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.

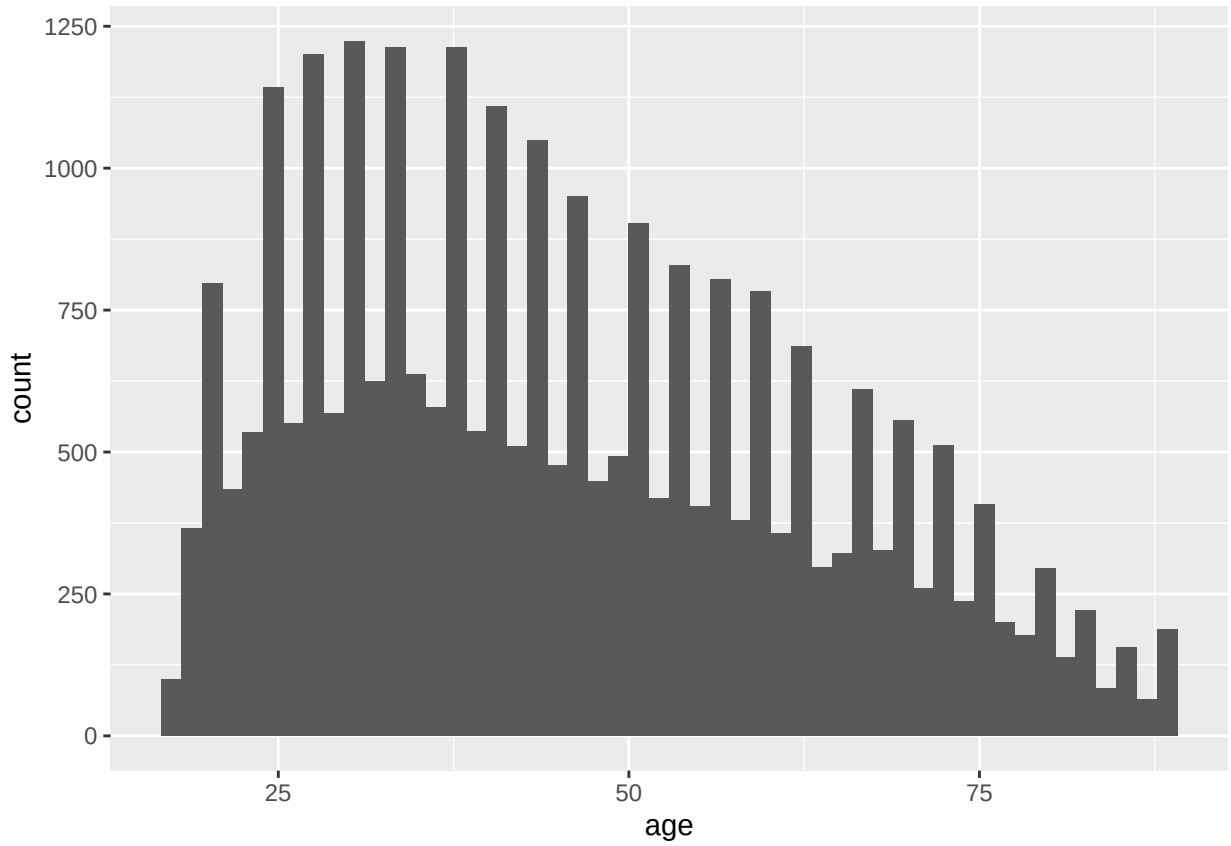
Load up the `GSSvocab` dataset in package `carData` as `X` and drop all observations with missing measurements.

```
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? #TO-DO - year is the year they took the test, which are numerics - educ is how much education they have which is also the same as educgroup which are factors - age is the same as age group which are factors - the response variable is the vocabulary of a person however a test with only 10 questions does not provide enough data to make this prediction either - this data set has a lot of duplications with in the data thus it would not be so useful for creating a model, more over there isn't enough features in this data set to model someones 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.

```
#we want graphs for one variable graphs
pacman::p_load(ggplot2)
ggplot(GSSvocab) +
  aes(x=age) +
  geom_histogram(bins = 50)#they gave the test for every other grade level for continous data
```




```
mygraph = ggplot(GSSvocab)+

  aes(x= age)+
  geom_density(stat= "bin", fill = "gray", bins =40,)+
  theme_classic()
ggsave("myplot.png")
```

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

```
  #need to save better graph
```

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.

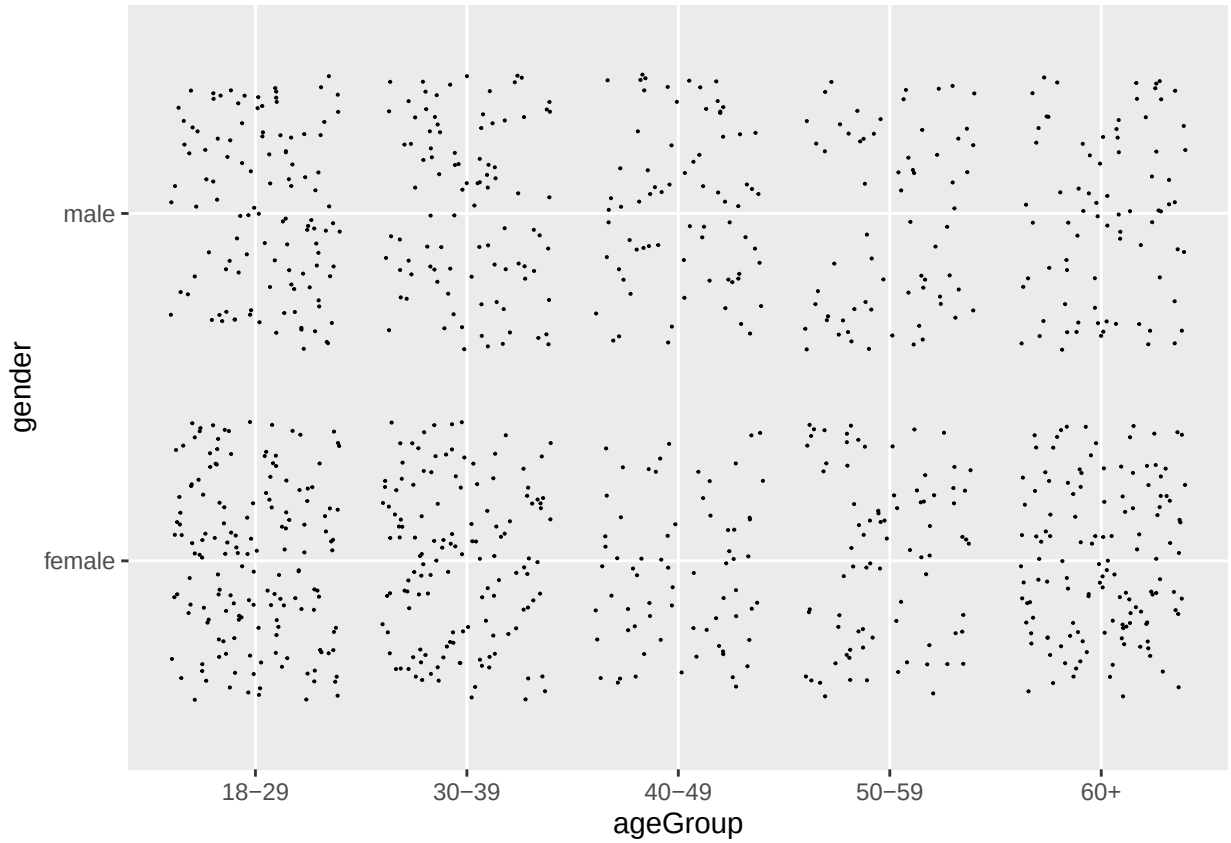
```
#catigorical.. ordinal metrics
better_graph = ggplot(GSSvocab) +
  aes(x=factor(vocab)) +
  geom_bar()
ggsave("myplot2.png")
```

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

```
my_graph2= ggplot(GSSvocab)+
  aes(x=factor(vocab) , y= educGroup) +
  geom_bin2d(binwidth = c(5, 0.5))
```

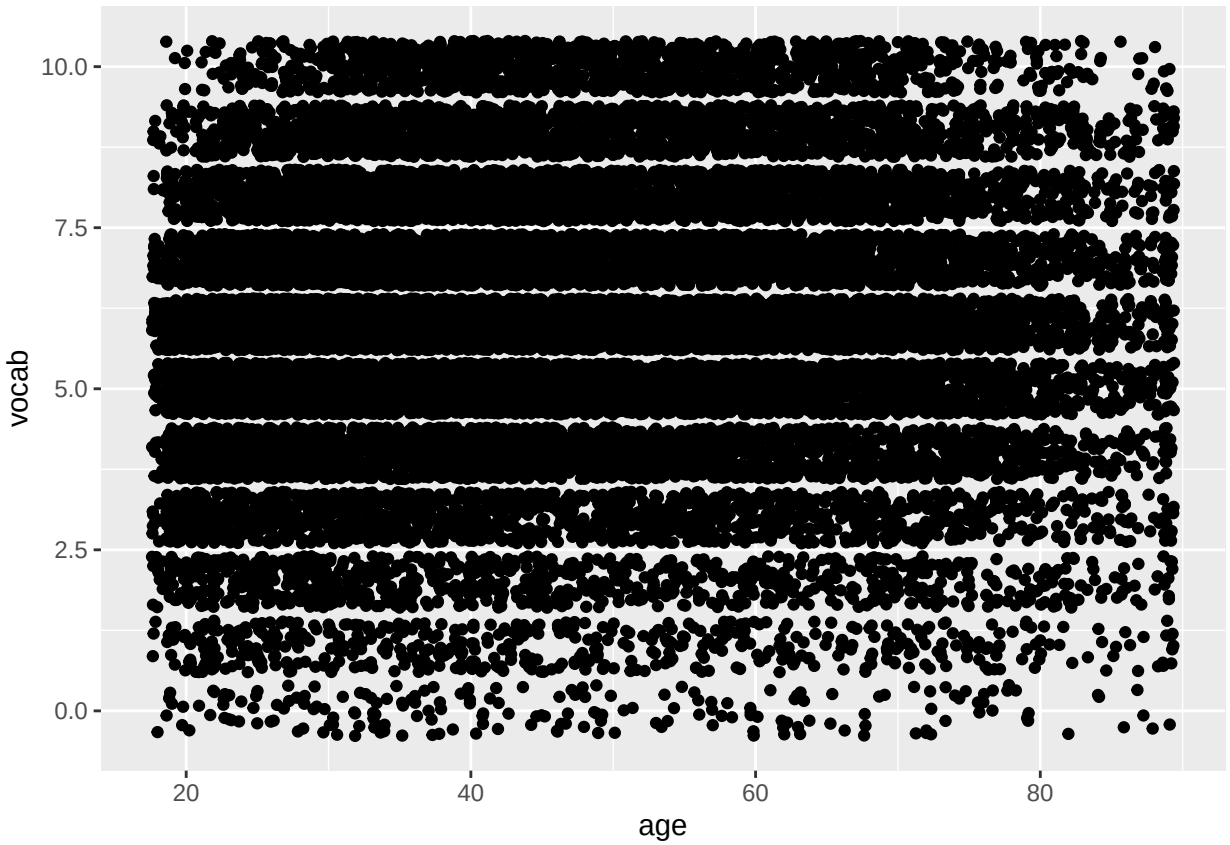
Create the best-looking plot you can to examine the `ageGroup` variable by `gender`. Does there appear to be an association? There are many ways to do this.

```
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?

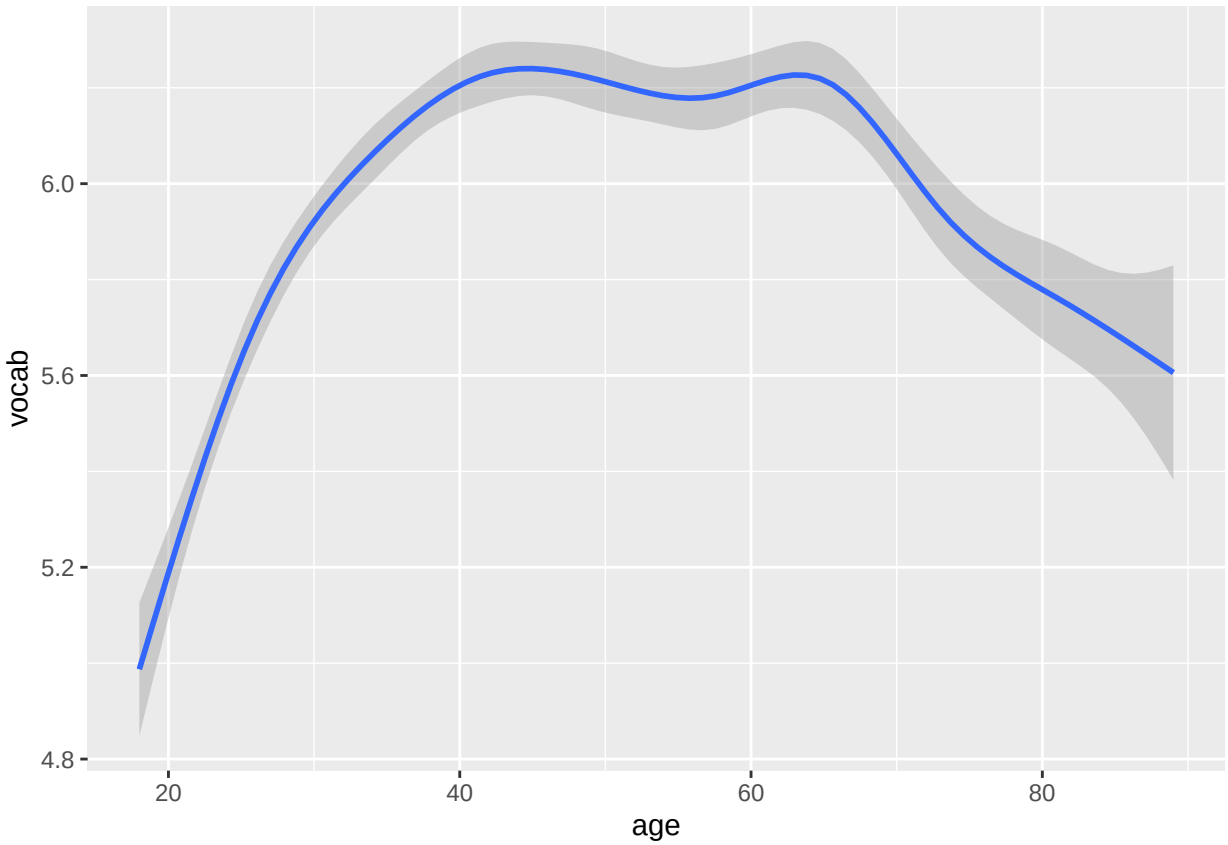
```
ggplot(GSSvocab) +
  aes(x=age, y=vocab) +
  geom_jitter()
```



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()
```

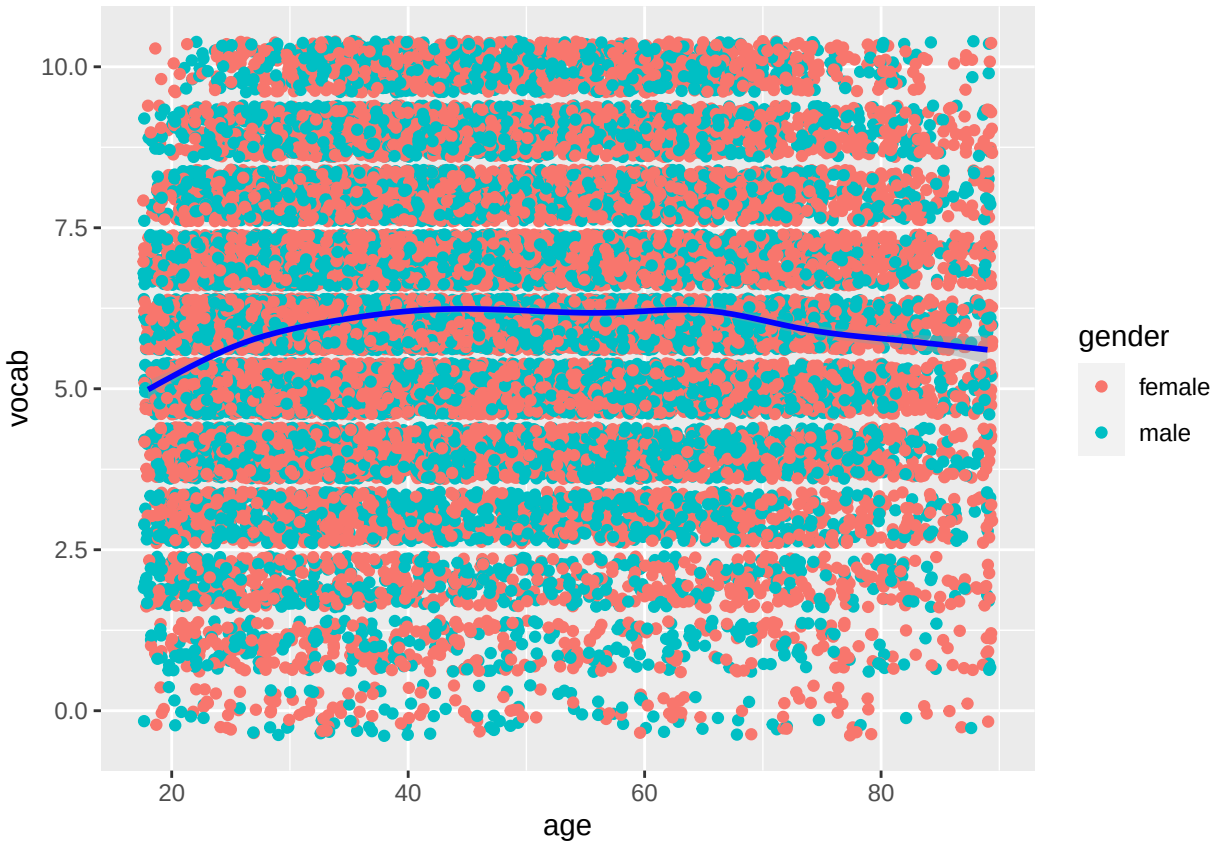
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



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")
```

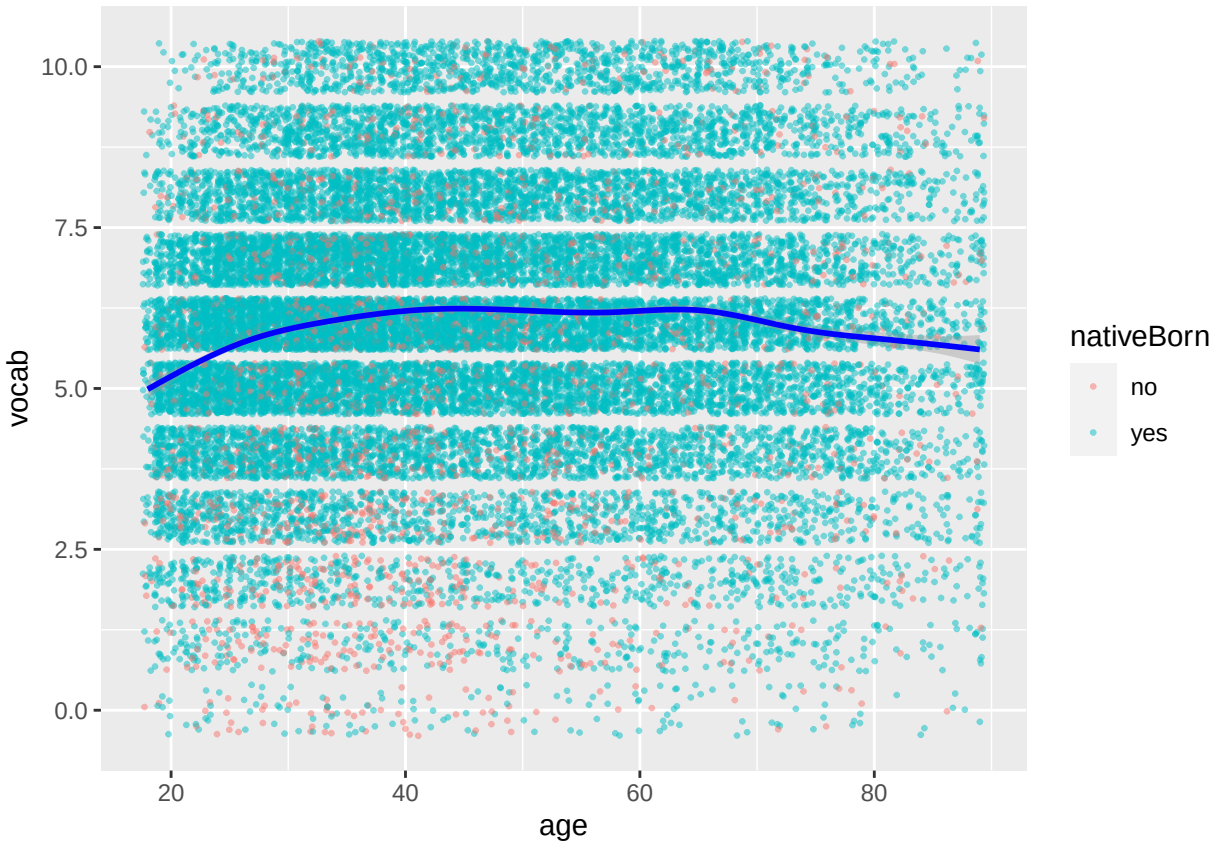
```
## `geom_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'
```



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`?

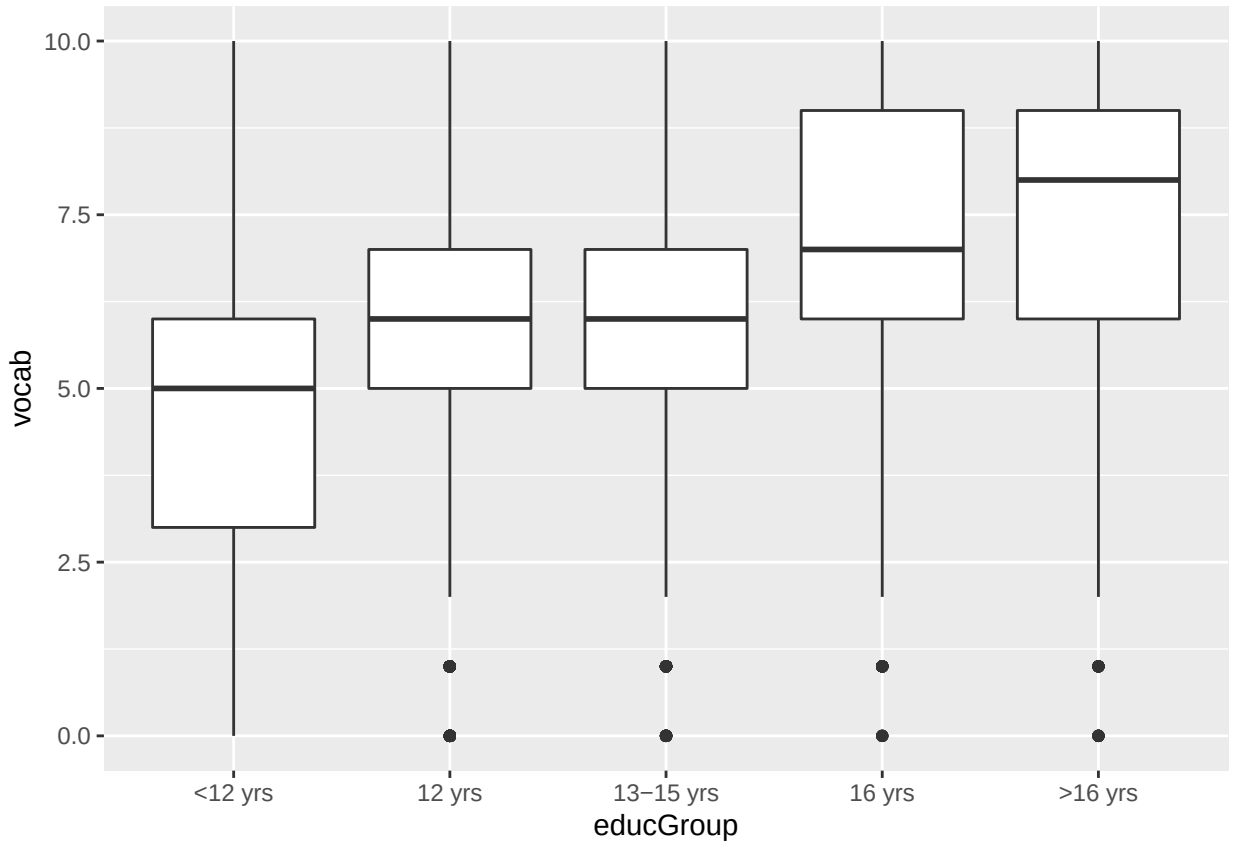
```
ggplot(GSSvocab) +
  aes(x=age, y=vocab) +
  geom_jitter(aes(col = nativeBorn), size =.5, alpha=0.5) +
  geom_smooth(col="blue")
```

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

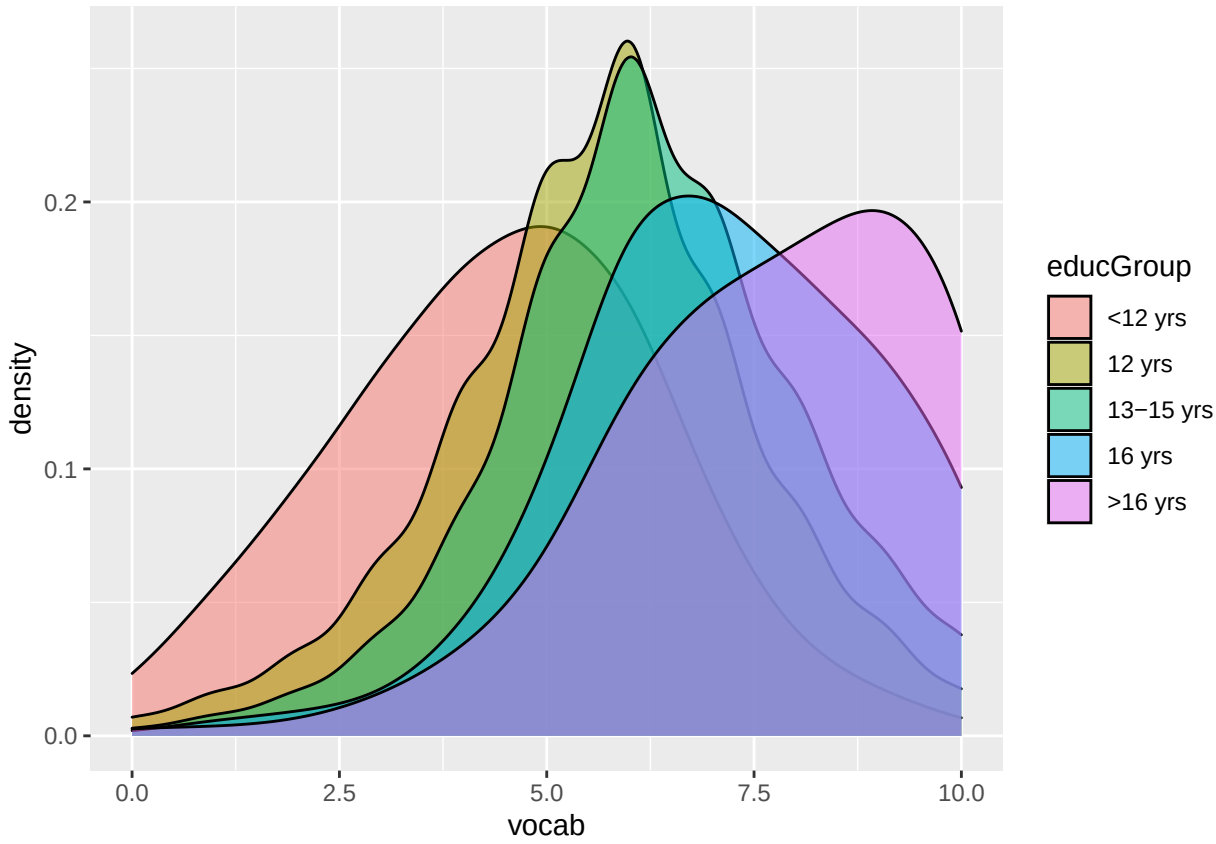


Create two different plots and identify the best-looking plot you can to examine the `vocab` variable by `educGroup`. Does there appear to be an association?

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

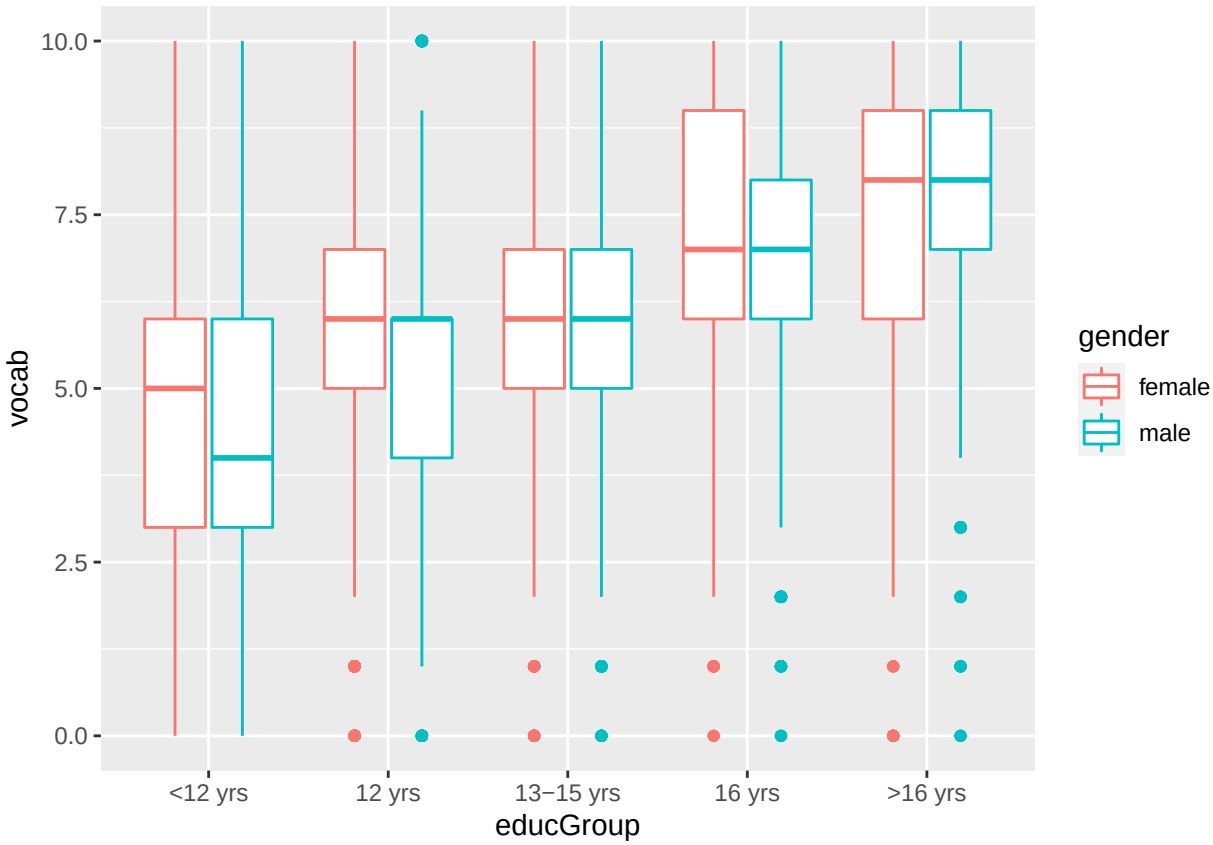



```
ggplot(GSSvocab) +
  aes(x=vocab) +
  geom_density(aes(fill = educGroup), adjust =2, alpha = .5)
```



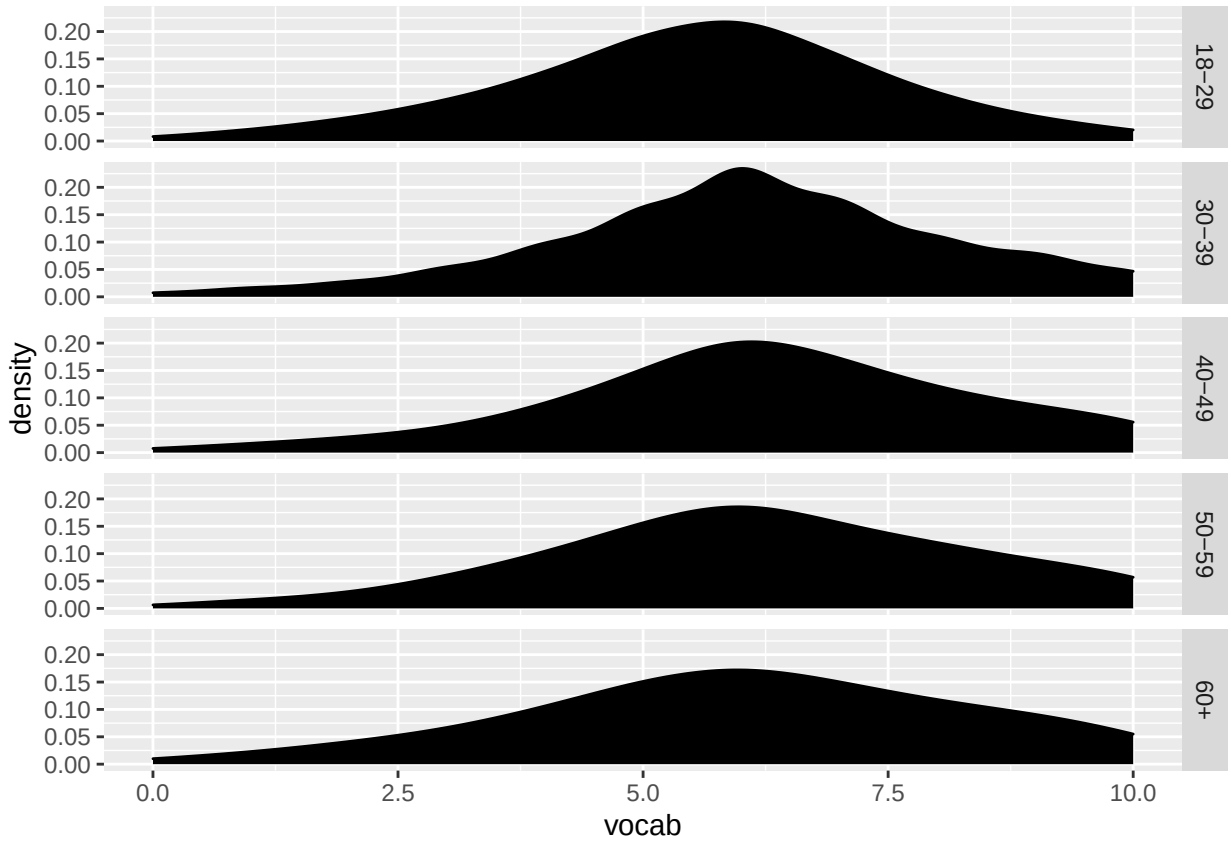
Using the best-looking plot from the previous question, create the best looking plot overloading with variable `gender`. Does there appear to be an interaction of `gender` and `educGroup`?

```
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 this will be a problem because they do not have enough data oints that could be usful for a model

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.

```
#TO-DO




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

tabworktype = sort(table(adult$worktype))

adult$occupation =NULL #get rid of dups
adult$workclass = NULL #get rid of dups

tabworktype
```

```
##
##           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.

```
#TO-DO


adult$worktype = ifelse(adult$worktype %in% names(tabworktype[tabworktype < 100]), "other", adult$workty
adult$worktype = as.factor(adult$worktype)
tableworktype2 = sort(table(adult$worktype))
tableworktype2
```

```
##
##        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.

```
#TO-DO
adult$relationship =as.character(adult$relationship)
adult$marital_status= as.character(adult$marital_status)

adult$relationship_status = paste(adult$relationship, adult$marital_status, sep =":")
tablerelationship_status = sort(table(adult$relationship_status))

adult$relationship_status = ifelse(adult$relationship_status %in% names(tablerelationship_status [table

tablerelationship_status2 = sort(table(adult$relationship_status))

adult$relationship =NULL # To get rid off this cols since the data is redundant
adult$marital_status= NULL # To get rid off this cols




tablerelationship_status2
```

```
##
##            Other-relative:Separated                  Own-child:Married
##                                  53                                 84
##                 Own-child:Separated            Other-relative:Divorced
##                                  90                                103
##               Other-relative:Married    Unmarried:Married-spouse-absent
##                                 119                                120
##                               OTHER Not-in-family:Married-spouse-absent
##                                 135                                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

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

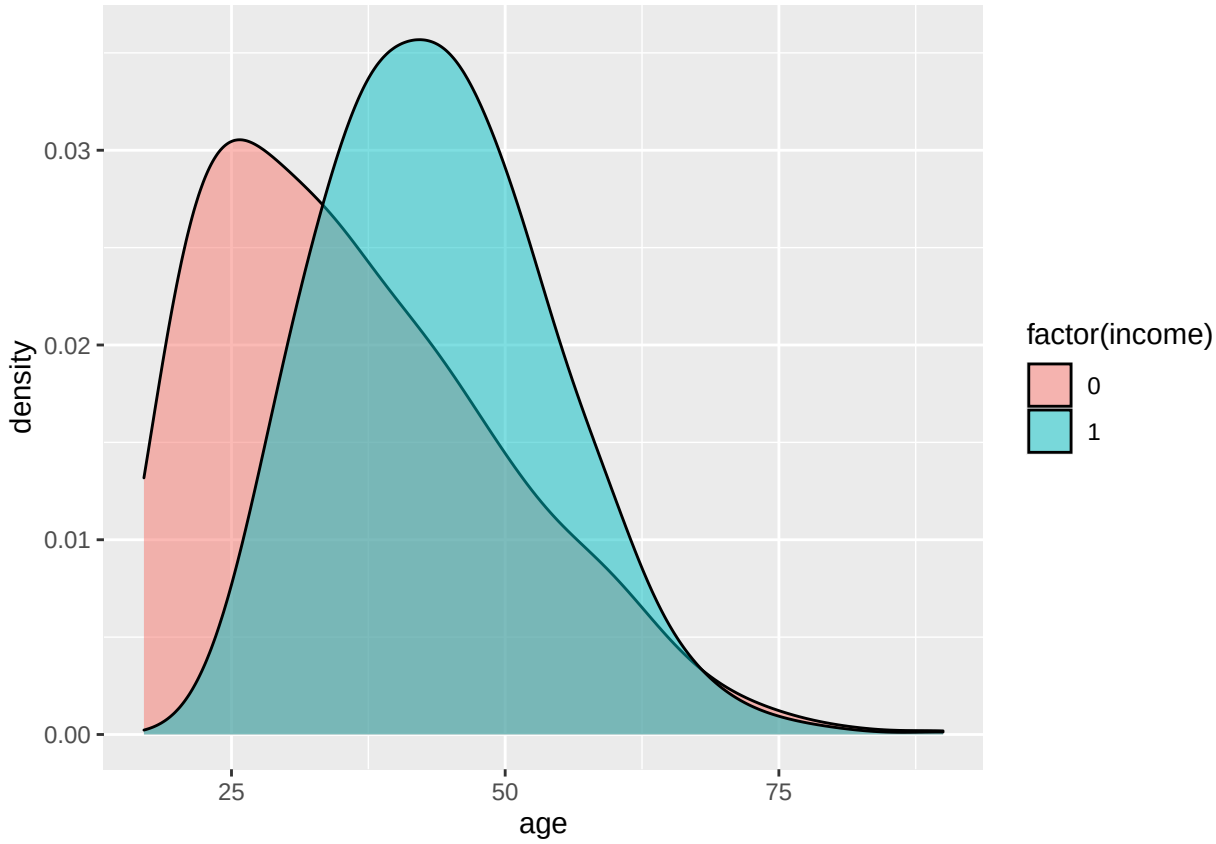
Now let's get fancier. Let's do some variable transforms. Add `log_capital_loss` derived from `capital_loss` and `log_capital_gain` derived from `capital_gain`. Since there are zeroes here, use log_x = log(1 + x) instead of log_x = log(x). That's always a neat trick. Just add them directly to the data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

```
#TO-DO
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`.

```
#TO-DO

ggplot(adult,aes(x=age))+
  geom_density(aes(fill =factor(income)), adjust=2, alpha=0.5)
```



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

there are more people who make over 50k> as they get older and less people making <50k as they get older as well. with more work experance you make more money. Younger people making less than 50k is more dense because these are people who are starting out in their careers. and some people but very few young people start out with a starting salary of over 50k.Moreover both graph starts to dip because either they are now in a differnt factor catigory such as making more money or entering retirment and making less money. Thus, yes this data is expected using common sense.

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.

```
#TO-DO

#not k fold, we only have one test set here
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(age_interactions, adult_tra
}
```

```
## 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

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

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)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading

## $`logit-vanilla`
## [1] -0.1037421
##
## $`probit-vanilla`
## [1] -0.1037971
##
## $`cloglog-vanilla`
## [1] -0.1048598
##
## $`cauchit-vanilla`
## [1] -0.1056259
##
```

```
## $`logit-age_interactions`
## [1] -0.09998096
##
## $`probit-age_interactions`
## [1] -0.1010082
##
## $`cloglog-age_interactions`
## [1] -0.3668416
##
## $`cauchit-age_interactions`
## [1] -0.1007156
```

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)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
## $`logit-vanilla`
## [1] -0.1008264
##
## $`probit-vanilla`
## [1] -0.100923
##
## $`cloglog-vanilla`
## [1] -0.1013155
##
## $`cauchit-vanilla`
## [1] -0.1019726
##
## $`logit-age_interactions`
## [1] -0.1001555
##
## $`probit-age_interactions`
## [1] -0.1008674
##
## $`cloglog-age_interactions`
## [1] -0.3638289
##
## $`cauchit-age_interactions`
## [1] -0.1030736
```

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

the logit model wins the in sample and out of same because it has the lowest brier score which means it has predictions which are better calibrated. this is expected b/c we expect the age modles to do better than the vanilla interactions because the age/interactions model has more complexities

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

#TO-DO there is only one test data set thus our oos could be very varriable.

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.

```r
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

adult_select = adult[select_indices, ]
y_select = adult_select$income
adult_select$income =NULL

adult_test = adult[test_indices, ]
y_test = adult_test$income
adult_test$income =NULL


mods = list()

for (link_function in link_functions){
  mods[[paste(link_function, "vanilla", sep = "-")]]=glm(formula = vanilla, data = adult_subtrain, famil
}
```

```
## 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

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

```r
for (link_function in link_functions){
  mods[[paste(link_function, "age_interactions", sep = "-")]]=glm(formula = age_interactions, data = adu
}
```

```
## 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

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

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

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

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

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

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

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

```
## [1] -0.1023796
```