

# Clase 16 de mayo

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```
library(faux)
```

```
## Warning: package 'faux' was built under R version 4.1.3
```

```
##  
## *****  
## Welcome to faux. For support and examples visit:  
## https://debruine.github.io/faux/  
## - Get and set global package options with: faux_options()  
## *****
```

```
set.seed(123)  
df <- rnorm_multi(n = 120,  
  mu = c(7, 100),  
  sd = c(1.5, 25),  
  varnames = c('DE', 'DDF'),  
  r = 0.7)
```

## Modelo

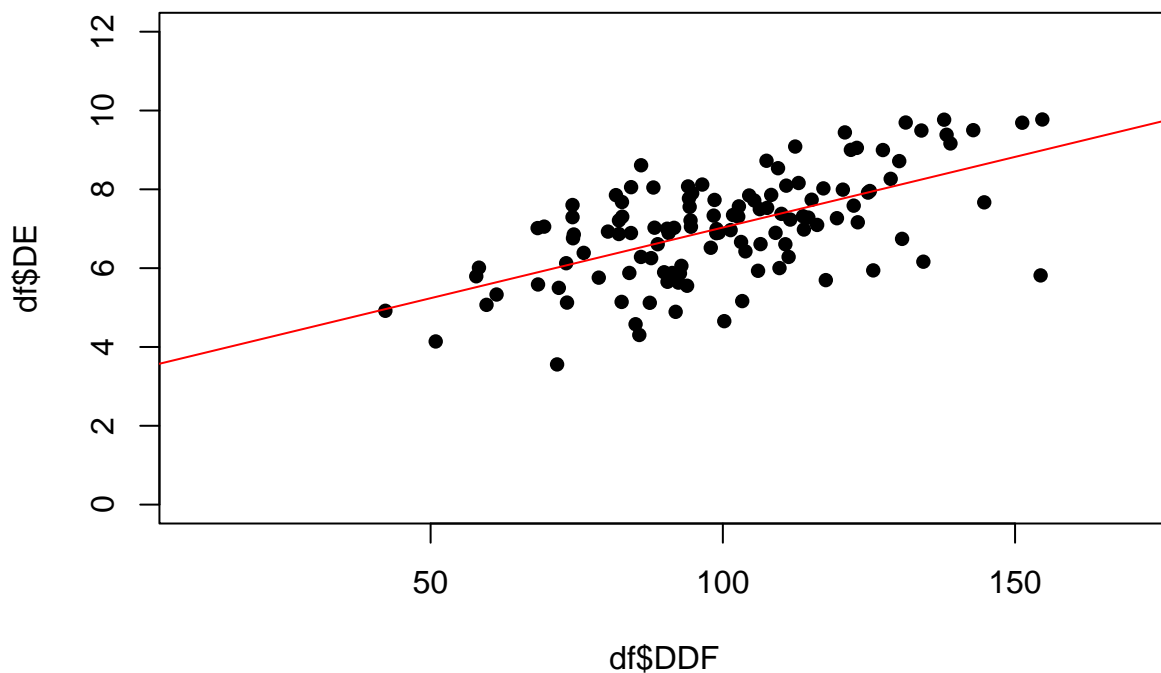
```
mod_lm <- lm(DE ~ DDF, data = df)  
summary(mod_lm)
```

```
##  
## Call:  
## lm(formula = DE ~ DDF, data = df)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -3.1641 -0.5972  0.1889  0.7415  2.0820   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  3.444790   0.441990   7.794 2.83e-12 ***  
## DDF          0.035857   0.004298   8.342 1.57e-13 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##
```

```
## Residual standard error: 1.049 on 118 degrees of freedom
## Multiple R-squared:  0.371, Adjusted R-squared:  0.3656
## F-statistic: 69.59 on 1 and 118 DF,  p-value: 1.573e-13
```

$$Y_{DE} = 3.444 + 0.036X$$

```
plot(df$DDF, df$DE, pch = 16, ylim = c(0,12), xlim = c(10,170))
abline(mod_lm, col = 'red')
```



Funcion que permite calcular el intercepto

```
fab <- function(x, y){
  n <- length(x) # Largo de x -> n
  b <- (sum(x * y) - n * mean(x) * mean(y)) / (sum(x**2) - n * (mean(x))**2)
  a <- mean(y) - b * mean(x)
  return(data.frame(Intercepto = a, Pendiente = b))
}
```

```
fab(df$DDF, df$DE)
```

```
## Intercepto Pendiente
## 1      3.44479 0.03585671
```

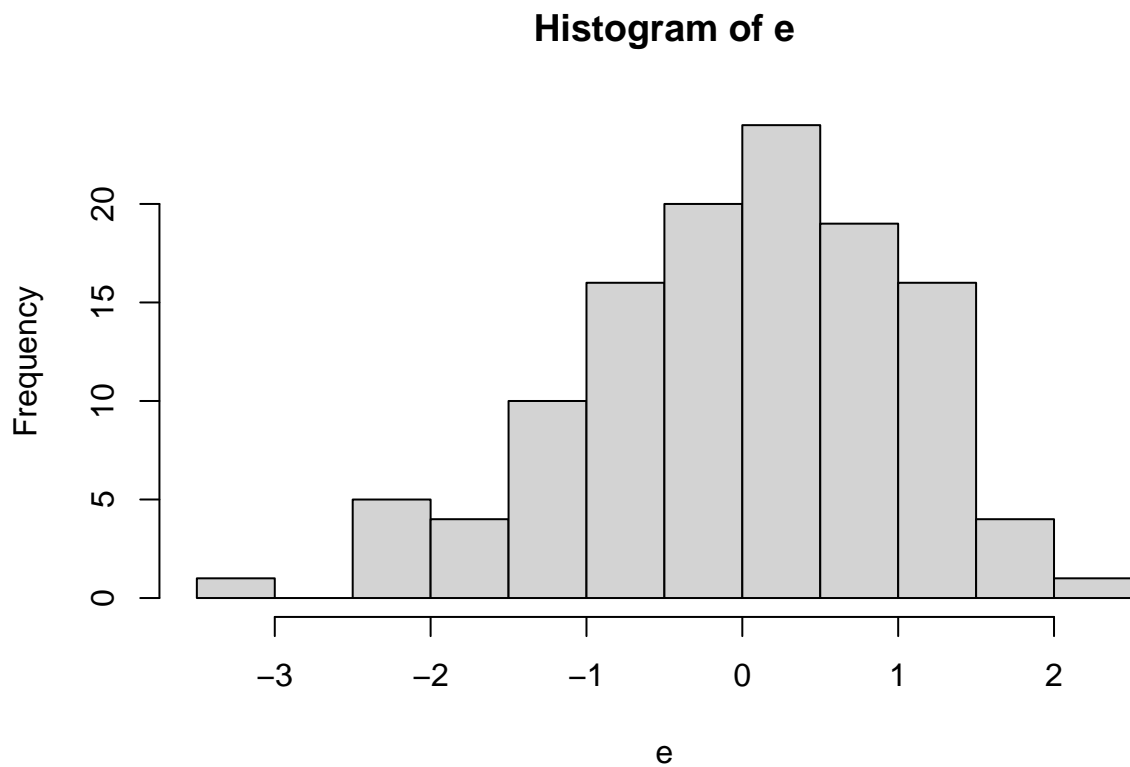
```
e <- mod_lm$residuals; sum(e)
```

```
## [1] 1.814521e-15
```

```
S <- sum(e**2); S
```

```
## [1] 129.7903
```

```
hist(e)
```



## Pruebas de normalidad

```
shapiro.test(e)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: e  
## W = 0.9737, p-value = 0.01876
```

```
nortest::sf.test(e)
```

```
##  
##  Shapiro-Francia normality test  
##  
## data:  e  
## W = 0.97495, p-value = 0.02561
```

```
nortest::ad.test(e)
```

```
##  
##  Anderson-Darling normality test  
##  
## data:  e  
## A = 0.78207, p-value = 0.04124
```

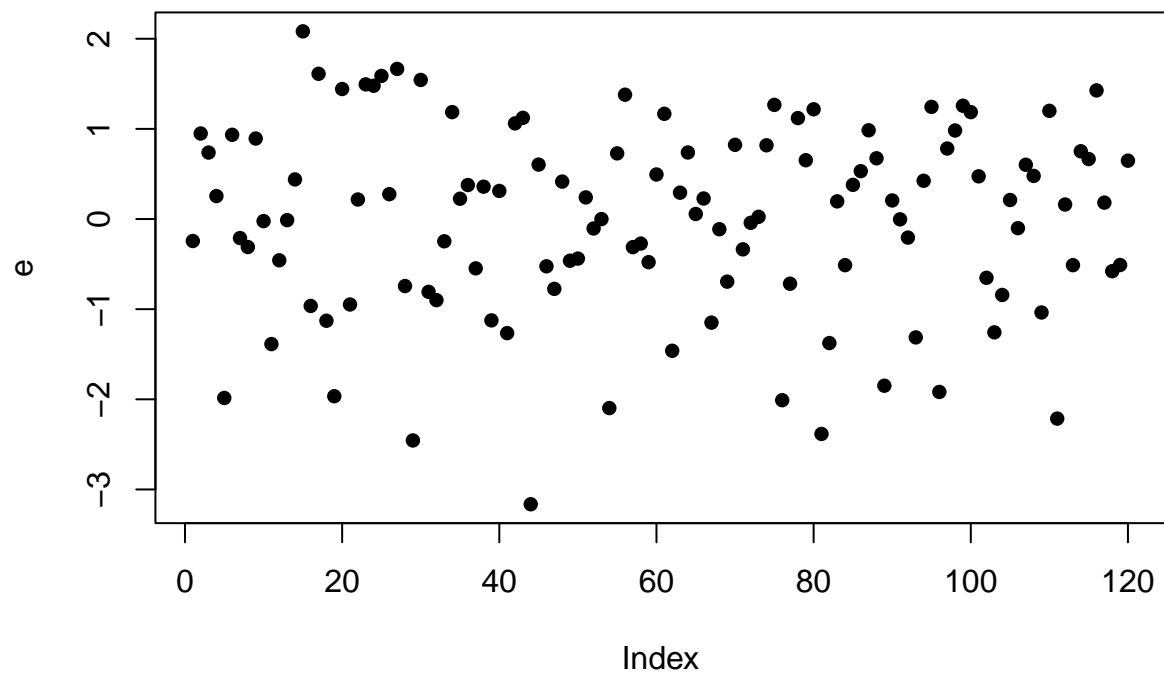
```
nortest::cvm.test(e) # Check
```

```
##  
##  Cramer-von Mises normality test  
##  
## data:  e  
## W = 0.10993, p-value = 0.08105
```

## Homoseasticidad

Revisando homogeniedad de varianzas

```
plot(e, pch = 16)
```

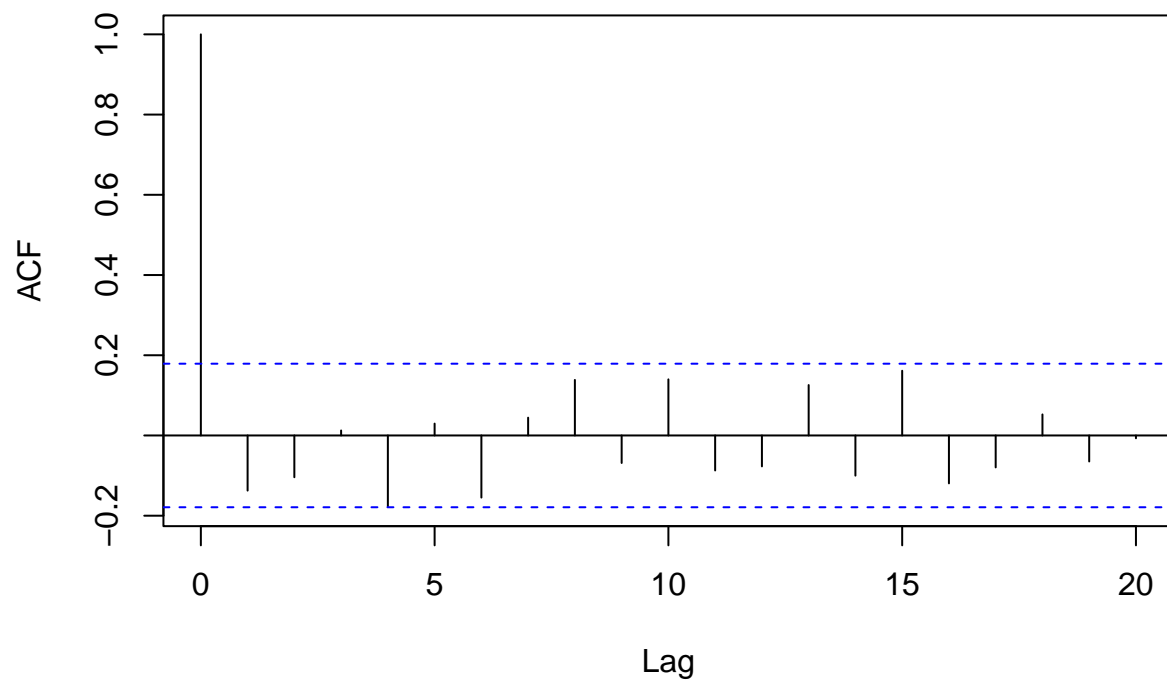


Revisando el supuesto de independencia (Temporal)

función de autocorrelación

```
acf(e)
```

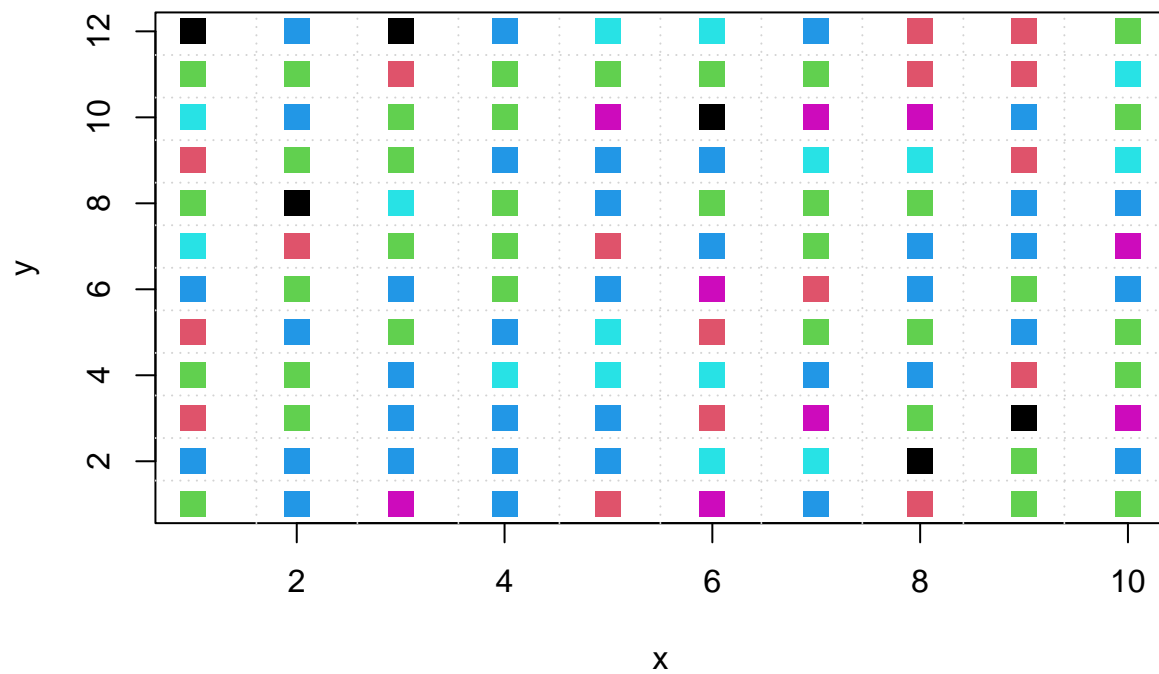
## Series e



```
library(faux)
set.seed(123)
df2 <- rnorm_multi(n = 120,
  mu = c(5, 10),
  sd = c(0.8, 1.2),
  varnames = c('Mol1', 'Mol2'),
  r = 0.7)

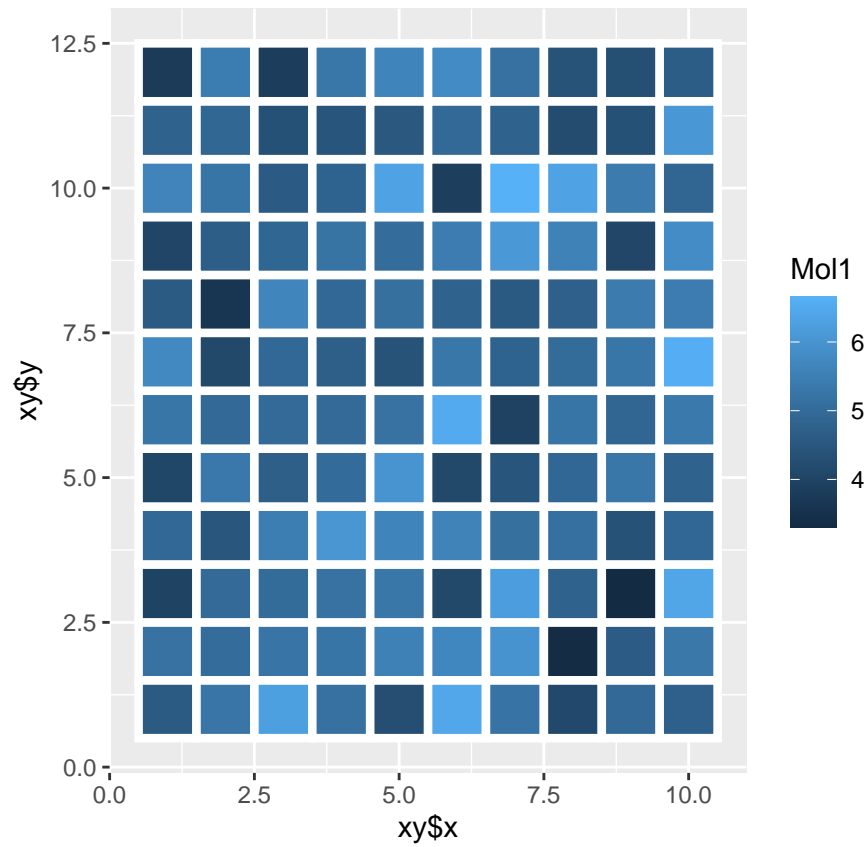
df2$Mol3 <- sort(df2$Mol2)
df2$Accession <- sample(gl(3,40,120, labels = c('A1', 'A2', 'A3')))
```

```
xy <- expand.grid(x = seq(1,10),
  y = seq(1,12))
color = cut(df2$Mol1, breaks = 6)
plot(xy, pch = 15, col = color, cex = 1.8)
grid(10,12)
```



```
library(ggplot2)

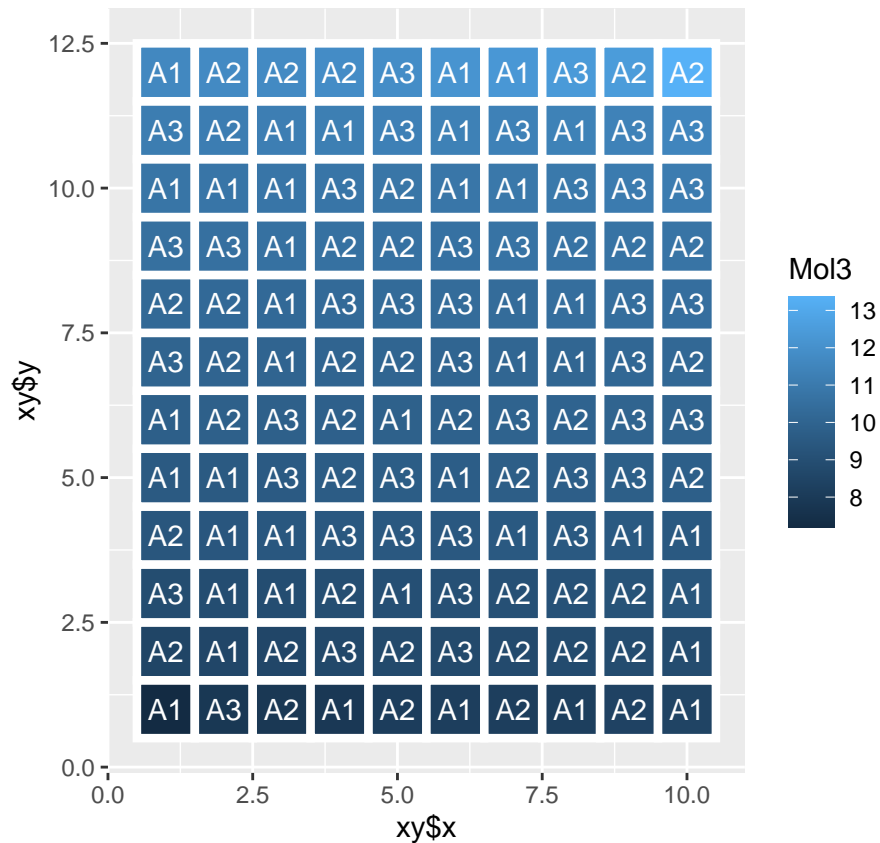
ggplot(df2, aes(x = xy$x, y = xy$y, fill = Mol1)) +
  geom_tile(color = "white",
            lwd = 1.5,
            linetype = 1) +
  coord_fixed()
```



```
library(ggplot2)

ggplot(df2, aes(x = xy$x, y = xy$y, fill = Mol3)) +
  geom_tile(color = "white",
            lwd = 1.5,
            linetype = 1) +
  geom_text(aes(label = Accession), color = "white", size = 4)+
  coord_fixed()
```





$$H_0 : \mu_{A1} = \mu_{A2} = \mu_{A3} H_a : \text{At least one is different}$$

## Análisis de varianza

```
mod_aov <- aov(Mol3 ~ Accesion, data = df2)
aa <-summary(mod_aov)
ifelse(aa[[1]][1,5] < 0.05, 'Rechazo Ho', 'No rechazo Ho')
```

```
## [1] "No rechazo Ho"
```

```
dist_matrix <- as.matrix(dist(cbind(xy$x,xy$y)))
dim(dist_matrix)
```

```
## [1] 120 120
```

```
inv_matrix <- 1/dist_matrix
diag(inv_matrix) <- 0
head(inv_matrix)
```

```
##          1          2          3          4          5          6          7
## 1 0.000000 1.000000 0.500000 0.333333 0.250000 0.200000 0.166667
```

```

## 2 1.0000000 0.0000000 1.0000000 0.5000000 0.3333333 0.2500000 0.2000000
## 3 0.5000000 1.0000000 0.0000000 1.0000000 0.5000000 0.3333333 0.2500000
## 4 0.3333333 0.5000000 1.0000000 0.0000000 1.0000000 0.5000000 0.3333333
## 5 0.2500000 0.3333333 0.5000000 1.0000000 0.0000000 1.0000000 0.5000000
## 6 0.2000000 0.2500000 0.3333333 0.5000000 1.0000000 0.0000000 1.0000000
##      8      9      10      11      12      13      14
## 1 0.1428571 0.1250000 0.1111111 1.0000000 0.7071068 0.4472136 0.3162278
## 2 0.1666667 0.1428571 0.1250000 0.7071068 1.0000000 0.7071068 0.4472136
## 3 0.2000000 0.1666667 0.1428571 0.4472136 0.7071068 1.0000000 0.7071068
## 4 0.2500000 0.2000000 0.1666667 0.3162278 0.4472136 0.7071068 1.0000000
## 5 0.3333333 0.2500000 0.2000000 0.2425356 0.3162278 0.4472136 0.7071068
## 6 0.5000000 0.3333333 0.2500000 0.1961161 0.2425356 0.3162278 0.4472136
##     15     16     17     18     19     20     21
## 1 0.2425356 0.1961161 0.1643990 0.1414214 0.1240347 0.1104315 0.5000000
## 2 0.3162278 0.2425356 0.1961161 0.1643990 0.1414214 0.1240347 0.4472136
## 3 0.4472136 0.3162278 0.2425356 0.1961161 0.1643990 0.1414214 0.3535534
## 4 0.7071068 0.4472136 0.3162278 0.2425356 0.1961161 0.1643990 0.2773501
## 5 1.0000000 0.7071068 0.4472136 0.3162278 0.2425356 0.1961161 0.2236068
## 6 0.7071068 1.0000000 0.7071068 0.4472136 0.3162278 0.2425356 0.1856953
##     22     23     24     25     26     27     28
## 1 0.4472136 0.3535534 0.2773501 0.2236068 0.1856953 0.1581139 0.1373606
## 2 0.5000000 0.4472136 0.3535534 0.2773501 0.2236068 0.1856953 0.1581139
## 3 0.4472136 0.5000000 0.4472136 0.3535534 0.2773501 0.2236068 0.1856953
## 4 0.3535534 0.4472136 0.5000000 0.4472136 0.3535534 0.2773501 0.2236068
## 5 0.2773501 0.3535534 0.4472136 0.5000000 0.4472136 0.3535534 0.2773501
## 6 0.2236068 0.2773501 0.3535534 0.4472136 0.5000000 0.4472136 0.3535534
##     29     30     31     32     33     34     35
## 1 0.1212678 0.1084652 0.3333333 0.3162278 0.2773501 0.2357023 0.2000000
## 2 0.1373606 0.1212678 0.3162278 0.3333333 0.3162278 0.2773501 0.2357023
## 3 0.1581139 0.1373606 0.2773501 0.3162278 0.3333333 0.3162278 0.2773501
## 4 0.1856953 0.1581139 0.2357023 0.2773501 0.3162278 0.3333333 0.3162278
## 5 0.2236068 0.1856953 0.2000000 0.2357023 0.2773501 0.3162278 0.3333333
## 6 0.2773501 0.2236068 0.1714986 0.2000000 0.2357023 0.2773501 0.3162278
##     36     37     38     39     40     41     42
## 1 0.1714986 0.1490712 0.1313064 0.1170411 0.1054093 0.2500000 0.2425356
## 2 0.2000000 0.1714986 0.1490712 0.1313064 0.1170411 0.2425356 0.2500000
## 3 0.2357023 0.2000000 0.1714986 0.1490712 0.1313064 0.2236068 0.2425356
## 4 0.2773501 0.2357023 0.2000000 0.1714986 0.1490712 0.2000000 0.2236068
## 5 0.3162278 0.2773501 0.2357023 0.2000000 0.1714986 0.1767767 0.2000000
## 6 0.3333333 0.3162278 0.2773501 0.2357023 0.2000000 0.1561738 0.1767767
##     43     44     45     46     47     48     49
## 1 0.2236068 0.2000000 0.1767767 0.1561738 0.1386750 0.1240347 0.1118034
## 2 0.2425356 0.2236068 0.2000000 0.1767767 0.1561738 0.1386750 0.1240347
## 3 0.2500000 0.2425356 0.2236068 0.2000000 0.1767767 0.1561738 0.1386750
## 4 0.2425356 0.2500000 0.2425356 0.2236068 0.2000000 0.1767767 0.1561738
## 5 0.2236068 0.2425356 0.2500000 0.2425356 0.2236068 0.2000000 0.1767767
## 6 0.2000000 0.2236068 0.2425356 0.2500000 0.2425356 0.2236068 0.2000000
##     50     51     52     53     54     55     56
## 1 0.1015346 0.2000000 0.1961161 0.1856953 0.1714986 0.1561738 0.1414214
## 2 0.1118034 0.1961161 0.2000000 0.1961161 0.1856953 0.1714986 0.1561738
## 3 0.1240347 0.1856953 0.1961161 0.2000000 0.1961161 0.1856953 0.1714986
## 4 0.1386750 0.1714986 0.1856953 0.1961161 0.2000000 0.1961161 0.1856953
## 5 0.1561738 0.1561738 0.1714986 0.1856953 0.1961161 0.2000000 0.1961161
## 6 0.1767767 0.1414214 0.1561738 0.1714986 0.1856953 0.1961161 0.2000000

```

##	57	58	59	60	61	62	63
## 1	0.1280369	0.1162476	0.1059998	0.09712859	0.1666667	0.1643990	0.1581139
## 2	0.1414214	0.1280369	0.1162476	0.10599979	0.1643990	0.1666667	0.1643990
## 3	0.1561738	0.1414214	0.1280369	0.11624764	0.1581139	0.1643990	0.1666667
## 4	0.1714986	0.1561738	0.1414214	0.12803688	0.1490712	0.1581139	0.1643990
## 5	0.1856953	0.1714986	0.1561738	0.14142136	0.1386750	0.1490712	0.1581139
## 6	0.1961161	0.1856953	0.1714986	0.15617376	0.1280369	0.1386750	0.1490712
##	64	65	66	67	68	69	70
## 1	0.1490712	0.1386750	0.1280369	0.1178511	0.1084652	0.1000000	0.09245003
## 2	0.1581139	0.1490712	0.1386750	0.1280369	0.1178511	0.1084652	0.10000000
## 3	0.1643990	0.1581139	0.1490712	0.1386750	0.1280369	0.1178511	0.10846523
## 4	0.1666667	0.1643990	0.1581139	0.1490712	0.1386750	0.1280369	0.11785113
## 5	0.1643990	0.1666667	0.1643990	0.1581139	0.1490712	0.1386750	0.12803688
## 6	0.1581139	0.1643990	0.1666667	0.1643990	0.1581139	0.1490712	0.13867505
##	71	72	73	74	75	76	77
## 1	0.1428571	0.1414214	0.1373606	0.1313064	0.1240347	0.1162476	0.1084652
## 2	0.1414214	0.1428571	0.1414214	0.1373606	0.1313064	0.1240347	0.1162476
## 3	0.1373606	0.1414214	0.1428571	0.1414214	0.1373606	0.1313064	0.1240347
## 4	0.1313064	0.1373606	0.1414214	0.1428571	0.1414214	0.1373606	0.1313064
## 5	0.1240347	0.1313064	0.1373606	0.1414214	0.1428571	0.1414214	0.1373606
## 6	0.1162476	0.1240347	0.1313064	0.1373606	0.1414214	0.1428571	0.1414214
##	78	79	80	81	82	83	84
## 1	0.1010153	0.09407209	0.08770580	0.1250000	0.1240347	0.1212678	0.1170411
## 2	0.1084652	0.10101525	0.09407209	0.1240347	0.1250000	0.1240347	0.1212678
## 3	0.1162476	0.10846523	0.10101525	0.1212678	0.1240347	0.1250000	0.1240347
## 4	0.1240347	0.11624764	0.10846523	0.1170411	0.1212678	0.1240347	0.1250000
## 5	0.1313064	0.12403473	0.11624764	0.1118034	0.1170411	0.1212678	0.1240347
## 6	0.1373606	0.13130643	0.12403473	0.1059998	0.1118034	0.1170411	0.1212678
##	85	86	87	88	89	90	91
## 1	0.1118034	0.1059998	0.1000000	0.09407209	0.08838835	0.08304548	0.11111111
## 2	0.1170411	0.1118034	0.1059998	0.10000000	0.09407209	0.08838835	0.11043153
## 3	0.1212678	0.1170411	0.1118034	0.10599979	0.10000000	0.09407209	0.10846523
## 4	0.1240347	0.1212678	0.1170411	0.11180340	0.10599979	0.10000000	0.10540926
## 5	0.1250000	0.1240347	0.1212678	0.11704115	0.11180340	0.10599979	0.10153462
## 6	0.1240347	0.1250000	0.1240347	0.12126781	0.11704115	0.11180340	0.09712859
##	92	93	94	95	96	97	98
## 1	0.1104315	0.1084652	0.1054093	0.1015346	0.09712859	0.09245003	0.08770580
## 2	0.1111111	0.1104315	0.1084652	0.1054093	0.10153462	0.09712859	0.09245003
## 3	0.1104315	0.1111111	0.1104315	0.1084652	0.10540926	0.10153462	0.09712859
## 4	0.1084652	0.1104315	0.1111111	0.1104315	0.10846523	0.10540926	0.10153462
## 5	0.1054093	0.1084652	0.1104315	0.1111111	0.11043153	0.10846523	0.10540926
## 6	0.1015346	0.1054093	0.1084652	0.1104315	0.11111111	0.11043153	0.10846523
##	99	100	101	102	103	104	105
## 1	0.08304548	0.07856742	0.10000000	0.09950372	0.09805807	0.09578263	0.09284767
## 2	0.08770580	0.08304548	0.09950372	0.10000000	0.09950372	0.09805807	0.09578263
## 3	0.09245003	0.08770580	0.09805807	0.09950372	0.10000000	0.09950372	0.09805807
## 4	0.09712859	0.09245003	0.09578263	0.09805807	0.09950372	0.10000000	0.09950372
## 5	0.10153462	0.09712859	0.09284767	0.09578263	0.09805807	0.09950372	0.10000000
## 6	0.10540926	0.10153462	0.08944272	0.09284767	0.09578263	0.09805807	0.09950372
##	106	107	108	109	110	111	112
## 1	0.08944272	0.08574929	0.08192319	0.07808688	0.07432941	0.09090909	0.09053575
## 2	0.09284767	0.08944272	0.08574929	0.08192319	0.07808688	0.09053575	0.09090909
## 3	0.09578263	0.09284767	0.08944272	0.08574929	0.08192319	0.08944272	0.09053575
## 4	0.09805807	0.09578263	0.09284767	0.08944272	0.08574929	0.08770580	0.08944272

```
## 5 0.09950372 0.09805807 0.09578263 0.09284767 0.08944272 0.08543577 0.08770580
## 6 0.10000000 0.09950372 0.09805807 0.09578263 0.09284767 0.08276059 0.08543577
##      113      114      115      116      117      118      119
## 1 0.08944272 0.08770580 0.08543577 0.08276059 0.07980869 0.07669650 0.07352146
## 2 0.09053575 0.08944272 0.08770580 0.08543577 0.08276059 0.07980869 0.07669650
## 3 0.09090909 0.09053575 0.08944272 0.08770580 0.08543577 0.08276059 0.07980869
## 4 0.09053575 0.09090909 0.09053575 0.08944272 0.08770580 0.08543577 0.08276059
## 5 0.08944272 0.09053575 0.09090909 0.09053575 0.08944272 0.08770580 0.08543577
## 6 0.08770580 0.08944272 0.09053575 0.09090909 0.09053575 0.08944272 0.08770580
##      120
## 1 0.07035975
## 2 0.07352146
## 3 0.07669650
## 4 0.07980869
## 5 0.08276059
## 6 0.08543577
```

```
ape::Moran.I(mod_aov$residuals, inv_matrix)
```

```
## $observed
## [1] 0.3257745
##
## $expected
## [1] -0.008403361
##
## $sd
## [1] 0.009053756
##
## $p.value
## [1] 0
```

continuando... con los modelos de regresión espacial

Modelo autorregresivo puro

```
library(spatialreg)
```

```
## Warning: package 'spatialreg' was built under R version 4.1.3
```

```
## Loading required package: spData
```

```
## Warning: package 'spData' was built under R version 4.1.3
```

```
## To access larger datasets in this package, install the spDataLarge
## package with: 'install.packages('spDataLarge',
## repos='https://nowosad.github.io/drat/', type='source')'
```

```
## Loading required package: Matrix
```

```
## Loading required package: sf
```

```

## Warning: package 'sf' was built under R version 4.1.3

## Linking to GEOS 3.9.1, GDAL 3.2.1, PROJ 7.2.1; sf_use_s2() is TRUE

## Registered S3 method overwritten by 'spdep':
##   method      from
##   plot.mst ape

library(spdep)

## Warning: package 'spdep' was built under R version 4.1.3

## Loading required package: sp

## Warning: package 'sp' was built under R version 4.1.3

##
## Attaching package: 'spdep'

## The following objects are masked from 'package:spatialreg':
##
##   get.ClusterOption, get.coresOption, get.mcOption,
##   get.VerboseOption, get.ZeroPolicyOption, set.ClusterOption,
##   set.coresOption, set.mcOption, set.VerboseOption,
##   set.ZeroPolicyOption

library(sp)
XY <- as.matrix(xy)
contnb <- dnearneigh(coordinates(XY),0,380000,longlat = F)
dlist <- nbdists(contnb, XY)
dlist <- lapply(dlist, function(x) 1/x)
Wve <- nb2listw(contnb,glist=dlist,style = "W")
mod_map <- spautolm(Mol3 ~ 1, data = df2, listw = Wve)
summary(mod_map)

##
## Call: spautolm(formula = Mol3 ~ 1, data = df2, listw = Wve)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.310980 -0.344036 -0.018235  0.370445  2.842945
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  10.1932      3.8049   2.679 0.007385
##
## Lambda: 0.98197 LR test value: 85.62 p-value: < 2.22e-16
## Numerical Hessian standard error of lambda: 0.018086
##
## Log likelihood: -139.3803
## ML residual variance (sigma squared): 0.56491, (sigma: 0.75161)
## Number of observations: 120
## Number of parameters estimated: 3
## AIC: 284.76

```

$$Y_{Mol3} = \alpha + \lambda WY + \epsilon$$

$$Y_{Mol3} = 10.1932 + 0.98197WY_{Mol3}$$

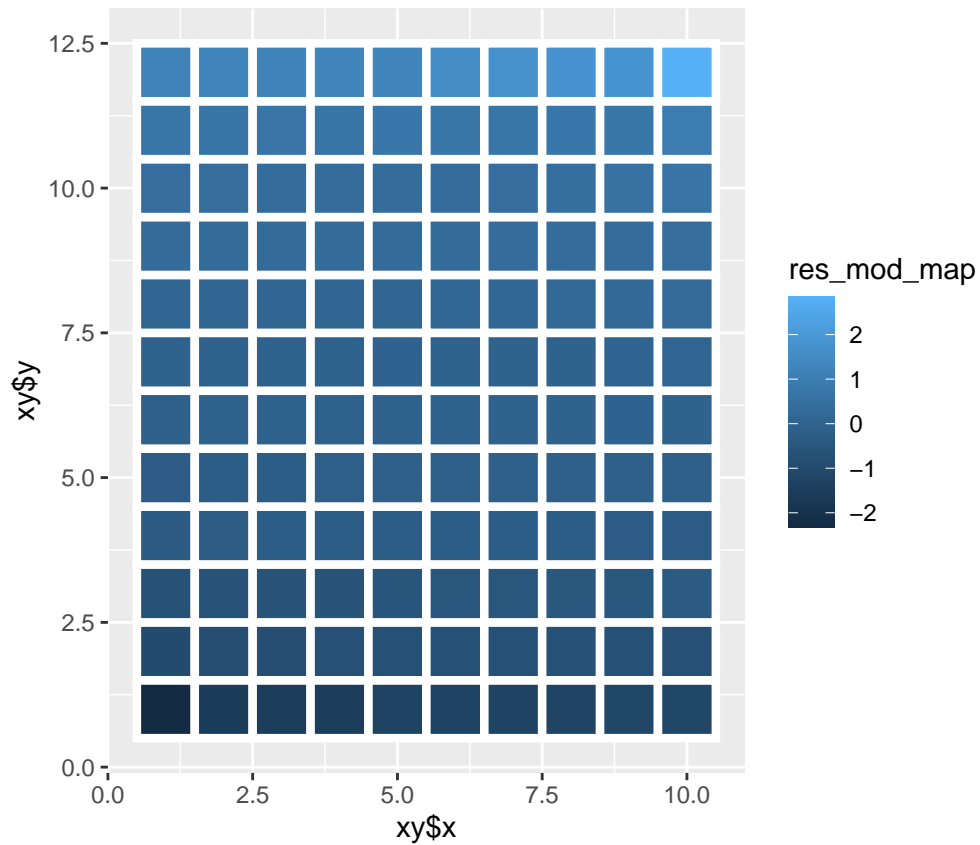
$$H_0 : \lambda = 0 H_a : \lambda \neq 0$$

*Se rechaza la  $H_0$*

```
res_mod_map <- mod_map$fit$residuals
ape::Moran.I(res_mod_map, inv_matrix)
```

```
## $observed
## [1] 0.2906574
##
## $expected
## [1] -0.008403361
##
## $sd
## [1] 0.008993576
##
## $p.value
## [1] 0
```

```
ggplot(df2, aes(x = xy$x, y = xy$y, fill = res_mod_map)) +
  geom_tile(color = "white",
            lwd = 1.5,
            linetype = 1) +
  coord_fixed()
```



```
pH <- sort(rnorm(120, 5.5, 0.2))
```

## Nuevo modelo

$$Y_{mol3} = \alpha + \lambda WY + \beta X_{pH} + \epsilon$$

## Modelo con variables explicativas

## Modelo espacial en rezago

```
mod_2 <- 0
```

## Asignación

- Correr el modelo espacial en rezago
- Buscar librería (Tip spatialreg, 'spatial lag model')

## Regresión Lineal Estándar (SLM - OLS)

```
model_SAR_1<-lm(DE ~ DDF, data = df)
summary(model_SAR_1)
```

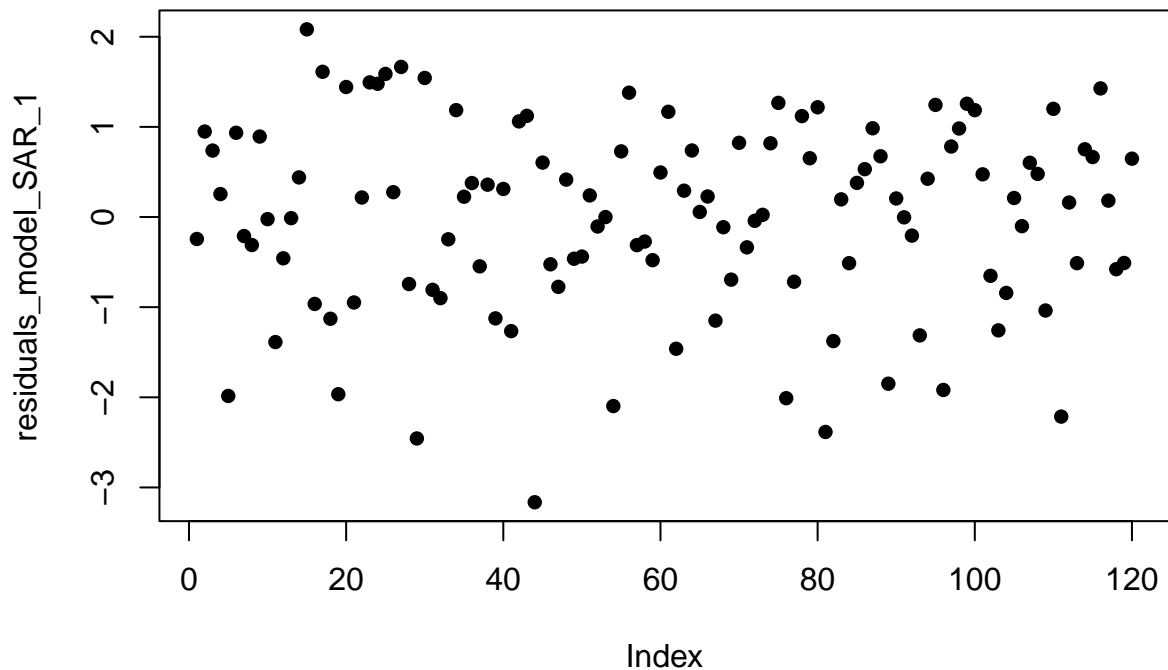
```
##
## Call:
## lm(formula = DE ~ DDF, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.1641 -0.5972  0.1889  0.7415  2.0820
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.444790    0.441990   7.794 2.83e-12 ***
## DDF          0.035857    0.004298   8.342 1.57e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.049 on 118 degrees of freedom
## Multiple R-squared:  0.371, Adjusted R-squared:  0.3656
## F-statistic: 69.59 on 1 and 118 DF, p-value: 1.573e-13
```

```
residuals_model_SAR_1<-residuals(model_SAR_1)
shapiro.test(residuals_model_SAR_1)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  residuals_model_SAR_1
## W = 0.9737, p-value = 0.01876
```

```
plot(residuals_model_SAR_1, pch = 16)
```





## Modelo de Error espacial (SEM)

```
sem1<-errorsarlm(DE ~ DDF, data = df, listw = Wve)
summary(sem1)
```

```
##
## Call:errorsarlm(formula = DE ~ DDF, data = df, listw = Wve)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.14929 -0.58177  0.18387  0.73513  2.09598
##
## Type: error
## Coefficients: (asymptotic standard errors)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.4254726  0.4356813  7.8623 3.775e-15
## DDF          0.0360561  0.0042771  8.4301 < 2.2e-16
##
## Lambda: -0.30341, LR test value: 0.17082, p-value: 0.67938
## Asymptotic standard error: 0.66617
##      z-value: -0.45545, p-value: 0.64879
## Wald statistic: 0.20743, p-value: 0.64879
##
```

```
## Log likelihood: -174.8929 for error model
## ML residual variance (sigma squared): 1.0789, (sigma: 1.0387)
## Number of observations: 120
## Number of parameters estimated: 4
## AIC: 357.79, (AIC for lm: 355.96)
```

## Spatial lag model

```
fit.lag<-lagsarlm(DE ~ DDF, data = df, listw = Wve)
summary(fit.lag)
```

```
##
## Call:lagsarlm(formula = DE ~ DDF, data = df, listw = Wve)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.16655 -0.59639  0.19013  0.74301  2.07985
##
## Type: lag
## Coefficients: (asymptotic standard errors)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.285996   3.818043  0.8606   0.3894
## DDF          0.035863   0.004273  8.3928  <2e-16
##
## Rho: 0.022424, LR test value: 0.0013794, p-value: 0.97037
## Asymptotic standard error: 0.53356
## z-value: 0.042027, p-value: 0.96648
## Wald statistic: 0.0017663, p-value: 0.96648
##
## Log likelihood: -174.9776 for lag model
## ML residual variance (sigma squared): 1.0816, (sigma: 1.04)
## Number of observations: 120
## Number of parameters estimated: 4
## AIC: 357.96, (AIC for lm: 355.96)
## LM test for residual autocorrelation
## test value: 2.1435, p-value: 0.14318
```

- ¿Este modelo me quita la dependencia espacial?

el p-valor  $>0.05$  NO hay dependencia especial.

## Bibliografía

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<https://rspatial.org/raster/analysis/7-spregression.html>

[https://crd230.github.io/lab8.html#Spatial\\_lag\\_model](https://crd230.github.io/lab8.html#Spatial_lag_model)

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