Lab 6

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#Visualization with the package ggplot2

I highly recommend using the ggplot cheat sheet as a reference resource. You will see questions that say "Create the best-looking plot". Among other things you may choose to do, remember to label the axes using real English, provide a title and subtitle. You may want to pick a theme and color scheme that you like and keep that constant throughout this lab. The default is fine if you are running short of time.

Load up the `GSSvocab` dataset in package `carData` as `X` and drop all observations with missing measurements. This will be a very hard visualization exercise since there is not a good model for vocab.

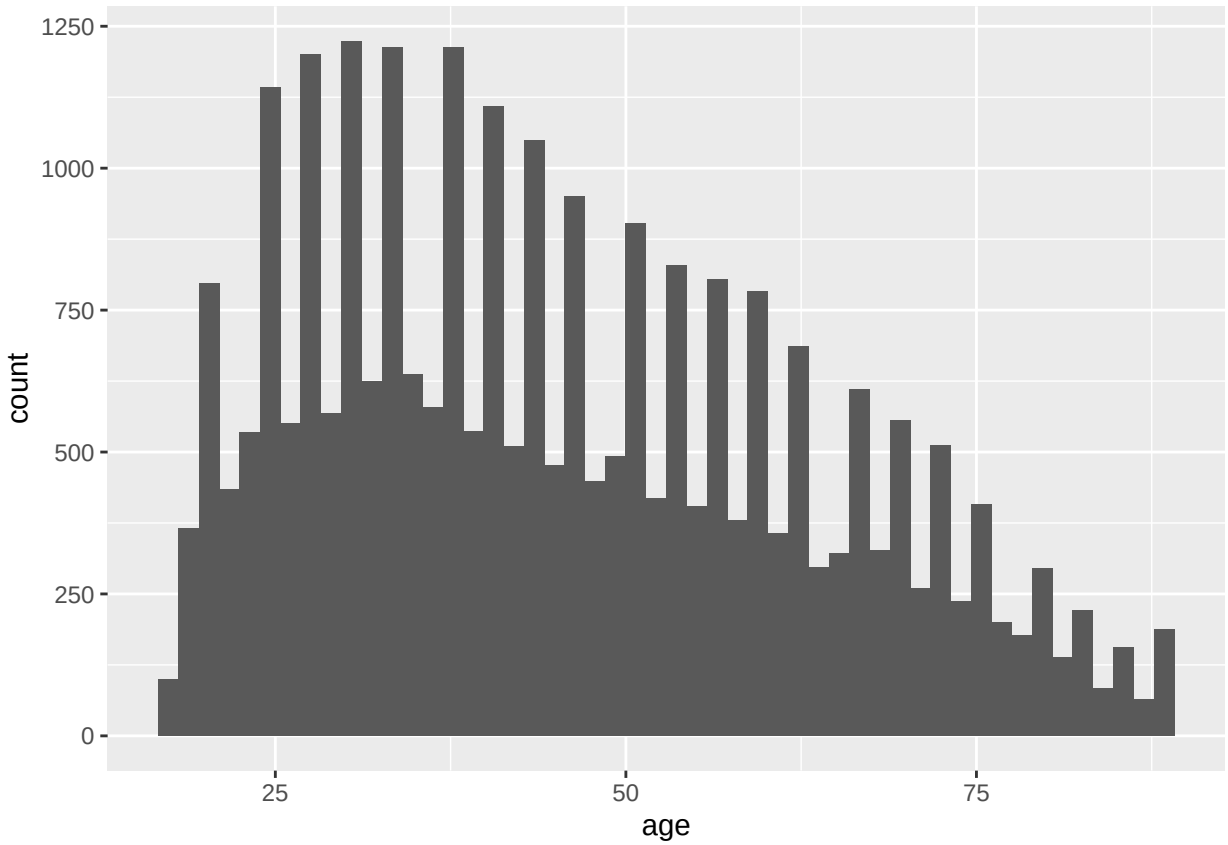
```
pacman::p_load(carData)

data(GSSvocab)
GSSvocab = na.omit(GSSvocab)

?GSSvocab
```

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?

#TO-DO

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.

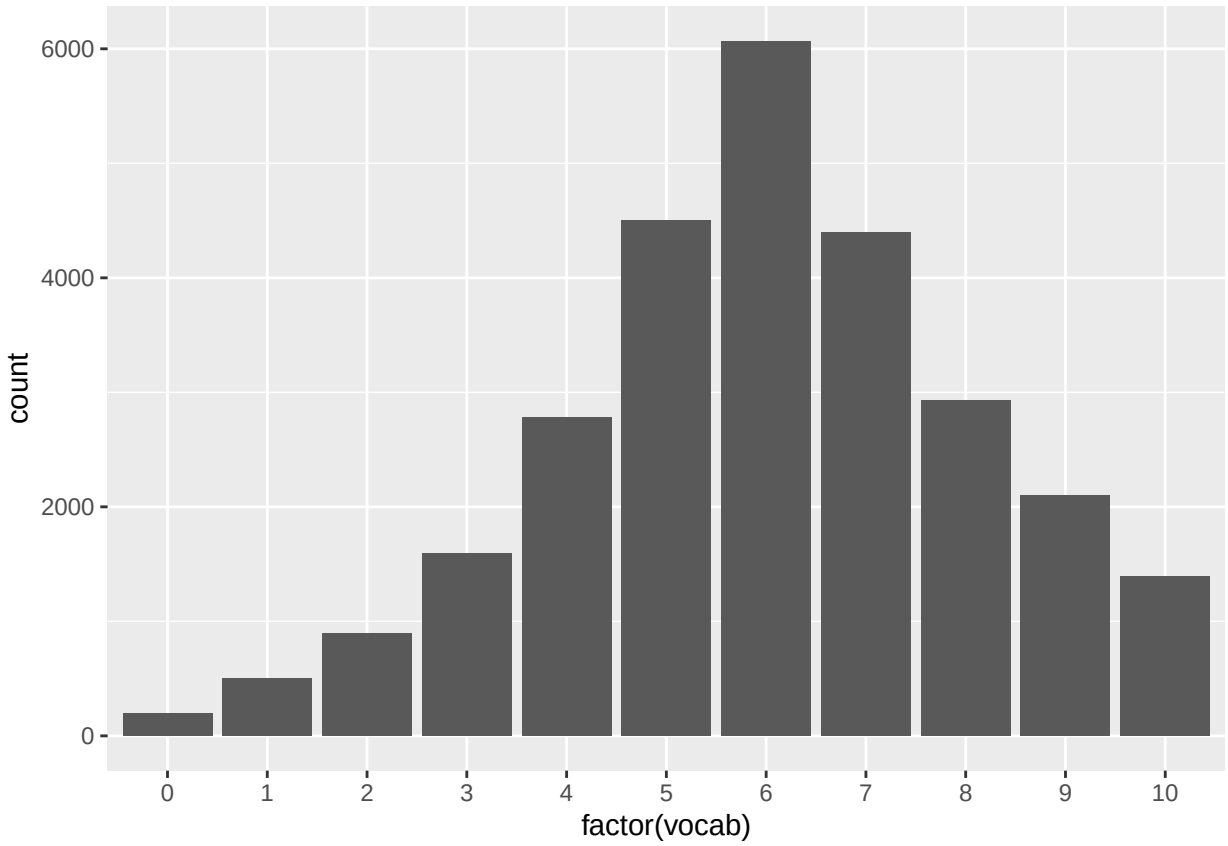
```
pacman::p_load(ggplot2)

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.

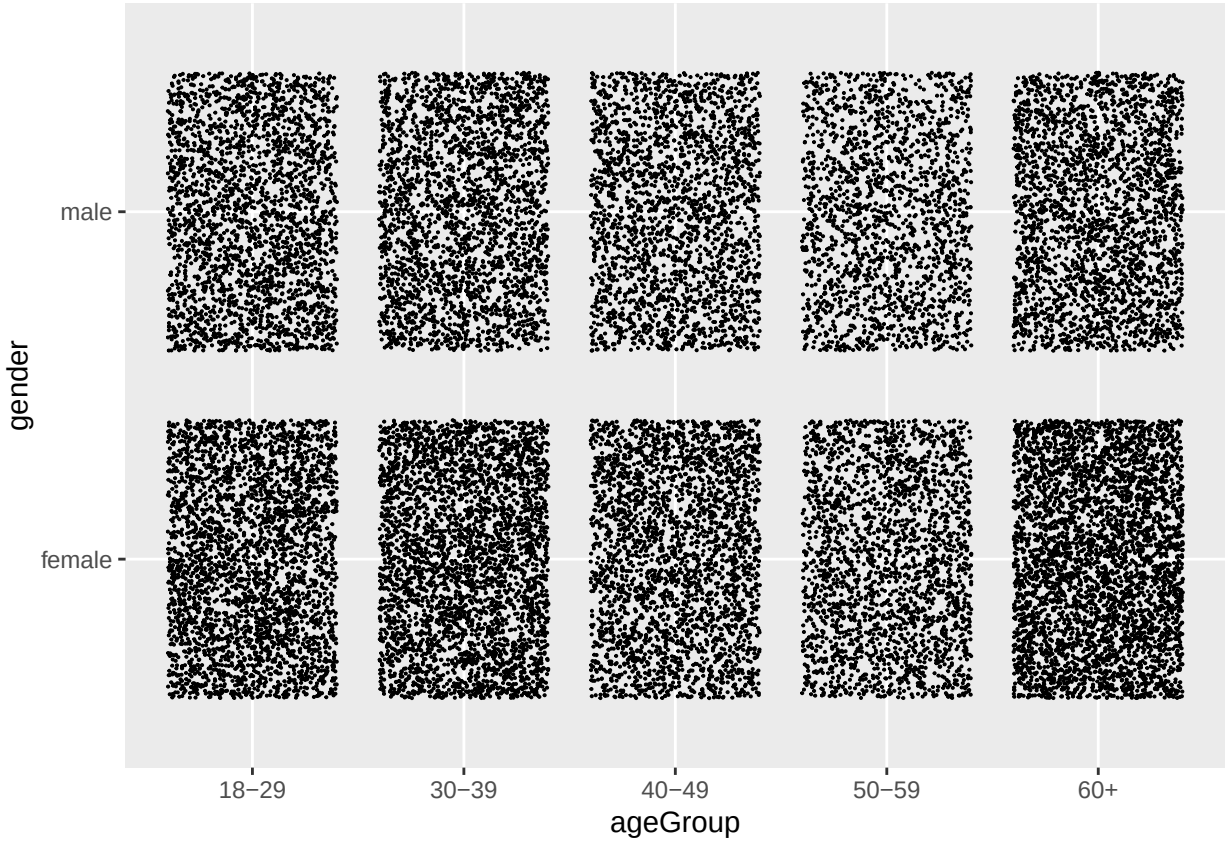
```
ggplot(GSSvocab) +
  aes(x = factor(vocab)) +
  geom_bar(bins = 50)
```

```
## Warning: Ignoring unknown parameters: bins
```



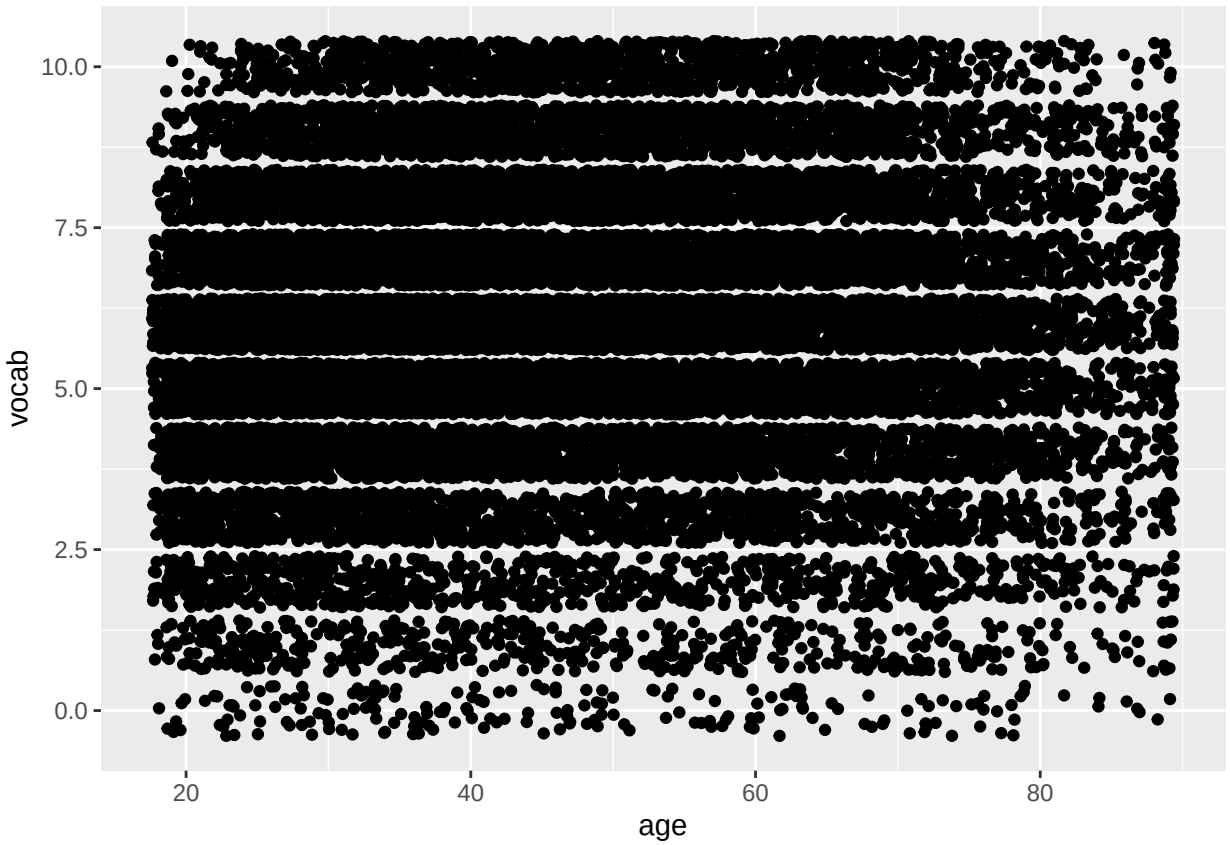
Create the best-looking plot you can to examine the `ageGroup` variable by `gender`. Does there appear to be an association? There are many ways to do this.

```
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?

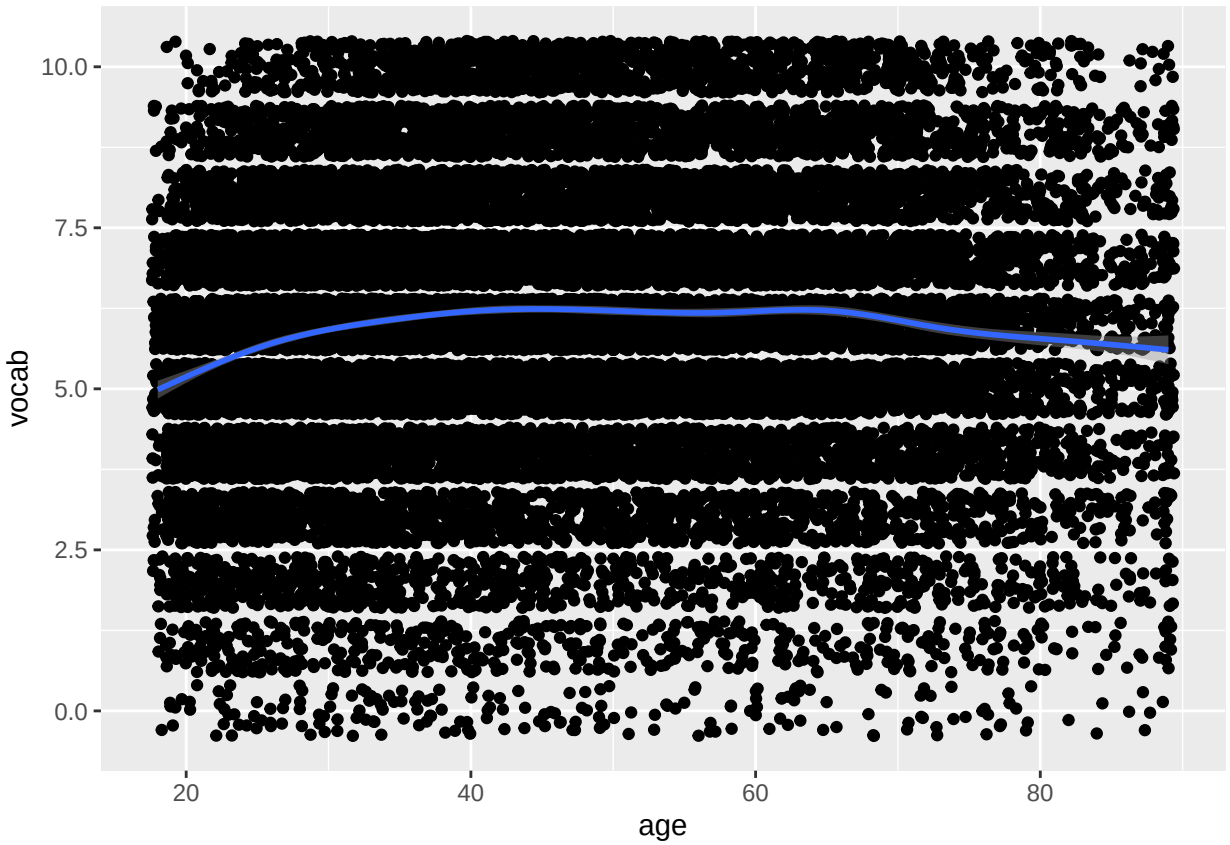
```
ggplot(GSSvocab) +
  aes(x = age, y = vocab) +
  geom_jitter()
```



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()
```

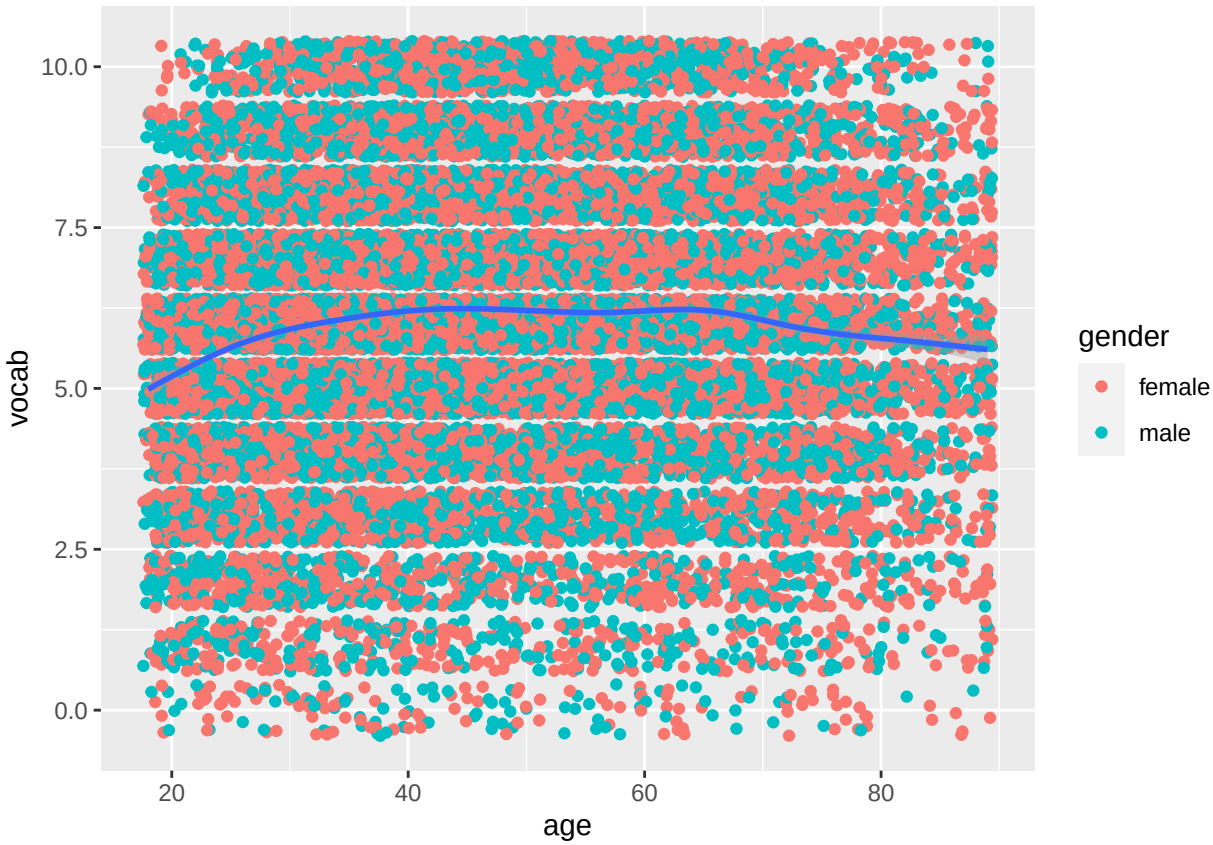
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



Using the plot from the previous question, create the best looking plot 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()
```

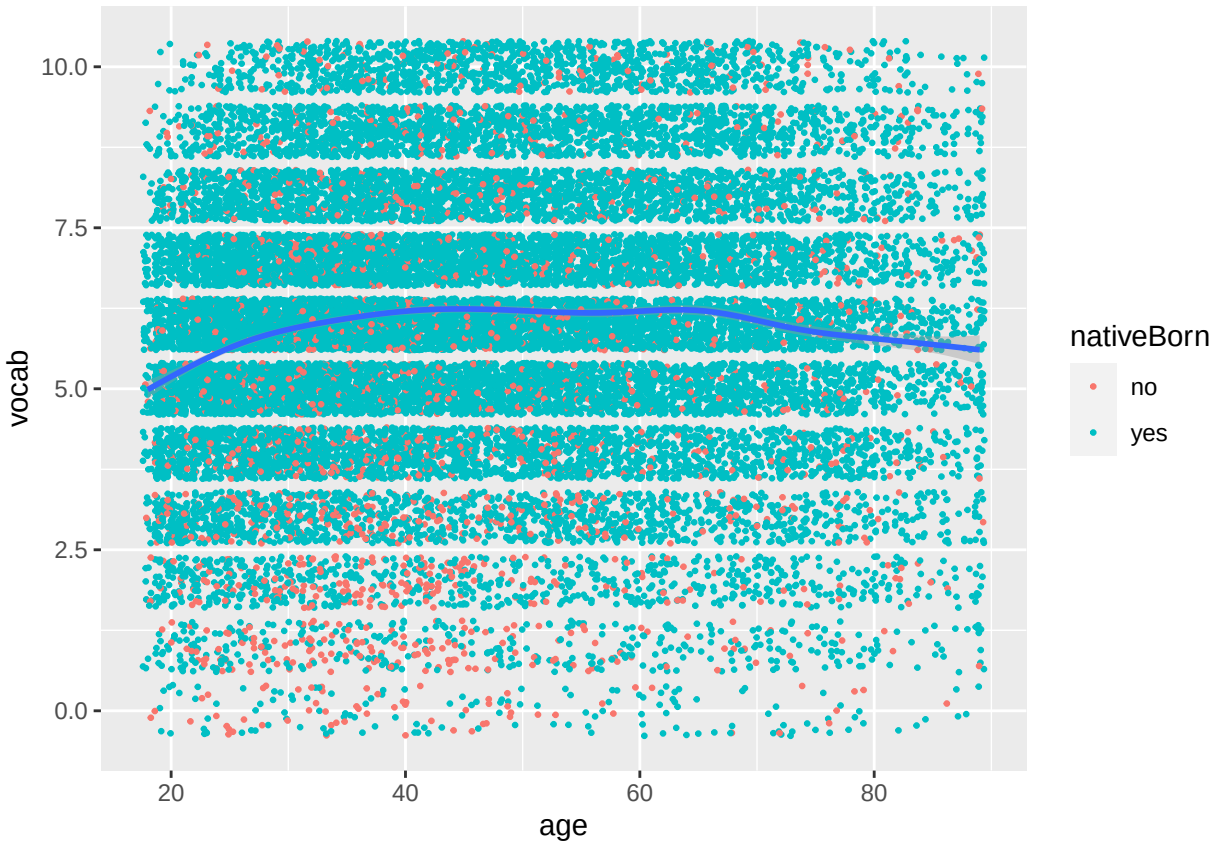
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



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

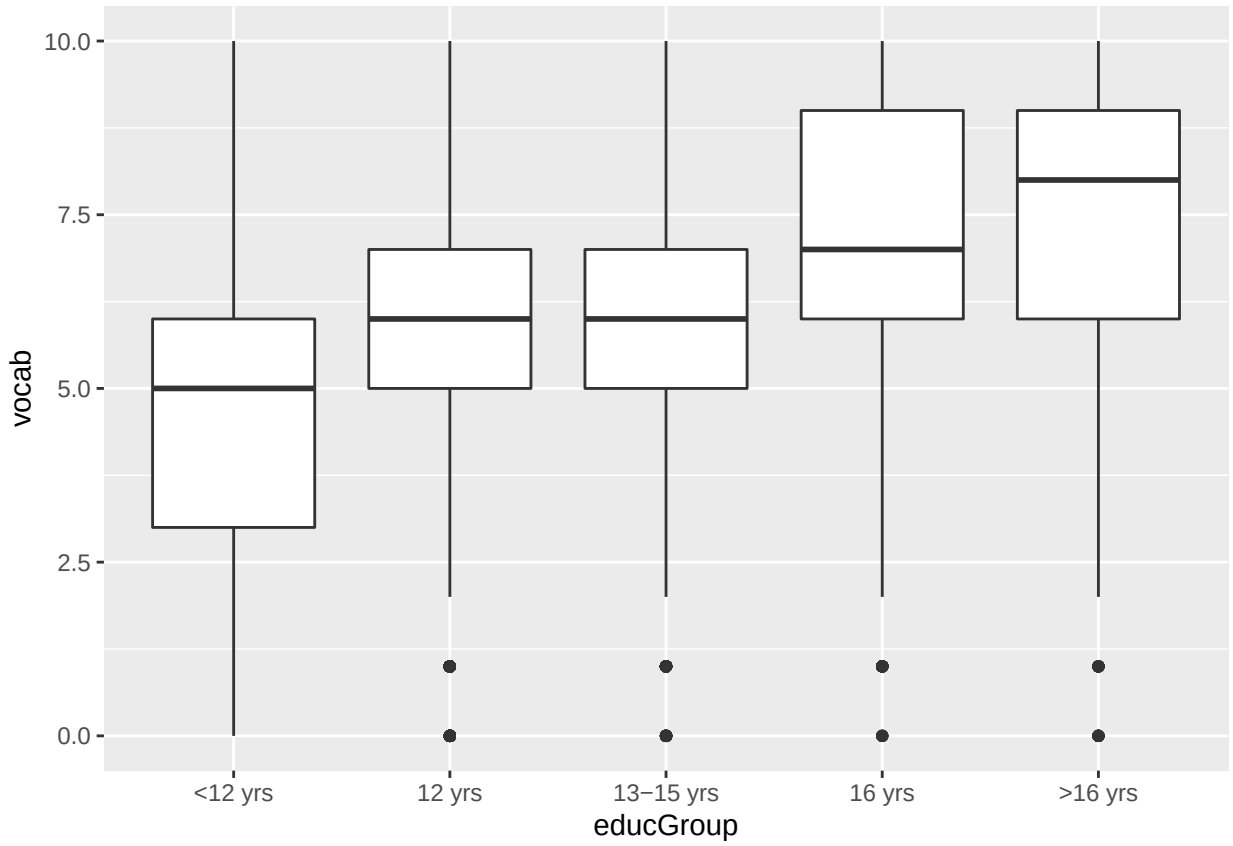
```
ggplot(GSSvocab) +
  aes(x = age, y = vocab) +
  geom_jitter(aes(col = nativeBorn), size = .5) +
  geom_smooth()
```

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

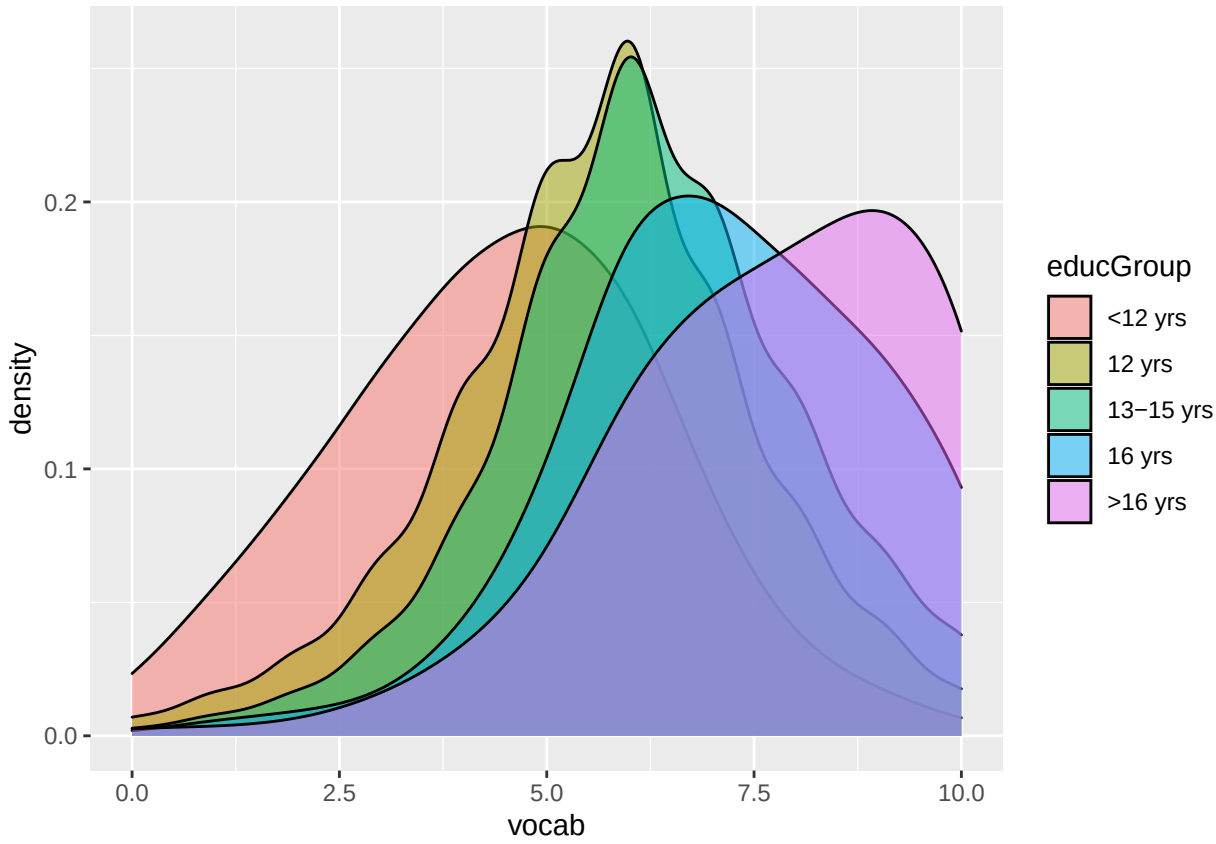


Create two different plots and identify the best-looking plot you can to examine the `vocab` variable by `educGroup`. Does there appear to be an association?

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

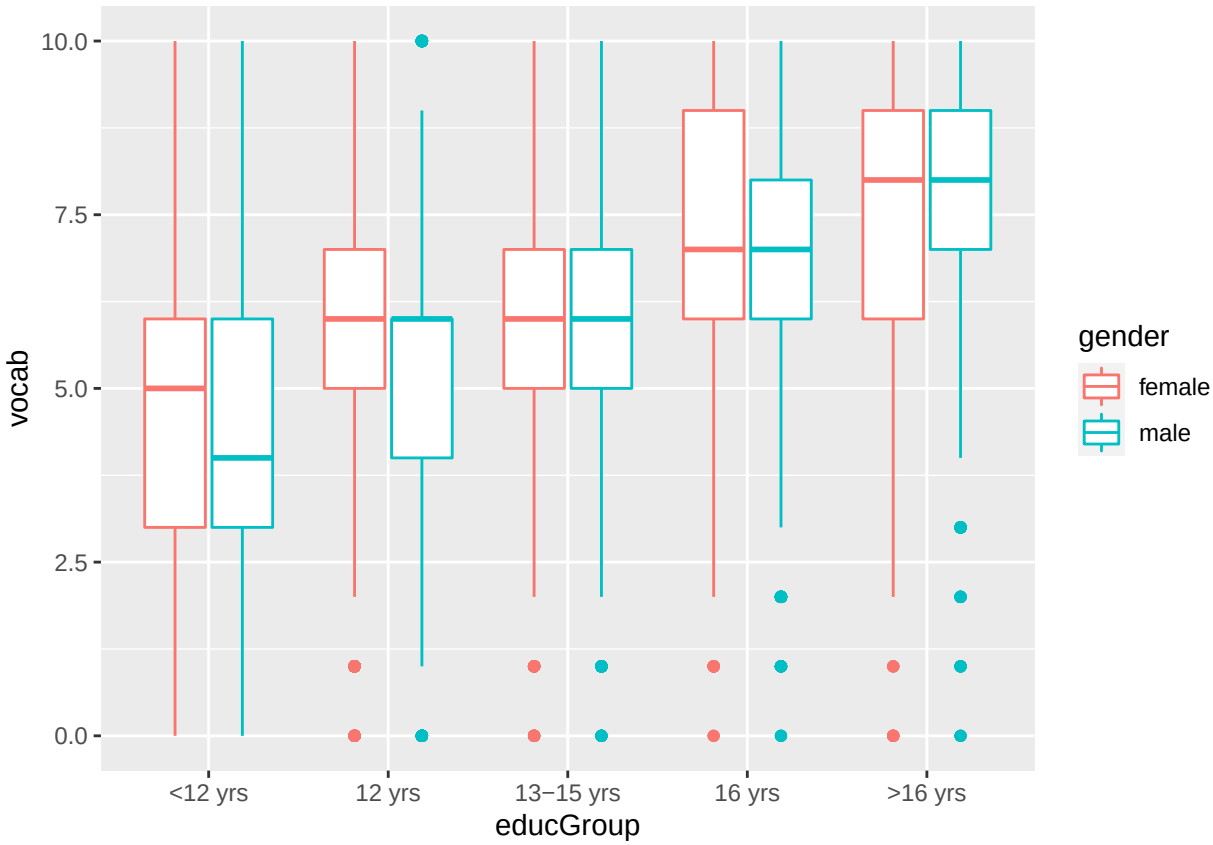



```
ggplot(GSSvocab) +
  aes(x = vocab) +
  geom_density(aes(fill = educGroup), adjust = 2, alpha = .5)
```



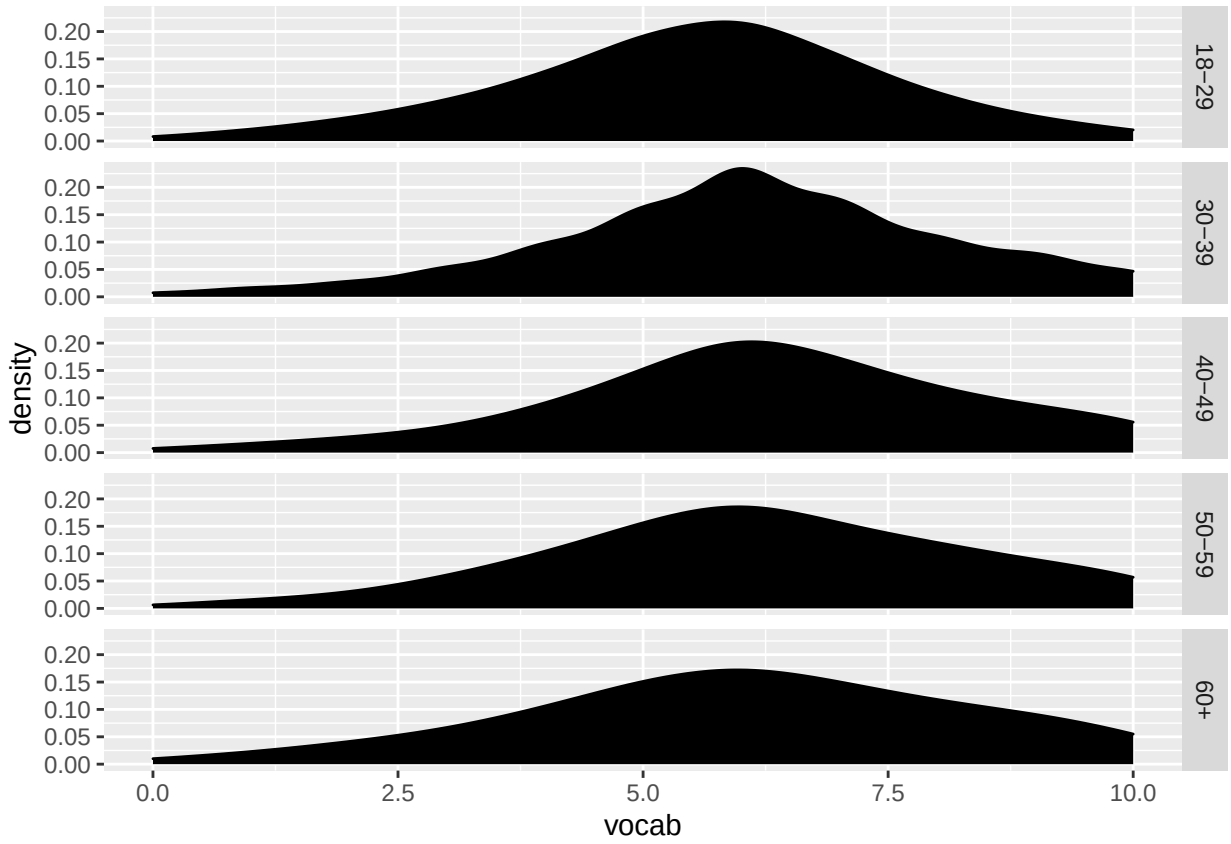
Using the best-looking plot from the previous question, create the best looking overloading with variable `gender`. Does there appear to be an interaction of `gender` and `educGroup`?

```
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~.)
```




```
#we are not getting dumber
```

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) #kill any observations with missingness
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$marital_status == "Ma
adult$marital_status = as.factor(adult$marital_status)

adult$education = as.character(adult$education)
adult$education = ifelse(adult$education == "1st-4th" | adult$education == "Preschool", "<=4th", adult$
adult$education = as.factor(adult$education)
```

Create a model matrix `Xmm` (for this prediction task on just the raw features) 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
```

```
#It is not full rank because something is absolutely the same
```

Now tabulate and sort the variable `native_country`.

```
tab = sort(table(adult$native_country))
```

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

There are rare levels, since the data is not full rank.

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(tab[tab < 50]), "other", adult$native_cou
adult$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?

```
Xmm = model.matrix(income~workclass + occupation,adult)
ncol(Xmm)
```

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

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

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

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$workclass, sep = ":")
adult$occupation = NULL
adult$workclass = NULL
tabulate_1 = sort(table(adult$worktype))
tabulate_1
```

```
##
##           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(tabulate_1[tabulate_1 < 100]), 'other', adult$worktype
adult$worktype = as.factor(adult$worktype)
tabulate_2 = sort(table(adult$worktype))
tabulate_2
```

```
##
##        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$overall_status = paste(adult$relationship, adult$marital_status, sep = ":")
tabulate_overall_status = sort(table(adult$overall_status))
adult$relationship = NULL
adult$marital_status = NULL

tabulate_overall_status
```

```
##
##                     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
test_prop = 1 / K
train_indices = sample(1 : nrow(adult), round((1 - test_prop) * nrow(adult)))
adult_train = adult[train_indices, ]
y_train = adult_train$income
X_train = adult_train
X_train$income = NULL
test_indices = setdiff(1 : nrow(adult), train_indices)
adult_test = adult[test_indices, ]
y_test = adult_test$income
X_test = adult_test
X_test$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, family = binomial(li
}
```

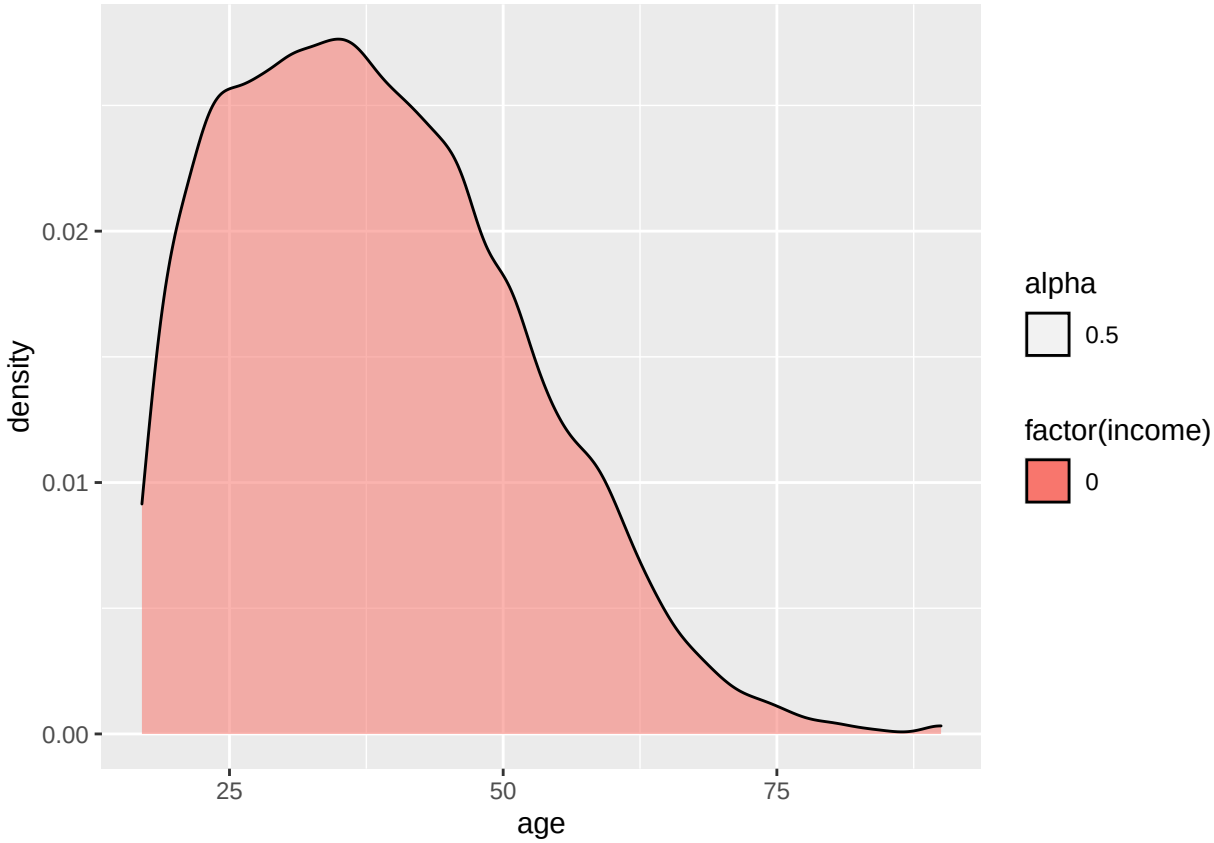
Now let's get fancier. Let's do some variable transforms. Add `log_capital_loss` derived from `capital_loss` and `log_capital_gain` derived from `capital_gain`. Since there are zeroes here, use log_x = log(1 + x) instead of log_x = log(x). That's always a neat trick. Just add them directly to the data 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(fill= factor(income), adjust=2,alpha=0.5 ))
```

```
## Warning: Ignoring unknown aesthetics: adjust
```



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

I only 0 which is the people who make under 50k, this does not make sense because I am missing data for 1 which is the people who make more than 50k.

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.

```
K = 5
test_prop = 1 / K
train_indices = sample(1 : nrow(adult), round((1 - test_prop) * nrow(adult)))
adult_train = adult[train_indices, ]
y_train = adult_train$income
X_train = adult_train
X_train$income = NULL
test_indices = setdiff(1 : nrow(adult), train_indices)
adult_test = adult[test_indices, ]
y_test = adult_test$income
X_test = adult_test
X_test$income = NULL

age_interactions = income ~ .*age

for(link_function in link_functions){
```

```
  prob_est_mods[[paste(link_function, "age_interactions", sep = "-")]] = glm(formula=age_interactions, 
}
```

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

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

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

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

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)
  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, X_train, y_train)
```

```
## Warning in y - phat: longer object length is not a multiple of shorter object
## length

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```

```
## $`logit-vanilla`
## [1] -705.756
##
## $`probit-vanilla`
## [1] -48.8772
##
## $`cloglog-vanilla`
## [1] -700.991
##
## $`cauchit-vanilla`
## [1] -2.109538e+15
##
## $`logit-age_interactions`
## [1] -705.756
##
## $`probit-age_interactions`
## [1] -48.8772
##
## $`cloglog-age_interactions`
## [1] -700.991
```

```
##
## $`cauchit-age_interactions`
## [1] -2.109538e+15
```

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, X_test, y_test)
```

```
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##
## $`cauchit-age_interactions`
## [1] -2.109538e+15
```

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

For in sample probit for both vanilla and age interactions win. For out of sample logit for vanilla and age interactions win. Since both probit and logit are from logistic and standard normal cdf I would expect for them to be similar.

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

The train set split selection have the issue. It would be used go assess the sample error metric in the end.

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.