Disclaimer: It is probably easier to read this assignment as `.Rmd` and not as PDF, because there are a lot of outputs and plots, which can get a little overwhelming when not viewed through RStudio.

Exercise 1

In this exercise we use the College data set from the ISLR package. We predict the number of applications received using the other variables.

```
library(ISLR)
library(tidymodels)

library(tidymodels)
library(funModeling)
library(ISLR)
library(vip)
library(forcats)
library(GGally)

?ISLR::College
```

```
College <- tibble(College)
College
```

```
## # A tibble: 777 x 18
##    Private  Apps Accept Enroll Top10perc Top25perc F.Undergrad P.Undergrad
##    <fct>   <dbl>  <dbl>  <dbl>     <dbl>     <dbl>       <dbl>       <dbl>
##  1 Yes      1660   1232    721        23        52        2885         537
##  2 Yes      2186   1924    512        16        29        2683        1227
##  3 Yes      1428   1097    336        22        50        1036          99
##  4 Yes       417    349    137        60        89         510          63
##  5 Yes       193    146     55        16        44         249         869
##  6 Yes       587    479    158        38        62         678          41
##  7 Yes       353    340    103        17        45         416         230
##  8 Yes      1899   1720    489        37        68        1594          32
##  9 Yes      1038    839    227        30        63         973         306
## 10 Yes       582    498    172        21        44         799          78
## # ... with 767 more rows, and 10 more variables: Outstate <dbl>,
## #   Room.Board <dbl>, Books <dbl>, Personal <dbl>, PhD <dbl>, Terminal <dbl>,
## #   S.F.Ratio <dbl>, perc.alumni <dbl>, Expend <dbl>, Grad.Rate <dbl>
```

```
basic_eda <- function(data) {
  glimpse(data)
  print(status(data))
  freq(data)
  print(profiling_num(data))
  plot_num(data)
  describe(data)
}

basic_eda(College)
```

```
## Rows: 777
## Columns: 18
## $ Private     <fct> Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes~
## $ Apps        <dbl> 1660, 2186, 1428, 417, 193, 587, 353, 1899, 1038, 582, 173~
```

```
## $ Accept      <dbl> 1232, 1924, 1097, 349, 146, 479, 340, 1720, 839, 498, 1425~
## $ Enroll      <dbl> 721, 512, 336, 137, 55, 158, 103, 489, 227, 172, 472, 484,~
## $ Top10perc   <dbl> 23, 16, 22, 60, 16, 38, 17, 37, 30, 21, 37, 44, 38, 44, 23~
## $ Top25perc   <dbl> 52, 29, 50, 89, 44, 62, 45, 68, 63, 44, 75, 77, 64, 73, 46~
## $ F.Undergrad <dbl> 2885, 2683, 1036, 510, 249, 678, 416, 1594, 973, 799, 1830~
## $ P.Undergrad <dbl> 537, 1227, 99, 63, 869, 41, 230, 32, 306, 78, 110, 44, 638~
## $ Outstate    <dbl> 7440, 12280, 11250, 12960, 7560, 13500, 13290, 13868, 1559~
## $ Room.Board  <dbl> 3300, 6450, 3750, 5450, 4120, 3335, 5720, 4826, 4400, 3380~
## $ Books       <dbl> 450, 750, 400, 450, 800, 500, 500, 450, 300, 660, 500, 400~
## $ Personal    <dbl> 2200, 1500, 1165, 875, 1500, 675, 1500, 850, 500, 1800, 60~
## $ PhD         <dbl> 70, 29, 53, 92, 76, 67, 90, 89, 79, 40, 82, 73, 60, 79, 36~
## $ Terminal    <dbl> 78, 30, 66, 97, 72, 73, 93, 100, 84, 41, 88, 91, 84, 87, 6~
## $ S.F.Ratio   <dbl> 18.1, 12.2, 12.9, 7.7, 11.9, 9.4, 11.5, 13.7, 11.3, 11.5, ~
## $ perc.alumni <dbl> 12, 16, 30, 37, 2, 11, 26, 37, 23, 15, 31, 41, 21, 32, 26,~
## $ Expend      <dbl> 7041, 10527, 8735, 19016, 10922, 9727, 8861, 11487, 11644,~
## $ Grad.Rate   <dbl> 60, 56, 54, 59, 15, 55, 63, 73, 80, 52, 73, 76, 74, 68, 55~
##                variable q_zeros     p_zeros q_na p_na q_inf p_inf    type
## Private         Private       0 0.000000000    0    0     0     0  factor
## Apps               Apps       0 0.000000000    0    0     0     0 numeric
## Accept           Accept       0 0.000000000    0    0     0     0 numeric
## Enroll           Enroll       0 0.000000000    0    0     0     0 numeric
## Top10perc     Top10perc       0 0.000000000    0    0     0     0 numeric
## Top25perc     Top25perc       0 0.000000000    0    0     0     0 numeric
## F.Undergrad F.Undergrad       0 0.000000000    0    0     0     0 numeric
## P.Undergrad P.Undergrad       0 0.000000000    0    0     0     0 numeric
## Outstate       Outstate       0 0.000000000    0    0     0     0 numeric
## Room.Board   Room.Board       0 0.000000000    0    0     0     0 numeric
## Books             Books       0 0.000000000    0    0     0     0 numeric
## Personal       Personal       0 0.000000000    0    0     0     0 numeric
## PhD                 PhD       0 0.000000000    0    0     0     0 numeric
## Terminal       Terminal       0 0.000000000    0    0     0     0 numeric
## S.F.Ratio     S.F.Ratio       0 0.000000000    0    0     0     0 numeric
## perc.alumni perc.alumni       2 0.002574003    0    0     0     0 numeric
## Expend           Expend       0 0.000000000    0    0     0     0 numeric
## Grad.Rate     Grad.Rate       0 0.000000000    0    0     0     0 numeric
##             unique
## Private          2
## Apps           711
## Accept         693
## Enroll         581
## Top10perc       82
## Top25perc       89
## F.Undergrad    714
## P.Undergrad    566
## Outstate       640
## Room.Board     553
## Books          122
## Personal       294
## PhD             78
## Terminal        65
## S.F.Ratio      173
## perc.alumni     61
## Expend         744
## Grad.Rate       81
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```

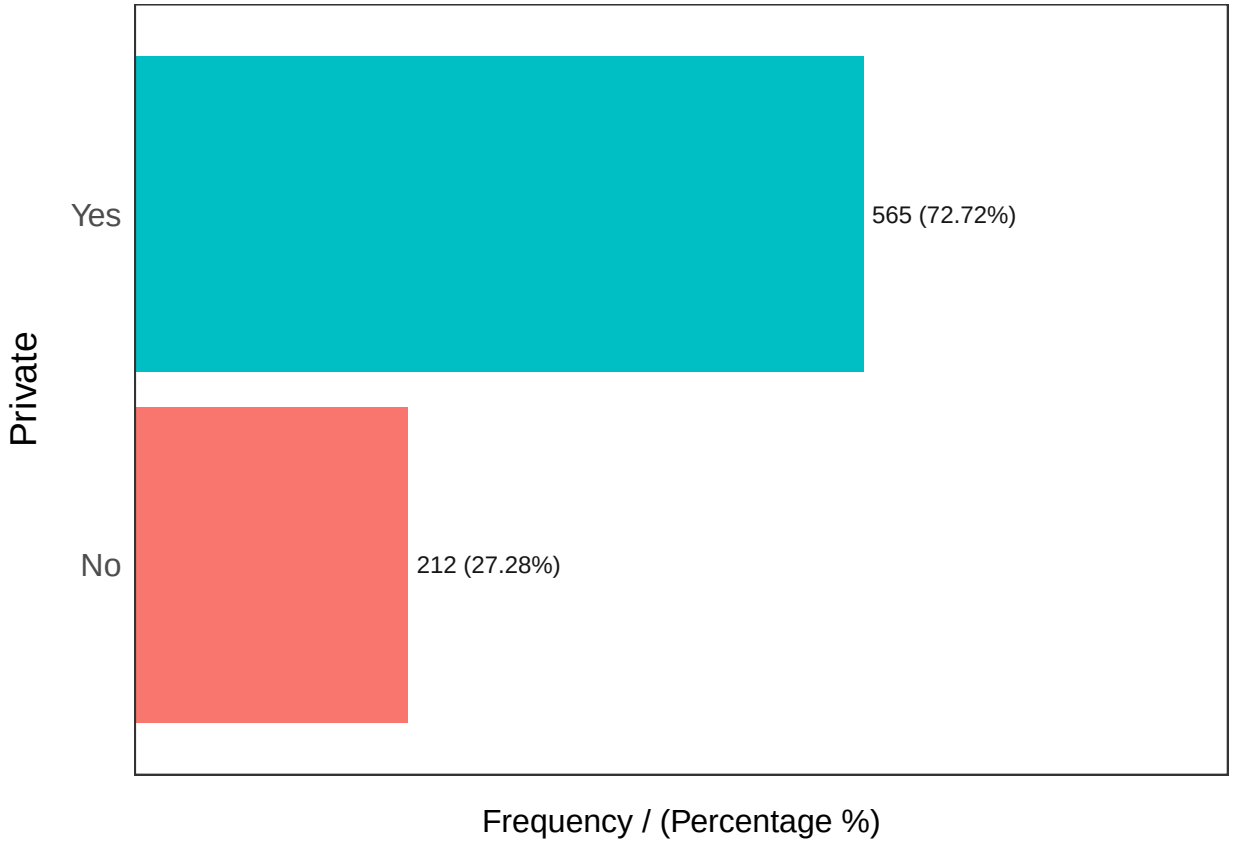
	variable	mean	std_dev	variation_coef	p_01	p_05	p_25
1	Apps	3001.63835	3870.201484	1.2893630	192.52	329.8	776.0
2	Accept	2018.80438	2451.113971	1.2141414	146.00	272.4	604.0
3	Enroll	779.97297	929.176190	1.1912928	78.04	118.6	242.0
4	Top10perc	27.55856	17.640364	0.6401048	3.00	7.0	15.0
5	Top25perc	55.79665	19.804778	0.3549456	18.76	25.8	41.0
6	F.Undergrad	3699.90734	4850.420531	1.3109573	324.36	509.8	992.0
7	P.Undergrad	855.29858	1522.431887	1.7800005	4.76	20.0	95.0
8	Outstate	10440.66924	4023.016484	0.3853217	3737.28	4601.6	7320.0
9	Room.Board	4357.52638	1096.696416	0.2516787	2377.60	2735.8	3597.0
10	Books	549.38095	165.105360	0.3005298	250.00	350.0	470.0
11	Personal	1340.64221	677.071454	0.5050352	400.00	500.0	850.0
12	PhD	72.66023	16.328155	0.2247193	28.28	43.8	62.0
13	Terminal	79.70270	14.722359	0.1847159	40.04	52.8	71.0
14	S.F.Ratio	14.08970	3.958349	0.2809391	5.00	8.3	11.5
15	perc.alumni	22.74389	12.391801	0.5448410	3.00	6.0	13.0
16	Expend	9660.17117	5221.768440	0.5405462	3869.32	4795.8	6751.0
17	Grad.Rate	65.46332	17.177710	0.2624021	23.52	37.0	53.0

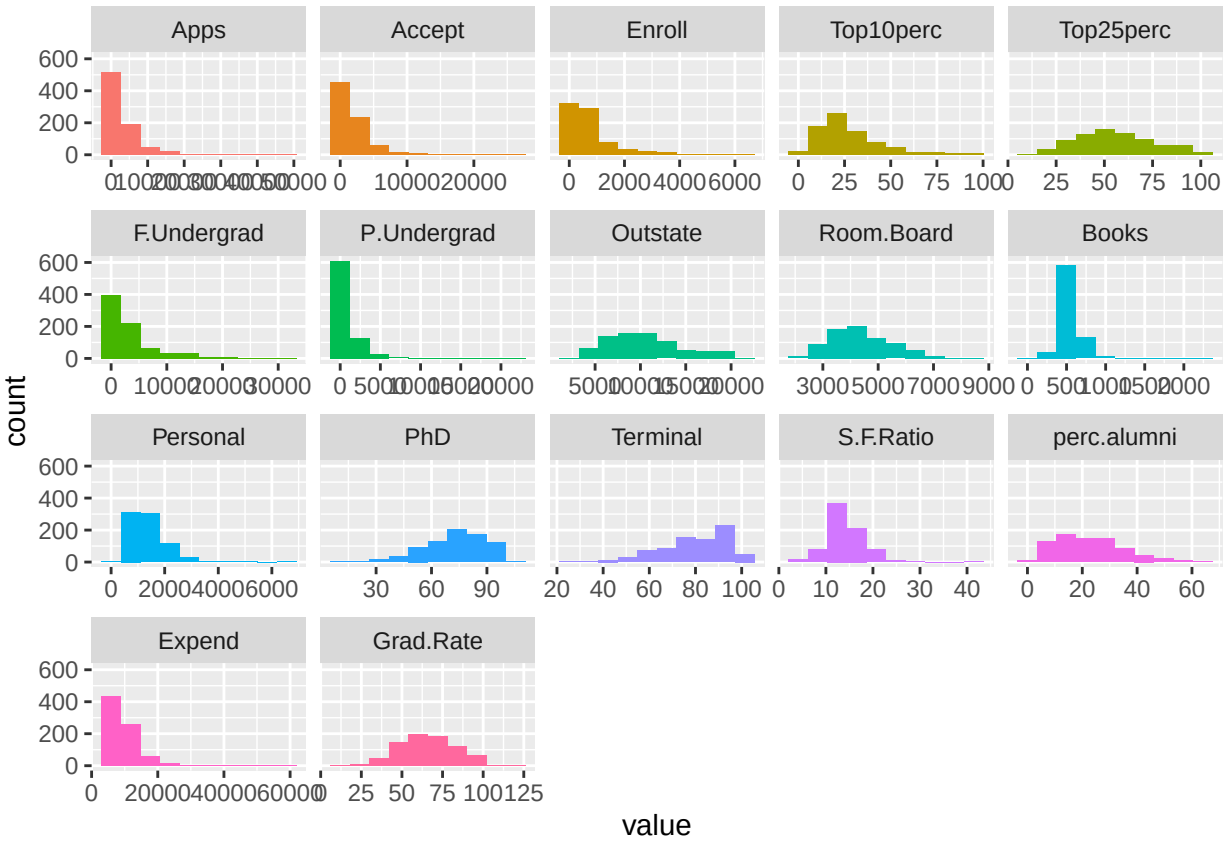
	p_50	p_75	p_95	p_99	skewness	kurtosis	iqr
1	1558.0	3624.0	11066.2	16026.12	3.7165574	29.594559	2848
2	1110.0	2424.0	6979.2	11668.08	3.4111259	21.808740	1820
3	434.0	902.0	2757.0	4618.84	2.6852679	11.767103	660
4	23.0	35.0	65.2	87.48	1.4104871	5.186169	20
5	54.0	69.0	93.0	99.00	0.2588394	2.431791	28
6	1707.0	4005.0	14477.8	24540.32	2.6054157	10.639436	3013
7	353.0	967.0	3303.6	7477.08	5.6813582	57.673296	872
8	9990.0	12925.0	18498.0	19677.20	0.5082943	2.581114	5605
9	4200.0	5050.0	6382.0	7031.44	0.4764335	2.805940	1453
10	500.0	600.0	765.6	1143.00	3.4782933	31.143390	130
11	1200.0	1700.0	2488.8	3336.00	1.7391308	10.070544	850
12	75.0	85.0	95.0	99.00	-0.7666864	3.553433	23
13	82.0	92.0	98.0	100.00	-0.8149652	3.232752	21
14	13.6	16.5	21.0	23.72	0.6661462	5.537045	5
15	21.0	31.0	46.0	55.00	0.6057190	2.896103	18
16	8377.0	10830.0	17974.8	31335.48	3.4526399	21.643210	4079
17	65.0	78.0	94.2	100.00	-0.1135575	2.788380	25

	range_98	range_80
1	[192.52, 16026.12]	[457.6, 7675]
2	[146, 11668.08]	[361.6, 4814.2]
3	[78.04, 4618.84]	[154, 1903.6]
4	[3, 87.48]	[10, 50.4]
5	[18.76, 99]	[30.6, 85]
6	[324.36, 24540.32]	[641, 10024.4]
7	[4.76, 7477.08]	[35, 2016.6]
8	[3737.28, 19677.2]	[5568.8, 16552.8]
9	[2377.6, 7031.44]	[3051.2, 5950]
10	[250, 1143]	[400, 700]
11	[400, 3336]	[600, 2200]
12	[28.28, 99]	[50.6, 92]
13	[40.04, 100]	[59, 96]
14	[5, 23.72]	[9.9, 19.2]

```
## 15             [3, 55]           [8, 40]
## 16 [3869.32, 31335.48]   [5558.2, 14841]
## 17        [23.52, 100]        [44.6, 89]
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```






```
## data
##
##  18  Variables      777  Observations
## --------------------------------------------------------------------------------
## Private
##        n  missing distinct
##      777        0        2
##
## Value          No   Yes
## Frequency     212   565
## Proportion 0.273 0.727
## --------------------------------------------------------------------------------
## Apps
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      711        1     3002     3350    329.8    457.6
##      .25      .50      .75      .90      .95
##    776.0   1558.0   3624.0   7675.0  11066.2
##
## lowest :    81   100   141   150   152, highest: 19315 19873 20192 21804 48094
## --------------------------------------------------------------------------------
## Accept
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      693        1     2019     2127    272.4    361.6
##      .25      .50      .75      .90      .95
##    604.0   1110.0   2424.0   4814.2   6979.2
##
## lowest :    72    90   118   128   130, highest: 13007 13243 15096 18744 26330
```

```
## ------------------------------------------------------------------------------
## Enroll
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      581        1      780    821.5    118.6    154.0
##      .25      .50      .75      .90      .95
##    242.0    434.0    902.0   1903.6   2757.0
##
## lowest :   35   46   51   55   63, highest: 5705 5873 5874 6180 6392
## ------------------------------------------------------------------------------
## Top10perc
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       82    0.999    27.56    18.52      7.0     10.0
##      .25      .50      .75      .90      .95
##     15.0     23.0     35.0     50.4     65.2
##
## lowest :  1  2  3  4  5, highest: 87 89 90 95 96
## ------------------------------------------------------------------------------
## Top25perc
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       89        1     55.8    22.58     25.8     30.6
##      .25      .50      .75      .90      .95
##     41.0     54.0     69.0     85.0     93.0
##
## lowest :   9  12  13  14  16, highest:  96  97  98  99 100
## ------------------------------------------------------------------------------
## F.Undergrad
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      714        1     3700     4215    509.8    641.0
##      .25      .50      .75      .90      .95
##    992.0   1707.0   4005.0  10024.4  14477.8
##
## lowest :   139   199   201   249   282, highest: 26640 27378 28938 30017 31643
## ------------------------------------------------------------------------------
## P.Undergrad
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      566        1    855.3     1131       20       35
##      .25      .50      .75      .90      .95
##       95      353      967     2017     3304
##
## lowest :     1     2     3     4     5, highest:  9054  9310 10221 10962 21836
## ------------------------------------------------------------------------------
## Outstate
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      640        1    10441     4547     4602     5569
##      .25      .50      .75      .90      .95
##     7320     9990    12925    16553    18498
##
## lowest :  2340  2580  2700  3040  3460, highest: 19900 19960 19964 20100 21700
## ------------------------------------------------------------------------------
## Room.Board
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      553        1     4358     1236     2736     3051
##      .25      .50      .75      .90      .95
##     3597     4200     5050     5950     6382
```

```
##
## lowest : 1780 1880 1920 2146 2190, highest: 7350 7398 7400 7425 8124
## ---------------------------------------------------------------------------
## Books
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      122    0.982    549.4    152.2    350.0    400.0
##      .25      .50      .75      .90      .95
##    470.0    500.0    600.0    700.0    765.6
##
## lowest :   96  110  120  200  221, highest: 1300 1400 1495 2000 2340
## ---------------------------------------------------------------------------
## Personal
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      294    0.999     1341    710.3      500      600
##      .25      .50      .75      .90      .95
##      850     1200     1700     2200     2489
##
## lowest :  250  300  350  400  420, highest: 4110 4200 4288 4913 6800
## ---------------------------------------------------------------------------
## PhD
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       78        1    72.66    18.18     43.8     50.6
##      .25      .50      .75      .90      .95
##     62.0     75.0     85.0     92.0     95.0
##
## lowest :   8  10  14  16  22, highest:  97  98  99 100 103
## ---------------------------------------------------------------------------
## Terminal
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       65    0.999     79.7    16.37     52.8     59.0
##      .25      .50      .75      .90      .95
##     71.0     82.0     92.0     96.0     98.0
##
## lowest :  24  25  30  33  35, highest:  96  97  98  99 100
## ---------------------------------------------------------------------------
## S.F.Ratio
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      173        1    14.09    4.325      8.3      9.9
##      .25      .50      .75      .90      .95
##     11.5     13.6     16.5     19.2     21.0
##
## lowest :  2.5  2.9  3.3  3.9  4.3, highest: 27.2 27.6 27.8 28.8 39.8
## ---------------------------------------------------------------------------
## perc.alumni
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       61    0.999    22.74    13.95        6        8
##      .25      .50      .75      .90      .95
##       13       21       31       40       46
##
## lowest :  0  1  2  3  4, highest: 57 58 60 63 64
## ---------------------------------------------------------------------------
## Expend
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0      744        1     9660     4650     4796     5558
```

```
##      .25      .50      .75      .90      .95
##     6751     8377    10830    14841    17975
##
## lowest :  3186  3365  3480  3605  3733, highest: 40386 41766 42926 45702 56233
## ------------------------------------------------------------------------------
## Grad.Rate
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      777        0       81        1    65.46    19.48     37.0     44.6
##      .25      .50      .75      .90      .95
##     53.0     65.0     78.0     89.0     94.2
##
## lowest :  10  15  18  21  22, highest:  97  98  99 100 118
## ------------------------------------------------------------------------------
```

Split the data set into a training set and a test set.

```
College_split <- initial_split(College, strata = Apps, prop = 0.5)
College_split
```

```
## <Analysis/Assess/Total>
## <388/389/777>
```

```
College_train <- training(College_split)
College_test <- testing(College_split)
```

Fit a linear model using least squares on the training set, and report the test error obtained.

```
lm_spec <- linear_reg() %>%
  set_mode("regression") %>%
  set_engine("lm")
```

```
lm_recipe <-
  recipe(formula = Apps ~ ., data = College_train) %>%
  step_dummy(all_nominal_predictors()) %>%
  step_normalize(all_numeric_predictors())
```

Note: We use the variables `Accept` and `Enroll` as independent variables here. These variables describe the number of accepted applicants and the number of new enrolled students, respectively. Depending on the application one might not know these variables when predicting the the number of applications.

```
lm_workflow <- workflow() %>%
  add_recipe(lm_recipe) %>%
  add_model(lm_spec)
```

```
lm_fit <- lm_workflow %>% fit(College_train)
```

```
augment(lm_fit, new_data = College_test) %>%
  select(Apps, .pred)
```

```
## # A tibble: 389 x 2
##     Apps  .pred
##    <dbl>  <dbl>
##  1  1660  1349.
##  2   587   625.
##  3  1038   984.
##  4   582   574.
##  5  1179  1731.
##  6  1420  1211.
```

```
##  7  1130   463.
##  8  3540  3107.
##  9   619   390.
## 10 12809 15205.
## # ... with 379 more rows
```

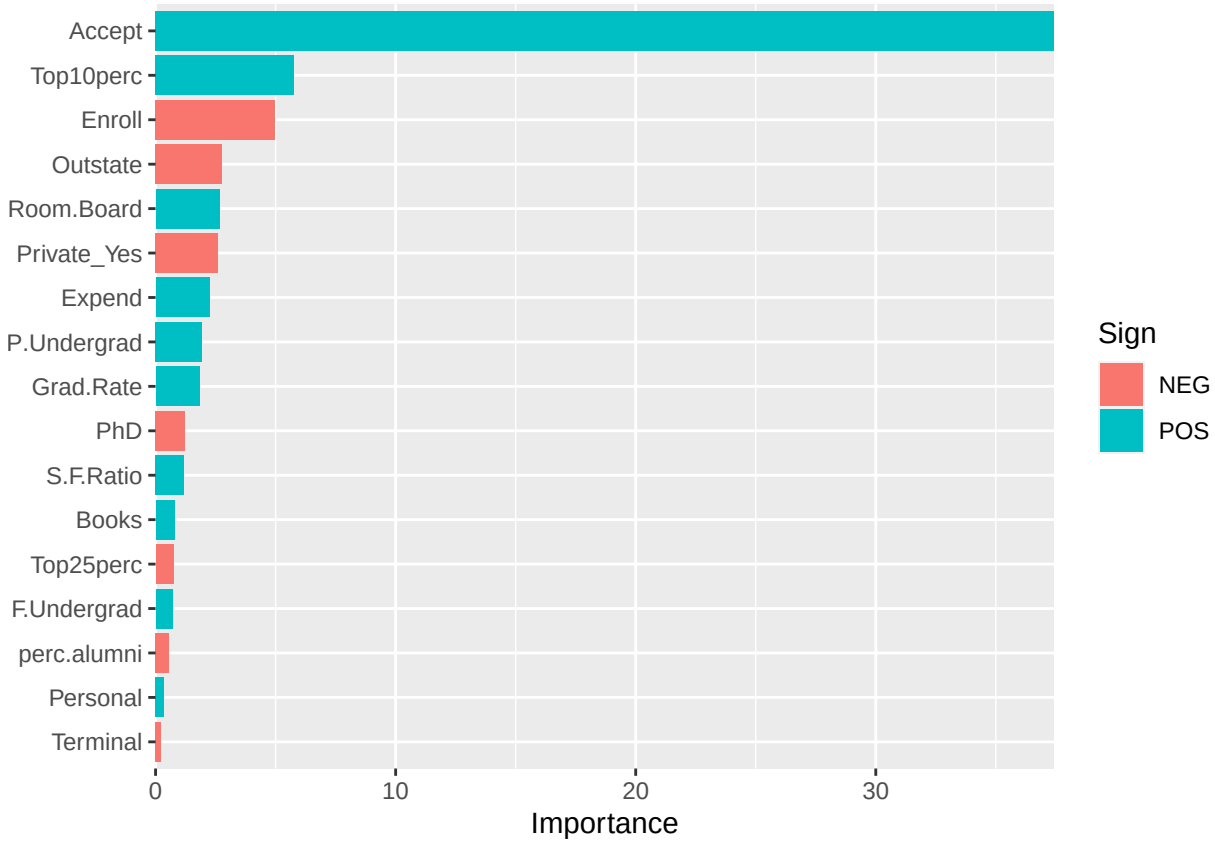
```
augment(lm_fit, new_data = College_test) %>%
  rmse(truth = Apps, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       1183.
```

The rmse of the test error is 1183.

Out of curiosity, let's look at the feature importance.

```
lm_fit %>%
  extract_fit_parsnip() %>%
  vi(lambda = best_penalty$penalty) %>%
  mutate(
    Importance = abs(Importance),
    Variable = fct_reorder(Variable, Importance)
  ) %>%
  ggplot(aes(x = Importance, y = Variable, fill = Sign)) +
  geom_col() +
  scale_x_continuous(expand = c(0, 0)) +
  labs(y = NULL)
```



Fit a ridge regression model on the training set, with λ chosen by cross-validation. Report the test error obtained.

```
ridge_spec <- linear_reg(mixture = 0, penalty = tune()) %>%
  set_mode("regression") %>%
  set_engine("glmnet")

ridge_workflow <- workflow() %>%
  add_recipe(recipe = lm_recipe) %>%
  add_model(ridge_spec)
```

```
College_fold <- vfold_cv(College_train, v = 10)
College_fold
```

```
## #  10-fold cross-validation
## # A tibble: 10 x 2
##    splits           id
##    <list>           <chr>
##  1 <split [349/39]> Fold01
##  2 <split [349/39]> Fold02
##  3 <split [349/39]> Fold03
##  4 <split [349/39]> Fold04
##  5 <split [349/39]> Fold05
##  6 <split [349/39]> Fold06
##  7 <split [349/39]> Fold07
##  8 <split [349/39]> Fold08
##  9 <split [350/38]> Fold09
## 10 <split [350/38]> Fold10
```

```
penalty_grid <- grid_regular(
  penalty(range = c(-5, 5)), # penalty automatically uses log scale
  levels = 50
)
penalty_grid
```

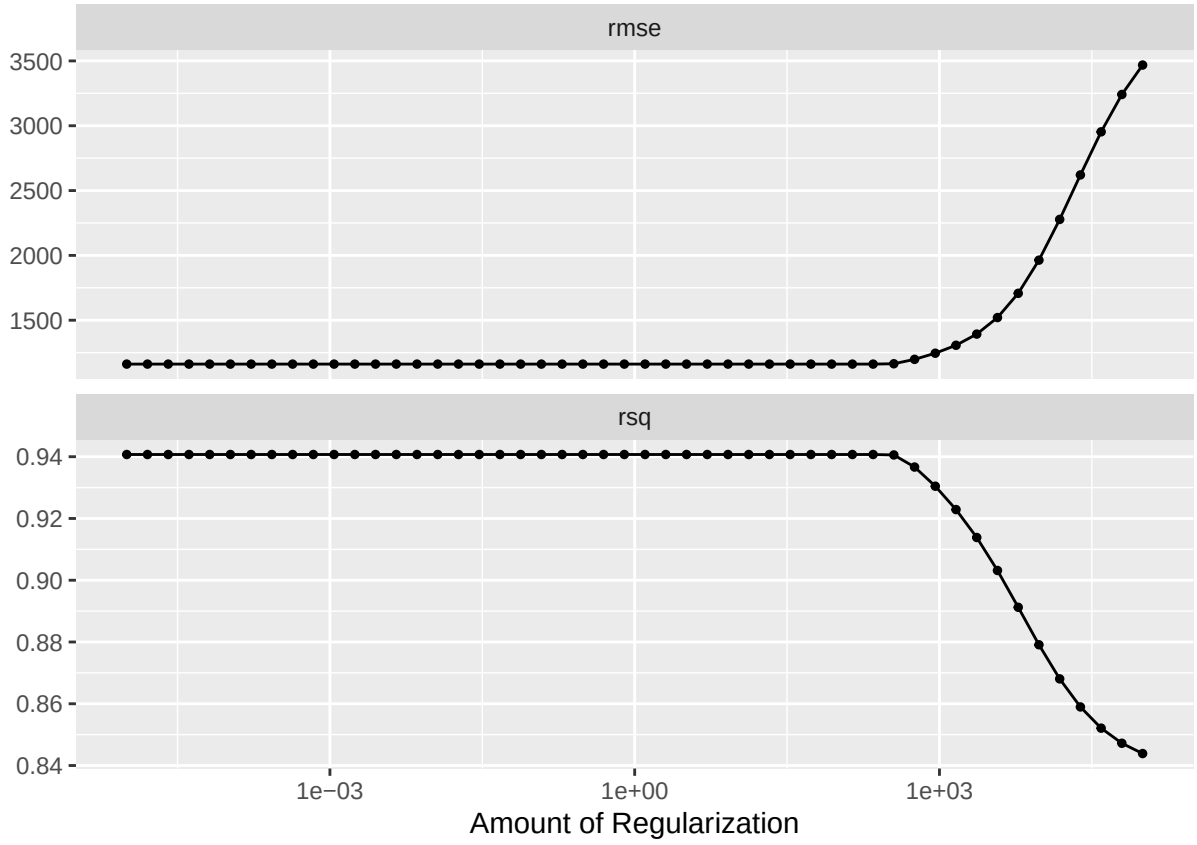
```
## # A tibble: 50 x 1
##      penalty
##        <dbl>
##  1 0.00001
##  2 0.0000160
##  3 0.0000256
##  4 0.0000409
##  5 0.0000655
##  6 0.000105
##  7 0.000168
##  8 0.000268
##  9 0.000429
## 10 0.000687
## # ... with 40 more rows
```

```
tune_res <- tune_grid(
  ridge_workflow,
  resamples = College_fold,
  grid = penalty_grid
)
```

```
tune_res
```

```
## # Tuning results
## # 10-fold cross-validation
## # A tibble: 10 x 4
##    splits           id     .metrics           .notes
##    <list>           <chr>  <list>             <list>
##  1 <split [349/39]> Fold01 <tibble [100 x 5]> <tibble [0 x 3]>
##  2 <split [349/39]> Fold02 <tibble [100 x 5]> <tibble [0 x 3]>
##  3 <split [349/39]> Fold03 <tibble [100 x 5]> <tibble [0 x 3]>
##  4 <split [349/39]> Fold04 <tibble [100 x 5]> <tibble [0 x 3]>
##  5 <split [349/39]> Fold05 <tibble [100 x 5]> <tibble [0 x 3]>
##  6 <split [349/39]> Fold06 <tibble [100 x 5]> <tibble [0 x 3]>
##  7 <split [349/39]> Fold07 <tibble [100 x 5]> <tibble [0 x 3]>
##  8 <split [349/39]> Fold08 <tibble [100 x 5]> <tibble [0 x 3]>
##  9 <split [350/38]> Fold09 <tibble [100 x 5]> <tibble [0 x 3]>
## 10 <split [350/38]> Fold10 <tibble [100 x 5]> <tibble [0 x 3]>
```

```
autoplot(tune_res)
```




```
best_penalty <- select_best(tune_res, metric = "rmse")
best_penalty
```

```
## # A tibble: 1 x 2
##   penalty .config
##     <dbl> <chr>
## 1 0.00001 Preprocessor1_Model01
```

```
ridge_final <- finalize_workflow(ridge_workflow, best_penalty)
ridge_final_fit <- ridge_final %>% fit(College_train)
```

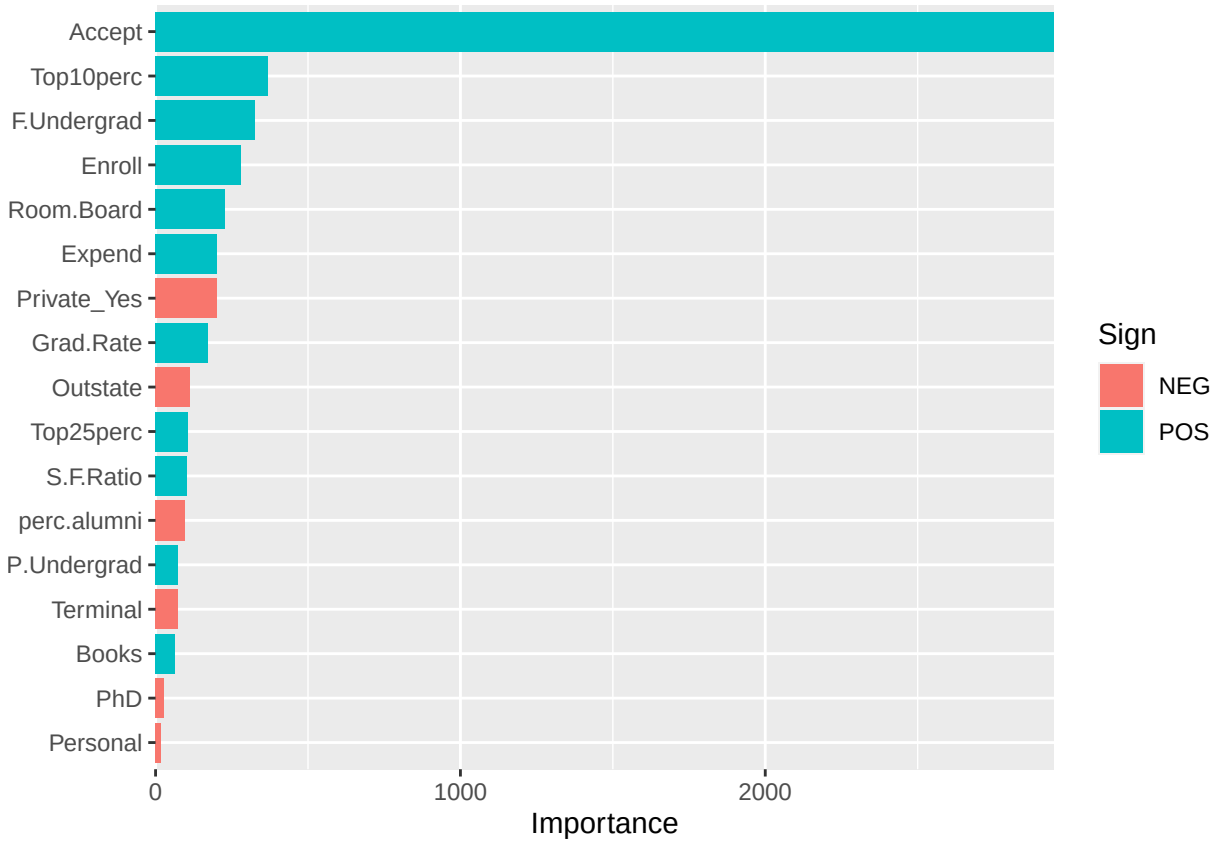
```
augment(ridge_final_fit, new_data = College_test) %>%
  rmse(truth = Apps, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       1178.
```

The test error is 1178, which is slightly lower than a linear model without regularization.

Again let's also look at the feature importance.

```
ridge_final_fit %>%
  extract_fit_parsnip() %>%
  vi(lambda = best_penalty$penalty) %>%
  mutate(
    Importance = abs(Importance),
    Variable = fct_reorder(Variable, Importance)
  ) %>%
  ggplot(aes(x = Importance, y = Variable, fill = Sign)) +
  geom_col() +
  scale_x_continuous(expand = c(0, 0)) +
  labs(y = NULL)
```



Fit a lasso model on the training set, with λ chosen by cross-validation. Report the test error obtained, along with the number of non-zero coefficient estimates.

```
lasso_spec <- linear_reg(mixture = 1, penalty = tune()) %>%
  set_mode("regression") %>%
  set_engine("glmnet")

lasso_workflow <- workflow() %>%
  add_recipe(recipe = lm_recipe) %>%
  add_model(lasso_spec)
```

```
penalty_grid <- grid_regular(
  penalty(range = c(-5, 2)),
  levels = 50
)
```

```
tune_res <- tune_grid(
  lasso_workflow,
  resamples = College_fold,
  grid = penalty_grid
)
tune_res
```

```
## # Tuning results
## # 10-fold cross-validation
## # A tibble: 10 x 4
##    splits           id     .metrics           .notes
##    <list>           <chr>  <list>             <list>
##  1 <split [349/39]> Fold01 <tibble [100 x 5]> <tibble [0 x 3]>
##  2 <split [349/39]> Fold02 <tibble [100 x 5]> <tibble [0 x 3]>
##  3 <split [349/39]> Fold03 <tibble [100 x 5]> <tibble [0 x 3]>
##  4 <split [349/39]> Fold04 <tibble [100 x 5]> <tibble [0 x 3]>
##  5 <split [349/39]> Fold05 <tibble [100 x 5]> <tibble [0 x 3]>
##  6 <split [349/39]> Fold06 <tibble [100 x 5]> <tibble [0 x 3]>
##  7 <split [349/39]> Fold07 <tibble [100 x 5]> <tibble [0 x 3]>
##  8 <split [349/39]> Fold08 <tibble [100 x 5]> <tibble [0 x 3]>
##  9 <split [350/38]> Fold09 <tibble [100 x 5]> <tibble [0 x 3]>
## 10 <split [350/38]> Fold10 <tibble [100 x 5]> <tibble [0 x 3]>
```

```
best_penalty <- select_best(tune_res, metric = "rmse")
best_penalty
```

```
## # A tibble: 1 x 2
##   penalty .config
##     <dbl> <chr>
## 1    26.8 Preprocessor1_Model46
```

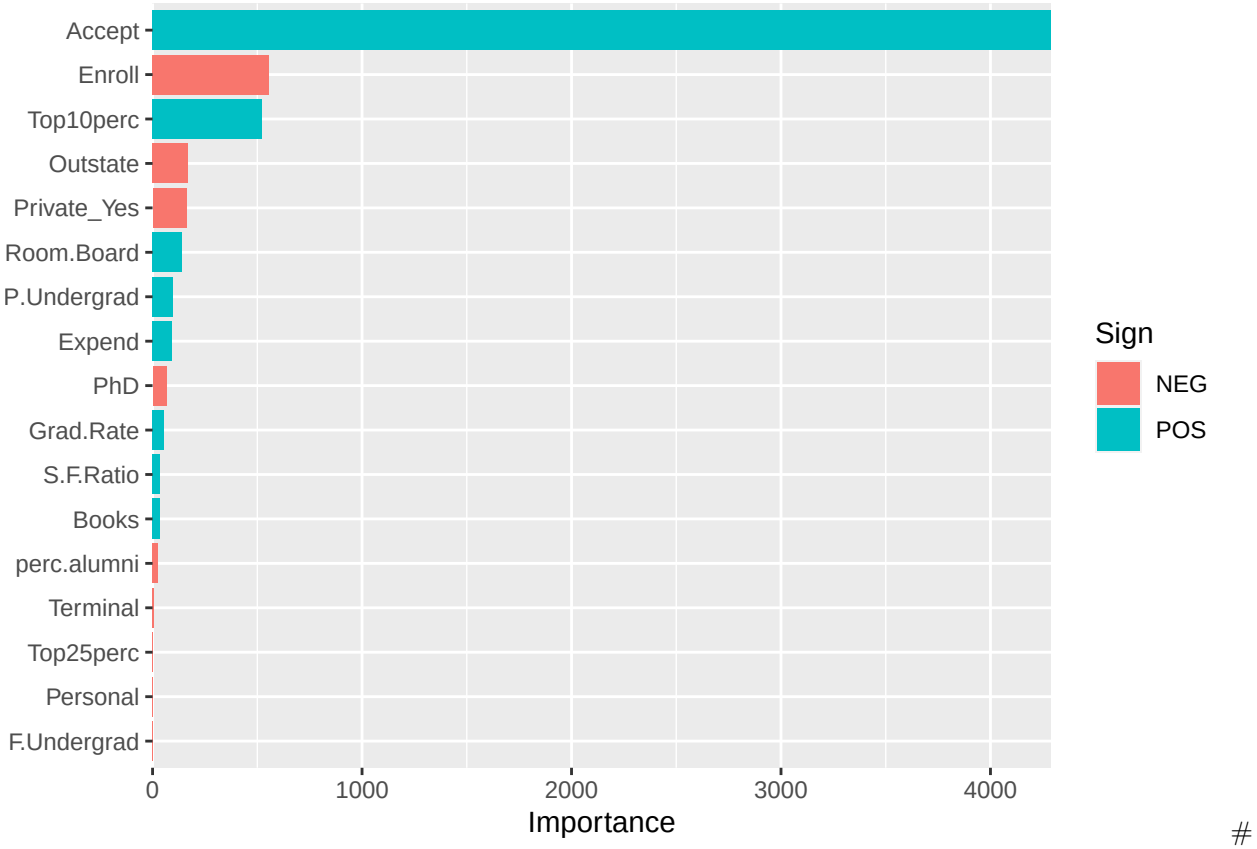
```
lasso_final <- finalize_workflow(lasso_workflow, best_penalty)

lasso_final_fit <- fit(lasso_final, data = College_train)
```

```
augment(lasso_final_fit, new_data = College_test) %>%
  rmse(truth = Apps, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard       1193.
```

The rmse is 1192.677, which is worse than Ridge and a simple linear model.

```
lasso_final_fit %>%
  extract_fit_parsnip() %>%
  vi(lambda = best_penalty$penalty) %>%
  mutate(
    Importance = abs(Importance),
    Variable = fct_reorder(Variable, Importance)
  ) %>%
  ggplot(aes(x = Importance, y = Variable, fill = Sign)) +
  geom_col() +
  scale_x_continuous(expand = c(0, 0)) +
  labs(y = NULL)
```



#

Exercise 2

Fit some of the non-linear models (polynomial regression, splines) discussed in the lecture to the Auto data set. Is there evidence for non-linear relationships in this data set? Create some informative plots to justify your answer.

```
Auto <- tibble(Auto)

basic_eda(Auto)
```

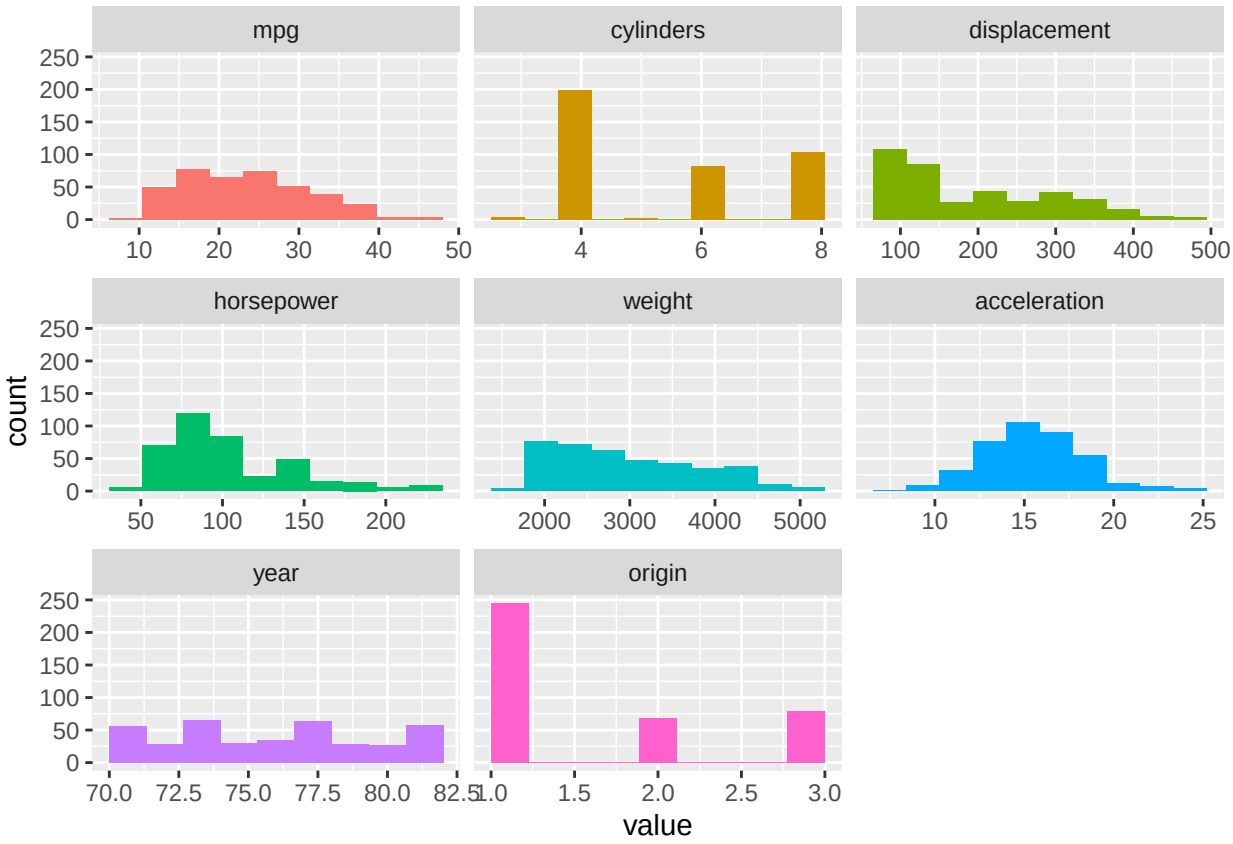
```
## Rows: 392
## Columns: 9
## $ mpg          <dbl> 18, 15, 18, 16, 17, 15, 14, 14, 14, 15, 15, 14, 15, 14, 2~
## $ cylinders    <dbl> 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 4, 6, 6, 6, 4, ~
## $ displacement <dbl> 307, 350, 318, 304, 302, 429, 454, 440, 455, 390, 383, 34~
## $ horsepower   <dbl> 130, 165, 150, 150, 140, 198, 220, 215, 225, 190, 170, 16~
```

```
## $ weight       <dbl> 3504, 3693, 3436, 3433, 3449, 4341, 4354, 4312, 4425, 385~
## $ acceleration <dbl> 12.0, 11.5, 11.0, 12.0, 10.5, 10.0, 9.0, 8.5, 10.0, 8.5, ~
## $ year         <dbl> 70, 70, 70, 70, 70, 70, 70, 70, 70, 70, 70, 70, 70, 70, 7~
## $ origin       <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 1, 1, 1, 3, ~
## $ name         <fct> chevrolet chevelle malibu, buick skylark 320, plymouth sa~
##                  variable q_zeros p_zeros q_na p_na q_inf p_inf    type unique
## mpg                   mpg       0       0    0    0     0     0 numeric    127
## cylinders       cylinders       0       0    0    0     0     0 numeric      5
## displacement displacement       0       0    0    0     0     0 numeric     81
## horsepower     horsepower       0       0    0    0     0     0 numeric     93
## weight             weight       0       0    0    0     0     0 numeric    346
## acceleration acceleration       0       0    0    0     0     0 numeric     95
## year                 year       0       0    0    0     0     0 numeric     13
## origin             origin       0       0    0    0     0     0 numeric      3
## name                 name       0       0    0    0     0     0  factor    301
```

```
## Warning in freq_logic(data = data, input = input, plot, na.rm, path_out =
## path_out): Skipping plot for variable 'name' (more than 100 categories)
```

```
##       variable        mean     std_dev variation_coef     p_01     p_05
## 1          mpg   23.445918   7.8050075     0.33289408   11.000   13.000
## 2    cylinders    5.471939   1.7057832     0.31173288    3.910    4.000
## 3 displacement  194.411990 104.6440039     0.53825900   70.910   85.000
## 4   horsepower  104.469388  38.4911599     0.36844439   48.000   60.550
## 5       weight 2977.584184 849.4025600     0.28526567 1771.830 1931.600
## 6 acceleration   15.541327   2.7588641     0.17751793    9.455   11.255
## 7         year   75.979592   3.6837365     0.04848324   70.000   70.000
## 8       origin    1.576531   0.8055182     0.51094357    1.000    1.000
##       p_25    p_50     p_75     p_95     p_99   skewness kurtosis     iqr
## 1   17.000   22.75   29.000   37.000   43.454 0.45534138 2.475297   12.00
## 2    4.000    4.00    8.000    8.000    8.000 0.50616287 1.604305    4.00
## 3  105.000  151.00  275.750  400.000  441.260 0.69898128 2.216308  170.75
## 4   75.000   93.50  126.000  180.000  220.450 1.08316116 3.672822   51.00
## 5 2225.250 2803.50 3614.750 4464.000 4951.090 0.51759535 2.185759 1389.50
## 6   13.775   15.50   17.025   20.235   22.317 0.29046997 3.423320    3.25
## 7   73.000   76.00   79.000   82.000   82.000 0.01961288 1.832124    6.00
## 8    1.000    1.00    2.000    3.000    3.000 0.91167909 2.153547    1.00
##             range_98       range_80
## 1       [11, 43.454]    [14, 34.19]
## 2          [3.91, 8]         [4, 8]
## 3    [70.91, 441.26]      [90, 350]
## 4       [48, 220.45]    [67, 157.7]
## 5 [1771.83, 4951.09] [1990, 4277.6]
## 6    [9.455, 22.317]       [12, 19]
## 7           [70, 82]       [71, 81]
## 8             [1, 3]         [1, 3]
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```

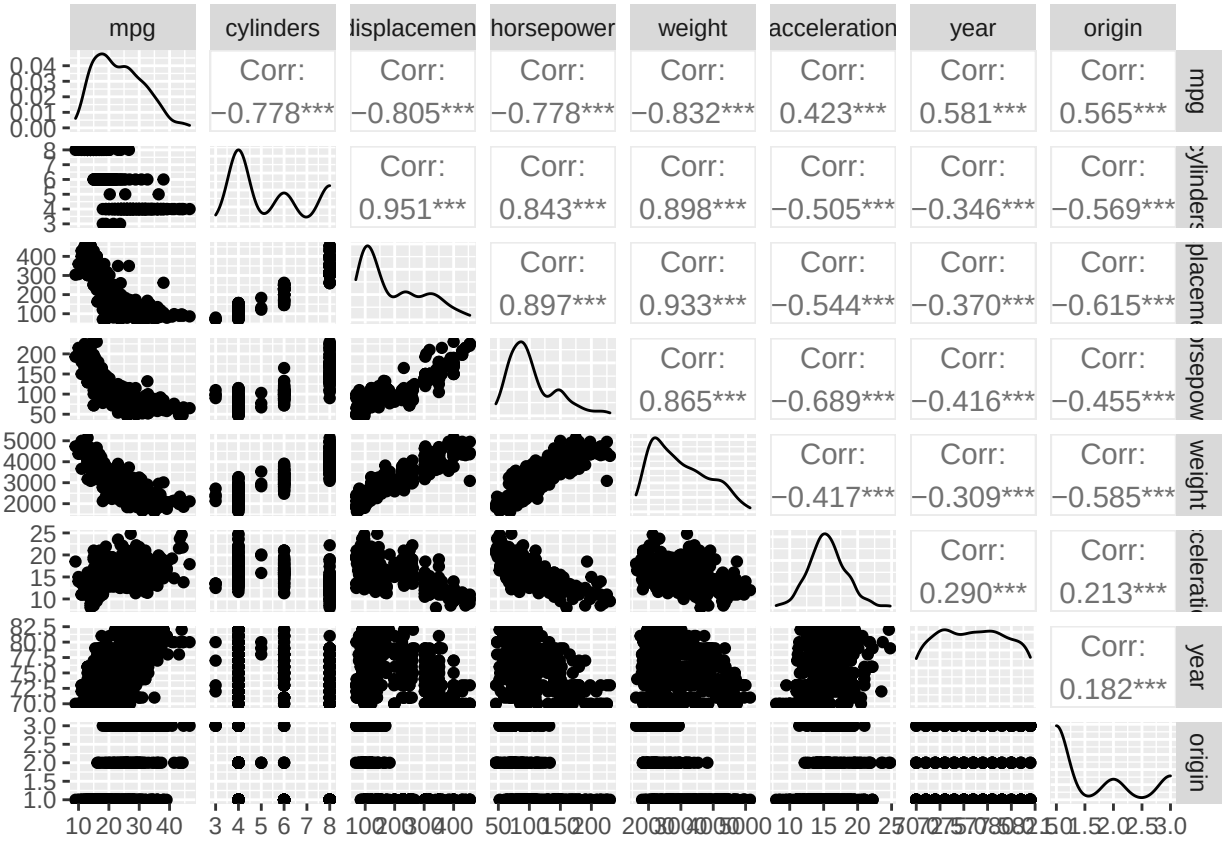



```
## data
##
##  9  Variables      392  Observations
## --------------------------------------------------------------------------------
## mpg
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0      127    0.999    23.45    8.879    13.00    14.00
##      .25      .50      .75      .90      .95
##    17.00    22.75    29.00    34.19    37.00
##
## lowest :  9.0 10.0 11.0 12.0 13.0, highest: 43.4 44.0 44.3 44.6 46.6
## --------------------------------------------------------------------------------
## cylinders
##        n  missing distinct     Info     Mean      Gmd
##      392        0        5    0.842    5.472    1.798
##
## lowest : 3 4 5 6 8, highest: 3 4 5 6 8
##
## Value          3     4     5     6     8
## Frequency      4   199     3    83   103
## Proportion 0.010 0.508 0.008 0.212 0.263
## --------------------------------------------------------------------------------
## displacement
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0       81    0.999    194.4    115.7     85.0     90.0
##      .25      .50      .75      .90      .95
##    105.0    151.0    275.8    350.0    400.0
```

```
##
## lowest :  68  70  71  72  76, highest: 400 429 440 454 455
## ---------------------------------------------------------------------------
## horsepower
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0       93    0.999    104.5    41.48    60.55    67.00
##      .25      .50      .75      .90      .95
##    75.00    93.50   126.00   157.70   180.00
##
## lowest :  46  48  49  52  53, highest: 210 215 220 225 230
## ---------------------------------------------------------------------------
## weight
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0      346        1     2978    964.1     1932     1990
##      .25      .50      .75      .90      .95
##     2225     2804     3615     4278     4464
##
## lowest : 1613 1649 1755 1760 1773, highest: 4951 4952 4955 4997 5140
## ---------------------------------------------------------------------------
## acceleration
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0       95    0.999    15.54    3.079    11.26    12.00
##      .25      .50      .75      .90      .95
##    13.78    15.50    17.02    19.00    20.23
##
## lowest :  8.0  8.5  9.0  9.5 10.0, highest: 22.2 23.5 23.7 24.6 24.8
## ---------------------------------------------------------------------------
## year
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      392        0       13    0.994    75.98    4.245       70       71
##      .25      .50      .75      .90      .95
##       73       76       79       81       82
##
## lowest : 70 71 72 73 74, highest: 78 79 80 81 82
##
## Value         70    71    72    73    74    75    76    77    78    79    80
## Frequency     29    27    28    40    26    30    34    28    36    29    27
## Proportion 0.074 0.069 0.071 0.102 0.066 0.077 0.087 0.071 0.092 0.074 0.069
##
## Value         81    82
## Frequency     28    30
## Proportion 0.071 0.077
## ---------------------------------------------------------------------------
## origin
##        n  missing distinct     Info     Mean      Gmd
##      392        0        3    0.742    1.577   0.7926
##
## Value          1     2     3
## Frequency    245    68    79
## Proportion 0.625 0.173 0.202
## ---------------------------------------------------------------------------
## name
##        n  missing distinct
##      392        0      301
```

```
##
## lowest : amc ambassador brougham amc ambassador dpl      amc ambassador sst      amc concord
## highest: vw dasher (diesel)      vw pickup               vw rabbit               vw rabbit c (diesel)
## ----------------------------------------------------------------------------------------------
```

```
ggpairs(Auto[, names(Auto) != "name"])
```



There are some non linear looking relationships. Let's look at `mpg` and `horsepower`

We will not perform train-test-split or hyper-parameter tuning here, as we are only interested in exploring the relations.

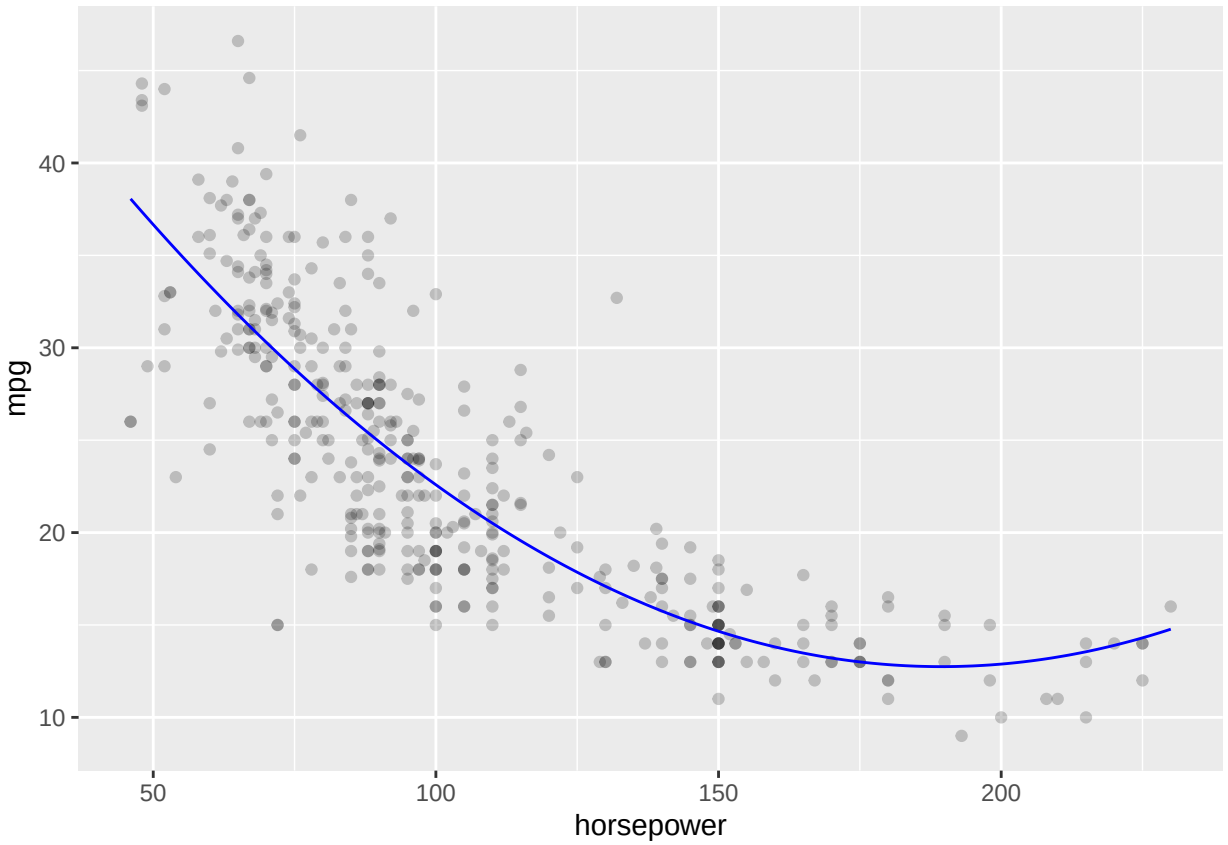
```
# Recipe
polynomial_recipe <-
  recipe(formula = mpg ~ horsepower, data = Auto) %>%
  step_poly(all_numeric_predictors(), degree = 2, options = list(raw = TRUE)) %>%
  step_normalize(all_predictors())

# Specification
polynomial_spec <-
  linear_reg(mixture = 1, penalty = tune()) %>%
  set_mode("regression") %>%
  set_engine("lm")


# Workflow
polynomial_workflow <- workflow() %>%
  add_recipe(polynomial_recipe) %>%
  add_model(polynomial_spec)
```

```r
# Finalize model
polynomial_fit <- fit(polynomial_workflow, data = Auto)
```

```r
horsepower_min <- min(Auto$horsepower)
horsepower_max <- max(Auto$horsepower)
horsepower_range <- tibble(horsepower = seq(horsepower_min, horsepower_max))
horsepower_range
```

```
## # A tibble: 185 x 1
##    horsepower
##         <int>
##  1         46
##  2         47
##  3         48
##  4         49
##  5         50
##  6         51
##  7         52
##  8         53
##  9         54
## 10         55
## # ... with 175 more rows
```

```r
regression_lines <- bind_cols(
  predict(polynomial_fit, new_data = horsepower_range),
  horsepower_range
)

Auto %>%
  ggplot(aes(horsepower, mpg)) +
  geom_point(alpha = 0.2) +
  geom_line(aes(y = .pred), data = regression_lines, color = "blue")
```

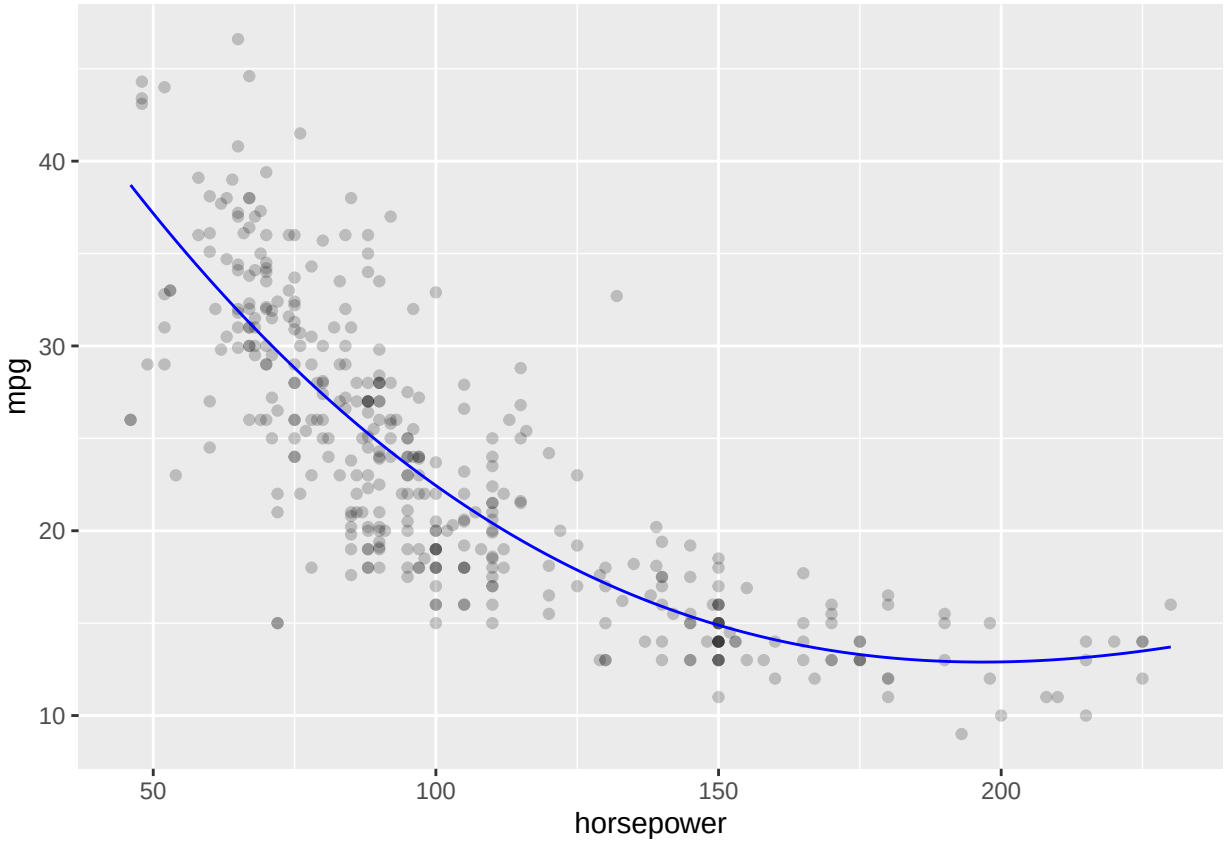


We can see that the relation between `mpg` and `horsepower` is nicely fit by a polynomial of degree 2, which would not be possible with a simple linear regression.

```
# Recipe
spline_recipe <-
  recipe(formula = mpg ~ horsepower, data = Auto) %>%
  step_bs(horsepower, options = list(knots = 70, 100, 130, 160, 190, 220))

# Specification
spline_spec <-
  linear_reg(mixture = 1, penalty = tune()) %>%
  set_mode("regression") %>%
  set_engine("lm")


# Workflow
spline_workflow <- workflow() %>%
  add_recipe(spline_recipe) %>%
  add_model(spline_spec)

# Finalize model
spline_fit <- fit(spline_workflow, data = Auto)
```

```
regression_lines <- bind_cols(
  predict(spline_fit, new_data = horsepower_range),
  horsepower_range
)
```

```
Auto %>%
  ggplot(aes(horsepower, mpg)) +
  geom_point(alpha = 0.2) +
  geom_line(aes(y = .pred), data = regression_lines, color = "blue")
```



We see that the fit created by splines is very similar to the polynomial regression. The only noticeable difference is that splines seem to act less extreme at the borders of our data, e.g. `horsepower > 200`.

Exercise 3

The Wage data set contains a number of features, such as marital status (marital), job class (jobclass), and others. Explore the relationships between some of these predictors and wage, and use non-linear fitting techniques in order to fit flexible models to the data. Create plots of the results obtained, and write a summary of your findings.

```
Wage <- tibble(Wage)

basic_eda(Wage)
```

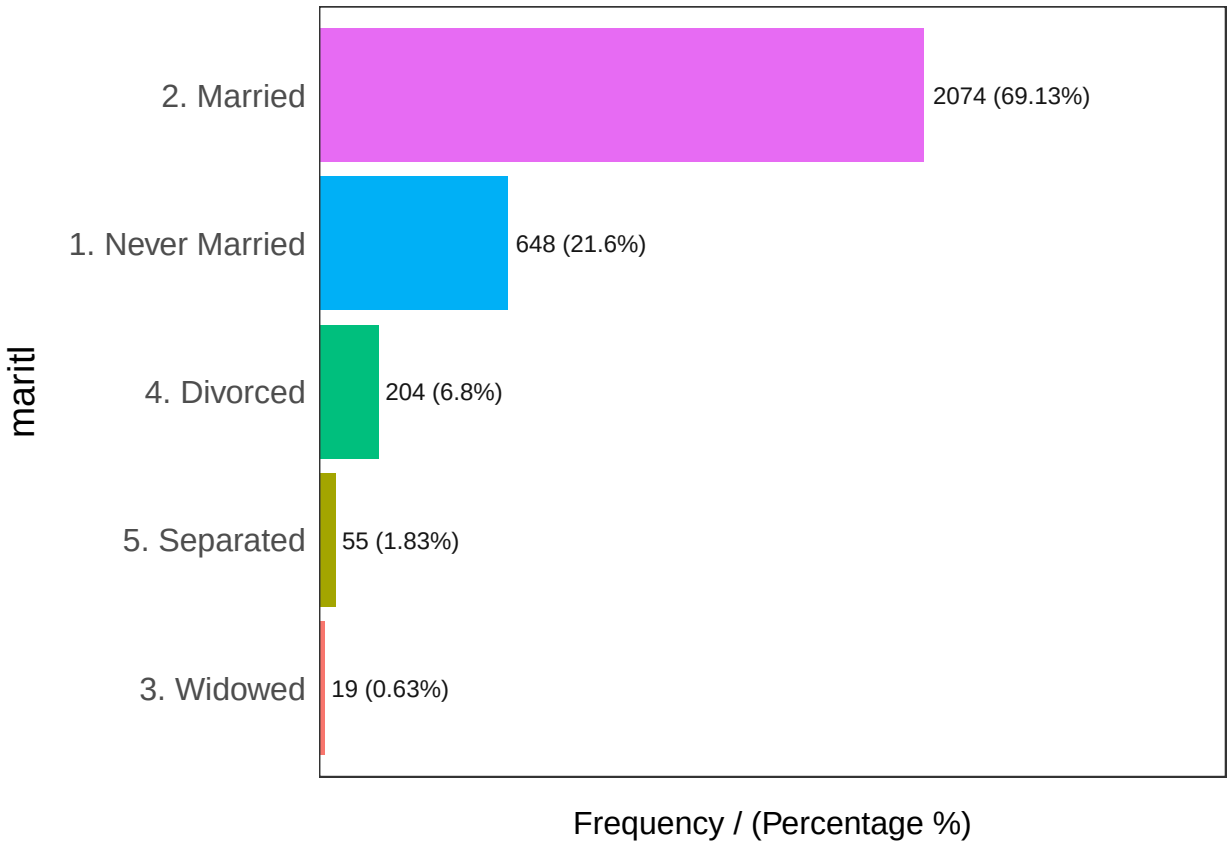
```
## Rows: 3,000
## Columns: 11
## $ year       <int> 2006, 2004, 2003, 2003, 2005, 2008, 2009, 2008, 2006, 2004,~
## $ age        <int> 18, 24, 45, 43, 50, 54, 44, 30, 41, 52, 45, 34, 35, 39, 54,~
## $ maritl     <fct> 1. Never Married, 1. Never Married, 2. Married, 2. Married,~
## $ race       <fct> 1. White, 1. White, 1. White, 3. Asian, 1. White, 1. White,~
## $ education  <fct> 1. < HS Grad, 4. College Grad, 3. Some College, 4. College ~
## $ region     <fct> 2. Middle Atlantic, 2. Middle Atlantic, 2. Middle Atlantic,~
```

```
## $ jobclass   <fct> 1. Industrial, 2. Information, 1. Industrial, 2. Informatio~
## $ health     <fct> 1. <=Good, 2. >=Very Good, 1. <=Good, 2. >=Very Good, 1. <=~
## $ health_ins <fct> 2. No, 2. No, 1. Yes, 1. Yes, 1. Yes, 1. Yes, 1. Yes, 1. Ye~
## $ logwage    <dbl> 4.318063, 4.255273, 4.875061, 5.041393, 4.318063, 4.845098,~
## $ wage       <dbl> 75.04315, 70.47602, 130.98218, 154.68529, 75.04315, 127.115~
##              variable q_zeros p_zeros q_na p_na q_inf p_inf    type unique
## year             year       0       0    0    0     0     0 integer      7
## age               age       0       0    0    0     0     0 integer     61
## maritl         maritl       0       0    0    0     0     0  factor      5
## race             race       0       0    0    0     0     0  factor      4
## education   education       0       0    0    0     0     0  factor      5
## region         region       0       0    0    0     0     0  factor      1
## jobclass     jobclass       0       0    0    0     0     0  factor      2
## health         health       0       0    0    0     0     0  factor      2
## health_ins health_ins       0       0    0    0     0     0  factor      2
## logwage       logwage       0       0    0    0     0     0 numeric    508
## wage             wage       0       0    0    0     0     0 numeric    508
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```

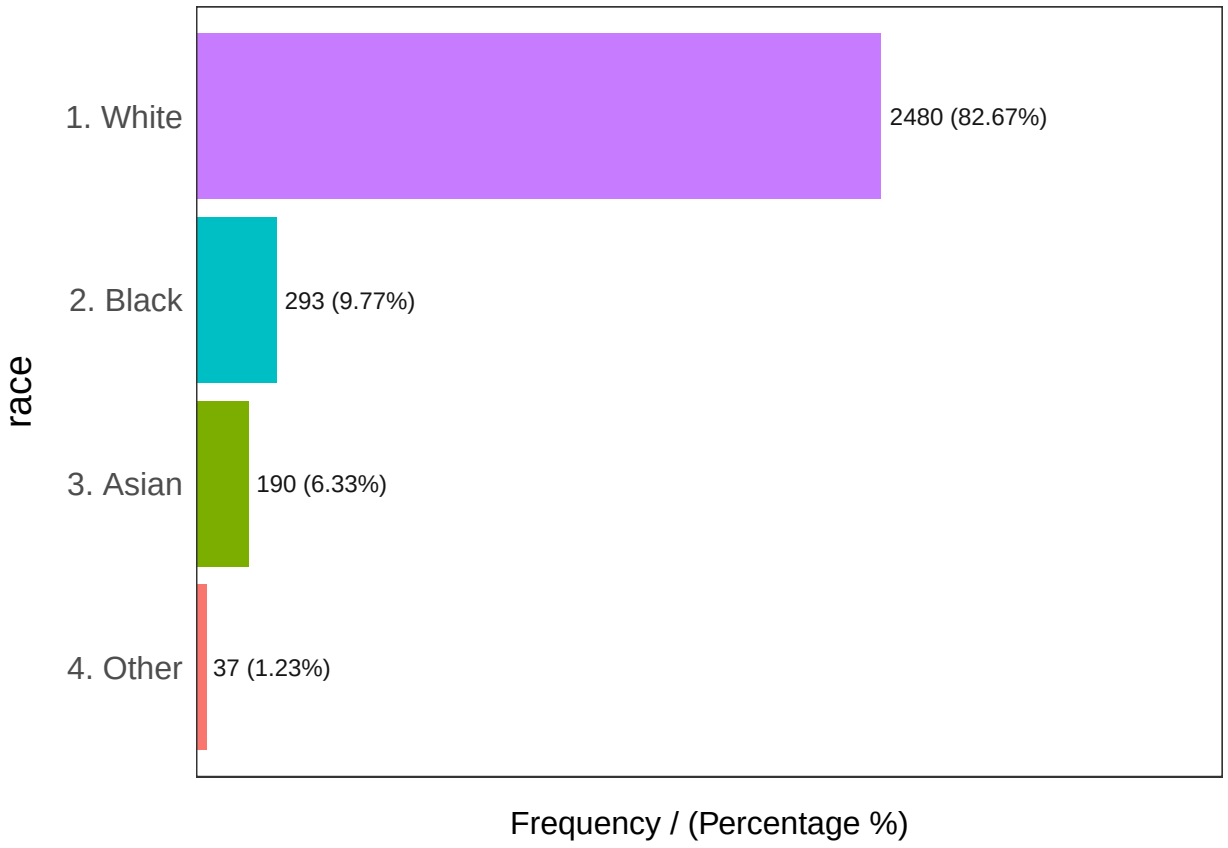
```
##             maritl frequency percentage cumulative_perc
## 1       2. Married      2074      69.13           69.13
## 2 1. Never Married       648      21.60           90.73
## 3      4. Divorced       204       6.80           97.53
## 4     5. Separated        55       1.83           99.36
## 5       3. Widowed        19       0.63          100.00
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```



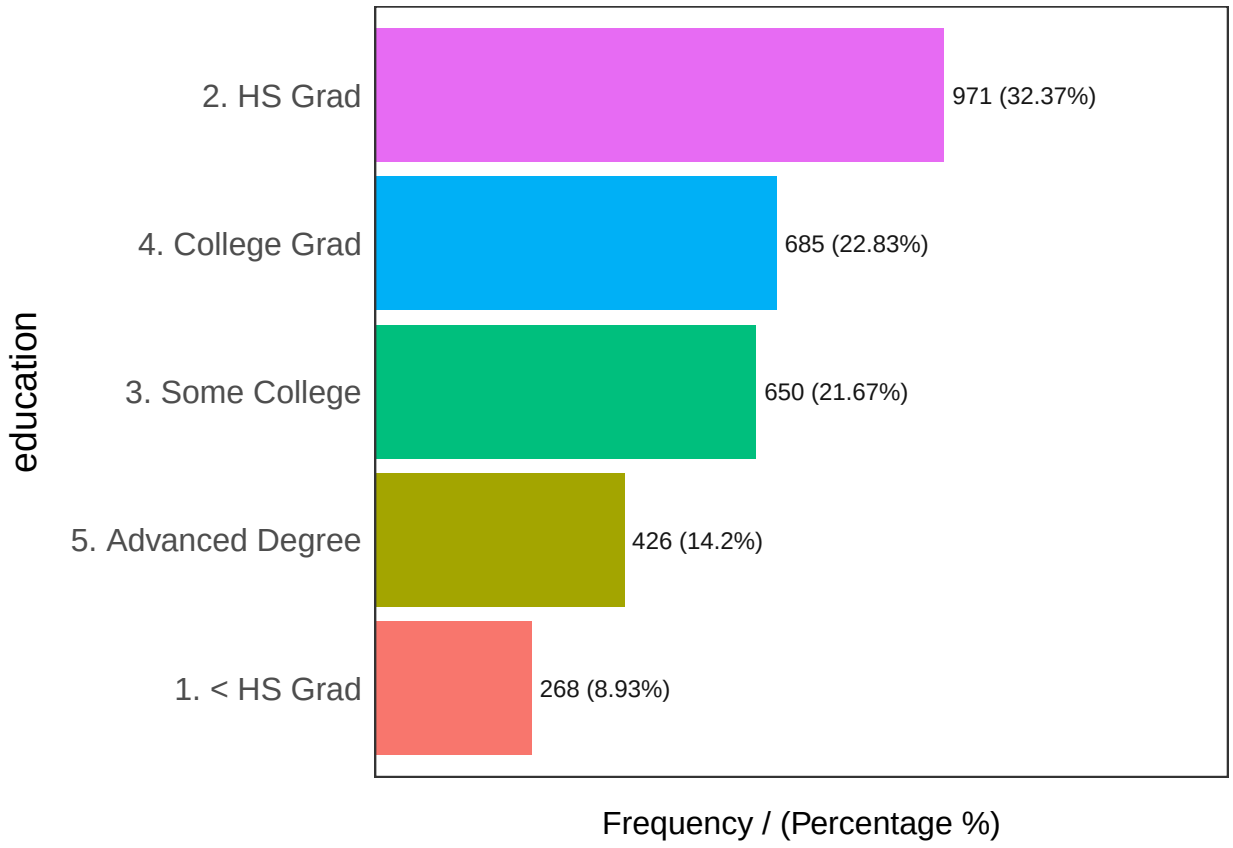

```
##       race frequency percentage cumulative_perc
## 1 1. White      2480      82.67           82.67
## 2 2. Black       293       9.77           92.44
## 3 3. Asian       190       6.33           98.77
## 4 4. Other        37       1.23          100.00
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```



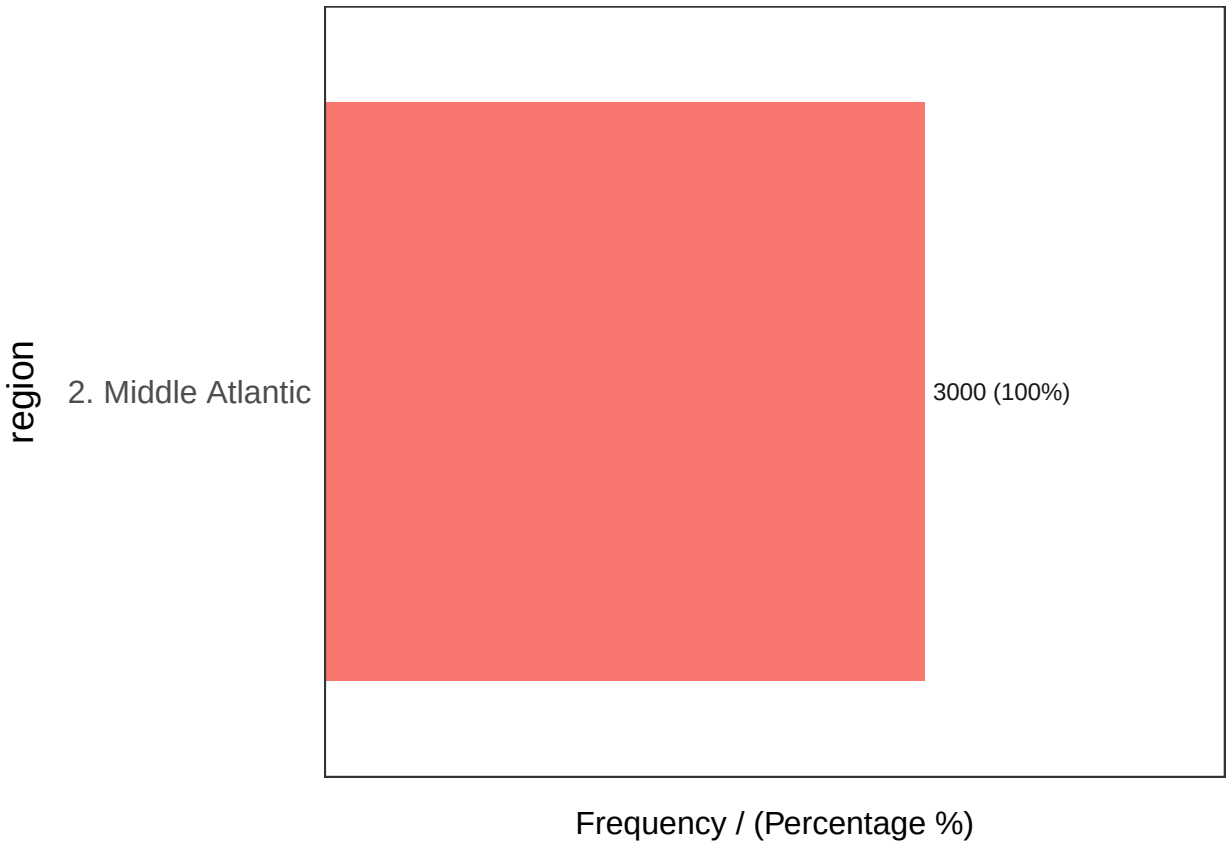

```
##            education frequency percentage cumulative_perc
## 1         2. HS Grad       971      32.37           32.37
## 2    4. College Grad       685      22.83           55.20
## 3    3. Some College       650      21.67           76.87
## 4 5. Advanced Degree       426      14.20           91.07
## 5       1. < HS Grad       268       8.93          100.00
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```



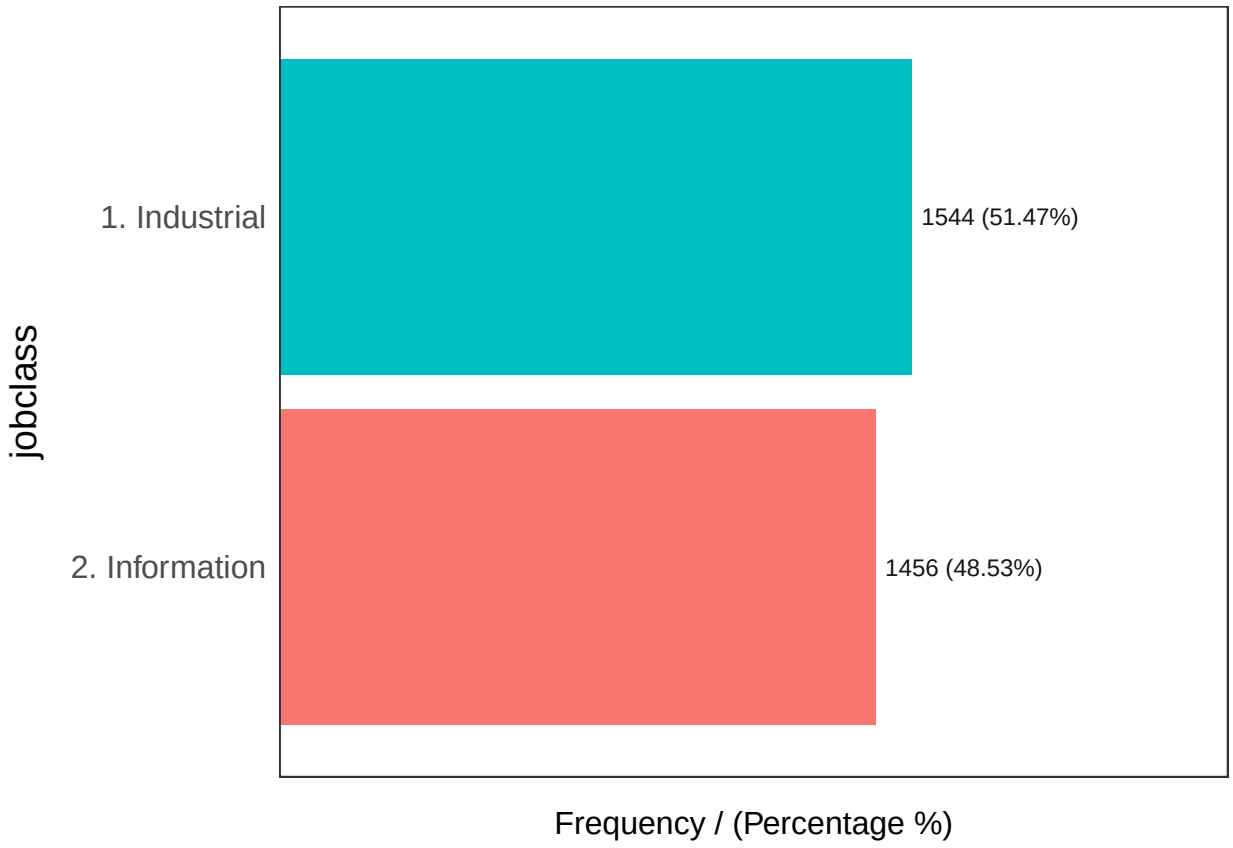

```
##               region frequency percentage cumulative_perc
## 1 2. Middle Atlantic      3000        100             100
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```



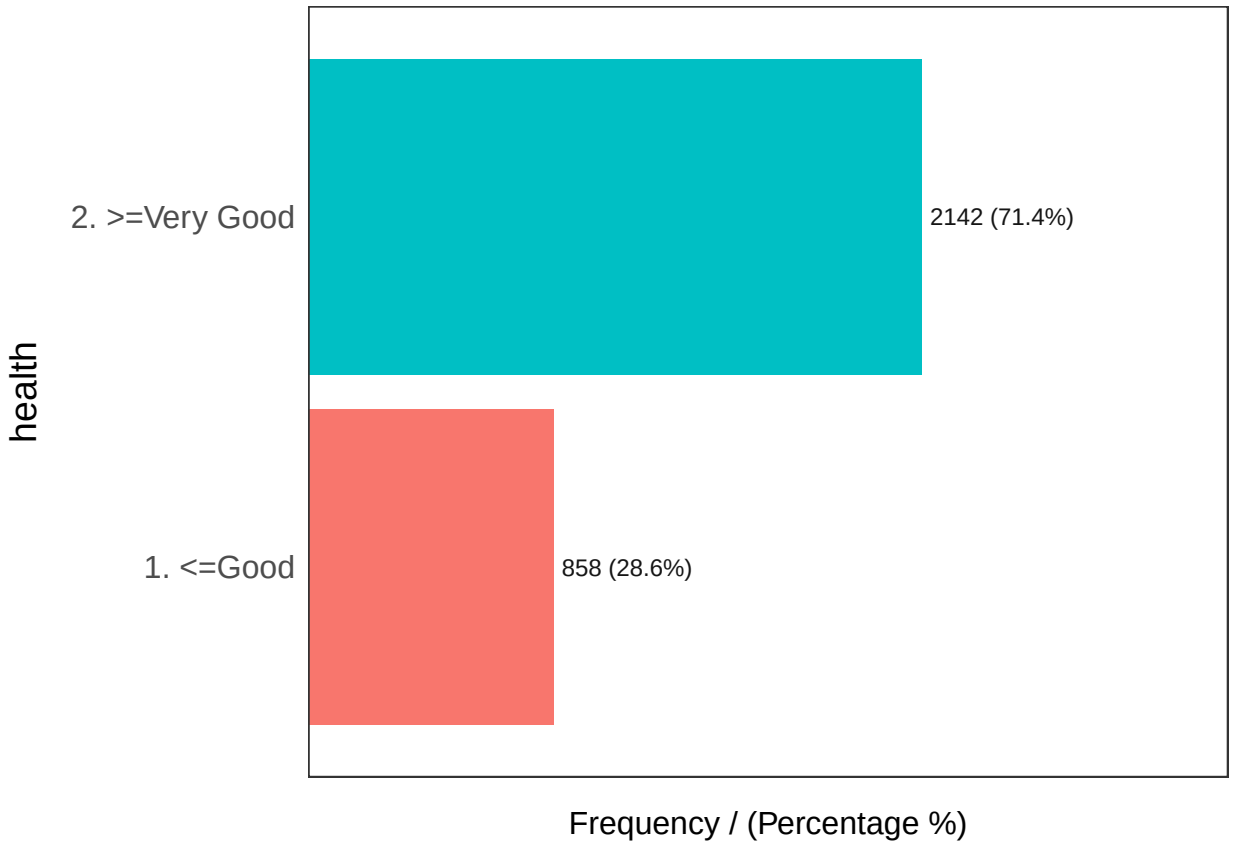

```
##         jobclass frequency percentage cumulative_perc
## 1  1. Industrial      1544      51.47           51.47
## 2 2. Information      1456      48.53          100.00
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```



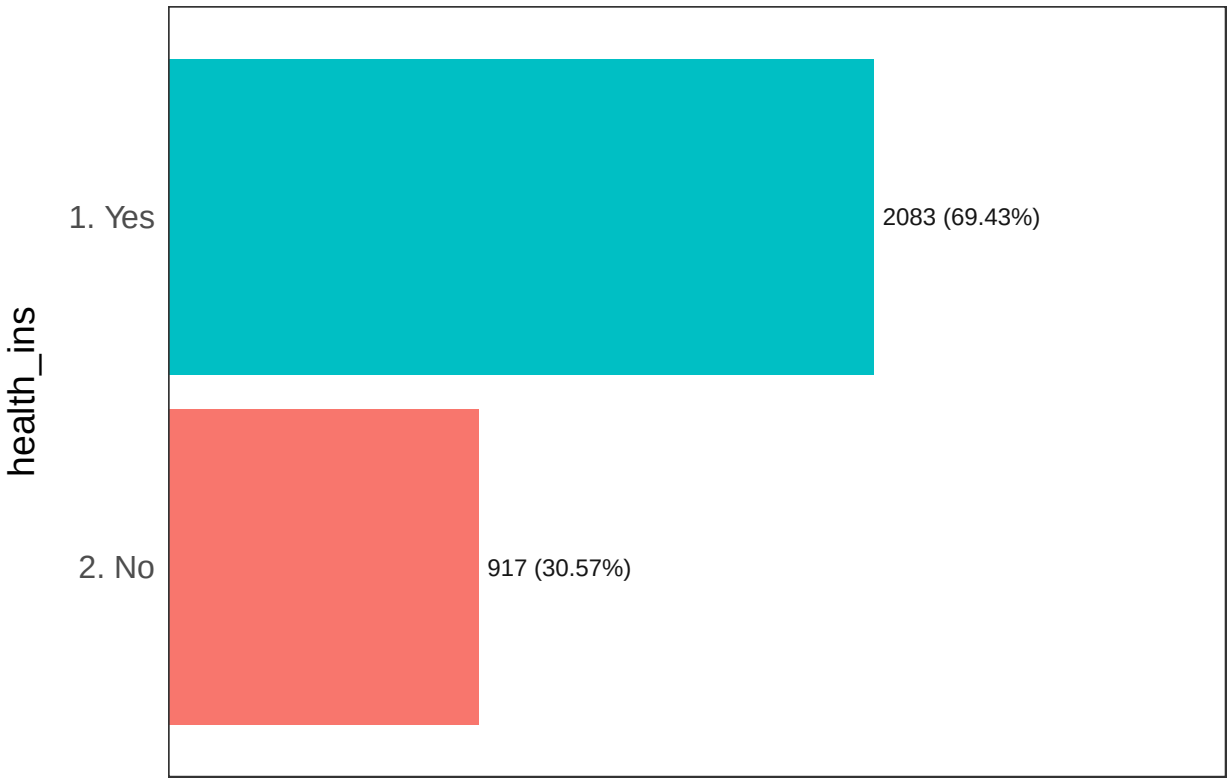

```
##           health frequency percentage cumulative_perc
## 1 2. >=Very Good      2142       71.4            71.4
## 2      1. <=Good       858       28.6           100.0
```

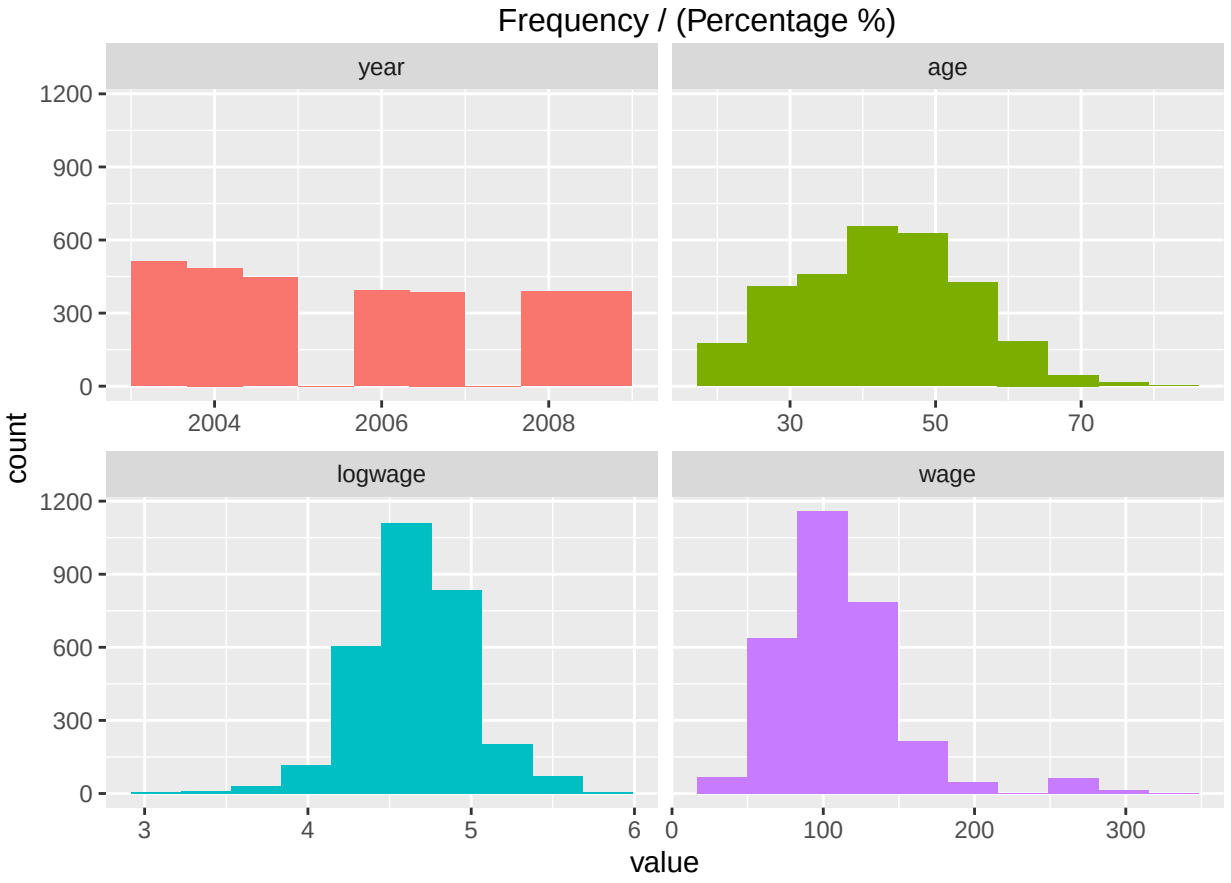
```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```




```
##   health_ins frequency percentage cumulative_perc
## 1     1. Yes      2083      69.43           69.43
## 2      2. No       917      30.57          100.00
##
##   variable        mean    std_dev variation_coef        p_01        p_05
## 1     year 2005.791000  2.0261673    0.001010159 2003.000000 2003.000000
## 2      age   42.414667 11.5424056    0.272132414   20.000000   24.000000
## 3  logwage    4.653905  0.3517526    0.075582244    3.698918    4.113943
## 4     wage  111.703608 41.7285955    0.373565332   40.403552   61.187526
##          p_25        p_50        p_75        p_95        p_99   skewness
## 1 2004.000000 2006.000000 2008.000000 2009.000000 2009.000000  0.1428111
## 2   33.750000   42.000000   51.000000   61.000000   70.000000  0.1477340
## 3    4.447158    4.653213    4.857332    5.176091    5.626186 -0.1235535
## 4   85.383940  104.921507  128.680488  176.989650  277.601418  1.6814889
##   kurtosis        iqr                              range_98
## 1 1.733853  4.0000000                          [2003, 2009]
## 2 2.552129 17.2500000                              [20, 70]
## 3 4.728038  0.4101745  [3.6989175737819, 5.62618633492728]
## 4 7.828952 43.2965478 [40.4035523122557, 277.601417511009]
##                              range_80
## 1                          [2003, 2009]
## 2                             [27, 58]
## 3 [4.25527250510331, 5.04151096788643]
## 4 [70.4760196469445, 154.703600419223]
```

```
## Warning: `guides(<scale> = FALSE)` is deprecated. Please use `guides(<scale> =
## "none")` instead.
```


health_ins
1. Yes
2. No
2083 (69.43%)
917 (30.57%)


Frequency / (Percentage %)
year
age
logwage
wage
count
value
1200
900
600
300
0
2004
2006
2008
30
50
70
3
4
5
6
0
100
200
300

```
## data
```

```
##
##  11  Variables      3000  Observations
## --------------------------------------------------------------------------------
## year
##        n  missing distinct     Info     Mean      Gmd
##     3000        0        7    0.979     2006    2.312
##
## lowest : 2003 2004 2005 2006 2007, highest: 2005 2006 2007 2008 2009
##
## Value       2003  2004  2005  2006  2007  2008  2009
## Frequency    513   485   447   392   386   388   389
## Proportion 0.171 0.162 0.149 0.131 0.129 0.129 0.130
## --------------------------------------------------------------------------------
## age
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     3000        0       61    0.999    42.41    13.16    24.00    27.00
##      .25      .50      .75      .90      .95
##    33.75    42.00    51.00    58.00    61.00
##
## lowest : 18 19 20 21 22, highest: 74 75 76 77 80
## --------------------------------------------------------------------------------
## maritl
##        n  missing distinct
##     3000        0        5
##
## lowest : 1. Never Married 2. Married       3. Widowed       4. Divorced      5. Separated
## highest: 1. Never Married 2. Married       3. Widowed       4. Divorced      5. Separated
##
## Value      1. Never Married       2. Married       3. Widowed      4. Divorced
## Frequency               648              2074               19              204
## Proportion            0.216             0.691            0.006            0.068
##
## Value          5. Separated
## Frequency                55
## Proportion            0.018
## --------------------------------------------------------------------------------
## race
##        n  missing distinct
##     3000        0        4
##
## Value      1. White 2. Black 3. Asian 4. Other
## Frequency      2480      293      190       37
## Proportion    0.827    0.098    0.063    0.012
## --------------------------------------------------------------------------------
## education
##        n  missing distinct
##     3000        0        5
##
## lowest : 1. < HS Grad       2. HS Grad         3. Some College    4. College Grad    5. Advanced Degr
## highest: 1. < HS Grad       2. HS Grad         3. Some College    4. College Grad    5. Advanced Degr
##
## Value            1. < HS Grad         2. HS Grad    3. Some College
## Frequency                 268                971                650
## Proportion              0.089              0.324              0.217
```

```
##
## Value         4. College Grad 5. Advanced Degree
## Frequency                 685                426
## Proportion              0.228              0.142
## ---------------------------------------------------------------------------
## region
##                  n            missing           distinct              value
##               3000                  0                  1 2. Middle Atlantic
##
## Value      2. Middle Atlantic
## Frequency                3000
## Proportion                  1
## ---------------------------------------------------------------------------
## jobclass
##        n  missing distinct
##     3000        0        2
##
## Value       1. Industrial 2. Information
## Frequency            1544           1456
## Proportion          0.515          0.485
## ---------------------------------------------------------------------------
## health
##        n  missing distinct
##     3000        0        2
##
## Value           1. <=Good 2. >=Very Good
## Frequency              858           2142
## Proportion          0.286          0.714
## ---------------------------------------------------------------------------
## health_ins
##        n  missing distinct
##     3000        0        2
##
## Value      1. Yes  2. No
## Frequency    2083    917
## Proportion  0.694  0.306
## ---------------------------------------------------------------------------
## logwage
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     3000        0      508        1    4.654   0.3824    4.114    4.255
##      .25      .50      .75      .90      .95
##    4.447    4.653    4.857    5.042    5.176
##
## lowest : 3.000000 3.041393 3.133858 3.147367 3.176091
## highest: 5.701323 5.735190 5.742793 5.750441 5.763128
## ---------------------------------------------------------------------------
## wage
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     3000        0      508        1    111.7    42.64    61.19    70.48
##      .25      .50      .75      .90      .95
##    85.38   104.92   128.68   154.70   176.99
##
## lowest :  20.08554  20.93438  22.96240  23.27470  23.95294
## highest: 299.26298 309.57177 311.93457 314.32934 318.34243
```

```
## ------------------------------------------------------------------------------
```

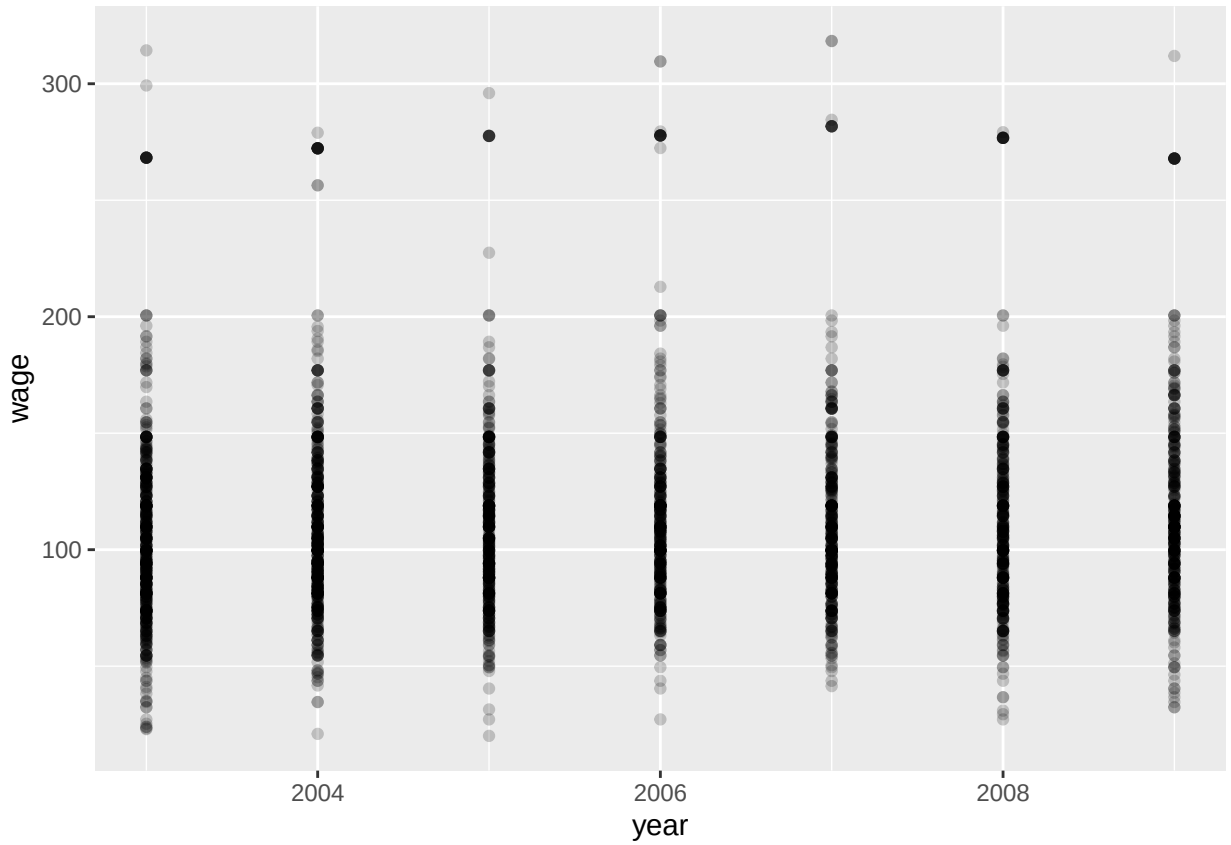
```
Wage_split <- initial_split(Wage, strata = wage, prop = 0.5)
Wage_split
```

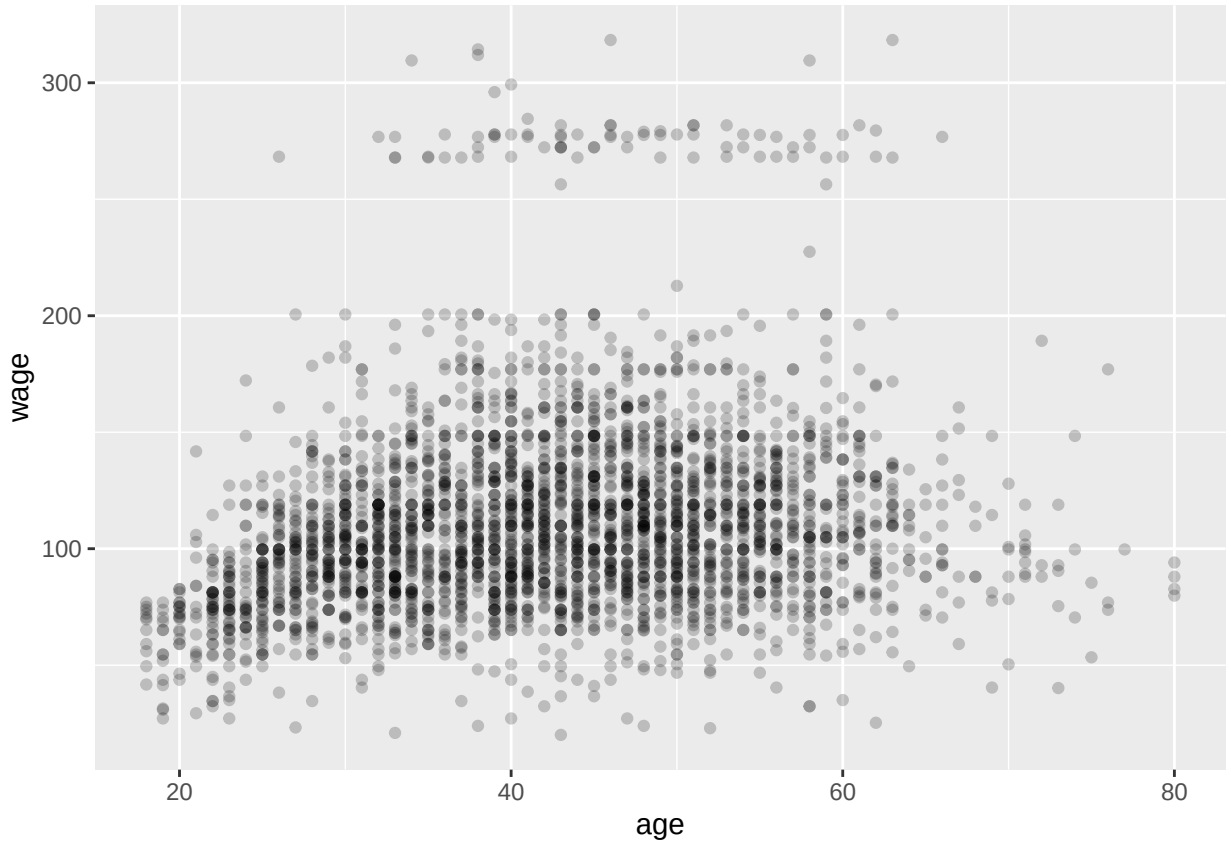
```
## <Analysis/Assess/Total>
## <1499/1501/3000>
```

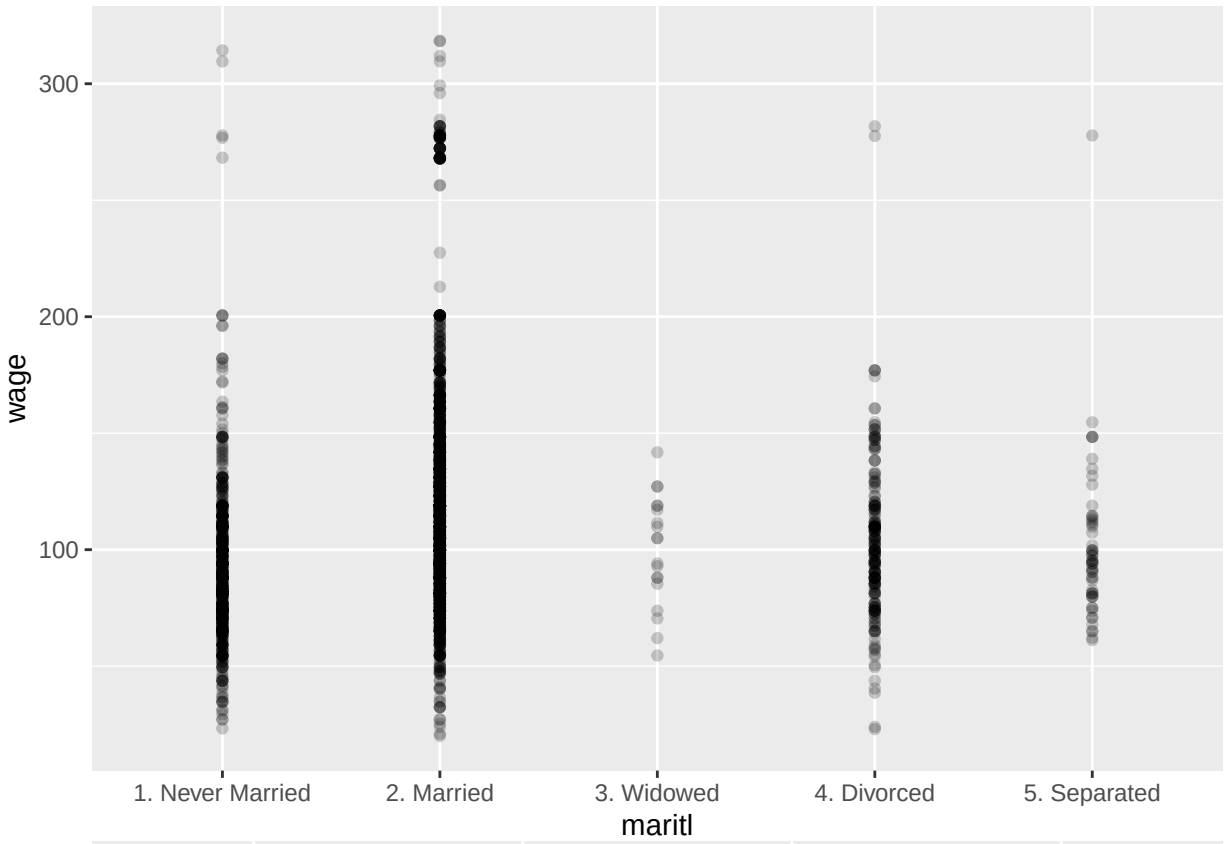
```
Wage_train <- training(Wage_split)
Wage_test <- testing(Wage_split)

Wage_fold <- vfold_cv(Wage_train, v = 10)
Wage_fold
```

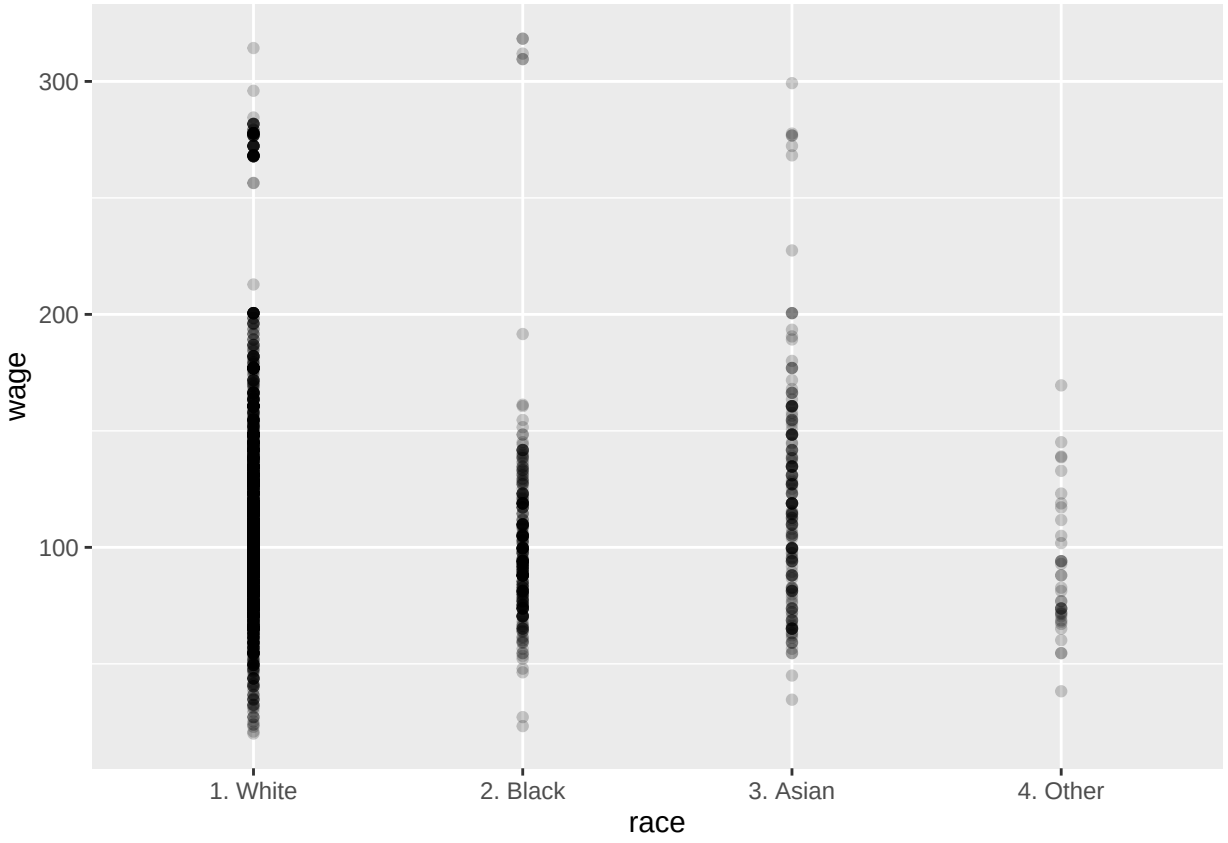
```
## #  10-fold cross-validation
## # A tibble: 10 x 2
##    splits             id
##    <list>             <chr>
##  1 <split [1349/150]> Fold01
##  2 <split [1349/150]> Fold02
##  3 <split [1349/150]> Fold03
##  4 <split [1349/150]> Fold04
##  5 <split [1349/150]> Fold05
##  6 <split [1349/150]> Fold06
##  7 <split [1349/150]> Fold07
##  8 <split [1349/150]> Fold08
##  9 <split [1349/150]> Fold09
## 10 <split [1350/149]> Fold10
```

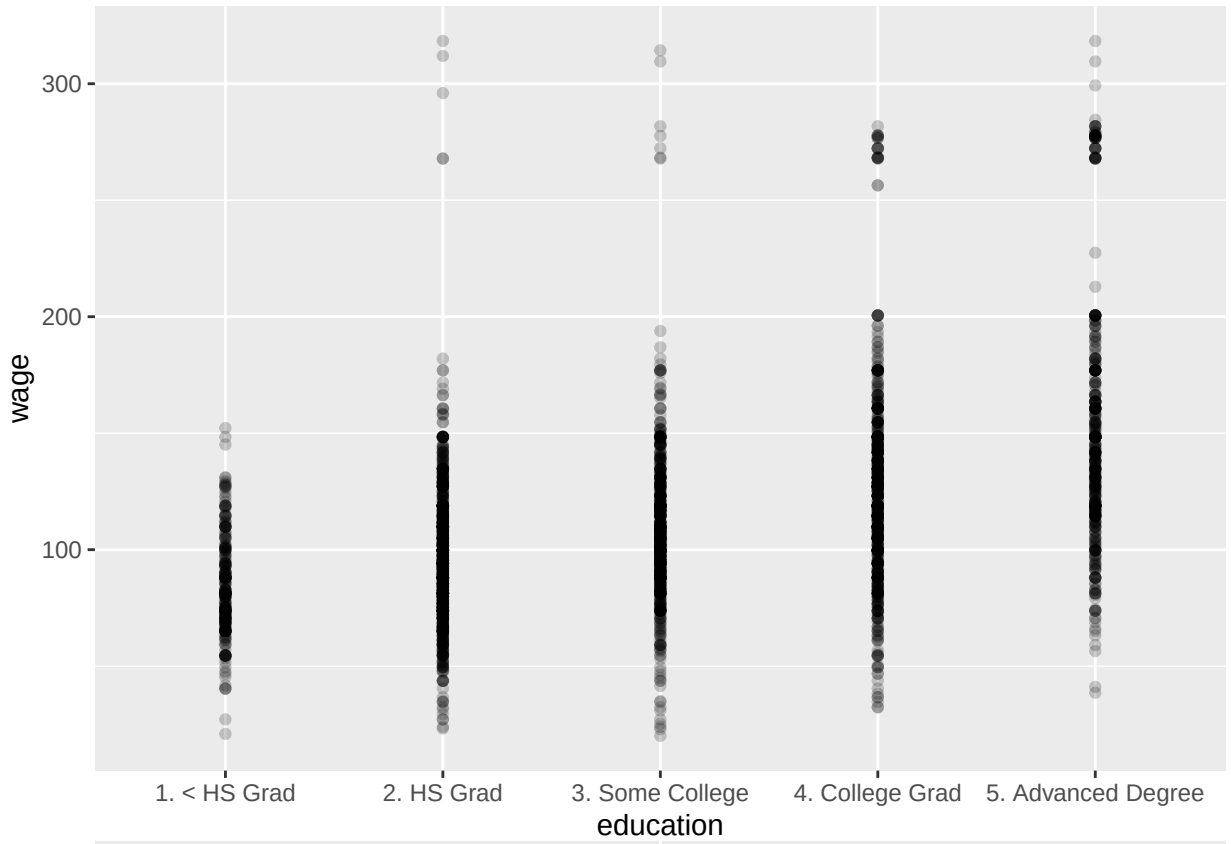
```
colnames <- colnames(Wage)
colnames <- colnames[colnames != "wage"]

for (colname in colnames) {
  pl <- Wage %>%
    ggplot(aes_string(x = colname, y = "wage")) +
    geom_point(alpha = 0.2)
  print(pl)
}
```

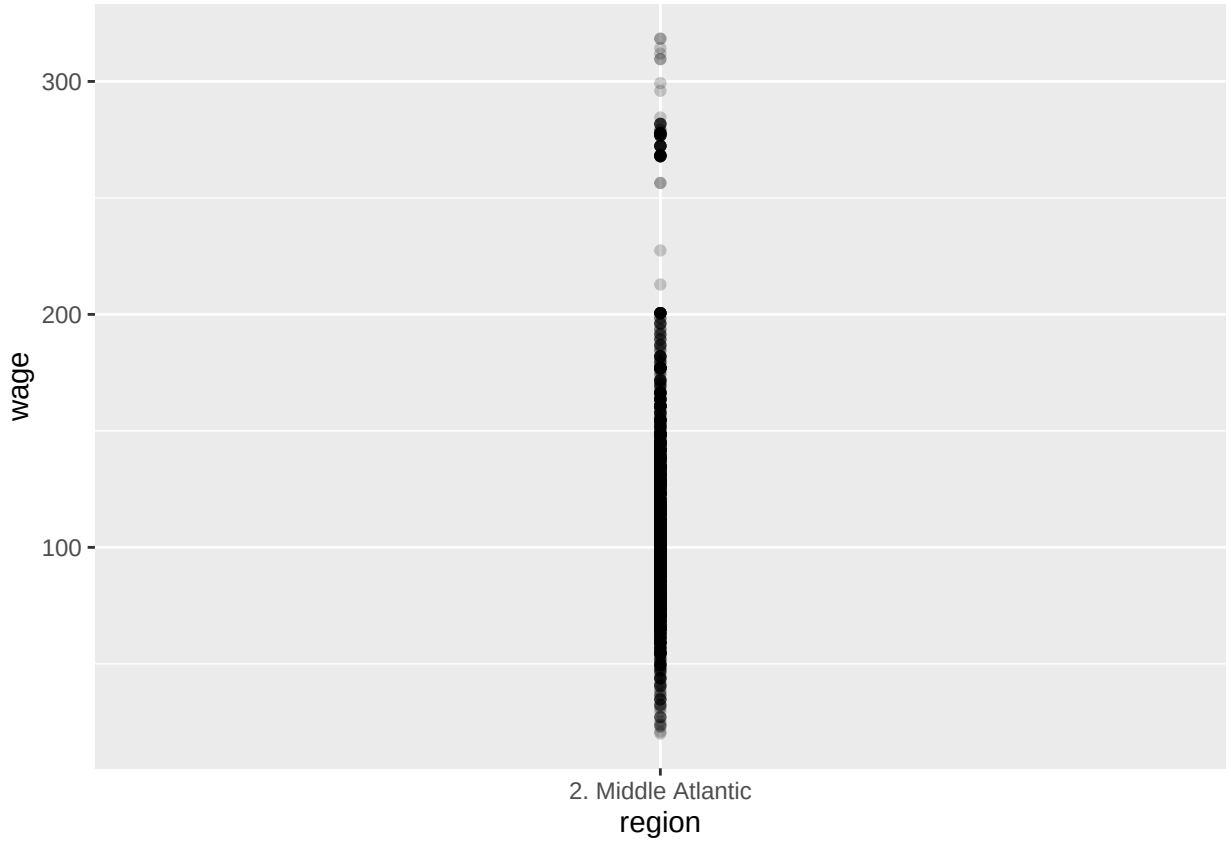

300
200
100
wage
2004
2006
2008
year

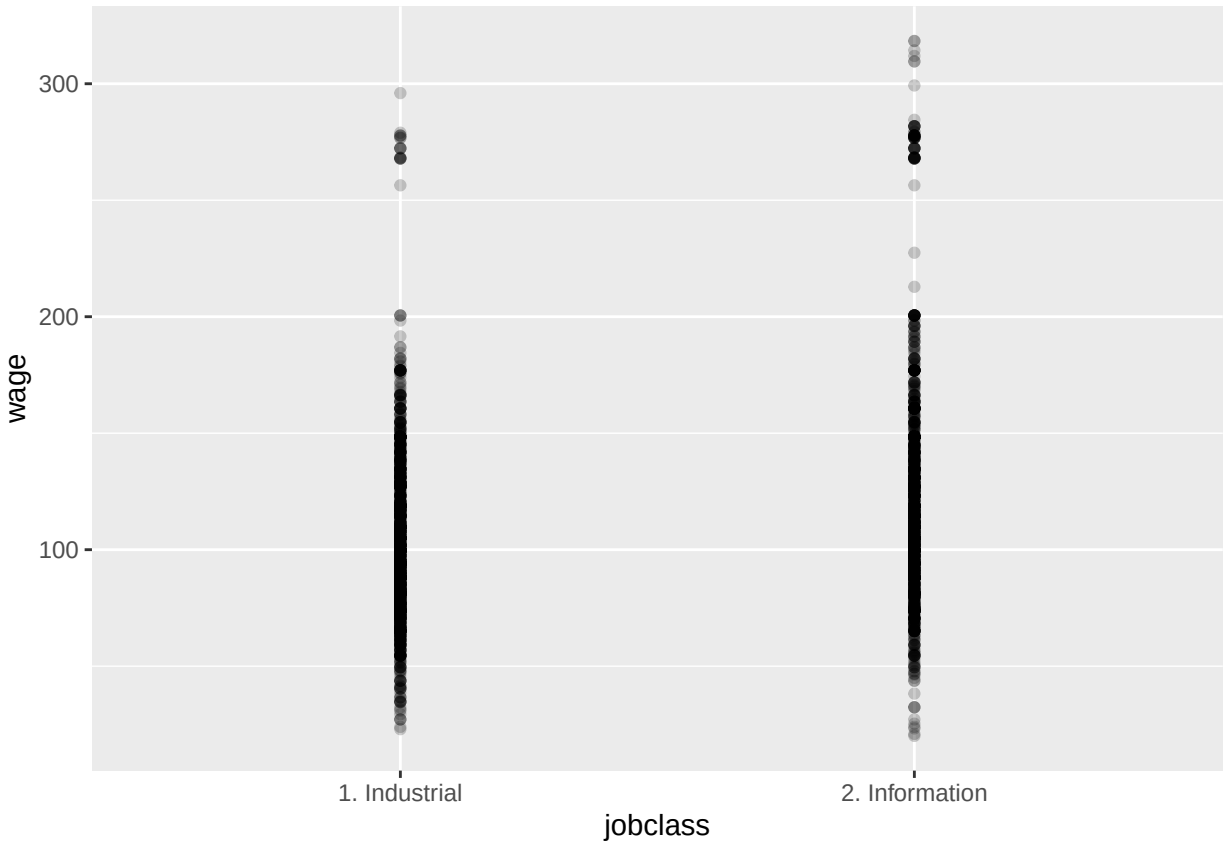

300
200
100
wage
20
40
60
80
age

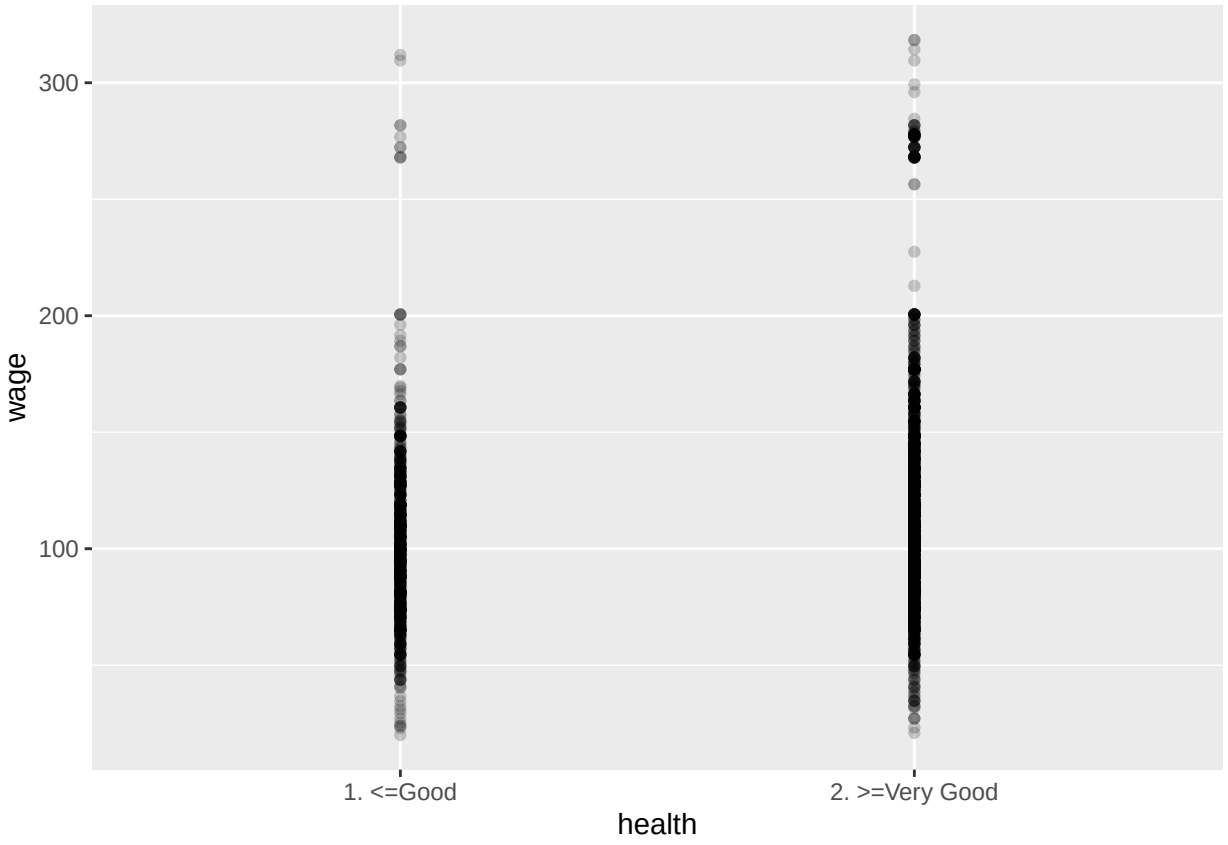

300
200
100
wage
1. Never Married
2. Married
3. Widowed
4. Divorced
5. Separated
maritl

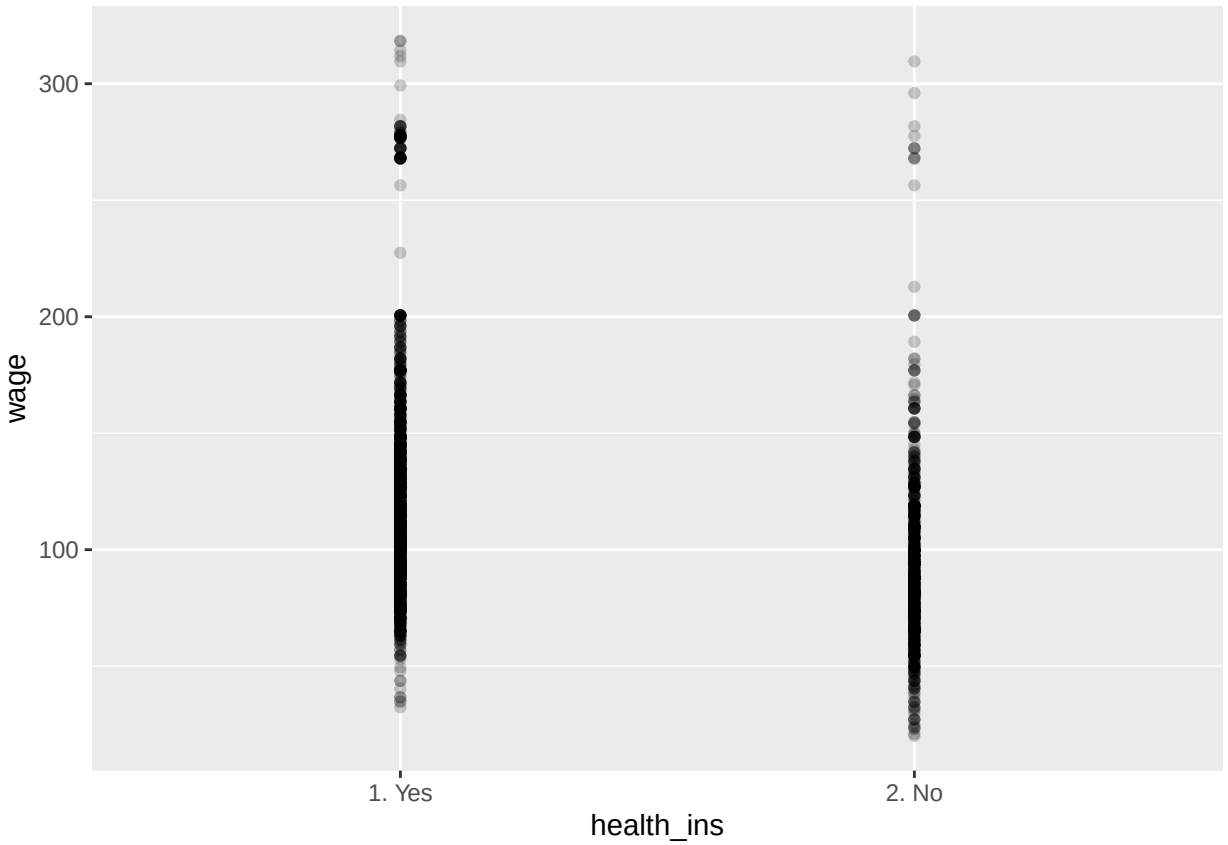

300
200
100
wage
1. White
2. Black
3. Asian
4. Other
race

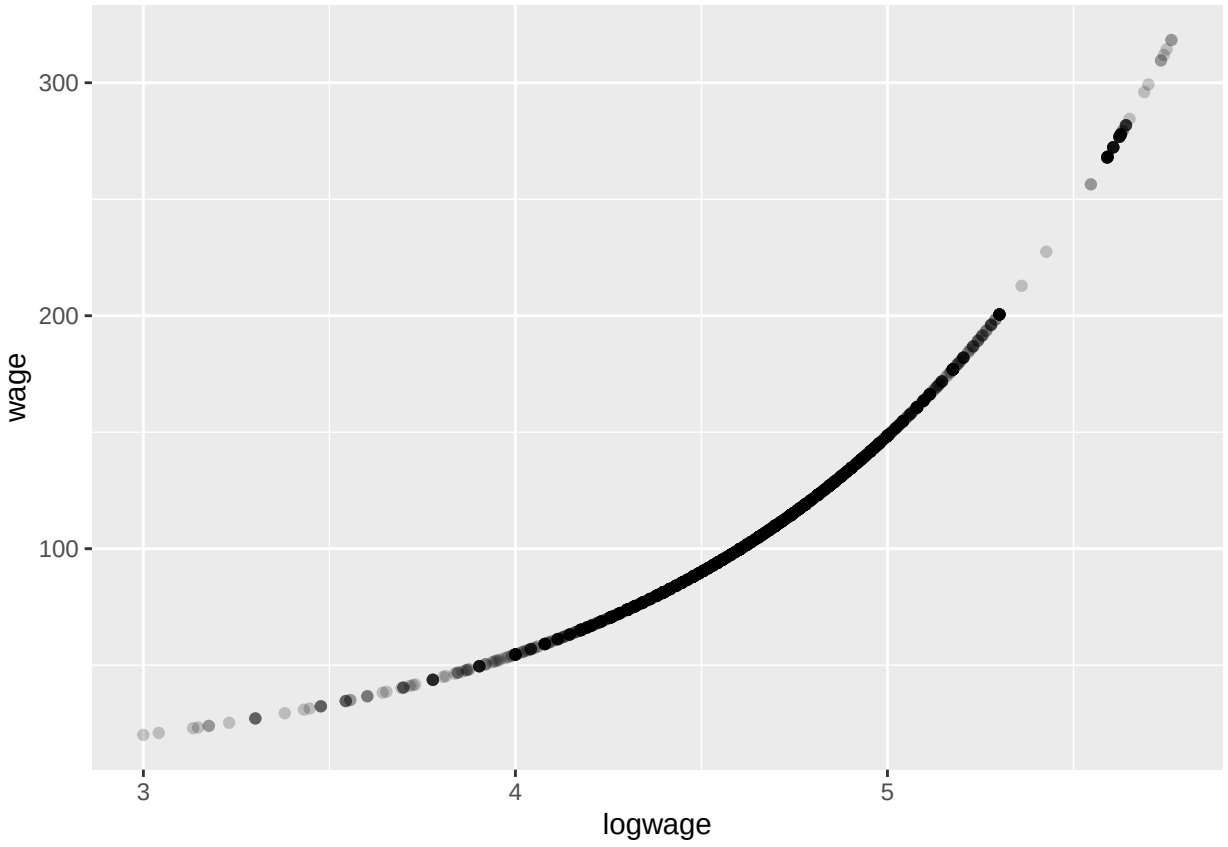

300
200
100
wage
1. < HS Grad
2. HS Grad
3. Some College
4. College Grad
5. Advanced Degree
education


300
200
100
wage
2. Middle Atlantic
region


300
200
100
wage
1. Industrial
2. Information
jobclass


300
200
100
wage
1. <=Good
2. >=Very Good
health


300
200
100
wage
1. Yes
2. No
health_ins


300
200
100
wage
3
4
5
logwage

```r
# Recipe
lm_pl_recipe <-
  recipe(formula = wage ~ age, data = Wage_train) %>%
  step_poly(age, degree = 2, options = list(raw = TRUE)) %>%
  step_normalize(all_predictors())

# Specification
lm_pl_spec <-
  linear_reg() %>%
  set_mode("regression") %>%
  set_engine("lm")

# Workflow
lm_pl_workflow <- workflow() %>%
  add_recipe(lm_pl_recipe) %>%
  add_model(lm_pl_spec)

# Finalize model
lm_pl_fit <- fit(lm_pl_workflow, data = Wage_train)

# Check RMSE
augment(lm_pl_fit, new_data = Wage_test) %>%
  rmse(truth = wage, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard        40.6
```

```r
tidy(lm_pl_fit)
```

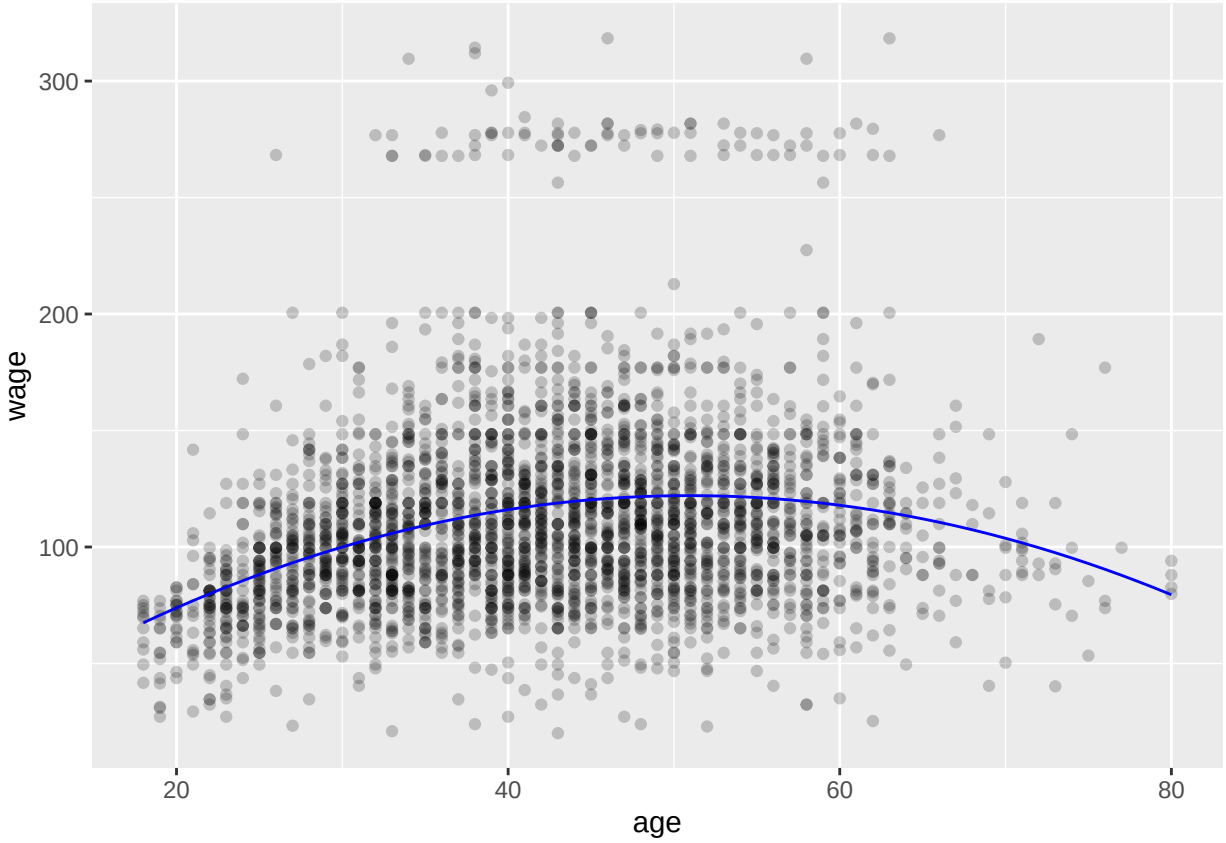
```
## # A tibble: 3 x 5
##   term        estimate std.error statistic  p.value
##   <chr>          <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)    112.       1.02    110.   0
## 2 age_poly_1      58.7      6.22      9.43 1.45e-20
## 3 age_poly_2     -50.2      6.22     -8.07 1.39e-15
```

```r
age_min <- min(Wage$age)
age_max <- max(Wage$age)
age_range <- tibble(age = seq(age_min, age_max))
age_range
```

```
## # A tibble: 63 x 1
##      age
##    <int>
##  1    18
##  2    19
##  3    20
##  4    21
##  5    22
##  6    23
##  7    24
##  8    25
##  9    26
```

```
## 10    27
## # ... with 53 more rows
```

```
regression_lines <- bind_cols(
  predict(lm_pl_fit, new_data = age_range),
  age_range
)

Wage %>%
  ggplot(aes(age, wage)) +
  geom_point(alpha = 0.2) +
  geom_line(aes(y = .pred), data = regression_lines, color = "blue")
```



All the other variables are categorical. Hot encoding these variables basically results in a "piecewise non-linear" function. However, exploring this most likely is not very interesting. Therefor we will now test splines also on the relationships of age and wage.

```
min(Wage$age)
```

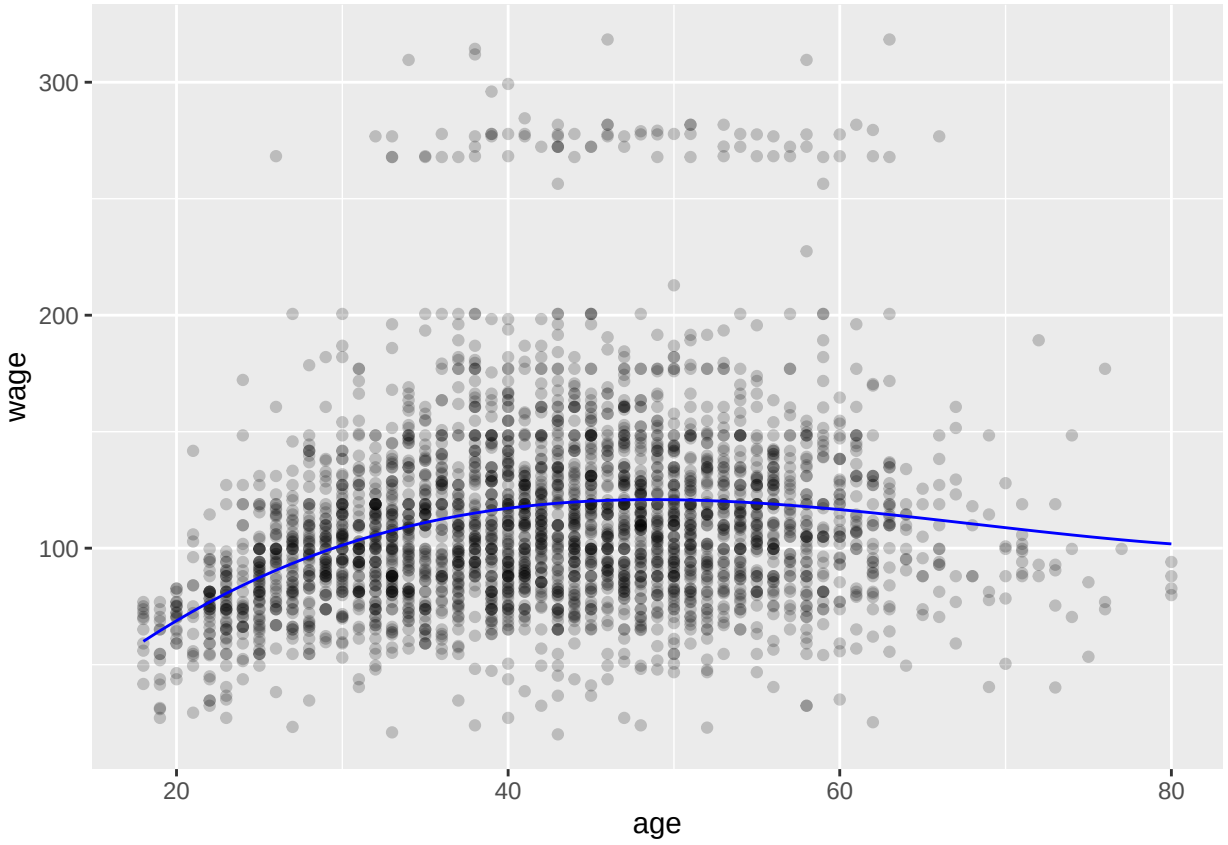
```
## [1] 18
```

```
spline_recipe <- recipe(formula = wage ~ age, data = Wage_train) %>%
  step_bs(age, options = list(knots = 20, 30, 40, 50, 60, 70))

# Specification
spline_spec <-
  linear_reg() %>%
  set_mode("regression") %>%
  set_engine("lm")
```

```r
# Workflow
spline_workflow <- workflow() %>%
  add_recipe(spline_recipe) %>%
  add_model(spline_spec)

# Finalize model
spline_fit <- fit(spline_workflow, data = Wage_train)

# Check RMSE
augment(spline_fit, new_data = Wage_test) %>%
  rmse(truth = wage, estimate = .pred)
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard        40.6
```

```r
regression_lines <- bind_cols(
  predict(spline_fit, new_data = age_range),
  age_range
)

Wage %>%
  ggplot(aes(age, wage)) +
  geom_point(alpha = 0.2) +
  geom_line(aes(y = .pred), data = regression_lines, color = "blue")
```



Both the polynomial regression as well as splines capture the relationship between age and wage better than a simple linear regression. We can see that the splines fit the data even better than the polynomial regression, especially at the border regions.