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, 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.

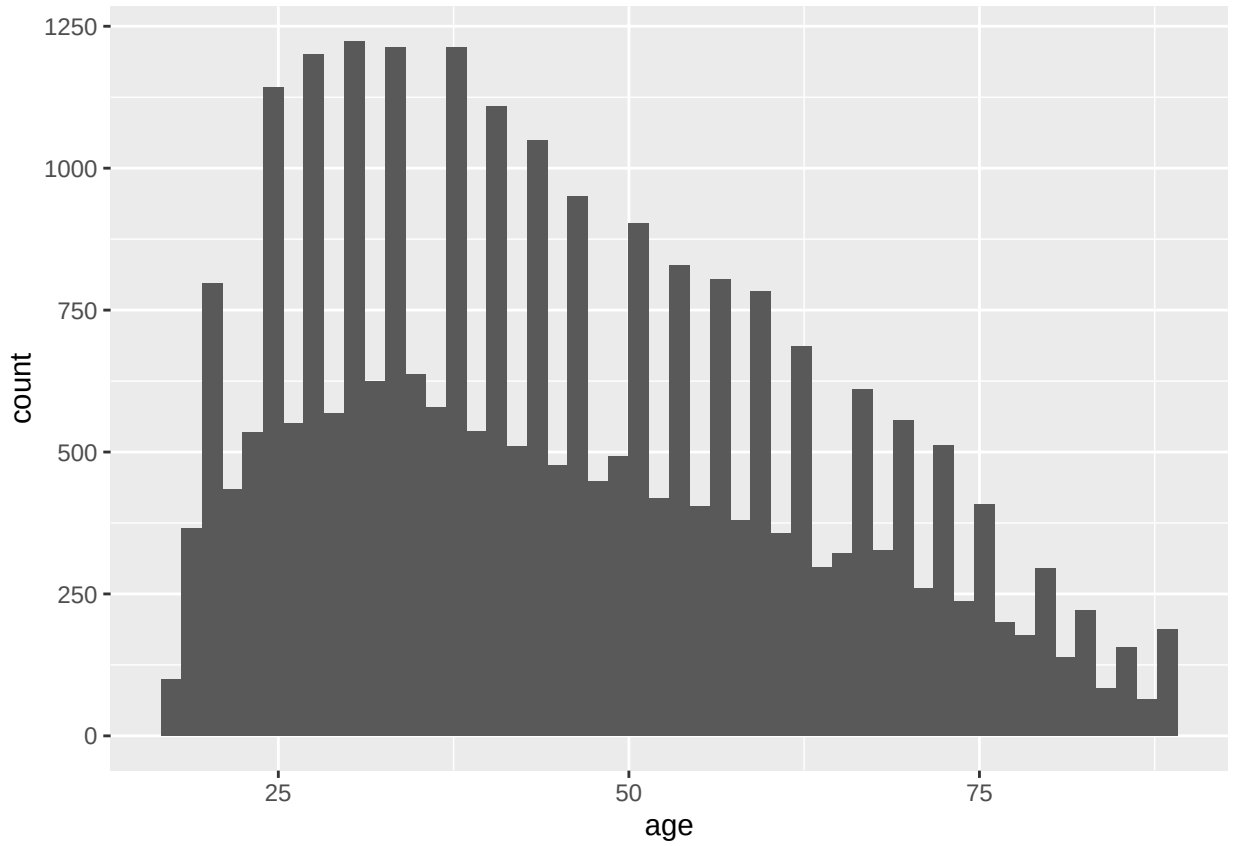
```
pacman:: p_load(carData)
data("GSSvocab")
GSSvocab = na.omit(GSSvocab)
?GSSvocab
```

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?

There are 8 variables: year, gender, nativeBorn, ageGroup, educGroup, vocab, age, and educ. Year, gender, nativeBorn, ageGroup, eduGroup, educ are categorical variables. Age and education are continuous variables. The response variable I think was to see what features correlated with a higher vocabulary.

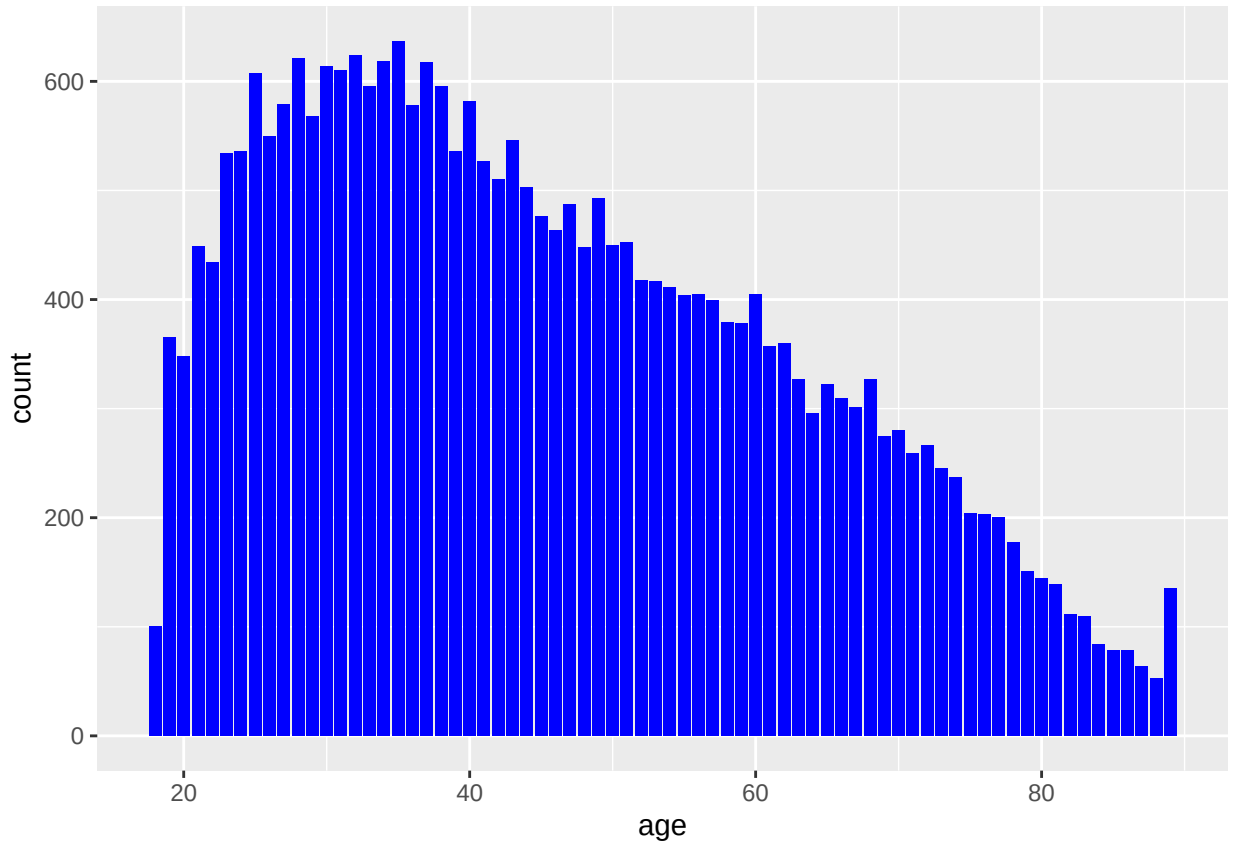
Create two different plots and identify the best-looking plot you can to examine the `age` variable. Save the best looking plot as an appropriately-named PDF.

```
pacman::p_load(ggplot2)
ggplot(GSSvocab) +
  aes(x=age) +
  geom_histogram(bins = 50)
```




```
ggplot(GSSvocab) +
  aes(x=age) +
  geom_bar(fill = "blue", kernel = "gaussian")
```

```
## Warning: Ignoring unknown parameters: kernel
```




```
chart=ggplot(GSSvocab) +
  aes(x=age) +
  geom_bar(fill = "blue", kernel = "gaussian")
```

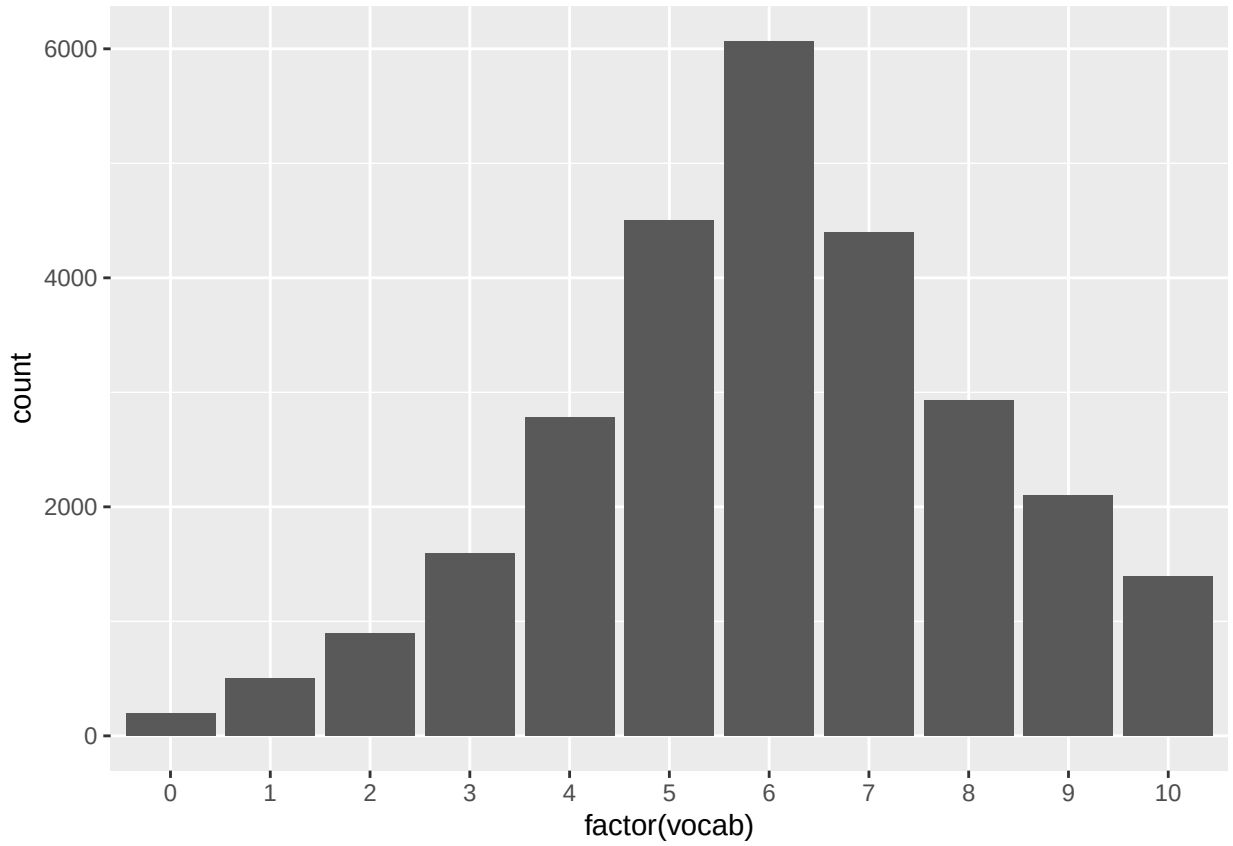
```
## Warning: Ignoring unknown parameters: kernel
```

```
ggsave("age_plot.pdf", chart)
```

```
## Saving 6.5 x 4.5 in image
```

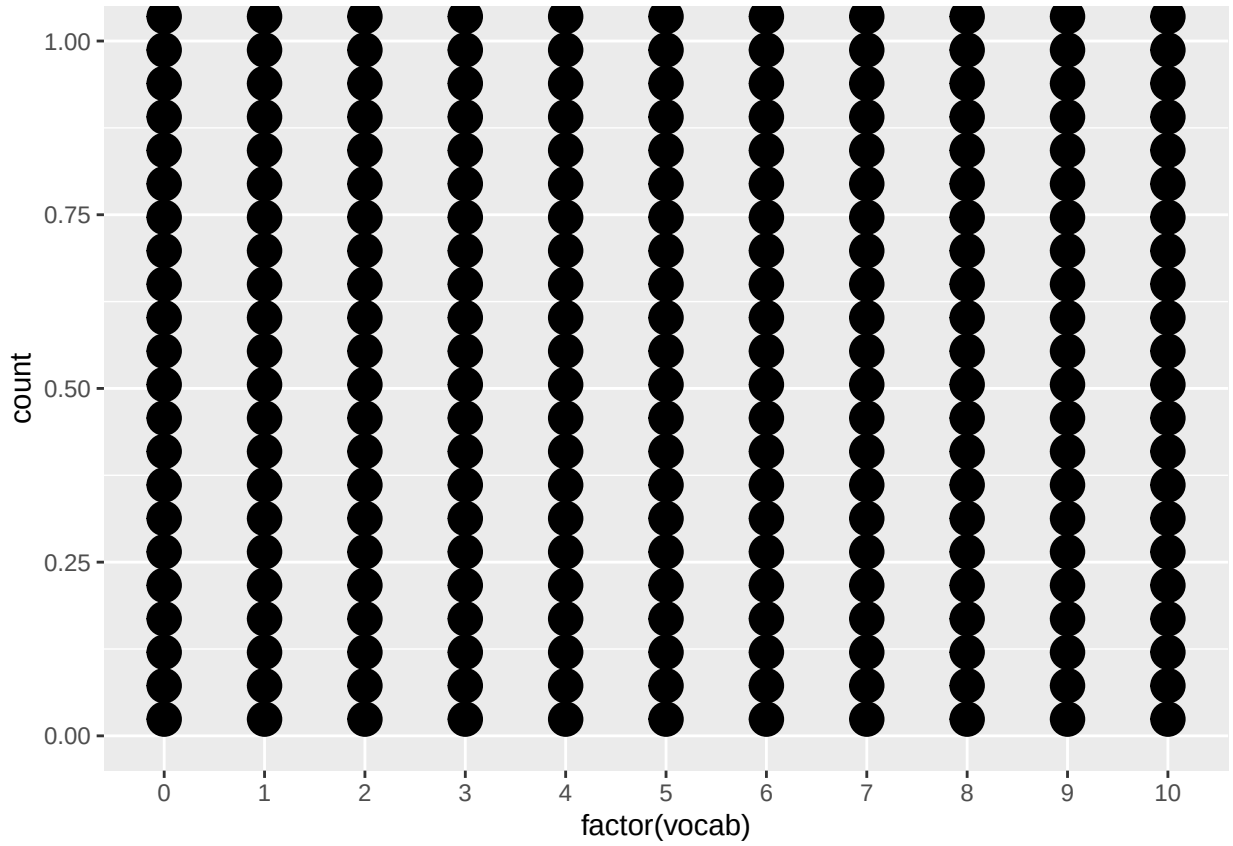
Create two different plots and identify the best looking plot you can to examine the `vocab` variable. Save the best looking plot as an appropriately-named PDF.

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




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

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

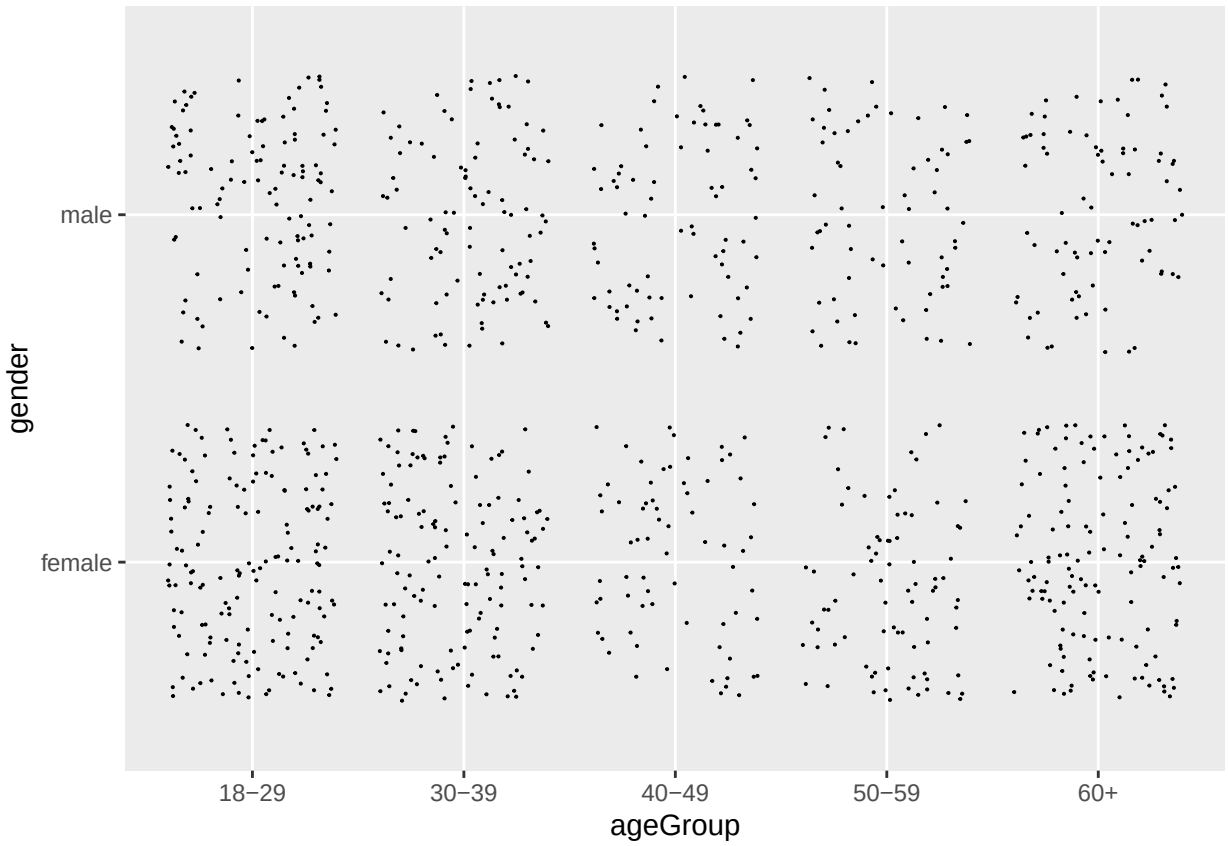



```
ggsave("vocab_plot.pdf", chart)
```

```
## Saving 6.5 x 4.5 in image
```

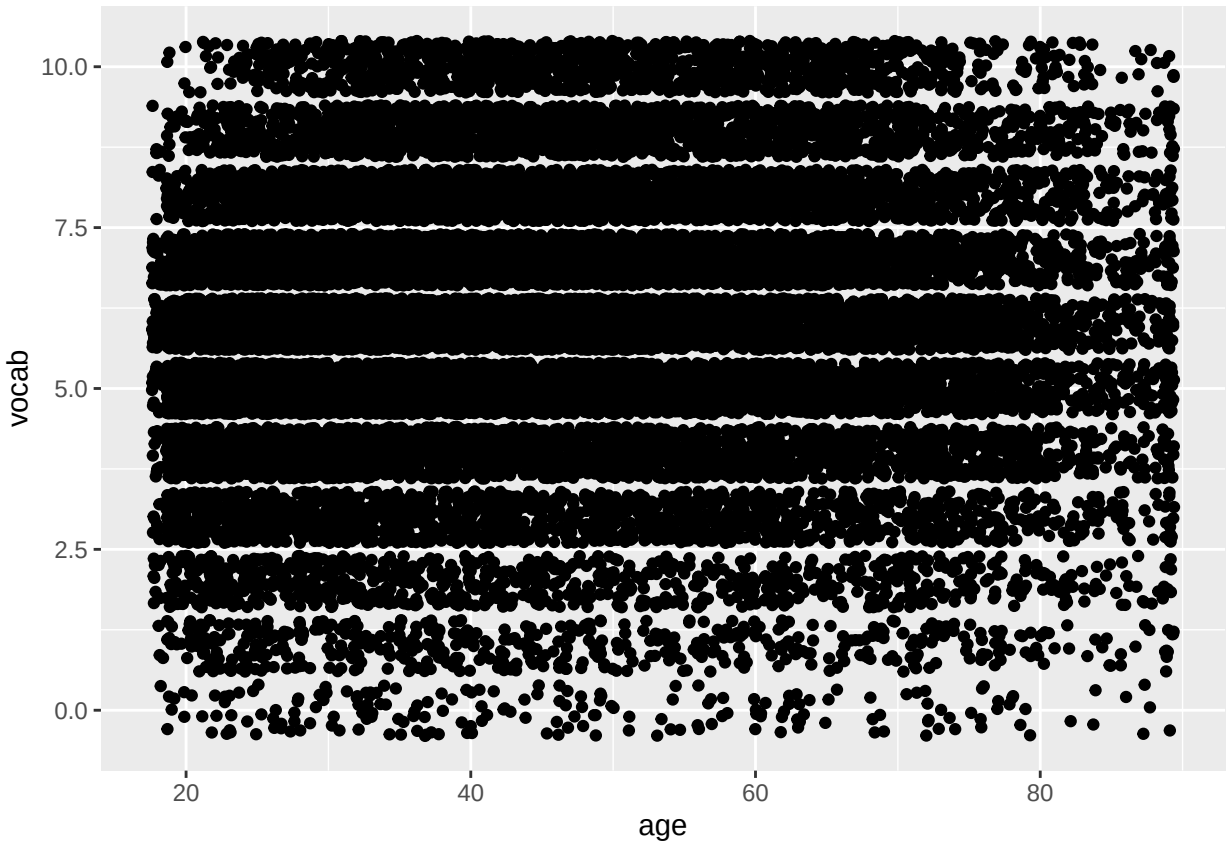
Create the best-looking plot you can to examine the `ageGroup` variable by `gender`. Does there appear to be an association? There are many ways to do this.

```
ggplot(GSSvocab[1:1000, ]) +
  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?

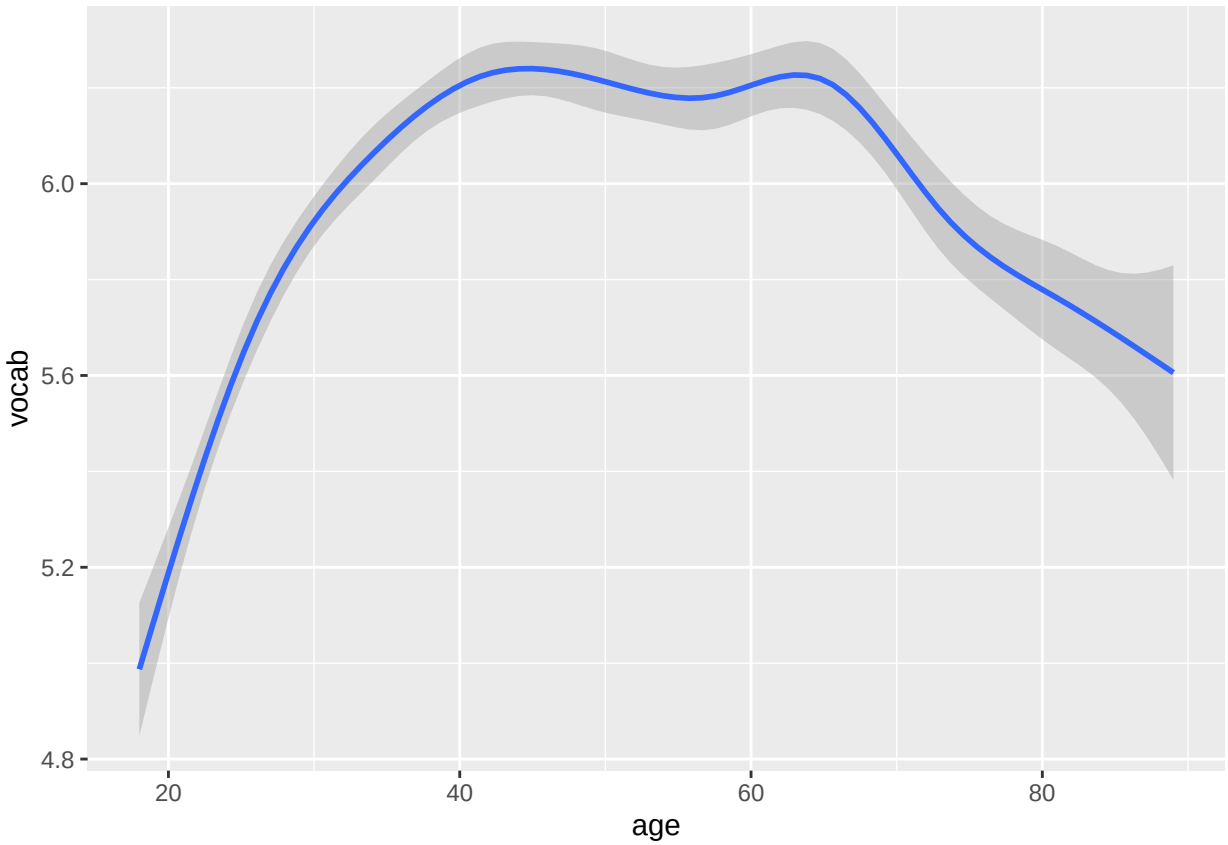
```
ggplot(GSSvocab) +
  aes(x=age, y=vocab) +
  geom_jitter()
```



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_smooth()
```

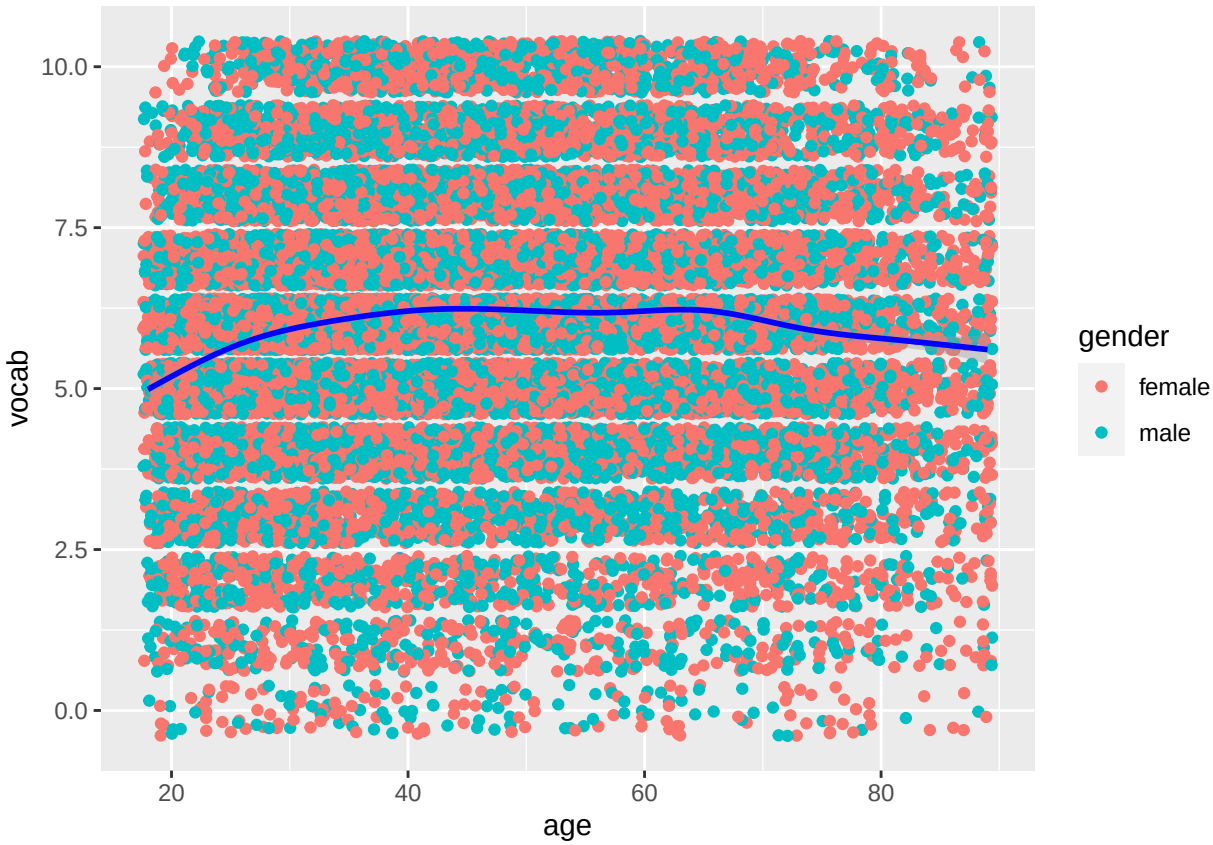
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



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(col="blue")
```

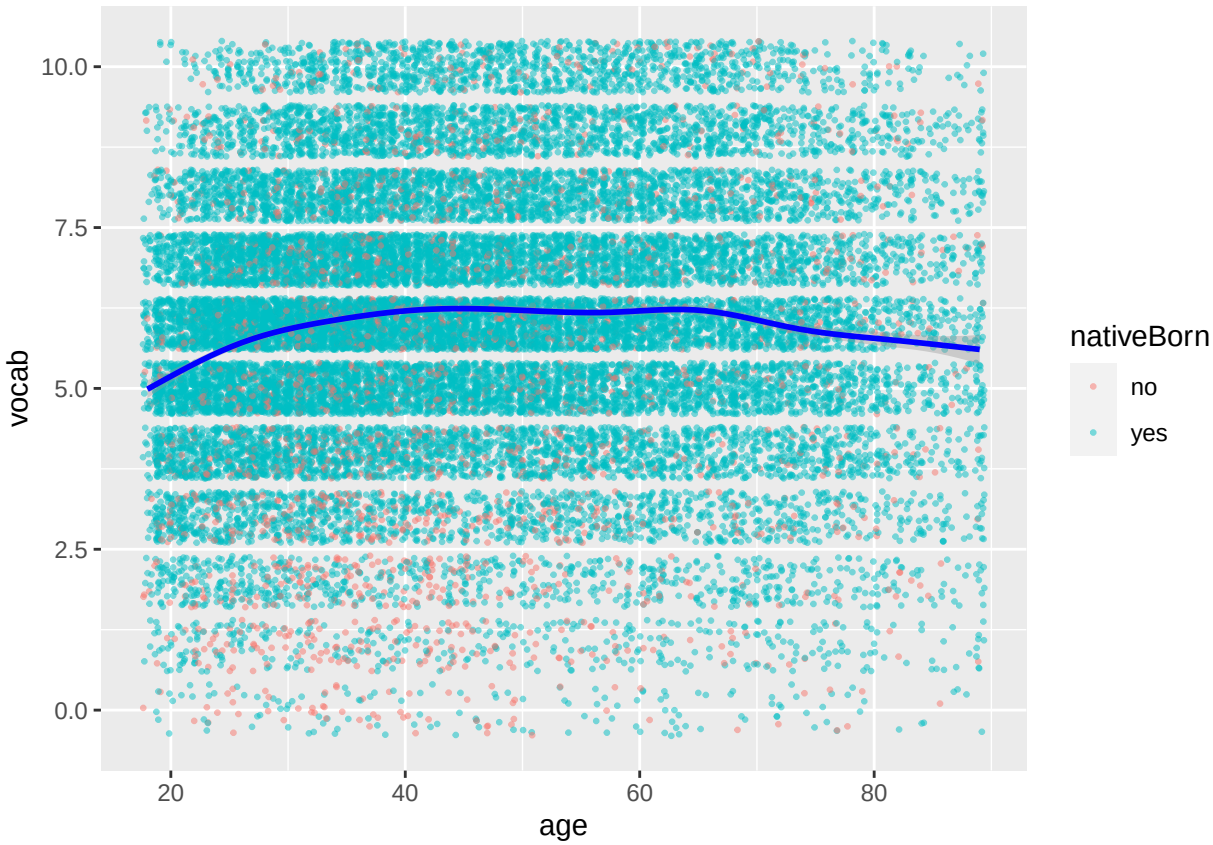
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



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`?

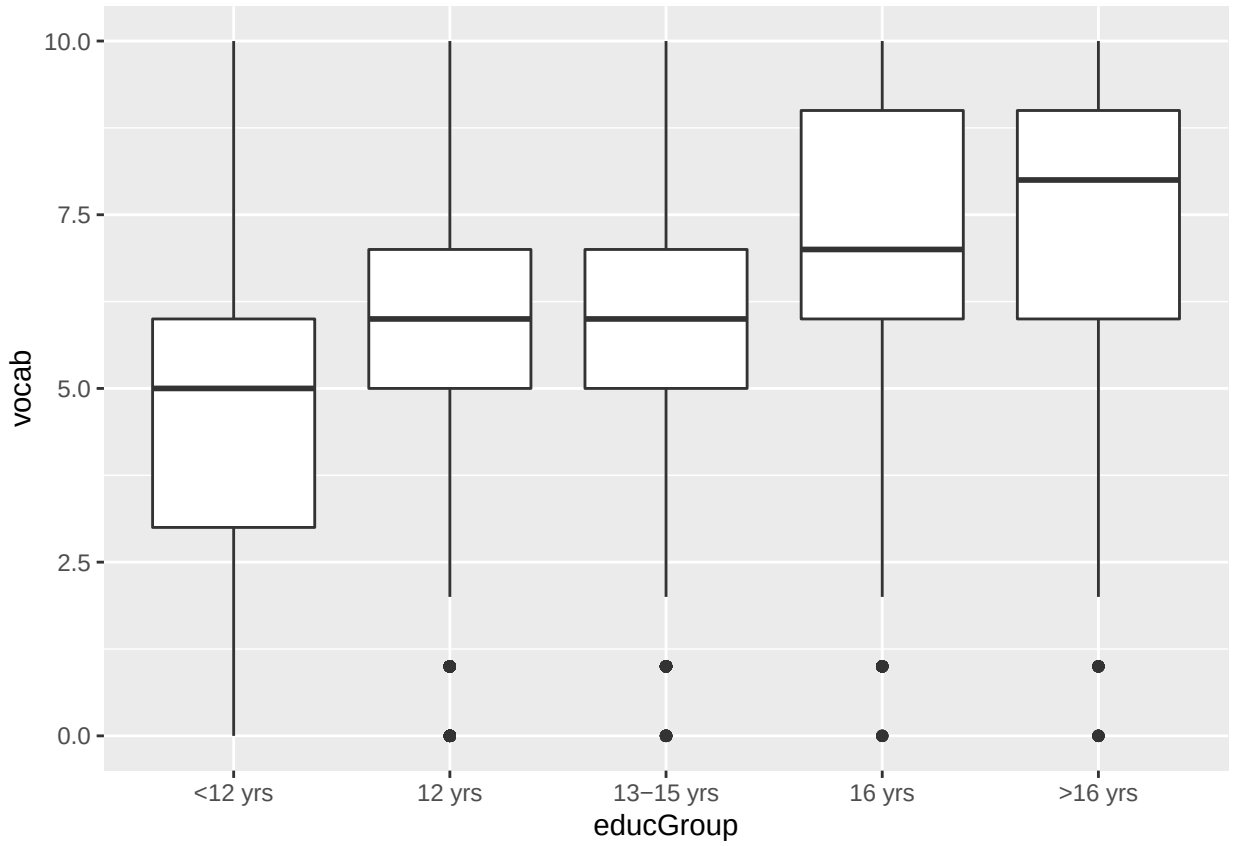
```
ggplot(GSSvocab) +
  aes(x=age, y=vocab) +
  geom_jitter(aes(col = nativeBorn), size =.5, alpha=0.5) +
  geom_smooth(col="blue")
```

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

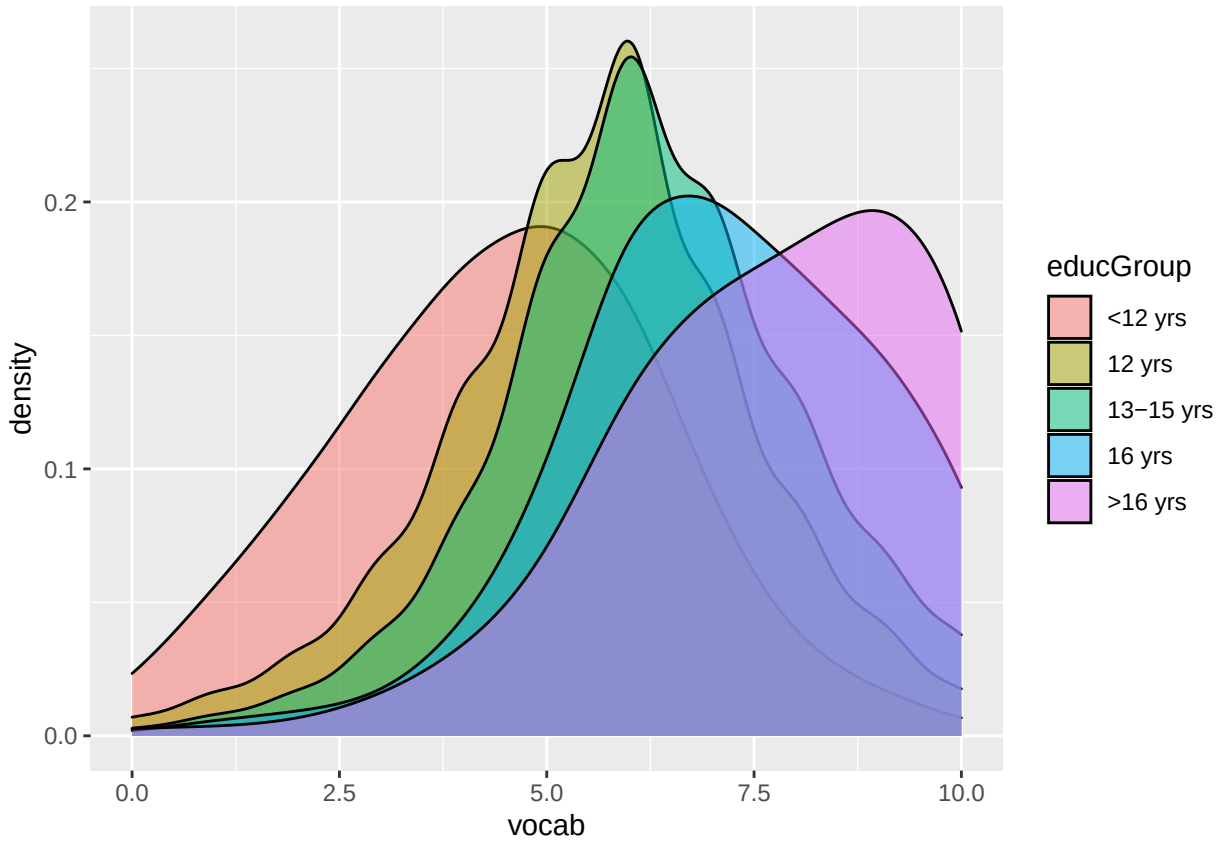


Create two different plots and identify the best-looking plot you can to examine the `vocab` variable by `educGroup`. Does there appear to be an association?

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

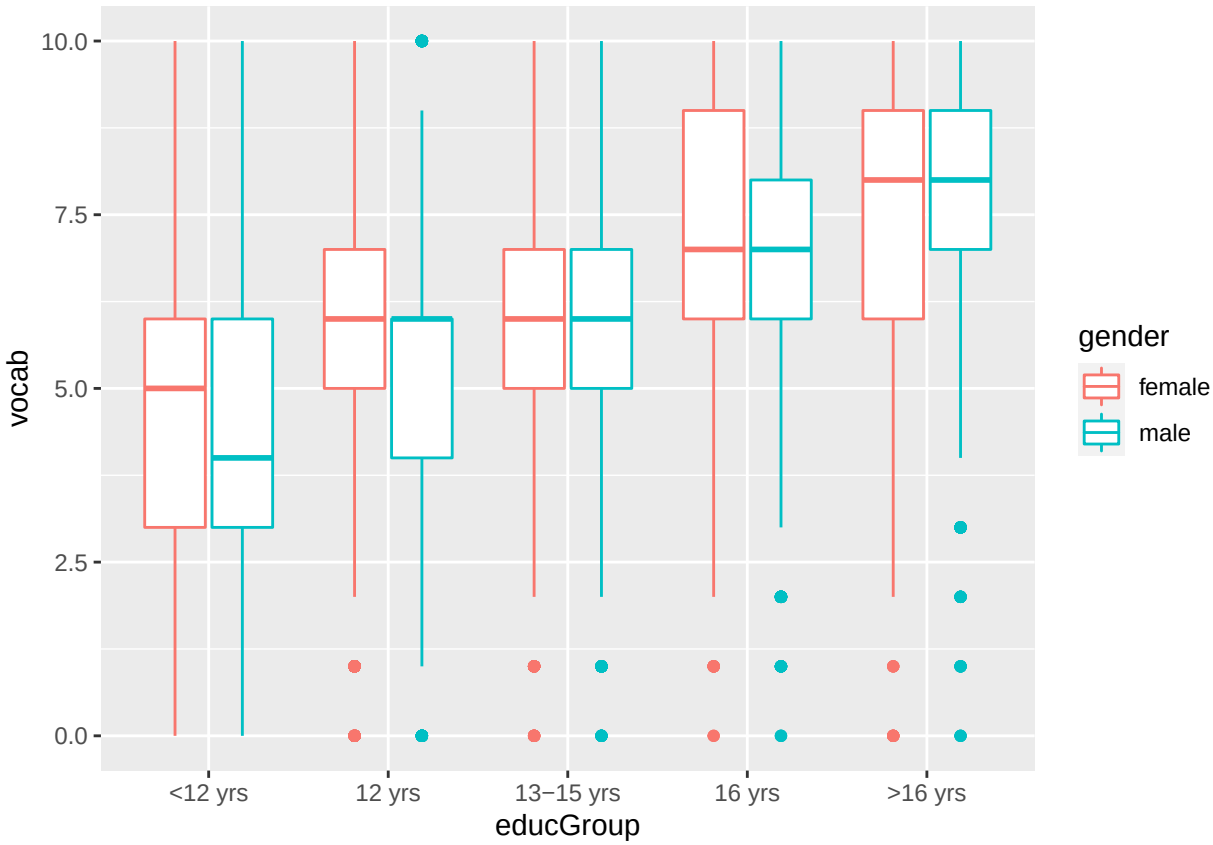



```
ggplot(GSSvocab) +
  aes(x=vocab) +
  geom_density(aes(fill = educGroup), adjust =2, alpha = .5)
```



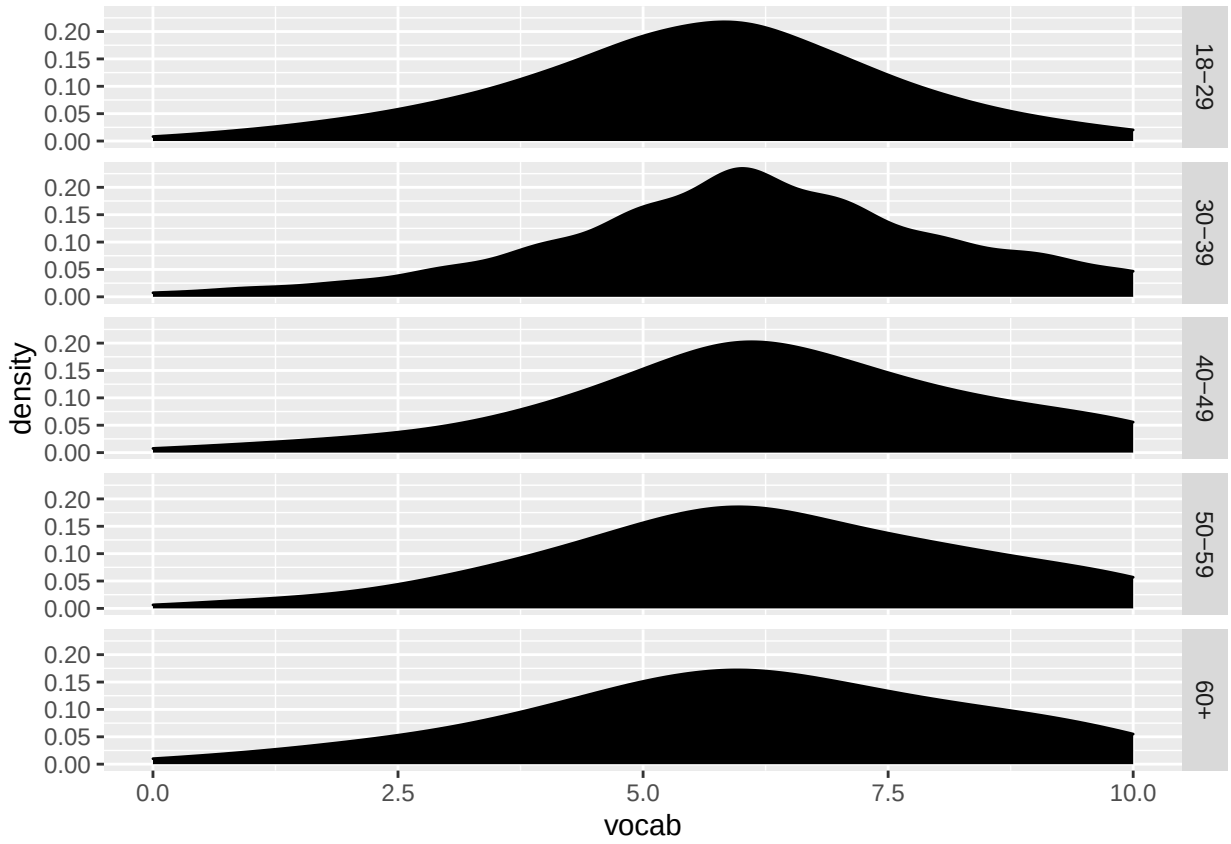
Using the best-looking plot from the previous question, create the best looking plot overloading with variable `gender`. Does there appear to be an interaction of `gender` and `educGroup`?

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



Using facets, examine the relationship between `vocab` and `ageGroup`. 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) #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
```

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.

Yes we do see rare levels in this variable (holland, laos, etc.) You are going to start not seeing them and the computer is not going to know what to do

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? No, this is not 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$workclass, sep = ":")
tab_worktype = sort(table(adult$worktype))
adult$occupation = NULL
adult$workclass = NULL
tab_worktype
```

```
##
##           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(tab_worktype[tab_worktype <100]), "other", adult$work
adult$worktype = as.factor(adult$worktype)
tab_worktype2 = sort(table(adult$worktype))
tab_worktype2
```

```
##
##        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$marital_status, sep = ":")
tab_status = sort(table(adult$status))
adult$relationship = NULL
adult$marital_status = NULL
tab_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_train, family=binomia
}
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

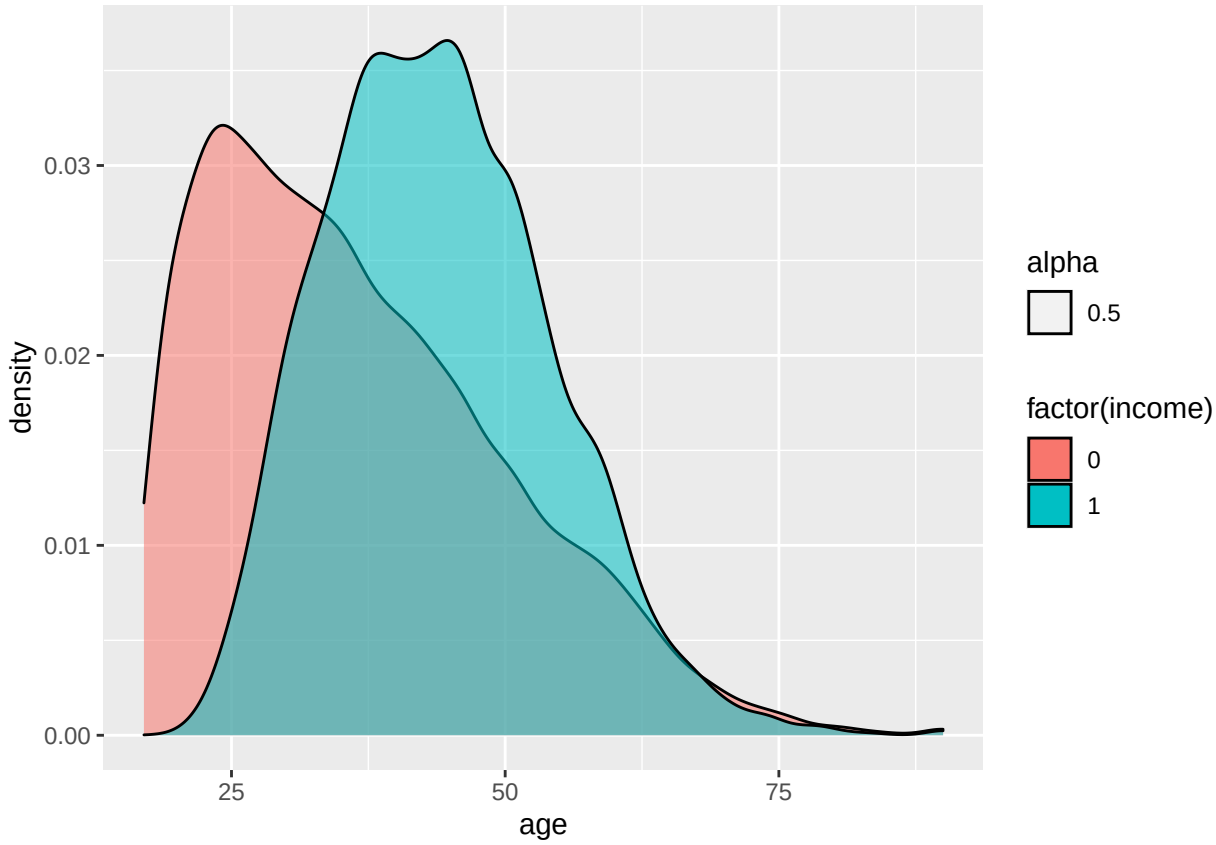
Now let's get fancier. Let's do some variable transforms. Add `log_capital_loss` derived from `capital_loss` and `log_capital_gain` derived from `capital_gain`. Since there are zeroes here, use log_x = log(1 + x) instead of log_x = log(x). That's always a neat trick. Just add them directly to the data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

1 for people that that make greater thann 50k and 0 for people that make less than 50k. This makes sense because older individuals tend to make more money compared to younger individuals in most professions including "unskilled" labor.

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: fitted probabilities numerically 0 or 1 occurred
```

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

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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```
## 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, X, type = "response")
  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)
```

```
## $`logit-vanilla`
## [1] -0.1039117
##
## $`probit-vanilla`
## [1] -0.1039676
##
## $`cloglog-vanilla`
## [1] -0.1047697
##
## $`cauchit-vanilla`
## [1] -0.1053335
##
## $`logit-age_interactions`
## [1] -0.1001253
##
## $`probit-age_interactions`
## [1] -0.1011932
##
## $`cloglog-age_interactions`
## [1] -0.4907636
##
## $`cauchit-age_interactions`
## [1] -0.1009101
```

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)
```

```
## $`logit-vanilla`
## [1] -0.1003465
##
## $`probit-vanilla`
## [1] -0.1003978
##
## $`cloglog-vanilla`
## [1] -0.1013593
##
## $`cauchit-vanilla`
## [1] -0.1027239
##
## $`logit-age_interactions`
## [1] -0.09918788
##
## $`probit-age_interactions`
## [1] -0.0998922
##
## $`cloglog-age_interactions`
## [1] -0.497259
##
## $`cauchit-age_interactions`
## [1] -0.1019355
```

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

Logit wins in sample for both vanilla and age-interaction with probit a close second. For out of sample probit vanilla barely beats out logit vanilla and logit beatss out probit in age-interactions. I would expect the logit and probit to be similar because they are based off of the logistic CDF and the standard normal CDF, which are both very similar and almost indistinguishable, with the logistic having possessing thicker tails. The data most likely also follows a normal/logistic distribution which would explain the better performance by either of those two models.

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

The train test split selection procedure does not involve nested sampling, which would be a more robust model selection procedure where we would separate a test set from the train and select set. The train and select set would be used to select the model and then the test set at the end would be used to assess the out of sample error metric.

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
test_indices = sample(1 : n, size = n * 1 / K)
master_train_indices = setdiff(1 : n, test_indices) ##overall train
select_indices = sample(master_train_indices, size = n * 1 / K)
subtrain_indices = setdiff(master_train_indices, select_indices)


adult_subtrain = adult[subtrain_indices, ]
y_subtrain = adult_subtrain$income
```

```r
adult_select = adult[select_indices, ]
y_select = adult_select$income
adult_test = adult[test_indices, ]
y_test = adult_test$income
```

```r
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(formula = vanilla, data = adult_subtra
}
```

```
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```
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```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

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

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

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

```r
briers = lapply(prob_est_mods, brier_score, adult_select, y_select)
which_final = which.max(briers)
which_final
```

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

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

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
brier_score(g_final, adult_test, y_test)
```

```
## [1] -0.1043595
```