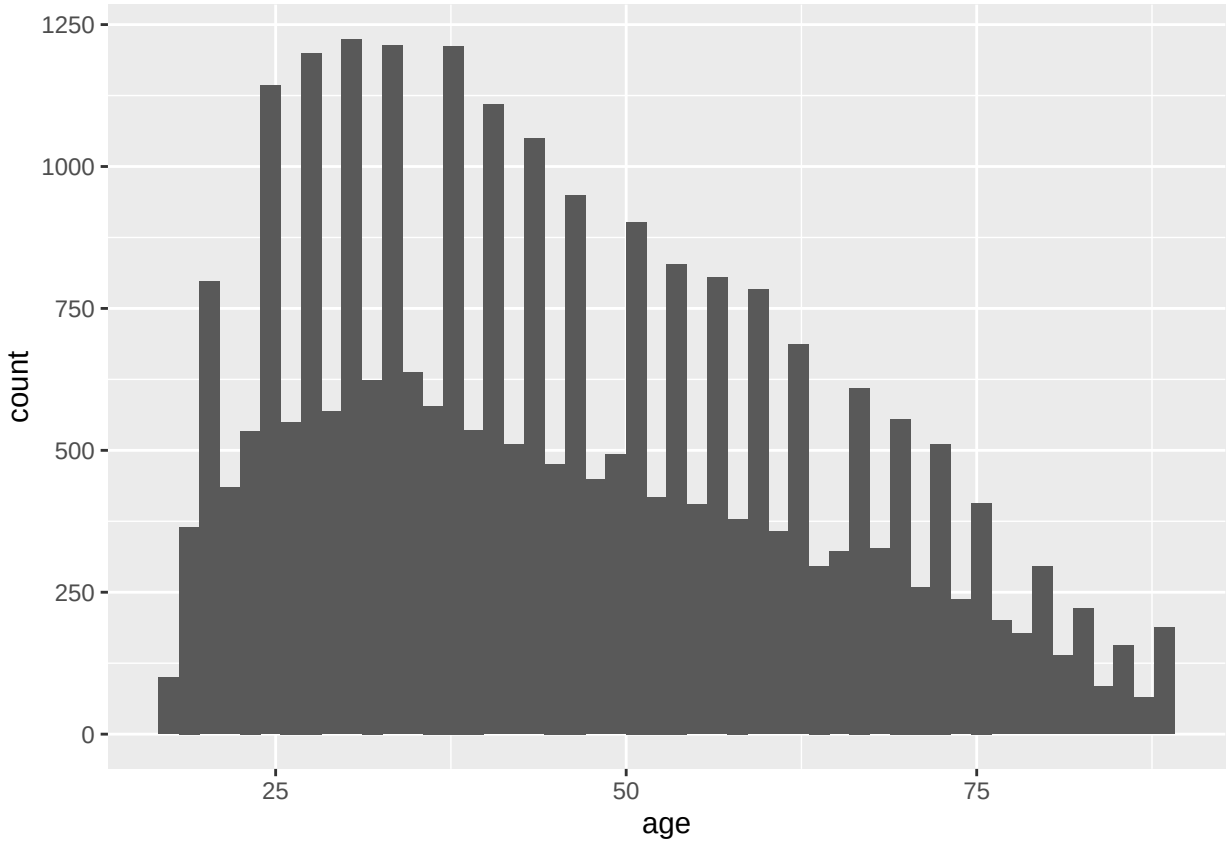
Briefly summarize the documentation on this dataset. What is the data type of each variable? What do you think is the response variable the collectors of this data had in mind?

We see that this data set will consist of 8 different factors the year, a continuous variable, the gen

Create two different plots and identify the best-looking plot you can to examine the `age` variable. Save the best looking plot as an appropriately-named PDF.

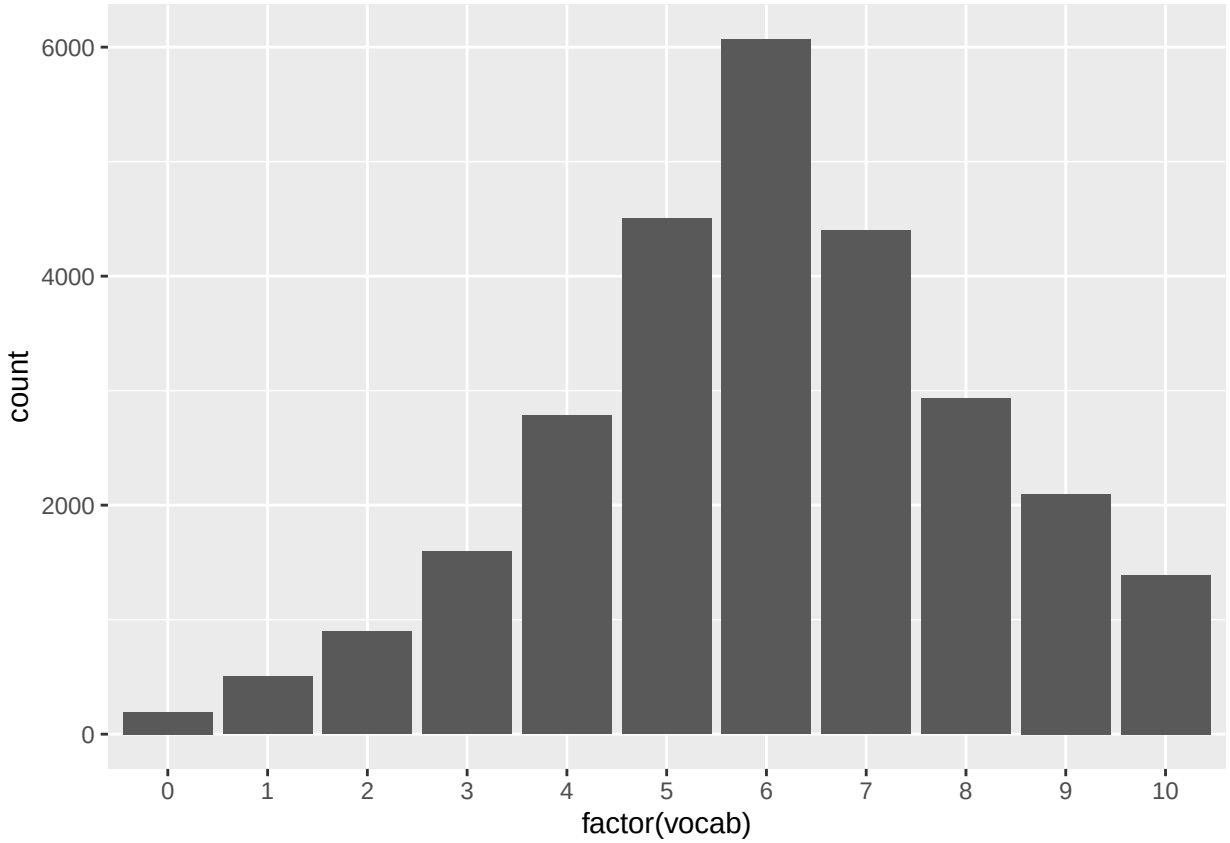
```
pacman::p_load(ggplot2)

ggplot(GSSvocab) +
    aes(x = age) +
    geom_histogram(bins = 50)
```



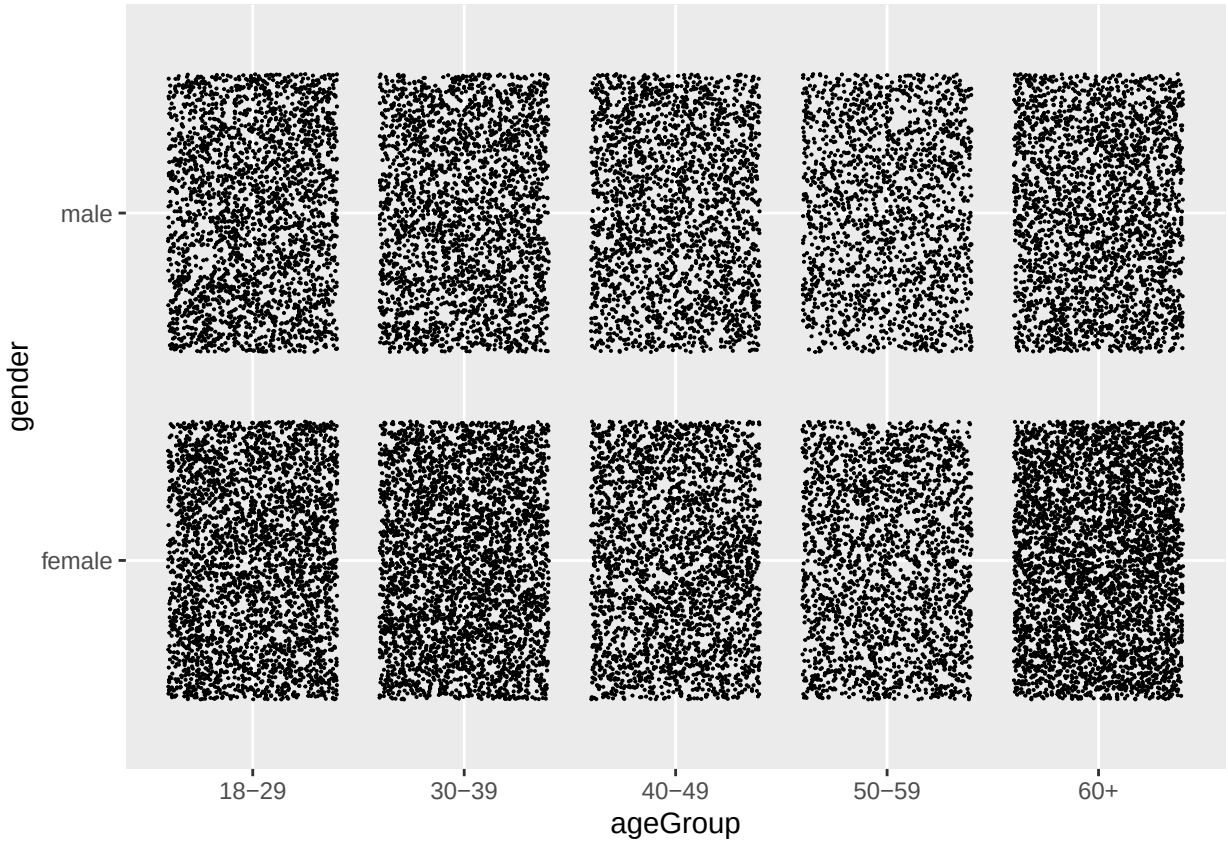
Create two different plots and identify the best looking plot you can to examine the `vocab` variable. Save the best looking plot as an appropriately-named PDF.

```
ggplot(GSSvocab) +
    aes(x = factor(vocab)) +
    geom_bar()
```



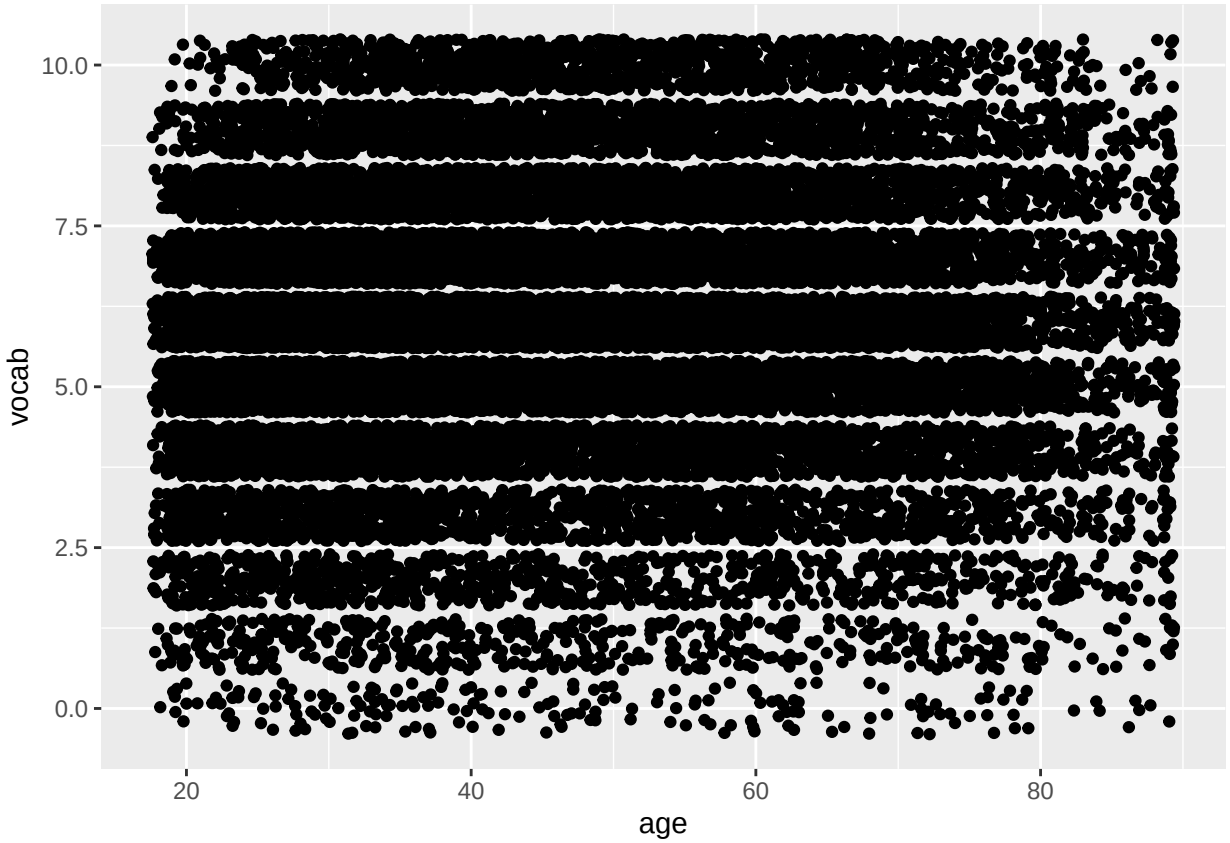
Create the best-looking plot you can to examine the `ageGroup` variable by `gender`. Does there appear to be an association? There are many ways to do this.

```
ggplot(GSSvocab) +
    aes(x = ageGroup, y = gender) +
    geom_jitter(size = .05)
```



Create the best-looking plot you can to examine the `vocab` variable by `age`. Does there appear to be an association?

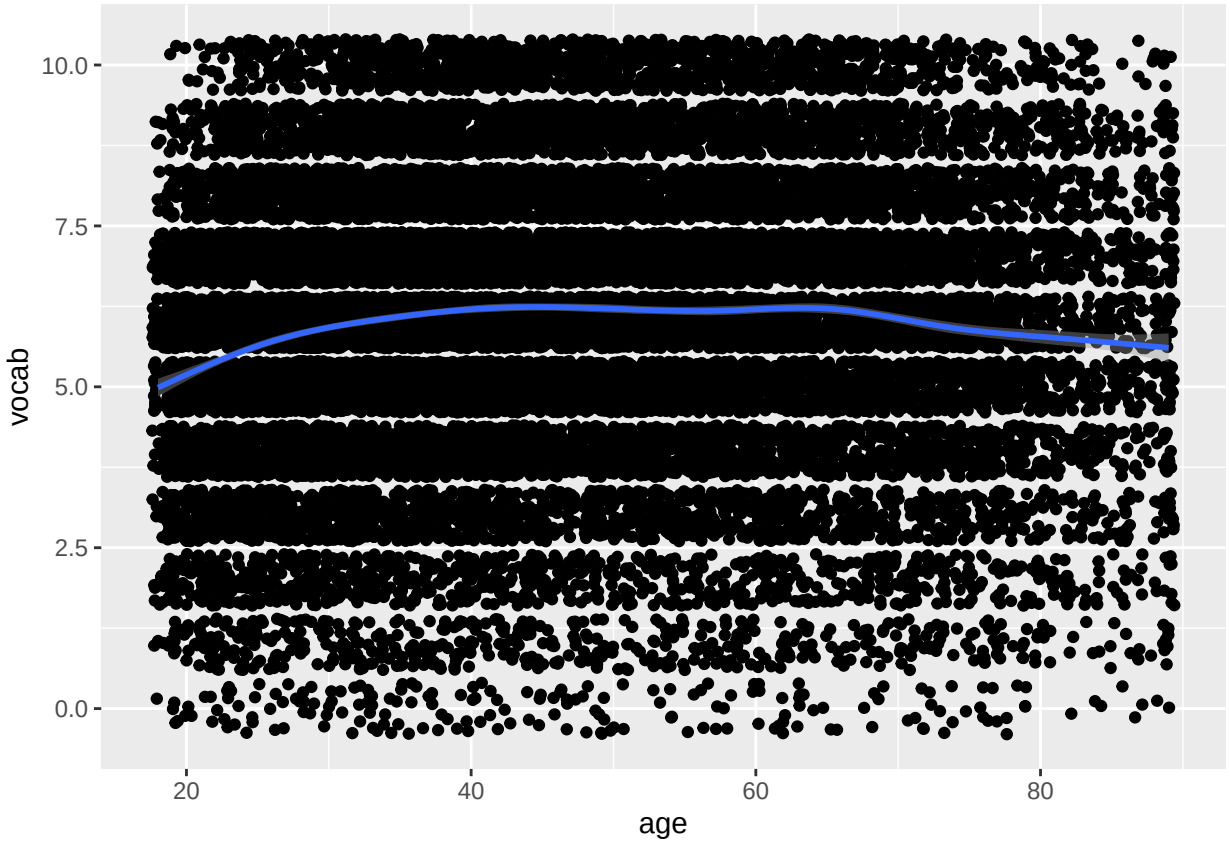
```
ggplot(GSSvocab) +
    aes(x = age, y = vocab) +
    geom_jitter()
```



Add an estimate of $f(x)$ using the smoothing geometry to the previous plot. Does there appear to be an association now?

```
ggplot(GSSvocab) +
    aes(x = age, y = vocab) +
    geom_jitter() +
    geom_smooth()
```

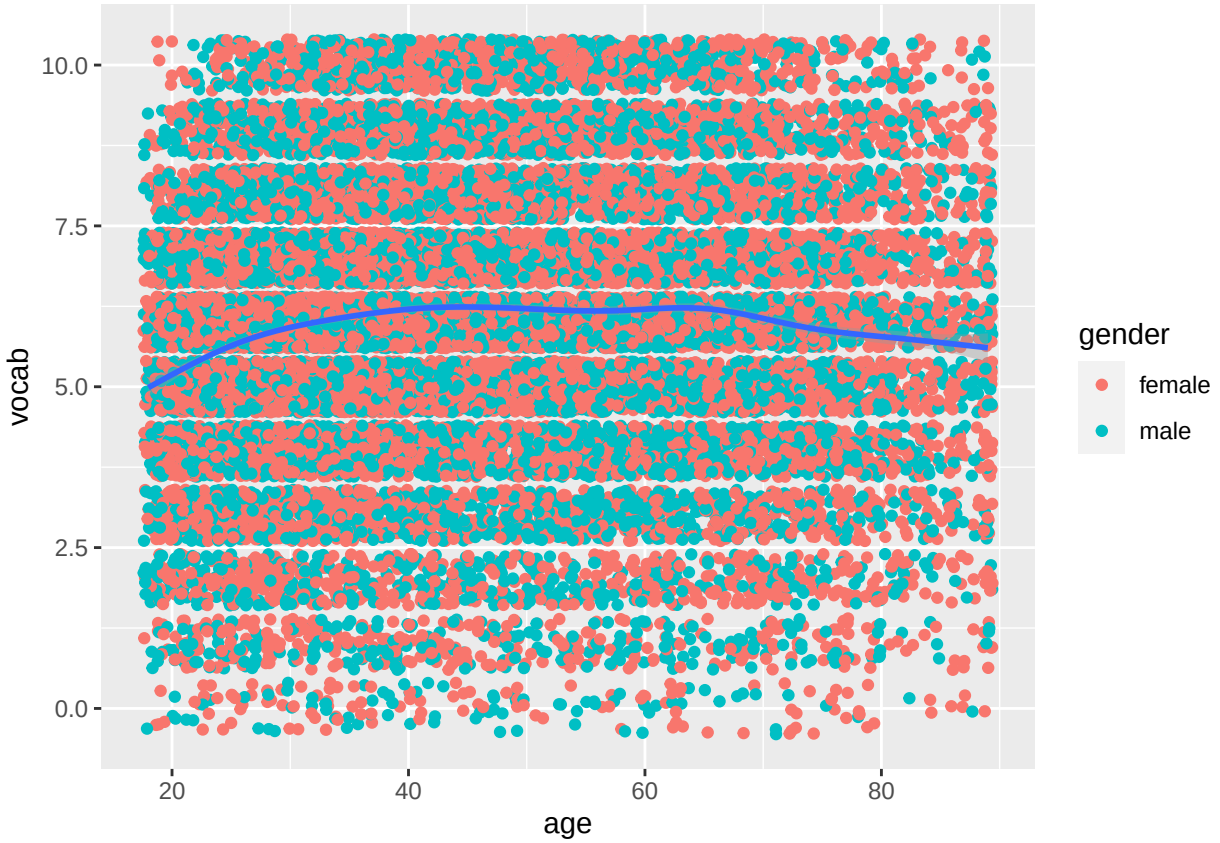
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



Using the plot from the previous question, create the best looking overloading with variable `gender`. Does there appear to be an interaction of `gender` and `age`?

```
ggplot(GSSvocab) +
    aes(x = age, y = vocab) +
    geom_jitter(aes(col = gender)) +
    geom_smooth()
```

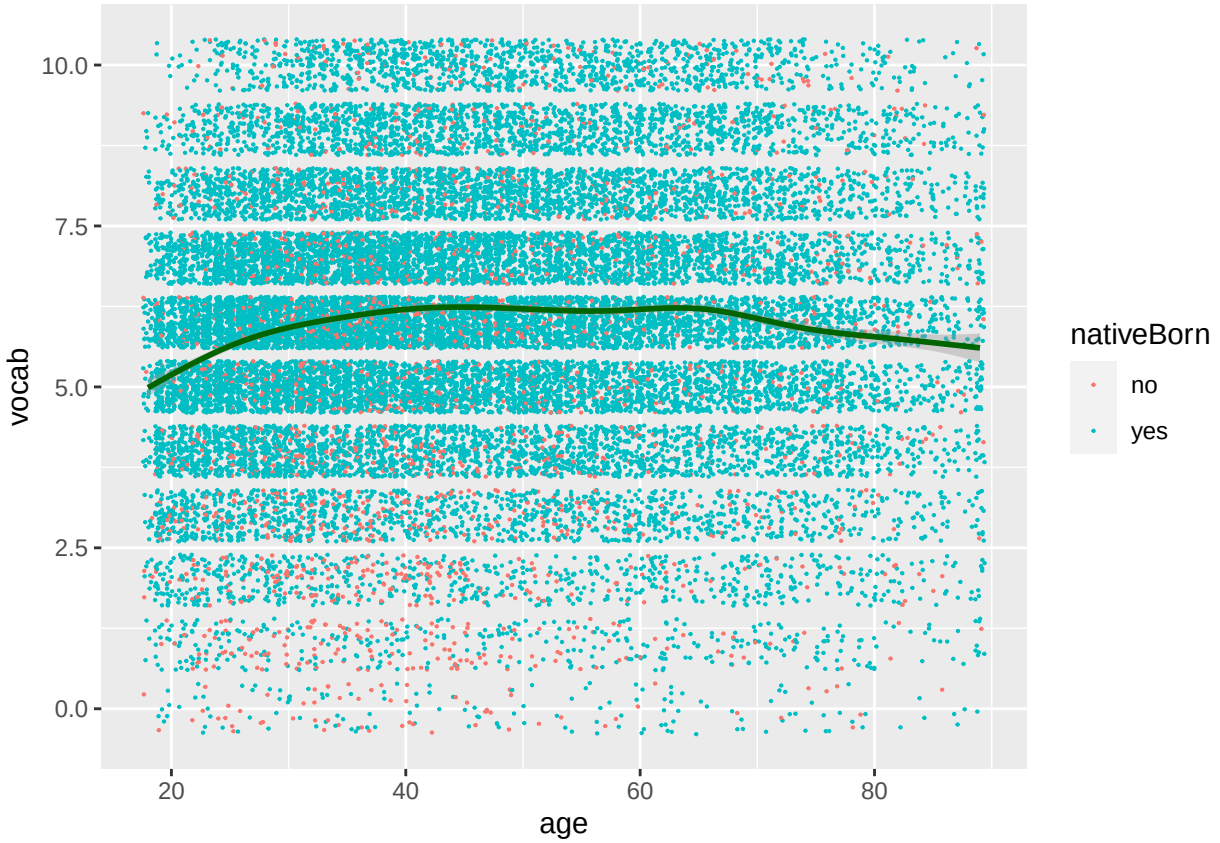
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



Using the plot from the previous question, create the best looking overloading with variable `nativeBorn`. Does there appear to be an interaction of `nativeBorn` and `age`?

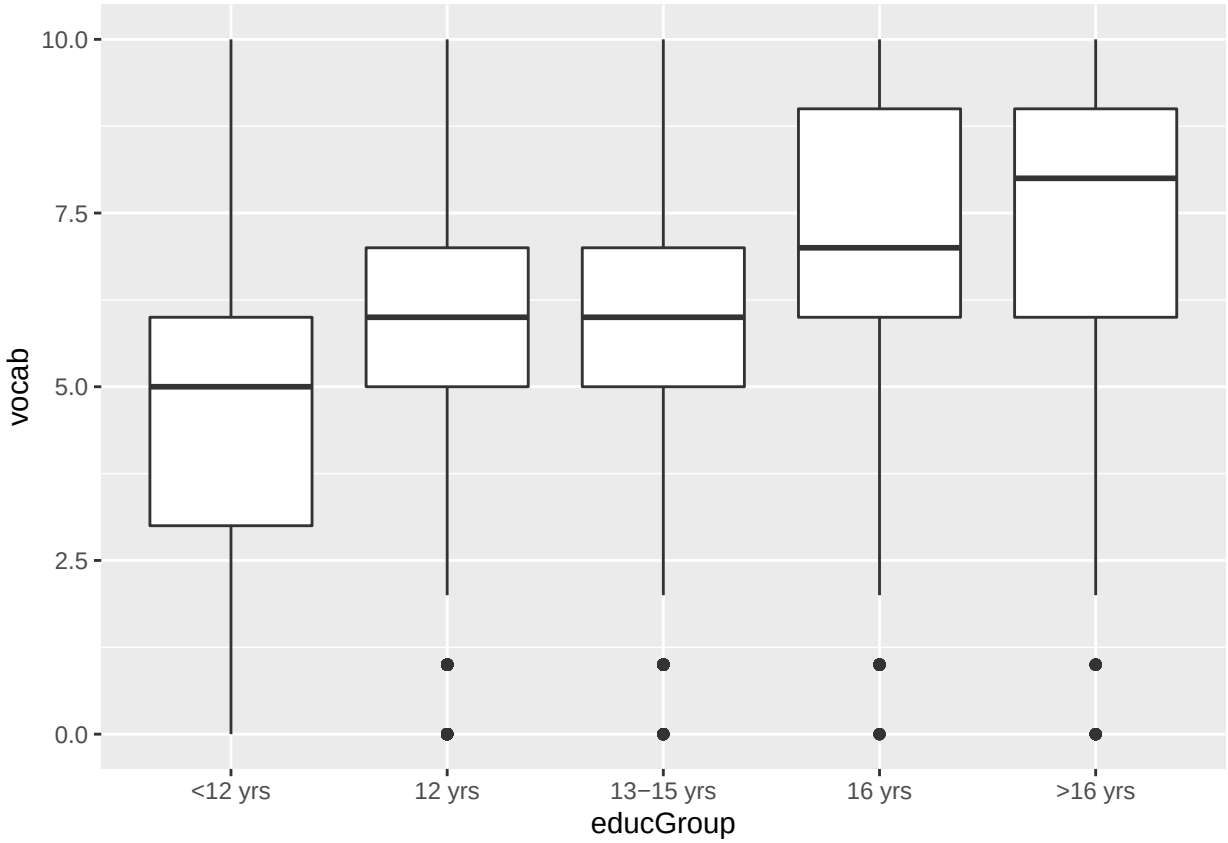
```
ggplot(GSSvocab) +
    aes(x = age, y = vocab) +
    geom_jitter(aes(col = nativeBorn), size = .1) +
    geom_smooth(col = "darkgreen")
```

```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```

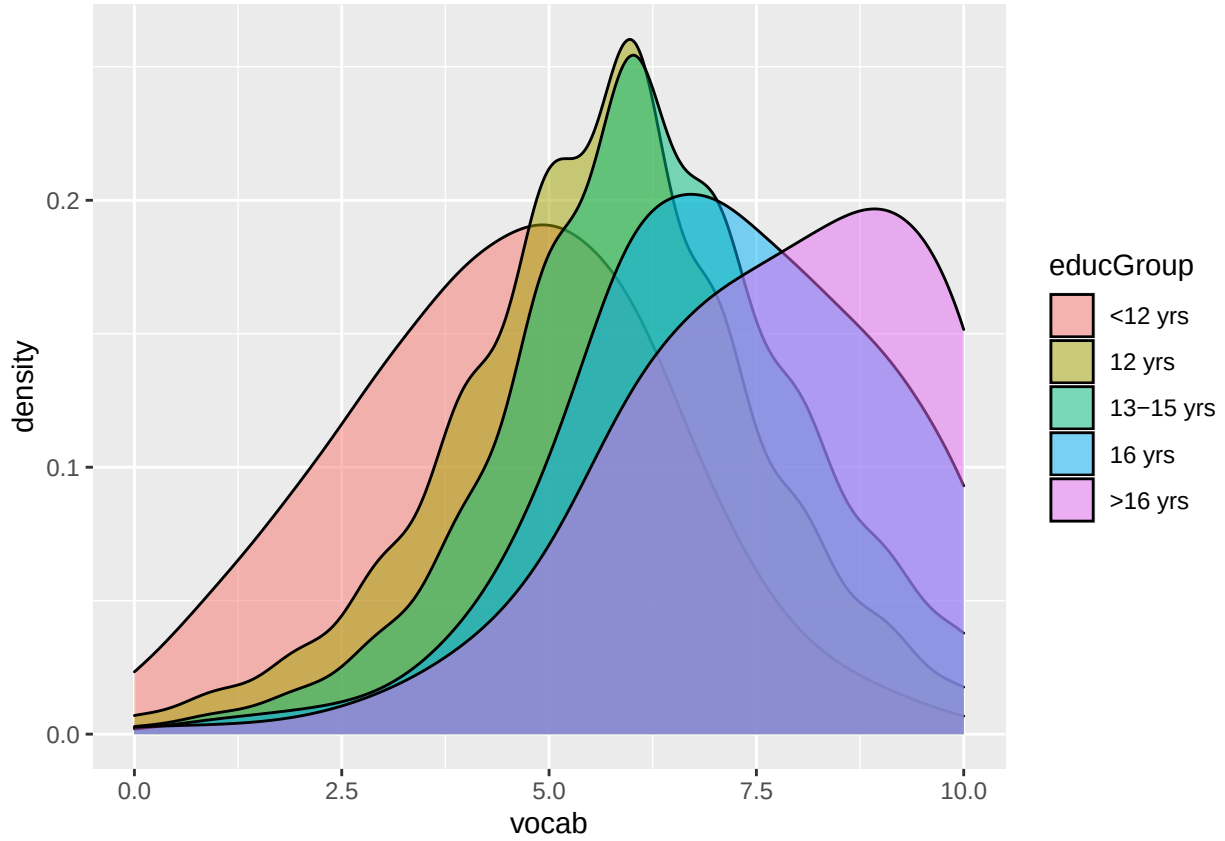


Create two different plots and identify the best-looking plot you can to examine the `vocab` variable by `educGroup`. Does there appear to be an association?

```
ggplot(GSSvocab) +
    aes(x = educGroup, y = vocab) +
    geom_boxplot()
```

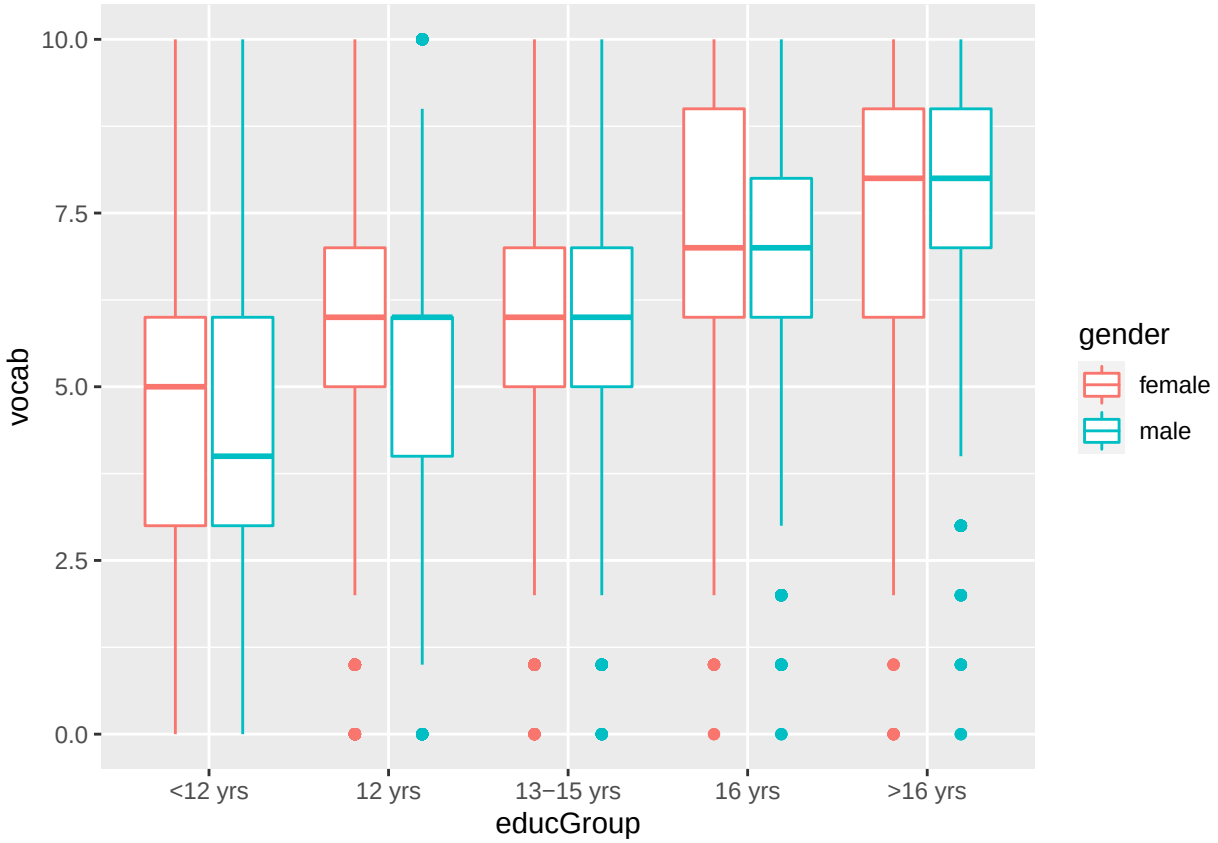



```
ggplot(GSSvocab) +
    aes(x = vocab) +
    geom_density(aes(fill = educGroup), adjust = 2, alpha = .5)
```



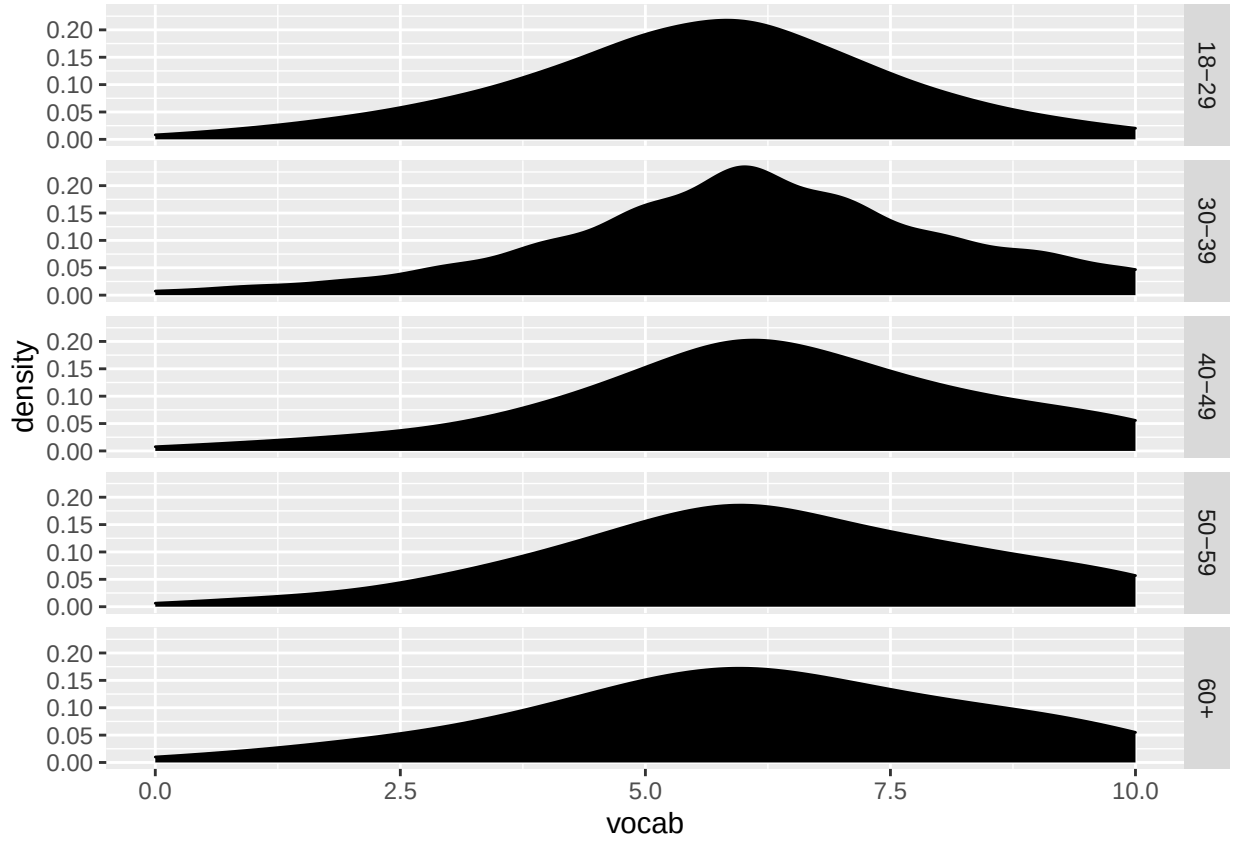
Using the best-looking plot from the previous question, create the best looking overloading with variable `gender`. Does there appear to be an interaction of `gender` and `educGroup`?

```
ggplot(GSSvocab) +
    aes(x = educGroup, y = vocab) +
    geom_boxplot(aes(col = gender))
```



Using facets, examine the relationship between `vocab` and `ageGroup`. You can drop year level `(Other)`. Are we getting dumber?

```
ggplot(GSSvocab) +
    aes(x = vocab) +
    geom_density(adjust = 2, fill = "black") +
    facet_grid(ageGroup ~ .)
```



Probability Estimation and Model Selection

Load up the `adult` in the package `ucidata` dataset and remove missingness and the variable `fnlwgt`:

```
pacman::p_load_gh("coatless/ucidata")

data(adult)
adult = na.omit(adult)
adult$fnlwgt = NULL
```

Cast income to binary where 1 is the `>50K` level.

```
adult$income = ifelse(adult$income == ">50K",1,0)
```

We are going to do some dataset cleanup now. But in every cleanup job, there's always more to clean! So don't expect this cleanup to be perfect.

Firstly, a couple of small things. In variable `marital_status` collapse the levels `Married-AF-spouse` (armed force marriage) and `Married-civ-spouse` (civilian marriage) together into one level called `Married`. Then in variable `education` collapse the levels `1st-4th` and `Preschool` together into a level called `<=4th`.

```
adult$marital_status = as.character(adult$marital_status)

adult$marital_status = ifelse(
```

```
    adult$marital_status == "Married-AF-spouse" | adult$marital_status == "Married-civ-spouse",
    "Married", adult$marital_status
)

adult$marital_status = as.factor(adult$marital_status)

adult$education = as.character(adult$education)

adult$education = ifelse(
    adult$education == "1st-4th" | adult$education == "Preschool",
    "<= 4th",
    adult$education
)

adult$education = as.factor(adult$education)
```

Create a model matrix `Xmm` (for this prediction task) and show that it is *not* full rank (i.e. the result of `ncol` is greater than the result of `Matrix::rankMatrix`).

```
Xmm <- model.matrix(income ~ . , adult)

ncol(Xmm)
```

```
## [1] 95
```

```
Matrix::rankMatrix(Xmm)
```

```
## [1] 94
## attr(,"method")
## [1] "tolNorm2"
## attr(,"useGrad")
## [1] FALSE
## attr(,"tol")
## [1] 6.697087e-12
```

Now tabulate and sort the variable `native_country`.

```
t <- sort(
    table(
        adult$native_country
))
```

Do you see rare levels in this variable? Explain why this may be a problem.

We do see the rare levels in the variable as the computational complexity for the computer starts causes it to be erased.

Collapse all levels that have less than 50 observations into a new level called `other`. This is a very common data science trick that will make your life much easier. If you can't hope to model rare levels, just give up and do something practical! I would recommend first casting the variable to type "character" and then do the level reduction and then recasting back to type `factor`. Tabulate and sort the variable `native_country` to make sure you did it right.

```
adult$native_country = as.character(adult$native_country)

adult$native_country = ifelse(
    adult$native_country %in% names(t[t < 50]),
    "other", adult$native_country
)

adult$native_country = as.factor(adult$native_country)
```

We're still not done getting this data down to full rank. Take a look at the model matrix just for `workclass` and `occupation`. Is it full rank?

```
model <- model.matrix(income ~ workclass + occupation, adult)

ncol(model)
```

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

```
Matrix::rankMatrix(model)
```

```
## [1] 20
## attr(,"method")
## [1] "tolNorm2"
## attr(,"useGrad")
## [1] FALSE
## attr(,"tol")
## [1] 6.697087e-12
```

Not full rank.

These variables are similar and they probably should be interacted anyway eventually. Let's combine them into one factor. Create a character variable named `worktype` that is the result of concatenating `occupation` and `workclass` togetther with a ":" in between. Use the `paste` function with the `sep` argument (this casts automatically to type `character`). Then tabulate its levels and sort.

```
#adult$occupation = as.character(adult$occupation)

#adult$workclass = as.character(adult$workclass)

adult$worktype = paste(adult$occupation, adult$workclass, sep = ":")

tw <- sort(
    table(
        adult$worktype
))

adult$occupation = NULL

adult$workclass = NULL

tw
```

```
##
##           Craft-repair:Without-pay      Handlers-cleaners:Without-pay
##                                  1                                  1
##      Machine-op-inspct:Without-pay          Other-service:Without-pay
##                                  1                                  1
##       Transport-moving:Without-pay     Handlers-cleaners:Self-emp-inc
##                                  1                                  2
##           Adm-clerical:Without-pay          Tech-support:Self-emp-inc
##                                  3                                  3
##       Protective-serv:Self-emp-inc        Farming-fishing:Without-pay
##                                  5                                  6
##   Protective-serv:Self-emp-not-inc                  Sales:Local-gov
##                                  6                                  7
##        Farming-fishing:Federal-gov          Armed-Forces:Federal-gov
##                                  8                                  9
##        Handlers-cleaners:State-gov     Machine-op-inspct:Self-emp-inc
##                                  9                                 10
##        Machine-op-inspct:Local-gov                 Sales:State-gov
##                                 11                                 11
##        Machine-op-inspct:State-gov      Machine-op-inspct:Federal-gov
##                                 13                                 14
##                 Sales:Federal-gov          Farming-fishing:State-gov
##                                 14                                 15
## Handlers-cleaners:Self-emp-not-inc      Handlers-cleaners:Federal-gov
##                                 15                                 22
##       Transport-moving:Federal-gov      Tech-support:Self-emp-not-inc
##                                 24                                 26
##      Transport-moving:Self-emp-inc         Other-service:Self-emp-inc
##                                 26                                 27
##        Protective-serv:Federal-gov          Adm-clerical:Self-emp-inc
##                                 27                                 28
##          Farming-fishing:Local-gov          Other-service:Federal-gov
##                                 29                                 34
## Machine-op-inspct:Self-emp-not-inc             Tech-support:Local-gov
##                                 35                                 38
##         Transport-moving:State-gov        Handlers-cleaners:Local-gov
##                                 41                                 46
##      Adm-clerical:Self-emp-not-inc       Farming-fishing:Self-emp-inc
##                                 49                                 51
##             Craft-repair:State-gov             Tech-support:State-gov
##                                 55                                 56
##           Craft-repair:Federal-gov           Tech-support:Federal-gov
##                                 63                                 66
##          Craft-repair:Self-emp-inc         Transport-moving:Local-gov
##                                 99                                115
##          Protective-serv:State-gov  Transport-moving:Self-emp-not-inc
##                                116                                118
##            Other-service:State-gov             Craft-repair:Local-gov
##                                123                                143
##            Priv-house-serv:Private        Prof-specialty:Self-emp-inc
##                                143                                157
##         Prof-specialty:Federal-gov     Other-service:Self-emp-not-inc
##                                167                                173
##        Exec-managerial:Federal-gov          Exec-managerial:State-gov
```

```
##                                 179                                 186
##            Protective-serv:Private            Other-service:Local-gov
##                                 186                                 189
##          Exec-managerial:Local-gov             Adm-clerical:State-gov
##                                 212                                 250
##             Adm-clerical:Local-gov                 Sales:Self-emp-inc
##                                 281                                 281
##          Protective-serv:Local-gov           Adm-clerical:Federal-gov
##                                 304                                 316
##    Prof-specialty:Self-emp-not-inc             Sales:Self-emp-not-inc
##                                 365                                 376
##   Exec-managerial:Self-emp-not-inc       Exec-managerial:Self-emp-inc
##                                 383                                 385
##           Prof-specialty:State-gov   Farming-fishing:Self-emp-not-inc
##                                 403                                 430
##            Farming-fishing:Private      Craft-repair:Self-emp-not-inc
##                                 450                                 523
##           Prof-specialty:Local-gov              Tech-support:Private
##                                 692                                 723
##           Transport-moving:Private         Handlers-cleaners:Private
##                                1247                                1255
##          Machine-op-inspct:Private            Prof-specialty:Private
##                                1882                                2254
##            Exec-managerial:Private             Other-service:Private
##                                2647                                2665
##               Adm-clerical:Private                       Sales:Private
##                                2793                                2895
##               Craft-repair:Private
##                                3146
```

Like the `native_country` exercise, there are a lot of rare levels. Collapse levels with less than 100 observations to type `other` and then cast this variable `worktype` as type `factor`. Recheck the tabulation to ensure you did this correct.

```
adult$worktype = as.character(adult$worktype)

adult$worktype = ifelse(
    adult$worktype %in% names(tw[tw <100]),
    "other",
    adult$worktype
)

adult$worktype = as.factor(adult$worktype)

tv <- sort(
    table(
        adult$worktype
))

tv
```

```
##
##        Transport-moving:Local-gov         Protective-serv:State-gov
##                                115                                116
```

```
## Transport-moving:Self-emp-not-inc          Other-service:State-gov
##                               118                              123
##           Craft-repair:Local-gov          Priv-house-serv:Private
##                               143                              143
##       Prof-specialty:Self-emp-inc       Prof-specialty:Federal-gov
##                               157                              167
##    Other-service:Self-emp-not-inc      Exec-managerial:Federal-gov
##                               173                              179
##         Exec-managerial:State-gov          Protective-serv:Private
##                               186                              186
##           Other-service:Local-gov        Exec-managerial:Local-gov
##                               189                              212
##            Adm-clerical:State-gov           Adm-clerical:Local-gov
##                               250                              281
##                Sales:Self-emp-inc        Protective-serv:Local-gov
##                               281                              304
##          Adm-clerical:Federal-gov  Prof-specialty:Self-emp-not-inc
##                               316                              365
##            Sales:Self-emp-not-inc Exec-managerial:Self-emp-not-inc
##                               376                              383
##      Exec-managerial:Self-emp-inc         Prof-specialty:State-gov
##                               385                              403
##  Farming-fishing:Self-emp-not-inc          Farming-fishing:Private
##                               430                              450
##     Craft-repair:Self-emp-not-inc         Prof-specialty:Local-gov
##                               523                              692
##              Tech-support:Private                            other
##                               723                             1008
##          Transport-moving:Private        Handlers-cleaners:Private
##                              1247                             1255
##         Machine-op-inspct:Private           Prof-specialty:Private
##                              1882                             2254
##           Exec-managerial:Private            Other-service:Private
##                              2647                             2665
##              Adm-clerical:Private                     Sales:Private
##                              2793                             2895
##              Craft-repair:Private
##                              3146
```

To do at home: merge the two variables `relationship` and `marital_status` together in a similar way to what we did here.

```
adult$relationship = as.character(adult$relationship)

adult$marital_status = as.character(adult$marital_status)

adult$status = paste(adult$relationship, adult$marital_status, sep = ":")

adult$status = as.character(adult$status)

ts <- sort(
    table(
        adult$status
))
```

```
adult$relationship = NULL
adult$marital_status = NULL

adult$status = as.factor(adult$status)

ts
```

```
##
##                     Own-child:Widowed                Not-in-family:Married
##                                    12                                   14
## Other-relative:Married-spouse-absent                Other-relative:Widowed
##                                    26                                   40
##      Own-child:Married-spouse-absent             Other-relative:Separated
##                                    43                                   53
##                     Own-child:Married                 Own-child:Separated
##                                    84                                   90
##              Other-relative:Divorced                Other-relative:Married
##                                   103                                  119
##      Unmarried:Married-spouse-absent  Not-in-family:Married-spouse-absent
##                                   120                                  181
##                    Own-child:Divorced                   Unmarried:Widowed
##                                   308                                  343
##              Not-in-family:Separated                 Unmarried:Separated
##                                   383                                  413
##                Not-in-family:Widowed         Other-relative:Never-married
##                                   432                                  548
##              Unmarried:Never-married                          Wife:Married
##                                   801                                 1406
##                    Unmarried:Divorced               Not-in-family:Divorced
##                                  1535                                 2268
##              Own-child:Never-married          Not-in-family:Never-married
##                                  3929                                 4447
##                       Husband:Married
##                                 12463
```

We are finally ready to fit some probability estimation models for `income`! In lecture 16 we spoke about model selection using a cross-validation procedure. Let's build this up step by step. First, split the dataset into `Xtrain`, `ytrain`, `Xtest`, `ytest` using K=5.

```
K = 5
p = 1 / K
trainindices = sample(1 : nrow(adult), round((1 - p) * nrow(adult)))


adult_train = adult[trainindices, ]

ytrain = adult_train$income
Xtrain = adult_train

Xtrain$income = NULL

testindices = setdiff(1 : nrow(adult), trainindices)
```

```
adult_test = adult[testindices, ]

ytest = adult_test$income
Xtest = adult_test

Xtest$income = NULL
```

Create the following four models on the training data in a `list` objected named `prob_est_mods`: logit, probit, cloglog and cauchit (which we didn't do in class but might as well). For the linear component within the link function, just use the vanilla raw features using the `formula` object `vanilla`. Each model's key in the list is its link function name + "-vanilla". One for loop should do the trick here.

```
link_functions = c("logit", "probit", "cloglog", "cauchit")
vanilla = income ~ .
prob_est_mods = list()

for(link_function in link_functions) {
  prob_est_mods[[ paste(link_function, "vanilla", sep ="-")]] =
    glm(vanilla,
            adult_train,
            family = binomial(link = link_function)
    )
}
```

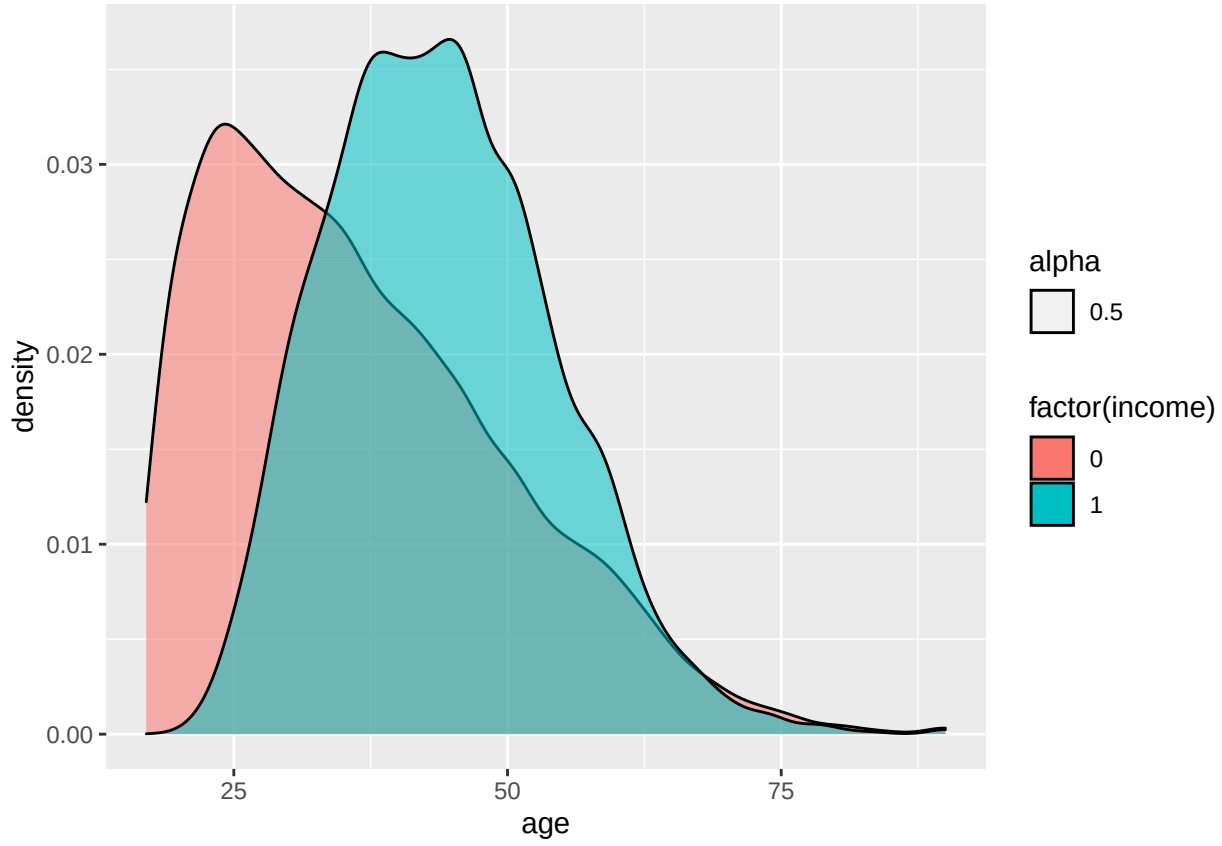
Now let's get fancier. Let's do some variable transforms. Add `log_capital_loss` derived from `capital_loss` and `log_capital_gain` derived from `capital_gain`. Since there are zeroes here, use log_x = log(1 + x) instead of log_x = log(x). That's always a neat trick. Just add them directly to the data frame so they'll be picked up with the `.` inside of a formula.

```
adult$log_capital_loss = log(1 + adult$capital_loss)

adult$log_capital_gain = log(1 + adult$capital_gain)
```

Create a density plot that shows the age distribution by `income`.

```
ggplot(adult) + aes(x = age) +
  geom_density(aes(alpha = 0.5, fill = factor(income)))
```



What do you see? Is this expected using common sense?

We can see that 0 is all the people who have made less than 50k and 1 is all the people who have made more than 50k. As age increases people tend to get better jobs.
This does make sense as 0 represents the people who have made less than 50,000 and 1 represents people who make greater than 50,000. As age increases, it makes sense that income also increases.

Now let's fit the same models with all link functions on a formula called `age_interactions` that uses interactions for `age` with all of the variables. Add all these models to the `prob_est_mods` list.

```
age_interactions = income ~. *age
for (link_function in link_functions) {
  prob_est_mods[[paste(link_function, "age_interactions", sep = "-")]] =
    glm(age_interactions,
            adult_train,
            family = binomial(link = link_function)
    )
}
```

Create a function called `brier_score` that takes in a probability estimation model, a dataframe `X` and its responses `y` and then calculates the brier score.

```
brier_score = function(prob_est_mod, X, y) {
 pHat <- predict(prob_est_mod, X, type = "response")
 return(mean(-(y - pHat) ^ 2))
}
```

Now, calculate the in-sample Brier scores for all models. You can use the function `lapply` to iterate over the list and pass in in the function `brier_score`.

```
lapply(prob_est_mods, brier_score, Xtrain, ytrain)
```

```
## $`logit-vanilla`
## [1] -0.1022602
##
## $`probit-vanilla`
## [1] -0.1023346
##
## $`cloglog-vanilla`
## [1] -0.1030941
##
## $`cauchit-vanilla`
## [1] -0.1037822
##
## $`logit-age_interactions`
## [1] -0.1008111
##
## $`probit-age_interactions`
## [1] -0.1009454
##
## $`cloglog-age_interactions`
## [1] -0.1018934
##
## $`cauchit-age_interactions`
## [1] -0.2029922
```

Now, calculate the out-of-sample Brier scores for all models. You can use the function `lapply` to iterate over the list and pass in the function `brier_score`.

```
lapply(prob_est_mods, brier_score, Xtest, ytest)
```

```
## $`logit-vanilla`
## [1] -0.1070876
##
## $`probit-vanilla`
## [1] -0.1069477
##
## $`cloglog-vanilla`
## [1] -0.1082288
##
## $`cauchit-vanilla`
## [1] -0.1095445
##
## $`logit-age_interactions`
## [1] -0.1065723
##
## $`probit-age_interactions`
## [1] -0.1064785
##
## $`cloglog-age_interactions`
```

```
## [1] -0.1081201
##
## $`cauchit-age_interactions`
## [1] -0.2133621
```

Which model wins in sample and which wins out of sample? Do you expect these results? Explain.

From the results above, we see that the logit model is superior against the rest with the probit model trailing. Both logit and probit models seem to be the best models to use.

What is wrong with this model selection procedure? There are a few things wrong.

One issue with this model is the splitting of the testing and training data. Because we are also not doing any k fold validation, our error will be more off.

Run all the models again. This time do three splits: subtrain, select and test. After selecting the best model, provide a true oos Brier score for the winning model.

```
n = nrow(adult)
K = 5

testindices = sample(1 : n, size = n * 1 / K)
mastertrainindices = setdiff(1 : n, testindices)

selectindices = sample(mastertrainindices, size = n * 1 / K)
subtrainindices = setdiff(mastertrainindices, selectindices)


adultTrain <- adult[mastertrainindices, ]

adultsubtrain = adult[subtrainindices, ]
ysubtrain = adultsubtrain$income
adultselect = adult[selectindices, ]
yselect = adultselect$income

adulttest = adult[testindices, ]
ytest = adulttest$income

mods = list()

for (link_function in link_functions){
  mods[[paste(link_function, "vanilla", sep = "-")]]=
    glm(formula = vanilla, data = adultsubtrain, family = binomial(link=link_function))
}

for (link_function in link_functions){
  mods[[paste(link_function, "age_interactions", sep = "-")]]=
    glm(formula = age_interactions, data = adultsubtrain, family = binomial(link=link_function))
}



briers = lapply(mods, brier_score, adultselect, yselect)

final = which.max(briers)
final
```

```
## logit-vanilla
##             1
```

```
g_final = glm(income ~., data = adult_train, family = binomial(link = logit))
brier_score(g_final, adulttest, ytest)
```

```
## [1] -0.1060404
```