

Laporan Praktikum 3 AMP

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Classification Methods

The Stock Market Data

```
library(ISLR2)

## Warning: package 'ISLR2' was built under R version 4.3.3

names(Smarket)

## [1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"
## [7] "Volume"    "Today"     "Direction"

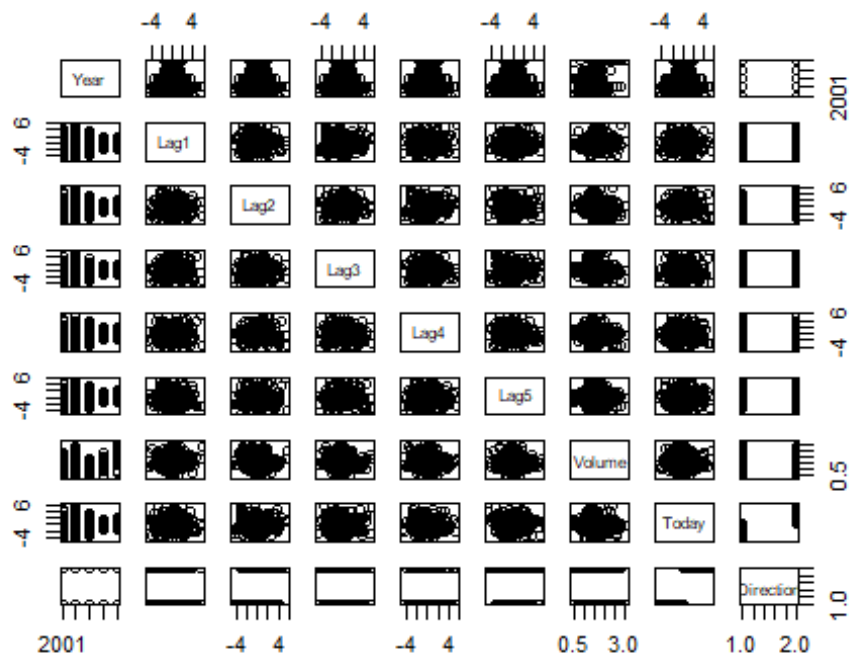
dim(Smarket)

## [1] 1250      9

summary(Smarket)

##      Year      Lag1      Lag2      Lag3
## Min.   :2001   Min.   :-4.922000   Min.   :-4.922000   Min.   :-4.922000
## 1st Qu.:2002   1st Qu.: -0.639500   1st Qu.: -0.639500   1st Qu.: -0.640000
## Median :2003   Median :  0.039000   Median :  0.039000   Median :  0.038500
## Mean   :2003   Mean   :  0.003834   Mean   :  0.003919   Mean   :  0.001716
## 3rd Qu.:2004   3rd Qu.:  0.596750   3rd Qu.:  0.596750   3rd Qu.:  0.596750
## Max.   :2005   Max.    :  5.733000   Max.    :  5.733000   Max.    :  5.733000
##      Lag4      Lag5      Volume      Today
## Min.   :-4.922000   Min.   :-4.922000   Min.    :0.3561   Min.   :-4.922000
## 1st Qu.: -0.640000   1st Qu.: -0.640000   1st Qu.:1.2574   1st Qu.: -0.639500
## Median :  0.038500   Median :  0.038500   Median :1.4229   Median :  0.038500
## Mean   :  0.001636   Mean   :  0.00561    Mean   :1.4783   Mean   :  0.003138
## 3rd Qu.:  0.596750   3rd Qu.:  0.59700    3rd Qu.:1.6417   3rd Qu.:  0.596750
## Max.    :  5.733000   Max.    :  5.73300    Max.    :3.1525   Max.    :  5.733000
## Direction
## Down:602
## Up  :648
##
##
##
##
```

```
pairs(Smarket)
```



Keterangan :

Melakukan eksplorasi awal terhadap data untuk memahami struktur dan distribusinya.

```
#cor(Smarket)
```

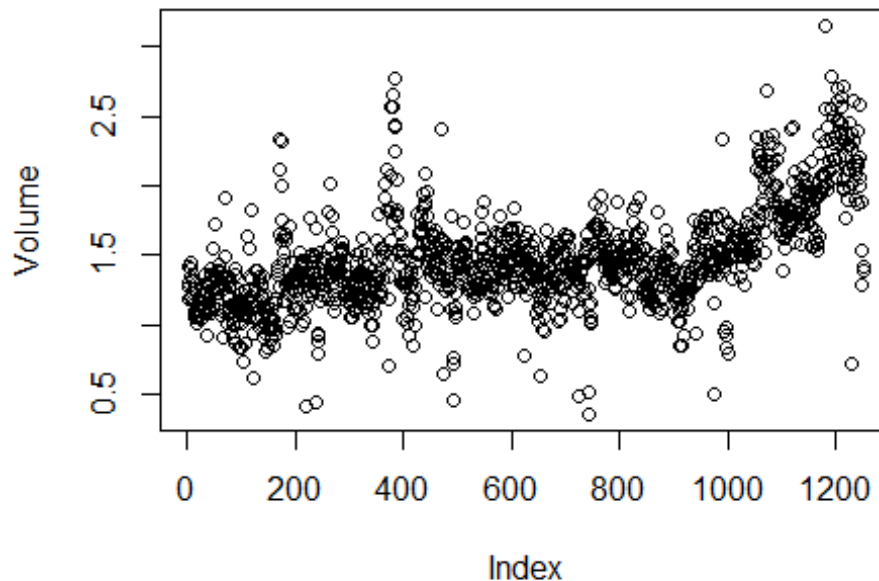
```
cor(Smarket[, -9])
```

```
##          Year          Lag1          Lag2          Lag3          Lag4
## Year  1.00000000  0.029699649  0.030596422  0.033194581  0.035688718
## Lag1  0.02969965  1.000000000 -0.026294328 -0.010803402 -0.002985911
## Lag2  0.03059642 -0.026294328  1.000000000 -0.025896670 -0.010853533
## Lag3  0.03319458 -0.010803402 -0.025896670  1.000000000 -0.024051036
## Lag4  0.03568872 -0.002985911 -0.010853533 -0.024051036  1.000000000
## Lag5  0.02978799 -0.005674606 -0.003557949 -0.018808338 -0.027083641
## Volume 0.53900647  0.040909908 -0.043383215 -0.041823686 -0.048414246
## Today 0.03009523 -0.026155045 -0.010250033 -0.002447647 -0.006899527
##          Lag5          Volume          Today
## Year  0.029787995  0.53900647  0.030095229
## Lag1 -0.005674606  0.04090991 -0.026155045
## Lag2 -0.003557949 -0.04338321 -0.010250033
## Lag3 -0.018808338 -0.04182369 -0.002447647
## Lag4 -0.027083641 -0.04841425 -0.006899527
## Lag5  1.000000000 -0.02200231 -0.034860083
## Volume -0.022002315  1.00000000  0.014591823
## Today -0.034860083  0.01459182  1.000000000
```

Keterangan :

Melihat hubungan linear antar variabel numerik untuk memahami mana yang mungkin berhubungan dengan Direction.

```
attach(Smarket)
plot(Volume)
```



Keterangan :

Melihat bagaimana tren Volume perdagangan berubah selama periode waktu yang ada dalam dataset.

Code Halaman 175

```
train <- (Year < 2005)
Smarket.2005 <- Smarket[!train, ]
dim(Smarket.2005)

## [1] 252  9

Direction.2005 <- Direction[!train]
```

Keterangan :

Pada baris awal kita mencoba memisahkan training set dengan test set. Data sebelum 2005 (training set), dan data dari 2005 ke atas (test set). Lalu dengan `Smarket[!train,]`, kita memilih hanya data dengan `Year >= 2005`, sehingga `Smarket.2005` berisi hanya test set.

Fungsi `dim()` menampilkan jumlah baris dan kolom dari `Smarket.2005`, yaitu 252×9 . Selanjutnya, `Direction` adalah variabel respons yang menunjukkan apakah pasar saham naik ("Up") atau turun ("Down"). `Direction[!train]` mengambil hanya nilai `Direction` dari test set (2005 ke atas) dan menyimpannya di `Direction.2005`.

K-Nearest Neighbors

```
library(class)
train.X <- cbind(Lag1, Lag2)[train, ]
test.X <- cbind(Lag1, Lag2)[!train, ]
train.Direction <- Direction[train]
```

Keterangan :

Dataset dipecah menjadi training set dan test set, hanya menggunakan prediktor `Lag1` dan `Lag2` karena diduga memiliki hubungan dengan `Direction`. Sementara `train.Direction` berisi label kategori untuk data latih.

```
set.seed(1)
knn.pred <- knn(train.X, test.X, train.Direction, k = 1)
table(knn.pred, Direction.2005)

##           Direction.2005
## knn.pred Down Up
##      Down   43 58
##      Up    68 83

(83 + 43) / 252

## [1] 0.5
```

Keterangan :

Model KNN dengan $k = 1$ dibuat dan hasilnya dibandingkan dengan data aktual. Akurasi dihitung dengan $(83 + 43)/252 = 50$, yang menunjukkan model ini tidak jauh lebih baik dari tebakan acak.

```
knn.pred <- knn(train.X, test.X, train.Direction, k = 3)
table(knn.pred, Direction.2005)

##           Direction.2005
## knn.pred Down Up
##      Down   48 54
##      Up    63 87

mean(knn.pred == Direction.2005)

## [1] 0.5357143
```

Keterangan :

Model KNN dengan $k = 3$ diuji untuk melihat apakah lebih baik dari $k = 1$. Menggunakan `mean(knn.pred == Direction.2005)`, akurasi dihitung dan dibandingkan dengan model sebelumnya.

```
dim(Caravan)
## [1] 5822    86

attach(Caravan)
summary(Purchase)

##    No    Yes
## 5474   348

348 / 5822

## [1] 0.05977327
```

Keterangan :

Dataset Caravan memiliki 5.822 observasi dan target variabel Purchase. Hanya 348 orang yang membeli asuransi (sekitar 6%), menunjukkan dataset sangat tidak seimbang.

```
standardized.X <- scale(Caravan[, -86])
var(Caravan[, 1])

## [1] 165.0378

var(Caravan[, 2])

## [1] 0.1647078

var(standardized.X[, 1])

## [1] 1

var(standardized.X[, 2])

## [1] 1
```

Keterangan :

Variabel prediktor distandarisasi menggunakan `scale()`, karena KNN sensitif terhadap skala variabel. Setelah standarisasi, semua variabel memiliki varians yang seragam.

```
test <- 1:1000
train.X <- standardized.X[-test, ]
test.X <- standardized.X[test, ]
train.Y <- Purchase[-test]
test.Y <- Purchase[test]
set.seed(1)
```

```
knn.pred <- knn(train.X, test.X, train.Y, k = 1)
mean(test.Y != knn.pred)

## [1] 0.118

mean(test.Y != "No")

## [1] 0.059
```

Keterangan :

1.000 observasi pertama digunakan sebagai test set, sisanya sebagai training set. Model KNN dengan $k = 1$ diuji dan error rate dihitung. Akurasi model tidak terlalu baik karena dataset tidak seimbang (`mean(test.Y != "No")` menunjukkan mayoritas prediksi adalah "No").

```
table(knn.pred, test.Y)

##           test.Y
## knn.pred  No  Yes
##      No   873  50
##      Yes   68   9

9 / (68 + 9)

## [1] 0.1168831
```

Keterangan :

Dari 77 prediksi "Yes", hanya 9 yang benar. Rasio keberhasilan deteksi pembelian asuransi sangat kecil, sekitar 11.7. Model cenderung bias ke "No" karena mayoritas sampel memang "No".

```
knn.pred <- knn(train.X, test.X, train.Y, k = 3)
table(knn.pred, test.Y)

##           test.Y
## knn.pred  No  Yes
##      No   920  54
##      Yes    21   5

5 / 26

## [1] 0.1923077

knn.pred <- knn(train.X, test.X, train.Y, k = 5)
table(knn.pred, test.Y)

##           test.Y
## knn.pred  No  Yes
##      No   930  55
##      Yes    11   4
```

4 / 15

```
## [1] 0.2666667
```

Keterangan :

Dengan $k = 3$, hanya 5 dari 26 prediksi “Yes” yang benar, sekitar 19.2 akurasi pada kelas “Yes”. Dengan $k = 5$, hanya 4 dari 15 prediksi “Yes” yang benar, sekitar 26.7 akurasi pada kelas “Yes”. Semakin besar k , semakin sedikit false positive, tetapi semakin banyak false negative.

```
glm.fits <- glm(Purchase ~ ., data = Caravan,
  family = binomial, subset = -test)

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

glm.probs <- predict(glm.fits, Caravan[test, ],
  type = "response")
glm.pred <- rep("No", 1000)
glm.pred[glm.probs > .5] <- "Yes"
table(glm.pred, test.Y)

##           test.Y
## glm.pred  No Yes
##          No 934 59
##          Yes  7  0

glm.pred <- rep("No", 1000)
glm.pred[glm.probs > .25] <- "Yes"
table(glm.pred, test.Y)

##           test.Y
## glm.pred  No Yes
##          No 919 48
##          Yes 22 11

11 / (22 + 11)

## [1] 0.3333333
```

Keterangan :

Model regresi logistik dibuat dan dilatih hanya pada training test. Jika menggunakan ambang batas probabilitas 50, hampir semua prediksi adalah “No”, karena dataset tidak seimbang. Jika ambang batas diturunkan ke 25, lebih banyak “Yes” yang terdeteksi. Akurasi untuk mendeteksi pembelian asuransi tetap rendah ($11/(22 + 11) = 33$ pada kategori “Yes”).

Exercise

Nomor 13

This question should be answered using the Weekly data set, which is part of the ISLR2 package. This data is similar in nature to the Smarket data from this chapter's lab, except that it contains 1,089 weekly returns for 21 years, from the beginning of 1990 to the end of 2010.

```
library(ISLR2)
library(class)
data(Weekly)
names(Weekly)

## [1] "Year"      "Lag1"      "Lag2"      "Lag3"      "Lag4"      "Lag5"
## [7] "Volume"    "Today"     "Direction"

dim(Weekly)

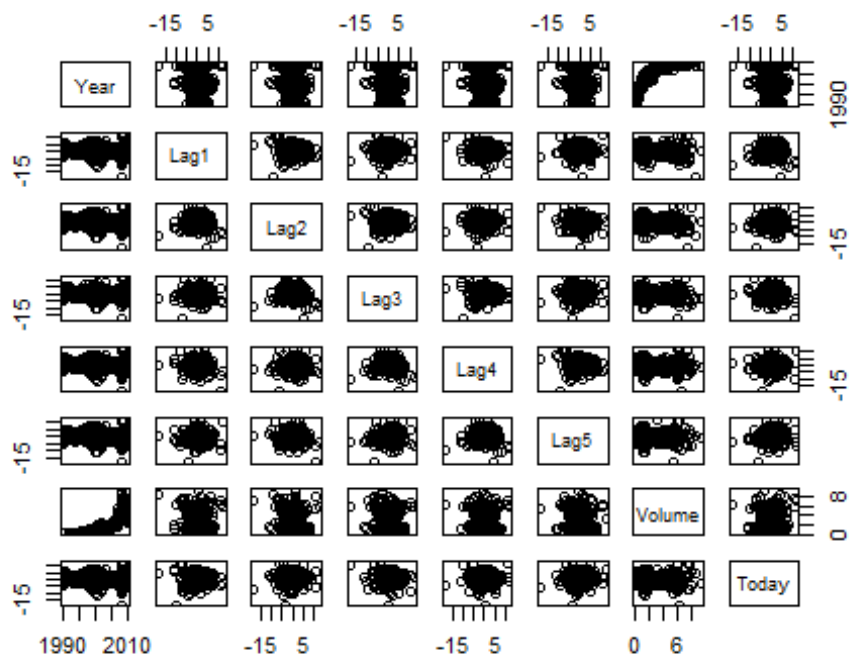
## [1] 1089      9
```

- a. Produce some numerical and graphical summaries of the Weekly data. Do there appear to be any patterns?

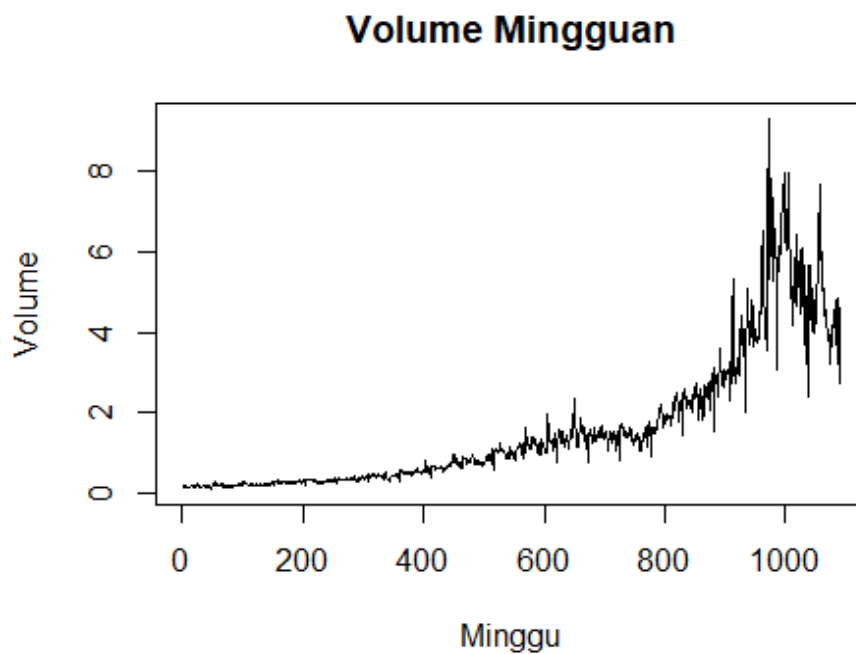
```
summary(Weekly)

##      Year      Lag1      Lag2      Lag3
## Min.   :1990   Min.   :-18.1950   Min.   :-18.1950   Min.   :-18.1950
## 1st Qu.:1995   1st Qu.: -1.1540   1st Qu.: -1.1540   1st Qu.: -1.1580
## Median :2000   Median :  0.2410   Median :  0.2410   Median :  0.2410
## Mean   :2000   Mean   :  0.1506   Mean   :  0.1511   Mean   :  0.1472
## 3rd Qu.:2005   3rd Qu.:  1.4050   3rd Qu.:  1.4090   3rd Qu.:  1.4090
## Max.   :2010   Max.   : 12.0260   Max.   : 12.0260   Max.   : 12.0260
##      Lag4      Lag5      Volume      Today
## Min.   :-18.1950   Min.   :-18.1950   Min.   :0.08747   Min.   :-18.1950
## 1st Qu.: -1.1580   1st Qu.: -1.1660   1st Qu.:0.33202   1st Qu.: -1.1540
## Median :  0.2380   Median :  0.2340   Median :1.00268   Median :  0.2410
## Mean   :  0.1458   Mean   :  0.1399   Mean   :1.57462   Mean   :  0.1499
## 3rd Qu.:  1.4090   3rd Qu.:  1.4050   3rd Qu.:2.05373   3rd Qu.:  1.4050
## Max.   : 12.0260   Max.   : 12.0260   Max.   :9.32821   Max.   : 12.0260
## Direction
## Down:484
## Up  :605
##
##
##
##

pairs(Weekly[, -9])
```

```
plot(Weekly$Volume, type = "l", main = "Volume Mingguan", ylab = "Volume",
xlab = "Minggu")
```



Year dan Volume tampaknya memiliki hubungan, trennya relatif positif.

- g. Repeat (d) using KNN with $K = 1$.

```
library(class)
train <- Weekly$Year < 2009
test <- Weekly$Year > 2008

knn_model <- knn(
  Weekly[train, "Lag2", drop = FALSE],
  Weekly[test, "Lag2", drop = FALSE],
  Weekly$Direction[train], k = 1
)
(confusion_matrix_knn <- table(Prediction = knn_model, Actual = Weekly[test,
]$Direction))

##           Actual
## Prediction Down Up
##           Down   21 29
##           Up    22 32

(akurasi_knn <- mean(knn_model == Weekly[test, ]$Direction))

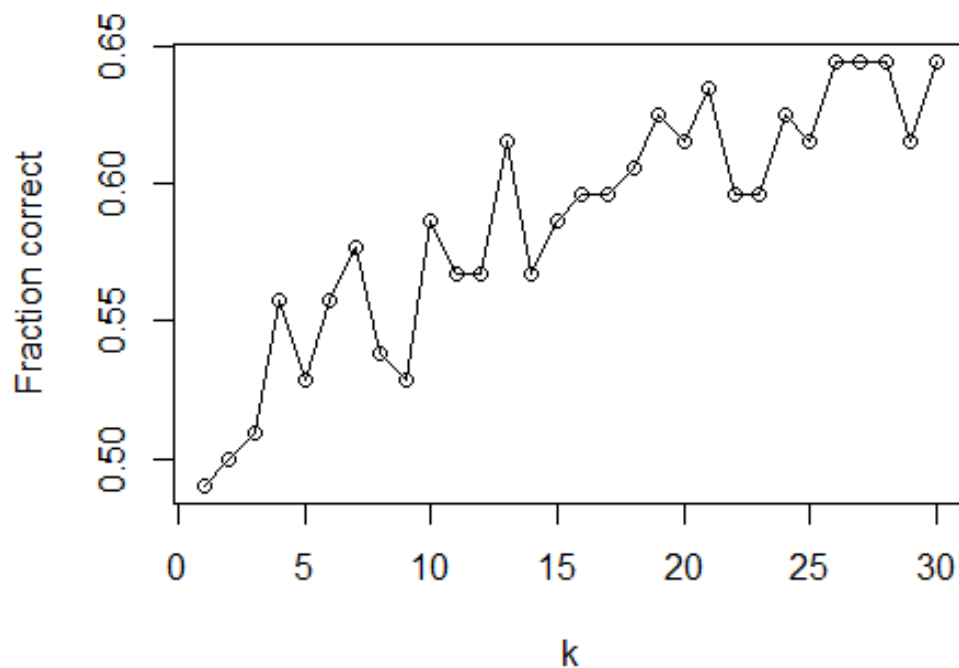
## [1] 0.5096154

#sum(diag(confusion_matrix_knn)) / sum(confusion_matrix_knn)
```

Dengan model KNN pada $k = 1$, didapat akurasi 50

- j. Experiment with different combinations of predictors, including possible transformations and interactions, for each of the methods. Report the variables, method, and associated confusion matrix that appears to provide the best results on the held out data. Note that you should also experiment with values for K in the KNN classifier.

```
set.seed(1)
res <- sapply(1:30, function(k) {
  fit <- knn(
    Weekly[train, 2:4, drop = FALSE],
    Weekly[test, 2:4, drop = FALSE],
    Weekly$Direction[train],
    k = k
  )
  mean(fit == Weekly[test, ]$Direction)
})
plot(1:30, res, type = "o", xlab = "k", ylab = "Fraction correct")
```



```
(k <- which.max(res))
## [1] 26
fit <- knn(
  Weekly[train, 2:4, drop = FALSE],
  Weekly[test, 2:4, drop = FALSE],
  Weekly$Direction[train],
  k = k
)
table(Prediction = fit, Aktual = Weekly[test, ]$Direction)

##           Aktual
## Prediction Down Up
##           Down  23 18
##           Up   20 43

mean(fit == Weekly[test, ]$Direction)
## [1] 0.6346154
```

KNN menggunakan variabel 3 Lag pertama performa marginalnya lebih baik dari regresi logistik dengan Lag2 jika kita setel k menjadi $k = 26$ dengan tingkat akurasi 63.46%

Nomor 14

In this problem, you will develop a model to predict whether a given car gets high or low gas mileage based on the Auto data set.

- Create a binary variable, `mpg01`, that contains a 1 if `mpg` contains a value above its median, and a 0 if `mpg` contains a value below its median. You can compute the median using the `median()` function. Note you may find it helpful to use the `data.frame()` function to create a single data set containing both `mpg01` and the other Auto variables.

```
library(ISLR2)
data(Auto)
mpg01 <- ifelse(Auto$mpg > median(Auto$mpg), 1, 0)
(data_auto <- data.frame(Auto[, -1], mpg01))
```

	cylinders	displacement	horsepower	weight	acceleration	year	origin
## 1	8	307.0	130	3504	12.0	70	1
## 2	8	350.0	165	3693	11.5	70	1
## 3	8	318.0	150	3436	11.0	70	1
## 4	8	304.0	150	3433	12.0	70	1
## 5	8	302.0	140	3449	10.5	70	1
## 6	8	429.0	198	4341	10.0	70	1
## 7	8	454.0	220	4354	9.0	70	1
## 8	8	440.0	215	4312	8.5	70	1
## 9	8	455.0	225	4425	10.0	70	1
## 10	8	390.0	190	3850	8.5	70	1
## 11	8	383.0	170	3563	10.0	70	1
## 12	8	340.0	160	3609	8.0	70	1
## 13	8	400.0	150	3761	9.5	70	1
## 14	8	455.0	225	3086	10.0	70	1
## 15	4	113.0	95	2372	15.0	70	3
## 16	6	198.0	95	2833	15.5	70	1
## 17	6	199.0	97	2774	15.5	70	1
## 18	6	200.0	85	2587	16.0	70	1
## 19	4	97.0	88	2130	14.5	70	3
## 20	4	97.0	46	1835	20.5	70	2
## 21	4	110.0	87	2672	17.5	70	2
## 22	4	107.0	90	2430	14.5	70	2
## 23	4	104.0	95	2375	17.5	70	2
## 24	4	121.0	113	2234	12.5	70	2
## 25	6	199.0	90	2648	15.0	70	1
## 26	8	360.0	215	4615	14.0	70	1
## 27	8	307.0	200	4376	15.0	70	1
## 28	8	318.0	210	4382	13.5	70	1
## 29	8	304.0	193	4732	18.5	70	1
## 30	4	97.0	88	2130	14.5	71	3
## 31	4	140.0	90	2264	15.5	71	1
## 32	4	113.0	95	2228	14.0	71	3
## 34	6	232.0	100	2634	13.0	71	1
## 35	6	225.0	105	3439	15.5	71	1

## 36	6	250.0	100	3329	15.5	71	1
## 37	6	250.0	88	3302	15.5	71	1
## 38	6	232.0	100	3288	15.5	71	1
## 39	8	350.0	165	4209	12.0	71	1
## 40	8	400.0	175	4464	11.5	71	1
## 41	8	351.0	153	4154	13.5	71	1
## 42	8	318.0	150	4096	13.0	71	1
## 43	8	383.0	180	4955	11.5	71	1
## 44	8	400.0	170	4746	12.0	71	1
## 45	8	400.0	175	5140	12.0	71	1
## 46	6	258.0	110	2962	13.5	71	1
## 47	4	140.0	72	2408	19.0	71	1
## 48	6	250.0	100	3282	15.0	71	1
## 49	6	250.0	88	3139	14.5	71	1
## 50	4	122.0	86	2220	14.0	71	1
## 51	4	116.0	90	2123	14.0	71	2
## 52	4	79.0	70	2074	19.5	71	2
## 53	4	88.0	76	2065	14.5	71	2
## 54	4	71.0	65	1773	19.0	71	3
## 55	4	72.0	69	1613	18.0	71	3
## 56	4	97.0	60	1834	19.0	71	2
## 57	4	91.0	70	1955	20.5	71	1
## 58	4	113.0	95	2278	15.5	72	3
## 59	4	97.5	80	2126	17.0	72	1
## 60	4	97.0	54	2254	23.5	72	2
## 61	4	140.0	90	2408	19.5	72	1
## 62	4	122.0	86	2226	16.5	72	1
## 63	8	350.0	165	4274	12.0	72	1
## 64	8	400.0	175	4385	12.0	72	1
## 65	8	318.0	150	4135	13.5	72	1
## 66	8	351.0	153	4129	13.0	72	1
## 67	8	304.0	150	3672	11.5	72	1
## 68	8	429.0	208	4633	11.0	72	1
## 69	8	350.0	155	4502	13.5	72	1
## 70	8	350.0	160	4456	13.5	72	1
## 71	8	400.0	190	4422	12.5	72	1
## 72	3	70.0	97	2330	13.5	72	3
## 73	8	304.0	150	3892	12.5	72	1
## 74	8	307.0	130	4098	14.0	72	1
## 75	8	302.0	140	4294	16.0	72	1
## 76	8	318.0	150	4077	14.0	72	1
## 77	4	121.0	112	2933	14.5	72	2
## 78	4	121.0	76	2511	18.0	72	2
## 79	4	120.0	87	2979	19.5	72	2
## 80	4	96.0	69	2189	18.0	72	2
## 81	4	122.0	86	2395	16.0	72	1
## 82	4	97.0	92	2288	17.0	72	3
## 83	4	120.0	97	2506	14.5	72	3
## 84	4	98.0	80	2164	15.0	72	1
## 85	4	97.0	88	2100	16.5	72	3

## 86	8	350.0	175	4100	13.0	73	1
## 87	8	304.0	150	3672	11.5	73	1
## 88	8	350.0	145	3988	13.0	73	1
## 89	8	302.0	137	4042	14.5	73	1
## 90	8	318.0	150	3777	12.5	73	1
## 91	8	429.0	198	4952	11.5	73	1
## 92	8	400.0	150	4464	12.0	73	1
## 93	8	351.0	158	4363	13.0	73	1
## 94	8	318.0	150	4237	14.5	73	1
## 95	8	440.0	215	4735	11.0	73	1
## 96	8	455.0	225	4951	11.0	73	1
## 97	8	360.0	175	3821	11.0	73	1
## 98	6	225.0	105	3121	16.5	73	1
## 99	6	250.0	100	3278	18.0	73	1
## 100	6	232.0	100	2945	16.0	73	1
## 101	6	250.0	88	3021	16.5	73	1
## 102	6	198.0	95	2904	16.0	73	1
## 103	4	97.0	46	1950	21.0	73	2
## 104	8	400.0	150	4997	14.0	73	1
## 105	8	400.0	167	4906	12.5	73	1
## 106	8	360.0	170	4654	13.0	73	1
## 107	8	350.0	180	4499	12.5	73	1
## 108	6	232.0	100	2789	15.0	73	1
## 109	4	97.0	88	2279	19.0	73	3
## 110	4	140.0	72	2401	19.5	73	1
## 111	4	108.0	94	2379	16.5	73	3
## 112	3	70.0	90	2124	13.5	73	3
## 113	4	122.0	85	2310	18.5	73	1
## 114	6	155.0	107	2472	14.0	73	1
## 115	4	98.0	90	2265	15.5	73	2
## 116	8	350.0	145	4082	13.0	73	1
## 117	8	400.0	230	4278	9.5	73	1
## 118	4	68.0	49	1867	19.5	73	2
## 119	4	116.0	75	2158	15.5	73	2
## 120	4	114.0	91	2582	14.0	73	2
## 121	4	121.0	112	2868	15.5	73	2
## 122	8	318.0	150	3399	11.0	73	1
## 123	4	121.0	110	2660	14.0	73	2
## 124	6	156.0	122	2807	13.5	73	3
## 125	8	350.0	180	3664	11.0	73	1
## 126	6	198.0	95	3102	16.5	74	1
## 128	6	232.0	100	2901	16.0	74	1
## 129	6	250.0	100	3336	17.0	74	1
## 130	4	79.0	67	1950	19.0	74	3
## 131	4	122.0	80	2451	16.5	74	1
## 132	4	71.0	65	1836	21.0	74	3
## 133	4	140.0	75	2542	17.0	74	1
## 134	6	250.0	100	3781	17.0	74	1
## 135	6	258.0	110	3632	18.0	74	1
## 136	6	225.0	105	3613	16.5	74	1

## 137	8	302.0	140	4141	14.0	74	1
## 138	8	350.0	150	4699	14.5	74	1
## 139	8	318.0	150	4457	13.5	74	1
## 140	8	302.0	140	4638	16.0	74	1
## 141	8	304.0	150	4257	15.5	74	1
## 142	4	98.0	83	2219	16.5	74	2
## 143	4	79.0	67	1963	15.5	74	2
## 144	4	97.0	78	2300	14.5	74	2
## 145	4	76.0	52	1649	16.5	74	3
## 146	4	83.0	61	2003	19.0	74	3
## 147	4	90.0	75	2125	14.5	74	1
## 148	4	90.0	75	2108	15.5	74	2
## 149	4	116.0	75	2246	14.0	74	2
## 150	4	120.0	97	2489	15.0	74	3
## 151	4	108.0	93	2391	15.5	74	3
## 152	4	79.0	67	2000	16.0	74	2
## 153	6	225.0	95	3264	16.0	75	1
## 154	6	250.0	105	3459	16.0	75	1
## 155	6	250.0	72	3432	21.0	75	1
## 156	6	250.0	72	3158	19.5	75	1
## 157	8	400.0	170	4668	11.5	75	1
## 158	8	350.0	145	4440	14.0	75	1
## 159	8	318.0	150	4498	14.5	75	1
## 160	8	351.0	148	4657	13.5	75	1
## 161	6	231.0	110	3907	21.0	75	1
## 162	6	250.0	105	3897	18.5	75	1
## 163	6	258.0	110	3730	19.0	75	1
## 164	6	225.0	95	3785	19.0	75	1
## 165	6	231.0	110	3039	15.0	75	1
## 166	8	262.0	110	3221	13.5	75	1
## 167	8	302.0	129	3169	12.0	75	1
## 168	4	97.0	75	2171	16.0	75	3
## 169	4	140.0	83	2639	17.0	75	1
## 170	6	232.0	100	2914	16.0	75	1
## 171	4	140.0	78	2592	18.5	75	1
## 172	4	134.0	96	2702	13.5	75	3
## 173	4	90.0	71	2223	16.5	75	2
## 174	4	119.0	97	2545	17.0	75	3
## 175	6	171.0	97	2984	14.5	75	1
## 176	4	90.0	70	1937	14.0	75	2
## 177	6	232.0	90	3211	17.0	75	1
## 178	4	115.0	95	2694	15.0	75	2
## 179	4	120.0	88	2957	17.0	75	2
## 180	4	121.0	98	2945	14.5	75	2
## 181	4	121.0	115	2671	13.5	75	2
## 182	4	91.0	53	1795	17.5	75	3
## 183	4	107.0	86	2464	15.5	76	2
## 184	4	116.0	81	2220	16.9	76	2
## 185	4	140.0	92	2572	14.9	76	1
## 186	4	98.0	79	2255	17.7	76	1

## 187	4	101.0	83	2202	15.3	76	2
## 188	8	305.0	140	4215	13.0	76	1
## 189	8	318.0	150	4190	13.0	76	1
## 190	8	304.0	120	3962	13.9	76	1
## 191	8	351.0	152	4215	12.8	76	1
## 192	6	225.0	100	3233	15.4	76	1
## 193	6	250.0	105	3353	14.5	76	1
## 194	6	200.0	81	3012	17.6	76	1
## 195	6	232.0	90	3085	17.6	76	1
## 196	4	85.0	52	2035	22.2	76	1
## 197	4	98.0	60	2164	22.1	76	1
## 198	4	90.0	70	1937	14.2	76	2
## 199	4	91.0	53	1795	17.4	76	3
## 200	6	225.0	100	3651	17.7	76	1
## 201	6	250.0	78	3574	21.0	76	1
## 202	6	250.0	110	3645	16.2	76	1
## 203	6	258.0	95	3193	17.8	76	1
## 204	4	97.0	71	1825	12.2	76	2
## 205	4	85.0	70	1990	17.0	76	3
## 206	4	97.0	75	2155	16.4	76	3
## 207	4	140.0	72	2565	13.6	76	1
## 208	4	130.0	102	3150	15.7	76	2
## 209	8	318.0	150	3940	13.2	76	1
## 210	4	120.0	88	3270	21.9	76	2
## 211	6	156.0	108	2930	15.5	76	3
## 212	6	168.0	120	3820	16.7	76	2
## 213	8	350.0	180	4380	12.1	76	1
## 214	8	350.0	145	4055	12.0	76	1
## 215	8	302.0	130	3870	15.0	76	1
## 216	8	318.0	150	3755	14.0	76	1
## 217	4	98.0	68	2045	18.5	77	3
## 218	4	111.0	80	2155	14.8	77	1
## 219	4	79.0	58	1825	18.6	77	2
## 220	4	122.0	96	2300	15.5	77	1
## 221	4	85.0	70	1945	16.8	77	3
## 222	8	305.0	145	3880	12.5	77	1
## 223	8	260.0	110	4060	19.0	77	1
## 224	8	318.0	145	4140	13.7	77	1
## 225	8	302.0	130	4295	14.9	77	1
## 226	6	250.0	110	3520	16.4	77	1
## 227	6	231.0	105	3425	16.9	77	1
## 228	6	225.0	100	3630	17.7	77	1
## 229	6	250.0	98	3525	19.0	77	1
## 230	8	400.0	180	4220	11.1	77	1
## 231	8	350.0	170	4165	11.4	77	1
## 232	8	400.0	190	4325	12.2	77	1
## 233	8	351.0	149	4335	14.5	77	1
## 234	4	97.0	78	1940	14.5	77	2
## 235	4	151.0	88	2740	16.0	77	1
## 236	4	97.0	75	2265	18.2	77	3

## 237	4	140.0	89	2755	15.8	77	1
## 238	4	98.0	63	2051	17.0	77	1
## 239	4	98.0	83	2075	15.9	77	1
## 240	4	97.0	67	1985	16.4	77	3
## 241	4	97.0	78	2190	14.1	77	2
## 242	6	146.0	97	2815	14.5	77	3
## 243	4	121.0	110	2600	12.8	77	2
## 244	3	80.0	110	2720	13.5	77	3
## 245	4	90.0	48	1985	21.5	78	2
## 246	4	98.0	66	1800	14.4	78	1
## 247	4	78.0	52	1985	19.4	78	3
## 248	4	85.0	70	2070	18.6	78	3
## 249	4	91.0	60	1800	16.4	78	3
## 250	8	260.0	110	3365	15.5	78	1
## 251	8	318.0	140	3735	13.2	78	1
## 252	8	302.0	139	3570	12.8	78	1
## 253	6	231.0	105	3535	19.2	78	1
## 254	6	200.0	95	3155	18.2	78	1
## 255	6	200.0	85	2965	15.8	78	1
## 256	4	140.0	88	2720	15.4	78	1
## 257	6	225.0	100	3430	17.2	78	1
## 258	6	232.0	90	3210	17.2	78	1
## 259	6	231.0	105	3380	15.8	78	1
## 260	6	200.0	85	3070	16.7	78	1
## 261	6	225.0	110	3620	18.7	78	1
## 262	6	258.0	120	3410	15.1	78	1
## 263	8	305.0	145	3425	13.2	78	1
## 264	6	231.0	165	3445	13.4	78	1
## 265	8	302.0	139	3205	11.2	78	1
## 266	8	318.0	140	4080	13.7	78	1
## 267	4	98.0	68	2155	16.5	78	1
## 268	4	134.0	95	2560	14.2	78	3
## 269	4	119.0	97	2300	14.7	78	3
## 270	4	105.0	75	2230	14.5	78	1
## 271	4	134.0	95	2515	14.8	78	3
## 272	4	156.0	105	2745	16.7	78	1
## 273	4	151.0	85	2855	17.6	78	1
## 274	4	119.0	97	2405	14.9	78	3
## 275	5	131.0	103	2830	15.9	78	2
## 276	6	163.0	125	3140	13.6	78	2
## 277	4	121.0	115	2795	15.7	78	2
## 278	6	163.0	133	3410	15.8	78	2
## 279	4	89.0	71	1990	14.9	78	2
## 280	4	98.0	68	2135	16.6	78	3
## 281	6	231.0	115	3245	15.4	79	1
## 282	6	200.0	85	2990	18.2	79	1
## 283	4	140.0	88	2890	17.3	79	1
## 284	6	232.0	90	3265	18.2	79	1
## 285	6	225.0	110	3360	16.6	79	1
## 286	8	305.0	130	3840	15.4	79	1

## 287	8	302.0	129	3725	13.4	79	1
## 288	8	351.0	138	3955	13.2	79	1
## 289	8	318.0	135	3830	15.2	79	1
## 290	8	350.0	155	4360	14.9	79	1
## 291	8	351.0	142	4054	14.3	79	1
## 292	8	267.0	125	3605	15.0	79	1
## 293	8	360.0	150	3940	13.0	79	1
## 294	4	89.0	71	1925	14.0	79	2
## 295	4	86.0	65	1975	15.2	79	3
## 296	4	98.0	80	1915	14.4	79	1
## 297	4	121.0	80	2670	15.0	79	1
## 298	5	183.0	77	3530	20.1	79	2
## 299	8	350.0	125	3900	17.4	79	1
## 300	4	141.0	71	3190	24.8	79	2
## 301	8	260.0	90	3420	22.2	79	1
## 302	4	105.0	70	2200	13.2	79	1
## 303	4	105.0	70	2150	14.9	79	1
## 304	4	85.0	65	2020	19.2	79	3
## 305	4	91.0	69	2130	14.7	79	2
## 306	4	151.0	90	2670	16.0	79	1
## 307	6	173.0	115	2595	11.3	79	1
## 308	6	173.0	115	2700	12.9	79	1
## 309	4	151.0	90	2556	13.2	79	1
## 310	4	98.0	76	2144	14.7	80	2
## 311	4	89.0	60	1968	18.8	80	3
## 312	4	98.0	70	2120	15.5	80	1
## 313	4	86.0	65	2019	16.4	80	3
## 314	4	151.0	90	2678	16.5	80	1
## 315	4	140.0	88	2870	18.1	80	1
## 316	4	151.0	90	3003	20.1	80	1
## 317	6	225.0	90	3381	18.7	80	1
## 318	4	97.0	78	2188	15.8	80	2
## 319	4	134.0	90	2711	15.5	80	3
## 320	4	120.0	75	2542	17.5	80	3
## 321	4	119.0	92	2434	15.0	80	3
## 322	4	108.0	75	2265	15.2	80	3
## 323	4	86.0	65	2110	17.9	80	3
## 324	4	156.0	105	2800	14.4	80	1
## 325	4	85.0	65	2110	19.2	80	3
## 326	4	90.0	48	2085	21.7	80	2
## 327	4	90.0	48	2335	23.7	80	2
## 328	5	121.0	67	2950	19.9	80	2
## 329	4	146.0	67	3250	21.8	80	2
## 330	4	91.0	67	1850	13.8	80	3
## 332	4	97.0	67	2145	18.0	80	3
## 333	4	89.0	62	1845	15.3	80	2
## 334	6	168.0	132	2910	11.4	80	3
## 335	3	70.0	100	2420	12.5	80	3
## 336	4	122.0	88	2500	15.1	80	2
## 338	4	107.0	72	2290	17.0	80	3

## 339	4	135.0	84	2490	15.7	81	1
## 340	4	151.0	84	2635	16.4	81	1
## 341	4	156.0	92	2620	14.4	81	1
## 342	6	173.0	110	2725	12.6	81	1
## 343	4	135.0	84	2385	12.9	81	1
## 344	4	79.0	58	1755	16.9	81	3
## 345	4	86.0	64	1875	16.4	81	1
## 346	4	81.0	60	1760	16.1	81	3
## 347	4	97.0	67	2065	17.8	81	3
## 348	4	85.0	65	1975	19.4	81	3
## 349	4	89.0	62	2050	17.3	81	3
## 350	4	91.0	68	1985	16.0	81	3
## 351	4	105.0	63	2215	14.9	81	1
## 352	4	98.0	65	2045	16.2	81	1
## 353	4	98.0	65	2380	20.7	81	1
## 354	4	105.0	74	2190	14.2	81	2
## 356	4	107.0	75	2210	14.4	81	3
## 357	4	108.0	75	2350	16.8	81	3
## 358	4	119.0	100	2615	14.8	81	3
## 359	4	120.0	74	2635	18.3	81	3
## 360	4	141.0	80	3230	20.4	81	2
## 361	6	145.0	76	3160	19.6	81	2
## 362	6	168.0	116	2900	12.6	81	3
## 363	6	146.0	120	2930	13.8	81	3
## 364	6	231.0	110	3415	15.8	81	1
## 365	8	350.0	105	3725	19.0	81	1
## 366	6	200.0	88	3060	17.1	81	1
## 367	6	225.0	85	3465	16.6	81	1
## 368	4	112.0	88	2605	19.6	82	1
## 369	4	112.0	88	2640	18.6	82	1
## 370	4	112.0	88	2395	18.0	82	1
## 371	4	112.0	85	2575	16.2	82	1
## 372	4	135.0	84	2525	16.0	82	1
## 373	4	151.0	90	2735	18.0	82	1
## 374	4	140.0	92	2865	16.4	82	1
## 375	4	105.0	74	1980	15.3	82	2
## 376	4	91.0	68	2025	18.2	82	3
## 377	4	91.0	68	1970	17.6	82	3
## 378	4	105.0	63	2125	14.7	82	1
## 379	4	98.0	70	2125	17.3	82	1
## 380	4	120.0	88	2160	14.5	82	3
## 381	4	107.0	75	2205	14.5	82	3
## 382	4	108.0	70	2245	16.9	82	3
## 383	4	91.0	67	1965	15.0	82	3
## 384	4	91.0	67	1965	15.7	82	3
## 385	4	91.0	67	1995	16.2	82	3
## 386	6	181.0	110	2945	16.4	82	1
## 387	6	262.0	85	3015	17.0	82	1
## 388	4	156.0	92	2585	14.5	82	1
## 389	6	232.0	112	2835	14.7	82	1

## 390	4	144.0	96	2665	13.9	82	3
## 391	4	135.0	84	2370	13.0	82	1
## 392	4	151.0	90	2950	17.3	82	1
## 393	4	140.0	86	2790	15.6	82	1
## 394	4	97.0	52	2130	24.6	82	2
## 395	4	135.0	84	2295	11.6	82	1
## 396	4	120.0	79	2625	18.6	82	1
## 397	4	119.0	82	2720	19.4	82	1
##				name mpg01			
## 1		chevrolet chevelle malibu		0			
## 2		buick skylark 320		0			
## 3		plymouth satellite		0			
## 4		amc rebel sst		0			
## 5		ford torino		0			
## 6		ford galaxie 500		0			
## 7		chevrolet impala		0			
## 8		plymouth fury iii		0			
## 9		pontiac catalina		0			
## 10		amc ambassador dpl		0			
## 11		dodge challenger se		0			
## 12		plymouth 'cuda 340		0			
## 13		chevrolet monte carlo		0			
## 14		buick estate wagon (sw)		0			
## 15		toyota corona mark ii		1			
## 16		plymouth duster		0			
## 17		amc hornet		0			
## 18		ford maverick		0			
## 19		datsum pl510		1			
## 20		volkswagen 1131 deluxe sedan		1			
## 21		peugeot 504		1			
## 22		audi 100 ls		1			
## 23		saab 99e		1			
## 24		bmw 2002		1			
## 25		amc gremlin		0			
## 26		ford f250		0			
## 27		chevy c20		0			
## 28		dodge d200		0			
## 29		hi 1200d		0			
## 30		datsum pl510		1			
## 31		chevrolet vega 2300		1			
## 32		toyota corona		1			
## 34		amc gremlin		0			
## 35		plymouth satellite custom		0			
## 36		chevrolet chevelle malibu		0			
## 37		ford torino 500		0			
## 38		amc matador		0			
## 39		chevrolet impala		0			
## 40		pontiac catalina brougham		0			
## 41		ford galaxie 500		0			
## 42		plymouth fury iii		0			

## 43	dodge monaco (sw)	0
## 44	ford country squire (sw)	0
## 45	pontiac safari (sw)	0
## 46	amc hornet sportabout (sw)	0
## 47	chevrolet vega (sw)	0
## 48	pontiac firebird	0
## 49	ford mustang	0
## 50	mercury capri 2000	1
## 51	opel 1900	1
## 52	peugeot 304	1
## 53	fiat 124b	1
## 54	toyota corolla 1200	1
## 55	datsum 1200	1
## 56	volkswagen model 111	1
## 57	plymouth cricket	1
## 58	toyota corona hardtop	1
## 59	dodge colt hardtop	1
## 60	volkswagen type 3	1
## 61	chevrolet vega	0
## 62	ford pinto runabout	0
## 63	chevrolet impala	0
## 64	pontiac catalina	0
## 65	plymouth fury iii	0
## 66	ford galaxie 500	0
## 67	amc ambassador sst	0
## 68	mercury marquis	0
## 69	buick lesabre custom	0
## 70	oldsmobile delta 88 royale	0
## 71	chrysler newport royal	0
## 72	mazda rx2 coupe	0
## 73	amc matador (sw)	0
## 74	chevrolet chevelle concours (sw)	0
## 75	ford gran torino (sw)	0
## 76	plymouth satellite custom (sw)	0
## 77	volvo 145e (sw)	0
## 78	volkswagen 411 (sw)	0
## 79	peugeot 504 (sw)	0
## 80	renault 12 (sw)	1
## 81	ford pinto (sw)	0
## 82	datsum 510 (sw)	1
## 83	toyouta corona mark ii (sw)	1
## 84	dodge colt (sw)	1
## 85	toyota corolla 1600 (sw)	1
## 86	buick century 350	0
## 87	amc matador	0
## 88	chevrolet malibu	0
## 89	ford gran torino	0
## 90	dodge coronet custom	0
## 91	mercury marquis brougham	0
## 92	chevrolet caprice classic	0

## 93	ford ltd	0
## 94	plymouth fury gran sedan	0
## 95	chrysler new yorker brougham	0
## 96	buick electra 225 custom	0
## 97	amc ambassador brougham	0
## 98	plymouth valiant	0
## 99	chevrolet nova custom	0
## 100	amc hornet	0
## 101	ford maverick	0
## 102	plymouth duster	1
## 103	volkswagen super beetle	1
## 104	chevrolet impala	0
## 105	ford country	0
## 106	plymouth custom suburb	0
## 107	oldsmobile vista cruiser	0
## 108	amc gremlin	0
## 109	toyota carina	0
## 110	chevrolet vega	0
## 111	datson 610	0
## 112	maxda rx3	0
## 113	ford pinto	0
## 114	mercury capri v6	0
## 115	fiat 124 sport coupe	1
## 116	chevrolet monte carlo s	0
## 117	pontiac grand prix	0
## 118	fiat 128	1
## 119	opel manta	1
## 120	audi 100ls	0
## 121	volvo 144ea	0
## 122	dodge dart custom	0
## 123	saab 99le	1
## 124	toyota mark ii	0
## 125	oldsmobile omega	0
## 126	plymouth duster	0
## 128	amc hornet	0
## 129	chevrolet nova	0
## 130	datson b210	1
## 131	ford pinto	1
## 132	toyota corolla 1200	1
## 133	chevrolet vega	1
## 134	chevrolet chevelle malibu classic	0
## 135	amc matador	0
## 136	plymouth satellite sebring	0
## 137	ford gran torino	0
## 138	buick century luxus (sw)	0
## 139	dodge coronet custom (sw)	0
## 140	ford gran torino (sw)	0
## 141	amc matador (sw)	0
## 142	audi fox	1
## 143	volkswagen dasher	1

## 144	opel manta	1
## 145	toyota corona	1
## 146	datsum 710	1
## 147	dodge colt	1
## 148	fiat 128	1
## 149	fiat 124 tc	1
## 150	honda civic	1
## 151	subaru	1
## 152	fiat x1.9	1
## 153	plymouth valiant custom	0
## 154	chevrolet nova	0
## 155	mercury monarch	0
## 156	ford maverick	0
## 157	pontiac catalina	0
## 158	chevrolet bel air	0
## 159	plymouth grand fury	0
## 160	ford ltd	0
## 161	buick century	0
## 162	chevroelt chevelle malibu	0
## 163	amc matador	0
## 164	plymouth fury	0
## 165	buick skyhawk	0
## 166	chevrolet monza 2+2	0
## 167	ford mustang ii	0
## 168	toyota corolla	1
## 169	ford pinto	1
## 170	amc gremlin	0
## 171	pontiac astro	1
## 172	toyota corona	1
## 173	volkswagen dasher	1
## 174	datsum 710	1
## 175	ford pinto	0
## 176	volkswagen rabbit	1
## 177	amc pacer	0
## 178	audi 100ls	1
## 179	peugeot 504	1
## 180	volvo 244dl	0
## 181	saab 99le	1
## 182	honda civic cvcc	1
## 183	fiat 131	1
## 184	opel 1900	1
## 185	capri ii	1
## 186	dodge colt	1
## 187	renault 12tl	1
## 188	chevrolet chevelle malibu classic	0
## 189	dodge coronet brougham	0
## 190	amc matador	0
## 191	ford gran torino	0
## 192	plymouth valiant	0
## 193	chevrolet nova	0

## 194	ford maverick	1
## 195	amc hornet	0
## 196	chevrolet chevette	1
## 197	chevrolet woody	1
## 198	vw rabbit	1
## 199	honda civic	1
## 200	dodge aspen se	0
## 201	ford granada ghia	0
## 202	pontiac ventura sj	0
## 203	amc pacer d/l	0
## 204	volkswagen rabbit	1
## 205	datsum b-210	1
## 206	toyota corolla	1
## 207	ford pinto	1
## 208	volvo 245	0
## 209	plymouth volare premier v8	0
## 210	peugeot 504	0
## 211	toyota mark ii	0
## 212	mercedes-benz 280s	0
## 213	cadillac seville	0
## 214	chevy c10	0
## 215	ford f108	0
## 216	dodge d100	0
## 217	honda accord cvcc	1
## 218	buick opel isuzu deluxe	1
## 219	renault 5 gtl	1
## 220	plymouth arrow gs	1
## 221	datsum f-10 hatchback	1
## 222	chevrolet caprice classic	0
## 223	oldsmobile cutlass supreme	0
## 224	dodge monaco brougham	0
## 225	mercury cougar brougham	0
## 226	chevrolet concours	0
## 227	buick skylark	0
## 228	plymouth volare custom	0
## 229	ford granada	0
## 230	pontiac grand prix lj	0
## 231	chevrolet monte carlo landau	0
## 232	chrysler cordoba	0
## 233	ford thunderbird	0
## 234	volkswagen rabbit custom	1
## 235	pontiac sunbird coupe	1
## 236	toyota corolla liftback	1
## 237	ford mustang ii 2+2	1
## 238	chevrolet chevette	1
## 239	dodge colt m/m	1
## 240	subaru dl	1
## 241	volkswagen dasher	1
## 242	datsum 810	0
## 243	bmw 320i	0

## 244	mazda rx-4	0
## 245	volkswagen rabbit custom diesel	1
## 246	ford fiesta	1
## 247	mazda glc deluxe	1
## 248	datsum b210 gx	1
## 249	honda civic cvcc	1
## 250	oldsmobile cutlass salon brougham	0
## 251	dodge diplomat	0
## 252	mercury monarch ghia	0
## 253	pontiac phoenix lj	0
## 254	chevrolet malibu	0
## 255	ford fairmont (auto)	0
## 256	ford fairmont (man)	1
## 257	plymouth volare	0
## 258	amc concord	0
## 259	buick century special	0
## 260	mercury zephyr	0
## 261	dodge aspen	0
## 262	amc concord d/l	0
## 263	chevrolet monte carlo landau	0
## 264	buick regal sport coupe (turbo)	0
## 265	ford futura	0
## 266	dodge magnum xe	0
## 267	chevrolet chevette	1
## 268	toyota corona	1
## 269	datsum 510	1
## 270	dodge omni	1
## 271	toyota celica gt liftback	0
## 272	plymouth sapporo	1
## 273	oldsmobile starfire sx	1
## 274	datsum 200-sx	1
## 275	audi 5000	0
## 276	volvo 264gl	0
## 277	saab 99gle	0
## 278	peugeot 604sl	0
## 279	volkswagen scirocco	1
## 280	honda accord lx	1
## 281	pontiac lemans v6	0
## 282	mercury zephyr 6	0
## 283	ford fairmont 4	0
## 284	amc concord dl 6	0
## 285	dodge aspen 6	0
## 286	chevrolet caprice classic	0
## 287	ford ltd landau	0
## 288	mercury grand marquis	0
## 289	dodge st. regis	0
## 290	buick estate wagon (sw)	0
## 291	ford country squire (sw)	0
## 292	chevrolet malibu classic (sw)	0
## 293	chrysler lebaron town @ country (sw)	0

## 294	vw rabbit custom	1
## 295	maxda glc deluxe	1
## 296	dodge colt hatchback custom	1
## 297	amc spirit dl	1
## 298	mercedes benz 300d	1
## 299	cadillac eldorado	1
## 300	peugeot 504	1
## 301	oldsmobile cutlass salon brougham	1
## 302	plymouth horizon	1
## 303	plymouth horizon tc3	1
## 304	datsum 210	1
## 305	fiat strada custom	1
## 306	buick skylark limited	1
## 307	chevrolet citation	1
## 308	oldsmobile omega brougham	1
## 309	pontiac phoenix	1
## 310	vw rabbit	1
## 311	toyota corolla tercel	1
## 312	chevrolet chevette	1
## 313	datsum 310	1
## 314	chevrolet citation	1
## 315	ford fairmont	1
## 316	amc concord	1
## 317	dodge aspen	0
## 318	audi 4000	1
## 319	toyota corona liftback	1
## 320	mazda 626	1
## 321	datsum 510 hatchback	1
## 322	toyota corolla	1
## 323	mazda glc	1
## 324	dodge colt	1
## 325	datsum 210	1
## 326	vw rabbit c (diesel)	1
## 327	vw dasher (diesel)	1
## 328	audi 5000s (diesel)	1
## 329	mercedes-benz 240d	1
## 330	honda civic 1500 gl	1
## 332	subaru dl	1
## 333	vokswagen rabbit	1
## 334	datsum 280-zx	1
## 335	mazda rx-7 gs	1
## 336	triumph tr7 coupe	1
## 338	honda accord	1
## 339	plymouth reliant	1
## 340	buick skylark	1
## 341	dodge aries wagon (sw)	1
## 342	chevrolet citation	1
## 343	plymouth reliant	1
## 344	toyota starlet	1
## 345	plymouth champ	1

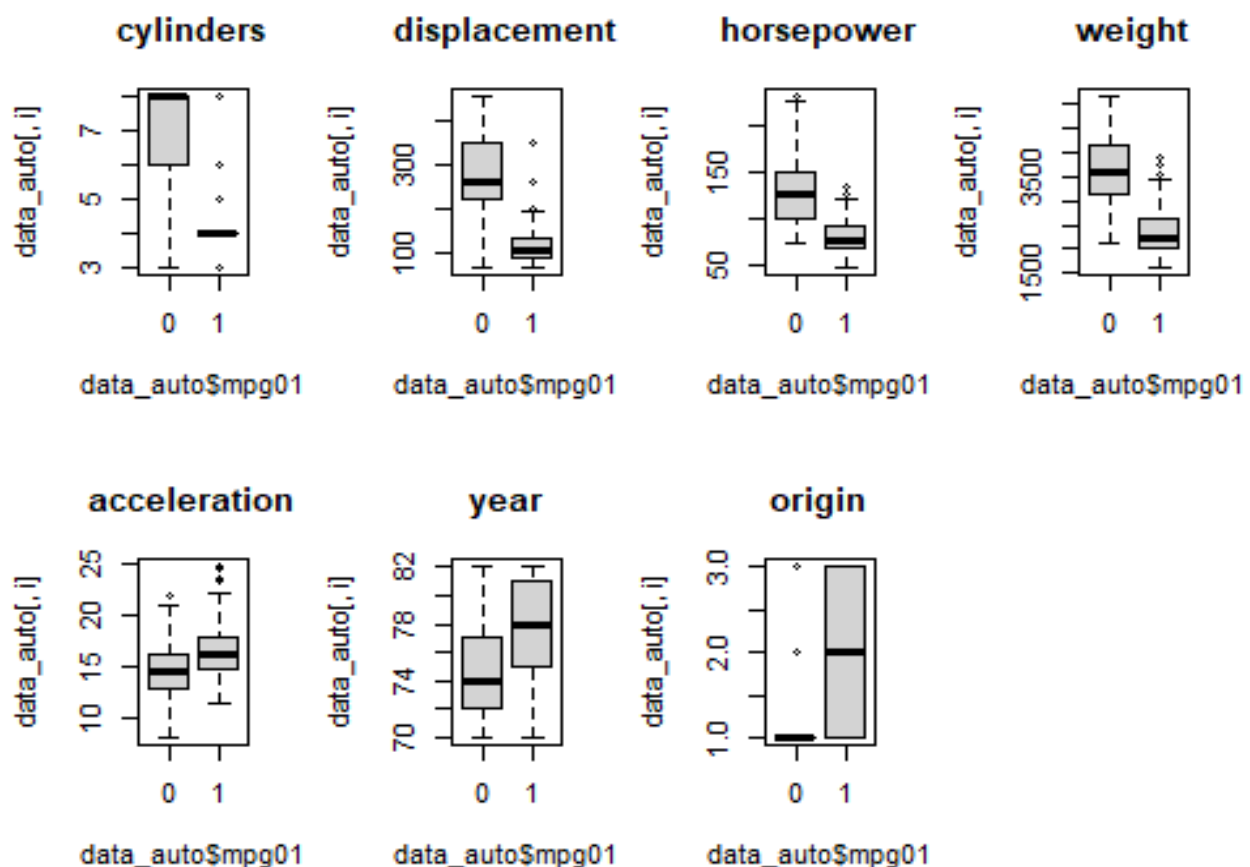
## 346	honda civic 1300	1
## 347	subaru	1
## 348	datsum 210 mpg	1
## 349	toyota tercel	1
## 350	mazda glc 4	1
## 351	plymouth horizon 4	1
## 352	ford escort 4w	1
## 353	ford escort 2h	1
## 354	volkswagen jetta	1
## 356	honda prelude	1
## 357	toyota corolla	1
## 358	datsum 200sx	1
## 359	mazda 626	1
## 360	peugeot 505s turbo diesel	1
## 361	volvo diesel	1
## 362	toyota cressida	1
## 363	datsum 810 maxima	1
## 364	buick century	0
## 365	oldsmobile cutlass ls	1
## 366	ford granada gl	0
## 367	chrysler lebaron salon	0
## 368	chevrolet cavalier	1
## 369	chevrolet cavalier wagon	1
## 370	chevrolet cavalier 2-door	1
## 371	pontiac j2000 se hatchback	1
## 372	dodge aries se	1
## 373	pontiac phoenix	1
## 374	ford fairmont futura	1
## 375	volkswagen rabbit l	1
## 376	mazda glc custom l	1
## 377	mazda glc custom	1
## 378	plymouth horizon miser	1
## 379	mercury lynx l	1
## 380	nissan stanza xe	1
## 381	honda accord	1
## 382	toyota corolla	1
## 383	honda civic	1
## 384	honda civic (auto)	1
## 385	datsum 310 gx	1
## 386	buick century limited	1
## 387	oldsmobile cutlass ciera (diesel)	1
## 388	chrysler lebaron medallion	1
## 389	ford granada l	0
## 390	toyota celica gt	1
## 391	dodge charger 2.2	1
## 392	chevrolet camaro	1
## 393	ford mustang gl	1
## 394	vw pickup	1
## 395	dodge rampage	1

```
## 396          ford ranger      1
## 397          chevy s-10      1

#(data_auto <- data.frame(Auto, mpg01))
```

- b. Explore the data graphically in order to investigate the association between mpg01 and the other features. Which of the other features seem most likely to be useful in predicting mpg01? Scatterplots and boxplots may be useful tools to answer this question. Describe your findings.

```
par(mfrow = c(2, 4))
for (i in 1:7) boxplot(data_auto[, i] ~ data_auto$mpg01, main =
colnames(data_auto)[i])
```



1. Cylinders : Mobil dengan sedikit silinder (misalnya 4) cenderung hemat BBM.
2. Displacement : Mobil dengan displacement (kapasitas mesin) lebih kecil cenderung hemat BBM.
3. Horsepower : Mobil dengan horsepower lebih rendah cenderung hemat BBM.
4. Weight : Mobil yang lebih ringan cenderung lebih hemat BBM.
5. Acceleration : Tidak ada perbedaan yang cukup signifikan.

6. Year : Mobil yang lebih baru (year tinggi) tidak selalu lebih hemat BBM.

7. Origin : Mobil yang berasal dari tempat 1,2,dan 3 banyak yang hemat BBM, tapi ada juga yang tidak, hubungan tidak cukup signifikan.

Kesimpulan:

Cylinders, Displacement, Horsepower, dan Weight bisa dijadikan prediktor yang kuat. Sementara Acceleration, Year, dan Origin kurang memiliki hubungan yang signifikan dengan mpg.

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

```
set.seed(1)
train_index <- sample(1:nrow(data_auto), nrow(data_auto) * 2/3)
train_data <- data_auto[train_index, ]
test_data <- data_auto[-train_index, ]
```

h. Perform KNN on the training data, with several values of K , in order to predict mpg01. Use only the variables that seemed most associated with mpg01 in (b). What test errors do you obtain? Which value of K seems to perform the best on this data set?

```
library(class)
train_X <- scale(train_data[, c("cylinders", "horsepower", "weight",
"displacement")])
test_X <- scale(test_data[, c("cylinders", "horsepower", "weight",
"displacement")])
train_Y <- train_data$mpg01

errors_knn <- c()
for (k in 1:10) {
  knn_predict <- knn(train_X, test_X, train_Y, k = k)
  error <- mean(knn_predict != test_data$mpg01)
  errors_knn <- c(errors_knn, error)
}
errors_knn

## [1] 0.13740458 0.09923664 0.12977099 0.12977099 0.12213740 0.12213740
## [7] 0.13740458 0.12977099 0.12977099 0.11450382

which.min(errors_knn)

## [1] 2
```

Untuk memprediksi mpg dengan prediktor Cylinders, Displacement, Horsepower, dan Weight menggunakan model K-Nearest Neighbors (KNN) nilai K yang paling bagus untuk data ini adalah $K = 2$ dengan error (potensi salah) sebesar 9.92%.

Nomor 16

Using the Boston data set, fit classification models in order to predict whether a given census tract has a crime rate above or below the median. Explore logistic regression, LDA, naive Bayes and KNN models using various sub-sets of the predictors. Describe your findings.

```
library(ISLR2)
data(Boston)
crime01 <- ifelse(Boston$crim > median(Boston$crim), 1, 0)
data_boston <- data.frame(Boston, crime01)

# Membagi data
set.seed(123)
train_index2 <- sample(1:nrow(data_boston), nrow(data_boston) * 2/3)
train_data2 <- data_boston[train_index2, ]
test_data2 <- data_boston[-train_index2, ]

# KNN
library(class)
train2_X <- scale(train_data2[, c("lstat", "dis", "nox", "rm")])
test2_X <- scale(test_data2[, c("lstat", "dis", "nox", "rm")])
train2_Y <- train_data2$crime01

errors2_knn <- c()
for (k in 1:16) {
  knn_predict2 <- knn(train2_X, test2_X, train2_Y, k = k)
  error2 <- mean(knn_predict2 != test_data2$crime01)
  errors2_knn <- c(errors2_knn, error2)
}
errors2_knn

## [1] 0.1834320 0.1952663 0.1538462 0.1834320 0.1656805 0.1715976 0.1538462
## [8] 0.1656805 0.1656805 0.1715976 0.1715976 0.1715976 0.1715976 0.1715976
## [15] 0.1834320 0.1893491

which.min(errors2_knn)

## [1] 3
```

Untuk model K-Nearest Neighbors (KNN), nilai K yang paling bagus untuk data ini adalah $K = 3$ dengan error (potensi salah) sebesar 15.38%.