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<b>Unit Number and Title</b>	<b>12: Data Analytics</b>
Academic Year	2020
Unit Tutor	Eduardo Caro
<b>Assignment Title</b>	<b>Data Analytics: Descriptive, inference, and predictive techniques</b>
<b>Issue Date</b>	<b>January 29<sup>th</sup>, 2020</b>
Submission Date	March 27 <sup>th</sup> , 2020
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### DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

#### A. Introduction to data analytics

1. Give an example for the following terms:
  - a. Data. - Representación de un atributo o variable cuantitativa o cualitativa.
    - i. Nombres de las calles -
  - b. Information. - Datos procesados con significado.
    - i. Mapa -
  - c. Knowledge. - Integrar datos e información con experiencia para la toma de decisiones. - Inferencia.
    - i. Ruta -

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

2. Go to the web <https://www.teoalida.com/cardatabase/>, section "European Car Models", and download the "Demo/sample free" Excel database.

Please, organize the data in the following categories:

- Categorical data
  - *Nominal data*
  - *Ordinal data*
- Numerical data
  - *Discrete data*
  - *Continuous data*

**Categorical data - Cualitativos** - NO medibles - determinan modalidades

- **Nominal data** - Nominales - no Ordinales - no se pueden ordenar, no tiene sentido ordenarlas, No puedo calcular la media, Los datos son principalmente alfabéticos, son datos "etiquetados" o "nombrados" que pueden dividirse en varios grupos

*European / World classification*

*Make*

*Model*

*Country of origin*

*Country*

*American classification*

*Description*

*Pre-1990 car models*

- **Ordinal data** - Ordinales - se pueden ordenar, tiene sentido ordenarlas, tienen un orden de categorías mientras que los nominales no.

*Platform / generation number*

*Sold in Western Europe*

*Sold in North America*

*Sold in Europe*

*Sold in North America*

*Sold in India*

*Timeline included*

*Class*

**Numerical data - Cuantitativos** - medibles

- **Discrete data** - Discretos - número finito de valores enteros. - barras

*Units produced*

*Production years*

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

*Model Years (US/Canada)  
Model Years (North America)  
Units produced  
Models included (WORLD)  
Models included (EURO)  
Company Founded  
First car produced  
Last car produced  
Years produced  
Year  
models  
Number of car models by the year of launch*

- **Continuous data** - Continuos - cualquier valor real infinito dentro de un intervalo. - histogramas

## B. Descriptive Analytics

3. For the data file “*Tablet Computer Sales.txt*”, find the average number, standard deviation, variance, and interquartile range of units sold per week.

```
(base) hadoop@ubuntu-hokkaido-3568:~/R/Data$ cat Tablet_Computer_Sales.txt
Week    Units_Sold
1       88
2       44
3       60
4       56
5       70
6       91
7       54
8       60
9       48
10      35
11      49
12      44
13      61
14      68
15      82
16      71
17      50
(base) hadoop@ubuntu-hokkaido-3568:~/R/Data$ █
```

Leer el fichero

```
> TablaVentas=read.table("Tablet_Computer_Sales.txt", header=T)
```

El fichero contiene 17 pares de valores Units\_Sold y Week:

```
> length(TablaVentas[[1]])
[1] 17
```

Los nombres de los campos de los ficheros son:

```
> names(TablaVentas)
[1] "Week"    "Units_Sold"
```

La media de las unidades vendidas es:

```
> mean(TablaVentas$Units_Sold)
[1] 60.64706
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

La varianza de las unidades vendidas es:

```
> varTablaVentas$Units_Sold)  
[1] 253.8676
```

La desviación estándar de las unidades vendidas es:

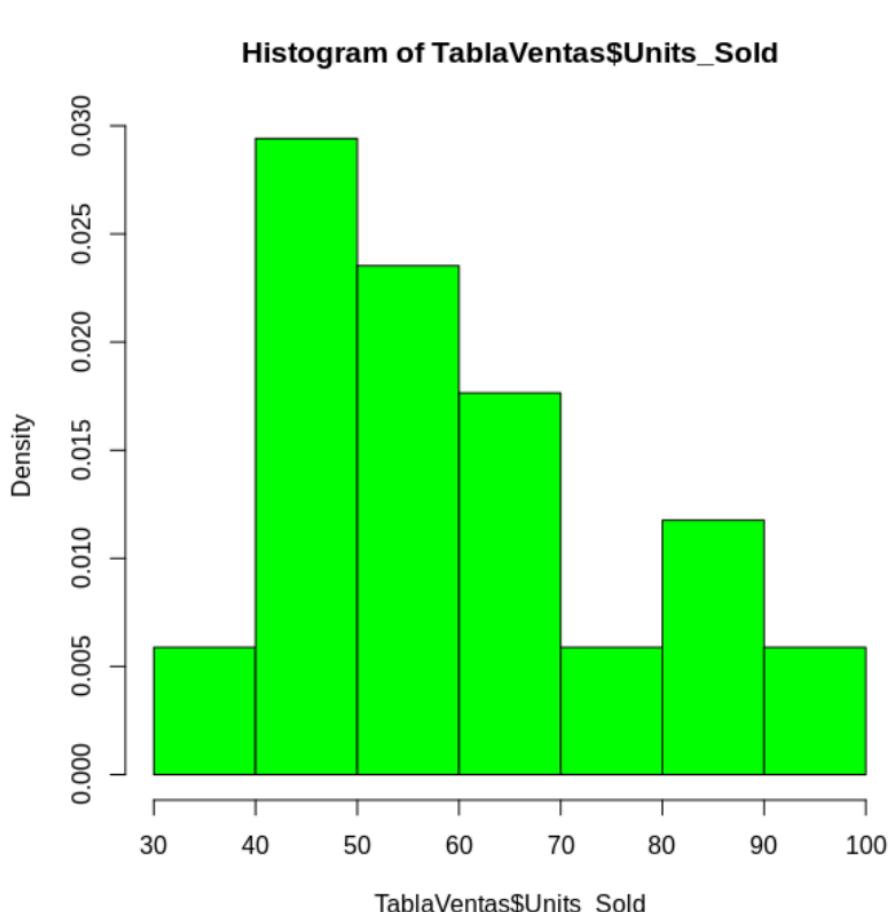
```
> sqrt(varTablaVentas$Units_Sold))  
[1] 15.93322
```

La mediana de las unidades vendidas es:

```
> medianTablaVentas$Units_Sold)  
[1] 60
```

El eje x de la gráfica nos muestra las Unidades Vendidas y en el eje y podemos ver la frecuencia relativa de estas ventas por semana.

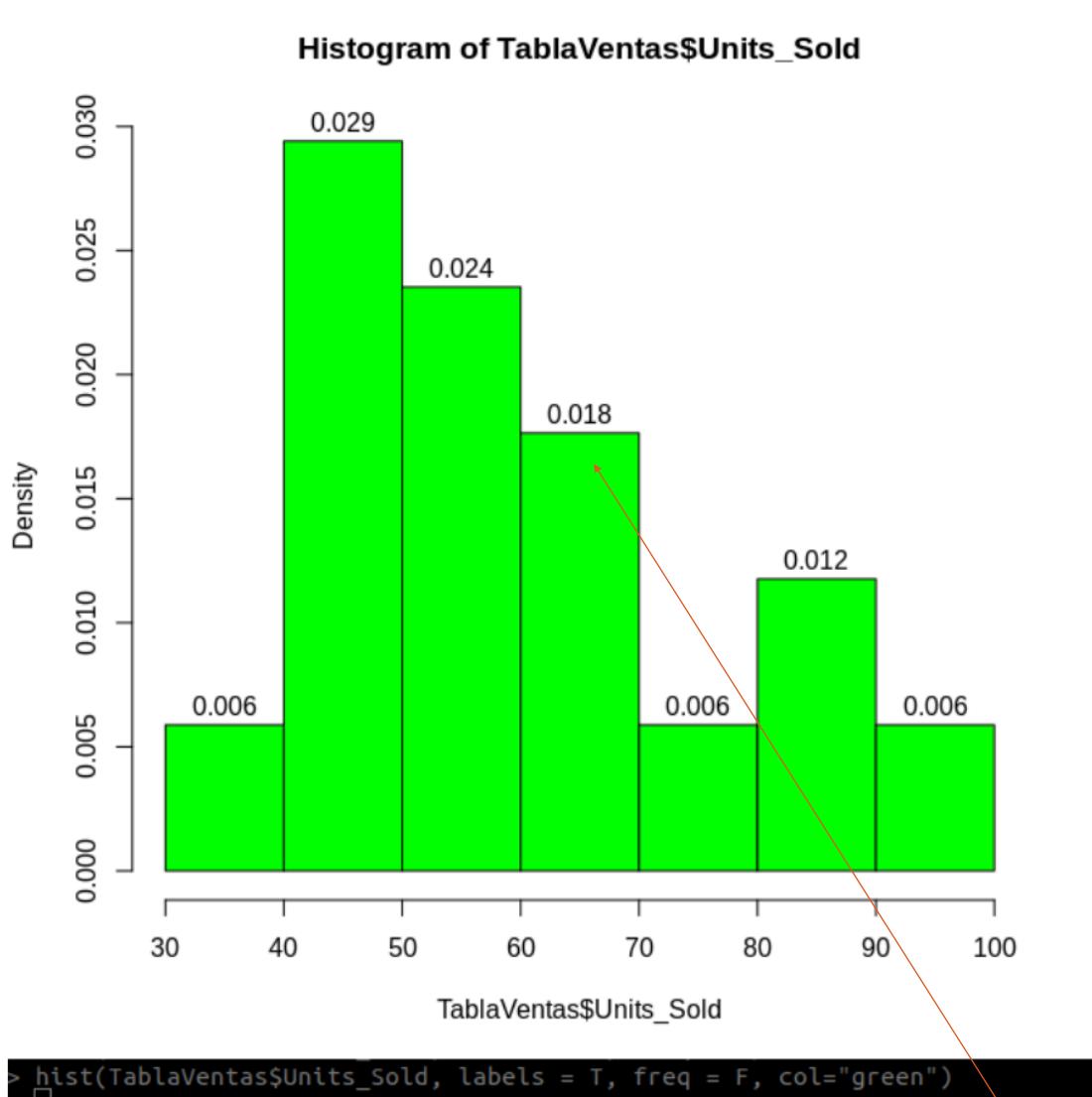
```
> histTablaVentas$Units_Sold, col = "green", freq=0)
```



```
> histTablaVentas$Units_Sold)  
> histTablaVentas$Units_Sold, col = "green")  
> histTablaVentas$Units_Sold, col = "green", freq=0)  
□
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> histTablaVentas$Units_Sold, labels = T, freq = F, col="green")
```

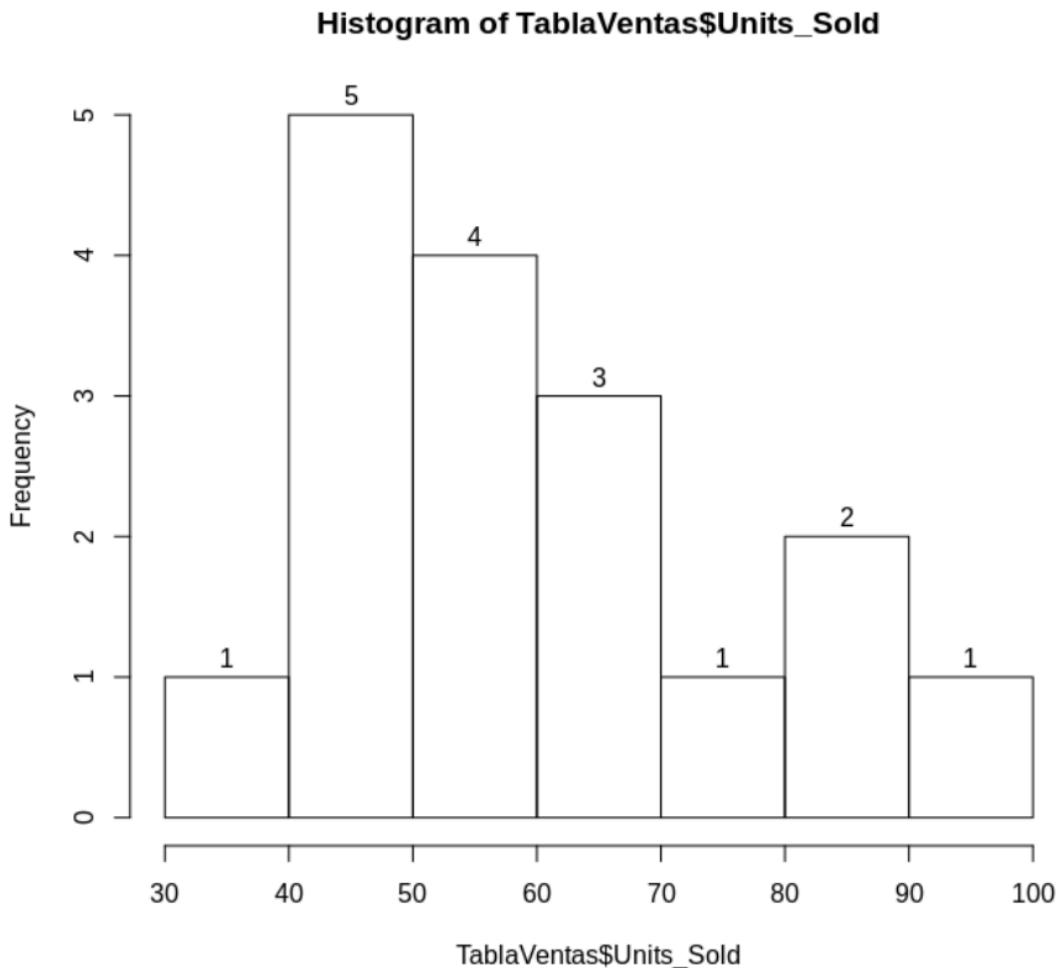


esta frecuencia se multiplica por la amplitud del rango (el ancho de la base) y nos indica que el 18% de las unidades vendidas esta entre 60 y 70.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

En el Histograma podemos ver el comportamiento de las ventas

```
> histTablaVentas$Units_Sold, labels = T)
```



```
> TablaVentas=read.table("Tablet_Computer_Sales.txt", header=T)
> histTablaVentas$Units_Sold, labels = T)
□
```

El eje x de la gráfica nos muestra las Unidades Vendidas y en el eje y podemos ver la frecuencia absoluta de estas ventas.

El 50% de las unidades vendidas están por debajo de la mediana, entre 30 y 60,  
El 50% de las unidades vendidas están por encima de la mediana, entre 60 y 100.

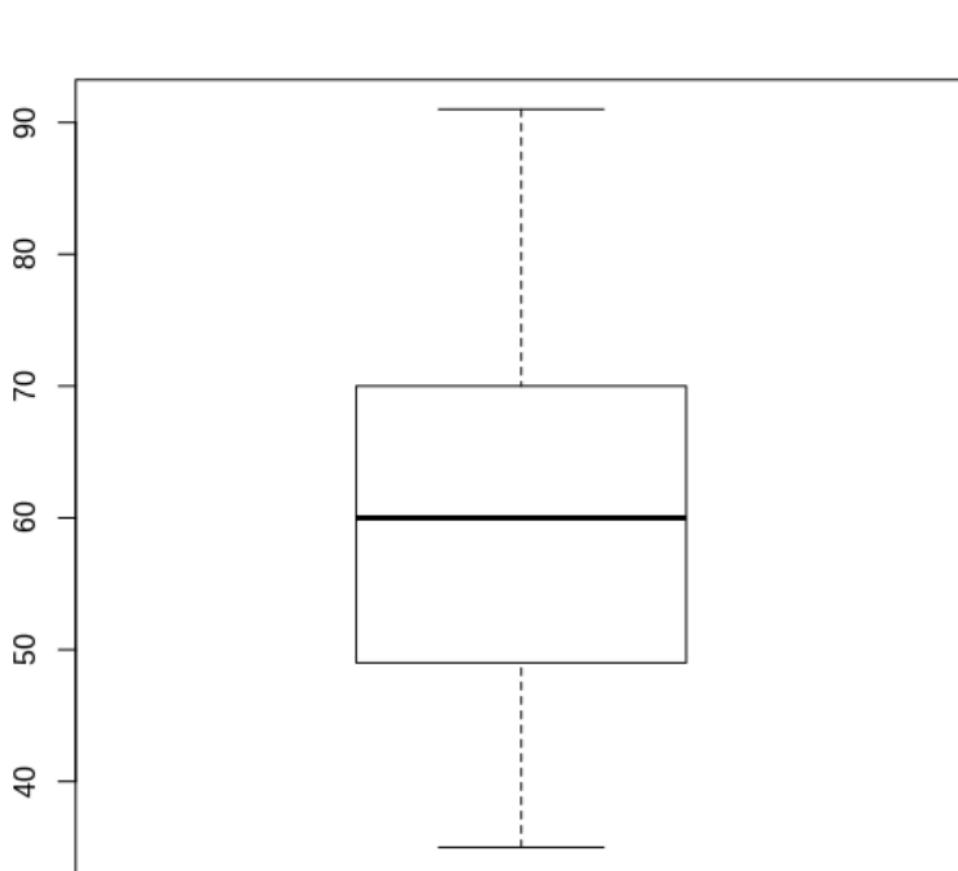
Por debajo de la mediana se han hecho  $1+5+4 = 9$  ventas, el 25%.

Por encima de la mediana se han hecho  $3+1+2+1 = 7$  ventas, el 25%

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> quantileTablaVentas$Units_Sold)
0% 25% 50% 75% 100%
Q1 60 Q3
35 49 60 70 91
```

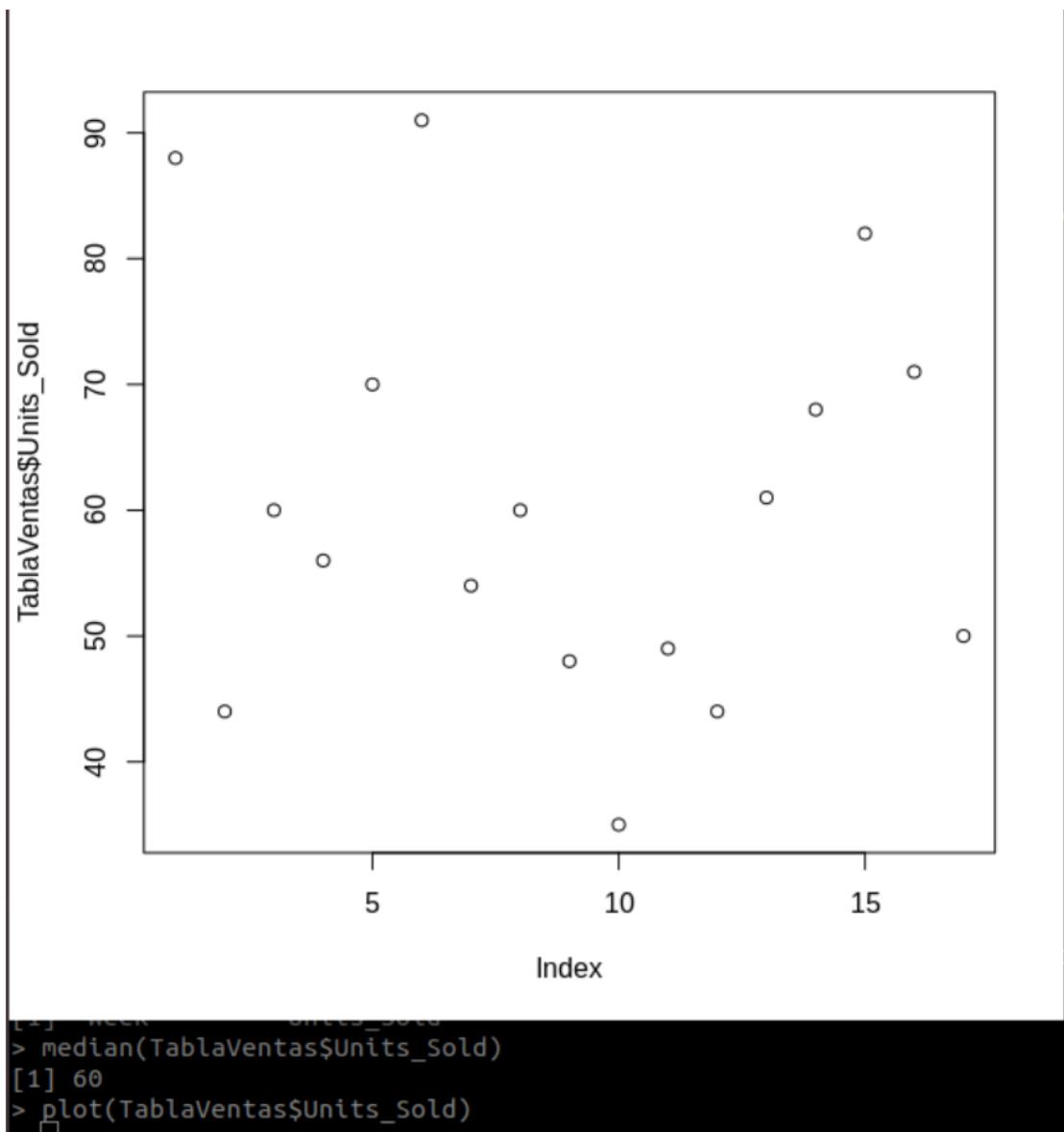
El 25% de las unidades vendidas están por debajo de el Q1= y  
El 25% de las unidades vendidas están por encima de el Q3  
La mitad de las ventas se hacen entre el Q1=50 y el Q3=70.  
El Rango InterQuartil = Q3 - Q1 = 20 que nos indica la dispersión de los datos.



```
> median(tablaVentas$Units_Sold)
[1] 60
> plot(tablaVentas$Units_Sold)
> boxplot(tablaVentas$Units_Sold)
```

No tenemos puntos atípicos.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES



## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

### C. Probability -

4. Let us define X as a random variable Gaussian-distributed with  $\mu = 4$  and  $\sigma = 3$ .
  - Compute  $P(X \leq 6)$
  - Compute  $P(3 \leq X \leq 6)$
  - Compute a such as  $P(X \leq a) = 0.85$
  - Generate 1000 random numbers distributed as X.
    - Plot a histogram with these numbers, and superimpose the theoretical density function
    - Compute the proportion of the numbers that has been generated in the interval [3, 6], and compare with the probability computed above in  $P(3 \leq X \leq 6)$
    - Check if the generated random numbers have a Gaussian distribution.

RNORM -> Crea n valores aleatorios con un mu y un sigma dado.

rnorm random de la distribución normal

rnorm(n, mean, sd)

Generate 1000 random numbers distributed as X.

```
> x = rnorm( 1000, 4, 3)
> x
[1] 9.722570951 6.211427198 2.508262913 4.139724814 4.677790110
[6] 1.230995381 1.965396672 6.488571367 3.072921287 6.790270359
[11] 8.320486977 7.315415223 9.037359923 6.458714038 6.009824193
[16] 4.607721569 4.207768344 4.719899337 2.479265433 2.602571266
[21] 5.671424456 5.444647257 3.723626253 1.837756028 2.930583570
[26] 7.917282936 3.012074310 5.188248465 8.024267729 5.421459376
[31] 3.981487017 6.361560591 4.271581798 1.243004533 1.944055671
[36] 1.530621602 2.480864685 4.240728436 1.882294691 1.337529812
[41] -1.882293641 3.585676118 6.929947789 7.849017666 0.339912836
[46] 1.983010350 2.730427892 3.896994672 5.918259763 7.162565008
[51] -0.287221541 5.187820980 3.548050820 4.830088653 3.311645221
[56] 0.915211273 3.612222944 9.842090769 4.742765099 -0.835973072
[61] 1.766909070 1.671513668 6.495753925 5.129725893 3.918217479
[66] 6.768604611 5.834482601 1.516918895 6.140512728 8.874400451
[71] 4.514966635 2.532810399 5.432233809 0.726443464 4.271291944
[76] 1.774256967 7.597992599 13.055332535 3.576914728 1.751239379
[81] 4.952006568 2.370382055 1.079241610 6.795152411 3.321105427
```

[86] -0.576366567 4.409198008 -1.238873051 -0.335542623 2.932252428  
 [91] -0.822976474 5.862416781 5.224077734 1.298535381 5.560786148  
 [96] 1.726152640 4.405386415 6.062141376 6.933085281 0.083971564  
 [101] 5.939252510 0.712851474 8.258705038 6.061144946 4.468130686  
 [106] 0.289010919 0.525983395 2.998358336 0.514076221 3.643954712  
 [111] 7.995448922 3.230590080 4.657879228 2.641335486 3.178088515  
 [116] 7.152351631 4.917588796 4.092624350 3.149892615 0.869055959  
 [121] 8.543357113 9.895700597 9.641745611 -0.903208267 1.698466801  
 [126] 3.741987027 2.600176448 8.851360217 5.114223753 3.378683645  
 [131] -5.468752355 0.219529107 4.177014481 7.445974180 1.282261997  
 [136] 6.364841480 4.158220335 2.429991719 7.112274650 1.523045448  
 [141] 0.177278636 2.817009377 3.879597499 1.458014354 8.364717483  
 [146] 2.626763080 5.992223951 1.497974660 1.471208855 2.472373746  
 [151] 2.140080913 -0.173138318 0.738701084 1.100190538 3.093848425  
 [156] 2.614752807 -1.269680625 4.113679107 0.630165691 8.225266756  
 [161] 0.390878421 1.328138590 4.312852878 4.624936995 -0.638777809  
 [166] 4.066598692 2.215765286 5.690783357 -0.910915638 4.446947131  
 [171] 0.811697070 10.765247879 1.208862971 4.663853639 6.174358129  
 [176] 5.210056644 2.756640294 5.905663114 6.637139488 -1.526801276  
 [181] 4.850419670 2.454648589 6.042974894 5.672352385 3.957725545  
 [186] 1.770495991 -0.236739938 3.628012973 3.027004404 0.254988469  
 [191] 5.506717494 1.850413858 -0.563487826 4.751301635 9.866927720  
 [196] -1.535536387 5.071618159 6.144802877 3.687932530 5.955797143  
 [201] 4.215097928 5.822850543 7.654388015 1.647258955 3.539643139  
 [206] -0.233199808 1.037190762 1.558937496 -0.686512648 3.841825701  
 [211] 2.392496050 5.991446739 8.566035726 4.111370956 4.371670295  
 [216] 8.282059268 -6.113036001 11.402304920 3.474051749 4.239006719  
 [221] -0.114112348 5.079776356 -3.809169347 7.036561787 -1.514828920  
 [226] 3.360214337 4.365131538 4.461060799 7.383020658 11.699878215  
 [231] 6.186755272 6.123775530 6.539739394 1.794553599 2.485610905  
 [236] 2.608139050 3.566808815 0.497721853 2.866089227 5.828394493  
 [241] 2.178345540 5.093038819 4.961607481 2.437286659 1.363423225  
 [246] 7.491729676 2.414379528 0.106438284 4.265413101 0.681171206  
 [251] 3.482857725 2.574357004 4.548963722 10.896553245 0.959729015  
 [256] 6.357540064 -2.745009234 6.829742809 0.721179865 6.199110413  
 [261] 3.765789212 1.705341167 0.278667849 1.696325044 4.077781824  
 [266] 3.432137284 7.761687800 3.724041081 8.545637001 9.422028957  
 [271] 5.415925932 4.638817511 8.386504230 6.678765443 1.897813242  
 [276] 3.423741539 1.793430722 2.329396411 6.039721013 2.264599874  
 [281] 7.161069995 1.220731111 1.314265577 7.696737849 12.913710838  
 [286] 7.666838966 4.385567897 -0.025855143 8.174583388 7.421116900  
 [291] 1.936413434 5.222448047 5.433769895 6.152562759 -2.393373931  
 [296] 10.550173858 -2.381103694 -0.259253982 2.798480173 2.904275533  
 [301] 1.619783402 5.069009040 5.284249074 5.996968546 4.768729185  
 [306] 7.487155127 6.990478337 0.558350666 7.996831624 9.180178705  
 [311] 1.096819799 0.708577377 3.173212465 3.401918301 1.099976911  
 [316] 1.728649864 5.812703433 0.959233117 2.754107096 10.343180638  
 [321] 6.002077412 4.806700449 5.513053738 2.441421099 4.266799649  
 [326] 6.718228634 3.976782440 7.893239060 8.171056814 5.700936398

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 [336] 0.313950185 0.139520466 -1.984582319 -0.358700320 -0.263102154  
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 [361] 4.017437234 -3.419899582 4.577251596 -0.219982295 6.666242077  
 [366] 3.754189859 9.072962750 2.681111516 5.663441872 6.332012385  
 [371] 10.220133183 5.714244418 3.474496491 3.372059874 2.454697039  
 [376] 4.194899577 5.468510852 -0.783665169 1.734988793 2.897535699  
 [381] 2.008500508 0.747606127 6.645002321 2.958695091 6.995609988  
 [386] 1.099431493 2.561533184 3.565269981 2.181268612 4.715741589  
 [391] 3.334422765 6.078309463 6.479170667 5.641301272 2.351223746  
 [396] 6.748727574 3.438648621 -0.984403643 3.258230305 3.916405463  
 [401] 6.523336276 2.742001492 4.888083652 1.221543887 5.796572221  
 [406] 2.615260506 2.020880629 8.423752873 7.753089644 3.649085955  
 [411] 2.144595410 3.583692428 3.418949356 2.614139292 8.880841274  
 [416] 3.715306563 -0.644387593 2.174673450 5.619982301 0.554610257  
 [421] 3.664605347 6.653025570 6.306438095 -3.125562697 7.915400069  
 [426] 3.681465943 0.023515992 5.496227963 1.912540843 2.301665062  
 [431] 1.425172971 6.289315635 4.137596070 8.652135426 4.357716195  
 [436] 9.688389615 11.097061609 2.177468042 6.773638776 3.236352421  
 [441] 3.424033871 -0.529310312 4.871063188 -1.641336992 4.631817378  
 [446] 9.633210482 12.245507500 4.226492924 -2.446737578 4.645199327  
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 [456] 4.631088143 3.675709009 4.379561070 3.192372357 5.061189990  
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 [466] 2.699422596 6.403515983 4.059579128 4.595158721 2.128305872  
 [471] 1.337695568 9.376709660 6.116801496 6.095803707 1.756079230  
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 [481] 7.399036990 3.916130322 4.679054670 0.979837858 4.908624780  
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 [491] 4.964946817 3.393052994 6.082636278 3.123121926 11.364334899  
 [496] 13.422952710 1.817754779 9.795658809 2.738309621 5.964871948  
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 [506] 2.785994358 -1.177333526 1.043135236 5.571551876 4.071726459  
 [511] 5.802865302 6.458471352 4.494384196 0.672108448 8.339207597  
 [516] -0.694187917 5.753471120 6.161758453 3.813362365 9.026642099  
 [521] 4.920723262 3.017662911 5.758058290 3.776638176 5.713066712  
 [526] 6.717520510 8.571852809 8.356271972 8.425171910 7.384317832  
 [531] 4.607066626 -1.833863776 2.120880818 7.261128695 4.810269152  
 [536] 2.199796221 3.540722374 1.206079789 0.586302636 0.909893323  
 [541] 5.924383252 6.127433614 7.475842428 2.671882303 1.786570889  
 [546] 3.134906336 2.636938477 7.564451876 3.783923923 7.074039609  
 [551] 0.747876358 5.029983622 3.123774359 1.567869069 3.924607543  
 [556] 1.696671031 7.280866206 0.265342285 4.240395833 5.916836214  
 [561] 2.303462153 3.203209429 7.468445875 3.684980977 5.530153561  
 [566] 4.160483592 -0.617730561 -0.559640075 0.267257765 5.437319434  
 [571] 5.829950364 1.057053985 -0.021887972 4.504516478 6.898440572

[576] 0.049168339 4.865983276 5.728722430 8.603317305 3.228644984  
 [581] 1.643562299 6.563363507 6.713575327 1.866850151 4.396785748  
 [586] 2.329852467 5.867410206 3.218018960 5.706537515 2.155291382  
 [591] 5.186967216 -4.343854430 6.875426612 3.481984436 3.245776003  
 [596] -0.619837891 3.967382207 0.785835133 2.896925374 0.447481059  
 [601] 5.388519671 7.895643684 6.050256180 6.065210797 3.538405686  
 [606] -1.980923129 3.991151349 2.560672766 2.916720680 3.200498488  
 [611] 0.987199092 0.123714759 6.870618245 -1.362221688 7.088870504  
 [616] -0.952470179 9.134490592 5.195534531 9.434308379 2.378293089  
 [621] 9.949477513 2.720707511 0.399286765 7.737786508 0.845552136  
 [626] 4.532702079 4.275943296 9.973260229 5.462484125 5.209040066  
 [631] 3.190813404 7.695102069 3.203859661 3.221599937 6.647455026  
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 [641] 9.082012558 6.879933416 6.675219604 8.247169701 6.772527837  
 [646] 3.317865782 0.172107422 6.462343934 7.089053815 12.100819190  
 [651] 1.448039004 3.427384559 7.074528827 0.752427279 3.489820925  
 [656] 4.902163835 -0.405603491 2.348873931 6.286238261 6.236264022  
 [661] 6.689746628 -2.311298212 1.150579425 1.052796893 1.666651591  
 [666] 6.484820202 2.614540236 4.447779956 1.834115823 8.222455673  
 [671] 9.478416393 11.807093745 9.066914003 6.480361868 0.331249637  
 [676] 3.116467422 1.607748409 3.011952100 6.851059334 2.288312692  
 [681] 1.318825090 3.113127101 7.149866598 6.353973581 4.041625919  
 [686] 6.540997495 5.657859450 5.784999260 4.921612570 0.569106047  
 [691] 6.899596937 8.278806612 9.418848635 4.667785765 5.010480439  
 [696] 6.849067150 2.998923418 0.194999569 0.830643034 -1.703665134  
 [701] 4.423620743 5.530128807 5.832168866 7.295113537 5.430939950  
 [706] 3.798712695 -0.659069454 5.064475439 8.981936789 3.448453669  
 [711] 5.931427932 7.547698140 -0.068651111 0.876545805 4.311691798  
 [716] 2.782839192 4.436149155 3.657116238 2.400586382 6.195525581  
 [721] 5.433768829 -0.419938931 4.776671529 6.977721657 9.252854790  
 [726] 1.188472478 8.622609738 3.676219656 2.918144141 3.462001367  
 [731] 3.192548547 4.633496694 6.686889015 2.423551924 4.858554560  
 [736] -3.826658525 2.016617221 6.294495910 0.742242710 5.513646668  
 [741] 3.682213357 2.432986208 1.714940422 8.536148499 1.727820631  
 [746] 7.400382993 6.268730238 -0.100547394 2.992598117 10.239088016  
 [751] 0.377079593 1.307163822 9.481052138 -0.610184480 3.409957928  
 [756] -0.157292930 6.301604399 4.216543625 9.533605964 8.633555938  
 [761] 6.096183524 3.638639635 0.975317044 5.125299917 7.725145457  
 [766] 2.039650909 3.473240677 -3.823699615 4.323735351 9.584445785  
 [771] 8.441958706 4.973996546 1.391446783 0.197915150 2.350267556  
 [776] 6.655826449 3.217182008 8.403025471 1.762704936 2.328387307  
 [781] -0.800270146 2.572068771 2.386047458 3.241964880 -0.366419675  
 [786] 2.256641122 2.875214488 7.341394895 -0.055212531 6.525665636  
 [791] 3.616757834 2.775267178 2.881864591 1.461219143 3.106719755  
 [796] 4.390606324 4.407141063 3.214795843 9.033697695 4.700564903  
 [801] 4.275098151 2.738830189 4.457127847 -0.201995279 7.033111677  
 [806] 6.893747737 0.298077240 0.112085491 -1.195432870 3.454119713  
 [811] 1.669384094 7.257897452 3.736462251 3.308560151 4.574995281  
 [816] 3.559881939 3.275774048 5.772927225 3.315348544 2.619204467

[821] 6.174814610 4.741439332 0.990673810 -0.609219512 2.734989995  
[826] 10.145072186 7.147153262 4.832156640 5.850977952 0.599510927  
[831] 5.947160676 0.666216323 6.676434553 -0.482537939 -1.900172763  
[836] 3.048900638 7.838839390 5.851302513 6.823795786 7.622565426  
[841] 2.155805800 4.454464392 -2.864232298 3.730787576 1.120894235  
[846] 0.104634148 -2.498893482 8.550164250 5.903829403 -0.780464293  
[851] 0.833347259 3.743421608 4.654216211 4.112404714 6.452046902  
[856] 2.115153668 3.292777150 4.460443593 5.803095809 1.986178477  
[861] 3.651534724 2.209781762 3.061074017 6.125712681 7.652292576  
[866] 5.954147369 0.641963218 -2.030439149 -0.221400731 5.813850201  
[871] 7.807039328 6.772659234 3.810651952 5.726720584 -0.127383625  
[876] 0.220868545 3.839319307 9.391743706 3.294372582 7.543433686  
[881] 6.240118606 9.815001498 4.164777359 2.643334865 4.923317586  
[886] 3.086636336 3.322454892 8.085314508 3.169242515 -0.292071627  
[891] 5.928410471 3.623712369 0.809973052 6.922605274 7.403139386  
[896] 7.094559573 5.496784410 2.855290592 2.978759222 -1.044969746  
[901] 2.410711240 3.870699755 6.478521724 1.187777273 5.772889807  
[906] 7.154531467 4.284654211 3.201363701 4.896757445 2.732244214  
[911] 7.676932284 3.289225515 2.501054648 4.199085588 8.234579629  
[916] 8.959128329 3.620792197 6.739632937 1.195287454 6.378219374  
[921] 1.169563754 -0.989844446 1.913297041 -2.248200791 3.369106795  
[926] 5.229325213 6.424564818 7.271546502 0.306133700 5.245739608  
[931] 6.541283057 0.532106227 8.508294597 9.272515031 -3.964967504  
[936] 5.908047796 0.329210230 0.851137323 4.710201587 3.689213706  
[941] 3.425921543 3.725367522 10.072711343 7.826463739 3.373082876  
[946] 2.211918808 5.076166422 1.831917174 4.838812525 1.821511528  
[951] 10.055279490 9.085432287 6.226849496 5.378771335 4.440647634  
[956] 0.898951431 8.990225899 8.137731194 10.412555275 1.548484348  
[961] 6.427600105 3.785829083 3.665892064 3.483239993 8.124939878  
[966] 8.236620858 4.214459737 5.700270755 6.415499418 6.353337432  
[971] 9.115362245 4.316094520 5.997749778 5.719000083 8.863206817  
[976] 5.727793109 3.708372726 2.664170473 1.084940086 -0.424586902  
[981] 2.033561889 2.115813583 4.310248773 1.551119406 4.185972246  
[986] 2.867766666 3.386759483 -1.161971444 6.829082800 4.699670773  
[991] 3.621348788 6.557779893 2.022140773 7.489283598 10.234863323  
[996] -0.466739909 8.887104089 4.004537421 6.949013300 2.850796691

`pnorm` —> Calcula la probabilidad - AREA - dando un mu y un sigma - sólo calcula las areas a la izquierda

- Compute  $P(X \leq 6)$

`pnorm(6, 4, 3) = 0.7475`

- Compute  $P(3 \leq X \leq 6)$

`pnorm(6, 4, 3) = 0.7475`

`pnorm(3, 4, 3) = 0.3694`

`pnorm(6, 4, 3) - pnorm(3, 4, 3) = 0.7475 - 0.3694 = 0.3780`

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- Compute a such as  $P(X \leq a) = 0.85$

`qnorm` —> devuelve la altura de la curva, con un mu= 4 y un sigma = 3.

`qnorm(0.85,4,3) = 7.1093` —> por tanto el 0,85% de los números están por debajo de 7.1093

Plot a histogram with these numbers, and superimpose the theoretical density function -

- Compute the proportion of the numbers that has been generated in the interval [3, 6], and compare with the probability computed above in  $P(3 \leq X \leq 6)$

`pnorm` —> me devuelve p; la probabilidad

`pnorm(1000, 4, 3) = 1` —> Teorico

Partiendo de que la muestra es de 1000 datos y sabiendo que se trata de una distribución normal...

Calculo la suma de los números que son mayores ó iguales a 3 de la muestra x

`> sum(x >= 3)`

`[1] 646`

Calculo la suma de los números menores ó iguales a 6 de la muestra x

`> sum(x <= 6)`

`[1] 732`

Saco la diferencia y lo divido entre la muestra 1000 y tenemos una probabilidad de:

**732 - 368 = 364**

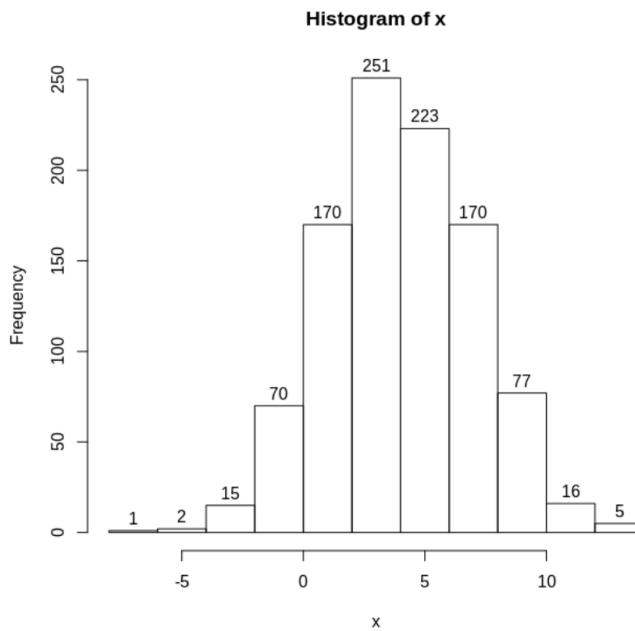
**364/1000 = 0,364**

Al realizar la comparación obtenida del calculo de los random de la variable Gaussian-distributed nos damos cuenta que la variación de la probabilidad es mínima.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

Este histograma tiene una distribución normal “Experimental”, —> tomando todos los x generados. (el histograma representa la curva de la muestra).

```
> hist(x, labels=T, freq=F)
```



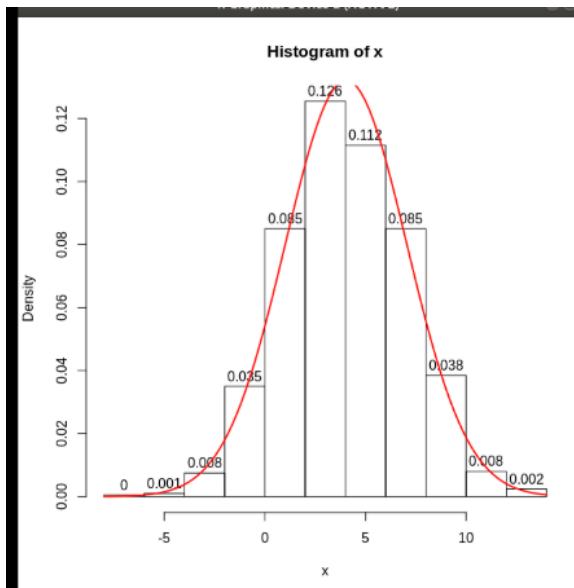
```
> hlst(x)
> hist(x, labels = T)
> }
```

Check if the generated random numbers have a Gaussian distribution.

```
> media = mean(x) # calculo la media de x
```

```
> desv = sd(x) # calculo la desviación típica de x
```

```
> curve(dnorm(x,media, desv), add = T, col = "red", lwd = 2) # superpongo la función de la densidad, previamente calculada la media y la desviación típica.
```



## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

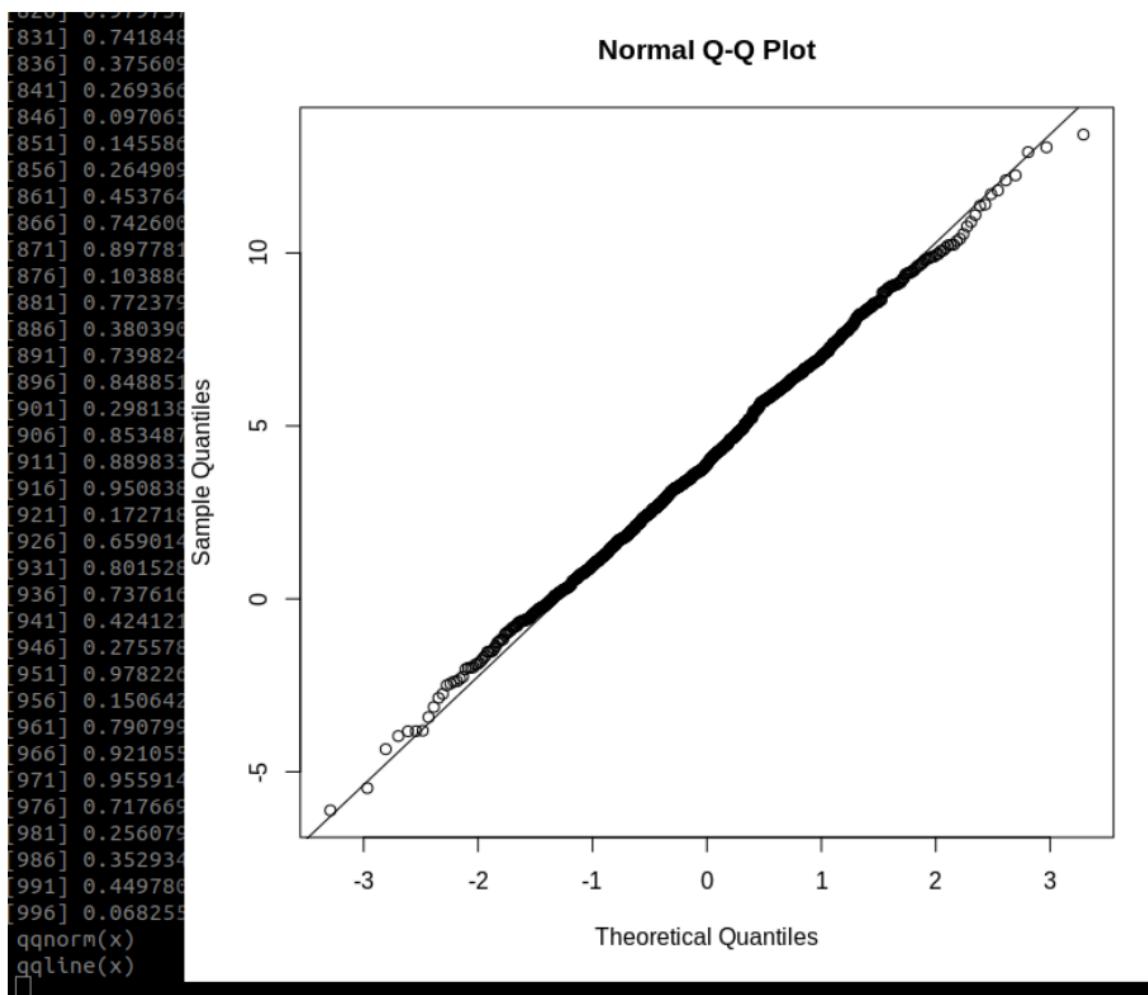
De esta manera defino de forma unívoca la distribución normal.

Curve me genera una gráfica de la función distribución de la distribución normal (**Teórica con infinitos datos..**), en función de  $x$ , con la media y desviación calculadas previamente.

Con el Q-QPlot —> Quantile-Quantile Plots - podemos ver gráficamente por medio de `qqnorm` y `qqline`.

Aquí podemos comprobar que las observaciones siguen una distribución normal siempre que los puntos de la gráfica de la distribución real “siguen” bastante bien la línea de la gráfica de la distribución teórica.

```
> qqnorm(x) # calculo de qq normal para x - distribución real  
> qqline(x) # adiciona la qqline al plot - distribución teórica
```



## D. Inference

5. Some studies suggest that there is a relationship between the cheese's flavour and their chemical composition, especially with the lactic acid content.

The lactic acid content has been measured in ten cheeses, resulting the following values:

0.86, 1.53, 1.57, 1.81, 0.99, 1.09, 1.29, 1.78, 1.29, 1.58

Assuming that the lactic acid content can be modelled as a Gaussian distributed random variable:

- Estimate a value for the mean  $\mu$  and variance  $\sigma^2$
- Compute a confidence interval for the mean  $\mu$  ( $\alpha = 0.05$ )
- Compute a confidence interval for the variance  $\sigma^2$  ( $\alpha = 0.05$ )
- Solve the following hypothesis test ( $\alpha = 0.05$ ):

$$H_0 : \mu = 1$$

$$H_1 : \mu \neq 1$$

- Estimate a value for the mean  $\mu$  and variance  $\sigma^2$

```
> acidL # lactic acid
```

```
> acidL = c( 0.86, 1.53, 1.57, 1.81, 0.99, 1.09, 1.29, 1.78, 1.29, 1.58 )
```

```
> acidL
[1] 0.86 1.53 1.57 1.81 0.99 1.09 1.29 1.78 1.29 1.58
```

```
> summary (acidL)
Min. 1st Qu. Median Mean 3rd Qu. Max.
0.860 1.140 1.410 1.379 1.577 1.810
```

<code>&gt; var (acidL)</code>	<code>&gt; sd( acidL )</code>	<code>&gt; sd( acidL ) ^2</code>	<code>&gt; sqrt(var(acidL))</code>
[1] 0.1073656	[1] 0.3276668	[1] 0.1073656	[1] 0.3276668

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> media = mean(acidL)
```

```
> media
```

```
[1] 1.379
```

```
> desv = sd(acidL)
```

```
> desv
```

```
[1] 0.3276668
```

```
> var ( acidL )
```

```
[1] 0.1073656
```

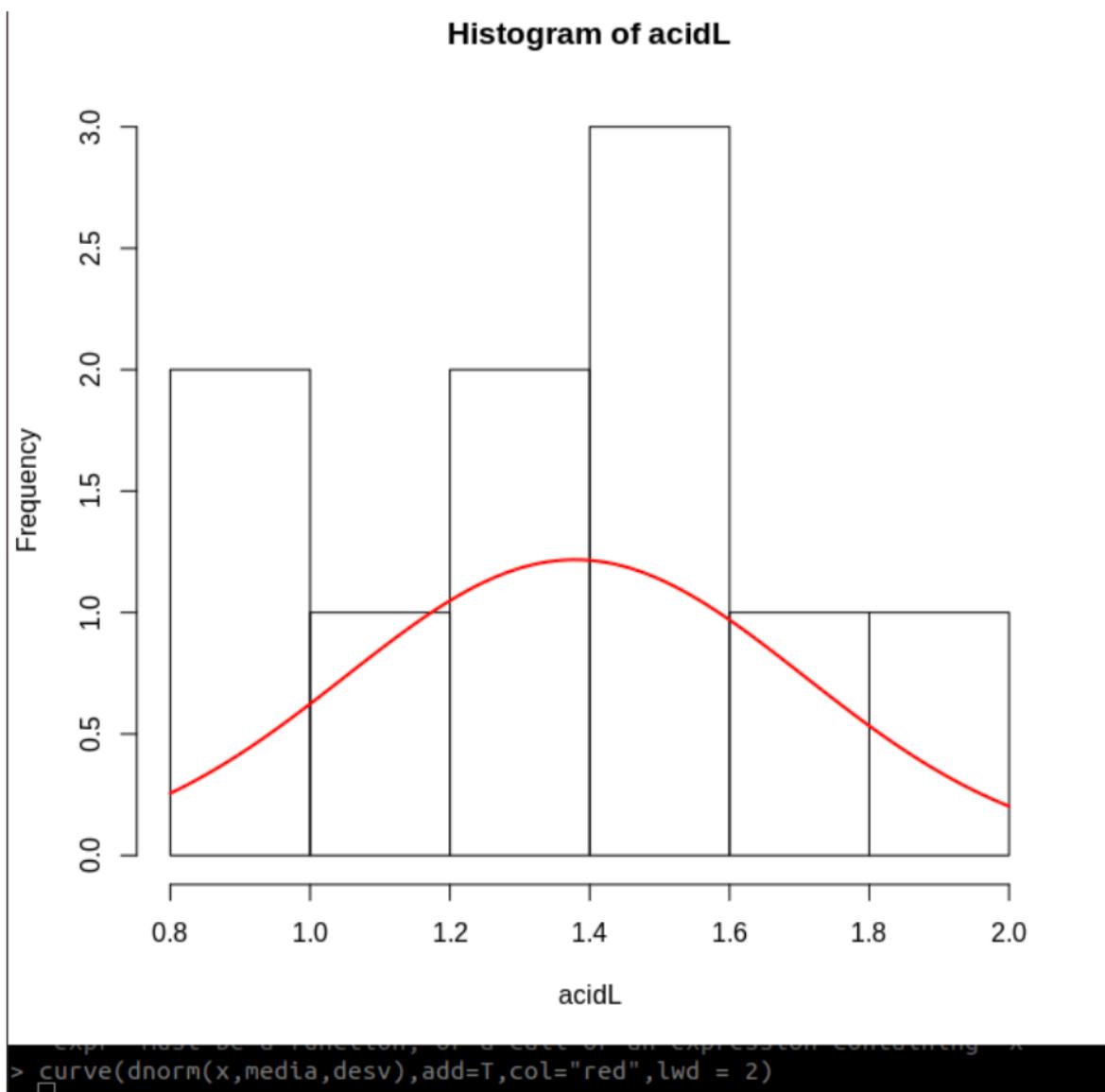
```
> n = length(acidL)
```

```
> n
```

```
[1] 10
```

```
> hist( acidL ) —> curva de la muestra
```

```
> curve( dnorm ( x, media, desv ), add=T, col="red", lwd = 2 ) —> curva de la distribución  
normal
```



## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- Compute a confidence interval for the mean  $\mu$  ( $\alpha = 0.05$ )

$$IC(\mu) = \bar{x} \pm \hat{s} \cdot t_{n-1} \cdot \frac{1}{\sqrt{n}}$$

> # Intervalo de confianza de la media con un 90% es:

```
media + desv * (tstudent(0.05), (n-1)) * (1 / sqrt(n))
media - desv * (tstudent(0.05), (n-1)) * (1 / sqrt(n))
```

```
> media-desv*qt(0.05,n-1)/sqrt(n)
[1] 1.568942
```

```
> media+desv*qt(0.05,n-1)/sqrt(n)
[1] 1.189058
```

```
> 1.568942-1.189058
[1] 0.379884
```

Con un **90%** de confianza puedo afirmar que la media del acidL está entre el **1.568942-1.189058**, con una precisión aproximada de: **0.379884**.

**Sé que entre 1.568942-1.189058 está la media del acidL # lactic acid, con una precisión aproximada de 0.379884.**

- Compute a confidence interval for the variance  $\sigma^2$  ( $\alpha = 0.05$ )

$$IC(\sigma^2) = \left( \frac{(n-1)\hat{s}^2}{\chi^2_{\alpha}}, \frac{(n-1)\hat{s}^2}{\chi^2_{\alpha}} \right)$$

> # Intervalo de confianza para la varianza

```
(n-1) * desv ^ 2 / qchisq(1-0.05, n-1)
(n-1) * desv ^ 2 / qchisq(0.05, n-1)
```

```
> (n-1) * desv ^ 2 / qchisq(1 - 0.05, n-1)
[1] 0.05711279
```

```
> (n-1) * desv ^ 2 / qchisq(0.05, n-1)
[1] 0.2906037
```

Con un **90%** de confianza puedo afirmar que la  $\sigma$  del acidL está entre **1.44601 y 1.613399**

Con un **90%** de confianza puedo afirmar que ( $\sigma$ ), esta entre estos valores

Límite de las (X).

```
> Xa = qchisq(0.05 , n-1)
```

```
> Xa
```

```
[1] 3.325113
```

```
> Xb = qchisq(1 - 0.05 , n-1)
```

```
> Xb
```

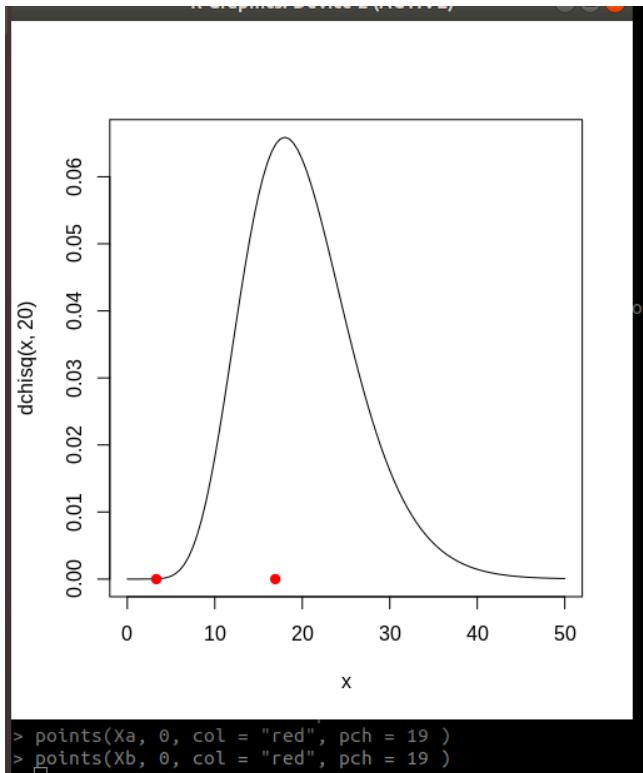
```
[1] 1.613399
```

```
> (n-1) * desv ^ 2 / Xb
```

```
[1] 0.05711279
```

```
> (n-1) * desv ^ 2 / Xa
```

```
[1] 0.2906037
```



```
> curve(dchisq (x, 20) , xlim = c(0, 50))
```

```
> points (qchisq(1 - 0.05,5) , 0, col = “red” , pch = 19)
```

```
> points (qchisq(0.05,5) , 0, col = “red” , pch = 19)
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- Solve the following hypothesis test ( $\alpha = 0.05$ ):

$$H_0 : \mu = 1$$

$$H_1 : \mu \neq 1$$

Queremos comprobar que la  $\mu = 1$  ó es diferente de 1.

Seguramente para cualquier muestra que seleccione.., la  $\mu$  va a estar a la derecha ó a la izquierda de este valor. - Por lo tanto es un Contraste Bilateral, ya que tiene una región de rechazo. RRH0 a cada lado, estas serán las regiones en las que puedo decir que  $\mu$  no es igual a 1.

Es decir, si **H0 :  $\mu = 1$** , y suponiendo que esto es cierto, entonces siempre va a dar una  $1 < \mu < 1$ ; por tanto **H1:  $\mu \neq 1$** .

Si  $\alpha = 0.05$ , entonces se establece un límite

de 90% para el cual  **$\mu = 1$**

Si quiero saber si  **$\mu \neq 1$**

> **t.test(acidL)  $\mu = 0$  —> default de R**

One Sample t-test

data: acidL

$t = 13.309$ , df = 9, **p-value = 3.174e-07**

alternative hypothesis: true mean is not equal to 0

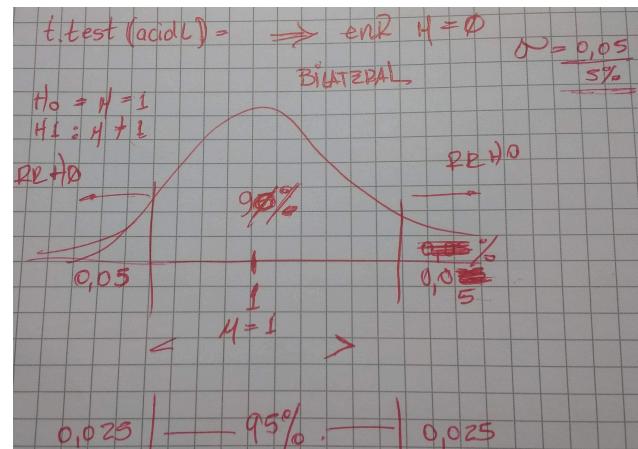
95 percent confidence interval:

1.144601 1.613399

sample estimates:

mean of x

1.379



> **t.test(acidL, mu = 1, conf.level = 0.90, alternative = "two.sided") =>  $\mu = 1$**

One Sample t-test

data: acidL

$t = 3.6577$ , df = 9, **p-value = 0.005254 < 0.05** => p-value <  $\alpha$  => **rechazo H0**

alternative hypothesis: true mean is not equal to 1

95 percent confidence interval:

1.144601 1.613399

sample estimates:

mean of x

1.379

Con un **90 %** de confianza puedo decir que  **$\mu \neq 1$  porque p-valor es menor que  $\alpha$** , No tengo evidencias suficientes como para decir que  **$\mu = 1$** .

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

6. A laboratory is analysing the performance of two chemical formulas. The results for both types are the following:

A: 0.0105 0.0145 0.1060 0.0130 0.0156 0.0104

B: 0.0222 0.0245 0.0320 0.015

Assuming that each of the previous formula values

are independent Gaussian-distributed random variables:

- Test if there is a significative difference between the means. ( $\alpha=0.05$ )
- Test if there is a significative difference between the variances. ( $\alpha=0.05$ )
- **Test if there is a significative difference between the means.**  
**( $\alpha=0.05$ )**

Definición del modelo de distribución de probabilidad: Hipótesis Parámetros

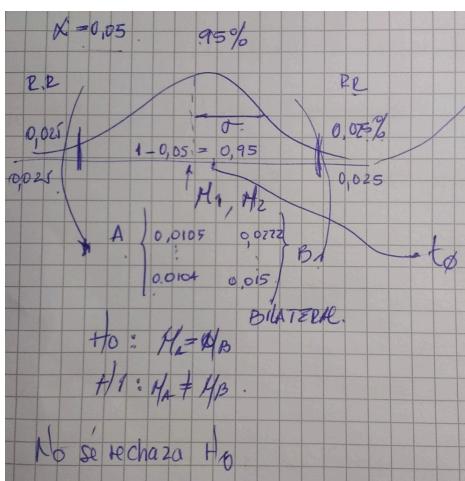
Estimación de los parámetros

Diagnosis de las hipótesis

Aplicación

A: 0.0105 0.0145 0.1060 0.0130 0.0156 0.0104

B: 0.0222 0.0245 0.0320 0.015



```
> A = c(0.0105,0.0145,0.1060,0.0130,0.0156,0.0104)
```

```
> B = c(0.0222,0.0245,0.0320,0.015)
```

```
> A
```

```
[1] 0.0105 0.0145 0.1060 0.0130 0.0156 0.0104
```

```
> B
```

```
[1] 0.0222 0.0245 0.0320 0.0150
```

```
> nA = length(A)
```

```
> nB = length(B)
```

$$H_0: \mu_1 = \mu_2$$

```
> nA
```

$$H_1: \mu_1 \neq \mu_2$$

```
[1] 6
```

```
> nB
```

```
[1] 4
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> summary (A)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.01040 0.01112 0.01375 0.02833 0.01533 0.10600
> summary (B)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.01500 0.02040 0.02335 0.02343 0.02637 0.03200
```

Utilizando la formula de la Varianza Residual tenemos:

$$\hat{S}_R^2 = \frac{(n_A - 1) \hat{S}_A^2 + (n_B - 1) \hat{S}_B^2}{n_A + n_B - 2}$$

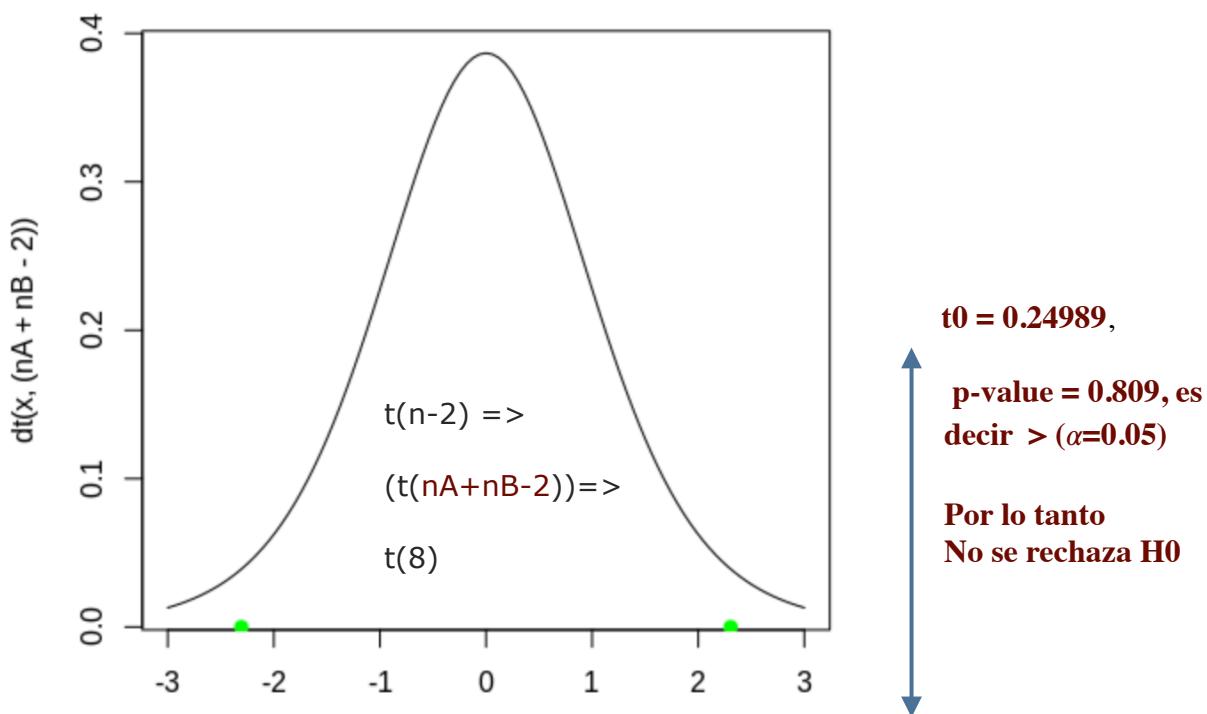
```
> mediaA = mean(A)
> mediaB = mean(B)
> varA = var(A)
> varA
[1] 0.001452071
> varB = var(B)
> varB
[1] 4.905583e-05
> numerador = (nA - 1) * varA + (nB - 1) * varB
> denominador = nA + nB - 2
> denominador
[1] 8
> ResiVar = numerador / denominador
> ResiVar = sqrt( numerador / denominador )
> ResiVar
[1] 0.0009259401
```

$$t_0 = \frac{\bar{y}_{1\bullet} - \bar{y}_{2\bullet}}{\hat{S}_R \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \rightarrow t_{n-2}$$

```
> numeradort0 = mediaA - mediaB
> denominadort0 = sqrt(ResiVar) * sqrt( 1/nA + 1/nB )
> t0 = numeradort0 / denominadort0
> t0
[1] 0.2498896
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> curve(dt(x, (nA+nB-2)), xlim = c(-3, 3))
> points(qt(0.975, (nA+nB-2)), 0, col = 'green', pch = 19)
> points(qt(0.025, (nA+nB-2)), 0, col = 'green', pch = 19)
```



Está dentro de la zona de aceptación muy cerca a 0 por lo tanto puedo

dicho que  $H_0$  es cierto y que no hay diferencias significativas.

En R lo haríamos con la función `t.test`:

```
> t.test(A, B, var.equal = T)
```

Two Sample t-test

```
data: A and B
t = 0.24989, df = 8, p-value = 0.809 > (alpha=0.05)
alternative hypothesis: true difference in means is not
equal to 0
95 percent confidence interval:
-0.04038621 0.05020288
sample estimates:
mean of x mean of y
0.02833333 0.02342500
```

Las dos muestras

Contraste de la t-student

- $t$  = donde está posicionado el estadístico
- $df$  = grados de libertad
- $p\text{-value}$  = seguridad para aceptar ó rechazar Hipótesis

hipótesis alternativa: indica que es bilateral

Intervalo de confianza: 95 % que → la diferencia de las muestras está entre -0.04038621 y -0.05020288

sample estimates: medias estimadas

mean of x mean of y

0.02833333 0.02342500

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- **Test if there is a significative difference between the variances.**
- ( $\alpha=0.05$ )**

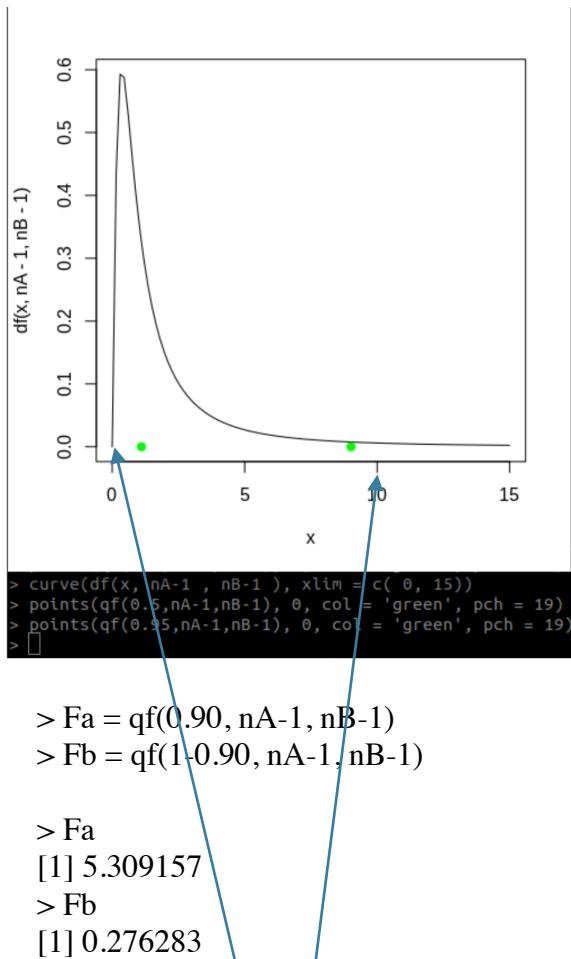
```
> A = c(0.0105,0.0145,0.1060,0.0130,0.0156,0.0104)
> B = c(0.0222,0.0245,0.0320,0.015)
```

Puede ser que aunque las medias son iguales, pero que las dispersiones de una ú otra son significativamente diferente.

Si  $H_0$  es cierto => Siguen una distribución **F de Fisher-Snedecor**.

Si  $H_0$  es cierto podemos decir que

La región de aceptación estará en el medio de la distribución.



```
> curve(df(x, nA-1 , nB-1 ), xlim = c( 0, 15))
> points(qf(0.5,nA-1,nB-1), 0, col = 'green', pch = 19)
> points(qf(0.95,nA-1,nB-1), 0, col = 'green', pch = 19)
```

```
> Fa = qf(0.90, nB-1, nA-1)
> Fb = qf(1-0.90, nB-1, nA-1)
```

```
> Fa
[1] 3.619477
> Fb
[1] 0.1883538
```

Si las varianzas son diferentes el valor  $qf$  va a estar fuera de la región delimitada por  $F_a$  y  $F_b$

Si  $H_0$  es cierto, la región de aceptación estará en el medio de la distribución.

```
> nA = length(A)
> nA
[1] 6
> nB = length(B)
> nB
[1] 4
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

En R podemos hacerlo de la siguiente manera:

```
> A = c(0.0105,0.0145,0.1060,0.0130,0.0156,0.0104)
> B = c(0.0222,0.0245,0.0320,0.015)
> mediaA = mean(A)
> varA = var(A)
> varB = var(B)
> mediaB = mean(B)
> qf(0.90, nB, nA)
[1] 3.180763
> varA / varB
[1] 29.60037
> varB / varA
[1] 0.03378336
>
```

**p-value < α => Rechazo H<sub>0</sub>**

**No quiere decir que estoy demostrando H<sub>1</sub>,**

Quiere decir que **NO** tengo evidencias suficientes como para demostrar lo contrario.

```
>
> var.test(A, B)
```

F test to compare two variances

data: A and B

**F = 29.6**, num df = 5, denom df = 3, **p-value = 0.01868**

alternative hypothesis: true ratio of variances is not equal to 1

95 percent confidence interval:

1.988627 229.805097

sample estimates:

ratio of variances

29.60037

```
> var.test(B, A)
```

F test to compare two variances

data: B and A

**F = 0.033783**, num df = 3, denom df = 5, **p-value = 0.01868**

alternative hypothesis: true ratio of variances is not equal to 1

95 percent confidence interval:

0.004351514 0.502859406

sample estimates:

ratio of variances

**0.03378336**

95 percent confidence interval:

0.1679171 8.5756582

sample estimates:

ratio of variances

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

7. Using the data file "Facebook\_Survey.txt", determine if the mean number of hours spent online per week is the same for males as it is for females.

```
> facebook = read.table('Facebook_survey.txt', header = T)
```

```
> facebook
```

	Student	Gender	Hours_week	Friends
1	1	female	4	150
2	2	female	10	400
3	3	male	7	120
4	4	male	15	500
5	5	female	9	260
6	6	female	5	70
7	7	female	7	90
8	8	male	5	250
9	9	female	12	110
10	10	female	2	30
11	11	female	6	80
12	12	female	2	30
13	13	male	3	200
14	14	female	6	240
15	15	male	6	150
16	16	male	4	90
17	17	female	8	340
18	18	male	10	450
19	19	female	4	50
20	20	male	4	120
21	21	male	6	180
22	22	female	4	280
23	23	female	5	60
24	24	female	9	100
25	25	female	12	380
26	26	male	8	430
27	27	female	2	80
28	28	female	7	170
29	29	male	6	90
30	30	male	4	50
31	31	female	2	50
32	32	male	5	70
33	33	female	7	170

```
> names(facebook)
[1] "Student"    "Gender"     "Hours_week"  "Friends"
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> summary(facebook)
  Student   Gender   Hours_week   Friends
Min. : 1 female:20 Min. :2.000  Min. :30
1st Qu.: 9 male :13 1st Qu.:4.000  1st Qu.:80
Median :17          Median :6.000  Median :120
Mean  :17          Mean  :6.242  Mean  :177
3rd Qu.:25          3rd Qu.:8.000  3rd Qu.:250
Max.  :33          Max. :15.000  Max. :500

> length(facebook)
[1] 4 --> columns
> lf = length(facebook[[1]])
> lf
[1] 33 --> registros

> names(facebook)
[1] "Student"    "Gender"     "Hours_week"  "Friends"
> facebook$Gender
[1] female female male  male  female female female male  female female
[11] female female male  female male  male  female male  female male
[21] male  female female female male  female female male  male
[31] female male  female
Levels: female male

> facebook$Gender == "female"
[1] TRUE TRUE FALSE FALSE TRUE TRUE TRUE FALSE TRUE TRUE TRUE
TRUE
[13] FALSE TRUE FALSE FALSE TRUE FALSE TRUE FALSE FALSE TRUE TRUE
TRUE
[25] TRUE FALSE TRUE TRUE FALSE FALSE TRUE FALSE TRUE

> facebook$Hours_week
[1] 4 10 7 15 9 5 7 5 12 2 6 2 3 6 6 4 8 10 4 4 6 4 5 9 12
[26] 8 2 7 6 4 2 5 7

> F = facebook$Hours_week [facebook$Gender == "female"]
> nF = length(F)
> nF
[1] 20
> mediaF = mean(F)
> mediaF
[1] 6.15
> varF = var(F)
> varF
[1] 10.02895
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> M = facebook$Hours_week [facebook$Gender == "male"]
> varM = var(M)
> varM
[1] 10.25641
> mediaM = mean(M)
> mediaM
[1] 6.384615
> nM = length(M)
> nM
[1] 13
```

$$\hat{S}_R^2 = \frac{(n_A - 1) \hat{S}_A^2 + (n_B - 1) \hat{S}_B^2}{n_A + n_B - 2}$$

```
> numerador = (nF - 1) * varF + (nM - 1) * varM
> denominador = nF + nM - 2
> ResiVar = sqrt ( numerador / denominador )
> ResiVar
[1] 3.180723
```

$$t_0 = \frac{\bar{y}_{1\bullet} - \bar{y}_{2\bullet}}{\hat{S}_R \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \rightarrow t_{n-2}$$

```
> numeradort0 = mediaF - mediaM
> denominadort0 = sqrt(ResiVar) * sqrt ( 1/nF + 1/nM )
> t0 = numeradort0 / denominadort0
> t0
[1] -0.3692524
```

**> t.test(F,M)**

Welch Two Sample t-test

data: F and M  
**t = -0.20654**, df = 25.576, **p-value = 0.838 > α => Acepto H0**  
 alternative hypothesis: true difference in means is not equal to 0  
 95 percent confidence interval:  
 -2.571496 2.102266  
 sample estimates:  
 mean of x mean of y  
 6.150000 6.384615

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

> t.test(M,F)

Welch Two Sample t-test

data: M and F

**t = 0.20654, df = 25.576, p-value = 0.838 >  $\alpha$  => Acepto H0**

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

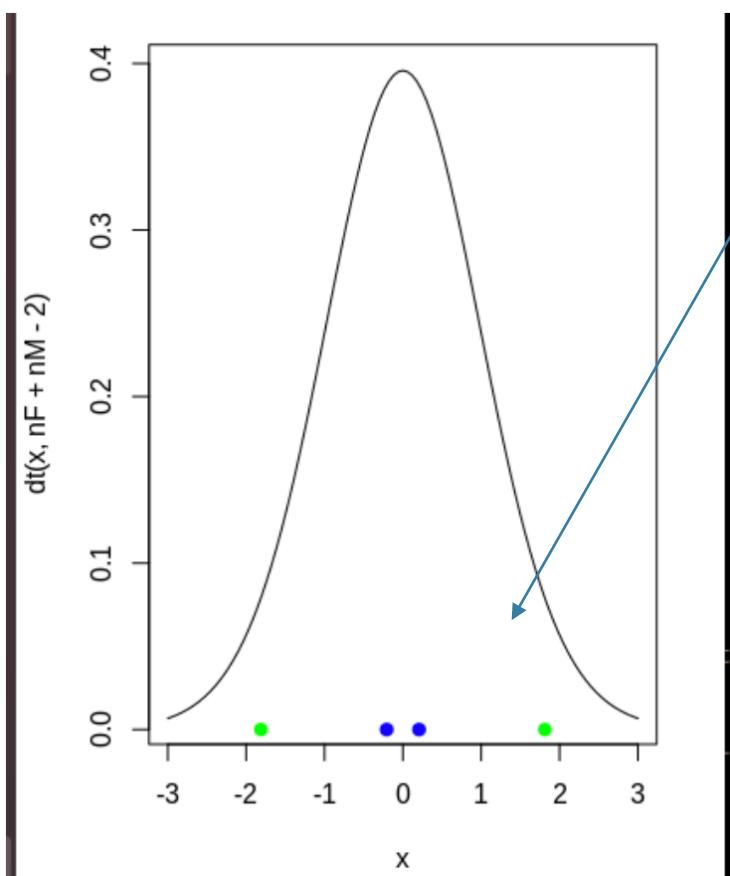
-2.102266 2.571496

sample estimates:

mean of x mean of y

6.384615 6.150000

```
> curve(dt(x,nF+nM-2), xlim= c(-3,3))
> points(qt(0.05,10), 0, col='green',pch=19)
> points(qt(0.95,10), 0, col='green',pch=19)
> points(-0.20654, 0, col='blue', pch=19)
> points(0.20654, 0, col='blue', pch=19)
```



```
> curve(dt(x,nF+nM-2), xlim= c(-3,3))
> points(qt(0.05,10), 0, col='green',pch=19)
> points(qt(0.95,10), 0, col='green',pch=19)
> points(-0.20654, 0, col='blue', pch=19)
> points(0.20654, 0, col='blue', pch=19)
> □
```

Podemos concluir que: No hay diferencia significativa porque al calcular el valor

Al ubicarlo en la t-student con  $nF+nM-2$  grados de libertad y ubicamos la RR que esta en -2,2 y 2,2.

No hay referencia suficiente entre las medias de las muestras para Poder afirmar que hay diferencias significativas.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

### E. Predictive Analysis

8. The file Credit\_Card\_Spending.csv provides a database of 49 families, their income and the family size.

```
> credCard <- read.csv(  
+   file = 'Credit_Card_Spending.csv',  
+   stringsAsFactors = FALSE,  
+   strip.white = TRUE,  
+   sep = ';'  
+ )  
  
> head (credCard)  
CreditCardExp.x1000.. Income.x1000.. FamilySize  
1      1.6      49      4  
2      1.5      34      3  
3      1.0      11      1  
4      2.7     100      1  
5      1.0      45      4  
6      0.4      29      4
```

```
> names (credCard)  
[1] "CreditCardExp.x1000.." "Income.x1000.."    "FamilySize"  
>
```

```
> length (credCard [[1]])  
[1] 49  
>
```

- a. Identify and describe which analytic technique can be used to analyse the influence of income and family size in the credit card spending.

**Linear Regression Model. - REGRESIÓN SIMPLE**  
**Variable de estudio Y = credit card spending**  
**Regresores X = income and family size**

- b. Make a scatter plot for credit card spending versus income and credit card spending versus family size, and describe the relation between each pair of variables.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> print ( var (credCard), digits = 2 )
```

```
spend income FamilySize
spend 3.59 58.4 -0.51
income 58.45 2299.5 -1.37
FamilySize -0.51 -1.4 1.54
```

Diagonales => Varianza de las variables

NO Diagonales => COVarianza entre las variables

Me pareció raro el valor de la varianza para income, la he comprobado y es la que hay...

```
> testincome = (credCard)[2]
```

```
> head(testincome)
```

```
income
1 49
2 34
3 11
4 100
5 45
6 29
```

```
>
```

```
> var(testincome)
```

```
income
income 2299.526
```

```
> print ( cor (credCard), digits = 2 )
```

```
spend income FamilySize
spend 1.00 0.644 -0.218
income 0.64 1.000 -0.023
FamilySize -0.22 -0.023 1.000
```

Diagonales => Binarios

NO Diagonales => Correlación → entran escalados entre -1 y 1.

Las variables más correlacionadas son income vs spend.

Hay una correlación baja entre spend and FamilySize al igual que entre income vs FamilySize

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

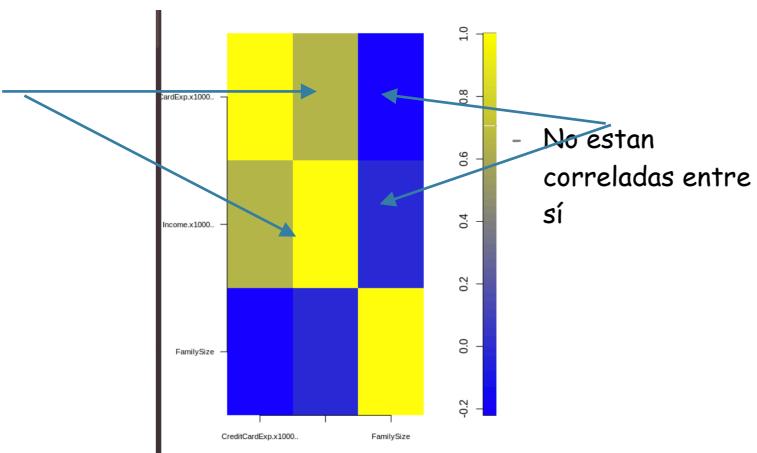
```
> source( "myImagePlot.R" )
> myImagePlot( cor ( credCard ) )
```

Sé ve la correlación entre el spend y el income..

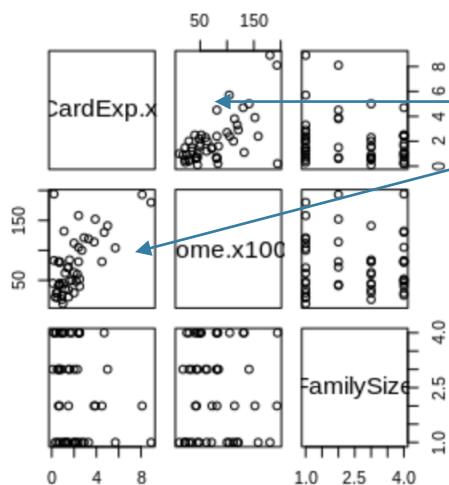
y la "baja" relación con el FamilySize.

```
> pairs (credCard)
```

- Están correladas



No están correladas entre sí



Cuanto más definida está el gráfico hay más correlación

FamilySize es una variable numérica cuantitativa discreta.

Puedo ver la tendencia de los datos y datos outlier... La variant muestra la dispersion de los datos al rededor de la linea..

```
> pairs (credCard)
```

> mod

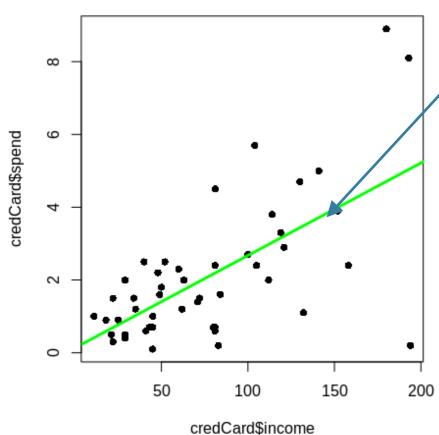
Call:

lm(formula = credCard\$spend ~ credCard\$income)

Coefficients:

(Intercept)	credCard\$income
<b>0.13259</b>	<b>0.02542</b>

```
> plot(credCard$spend ~ credCard$income, pch = 16)
> mod = lm (credCard$spend ~ credCard$income)
> abline ( mod, col='green', lwd=3 )
```



> summary ( mod )

Call:

lm(formula = credCard\$spend ~ credCard\$income)

Residuals:

Min	1Q	Median	3Q	Max
-4.8634	-0.5372	-0.0959	0.6424	4.1925

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	<b>0.132586</b>	<b>0.395552</b>	0.335	0.739
credCard\$income	<b>0.025416</b>	<b>0.004409</b>	5.764	6.11e-07 ***

Signif. codes: 0 \*\*\*\* 0.001 \*\*\* 0.01 \*\* 0.05 \* 0.1 ' ' 1

Residual standard error: 1.465 on 47 degrees of freedom

Assignment Brief Number: 1  
Multiple R-squared: **0.4141**, Adjusted R-squared: 0.4017

34

F-statistic: 33.23 on 1 and 47 DF, p-value: **6.113e-07**

```
> plot(credCard$spend ~ credCard$income, pch = 16)
> mod = lm (credCard$spend ~ credCard$income)
> abline ( mod, col='green', lwd=3 )
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

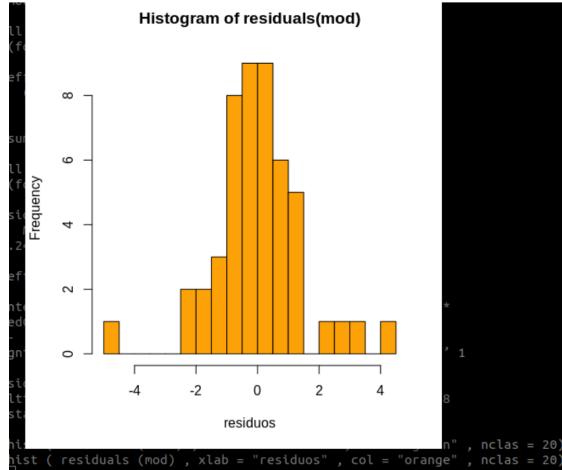
```
(Intercept) 0.132586 0.395552 0.335 0.739
credCard$income 0.025416 0.004409 5.764 6.11e-07 ***
```

Para este caso nuestro B0 tiene unidades de dólares,  
B1 Tiene unidades de dólares / unidades de dólares

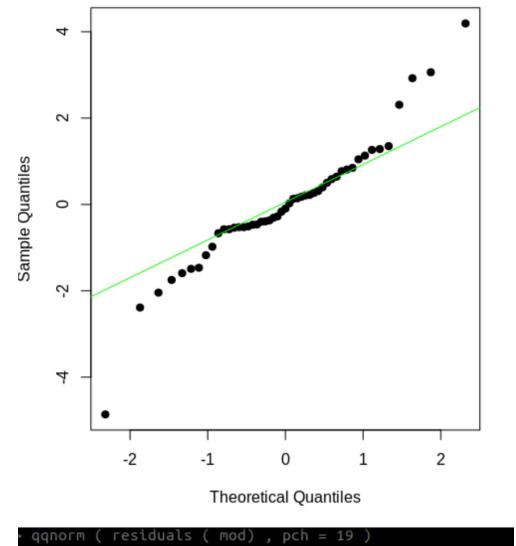
**B0 -> 0.132586 -> Con el aumento de una unidad del income ( dolar ) en promedio la variable spend aumenta en un 0.025416 ( dolar )**

Desviación típica = 0.004409 = Std. Error - Precisión con la que se ha calculado 0.025416  
**B1 -> <0.001 \*\*\* 0.001 -> Con un 99,9% de confianza**

```
> hist( residuals(mod) , xlab = "residuos" , col = "orange" ,
nclas = 20)
```



```
> qqnorm( residuals( mod) , pch = 19 )
> qqline( residuals( mod) , col = "green" , pch = 19 )
```



```
> credCard$Pred = predict(mod)
> credCard$Resid = residuals(mod)
> print(credCard, digits=3, print.gap=4)
  spend income FamilySize Pred Resid
1   1.6     49      4  1.378  0.2220
2   1.5     34      3  0.997  0.5033
3   1.0     11      1  0.412  0.5878
4   2.7    100      1  2.674  0.0258
5   1.0     45      4  1.276 -0.2763
6   0.4     29      4  0.870 -0.4697
7   1.5     72      2  1.963 -0.4626
8   0.3     22      1  0.692 -0.3917
9   0.6     81      3  2.191 -1.5913
10  8.9    180      1  4.708  4.1925
11  2.4    105      4  2.801 -0.4013
12  0.1     45      3  1.276 -1.1763
13  3.8    114      2  3.030  0.7699
14  2.5     40      4  1.149  1.3508
15  2.0    112      1  2.979 -0.9792
16  1.5     22      1  0.692  0.8083
17  4.7    130      4  3.437  1.2633
18  2.4     81      4  2.191  0.2087
19  8.1    193      2  5.038  3.0620
20  0.5     21      1  0.666 -0.1663
21  0.9     25      4  0.768  0.1320
22  2.0     63      3  1.734  0.2662
23  1.2     62      1  1.708 -0.5084
24  0.7     43      2  1.225 -0.5255
25  3.9    152      2  3.996 -0.0959
```

	26	0.5	29	3	0.870	-0.3697
27	0.2	83	4	2.242	-2.0421	
28	2.4	158	1	4.148	-1.7484	
29	2.2	48	1	1.353	0.8474	
30	3.3	119	1	3.157	0.1429	
31	1.2	35	1	1.022	0.1778	
32	2.0	29	1	0.870	1.1303	
33	0.6	41	2	1.175	-0.5747	
34	0.9	18	3	0.590	0.3099	
35	1.8	50	4	1.403	0.3966	
36	0.7	81	3	2.191	-1.4913	
37	2.9	121	1	3.208	-0.3080	
38	1.4	71	1	1.937	-0.5372	
39	5.0	141	3	3.716	1.2837	
40	0.7	80	4	2.166	-1.4659	
41	1.6	84	3	2.268	-0.6676	
42	2.3	60	3	1.658	0.6424	
43	1.1	132	4	3.488	-2.3876	
44	0.7	45	1	1.276	-0.5763	
45	5.7	104	1	2.776	2.9241	
46	2.5	52	4	1.454	1.0458	
47	0.7	43	3	1.225	-0.5255	
48	0.2	194	4	5.063	-4.8634	
49	4.5	81	2	2.191	2.3087	

Los residuos del modelo siguen una normal - se comprueba la linealidad y homocedasticidad

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```

> plot(credCard$spend ~ credCard$FamilySize, pch = 16)
> mod1 = lm (credCard$spend ~ credCard$FamilySize)
> abline ( mod1, col='green', lwd=3 )

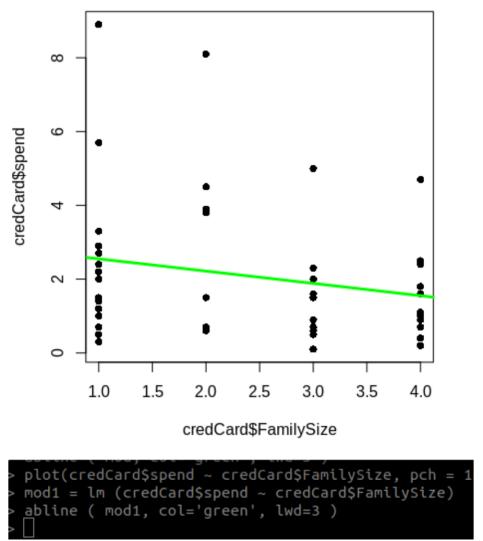
> mod1

```

Call:  
`lm(formula = credCard$spend ~ credCard$FamilySize)`

Coefficients:

(Intercept)	credCard\$FamilySize
<b>2.883</b>	<b>-0.333</b>



Podría significar que existe una relación inversa entre el tamaño de la Familia (FamilySize) versus el Gasto(spend)

Por medio de los residuos, se comprueba la NO linealidad y homocedasticidad -

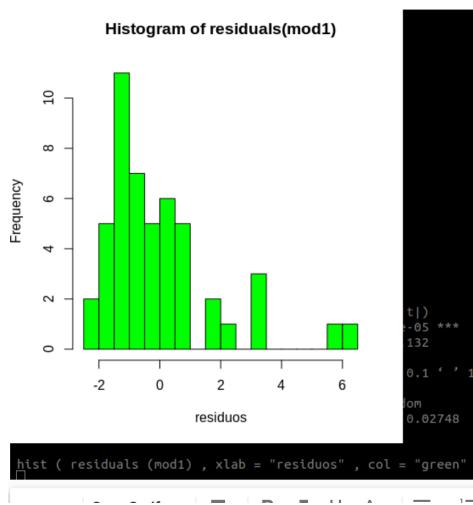
```

> credCard$Pred = predict(mod1)
> credCard$Resid = residuals(mod1)
> print(credCard, digits=3, print.gap=4)
  spend income FamilySize Pred
Resid
1  1.6    49      4  1.55  0.0491
2  1.5    34      3  1.88 -0.3839
3  1.0    11      1  2.55 -1.5498
4  2.7   100      1  2.55  0.1502
5  1.0    45      4  1.55 -0.5509
6  0.4    29      4  1.55 -1.1509
7  1.5    72      2  2.22 -0.7169
8  0.3    22      1  2.55 -2.2498
9  0.6    81      3  1.88 -1.2839
10 8.9   180      1  2.55  6.3502
11 2.4   105      4  1.55  0.8491
12 0.1    45      3  1.88 -1.7839
13 3.8   114      2  2.22  1.5831
14 2.5    40      4  1.55  0.9491
15 2.0   112      1  2.55 -0.5498
16 1.5    22      1  2.55 -1.0498
17 4.7   130      4  1.55  3.1491
18 2.4    81      4  1.55  0.8491
19 8.1   193      2  2.22  5.8831
20 0.5    21      1  2.55 -2.0498
21 0.9    25      4  1.55 -0.6509
22 2.0    63      3  1.88  0.1161
23 1.2    62      1  2.55 -1.3498
24 0.7    43      2  2.22 -1.5169
25 3.9   152      2  2.22  1.6831

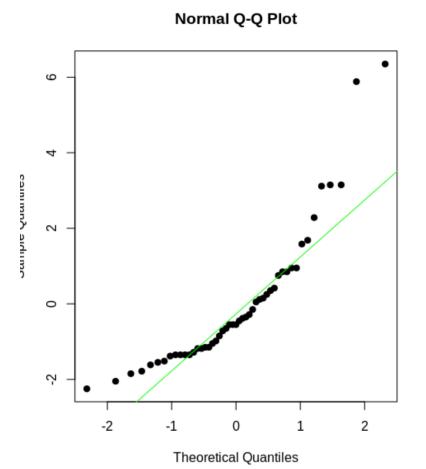
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> hist ( residuals (mod1) , xlab = "residuos" , col =  
"green" , nclas = 20)
```



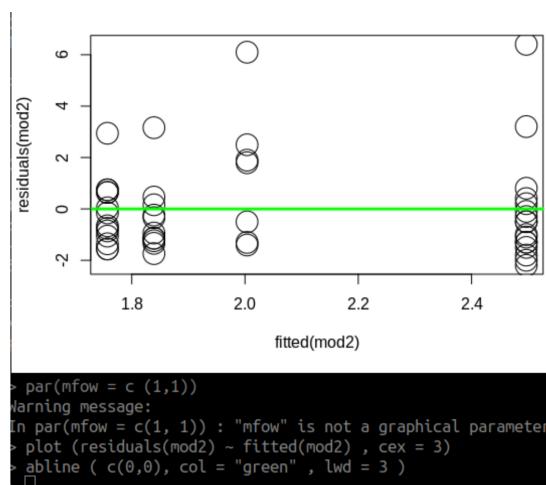
```
> qqnorm ( residuals ( mod1 ) , pch = 19 )  
> qqline ( residuals ( mod1 ) , col = "green" , pch =  
19 )
```



Tendríamos que utilizar alguna transformación para ver si podemos mejorar el modelo.

- Aplicando una transformación inversa:  $1/\text{credCard\$FamilySize}$

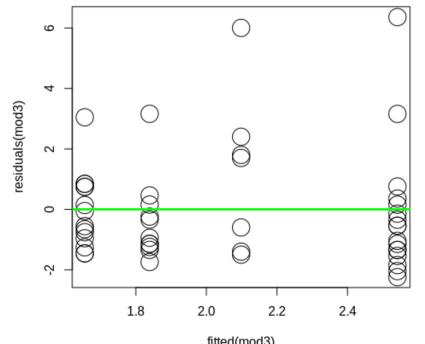
```
> credCard2[, 3] = 1/credCard2[,3]  
> print(credCard2, digits=3, print.gap=4)  
CreditCardExp.x1000.. Income.x1000.. FamilySize  
1 1.6 49 0.250  
2 1.5 34 0.333  
3 1.0 11 1.000  
4 2.7 100 1.000  
5 1.0 45 0.250  
6 0.4 29 0.250  
> names (credCard2)[1] = 'spend'  
> names (credCard2)[2] = 'income'  
> names (credCard2)  
[1] "spend" "income" "FamilySize"  
> mod2 = lm (credCard2$spend ~ credCard2$FamilySize)  
> par(mfrow = c (1,1))  
Warning message:  
In par(mfrow = c(1, 1)) : "mfrow" is not a graphical parameter  
> plot (residuals(mod2) ~ fitted(mod2) , cex = 3)  
> abline ( c(0,0), col = "green" , lwd = 3 )
```



## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- Aplicando una transformación logarítmica: (`log (credCard$spend ~ credCard$FamilySize)`)

```
> credCard3 = credCard
> names (credCard3)
[1] "CreditCardExp.x1000.." "Income.x1000.."      "FamilySize"
> names (credCard3)[1] = 'spend'
> names (credCard3)[2] = 'income'
> names (credCard3)
[1] "spend"    "income"   "FamilySize"
> mod3 = lm (credCard3$spend ~ log(credCard3$FamilySize) )
> plot (residuals(mod3) ~ fitted(mod3) , cex = 3)
> abline ( c(0,0), col = "green" , lwd = 3 )
>
```



- c. Does the **income** variable appear to be a significant factor on **credit card spending**?

$B_0 \rightarrow 0.132586$   $\rightarrow$  Con el aumento de una unidad del regresor (income) en promedio la variable respuesta (credit card spending) aumenta en un **0.025416**.

**p-value:** indica si el regresor influye ó no influye en la variable de respuesta.

p-value:  $6.113e-07$  si  $< 0.05 \Rightarrow$  El regresor income SI influye en el credit card spending.

```
> confint ( mod )
2.5 % 97.5 %
(Intercept) -0.66316211 0.92833436
credCard$income 0.01654584 0.03428702
```

Con un intervalo de confianza de 95%, puedo decir que el **B1 Poblacional** va a estar entre **0.01654584 0.03428702**

**Signif. codes:** uno ó mas asteriscos quiere decir que con un 99,9% de confianza puedo afirmar que es significativa, el **p-value** va a estar por debajo de 0.001.

Signif. codes: **0 \*\*\*\* 0.001 \*\* 0.01 \* 0.05 . 0.1 ' 1**

Estoy muy segura de este **0.025416**

Puedo decir qué porcentaje de variación del credit card spending con respecto al income es del 40%. Puedo explicar el 40% de la variación del credit card spending. - (gasto con respecto a los ingresos).

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- d. Does the **family size** variable appear to be a significant factor on credit card **spending?**

La variable FamilySize es una variable numérica cuantitativa discreta.

Podría significar que existe una relación inversa entre el tamaño de la Familia (FamilySize) versus el Gasto(spend), sin embargo revisando los indices del modelo podemos decir que:

```
> summary ( mod1 )
```

Call:

```
lm(formula = credCard$spend ~ credCard$FamilySize)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.2498	-1.2839	-0.5498	0.7502	6.3502

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.8828	0.5945	4.849	1.4e-05 ***
credCard\$FamilySize	-0.3330	0.2169	-1.535	0.132

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.868 on 47 degrees of freedom  
Multiple R-squared: 0.04774, Adjusted R-squared: 0.02748  
F-statistic: 2.356 on 1 and 47 DF, p-value: 0.1315

BO: 2.8828 0.5945

B1: credCard\$FamilySize -0.3330

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.868 on 47 degrees of freedom

Multiple R-squared: 0.04774, Indica que no tienen correlación.

p-value: 0.1315 > 0.05 => indica que el regresor NO influye, No tenemos evidencia suficiente para decir que este regreso influya significativamente.

Sin embargo podemos ver con estos datos inequívocamente que no hay ningún tipo de relación entre estas variables.

- e. Explain how this analytic technique can be used for forecasting.

Se utiliza para poder explicar cuál de las variables independientes (**income and family size**) está relacionada con la variable dependiente(**credit card spending**), y también se puede utilizar para explorar las formas de estas relaciones.

Algunos objetivos podrían ser:

Ver que valor tiene el coeficiente de B1

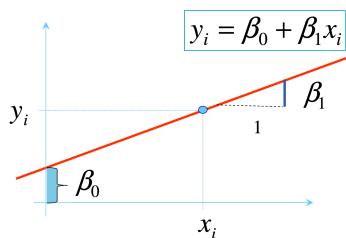
A partir de unos regresores, poder hacer predicciones.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- f. Predict de average expense of a family that has two members and an income of \$188,00 per annum, and another that has three members and an income of \$39,000 per annum.

Teniendo en cuenta la ecuación de la recta:

### Ecuación de una recta



La forma de calcular la predicción en este modelo de regresión es:

$$\frac{y_i}{\text{Valor observado}} = \frac{\hat{\beta}_0 + \hat{\beta}_1 x_i}{\text{Valor Previsto}}$$

$$Y_i = B_0 + B_1 X_i \Rightarrow 0.132586 + 0.025416 * 188,00 \\ \Rightarrow + 0.132586 + 4,778208 \Rightarrow 4,910794$$

$$Y_i = B_0 + B_1 X_i \Rightarrow 0.132586 + 0.025416 * 39,00 \\ \Rightarrow + 0.132586 + 0,991224 \Rightarrow 1,256396$$

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

9. The file Credit\_Risk\_Data.csv provides a database about loan applications, along with a classification of credit risk:

```
(base) hadoop@ubuntu-hokkaido-3568:~/R/Data$ cat Credit_Risk*
Loan Purpose;Checking($);Savings($);Months Customer;Months Employed;Gender;Marital Status;Age;Housing;Years;Job;Credit Risk
Small Appliance;0;739;13;12;M;Single;23;Own;3;Unskilled;Low
Furniture;0;1230;25;0;M;Divorced;32;Own;1;Skilled;High
New Car;0;389;19;119;M;Single;38;Own;4;Management;High
Furniture;638;347;13;14;M;Single;36;Own;2;Unskilled;High
Education;963;4754;40;45;M;Single;31;Rent;3;Skilled;Low
Furniture;2827;0;11;13;M;Married;25;Own;1;Skilled;Low
New Car;0;229;13;16;M;Married;26;Own;3;Unskilled;Low
Business;0;533;14;2;M;Single;27;Own;1;Unskilled;Low
Small Appliance;6509;493;37;9;M;Single;25;Own;2;Skilled;High
Small Appliance;966;0;25;4;F;Divorced;43;Own;1;Skilled;High
Business;0;989;49;0;M;Single;32;Rent;2;Management;High
New Car;0;3305;11;15;M;Single;34;Rent;2;Unskilled;Low
Business;322;578;10;14;M;Married;26;Own;1;Skilled;Low
New Car;0;821;25;63;M;Single;44;Own;1;Skilled;High
```

```
> credRisk <- read.csv(file='Credit_Risk_Data.csv',stringsAsFactors=FALSE,strip.white=TRUE,sep = ';')
> names(credRisk)
[1] "Loan.Purpose"    "Checking..."   "Savings..."    "Months.Customer"
[5] "Months.Employed" "Gender"        "Marital.Status" "Age"
[9] "Housing"         "Years"         "Job"          "Credit.Risk"
> head(credRisk)
  Loan.Purpose Checking... Savings... Months.Customer Months.Employed Gender
1 Small Appliance      0       739        13        12      M
2   Furniture        0     1230        25        0      M
3   New Car          0       389        19       119      M
4   Furniture        638      347        13        14      M
5   Education        963     4754        40        45      M
6   Furniture       2827        0       11       13      M
  Marital.Status Age Housing Years Job Credit.Risk
1       Single  23   Own  3 Unskilled  Low
2   Divorced  32   Own  1 Skilled  High
3       Single  38   Own  4 Management  High
4       Single  36   Own  2 Unskilled  High
5       Single  31  Rent  3 Skilled  Low
6   Married  25   Own  1 Skilled  Low
> length(credRisk[[1]])
[1] 425
> length(credRisk)
[1] 12

names(credRisk)[1] = "Purpose"
names(credRisk)[2] = "Checking"
names(credRisk)[3] = "Savings"
names(credRisk)[4] = "mCustomer"
names(credRisk)[5] = "mEmployed"
names(credRisk)[6] = "Gender"
names(credRisk)[7] = "mStatus"
names(credRisk)[12] = "cRisk"

> names(credRisk)
[1] "Purpose"    "Checking"   "Savings"    "mCustomer" "mEmployed" "Gender"
[7] "mStatus"   "Age"        "Housing"   "Years"      "Job"        "cRisk"
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- a. Identify and describe which predictive analytic techniques can be applied to classify the data.

Linear Regression Model. - **REGRESIÓN LOGISTICA** -

Los modelos se usan para:

Conocer si hay relación entre los regresores y la variable de decisión (Credit.Risk = "cRisk")

También se usan para clasificar, predecir etc., en este caso de estudio en el que tenemos datos acerca de el estudio de crédito y el riesgo tipo de riesgo. Podemos predecir el tipo de riesgo del crédito cRisk como High ó Low dependiendo de una serie de regresores que podrán ser más o menos significativos para el modelo.

Vamos a estudiar el cRisk en función de todos sus regresores

Variable de Estudio => cRisk

Regresores => ( "Purpose", "Checking", "Savings", "mCustomer",  
"mEmployed", "Gender", "mStatus", "Age", "Housing", "Years", "Job" )

Podemos hacer una regresión LOGISTICA

Las relaciones Logísticas se emplean para tratar variables de respuesta cualitativa binarias, es decir, en este caso por ejemplo la variable Decisión sólo tiene dos valores - Low, High.

Podemos hacer una regresión para ver cual regresor tiene ó no sentido para que se considere el riesgo del crédito (cRisk) como Low ó High.

Variable de estudio Y = Credit.Risk = cRisk

Regresores X = Cuantitativos - medibles - && Cualitativos - NO medibles

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

- b. Explain how logistic regression can be used to classify these data.

La regresión logística es un análisis predictivo, que nos permite describir la relación entre nuestra variable binaria dependiente  $Y = \text{Credit.Risk} = \text{cRisk}$ , y las demás variables independientes - regresores. También nos permite ver la probabilidad de que el riesgo de el crédito se considere Low ó High.

- c. Sample 200 records from the data set and form the training and validation data sets.

Queremos intentar explicar el comportamiento de cRisk en función de las demás variables del modelo:

Las variables alfanuméricas ya las va a tomar como factor

```
> pos00 = sample(1:425, 200, replace = FALSE)
> pos00
[1] 311 365 145 209 360 163 305 286 353 14 303 198 241 86 12 400 102 49
[19] 279 299 131 328 158 240 137 288 378 33 94 144 129 165 199 242 229 351
[37] 224 122 186 230 26 283 247 385 266 133 120 372 384 381 84 96 243 386
[55] 397 192 16 174 322 348 276 338 203 225 337 392 19 64 197 72 3 256
[73] 327 326 67 125 34 27 66 92 43 355 9 135 55 126 150 364 277 399
[91] 221 201 36 212 87 193 321 424 216 132 32 104 367 234 335 202 257 173
[109] 274 312 387 18 166 194 51 292 30 250 419 414 78 358 249 83 251 420
[127] 377 245 410 317 389 149 261 40 38 268 217 369 255 325 169 80 374 141
[145] 167 119 82 416 412 373 421 390 269 275 411 409 15 206 310 258 281 29
[163] 50 417 171 309 154 124 361 74 75 382 24 73 189 336 246 69 375 13
[181] 22 302 62 88 179 170 187 406 237 79 21 200 388 232 98 53 253 205
[199] 58 371
```

```
> pos01 = sample(1:200, 40, replace = FALSE)
> pos01
[1] 19 162 121 108 169 57 10 51 63 109 177 147 9 178 175 116 13 97 22
[20] 106 65 58 33 144 142 96 55 29 132 186 46 14 107 88 161 192 153 122
[39] 168 131
>
```

```
> train = credRisk[pos00, ]
> length (train [[1]])
```

```
[1] 200
```

```
> test = credRisk[pos01, ]
```

```
> length (test [[1]])
```

```
[1] 40
```

d. Apply logistic regression to classify training and validation data set.

En teoría para este caso de uso no es necesario transformar la variable cRisk porque es “alfanumérica” y en teoría debería funcionar el relevel, pero por la razón que sea me esta devolviendo el error:

( — Error in relevel.default( train\$cRisk, ref="Low" ) — );

Por tanto he tenido que hacerlo para poder ejecutar el relevel e indicarle a R cuál va ser la variable que quiero que tome como referencia:

```
> train$cRisk = factor(train$cRisk)  
> train$cRisk = relevel( train$cRisk, ref="Low" )
```

Creo el modelo de entrenamiento teniendo en cuenta todas las variables:

```
> modcredRisk = glm( cRisk ~ ., data = train, family = 'binomial' )
```

Hago predicciones para saber la bondad del modelo

```
> ProbmodcredRisk = predict(modcredRisk, test, type = 'response')
```

```
> ProbmodcredRisk  
19    162    121    108    169     57     10  
0.14700299 0.78826589 0.45589905 0.72120201 0.43651558 0.49509510 0.24798280  
51     63    109    177    147      9    178  
0.40264191 0.10609039 0.93251345 0.05837522 0.15145920 0.45430283 0.29243356  
175    116     13     97     22    106     65  
0.21161362 0.54653386 0.31914156 0.91771874 0.66452089 0.38099117 0.28801284  
58     33    144    142     96     55     29  
0.71271535 0.30710948 0.06192601 0.11041014 0.22973316 0.26024442 0.73827878  
132    186     46     14    107     88    161  
0.43893156 0.16547648 0.16356582 0.40153858 0.46437534 0.28276457 0.74782993  
192    153    122    168     131  
0.86388797 0.27035637 0.07195667 0.07955092 0.30098577
```

Saco la tabla de resultados del modelo:

```
> cRiskTest = rep('Low', length(test[[1]]))
```

```
> cRiskTest
```

```
[1] "Low" "Low"
```

```
[13] "Low" "Low"
```

```
[25] "Low" "Low"
```

```
[37] "Low" "Low" "Low" "Low"
```

```
> cRiskTest[ProbmodcredRisk > 0.5] = 'High'
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> cRiskTest
[1] "Low" "High" "Low" "High" "Low" "Low" "Low" "Low" "Low" "High"
[11] "Low" "Low" "Low" "Low" "Low" "High" "Low" "High" "High" "Low"
[21] "Low" "High" "Low" "Low" "Low" "Low" "Low" "High" "Low" "Low"
[31] "Low" "Low" "Low" "Low" "High" "High" "Low" "Low" "Low" "Low"

> table(test$cRisk, cRiskTest)
   cRiskTest
   High Low
High  5 12
Low   5 18
```

e. Summarize your findings.

```
> summary (modcredRisk)
```

Call:

```
glm(formula = cRisk ~ ., family = "binomial", data = train)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9086	-0.9283	-0.4270	1.0051	2.3587

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	1.815e+00	1.437e+00	1.264	0.2064
PurposeEducation	-2.906e-01	1.068e+00	-0.272	0.7856
PurposeFurniture	9.132e-02	6.360e-01	0.144	0.8858
PurposeLarge Appliance	7.001e-01	1.403e+00	0.499	0.6177
PurposeNew Car	5.700e-01	5.668e-01	1.006	0.3146
PurposeOther	1.392e-01	1.422e+00	0.098	0.9220
PurposeRepairs	-1.084e+00	1.022e+00	-1.061	0.2889
PurposeRetraining	1.406e+01	8.827e+02	0.016	0.9873
PurposeSmall Appliance	-6.411e-01	5.717e-01	-1.122	0.2621
<b>PurposeUsed Car</b>	<b>-1.536e+00</b>	<b>7.703e-01</b>	<b>-1.994</b>	<b>0.0462 *</b>
Checking	-7.076e-05	5.607e-05	-1.262	0.2069
Savings	-1.875e-05	4.598e-05	-0.408	0.6834
<b>mCustomer</b>	<b>4.978e-02</b>	<b>1.665e-02</b>	<b>2.989</b>	<b>0.0028 **</b>
mEmployed	-5.427e-03	5.908e-03	-0.919	0.3583
GenderM	-3.880e-01	9.585e-01	-0.405	0.6856
mStatusMarried	1.449e-01	1.100e+00	0.132	0.8952
mStatusSingle	1.968e-01	9.077e-01	0.217	0.8283
<b>Age</b>	<b>-4.235e-02</b>	<b>1.914e-02</b>	<b>-2.213</b>	<b>0.0269 *</b>
HousingOwn	-1.203e+00	6.760e-01	-1.779	0.0752 .
HousingRent	-8.071e-01	7.618e-01	-1.059	0.2894
Years	1.863e-01	1.755e-01	1.061	0.2886
JobSkilled	-6.005e-01	5.981e-01	-1.004	0.3154

```
JobUnemployed      -6.979e-01 1.069e+00 -0.653  0.5138  
JobUnskilled       -6.309e-01 7.112e-01 -0.887  0.3750
```

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 276.54 on 199 degrees of freedom

Residual deviance: 230.65 on 176 degrees of freedom

**AIC: 278.65**

Number of Fisher Scoring iterations: 13

Nos damos cuenta que PurposeUsed Car and Age son variables que influyen y son significativas: '\*' 0.05, y que mCustomer es significativa '\*\*' 0.01

En regresión logística no tienen interpretación estos valores: Estimate Std. Error z value Pr(>|z|)

```
PurposeUsed Car      -1.536e+00 7.703e-01 -1.994  0.0462 *  
mCustomer           4.978e-02 1.665e-02  2.989  0.0028 **  
Age                 -4.235e-02 1.914e-02 -2.213  0.0269 *
```

Sólo se pueden evaluar si son negativos ó positivos, es decir,

```
mCustomer           4.978e-02 1.665e-02  2.989  0.0028 ** A mayor valor .... mayor cRisk  
Age                 -4.235e-02 1.914e-02 -2.213  0.0269 *
```

Al hacer un step con este modelo: Nos damos cuenta que el mejor modelo es: cRisk ~ mCustomer + Age ya que el **AIC: 262.43** es mejor cuanto menor sea este valor.

```
> mod2credRisk=step(modcredRisk, direction = 'both')  
Start: AIC=278.65  
cRisk ~ Purpose + Checking + Savings + mCustomer + mEmployed +  
      Gender + mStatus + Age + Housing + Years + Job
```

	Df	Deviance	AIC
- Job	3	231.75	273.75
- mStatus	2	230.70	274.70
- Gender	1	230.82	276.82
- Savings	1	230.82	276.82
- mEmployed	1	231.50	277.50
- Years	1	231.78	277.79
- Purpose	9	248.06	278.06
- Housing	2	234.34	278.34
- Checking	1	232.41	278.41
<none>		230.65	278.65
- Age	1	235.90	281.90

- mCustomer 1 240.42 286.42

Step: AIC=273.75

cRisk ~ Purpose + Checking + Savings + mCustomer + mEmployed +  
Gender + mStatus + Age + Housing + Years

	Df	Deviance	AIC
- mStatus	2	231.81	269.81
- Gender	1	231.92	271.92
- Savings	1	231.94	271.94
- mEmployed	1	232.60	272.60
- Years	1	232.72	272.72
- Housing	2	235.00	273.00
- Purpose	9	249.09	273.09
- Checking	1	233.58	273.58
<none>		231.75	273.75
- Age	1	237.07	277.07
+ Job	3	230.65	278.65
- mCustomer	1	243.06	283.06

Step: AIC=269.81

cRisk ~ Purpose + Checking + Savings + mCustomer + mEmployed +  
Gender + Age + Housing + Years

	Df	Deviance	AIC
- Savings	1	232.00	268.00
- Gender	1	232.05	268.05
- mEmployed	1	232.62	268.62
- Years	1	232.76	268.76
- Housing	2	235.10	269.10
- Purpose	9	249.19	269.19
- Checking	1	233.65	269.65
<none>		231.81	269.81
- Age	1	237.41	273.41
+ mStatus	2	231.75	273.75
+ Job	3	230.70	274.70
- mCustomer	1	243.25	279.25

Step: AIC=268

cRisk ~ Purpose + Checking + mCustomer + mEmployed + Gender +  
Age + Housing + Years

	Df	Deviance	AIC
- Gender	1	232.22	266.22
- mEmployed	1	232.91	266.91
- Years	1	232.97	266.98
- Purpose	9	249.34	267.34
- Housing	2	235.50	267.50
- Checking	1	233.96	267.96

```

<none>      232.00 268.00
+ Savings   1  231.81 269.81
- Age       1  237.67 271.67
+ mStatus   2  231.94 271.94
+ Job       3  230.87 272.87
- mCustomer 1  243.53 277.53

```

Step: AIC=266.22

cRisk ~ Purpose + Checking + mCustomer + mEmployed + Age + Housing + Years

	Df	Deviance	AIC
- mEmployed	1	233.37	265.37
- Years	1	233.38	265.38
- Housing	2	235.74	265.74
- Purpose	9	249.76	265.76
- Checking	1	234.14	266.14
<none>		232.22	266.22
+ Gender	1	232.00	268.00
+ Savings	1	232.05	268.05
+ mStatus	2	232.08	270.08
- Age	1	238.52	270.52
+ Job	3	231.13	271.13
- mCustomer	1	243.59	275.59

Step: AIC=265.37

cRisk ~ Purpose + Checking + mCustomer + Age + Housing + Years

	Df	Deviance	AIC
- Years	1	234.13	264.13
- Purpose	9	250.78	264.78
- Housing	2	236.88	264.88
- Checking	1	235.24	265.24
<none>		233.37	265.37
+ mEmployed	1	232.22	266.22
+ Gender	1	232.91	266.91
+ Savings	1	233.11	267.11
+ mStatus	2	233.02	269.02
+ Job	3	232.31	270.31
- Age	1	242.04	272.04
- mCustomer	1	244.25	274.25

Step: AIC=264.13

cRisk ~ Purpose + Checking + mCustomer + Age + Housing

	Df	Deviance	AIC
- Purpose	9	251.46	263.46
- Checking	1	235.85	263.85
<none>		234.13	264.13

```

- Housing  2  238.91 264.91
+ Years    1  233.37 265.37
+ mEmployed 1  233.38 265.38
+ Gender   1  233.53 265.52
+ Savings  1  233.87 265.87
+ mStatus  2  233.62 267.62
+ Job      3  233.24 269.24
- Age      1  242.04 270.04
- mCustomer 1  245.01 273.01

```

Step: AIC=263.46

cRisk ~ Checking + mCustomer + Age + Housing

	Df	Deviance	AIC
- Checking	1	252.43	262.43
<none>		251.46	263.46
- Housing	2	255.51	263.51
+ Purpose	9	234.13	264.13
+ Gender	1	250.65	264.65
+ Years	1	250.78	264.78
+ mEmployed	1	250.79	264.80
+ Savings	1	251.29	265.29
+ mStatus	2	250.83	266.83
+ Job	3	250.61	268.61
- Age	1	259.80	269.80
- mCustomer	1	260.92	270.92

Step: AIC=262.43

cRisk ~ mCustomer + Age + Housing

	Df	Deviance	AIC
- Housing	2	256.43	262.43
<none>		252.43	262.43
+ Checking	1	251.46	263.46
+ Gender	1	251.63	263.63
+ mEmployed	1	251.75	263.75
+ Years	1	251.83	263.83
+ Purpose	9	235.85	263.85
+ Savings	1	252.23	264.23
+ mStatus	2	251.77	265.77
+ Job	3	251.46	267.45
- Age	1	260.46	268.46
- mCustomer	1	262.18	270.18

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

Step: AIC=262.43

**cRisk ~ mCustomer + Age**

	Df	Deviance	AIC
<none>		256.43	262.43
+ Housing	2	252.43	262.43
+ Years	1	254.52	262.52
+ Gender	1	255.26	263.26
+ Checking	1	255.51	263.51
+ mEmployed	1	255.81	263.81
+ Savings	1	256.05	264.05
+ Purpose	9	240.26	264.26
+ mStatus	2	255.46	265.46
+ Job	3	255.54	267.54
- Age	1	264.74	268.74
- mCustomer	1	268.75	272.75
>			

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

10. The file Inflation\_Rates.csv provides data (in %) from January-1990 to December-2014.
  - a. Make a plot of the data.
  - b. Identify which predictive analytics techniques can be applied to these data and describe these techniques.
  - c. Explain how you would use these models to forecast, and how far into the future it would be appropriate to forecast.
  - d. Using MSE and MAPE as guidance, find the best forecasting model.
  - e. Use this model to generate forecasts for the next two months.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

**Inflation\_Rates.csv:** Esta serie contiene 300 registros, cada uno compuesto de dos columnas, una de ellas "Fecha" cuyo formato (mmm-yyy) y otra "Rate" de tipo double que contiene el porcentaje de inflación. (Ordenados en forma descendente to 2014 a 1990.)  
Desde enero de 1990 hasta diciembre de 2014.

```
> inflaRates <- read.csv(file='Inflation_Rates.csv',stringsAsFactors=FALSE,strip.white=TRUE,sep =';')
> names(inflaRates)
[1] "Month.Year" "Rate..."

> names(inflaRates)[1] = "Fecha"
> names(inflaRates)[2] = "Rate"

> names(inflaRates)
[1] "Fecha" "Rate"

> head(inflaRates)
  Fecha Rate
1 dic-2014 0.76
2 nov-2014 1.32
3 oct-2014 1.66
4 sep-2014 1.66
5 ago-2014 1.70
6 jul-2014 1.99

> length(inflaRates[[1]])
[1] 300
>
> length(inflaRates)
[1] 2
>
# Tenemos que "ordenar" en forma descendente, los datos 300 registros hasta el 1 de -1 en -1
para que se puedan representar en el tiempo..
> inflaRates=inflaRates[seq(300,1,-1),]

> head(inflaRates)
  Fecha Rate
300 ene-1990 5.20
299 feb-1990 5.26
298 mar-1990 5.23
297 abr-1990 4.71
296 may-1990 4.36
295 jun-1990 4.67
....
12 ene-2014 1.58
11 feb-2014 1.13
3 oct-2014 1.66
2 nov-2014 1.32
1 dic-2014 0.76
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

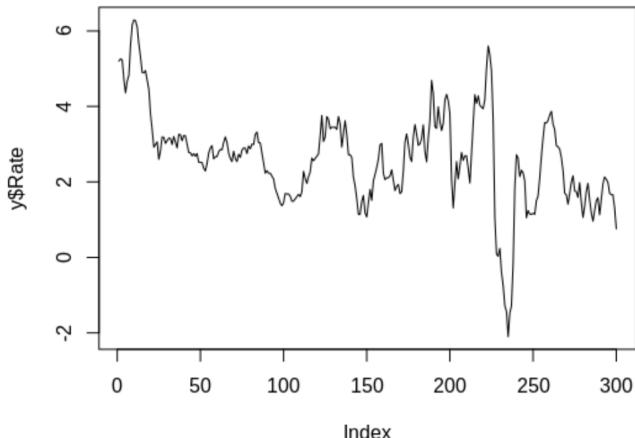
- a. Make a plot of the data.

#Defino la variable de respuesta => vamos a estudiar la taza de inflación en el tiempo...

```
> y = (inflaRates$Rate)
>y
[1] 5.20 5.26 5.23 4.71 4.36 4.67 4.82 5.62 6.16 6.29 6.27 6.11
[13] 5.65 5.31 4.90 4.89 4.95 4.70 4.45 3.80 3.39 2.92 2.99 3.06
[25] 2.60 2.82 3.19 3.18 3.02 3.09 3.16 3.15 2.99 3.20 3.05 2.90
[37] 3.26 3.25 3.09 3.23 3.22 3.00 2.78 2.77 2.69 2.75 2.68 2.75
[49] 2.52 2.52 2.51 2.36 2.29 2.49 2.77 2.90 2.96 2.61 2.67 2.67
[61] 2.80 2.86 2.85 3.05 3.19 3.04 2.76 2.62 2.54 2.81 2.61 2.54
[73] 2.73 2.65 2.84 2.90 2.89 2.75 2.95 2.88 3.00 2.99 3.26 3.32
[85] 3.04 3.03 2.76 2.50 2.23 2.30 2.23 2.23 2.15 2.08 1.83 1.70
[97] 1.57 1.44 1.37 1.44 1.69 1.68 1.68 1.62 1.49 1.49 1.55 1.61
[109] 1.67 1.61 1.73 2.28 2.09 1.96 2.14 2.26 2.63 2.56 2.62 2.68
[121] 2.74 3.22 3.76 3.07 3.19 3.73 3.66 3.41 3.45 3.45 3.45 3.39
[133] 3.73 3.53 2.92 3.27 3.62 3.25 2.72 2.72 2.65 2.13 1.90 1.55
[145] 1.14 1.14 1.48 1.64 1.18 1.07 1.46 1.80 1.51 2.03 2.20 2.38
[157] 2.60 2.98 3.02 2.22 2.06 2.11 2.11 2.16 2.32 2.04 1.77 1.88
[169] 1.93 1.69 1.74 2.29 3.05 3.27 2.99 2.65 2.54 3.19 3.52 3.26
[181] 2.97 3.01 3.15 3.51 2.80 2.53 3.17 3.64 4.69 4.35 3.46 3.42
[193] 3.99 3.60 3.36 3.55 4.17 4.32 4.15 3.82 2.06 1.31 1.97 2.54
[205] 2.08 2.42 2.78 2.57 2.69 2.69 2.36 1.97 2.76 3.54 4.31 4.08
[217] 4.28 4.03 3.98 3.94 4.18 5.02 5.60 5.37 4.94 3.66 1.07 0.09
[229] 0.03 0.24 -0.38 -0.74 -1.28 -1.43 -2.10 -1.48 -1.29 -0.18 1.84 2.72
[241] 2.63 2.14 2.31 2.24 2.02 1.05 1.24 1.15 1.14 1.17 1.14 1.50
[253] 1.63 2.11 2.68 3.16 3.57 3.56 3.63 3.77 3.87 3.53 3.39 2.96
[265] 2.93 2.87 2.65 2.30 1.70 1.66 1.41 1.69 1.99 2.16 1.76 1.74
[277] 1.59 1.98 1.46 1.06 1.36 1.75 1.96 1.52 1.18 0.96 1.24 1.50
[289] 1.58 1.13 1.53 1.95 2.13 2.07 1.99 1.70 1.66 1.66 1.32 0.76
```

#Grafico de la serie

```
> plot(y$Rate, type="l")
```



	Fecha	Rate
300	ene-1990	5.20
299	feb-1990	5.26
298	mar-1990	5.23
297	abr-1990	4.71
296	may-1990	4.36
295	jun-1990	4.67

```
> plot(y$Rate, type="l")
> 
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

#Primer paso: No hay que hacer transformación, sólo se hace cuando claramente la dispersión va aumentando

#Segundo paso: Estacionalidad - 1mes - time series - almacena el vector numérico como una serie temporal

```
> y = ts(y)
```

```
> y
```

Time Series:

Start = 1

End = 300

Frequency = 1

```
[1] 5.20 5.26 5.23 4.71 4.36 4.67 4.82 5.62 6.16 6.29 6.27 6.11  
[13] 5.65 5.31 4.90 4.89 4.95 4.70 4.45 3.80 3.39 2.92 2.99 3.06  
[25] 2.60 2.82 3.19 3.18 3.02 3.09 3.16 3.15 2.99 3.20 3.05 2.90  
[37] 3.26 3.25 3.09 3.23 3.22 3.00 2.78 2.77 2.69 2.75 2.68 2.75  
[49] 2.52 2.52 2.51 2.36 2.29 2.49 2.77 2.90 2.96 2.61 2.67 2.67  
[61] 2.80 2.86 2.85 3.05 3.19 3.04 2.76 2.62 2.54 2.81 2.61 2.54  
[73] 2.73 2.65 2.84 2.90 2.89 2.75 2.95 2.88 3.00 2.99 3.26 3.32  
[85] 3.04 3.03 2.76 2.50 2.23 2.30 2.23 2.23 2.15 2.08 1.83 1.70  
[97] 1.57 1.44 1.37 1.44 1.69 1.68 1.68 1.62 1.49 1.49 1.55 1.61  
[109] 1.67 1.61 1.73 2.28 2.09 1.96 2.14 2.26 2.63 2.56 2.62 2.68  
[121] 2.74 3.22 3.76 3.07 3.19 3.73 3.66 3.41 3.45 3.45 3.45 3.39  
[133] 3.73 3.53 2.92 3.27 3.62 3.25 2.72 2.72 2.65 2.13 1.90 1.55  
[145] 1.14 1.14 1.48 1.64 1.18 1.07 1.46 1.80 1.51 2.03 2.20 2.38  
[157] 2.60 2.98 3.02 2.22 2.06 2.11 2.11 2.16 2.32 2.04 1.77 1.88  
[169] 1.93 1.69 1.74 2.29 3.05 3.27 2.99 2.65 2.54 3.19 3.52 3.26  
[181] 2.97 3.01 3.15 3.51 2.80 2.53 3.17 3.64 4.69 4.35 3.46 3.42  
[193] 3.99 3.60 3.36 3.55 4.17 4.32 4.15 3.82 2.06 1.31 1.97 2.54  
[205] 2.08 2.42 2.78 2.57 2.69 2.69 2.36 1.97 2.76 3.54 4.31 4.08  
[217] 4.28 4.03 3.98 3.94 4.18 5.02 5.60 5.37 4.94 3.66 1.07 0.09  
[229] 0.03 0.24 -0.38 -0.74 -1.28 -1.43 -2.10 -1.48 -1.29 -0.18 1.84 2.72  
[241] 2.63 2.14 2.31 2.24 2.02 1.05 1.24 1.15 1.14 1.17 1.14 1.50  
[253] 1.63 2.11 2.68 3.16 3.57 3.56 3.63 3.77 3.87 3.53 3.39 2.96  
[265] 2.93 2.87 2.65 2.30 1.70 1.66 1.41 1.69 1.99 2.16 1.76 1.74  
[277] 1.59 1.98 1.46 1.06 1.36 1.75 1.96 1.52 1.18 0.96 1.24 1.50  
[289] 1.58 1.13 1.53 1.95 2.13 2.07 1.99 1.70 1.66 1.66 1.32 0.76
```

```
#Tercer paso: Crear el modelo - auto.arima - ordenes (p,d,q)(P,D,Q) -
> modInflaRates = auto.arima(y)
> modInflaRates

Call:
auto.arima(y = y, x = structure(list(x = structure(c(5.2, 5.26, 5.23, 4.71,
4.36, 4.67, 4.82, 5.62, 6.16, 6.29, 6.27, 6.11, 5.65, 5.31, 4.9, 4.89, 4.95,
4.7, 4.45, 3.8, 3.39, 2.92, 2.99, 3.06, 2.6, 2.82, 3.19, 3.18, 3.02, 3.09, 3.16,
3.15, 2.99, 3.2, 3.05, 2.9, 3.26, 3.25, 3.09, 3.23, 3.22, 3, 2.78, 2.77, 2.69,
2.75, 2.68, 2.75, 2.52, 2.52, 2.51, 2.36, 2.29, 2.49, 2.77, 2.9, 2.96, 2.61,
2.67, 2.67, 2.8, 2.86, 2.85, 3.05, 3.19, 3.04, 2.76, 2.62, 2.54, 2.81, 2.61,
2.54, 2.73, 2.65, 2.84, 2.9, 2.89, 2.75, 2.95, 2.88, 3, 2.99, 3.26, 3.32, 3.04,
3.03, 2.76, 2.5, 2.23, 2.3, 2.23, 2.23, 2.15, 2.08, 1.83, 1.7, 1.57, 1.44, 1.37,
1.44, 1.69, 1.68, 1.68, 1.62, 1.49, 1.49, 1.55, 1.61, 1.67, 1.61, 1.73, 2.28,
2.09, 1.96, 2.14, 2.26, 2.63, 2.56, 2.62, 2.68, 2.74, 3.22, 3.76, 3.07, 3.19,
3.73, 3.66, 3.41, 3.45, 3.45, 3.45, 3.39, 3.73, 3.53, 2.92, 3.27, 3.62, 3.25,
2.72, 2.72, 2.65, 2.13, 1.9, 1.55, 1.14, 1.14, 1.48, 1.64, 1.18, 1.07, 1.46,
1.8, 1.51, 2.03, 2.2, 2.38, 2.6, 2.98, 3.02, 2.22, 2.06, 2.11, 2.11, 2.16, 2.32,
2.04, 1.77, 1.88, 1.93, 1.69, 1.74, 2.29, 3.05, 3.27, 2.99, 2.65, 2.54, 3.19,
3.52, 3.26, 2.97, 3.01, 3.15, 3.51, 2.8, 2.53, 3.17, 3.64, 4.69, 4.35, 3.46,
3.42, 3.99, 3.6, 3.36, 3.55, 4.17, 4.32, 4.15, 3.82, 2.06, 1.31, 1.97, 2.54,
2.08, 2.42, 2.78, 2.57, 2.69, 2.69, 2.36, 1.97, 2.76, 3.54, 4.31, 4.08, 4.28,
4.03, 3.98, 3.94, 4.18, 5.02, 5.6, 5.37, 4.94, 3.66, 1.07, 0.09, 0.03, 0.24,
-0.38, -0.74, -1.28, -1.43, -2.1, -1.48, -1.29, -0.18, 1.84, 2.72, 2.63, 2.14,
2.31, 2.24, 2.02, 1.05, 1.24, 1.15, 1.14, 1.17, 1.14, 1.5, 1.63, 2.11, 2.68,
3.16, 3.57, 3.56, 3.63, 3.77, 3.87, 3.53, 3.39, 2.96, 2.93, 2.87, 2.65, 2.3,
1.7, 1.66, 1.41, 1.69, 1.99, 2.16, 1.76, 1.74, 1.59, 1.98, 1.46, 1.06, 1.36,
1.75, 1.96, 1.52, 1.18, 0.96, 1.24, 1.5, 1.58, 1.13, 1.53, 1.95, 2.13, 2.07,
1.99, 1.7, 1.66, 1.66, 1.32, 0.76), .Tsp = c(1, 300, 1), class = "ts"), .Names = "x", row.names = c(NA,
-300L), class = "data.frame"))
```

Coefficients:

ar1	ar2	ma1	ma2
-1.1870	-0.4897	1.6839	0.9756
s.e.	0.0538	0.0548	0.0165
			0.0161

**sigma^2 estimated as 0.1231: log likelihood = -111.08, aic = 232.16**

> summary(modInflaRates)

Series: y

ARIMA(2,1,2)

Coefficients:

ar1	ar2	ma1	ma2
-1.1870	-0.4897	1.6839	0.9756
s.e.	0.0538	0.0548	0.0165
			0.0161

**sigma^2 estimated as 0.1231: log likelihood=-111.08**

**AIC=232.16 AICc=232.36 BIC=250.66**

**Por ahora este es el mejor modelo - Determina si el modelo es bueno ó no.**

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

Training set error measures:

ME RMSE MAE MPE MAPE MASE

Training set -0.01079624 0.3479634 0.2414133 -4.929799 15.92422 0.8702987

ACF1

Training set 0.07466382

>

> arima(y, order = c(0,1,2), seasonal = c(0,1,2))

Call:

arima(x = y, order = c(0, 1, 2), seasonal = c(0, 1, 2))

Coefficients:

ma1	ma2	sma1	sma2
-0.2351	-0.2410	-0.2351	-0.2410
s.e.	0.0632	0.0564	0.0632
			0.0564

$\sigma^2$  estimated as 0.1565: log likelihood = -146.89, **aic = 303.79**, es mejor cuanto menor sea este valor.

**Hacer más pruebas para encontrar el mejor modelo porque este aumenta el AIC**

- b. Identify which predictive analytics techniques can be applied to these data and describe these techniques.

Las series temporales se clasifican en estacionaria si la media y la variabilidad se mantienen constantes a lo largo del tiempo. Y no estacionaria si la media y/o la variabilidad cambian a lo largo del tiempo.

Existen diferentes técnicas de predicción para este tipo de datos:

**Simple linear regression:** el modelo de regresión permite una relación lineal entre la variable de respuesta y y una única variable regresora x.

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t$$

**Least squares estimation:** El principio de mínimos cuadrados proporciona una manera de elegir los coeficientes  $\beta_0, \beta_1, \dots, \beta_k$  de manera eficaz mediante la minimización de la suma de los errores cuadrados. Porque da el menor valor para la suma de errores al cuadrado. La búsqueda de las mejores estimaciones de los coeficientes suele denominarse "adaptación" del modelo a los datos, o a veces "aprendizaje" o "capacitación" del modelo.

**Evaluating the regression model:** Se evalúan los residuos, Normalidad de los residuos.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

### 2.3. Técnicas de suavizado.

**Técnicas de suavizado:** hacer previsiones, preparar la serie temporal para otros tratamientos..

Las medias móviles y el suavizado exponencial.

MÉTODO DE HOLT

MÉTODO DE WINTERS

Ref:

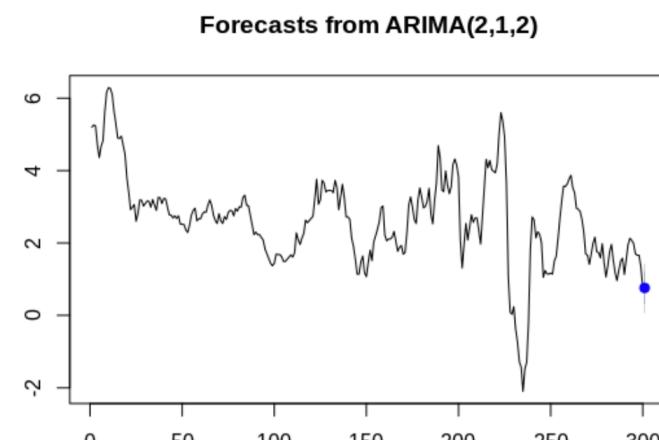
[https://www.researchgate.net/publication/31656405\\_Analisis\\_de\\_series\\_temporales\\_tecnicas\\_de\\_prevision\\_A\\_Carrion\\_Garcia](https://www.researchgate.net/publication/31656405_Analisis_de_series_temporales_tecnicas_de_prevision_A_Carrion_Garcia)

<https://bookdown.org/content/2274/series-temporales.html>

- c. Explain how you would use these models to forecast, and how far into the future it would be appropriate to forecast.

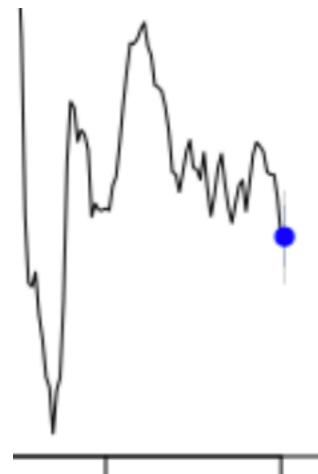
Depende del tipo del comportamiento de los datos se puede pronosticar con mayor certeza un futuro no muy lejano y por lo tanto cuanto mejor precisión tiene la predicción, mucho mejores beneficios para lo que se conciben estas predicciones... en el ejemplo que planteamos en clase de las eléctricas.. cuanto mejor resulte la predicción disminuye el costo de las reservas que tienen que hacer para cubrir la demanda.

#Cuarto paso: Crear predicciones: - h (horizonte)  
plot(forecast(modInflaRates, h = 1))



```
lot ( forecast ( modInflaRates, h=1 ) )
```

crea el mes siguiente (h=1) mes a mes de predicciones. 95% de confianza.



## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

El gris oscuro indica el 80% de IC y el gris claro indica el 95% de IC.

```
> plot ( forecast ( modInflaRates, h=1 ) )
> predicciones = ( forecast ( modInflaRates, h=1 ) )
> predicciones
  Point Forecast   Lo 80   Hi 80   Lo 95   Hi 95
301    0.7584848 0.3087828 1.208187 0.07072495 1.446245
```

d. Using MSE and MAPE as guidance, find the best forecasting model.

Usando algunas diferentes maneras de medir los errores, es decir, como cuantificar el error de predicción:

### MSE - Mean Square Error

```
> mse( lastdata,prediccion$mean )
[1] 0.07315672
```

Cuanto más pequeño sea el error al cuadrado, más cerca estará de encontrar la línea de mejor ajuste.

### MAPE - Mean Absolute Percentage Error

```
> mape ( lastdata,prediccion$mean )
[1] 0.3558882
```

Promedio de error de porcentaje absoluto para cada período de tiempo

### MAE - Mean Absolute Error

```
> mae ( lastdata,prediccion$mean )
[1] 0.270475
```

Es la media de las diferencias absolutas entre la predicción y la observación real en la muestra donde todas las diferencias individuales tienen el mismo peso.

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> inflaRates$Rate
[1] 5.20 5.26 5.23 4.71 4.36 4.67 4.82 5.62 6.16 6.29 6.27 6.11
[13] 5.65 5.31 4.90 4.89 4.95 4.70 4.45 3.80 3.39 2.92 2.99 3.06
[25] 2.60 2.82 3.19 3.18 3.02 3.09 3.16 3.15 2.99 3.20 3.05 2.90
[37] 3.26 3.25 3.09 3.23 3.22 3.00 2.78 2.77 2.69 2.75 2.68 2.75
[49] 2.52 2.52 2.51 2.36 2.29 2.49 2.77 2.90 2.96 2.61 2.67 2.67
[61] 2.80 2.86 2.85 3.05 3.19 3.04 2.76 2.62 2.54 2.81 2.61 2.54
[73] 2.73 2.65 2.84 2.90 2.89 2.75 2.95 2.88 3.00 2.99 3.26 3.32
[85] 3.04 3.03 2.76 2.50 2.23 2.30 2.23 2.23 2.15 2.08 1.83 1.70
[97] 1.57 1.44 1.37 1.44 1.69 1.68 1.68 1.62 1.49 1.49 1.55 1.61
[109] 1.67 1.61 1.73 2.28 2.09 1.96 2.14 2.26 2.63 2.56 2.62 2.68
[121] 2.74 3.22 3.76 3.07 3.19 3.73 3.66 3.41 3.45 3.45 3.45 3.39
[133] 3.73 3.53 2.92 3.27 3.62 3.25 2.72 2.72 2.65 2.13 1.90 1.55
[145] 1.14 1.14 1.48 1.64 1.18 1.07 1.46 1.80 1.51 2.03 2.20 2.38
[157] 2.60 2.98 3.02 2.22 2.06 2.11 2.11 2.16 2.32 2.04 1.77 1.88
[169] 1.93 1.69 1.74 2.29 3.05 3.27 2.99 2.65 2.54 3.19 3.52 3.26
[181] 2.97 3.01 3.15 3.51 2.80 2.53 3.17 3.64 4.69 4.35 3.46 3.42
[193] 3.99 3.60 3.36 3.55 4.17 4.32 4.15 3.82 2.06 1.31 1.97 2.54
[205] 2.08 2.42 2.78 2.57 2.69 2.69 2.36 1.97 2.76 3.54 4.31 4.08
[217] 4.28 4.03 3.98 3.94 4.18 5.02 5.60 5.37 4.94 3.66 1.07 0.09
[229] 0.03 0.24 -0.38 -0.74 -1.28 -1.43 -2.10 -1.48 -1.29 -0.18 1.84 2.72
[241] 2.63 2.14 2.31 2.24 2.02 1.05 1.24 1.15 1.14 1.17 1.14 1.50
[253] 1.63 2.11 2.68 3.16 3.57 3.56 3.63 3.77 3.87 3.53 3.39 2.96
[265] 2.93 2.87 2.65 2.30 1.70 1.66 1.41 1.69 1.99 2.16 1.76 1.74
[277] 1.59 1.98 1.46 1.06 1.36 1.75 1.96 1.52 1.18 0.96 1.24 1.50
[289] 1.58 1.13 1.53 1.95 2.13 2.07 1.99 1.70 1.66 1.66 1.32 0.76
> y = (inflaRates$Rate)
> lastdata = y[300]
> y = y[1:299]
> y
[1] 5.20 5.26 5.23 4.71 4.36 4.67 4.82 5.62 6.16 6.29 6.27 6.11
[13] 5.65 5.31 4.90 4.89 4.95 4.70 4.45 3.80 3.39 2.92 2.99 3.06
[25] 2.60 2.82 3.19 3.18 3.02 3.09 3.16 3.15 2.99 3.20 3.05 2.90
[37] 3.26 3.25 3.09 3.23 3.22 3.00 2.78 2.77 2.69 2.75 2.68 2.75
[49] 2.52 2.52 2.51 2.36 2.29 2.49 2.77 2.90 2.96 2.61 2.67 2.67
[61] 2.80 2.86 2.85 3.05 3.19 3.04 2.76 2.62 2.54 2.81 2.61 2.54
[73] 2.73 2.65 2.84 2.90 2.89 2.75 2.95 2.88 3.00 2.99 3.26 3.32
[85] 3.04 3.03 2.76 2.50 2.23 2.30 2.23 2.23 2.15 2.08 1.83 1.70
[97] 1.57 1.44 1.37 1.44 1.69 1.68 1.68 1.62 1.49 1.49 1.55 1.61
[109] 1.67 1.61 1.73 2.28 2.09 1.96 2.14 2.26 2.63 2.56 2.62 2.68
[121] 2.74 3.22 3.76 3.07 3.19 3.73 3.66 3.41 3.45 3.45 3.45 3.39
[133] 3.73 3.53 2.92 3.27 3.62 3.25 2.72 2.72 2.65 2.13 1.90 1.55
[145] 1.14 1.14 1.48 1.64 1.18 1.07 1.46 1.80 1.51 2.03 2.20 2.38
[157] 2.60 2.98 3.02 2.22 2.06 2.11 2.11 2.16 2.32 2.04 1.77 1.88
[169] 1.93 1.69 1.74 2.29 3.05 3.27 2.99 2.65 2.54 3.19 3.52 3.26
[181] 2.97 3.01 3.15 3.51 2.80 2.53 3.17 3.64 4.69 4.35 3.46 3.42
[193] 3.99 3.60 3.36 3.55 4.17 4.32 4.15 3.82 2.06 1.31 1.97 2.54
[205] 2.08 2.42 2.78 2.57 2.69 2.69 2.36 1.97 2.76 3.54 4.31 4.08
[217] 4.28 4.03 3.98 3.94 4.18 5.02 5.60 5.37 4.94 3.66 1.07 0.09
[229] 0.03 0.24 -0.38 -0.74 -1.28 -1.43 -2.10 -1.48 -1.29 -0.18 1.84 2.72
[241] 2.63 2.14 2.31 2.24 2.02 1.05 1.24 1.15 1.14 1.17 1.14 1.50
[253] 1.63 2.11 2.68 3.16 3.57 3.56 3.63 3.77 3.87 3.53 3.39 2.96
[265] 2.93 2.87 2.65 2.30 1.70 1.66 1.41 1.69 1.99 2.16 1.76 1.74
[277] 1.59 1.98 1.46 1.06 1.36 1.75 1.96 1.52 1.18 0.96 1.24 1.50
[289] 1.58 1.13 1.53 1.95 2.13 2.07 1.99 1.70 1.66 1.66 1.32
> length(y)
[1] 299
> length(lastdata)
[1] 1
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

```
> y = ts(y)
> y
Time Series:
Start = 1
End = 299
Frequency = 1
[1] 5.20 5.26 5.23 4.71 4.36 4.67 4.82 5.62 6.16 6.29 6.27 6.11
[13] 5.65 5.31 4.90 4.89 4.95 4.70 4.45 3.80 3.39 2.92 2.99 3.06
[25] 2.60 2.82 3.19 3.18 3.02 3.09 3.16 3.15 2.99 3.20 3.05 2.90
[37] 3.26 3.25 3.09 3.23 3.22 3.00 2.78 2.77 2.69 2.75 2.68 2.75
[49] 2.52 2.52 2.51 2.36 2.29 2.49 2.77 2.90 2.96 2.61 2.67 2.67
[61] 2.80 2.86 2.85 3.05 3.19 3.04 2.76 2.62 2.54 2.81 2.61 2.54
[73] 2.73 2.65 2.84 2.90 2.89 2.75 2.95 2.88 3.00 2.99 3.26 3.32
[85] 3.04 3.03 2.76 2.50 2.23 2.30 2.23 2.23 2.15 2.08 1.83 1.70
[97] 1.57 1.44 1.37 1.44 1.69 1.68 1.68 1.62 1.49 1.49 1.55 1.61
[109] 1.67 1.61 1.73 2.28 2.09 1.96 2.14 2.26 2.63 2.56 2.62 2.68
[121] 2.74 3.22 3.76 3.07 3.19 3.73 3.66 3.41 3.45 3.45 3.45 3.39
[133] 3.73 3.53 2.92 3.27 3.62 3.25 2.72 2.72 2.65 2.13 1.90 1.55
[145] 1.14 1.14 1.48 1.64 1.18 1.07 1.46 1.80 1.51 2.03 2.20 2.38
[157] 2.60 2.98 3.02 2.22 2.06 2.11 2.11 2.16 2.32 2.04 1.77 1.88
[169] 1.93 1.69 1.74 2.29 3.05 3.27 2.99 2.65 2.54 3.19 3.52 3.26
[181] 2.97 3.01 3.15 3.51 2.80 2.53 3.17 3.64 4.69 4.35 3.46 3.42
[193] 3.99 3.60 3.36 3.55 4.17 4.32 4.15 3.82 2.06 1.31 1.97 2.54
[205] 2.08 2.42 2.78 2.57 2.69 2.69 2.36 1.97 2.76 3.54 4.31 4.08
[217] 4.28 4.03 3.98 3.94 4.18 5.02 5.60 5.37 4.94 3.66 1.07 0.09
[229] 0.03 0.24 -0.38 -0.74 -1.28 -1.43 -2.10 -1.48 -1.29 -0.18 1.84 2.72
[241] 2.63 2.14 2.31 2.24 2.02 1.05 1.24 1.15 1.14 1.17 1.14 1.50
[253] 1.63 2.11 2.68 3.16 3.57 3.56 3.63 3.77 3.87 3.53 3.39 2.96
[265] 2.93 2.87 2.65 2.30 1.70 1.66 1.41 1.69 1.99 2.16 1.76 1.74
[277] 1.59 1.98 1.46 1.06 1.36 1.75 1.96 1.52 1.18 0.96 1.24 1.50
[289] 1.58 1.13 1.53 1.95 2.13 2.07 1.99 1.70 1.66 1.66 1.32
> modPred = auto.arima(y)
> summary(modPred)
```

Series: y  
ARIMA(2,1,2)

Coefficients:

	ar1	ar2	ma1	ma2
-	-1.1909	-0.4918	1.6850	0.9755
s.e.	0.0545	0.0546	0.0174	0.0162

sigma^2 estimated as 0.1233: log likelihood=-110.92

**AIC=231.84** AICc=232.05 BIC=250.33

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE	
Training set	-0.009958298	0.3482118	0.2414835	-4.839311	15.86612	0.8735382

ACF1

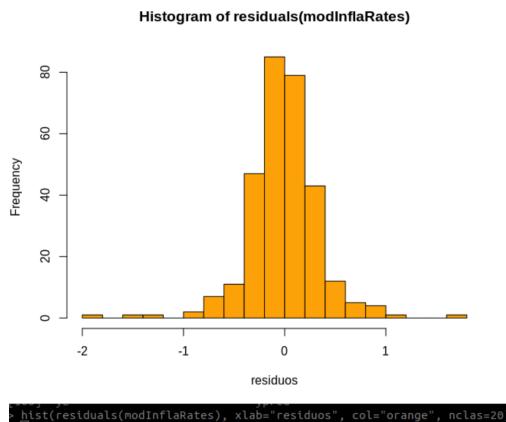
Training set 0.07519356

```
> predicción = forecast (modPred, h=1)
> predicción
Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
300 1.030475 0.5804391 1.480511 0.3422044 1.718746
```

## DATA ANALYTICS: DESCRIPTIVE, INFERENCE, AND PREDICTIVE TECHNIQUES

Con los residuos podemos comprobar la NO linealidad y homocedasticidad del modelo.

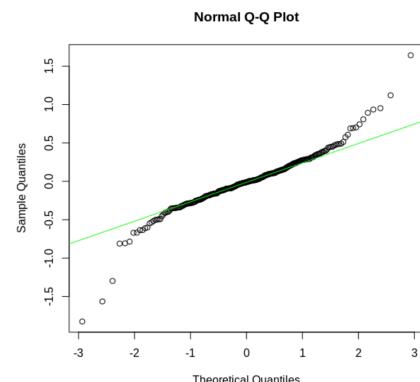
```
> hist(residuals(modInflaRates), xlab="residuos", col="orange", nclas=20)
```



Los residuos del modelo siguen una normal -  
se comprueba la linealidad y  
homocedasticidad.

Por medio de los residuos, se comprueba la NO linealidad y homocedasticidad

```
> predicción = forecast (modPred, h=1)
> predicción
Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
300 1.030475 0.5804391 1.480511 0.3422044 1.718746
> qqnorm(predicción$residuals)
> qqline(predicción$residuals, col="green")
```



e. Use this model to generate forecasts for the next two months.

```
> predicciones = ( forecast ( modInflaRates, h=2 ) )
> predicciones
Point Forecast Lo 80 Hi 80 Lo 95 Hi 95
301 0.7584848 0.30878280 1.208187 0.07072495 1.446245
302 0.7771131 -0.03245694 1.586683 -0.46101741 2.015244
```

**Student declaration**

I certify that the assignment submission is entirely my own work and I fully understand the consequences of plagiarism. I understand that making a false declaration is a form of malpractice.

Student signature:

Date: