

# Performance Analysis and Code (There are a total of 195 lines of code)

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#### Imported the packages

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```
1 import org.apache.spark.sql.functions._
```

- 2 import org.joda.time.format.DateTimeFormat
- 3 import org.apache.spark.ml.regression.LinearRegression
- 4 import org.apache.spark.ml.regression.LinearRegression
- 5 import org.apache.spark.mllib.util.MLUtils

```
import org.apache.spark.sql.functions._
import org.joda.time.format.DateTimeFormat
import org.apache.spark.ml.regression.LinearRegression
import org.apache.spark.ml.regression.LinearRegression
import org.apache.spark.mllib.util.MLUtils
```

#### Adjusted the path to the location of the data

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```
1 // Load data - adjust the path to the location of your data
    2 val inputPath = "/Users/joannariascos/Desktop/algorithm/aarhus_parking.csv"
    3 val parkingdata = sqlContext.read
               .format("com.databricks.spark.csv")
               .option("header", "true") // Use first line of all files as header
    5
               .option("delimiter", ",")
    6
               .option("inferSchema", "true") // Automatically infer data types
    7
    8
               .load(inputPath)
    9
              parkingdata.registerTempTable("parkingdata")
inputPath: String = /Users/joannariascos/Desktop/algorithm/aarhus_parking.csv
parkingdata: org.apache.spark.sql.DataFrame = [vehiclecount: int, totalspaces: int ... 2 mo
re fieldsl
warning: there was one deprecation warning; re-run with -deprecation for details
```

# Created the RDD pairs

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```
1 //To read the file
```

2 val csv = sc.textFile("/Users/joannariascos/Desktop/algorithm/aarhus\_parking.csv");

3 //To find the headers

4 val header = csv.first;

```
8 val parsedData = data.map { line =>
9     val parts = line.split(',')
10     LabeledPoint(parts(0).toDouble, Vectors.dense(parts(1).split(' ').map(_.toDouble)
11     }.cache()

csv: org.apache.spark.rdd.RDD[String] = /Users/joannariascos/Desktop/algorithm/aarhus_parki
ng.csv MapPartitionsRDD[49] at textFile at <console>:42
header: String = vehiclecount,totalspaces,garagecode,ozone
data: org.apache.spark.rdd.RDD[String] = MapPartitionsRDD[50] at filter at <console>:45
parsedData: org.apache.spark.rdd.RDD[org.apache.spark.mllib.regression.LabeledPoint] = MapP
artitionsRDD[51] at map at <console>:47
```

# Loaded the parking dataset with spark

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- 1 %spark.r
- 2 aarhus\_parking <- read.csv("/Users/joannariascos/Desktop/algorithm/aarhus\_parking.csv'</pre>
- 3 head(aarhus\_parking)

5 //To remove the header

6 val data = csv.filter(\_(0) != header(0));
7 //To create a RDD of (label, features) pairs

```
vehiclecount totalspaces
                           garagecode ozone
                               NORREPORT
1
                        65
                                           101
2
             0
                       512 SKOLEBAKKEN
                                           106
3
           869
                      1240 SCANDCENTER
                                           107
4
                       953
                                  BRUUNS
                                           103
            22
5
           124
                       130 BUSGADEHUSET
                                           105
           106
                                MAGASIN
                                           106
                       400
```

### Fitted the model and ran a multiple regression analysis

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- 1 %r
- 2 model = lm(ozone~vehiclecount+totalspaces+garagecode, data = aarhus\_parking)

#### Created the anova table

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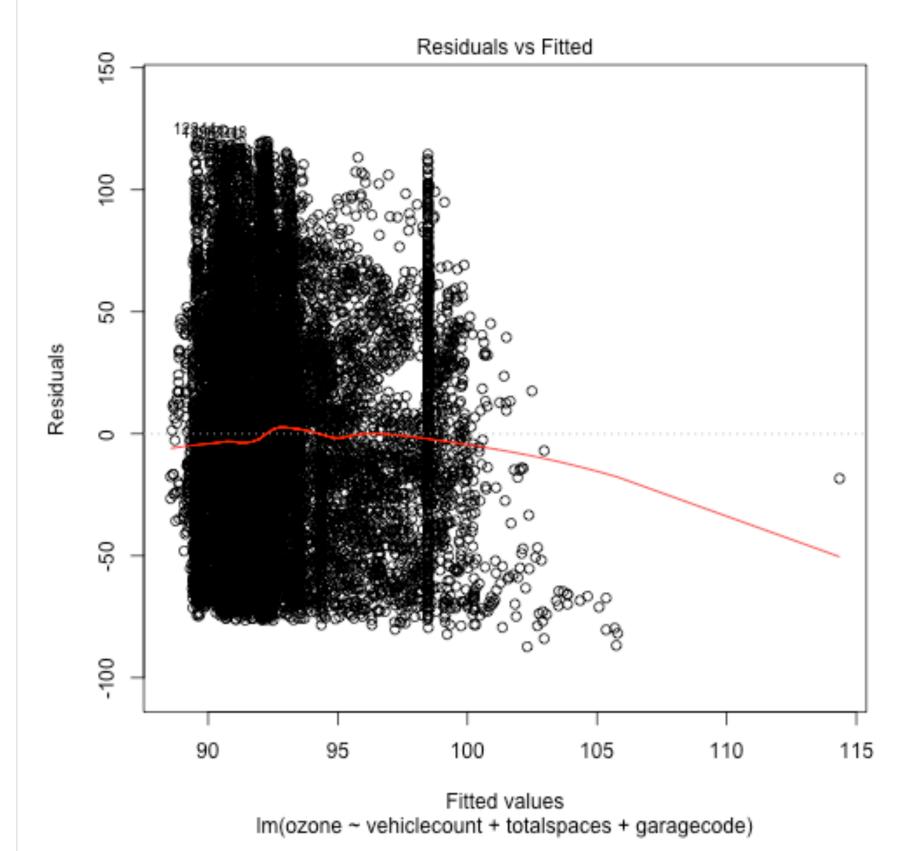
- 1 %r
- 2 modeltwo = lm(ozone~totalspaces, data = aarhus\_parking)
- 3 anova(model, modeltwo)

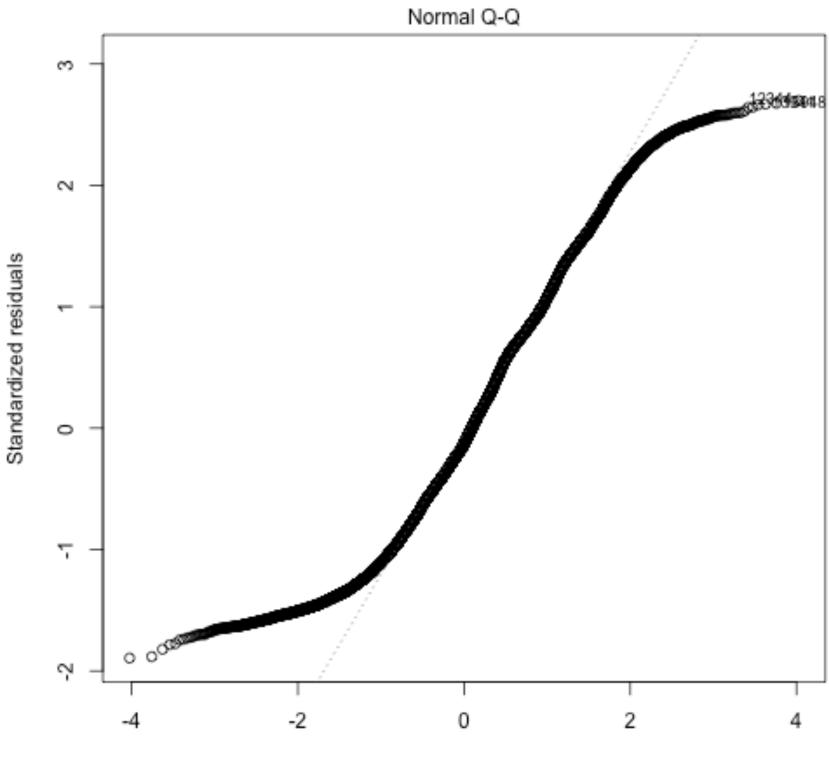
Analysis of Variance Table

# Plotted a residuals vs fitted graph

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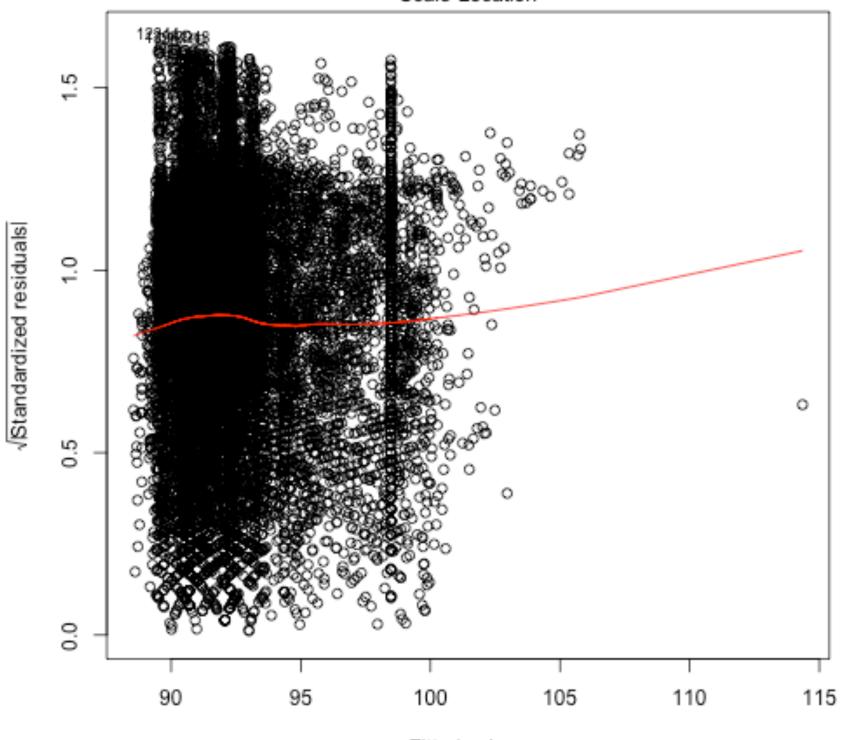
- 1 %r
- 2 plot(model)





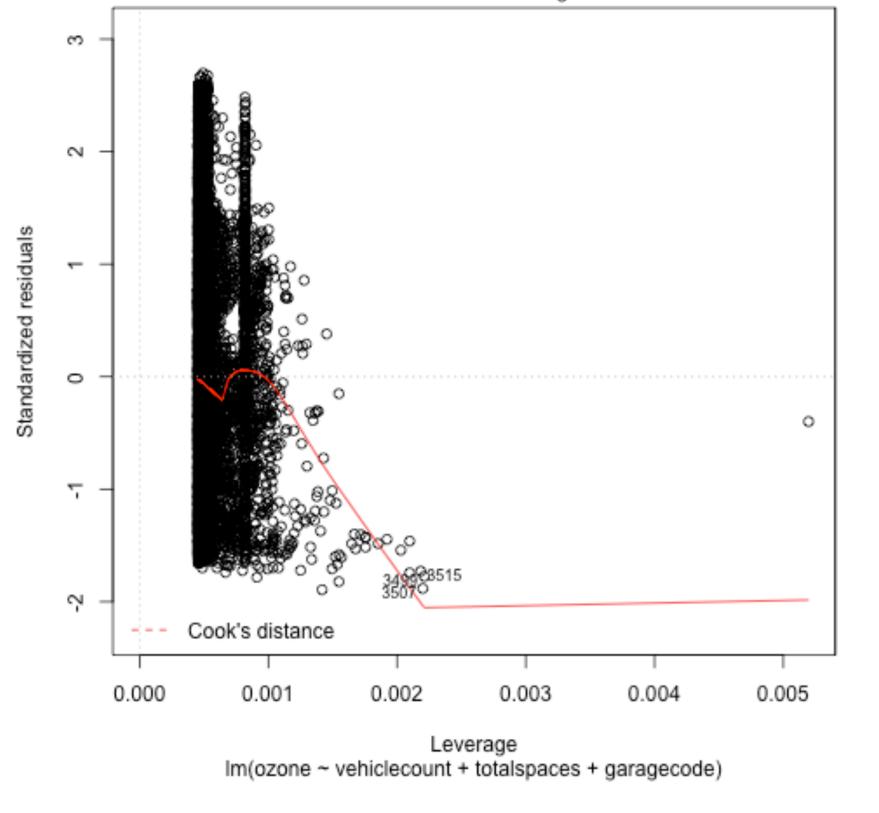
Theoretical Quantiles Im(ozone ~ vehiclecount + totalspaces + garagecode)

# Scale-Location



Fitted values Im(ozone ~ vehiclecount + totalspaces + garagecode)

#### Residuals vs Leverage



# Depicted the column names of the parking dataset

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- 1 %r
- 2 colnames(aarhus\_parking)
- [1] "vehiclecount" "totalspaces" "garagecode" "ozone"

# Depicted the structure of the parking dataset

- 1 %r
- 2 str(aarhus\_parking)

```
'data.frame': 55264 obs. of 4 variables:
$ vehiclecount: int 0 0 869 22 124 106 115 233 0 0 ...
$ totalspaces : int 65 512 1240 953 130 400 210 700 65 512 ...
$ garagecode : Factor w/ 8 levels "BRUUNS", "BUSGADEHUSET", ...: 5 8 7 1 2 4 3 6 5 8 ...
$ ozone : int 101 106 107 103 105 106 110 106 106 110 ...
```

### Showed the summary of the parking datatset

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- 1 %r
- 2 summary(aarhus\_parking)

```
vehiclecount
                                                      ozone<br />
               totalspaces
                                     garagecode
                Min. : 65.0
                                BRUUNS
                                                    Min. : 15.00<br />
Min. : 0.0
                                         : 6908
                1st Qu.: 190.0
                                BUSGADEHUSET: 6908
                                                    1st Qu.: 54.00<br />
1st Qu.: 32.0
Median: 96.0
                Median : 456.0
                                KALKVAERKSVEJ: 6908
                                                    Median : 87.00<br />
     : 192.2
                Mean : 526.2
                                                    Mean : 92.42<br />
Mean
                                MAGASIN
                                           : 6908
3rd Qu.: 296.0
                3rd Qu.: 763.2
                                NORREPORT
                                           : 6908
                                                    3rd Qu.:127.00<br />
Max. :1464.0
                Max. :1240.0
                                SALLING
                                            : 6908
                                                    Max.
                                                          :215.00<br />
                                (Other)
                                           :13816
                                                    NA's
                                                           :37696
```

### Calling the Im function

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1

2 %r

3 summary(lm(ozone~vehiclecount+totalspaces+garagecode, data = aarhus\_parking))

#### Call:

```
lm(formula = ozone ~ vehiclecount + totalspaces + garagecode,
    data = aarhus_parking)
```

## Showing the model

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1 %r

2 model

#### Call:

```
lm(formula = ozone ~ vehiclecount + totalspaces + garagecode,
    data = aarhus_parking)
```

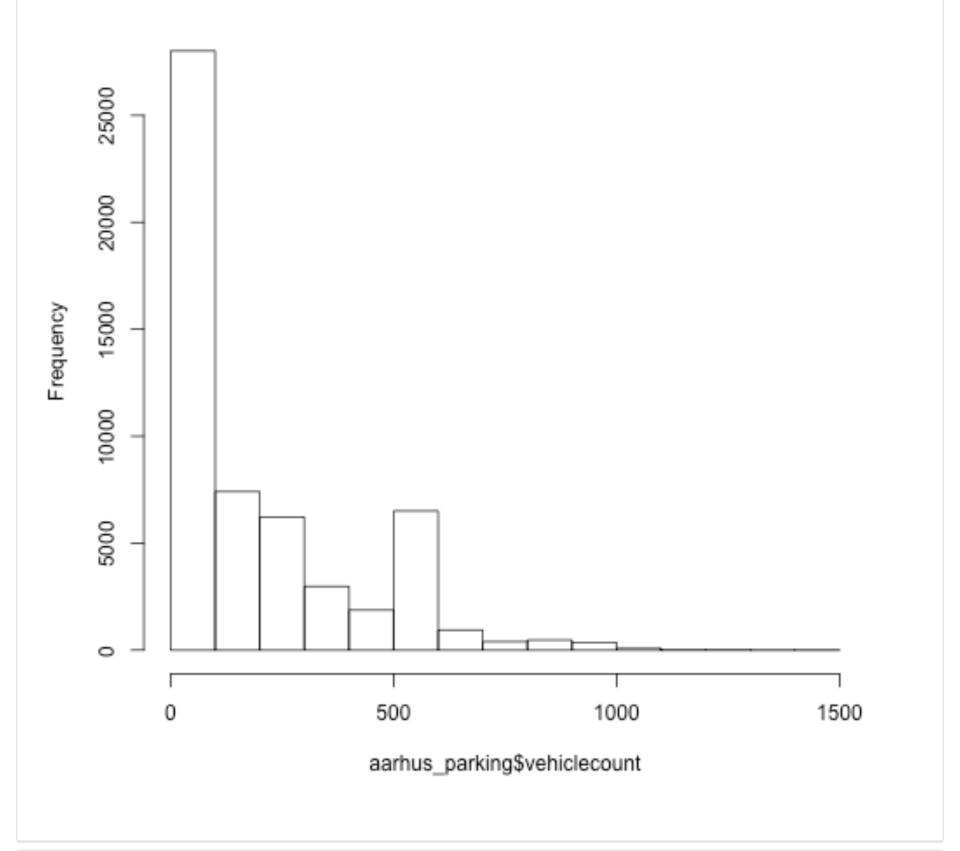
# Histogram depicting the vehicle count

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1 %r

2 hist(aarhus\_parking\$vehiclecount)

# Histogram of aarhus\_parking\$vehiclecount

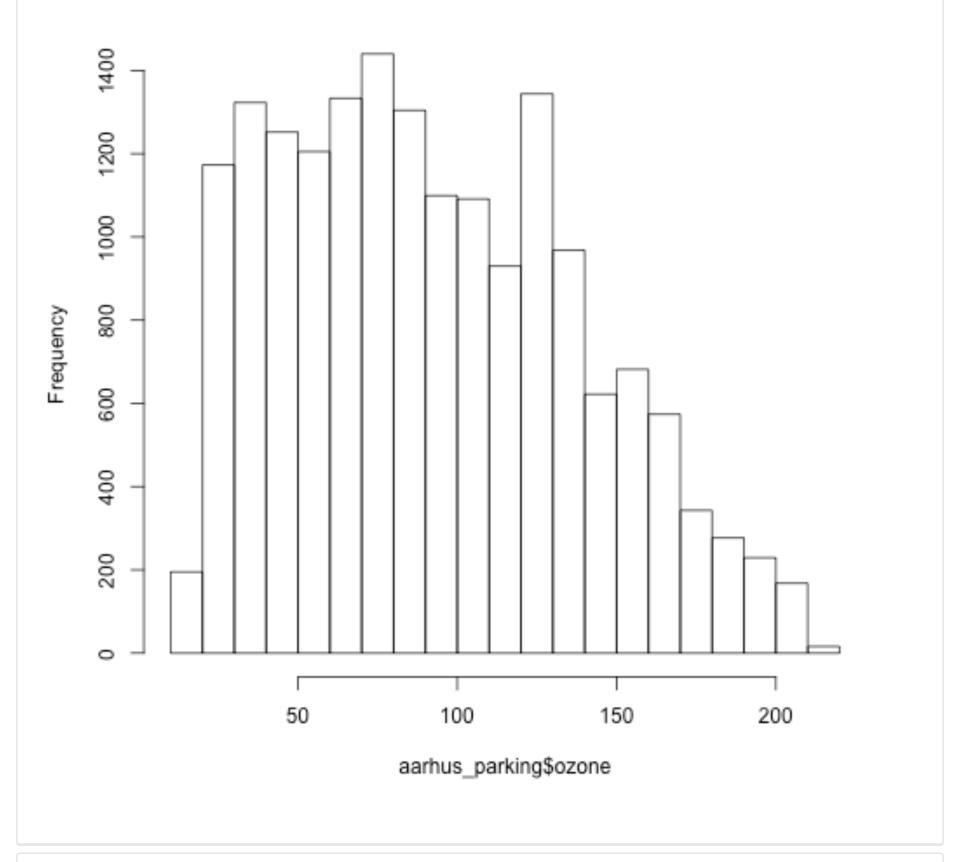


# Histogram depicting the ozone layer

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- 1 %i
- 2 hist(aarhus\_parking\$ozone)

# Histogram of aarhus\_parking\$ozone

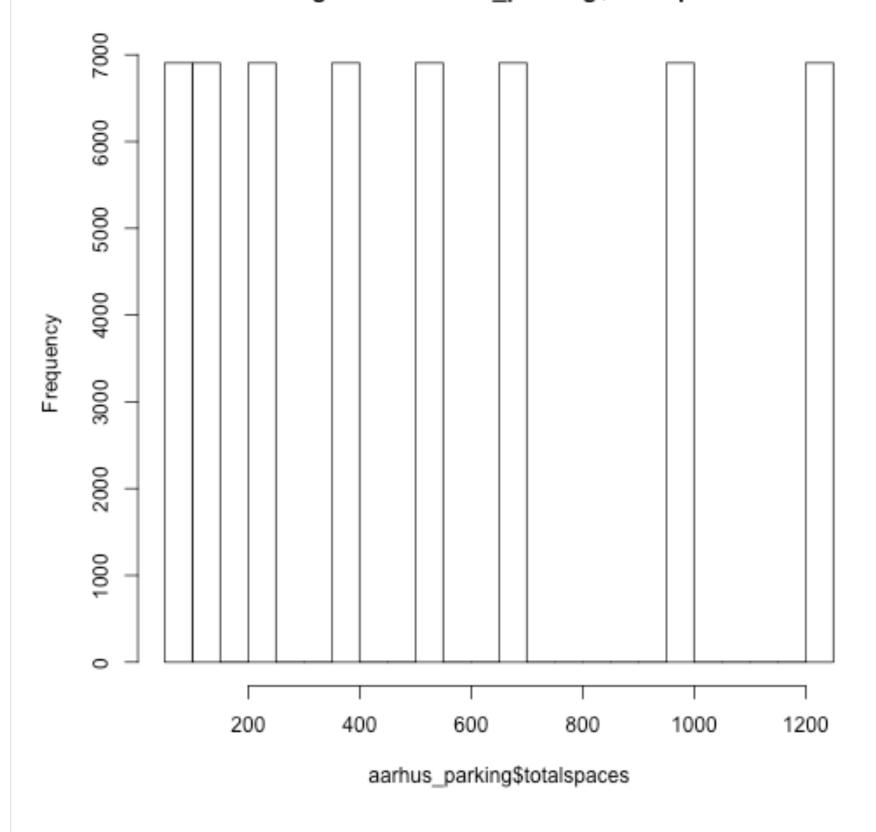


# Histogram depicting the total spaces

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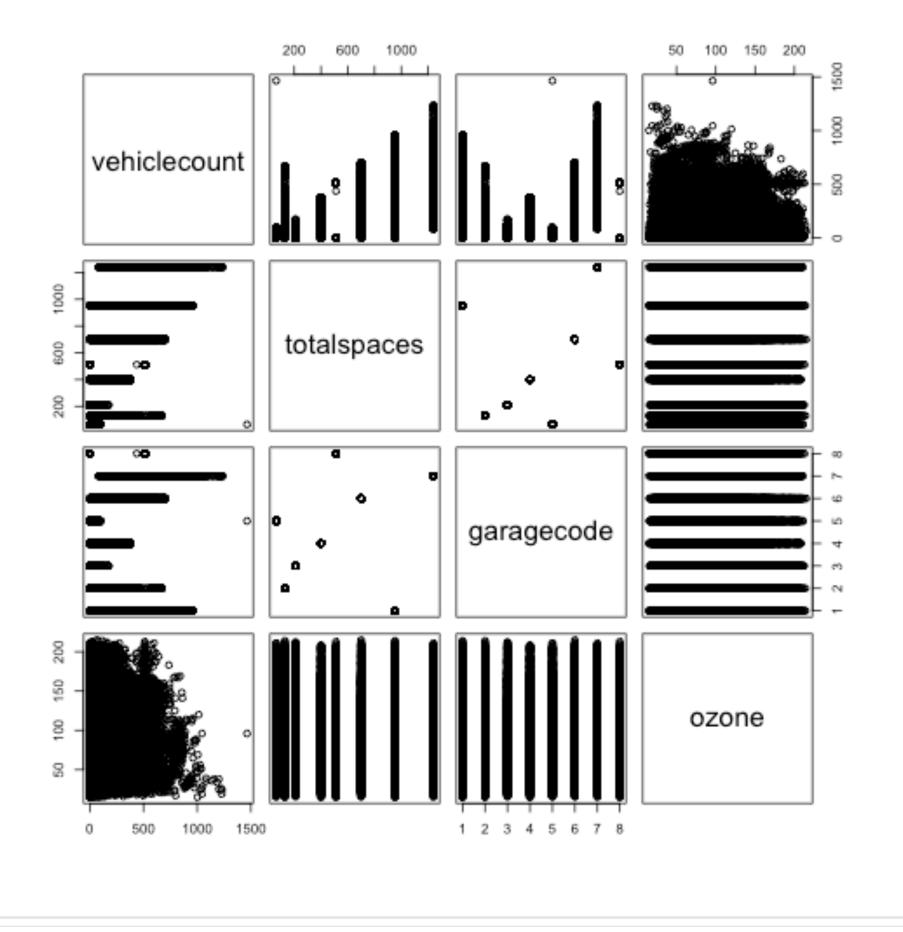
- 1 %
- 2 hist(aarhus\_parking\$totalspaces)

# Histogram of aarhus\_parking\$totalspaces



# Ggplot depicting the vehicle count, total spaces, garage code, FINISHED $\triangleright$ % and ozone layer

- 1 %r {"imageWidth":"400px}
- 2 library("ggplot2")
- 3 plot(aarhus\_parking)



- 1 %spark.r
- 2 frequency(aarhus\_parking)

[1] 1

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# Time series using the parking data set

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- 1 %r
- 2 modelone <- ts(aarhus\_parking, frequency=12, start=c(1946,1))</pre>

Printing the	-	r the the ti	me ser	ies	FINISHED D 光 目 袋
Jan 1946	0	65	5	101	Ţ
Feb 1946	0	512	8	106	
Mar 1946	869	1240	7	107	
Apr 1946	22	953	1	103	
May 1946	124	130	2	105	
Jun 1946	106	400	4	106	
Jul 1946	115	210	3	110	
Aug 1946	233	700	6	106	
Sep 1946	0	65	5	106	
Oct 1946	0	512	8	110	
Nov 1946	959	1240	7	115	
Dec 1946	22	953	1	114	
Jan 1947	124	130	2	118	
Feb 1947	119	400	4	113	
Mar 1947	121	210	3	114	
Apr 1947	282	700	6	115	
May 1947	0	65	5	115	
10/17 מוו	Λ	517	Q	170	^

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res0: org.apache.spark.SparkContext = org.apache.spark.SparkContext@5add6c08

#### Created some partitions from the dataset

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- 1 import org.apache.spark.mllib.util.LinearDataGenerator
- 2 val numRows = 10000
- 3 val numCols = 1000
- 4 val rawData = LinearDataGenerator.generateLinearRDD(sc, numRows, numCols, 1).toDF()
- 5 // Repartition into a more parallelism-friendly number of partitions
- 6 val data = rawData.repartition(64).cache()

import org.apache.spark.mllib.util.LinearDataGenerator

numRows: Int = 10000
numCols: Int = 1000

rawData: org.apache.spark.sql.DataFrame = [label: double, features: vector]

data: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [label: double, features: ve

ctor]

# Prints out the coefficients from the model

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- 1 %r
- 2 coefficients(model)

garagecodeBUSGADEHUSET garagecodeKALKVAERKSVEJ garagecodeMAGASIN
-2.191652364 0.238790550 -0.140165941
garagecodeNORREPORT garagecodeSALLING garagecodeSCANDCENTER
0.047225980 -0.504496446 -1.439290374
garagecodeSKOLEBAKKEN
NA

#### Calculated the 95% confidence interval

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1 %r

2 confint(model, level=0.95)

87.491821077 96.959928651 (Intercept) vehiclecount 0.010913491 0.019515627 totalspaces -0.009247282 0.003236974 garagecodeBUSGADEHUSET -6.649535257 2.266230530 garagecodeKALKVAERKSVEJ -3.766315284 4.243896385 garagecodeMAGASIN -3.274337972 2.994006090 garagecodeNORREPORT -4.711821775 4.806273736 garagecodeSALLING -2.884713945 1.875721053 -5.393283802 2.514703053 garagecodeSCANDCENTER garagecodeSKOLEBAKKEN NA NA

## Fitted my model

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1 %r

2 fitted(model)

```
92.07777
          90.68724 100.28165 89.69668 91.53016 92.49639 93.58326
        8
                   9
                             10
                                       11
                                                  12
                                                             13
93.16276
           92.07777
                      90.68724 101.65096
                                           89.69668
                                                      91.53016
                                                                 92.69418
       15
                  16
                             17
                                       18
                                                  19
                                                             20
                                                                        21
93.67454
           93.90828
                      92.07777
                                 90.68724 102.48776
                                                      89.69668
                                                                 91.54537
       22
                  23
                             24
                                       25
                                                  26
                                                             27
                                                                        28
           93.73540
 93.18105
                      95.23194
                                89.69668
                                           92.07777
                                                      90.68724 102.95941
       29
                  30
                                       32
                                                  33
                                                             34
                                                                        35
                             31
           93.72877
                      93.79626
                                 96.41868
                                            92.07777
                                                      90.68724
 91.83445
                                                                 93.34381
                                       39
       36
                  37
                             38
                                                  40
                                                             41
                                                                        42
           92.15395
                                                      92.07777
 89.69668
                      94.01785
                                 92.79210
                                            93.45184
                                                                 90.68724
       43
                  44
                                       46
                                                  47
                                                             48
                                                                        49
                             45
92.53743
           89.69668
                      91.98659
                                 93.80484
                                           92.77689
                                                      92.72154
                                                                 92.07777
                  51
                             52
                                       53
                                                  54
                                                             55
       50
                                                                        56
90.68724
           92.11143
                      89.69668
                                 92.18438
                                            93.34841
                                                      92.74646
                                                                 92.35639
       57
                  58
                             59
                                       60
                                                  61
                                                             62
                                                                        63
 92.07777
           90.68724
                      91.94407
                                 89.69668
                                            92.16917
                                                      93.16583
                                                                 92,67038
       61
                  65
                             66
                                       67
                                                  ሬያ
                                                             60
                                                                        70
```

#### Printed the residuals of the model

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1 %r

2 residuals(model)

8.922234149 1	5.312763851	6.718354712 1	3.303316362 1	3.469842217	ı
6	7	8	9	10	
13.503609360	16.416742630	12.837237043	13.922234149	19.312763851	
11	12	13	14	15	
13.349044437	24.303316362	26.469842217	20.305820098	20.325455279	
16	17	18	19	20	
21.091723671	22.922234149	29.312763851	17.512243713	25.303316362	
21	22	23	24	25	
18.454627659	14.818954223	13.264597044	6.768057071	11.303316362	
26	27	28	29	30	
11.922234149	10.312763851	-6.959407604	4.165551045	6.271230113	
31	32	33	34	35	
10.203738810	5.581321499	6.922234149	10.312763851	10.656193441	
36	37	38	39	40	
18.303316362	11.846045314	9.982153499	15.207899678	14.548160429	
41	42	43	44	45	
11.922234149	9.312763851	11.462565048	15.303316362	13.013405459	
16	17	ЛΩ	10	50	^

# Getting the analysis of the variance table

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1 %r

2 anova(model)

aanaaacadaCALLTNC

Analysis of Variance Table

#### FINISHED ▷ ♯ 圓 � Calculated the variance-covariance of the model 1 %r 2 vcov(model) 5.833246e+00 -6.449969e-05 -7.288449e-03 (Intercept) vehiclecount -6.449969e-05 4.815003e-06 -9.173920e-07 totalspaces -7.288449e-03 -9.173920e-07 1.014167e-05 garagecodeBUSGADEHUSET -4.873959e+00 -6.963061e-04 6.137709e-03 garagecodeKALKVAERKSVEJ -4.299779e+00 4.120483e-05 5.199843e-03 garagecodeMAGASIN -2.911121e+00 -7.214983e-05 3.327733e-03 garagecodeNORREPORT -5.358439e+00 4.512334e-05 6.644293e-03 garagecodeSALLING -7.188819e-01 -2.227684e-04 3.663671e-04 3.227003e+00 -4.830274e-04 -4.966160e-03 garagecodeSCANDCENTER garagecodeBUSGADEHUSET garagecodeKALKVAERKSVEJ (Intercept) -4.8739590503 -4.299779e+00 vehiclecount -0.0006963061 4.120483e-05 5.199843e-03 totalspaces 0.0061377092 garagecodeBUSGADEHUSET 5.1725089901 3.616269e+00 3.6162686153 4.175149e+00 garagecodeKALKVAERKSVEJ garagecodeMAGASIN 2.4917027598 2.215533e+00 4.4864332678 3.961114e+00 garagecodeNORREPORT

A 7110700076

6 510357<sub>0</sub> 01

# Checks for the quality of the regression fits

1 %r

2 influence(model)

:	\$hat				
	1	2	3	4	5
(	0.0004559825	0.0004832205	0.0010648366	0.0005230584	0.0004631889
	6	7	8	9	10
(	0.0004553779	0.0004665068	0.0004589876	0.0004559825	0.0004832205
	11	12	13	14	15
(	0.0012945228	0.0005230584	0.0004631889	0.0004558431	0.0004684927
	16	17	18	19	20
(	0.0004732811	0.0004559825	0.0004832205	0.0014529287	0.0005230584
	21	22	23	24	25
(	0.0004629252	0.0004602460	0.0004699072	0.0005254274	0.0005230584
	26	27	28	29	30
(	0.0004559825	0.0004832205	0.0015482434	0.0004587750	0.0004707375
	31	32	33	34	35
(	0.0004713940	0.0006012955	0.0004559825	0.0004832205	0.0004643620
	36	37	38	39	40
(	0.0005230584	0.0004560883	0.0004786388	0.0004561188	0.0004632405

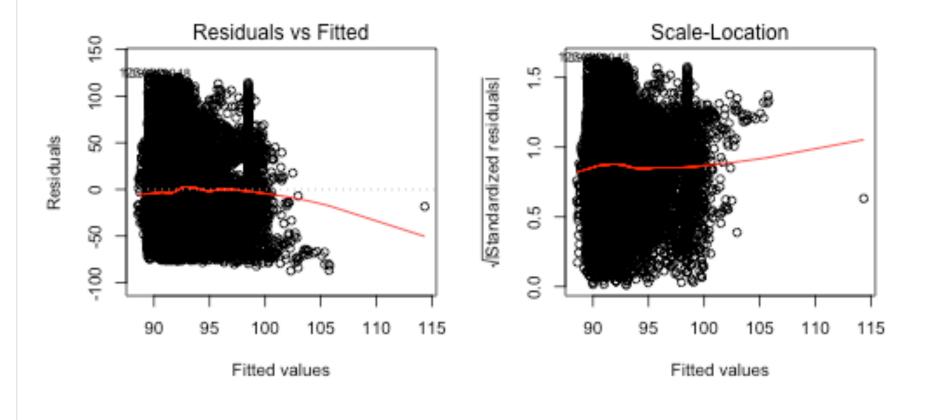
11 17 12 11

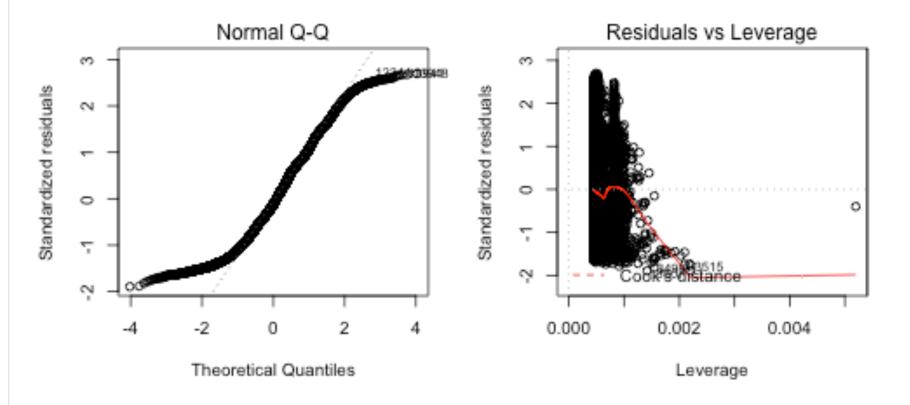
# **Shows the different plots**

2 layout(matrix(c(1,2,3,4),2,2))

3 plot(model)

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# Installed the Data Analysis and Graphics package

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- 1 %r
- 2 install.packages("DAAG", repos = "http://cran.us.r-project.org")

The downloaded binary packages are in /var/folders/ll/1mpcgfrd7nlgpz03y3z75t6w0000gn/T//RtmptTl8YT/downloaded\_packages

The downloaded binary packages are in /var/folders/ll/1mpcgfrd7nlgpz03y3z75t6w0000gn/T//RtmptTl8YT/downloaded\_packages

#### **Defined the functions**

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- 1 %r
- 2 library(bootstrap)
- 3 theta.model <- function(x,y){lsmodel(x,y)}</pre>
- 4 theta.predict <- function(model,x){cbind(1,x)%\*%model\$coef}

#### Converted the data frame to a numeric matrix

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- 1 %r
- 2 X <- as.matrix(model[c("ozone","vehiclecount","totalspaces")])</pre>
- 3 y <- as.matrix(model[c("garagecode")])</pre>

#### Installed the MASS package

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- 1 %r
- 2 install.packages("MASS", repos = "http://cran.us.r-project.org")

The downloaded binary packages are in /var/folders/ll/1mpcgfrd7nlgpz03y3z75t6w0000gn/T//RtmptTl8YT/downloaded\_packages

#### Performed a stepwise model selection by AIC

- 1 %r
- 2 library(MASS)
- 3 modelfit <- lm(ozone~vehiclecount+totalspaces+garagecode,data=aarhus\_parking)</pre>
- 4 step <- stepAIC(model, direction="both")</pre>
- 5 step\$anova

Start: AIC=134634.2 ozone ~ vehiclecount + totalspaces + garagecode

#### Installed the leaps package

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- 1 %r
- 2 install.packages("leaps", repos = "http://cran.us.r-project.org")

There is a binary version available (and will be installed) but the source version is later:

binary source
leaps 2.9 3.0

# Used the "leaps" function to get the best subsets of the variables

- 1 %r
- 2 library(leaps)
- 3 attach(aarhus\_parking)
- 4 leaps<-regsubsets(ozone~vehiclecount+totalspaces+garagecode,data=aarhus\_parking,nbest=

#### Printed the subset selection

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1

- 1 %r
- 2 summary(leaps)

Subset selection object

9 Variables (and intercept)

	Forced in	Forced out
vehiclecount	FALSE	FALSE
totalspaces	FALSE	FALSE
garagecodeBUSGADEHUSET	FALSE	FALSE
garagecodeKALKVAERKSVEJ	FALSE	FALSE
garagecodeMAGASIN	FALSE	FALSE
garagecodeNORREPORT	FALSE	FALSE
garagecodeSALLING	FALSE	FALSE
garagecodeSCANDCENTER	FALSE	FALSE
garagecodeSKOLEBAKKEN	FALSE	FALSE
10 subsets of each size	un +0 8	

10 subsets of each size up to 8 Selection Algorithm: exhaustive

vehiclecount totalspaces garagecodeBUSGADEHUSET

1 (1) "-om-"

""

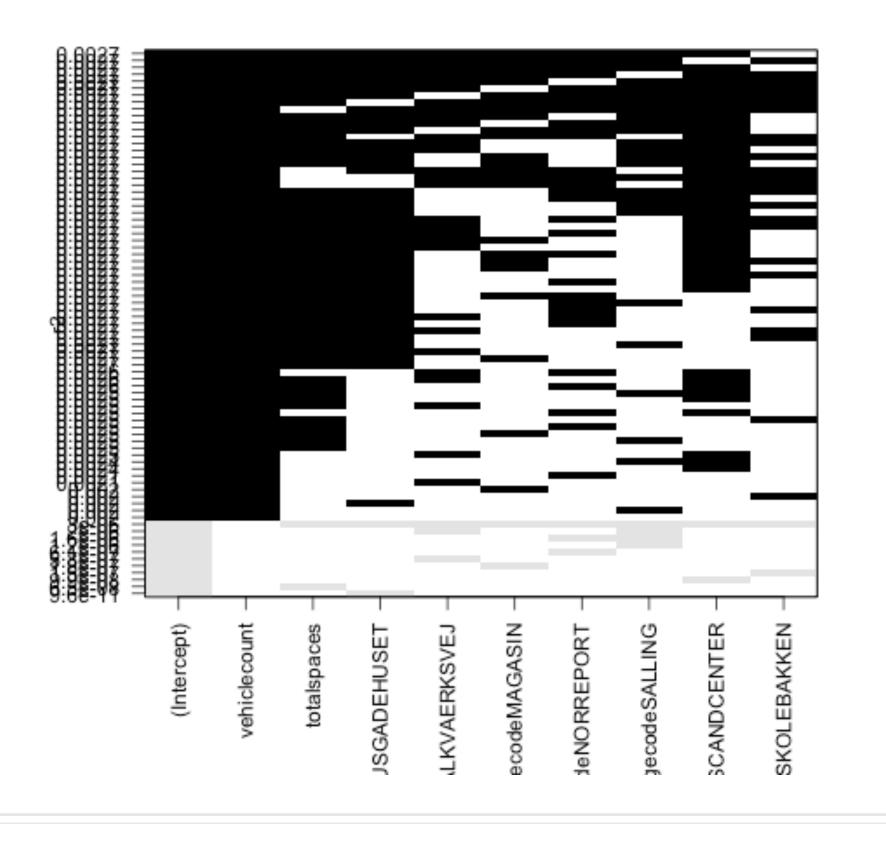
" " hn /

# Plotted the leaps model

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1 %r

2 plot(leaps,scale="r2")



# Installed the car package and got the subsets

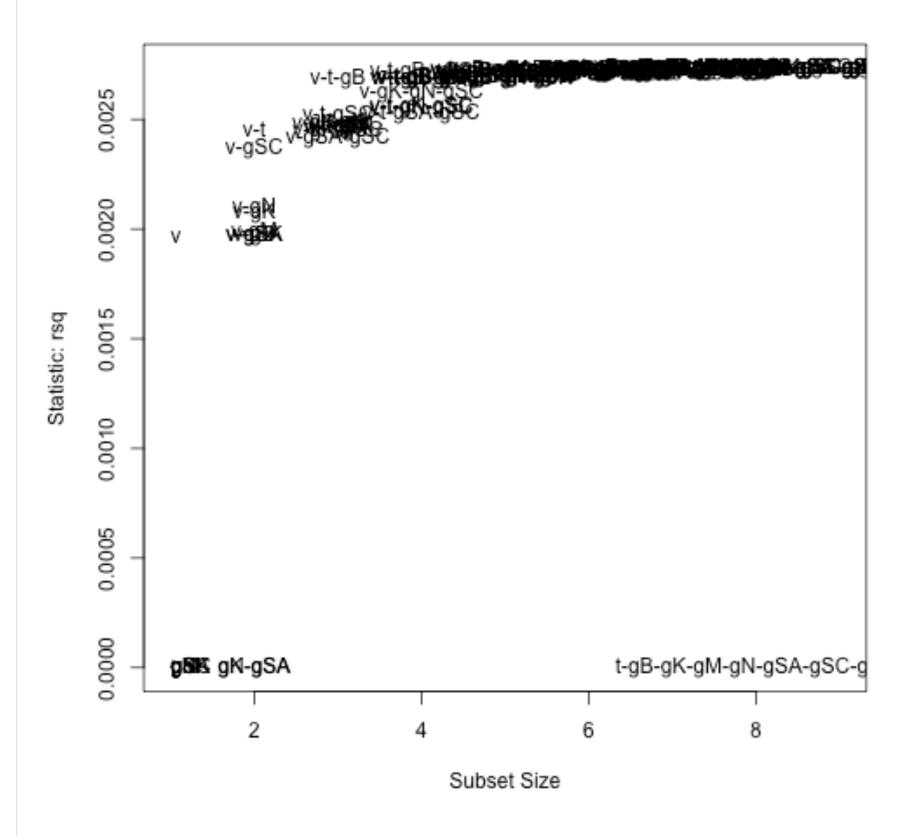
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- 1 %r
- 2 install.packages("car", repos = "http://cran.us.r-project.org")
- 3 library(car)
- 4 subsets(leaps, statistic="rsq")

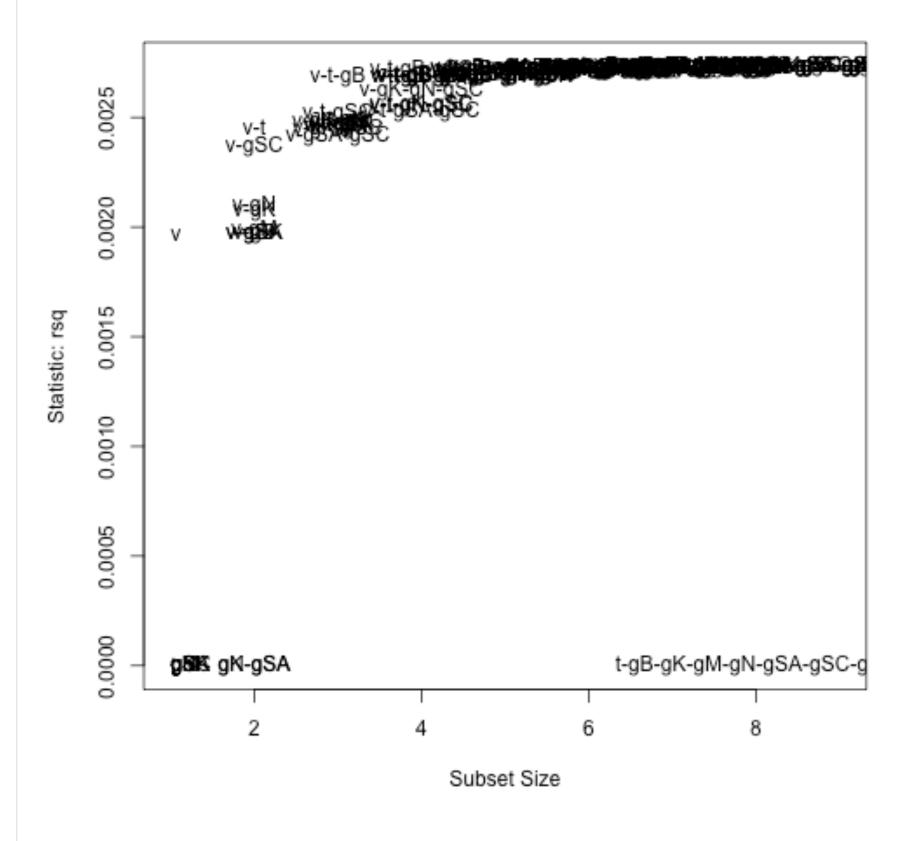
The downloaded binary packages are in

/var/folders/ll/1mpcgfrd7nlgpz03y3z75t6w0000gn/T//RtmptTl8YT/downloaded\_packages

Error in legend(if (!is.na(charmatch(legend[1], "interactive"))) locator(1) els e if (is.character(legend)) legend else if (is.numeric(legend) &&: invalid coordinate lengths



Error in legend(if (!is.na(charmatch(legend[1], "interactive"))) locator(1) els e if (is.character(legend)) legend else if (is.numeric(legend) &&: invalid coordinate lengths



# Installed the caret package

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- 1 %r
- 2 library(caret)

- 1 %r
- 2 data(aarhus\_parking)

1 %r

. . .

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2 train\_control <- trainControl(method="cv", number=10)</pre>

1 %r

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- 2 # fix the parameters of the algorithm
- 3 grid <- expand.grid(.fL=c(0), .usekernel=c(FALSE))</pre>

1 %r

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2 install.packages("klaR", repos = "http://cran.us.r-project.org")

The downloaded binary packages are in /var/folders/ll/1mpcgfrd7nlgpz03y3z75t6w0000gn/T//RtmpgvXzmi/downloaded\_packages

1 %spark.r

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2 aarhus\_parking <- read.csv("/Users/joannariascos/Desktop/algorithm/aarhus\_parking.csv'</pre>

1 %r

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- 2 colnames(aarhus\_parking)
- [1] "vehiclecount" "totalspaces" "garagecode" "ozone"

1 %r

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2 na.omit(aarhus\_parking)

1	0	65	NORREPORT	101
2	0	512	SKOLEBAKKEN	106
3	869	1240	SCANDCENTER	107
4	22	953	BRUUNS	103
5	124	130	BUSGADEHUSET	105
6	106	400	MAGASIN	106
7	115	210	KALKVAERKSVEJ	110
8	233	700	SALLING	106
9	0	65	NORREPORT	106
10	0	512	SKOLEBAKKEN	110
11	959	1240	SCANDCENTER	115
12	22	953	BRUUNS	114
13	124	130	BUSGADEHUSET	118
14	119	400	MAGASIN	113
15	121	210	KALKVAERKSVEJ	114
16	282	700	SALLING	115
17	0	65	NORREPORT	115
1 Ω	ρ	517	CKUI EBYKKENI	170

| FINISHED ト 光 国 袋 model <- train(ozone~vehiclecount, data=aarhus\_parking, trControl=train\_control, method="nl

**Error** in train.default(x, y, weights = w, ...): wrong model type for regression

READY ▷ ¾ 및 ۞