TUGAS BESAR DATA MINING EVALUATION CAR MENGGUNAKAN METODE CLASSIFICATION AND REGRESSION TREESS (CART)



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Alat :

R dan R Studio

Metode

CART (*Classification and Regression Tree*) merupakan metode eksplorasi yang digunakan untuk melihat hubungan antara variabel respon dengan variabel bebas yang meliputi variabel nominal, ordinal, maupun kontinu. Metode ini meliputi metode pohon klasifikasi dan pohon regresi.

CART merupakan pengembangan dari pohon keputusan. Metode ini merupakan metode eksplorasi yang mengubah data yang sangat besar menjadi pohon keputusan yang merepresentasikan suatu aturan. CART yaitu metode yang digunakan untuk mengelompokkan data secara berulang untuk mengestimasi distribusi kondisional dari data (pada kasus ini adalah variabel respon) jika diberikan variabel bebasnya (penjelasnya).

• Dataset :

Evaluation Car Database berasal dari model keputusan hierarki sederhana yang awalnya dikembangkan untuk demonstrasi DEX, M. Bohanec, V. Rajkovic: Sistem pakar untuk pengambilan keputusan. Sistemica 1 (1), hlm. 145-157, 1990.).

Evaluation Car Database berisi contoh-contoh dengan informasi struktural yang dihilangkan, yaitu, secara langsung menghubungkan CAR dengan enam atribut input: buying, maint, doors, persons, lug_boot, safety . Karena struktur konsep yang mendasari diketahui, database ini mungkin sangat berguna untuk menguji induksi konstruktif dan metode penemuan struktur.

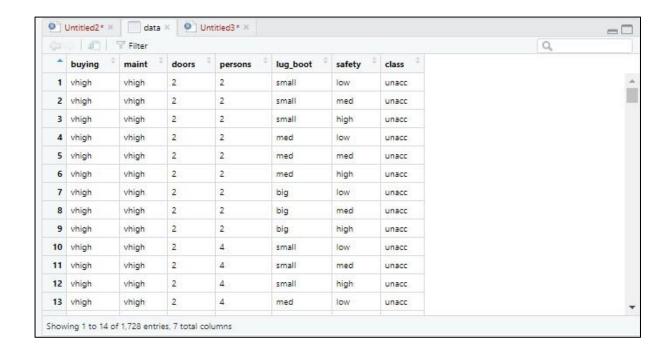
Jumlah Baris Data : 1728

Data yang Hilang : Tidak Ada

Jumlah Atribut: 6 ditambah target 1, total atribut 7

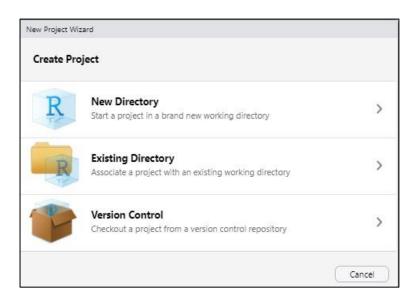
Nilai Class (target) : unacc, acc, good, vgood

Atribut: buying, maint, doors, persons, lug_boot, safety

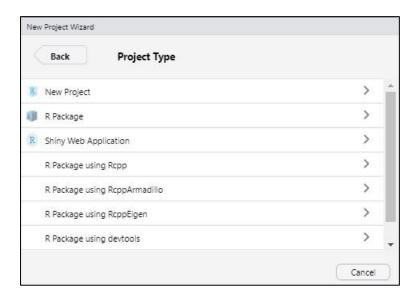


a. Persiapkan Rstudio dan Dataset

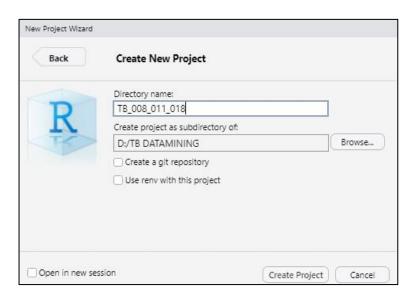
1. Buat sebuah project baru



2. Pilih New Directory

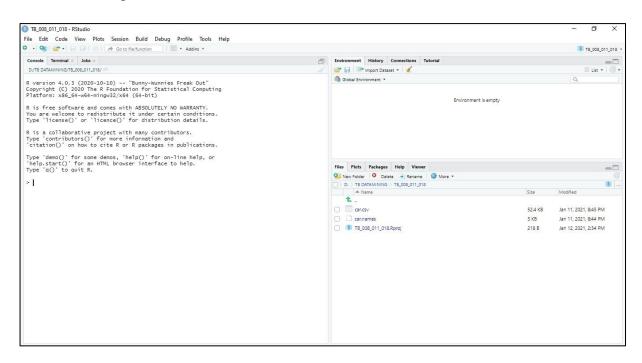


3. Lalu pilih New Project, beri nama direktori, lalu simpan di D:/TB DATAMINING



b. Lakukan preprosesing data

1. Buat script baru



2. Lihat lokasi direktori dengan perintah **getwd()**

```
> getwd()
[1] "D:/TB DATAMINING/TB_008_011_018"
> |
```

3. Import dataset dengan perintah data.car <- read.csv("car.csv", sep = ",")

data.car = nama untuk data

"car.csv" = nama file data yang akan kita import

sep = "," artinya setiap kolom dibatasi oleh koma (sebagai</pre>

```
1 getwd()
2 data.car <- read.csv("car.csv", sep = ",")
3 |
```

pembeda)

4. data.car berhasil di import, lihat pada panel kanan akan menampilkan:

```
Data
O data.car 1728 obs. of 7 variables
```

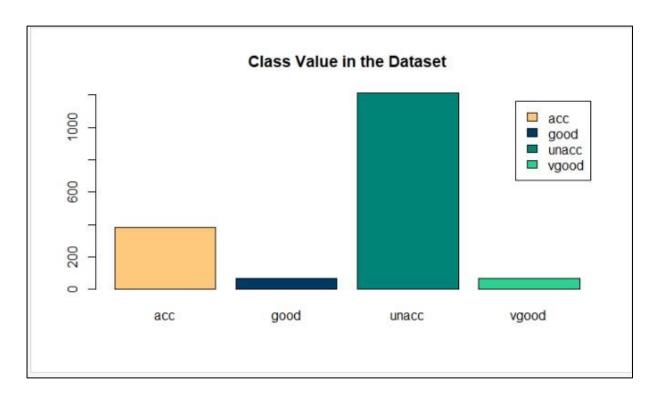
5. lihat jumlah baris data dan kolom dengan perintah **dim(data.car)**

6. lihat informasi data dengan perintah str(data.car) maka akan menunjukan jumlah baris data , jumlah kolom (variable) , nama kolom (variable) , tipe data kolom(variable) , dan beberapa contoh isi dari masing – masing kolom (variable)

```
> str(data.car)
'data.frame': 1728 obs. of 7 variables:
$ buying : chr "vhigh" "vhigh" "vhigh" "vhigh" ...
$ maint : chr "vhigh" "vhigh" "vhigh" "vhigh" ...
$ doors : chr "2" "2" "2" "2" ...
$ persons : chr "2" "2" "2" "2" ...
$ lug_boot: chr "small" "small" "small" "med" ...
$ safety : chr "low" "med" "high" "low" ...
$ class : chr "unacc" "unacc" "unacc" ...
```

7. Untuk mengetahui jumlah tiap tiap target yang ada pada variable class yaitu dengan perintah counts <- table(data.car\$class)

8. Selanjutnya untuk melihat hasil perhitungan perintah tersebut dengan perintah barplot(counts,col=c("#ffc97d","#003b66","#008478","#2ed194"),leg end = rownames(counts), main = "Class Value in the Dataset")



c. Mulai melakukan pembuatan model dan pohon keputusan

1. Tambahkan library untuk mendukung perintah yang akan digunakan pada pemprosesan data yang ada . libarary yang di butuhkan :

```
library(caret)
```

library(rpart)

library(rpart.plot)

library(tidyverse)

```
D:/TB DATAMINING/TB_008_011_018/
> library(caret)
Loading required package: lattice
Loading required package: ggplot2
> library(rpart)
> library(rpart.plot)
> library(tidyverse)
-- Attaching packages -
                                           ----- tidyverse 1.3.0 --
v tibble 3.0.4 v dplyr 1.0.2
v tidyr 1.1.2 v stringr 1.4.0
v readr 1.4.0
                  v forcats 0.5.0
v purrr
          0.3.4
-- Conflicts -----
                                         ------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag() masks stats::lag()
x purrr::lift() masks caret::lift()
```

2. Lihat beberapa sample data yang ada dengan perintah sample_n(data.car,10)

```
> sample_n(data.car,10)
  buying maint doors persons lug_boot safety class
   vhigh
         low 5more
                      more
                            small
                                     low unacc
     low high 3
                             med
                                    high acc
                       4
                             big
3
         med
                 4
     low
                                   low unacc
     low high
                4
                            small.
                                    med unacc
         low 5more
5
    high
                            small.
                                    med unacc
   vhigh vhigh 3
                            small high unacc
                 4
                      more
     low vhigh
                            small
                                    med unacc
   vhigh vhigh
                 3
                             small.
                                     med unacc
               4
    high med
                                     med acc
                      more
                              med
10
   high
          low
                                     low unacc
>
```

- 3. Acak sample data dengen perintah set.seed(123)
- 4. Bagi data sample yang ada menjadi 80 % untuk data train dan 20 % untuk data test dengan perintah training.samples <- data.car\$class %>%

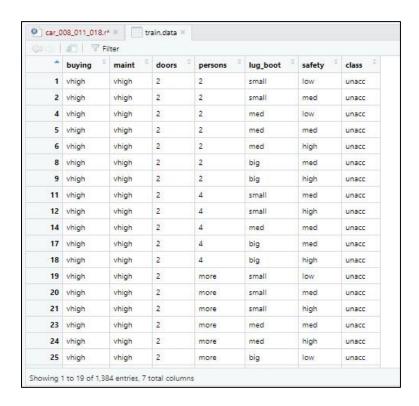
```
createDataPartition(p = 0.8, list = FALSE)
```

```
train.data <- data.car[training.samples, ]
test.data <- data.car[-training.samples, ]</pre>
```

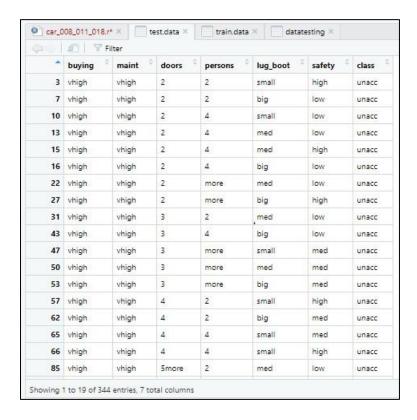
```
set.seed(123)
training.samples <- data.car$class %>%
   createDataPartition(p = 0.8, list = FALSE)
train.data <- data.car[training.samples, ]
test.data <- data.car[-training.samples, ]</pre>
```

5. Lihat data training dan data testing

view(train.data) untuk melihat data train, data train memiliki jumlah 1384 dan 7 variable atau data train memiliki 80% data dari data sample yang ada



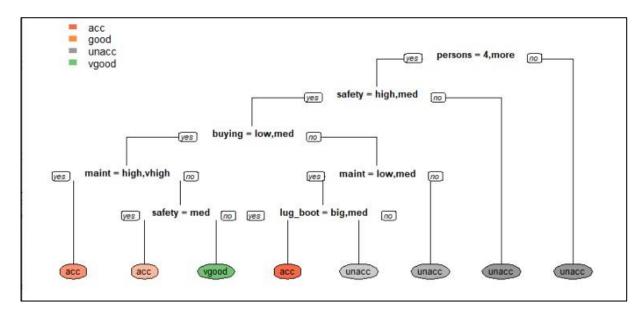
view(test.data) untuk melihat data test , data test memiliki jumlah 344 dan 7 variable atau data test memiliki 20% data dari data sample yang ada



6. Buat model untuk membentuk decision tree (pohon keputusan) dengan menggunakan data train yang ada dan gunakan package rpart untk membentuk model tersebut .

```
model.class <- rpart(class ~., data = train.data, method =
"class", control = rpart.control(minsplit = 100, cp =0))</pre>
```

7. Untuk melihat hasil dari model yang sudah terbentuk dengan perintah



8. Melihat Root Node Eror dengan perintah **printcp(model.class)**

```
D:/TB DATAMINING/TB_008_011_018/
> printcp(model.class)
Classification tree:
Variables actually used in tree construction:
[1] buying lug_boot maint
                          persons safety
Root node error: 416/1384 = 0.30058
n= 1384
       CP nsplit rel error xerror
             0 1.00000 1.00000 0.041004
1 0.137019
                 0.72596 0.77885 0.037867
2 0.111779
                 0.50240 0.53606 0.032878
4 0.024038
                 0.42308 0.43990 0.030293
5 0.000000
                 0.39904 0.42788 0.029938
```

9. Untuk melihat penjelasan mengenai model yang telah dibuat sebelumnya dengan perintah summary(model.class)

```
D:/TB DATAMINING/TB_008_011_018/
> rpart.plot(model.class, yesno = 2, type = 0, extra = 4)
> summary(model.class)
Call:
rpart(formula = class ~ ., data = train.data, method = "class",
   control = rpart.control(minsplit = 100, cp = 0))
          CP nsplit rel error
                                  xerror
2 0.7259615 0.7788462 0.03786728
2 0.11177885
3 0.03966346 4 0.5024038 0.5336538 0.03281846
4 0.02403846 6 0.4230769 0.4567308 0.03077638
5 0.00000000 7 0.3990385 0.4254808 0.02986613
                  4 0.5024038 0.5336538 0.03281846
Variable importance
  safety persons
                     maint buying lug_boot
                                                   doors
     42
           25
                      18
Node number 1: 1384 observations,
                                     complexity param=0.1370192
  predicted class=unacc expected loss=0.300578 P(node) =1
    class counts: 308
                          56 968 52
   probabilities: 0.223 0.040 0.699 0.038
  left son=2 (917 obs) right son=3 (467 obs)
  Primary splits:
      persons splits as RLL, improve=100.735200, (0 missing) safety splits as LRL, improve=100.410000, (0 missing)
      buying splits as RLLR, improve= 17.656390, (0 missing)
      maint splits as RLLR, improve= 11.344240, (0 missing)
      lug_boot splits as LLR, improve= 8.731054, (0 missing)
```

```
Node number 2: 917 observations, complexity param=0.1370192

predicted class=unacc expected loss=0.4536532 P(node) =0.6625723
    class counts: 308 56 501 52
    probabilities: 0.336 0.061 0.546 0.057
    left son=4 (610 obs) right son=5 (307 obs)

Primary splits:
    safety splits as LRL, improve=150.248200, (0 missing)
    buying splits as RLLR, improve= 26.817870, (0 missing)
    maint splits as RLLR, improve= 16.728220, (0 missing)
    lug_boot splits as LLR, improve= 12.733500, (0 missing)
    doors splits as RLLL, improve= 1.388815, (0 missing)

Node number 3: 467 observations
    predicted class=unacc expected loss=0 P(node) =0.3374277
    class counts: 0 0 467 0
    probabilities: 0.000 0.000 1.000 0.000
```

```
Node number 4: 610 observations,
                                           complexity param=0.1117788
  predicted class=acc expected loss=0.495082 P(node) =0.4407514
   class counts: 308 56 194 52
   probabilities: 0.505 0.092 0.318 0.085
  left son=8 (308 obs) right son=9 (302 obs)
  Primary splits:
      buying splits as RLLR, improve=36.931360, (0 missing)
                 splits as LLLR, improve=25.670540, (0 missing)
       maint
      lug_boot splits as LLR, improve=16.638600, (0 missing)
safety splits as R-L, improve= 9.254405, (0 missing)
doors splits as RLLL, improve= 2.314267, (0 missing)
  Surrogate splits:
      doors
                splits as LRLR, agree=0.526, adj=0.043, (0 split)
                 splits as LLRR, agree=0.521, adj=0.033, (0 split)
      safety splits as R-L, agree=0.511, adj=0.013, (0 split) lug_boot splits as LLR, agree=0.507, adj=0.003, (0 split)
```

```
D:/TB DATAMINING/TB 008 011 018/
Node number 5: 307 observations
 predicted class=unacc expected loss=0 P(node) =0.2218208
  class counts: 0 0 307 0
  probabilities: 0.000 0.000 1.000 0.000
Node number 8: 308 observations,
                                     complexity param=0.03966346
 predicted class=acc expected loss=0.461039 P(node) =0.2225434 class counts: 166 56 34 52
  probabilities: 0.539 0.182 0.110 0.169
 left son=16 (151 obs) right son=17 (157 obs)
 Primary splits:
              splits as LRRL, improve=27.474650, (0 missing)
      maint
      safety splits as R-L, improve=12.370240, (0 missing) lug_boot splits as RRL, improve= 9.018566, (0 missing)
             splits as RLLL, improve= 2.473101, (0 missing)
      buying
               splits as -RL-, improve= 2.259740, (0 missing)
  Surrogate splits:
      buying splits as -LR-, agree=0.529, adj=0.040, (0 split)
      doors
               splits as RRRL, agree=0.516, adj=0.013, (0 split)
      lug_boot splits as LRR, agree=0.516, adj=0.013, (0 split)
Node number 9: 302 observations,
                                     complexity param=0.1117788
 predicted class=unacc expected loss=0.4701987 P(node) =0.2182081
   class counts: 142 0 160 0
  probabilities: 0.470 0.000 0.530 0.000
  left son=18 (151 obs) right son=19 (151 obs)
 Primary splits:
               splits as RLLR, improve=46.728480, (0 missing)
      maint
      lug_boot splits as LLR, improve=12.491260, (0 missing)
      safety splits as L-R, improve= 8.767991, (0 missing)
      buying splits as L--R, improve= 4.988893, (0 missing)
               splits as RLLL, improve= 1.067564, (0 missing)
      doors
  Surrogate splits:
      doors
              splits as RLLR, agree=0.520, adj=0.040, (0 split)
      lug_boot splits as LRL, agree=0.520, adj=0.040, (0 split)
      safety splits as R-L, agree=0.517, adj=0.033, (0 split)
      buying splits as L--R, agree=0.507, adj=0.013, (0 split) persons splits as -LR, agree=0.503, adj=0.007, (0 split)
```

```
D:/TB DATAMINING/TB 008 011 018/ @
Node number 16: 151 observations
  predicted class=acc expected loss=0.2450331 P(node) =0.109104
   class counts: 114 0 26 11
   probabilities: 0.755 0.000 0.172 0.073
Node number 17: 157 observations,
                                          complexity param=0.03966346
  predicted class=good expected loss=0.6433121 P(node) =0.1134393 class counts: 52 56 8 41
   probabilities: 0.331 0.357 0.051 0.261
  left son=34 (80 obs) right son=35 (77 obs)
  Primary splits:
      safety splits as R-L, improve=19.238550, (0 missing) lug_boot splits as RRL, improve= 8.449274, (0 missing)
                splits as -RL-, improve= 4.592334, (0 missing)
      buying splits as -RL-, improve= 4.255466, (0 missing)
      doors splits as LRRR, improve= 1.666579, (0 missing)
  Surrogate splits:
      doors splits as LLRL, agree=0.522, adj=0.026, (0 split) lug_boot splits as RLR, agree=0.522, adj=0.026, (0 split) persons splits as -LR, agree=0.516, adj=0.013, (0 split)
Node number 18: 151 observations,
                                          complexity param=0.02403846
  predicted class=acc expected loss=0.2516556 P(node) =0.109104 class counts: 113 0 38 0
   probabilities: 0.748 0.000 0.252 0.000
  left son=36 (99 obs) right son=37 (52 obs)
  Primary splits:
      lug_boot splits as LLR, improve=18.82561000, (0 missing)
safety splits as L-R, improve=15.53944000, (0 missing)
                splits as RLLL, improve= 0.75791600, (0 missing)
      maint splits as -LR-, improve= 0.06650693, (0 missing)
      persons splits as -RL, improve= 0.06650693, (0 missing)
Node number 19: 151 observations
 predicted class=unacc expected loss=0.192053 P(node) =0.109104
    class counts: 29 0 122 0
   probabilities: 0.192 0.000 0.808 0.000
```

```
Node number 34: 80 observations
predicted class=acc expected loss=0.45 P(node) =0.05780347
class counts: 44 32 4 0
probabilities: 0.550 0.400 0.050 0.000

Node number 35: 77 observations
predicted class=vgood expected loss=0.4675325 P(node) =0.05563584
class counts: 8 24 4 41
probabilities: 0.104 0.312 0.052 0.532

Node number 36: 99 observations
predicted class=acc expected loss=0.07070707 P(node) =0.07153179
class counts: 92 0 7 0
probabilities: 0.929 0.000 0.071 0.000

Node number 37: 52 observations
predicted class=unacc expected loss=0.4038462 P(node) =0.03757225
class counts: 21 0 31 0
probabilities: 0.404 0.000 0.596 0.000
```

- 10. Lakukan uji data dengan memprediksi hasil dari model dan pohon keputusan yang terbentuk, data yang digunakan untuk memprediksi data adalah data test
- 11. Lihat hasil dari prediksi data dan jumlah tiap tiap class yang dihasilkan dari prediksi data tersebut .
- 12. Menunjukan bahwa jumlah tiap tiap class dapat terlihat yaitu

```
Acc = 74 baris data
```

Good = 13 baris data

Unacc = 242 baris data

Vgood = 15 baris data

```
D:/TB DATAMINING/TB_008_011_018/ P

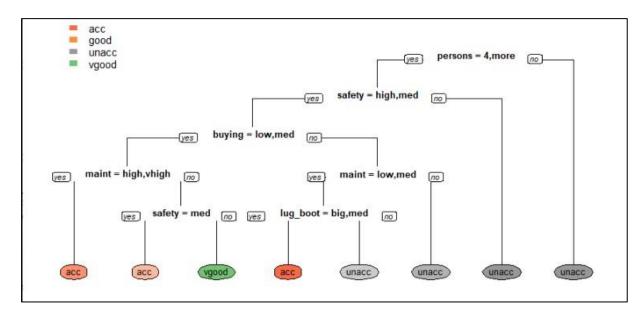
> predicted.classes <- model %>%
+ predict(test.data, type = "class")
> str(predicted.classes)
Factor w/ 4 levels "acc", "good", "unacc", ...: 3 3 3 3 3 3 3 3 3 3 ...
> summary(predicted.classes)
acc good unacc vgood
74 13 242 15
> head(predicted.classes)
[1] unacc unacc unacc unacc unacc
Levels: acc good unacc vgood
> head(test.data$class)
[1] "unacc" "unacc" "unacc" "unacc" "unacc" "unacc"
```

13. Bandingan hasil prediksi dari model dan pohon keputusan dengan data test yang ada untuk melihat keakurasian model dan pohon keputusan yang ada

Menunjukkan bahwa keakurasian dari model dan pohon keputusan = 98,8% dan tingkat terjadinya eror atau kesalahan sebesar 1,2%

```
> mean(predicted.classes == test.data$class)
[1] 0.9883721
> mean(predicted.classes != test.data$class)
[1] 0.01162791
```

Kesimpulan



- 1. Aturan klasifikasi yang didapat dari pohon keputusan adalah :
- Rule 1 : IF (person "!= 4 atau more") \rightarrow unacc
- Rule 2 : IF (person "= 4 atau more") ^ (safety "!= high atau med") → unacc
- Rule 3 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "!=low atau med") ^ (maint "!=low atau med") → unacc
- Rule 4 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "!=low atau med") ^ (maint "=low atau med") ^ (lug boot "!=big atau med") → unacc
- Rule 5 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "!=low atau med") ^ (maint "=low atau med") ^ (lug_boot "=big atau med") → acc
- Rule 6 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "= low atau med") ^ (maint "!= high atau highv") ^ (safety "!= med") → **vgood**
- Rule 7 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "= low atau med") ^ (maint "!= high atau highv") ^ (safety "= med") → acc
- Rule 8 : IF (person "= 4 atau more") ^ (safety "= high atau med") ^ (buying "= low atau med") ^ (maint "= high atau highv") → acc

Daftar Pustaka

 $\underline{http://muhammadilhammubarok19.blogspot.com/2018/06/classification-and-regression-tree-cart.html}$

https://repository.ipb.ac.id/handle/123456789/50394#:~:text=CART% 20(Classifcation% 20and% 20Regression% 20Tree,data% 20yaitu% 20teknik% 20pohon% 20keputusan.&text=CART% 20mengbasilkan% 20suatu% 20pobon% 20klasifikasi,regresi% 20jika% 20peubah% 20responnya% 20kontinu.

https://archive.ics.uci.edu/ml/datasets/car+evaluation

https://youtu.be/qS55tp5nuuo

http://ejurnal.its.ac.id/index.php/sains_seni/article/download/10673/2395#:~:text=Metode %20CART%20(Classification%20and%20Regression,variabel%20prediktor%20(variabe 1%20independen)