In [ ]:
```
library(dplyr)
library(ggplot2)
library(gridExtra)
library(rpart)
library(rpart.plot)
```

```
Attaching package: ‘dplyr’


The following objects are masked from ‘package:stats’:

    filter, lag


The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union



Attaching package: ‘gridExtra’


The following object is masked from ‘package:dplyr’:

    combine
```

Supervised model

In [ ]:
```
initial_adult <- read.csv("./datasets/adult.csv")
```

In [ ]:
```
adult <- select(initial_adult, -c(x, educational.num))
head(adult)
```

A data.frame: 6 × 8

age	workclass	education	marital.status	race	gender	hours.per.week	income

	age	workclass	education	marital.status	race	gender	hours.per.week	income
	<int>	<chr>	<chr>	<chr>	<chr>	<chr>	<int>	<chr>
1	25	Private	11th	Never-married	Black	Male	40	<=50K
2	38	Private	HS-grad	Married-civ-spouse	White	Male	50	<=50K
3	28	Local-gov	Assoc-acdm	Married-civ-spouse	White	Male	40	>50K
4	44	Private	Some-college	Married-civ-spouse	Black	Male	40	>50K
5	18	?	Some-college	Never-married	White	Female	30	<=50K
6	34	Private	10th	Never-married	White	Male	30	<=50K

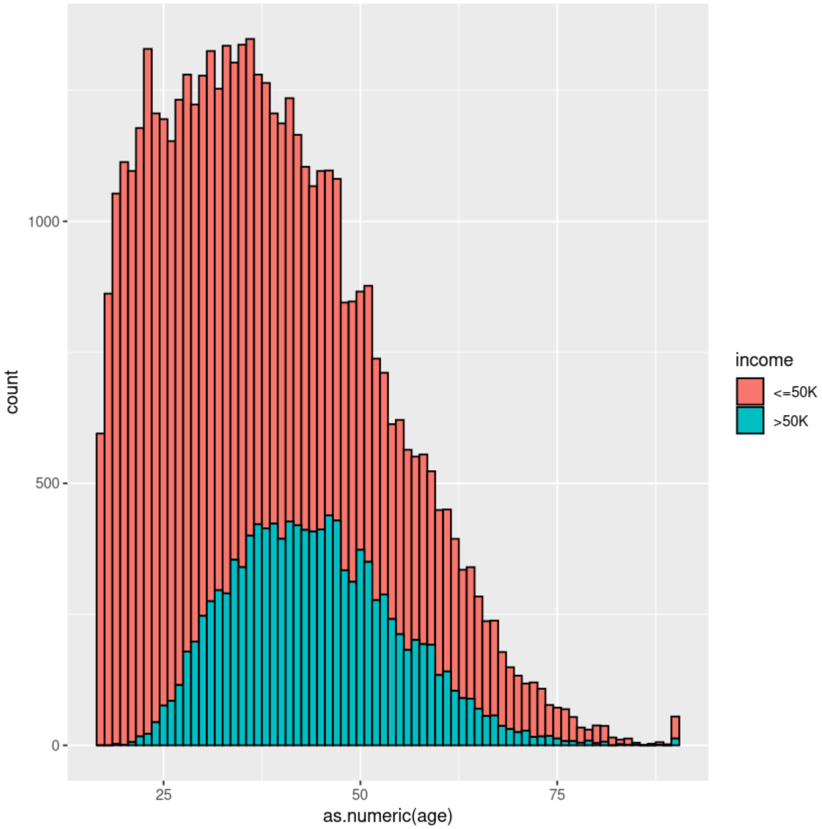
In [ ]:

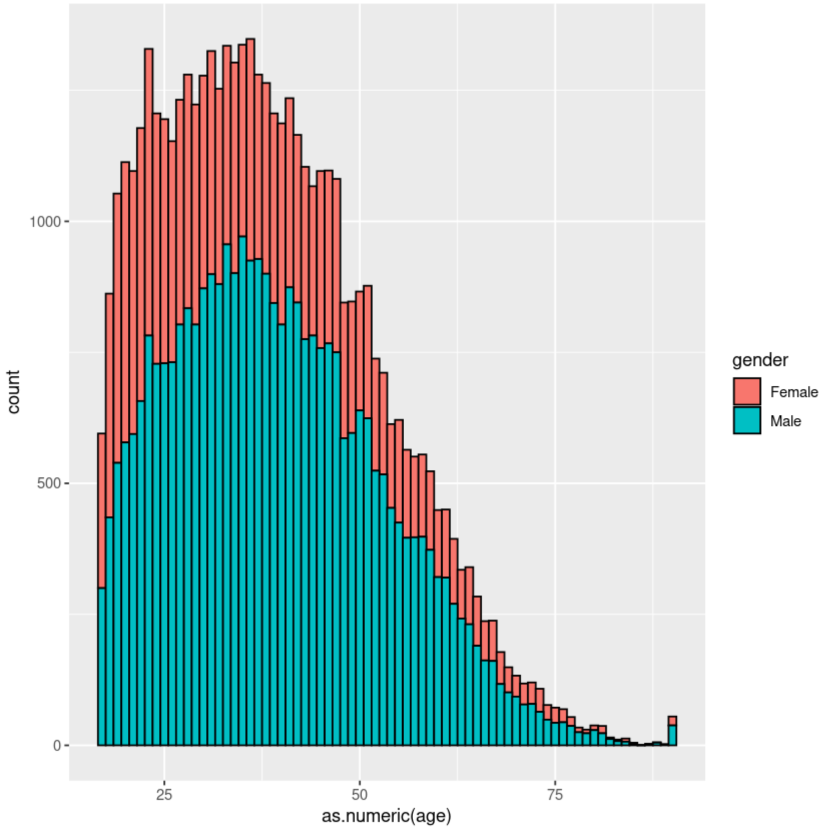
```
summary(adult)
```

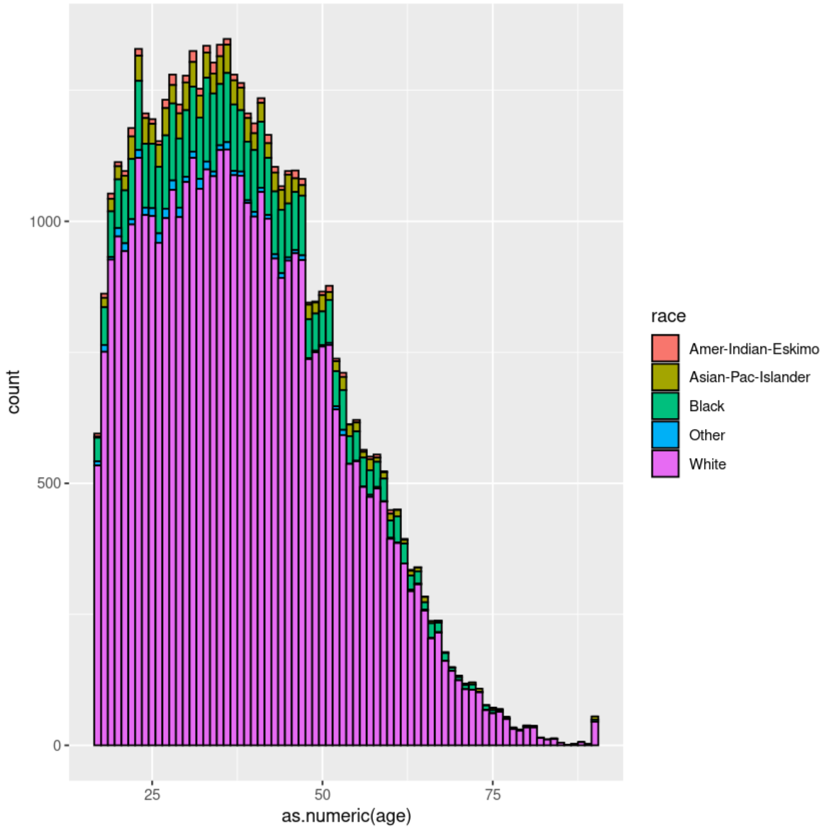
```
      age          workclass           education          marital.status    
 Min.   :17.00   Length:48842       Length:48842       Length:48842      
 1st Qu.:28.00   Class :character   Class :character   Class :character  
 Median :37.00   Mode  :character   Mode  :character   Mode  :character  
 Mean   :38.64                                                           
 3rd Qu.:48.00                                                           
 Max.   :90.00                                                           
     race              gender          hours.per.week     income         
 Length:48842       Length:48842       Min.   : 1.00   Length:48842      
 Class :character   Class :character   1st Qu.:40.00   Class :character  
 Mode  :character   Mode  :character   Median :40.00   Mode  :character  
                                       Mean   :40.42                     
                                       3rd Qu.:45.00                     
                                       Max.   :99.00                     
```

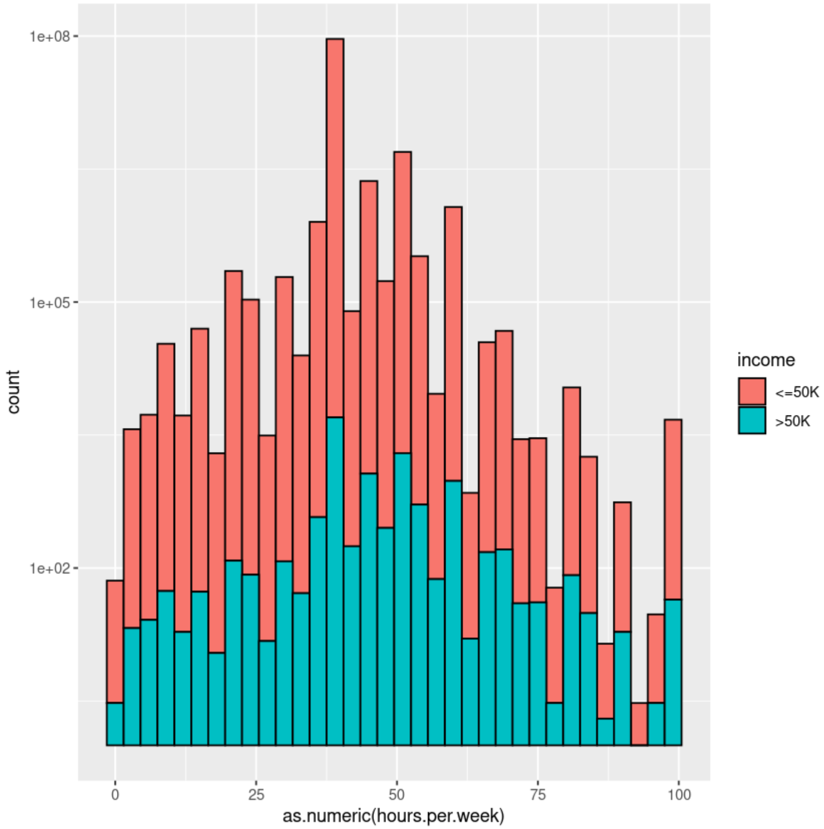
In [ ]:

```
ggplot(adult) + aes(x=as.numeric(age), group=income, fill=income) +
  geom_histogram(binwidth=1, color="black")
ggplot(adult) + aes(x=as.numeric(age), group=gender, fill=gender) +
  geom_histogram(binwidth=1, color='black')
ggplot(adult) + aes(x=as.numeric(age), group=race, fill=race) +
  geom_histogram(binwidth=1, color='black')
ggplot(adult) + aes(x=as.numeric(hours.per.week), group=income, fill=income) +
  geom_histogram(binwidth=3, color='black') +
  scale_y_log10()
```


count
1000
500
0
25
50
75
as.numeric(age)
income
<=50K
>50K


count
1000
500
0
25
50
75
as.numeric(age)
gender
Female
Male


count
1000
500
0
25
50
75
as.numeric(age)
race
Amer-Indian-Eskimo
Asian-Pac-Islander
Black
Other
White



In [ ]:
```
sum(is.na(adult))
```

0

There is no NA, but we want to investigate whether there are missing values categorized as some other way.

In [ ]:
```
for (col in colnames(adult)){
    print(c(unique(adult[col])))
}
```

```
$age
 [1] 25 38 28 44 18 34 29 63 24 55 65 36 26 58 48 43 20 37 40 72 45 22 23 54 32
[26] 46 56 17 39 52 21 42 33 30 47 41 19 69 50 31 59 49 51 27 57 61 64 79 73 53
[51] 77 80 62 35 68 66 75 60 67 71 70 90 81 74 78 82 83 85 76 84 89 88 87 86
```

```
$workclass
[1] "Private"          "Local-gov"        "?"                "Self-emp-not-inc"
[5] "Federal-gov"      "State-gov"        "Self-emp-inc"     "Without-pay"
[9] "Never-worked"

$education
 [1] "11th"         "HS-grad"      "Assoc-acdm"   "Some-college" "10th"
 [6] "Prof-school"  "7th-8th"      "Bachelors"    "Masters"      "Doctorate"
[11] "5th-6th"      "Assoc-voc"    "9th"          "12th"         "1st-4th"
[16] "Preschool"

$marital.status
[1] "Never-married"         "Married-civ-spouse"    "Widowed"
[4] "Divorced"              "Separated"             "Married-spouse-absent"
[7] "Married-AF-spouse"

$race
[1] "Black"              "White"              "Asian-Pac-Islander"
[4] "Other"              "Amer-Indian-Eskimo"

$gender
[1] "Male"   "Female"

$hours.per.week
 [1] 40 50 30 32 10 39 35 48 25 20 45 47  6 43 90 54 60 38 36 18 24 44 56 28 16
[26] 41 22 55 14 33 37  8 12 70 15 75 52 84 42 80 68 99 65  5 17 72 53 29 96 21
[51] 46  3  1 23 49 67 76  7  2 58 26 34  4 51 78 63 31 92 77 27 85 13 19 98 62
[76] 66 57 11 86 59  9 64 73 61 88 79 89 74 69 87 97 94 82 91 81 95

$income
[1] "<=50K" ">50K"
```

There are some `?` values in the `workclass` column and `Other` in the `race` column.

In [ ]:

```
sum(adult$workclass == "?") # number of `?`
sum(adult$race == "Other") # number of `Other`
```

2799

406

Drop "?" and "other" observations

In [ ]:

```
adult <- adult[!adult$workclass == "?",]
adult <- adult[!adult$race == "Other",]
```

Now label encode categorical values before feeding

In [ ]:

```
for (col in c("workclass", "education", "marital.status", "race", "gender", "income")){
    adult[[col]] <- as.integer(factor(adult[[col]], labels=1:length(unique(adult[[col]]))))-1
}
```

In [ ]:

```
create_train_test <- function(data, size=0.8, train=TRUE, seed=TRUE){
    if (seed) {
        set.seed(42)
    }
    smp_size <- floor(size * nrow(data))
    train_ind <- sample(seq_len(nrow(data)), size = smp_size)

    if (train) {
        return (data[train_ind, ])
    } else {
        return (data[-train_ind, ])
    }
}
data_train <- create_train_test(adult, size=0.8, train=TRUE)
data_test <- create_train_test(adult, size=0.8, train=FALSE)
# X_train <- select(data_train, -income)
# y_train <- select(data_train, income)
# X_test <- select(data_test, -income)
# y_test <- select(data_test, income)
```

In [ ]:

```
dim(data_train)
dim(data_test)
```

36534 · 8

9134 · 8

In [ ]:

```
prop.table(table(data_train$income))
prop.table(table(data_test$income))
```

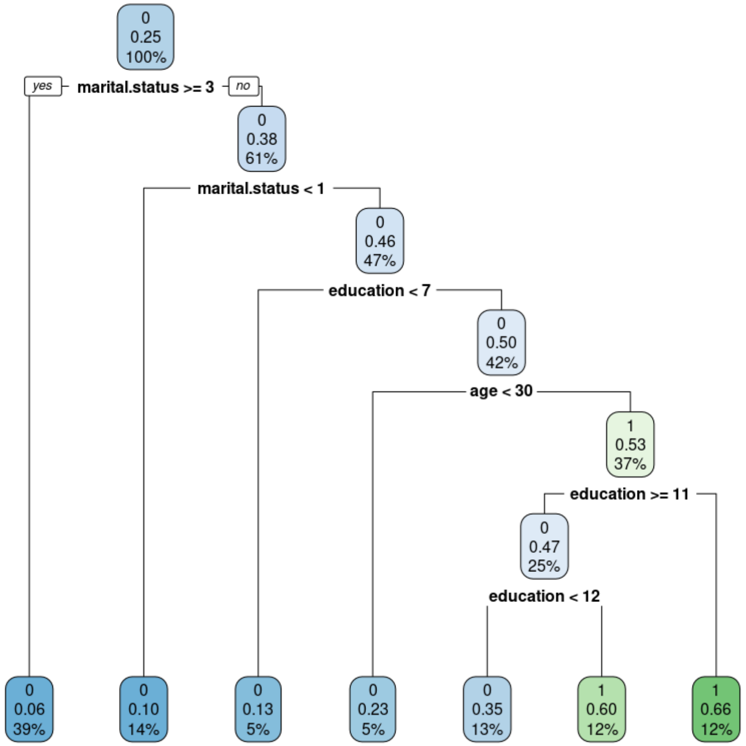
```
        0          1
```

```
0.7499589 0.2500411
        0         1
0.7547624 0.2452376
```

Plot decision tree

In [ ]:

```
fit <- rpart(income~., data_train, method="class")
rpart.plot(fit, extra=106)
```



Display confusion

In [ ]:

```
pred <- predict(fit, data_test, type="class")
conf_mat <- table(pred, data_test$income)
print(conf_mat)
```

```
pred    0    1
   0 6085  887
   1  809 1353
```

Deduce model accuracy

In [ ]:
```
accuracy <- sum(diag(conf_mat)) / sum(conf_mat)
print(paste("accuracy:", accuracy))
```

```
[1] "accuracy: 0.814320122618787"
```

Display model parameters

In [ ]:
```
rpart.control()
```

$minsplit	20
$minbucket	7
$cp	0.01
$maxcompete	4
$maxsurrogate	5
$usesurrogate	2
$surrogatestyle	0
$maxdepth	30
$xval	10

In [ ]:
```
control <- rpart.control()
fit <- rpart(income~., data_train, method="class", control=control)
pred <- predict(fit, data_test, type="class")
conf_mat <- table(pred, data_test$income)
print(conf_mat)
accuracy <- sum(diag(conf_mat)) / sum(conf_mat)
print(paste("accuracy:", accuracy))
```

```
pred    0    1
   0 6085  887
```

```
   1  809 1353
[1] "accuracy: 0.814320122618787"
```

Unsupervised model

In [ ]:

```
library(cluster)
library(factoextra)
library(magrittr)
```

```
Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

In [ ]:

```
initial_cars <- mtcars
cars <- data.frame(initial_cars)
head(initial_cars)
```

A data.frame: 6 × 11

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

In [ ]:

```
sum(is.na(cars_data)) # no NA
```

0

In [ ]:

```
for (col in colnames(cars)){
    print(c(unique(cars[col])))
}
```

```
$mpg
 [1] 21.0 22.8 21.4 18.7 18.1 14.3 24.4 19.2 17.8 16.4 17.3 15.2 10.4 14.7 32.4
[16] 30.4 33.9 21.5 15.5 13.3 27.3 26.0 15.8 19.7 15.0

$cyl
[1] 6 4 8

$disp
 [1] 160.0 108.0 258.0 360.0 225.0 146.7 140.8 167.6 275.8 472.0 460.0 440.0
[13]  78.7  75.7  71.1 120.1 318.0 304.0 350.0 400.0  79.0 120.3  95.1 351.0
[25] 145.0 301.0 121.0

$hp
 [1] 110  93 175 105 245  62  95 123 180 205 215 230  66  52  65  97 150  91 113
[20] 264 335 109

$drat
 [1] 3.90 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.07 2.93 3.00 3.23 4.08 4.93 4.22
[16] 3.70 3.73 4.43 3.77 3.62 3.54 4.11

$wt
 [1] 2.620 2.875 2.320 3.215 3.440 3.460 3.570 3.190 3.150 4.070 3.730 3.780
[13] 5.250 5.424 5.345 2.200 1.615 1.835 2.465 3.520 3.435 3.840 3.845 1.935
[25] 2.140 1.513 3.170 2.770 2.780

$qsec
 [1] 16.46 17.02 18.61 19.44 20.22 15.84 20.00 22.90 18.30 18.90 17.40 17.60
[13] 18.00 17.98 17.82 17.42 19.47 18.52 19.90 20.01 16.87 17.30 15.41 17.05
[25] 16.70 16.90 14.50 15.50 14.60 18.60

$vs
[1] 0 1

$am
[1] 1 0

$gear
[1] 4 3 5

$carb
[1] 4 1 2 3 6 8
```

In [ ]:

```
cars <- data.frame(scale(cars))
head(cars)
cars <- select(cars, -c(mpg))
```

A data.frame: 6 × 11

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
Mazda RX4	0.1508848	-0.1049878	-0.57061982	-0.5350928	0.5675137	-0.610399567	-0.7771651	-0.8680278	1.1899014	0.4235542	0.7352031
Mazda RX4 Wag	0.1508848	-0.1049878	-0.57061982	-0.5350928	0.5675137	-0.349785269	-0.4637808	-0.8680278	1.1899014	0.4235542	0.7352031
Datsun 710	0.4495434	-1.2248578	-0.99018209	-0.7830405	0.4739996	-0.917004624	0.4260068	1.1160357	1.1899014	0.4235542	-1.1221521
Hornet 4 Drive	0.2172534	-0.1049878	0.22009369	-0.5350928	-0.9661175	-0.002299538	0.8904872	1.1160357	-0.8141431	-0.9318192	-1.1221521
Hornet Sportabout	-0.2307345	1.0148821	1.04308123	0.4129422	-0.8351978	0.227654255	-0.4637808	-0.8680278	-0.8141431	-0.9318192	-0.5030337
Valiant	-0.3302874	-0.1049878	-0.04616698	-0.6080186	-1.5646078	0.248094592	1.3269868	1.1160357	-0.8141431	-0.9318192	-1.1221521

In [ ]:

```
km.res <- kmeans(cars, 3, nstart=25)
```

In [ ]:

```
fviz_cluster(km.res, data=cars, ellipse.type="convex")
```

In [ ]:

```
pam.res <- pam(cars, 3)
fviz_cluster(pam.res) #almost similar to kmeans results
```

We see that for the most part, K-means and PAM classify in the same way. Only some samples between the center and the upper-right classes change class when modifying the method.

In [ ]:

In [ ]: