

**DSCI561: Regression I**

**Lecture 2: November 20, 2017**

Gabriela Cohen Freue

Department of Statistics, UBC

# In Lect 1: two-sample t-test vs ANOVA

- In both cases we are interested in studying the expected number of runs per game
  - **Quantitative response variable**: tax assessment value for a property built in period  $i$ :  $Y_i$
  - **Population mean**:  $\mu_i = E[Y_i]$
- **two-sample t-test**: compares the means of two populations (groups)  
$$H_0 : \mu_C = \mu_M$$
- **one-way ANOVA**: compares the means of  $K$  groups  
1 factor,  $K$  levels)
  - **1 factor**: age period; **K=3 levels**: C, M, O  $H_0 : \mu_C = \mu_M = \mu_O$
  - **K=2**: it is equivalent to a two-sample t-test
- ANOVA: Study the effect of one or more **qualitative variables (factors)** on a **quantitative variable (response)**:
  - **Quantitative response**: tax property assessment value

## **Two-sample t-test as a special case of ANOVA**

```
#t-test vs ANOVA
#responses within each group
tax.M <-dat.small %>% subset(age_factor == "M", select=assessment_k)
tax.C <-dat.small %>% subset(age_factor == "C", select=assessment_k)

t.test(tax.M,tax.C,var.equal=T)
```

```
##
## Two Sample t-test
##
## data: tax.M and tax.C
## t = -2.2034, df = 18, p-value = 0.04083
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -180.111457 -4.288543
## sample estimates:
## mean of x mean of y
## 428.8 521.0
```

```
#subset of 2 age periods
summary(aov(assessment_k~age_factor,data=subset(dat.small,age_factor %in% c("M","C"))))
```

```
##           Df Sum Sq Mean Sq F value Pr(>F)
## age_factor  1  31878   31878    4.855 0.0408 *
## Residuals  18 118188    6566
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

$$(-2.2034)^2 = 4.855$$

```
#t-test vs ANOVA
#responses within each group
tax.M <-dat.small %>% subset(age_factor == "M", select=assessment_k)
tax.C <-dat.small %>% subset(age_factor == "C", select=assessment_k)

t.test(tax.M,tax.C,var.equal=T)
```

```
##
## Two Sample t-test
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## data: tax.M and tax.C
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## 95 percent confidence interval:
## -180.111457 -4.288543
## sample estimates:
## mean of x mean of y
## 428.8 521.0
```

$$H_0 : \mu_C = \mu_M$$

same test

```
#subset of 2 age periods
summary(aov(assessment_k~age_factor,data=subset(dat.small,age_factor %in% c("M","C"))))
```

```
##           Df Sum Sq Mean Sq F value Pr(>F)
## age_factor  1  31878   31878   4.855 0.0408 *
## Residuals  18 118188    6566
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## **ANOVA as a special case of Regression**

## Two groups

```
summary(lm(assessment_k~age_factor,data=subset(dat.small,age_factor %in% c("M","C"))))
```

```
##
```

```
## Call:
```

```
## lm(formula = assessment_k ~ age_factor, data = subset(dat.small,  
##      age_factor %in% c("M", "C")))
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -178.80  -17.55  -10.90   39.45  197.20
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)  
## (Intercept)    521.00     36.24   14.377 2.62e-11 ***  
## age_factorM    -92.20     41.84   -2.203  0.0408 *
```

← same as t-test

```
## ---
```

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

```
##
```

```
## Residual standard error: 81.03 on 18 degrees of freedom
```

```
## Multiple R-squared:  0.2124, Adjusted R-squared:  0.1687
```

```
## F-statistic: 4.855 on 1 and 18 DF, p-value: 0.04083
```

← same as ANOVA

# More than 2 groups

*#More than 2 groups*

*#LM with 3 age periods*

```
summary(lm(assessment_k~age_factor,data=dat.small))
```

```
##
## Call:
## lm(formula = assessment_k ~ age_factor, data = dat.small)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -250.14  -74.89  -16.97   51.36  612.86
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    521.00     54.10   9.631 2.87e-14 ***
## age_factorM    -92.20     62.46  -1.476   0.145
## age_factor0   -85.86     56.74  -1.513   0.135
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 121 on 67 degrees of freedom
## Multiple R-squared:  0.0353, Adjusted R-squared:  0.006498
## F-statistic: 1.226 on 2 and 67 DF, p-value: 0.3001
```

different from t-test!!

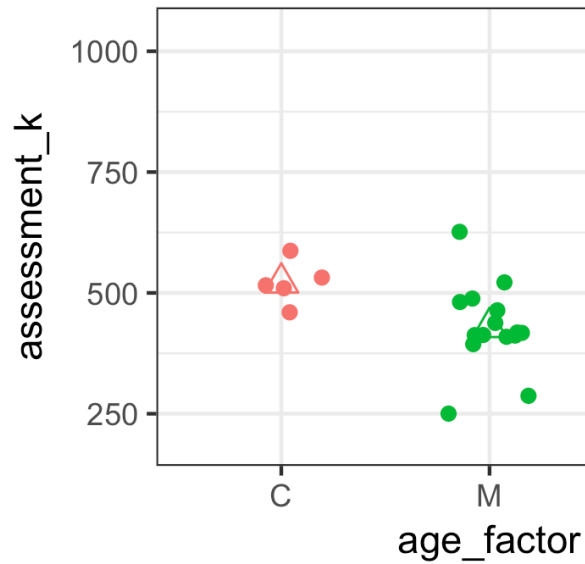
same test

*#ANOVA with 3 age periods*

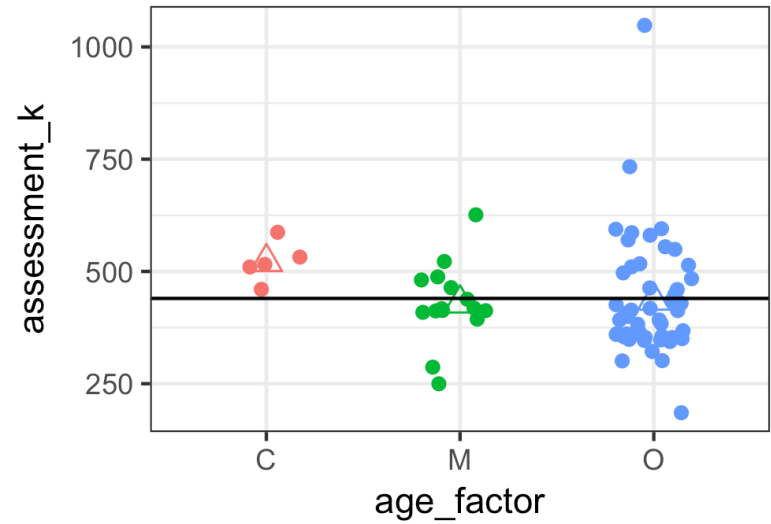
```
summary(aov(assessment_k~age_factor,data=dat.small))
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## age_factor    2  35867   17934    1.226   0.3
## Residuals    67 980328   14632
```

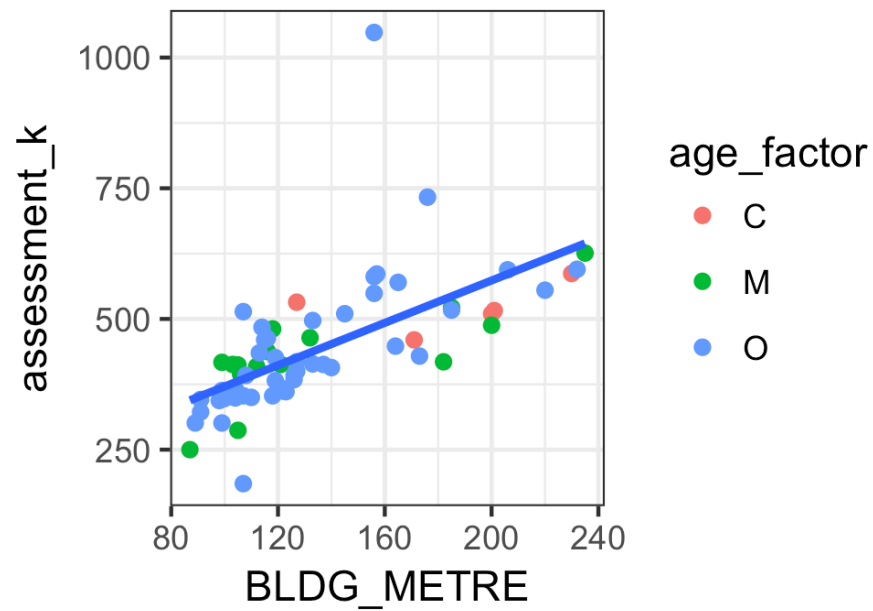




**two-samples t-test: 2 groups**



**one-way ANOVA: more than 2 groups**



**Linear regression: quantitative and qualitative explanatory variables**

# In today's lecture

- Comparison with the output of the ``lm()`` function in R
- Review of linear algebra operations
- Review the mathematical notation of a linear model and its connection with the R-code
- Build the matrix notation of a linear model

**Some linear algebra...**

# Sum of matrices

- Let **A** and **B** be  $n \times m$  matrices ( $n$  rows,  $m$  columns)
- **A+B** is an  $n \times m$  matrix with  $ij$ th element equal to  $a_{ij} + b_{ij}$

$$\begin{array}{ccc} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ \vdots & \vdots \\ a_{m1} & a_{m2} \end{bmatrix} & + & \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \\ \vdots & \vdots \\ b_{m1} & b_{m2} \end{bmatrix} \\ \mathbf{A} & & \mathbf{B} \end{array} = \begin{array}{c} \begin{bmatrix} a_{11} + b_{11} & a_{12} + b_{12} \\ a_{21} + b_{21} & a_{22} + b_{22} \\ \vdots & \vdots \\ a_{m1} + b_{m1} & a_{m2} + b_{m2} \end{bmatrix} \\ \mathbf{A+B} \end{array}$$

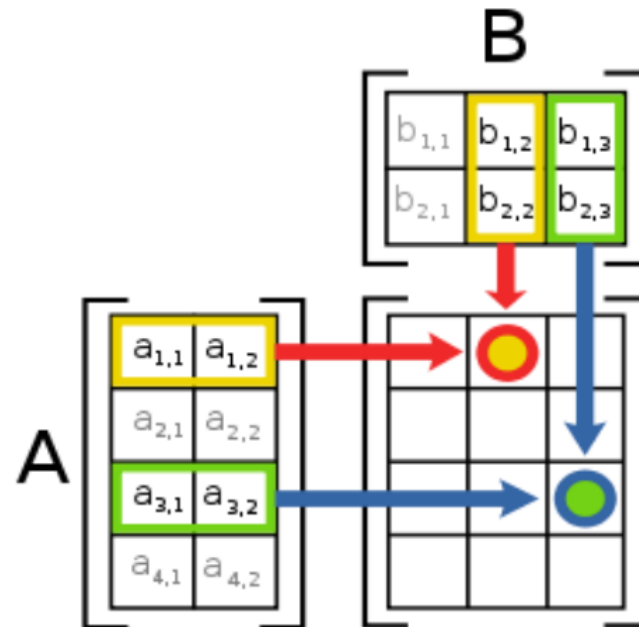
$$\begin{bmatrix} 1 & 0 & 3 & -1 \\ 0 & 1 & 1 & -1 \\ 0 & 4 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & -1 & 1 \\ 2 & 0 & 0 & 0 \\ 0 & -2 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 2 & 0 \\ 2 & 1 & 1 & -1 \\ 0 & 2 & 0 & 0 \end{bmatrix}$$

# Multiplication of matrices

- If  $\mathbf{A}$  is an  $n \times m$  matrix,  $\mathbf{AB}$  is defined only if  $\mathbf{B}$  has  $m$  rows (number of columns in  $\mathbf{B}$  doesn't matter)
- $\mathbf{AB}$  is an  $n \times m$  matrix

Dot product

$$a \cdot b = \sum a_i b_i$$



# Example

$$\begin{bmatrix} 1 & 2 \\ 1 & 4 \\ 0 & 5 \end{bmatrix} * \begin{bmatrix} -1 & -2 \\ -2 & 1 \end{bmatrix} = \begin{bmatrix} -5 & 0 \\ -9 & 2 \\ -10 & 5 \end{bmatrix}$$

(3x2)
(2x2)
(3x2)

*#Multiplication*

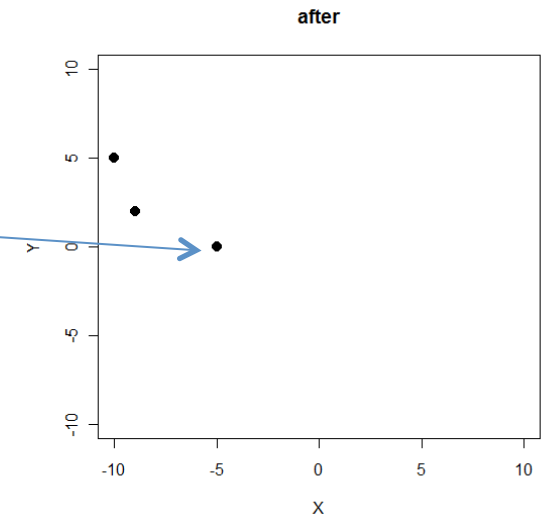
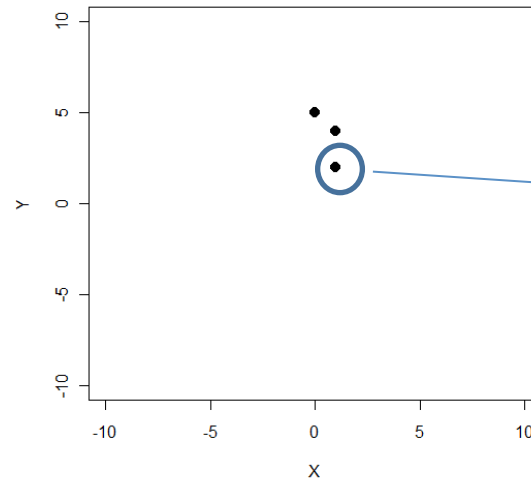
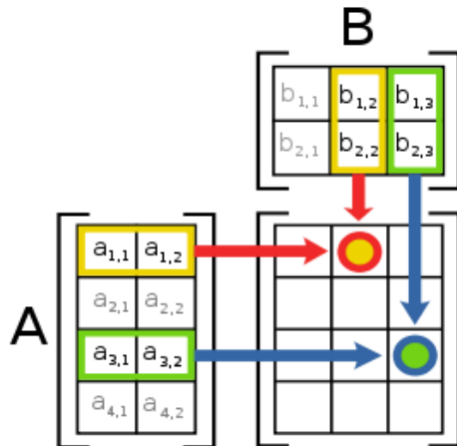
```
A <- matrix(c(1, 2, 1, 4, 0, 5), 3, 2, byrow=T)
```

```
B <- matrix(c(-1, -2, -2, 1), 2, 2, byrow=T)
```

```
A%*%B
```

```
##      [,1] [,2]
## [1,]  -5   0
## [2,]  -9   2
## [3,] -10   5
```

*#Note: A%\*%B is not the same as A\*B*



# Matrix operations as transformations in space

- Multiply by a scalar: moving the points further apart in space (or closer together)
- Multiply by another matrix: e.g., rotation, or projection
- Projection in particular is a fundamental operation: often want to project from original space to a reduced space that is “explanatory”

# Examples: Projections

$$\begin{bmatrix} 1 & 2 \\ 1 & 4 \\ 0 & 5 \end{bmatrix} \times \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix}$$

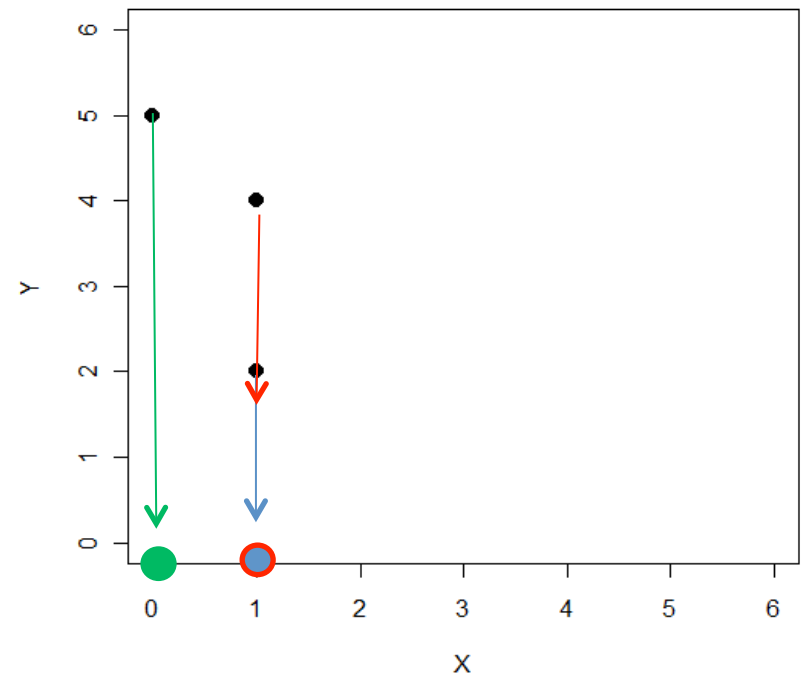
*#Projection*

```
A <- matrix(c(1,2,1,4,0,5),3,2,byrow=T)
```

```
Px <- matrix(c(rep(0,3),1),2,2)
```

```
A%*%Px
```

```
##      [,1] [,2]  
## [1,]    0    2  
## [2,]    0    4  
## [3,]    0    5
```



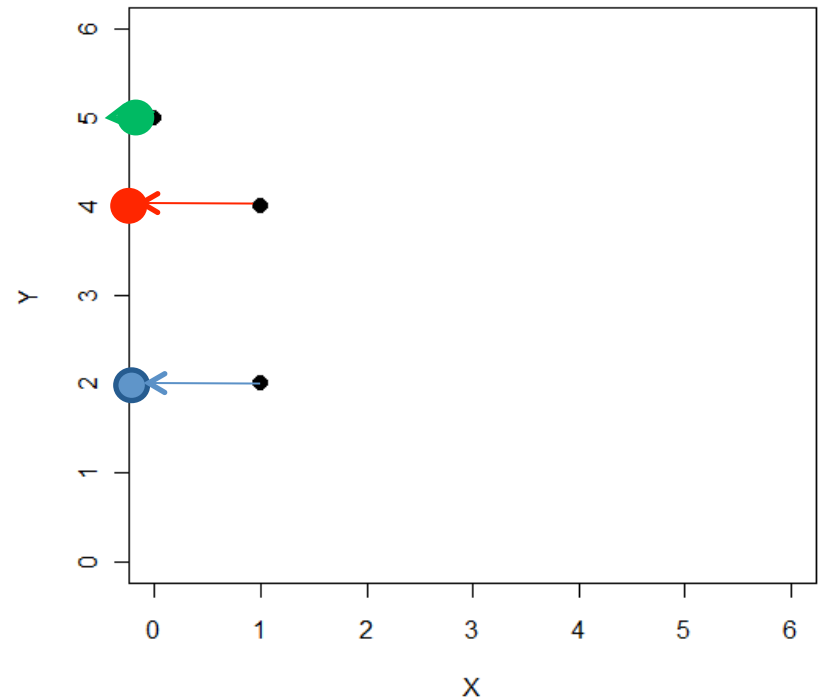


# Examples: Projections

$$\begin{bmatrix} 1 & 2 \\ 1 & 4 \\ 0 & 5 \end{bmatrix} \times \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 2 \\ 0 & 4 \\ 0 & 5 \end{bmatrix}$$

```
Py <- matrix(c(1,rep(0,3)),2,2)  
A%*%Py
```

```
##      [,1] [,2]  
## [1,]    1    0  
## [2,]    1    0  
## [3,]    0    0
```



We can project onto any line we like

# Inverse of a matrix

- An  $n \times n$  square matrix **A** is invertible, if there exist an  $n \times n$  square matrix **B** such that **AB=BA=I<sub>n</sub>**
- This matrix **B** is called the inverse of **A**: **A<sup>-1</sup>**

$$\begin{bmatrix} 7 & 2 & 1 \\ 0 & 3 & -1 \\ -3 & 4 & -2 \end{bmatrix}^{-1} = \begin{bmatrix} -2 & 8 & -5 \\ 3 & -11 & 7 \\ 9 & -34 & 21 \end{bmatrix}$$

```
#Inverse
```

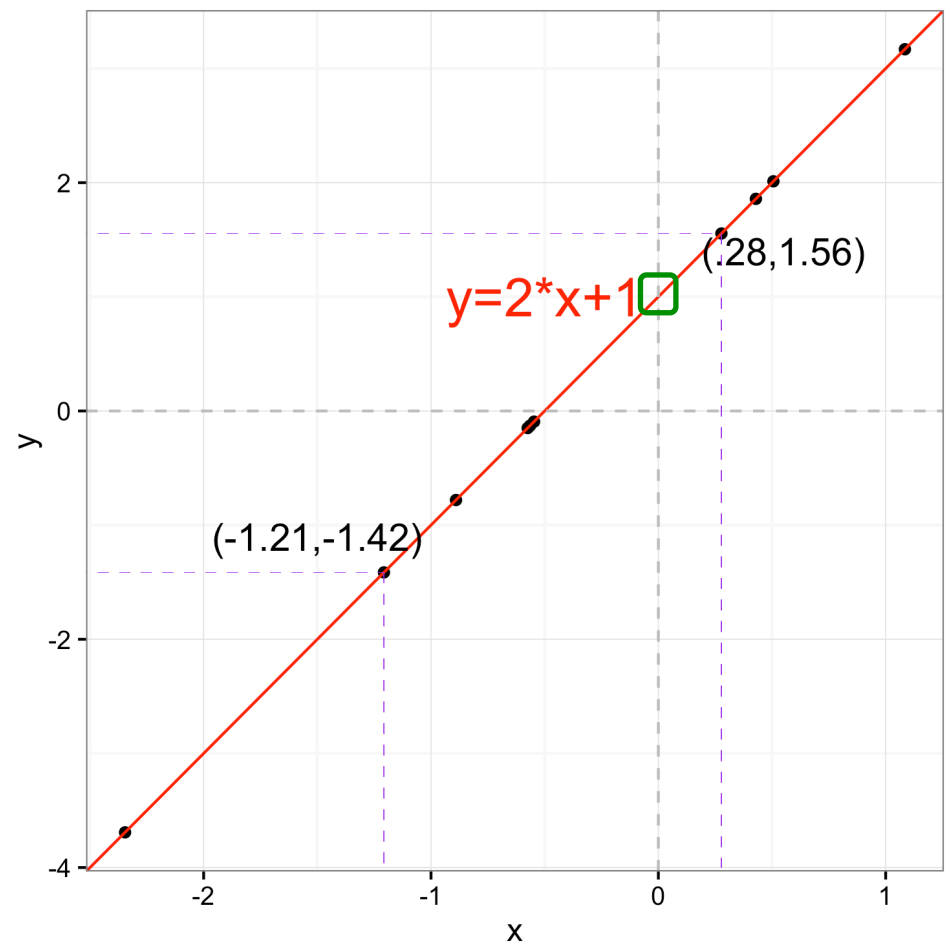
```
A <- matrix(c(7, 2, 1, 0, 3, -1, -3, 4, -2), 3, 3, byrow=T)
solve(A)
```

```
##      [,1] [,2] [,3]
## [1,]  -2    8  -5
## [2,]   3  -11   7
## [3,]   9  -34  21
```

# A line

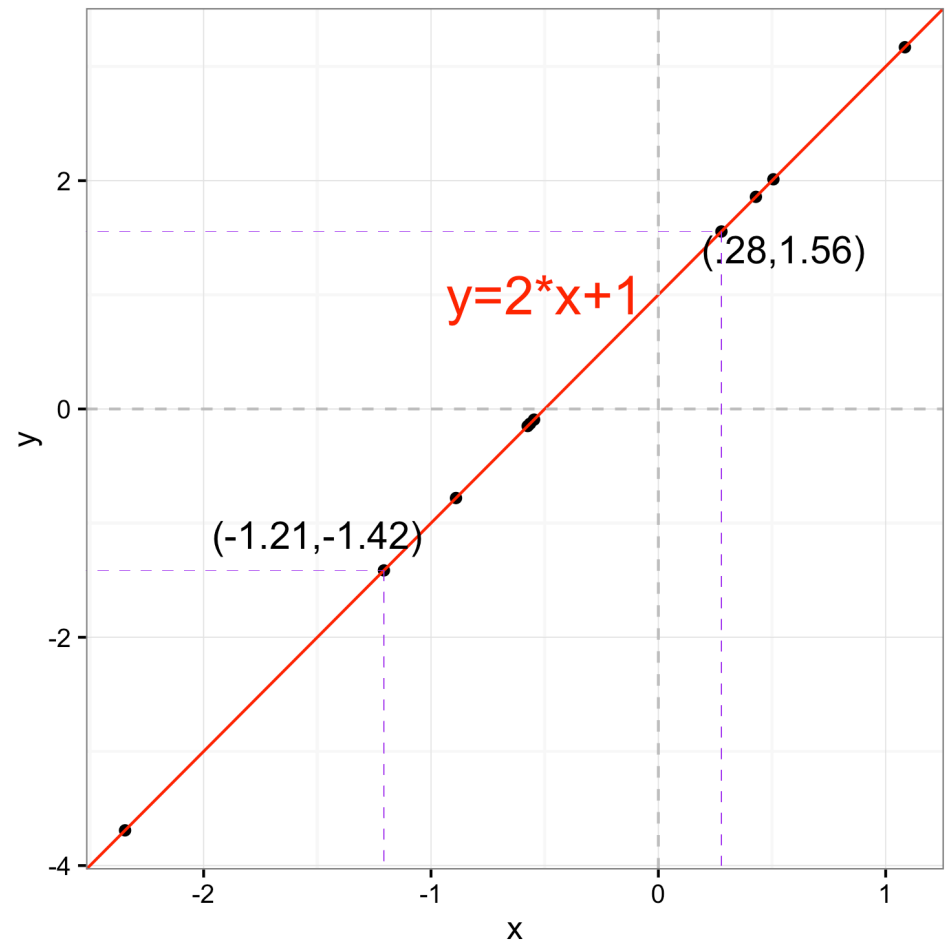
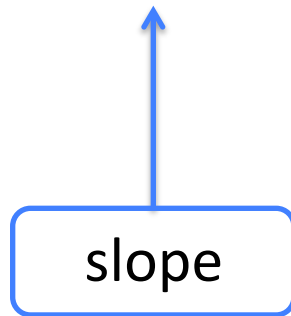
$$y = a + m * x$$

↑  
intercept



# A line

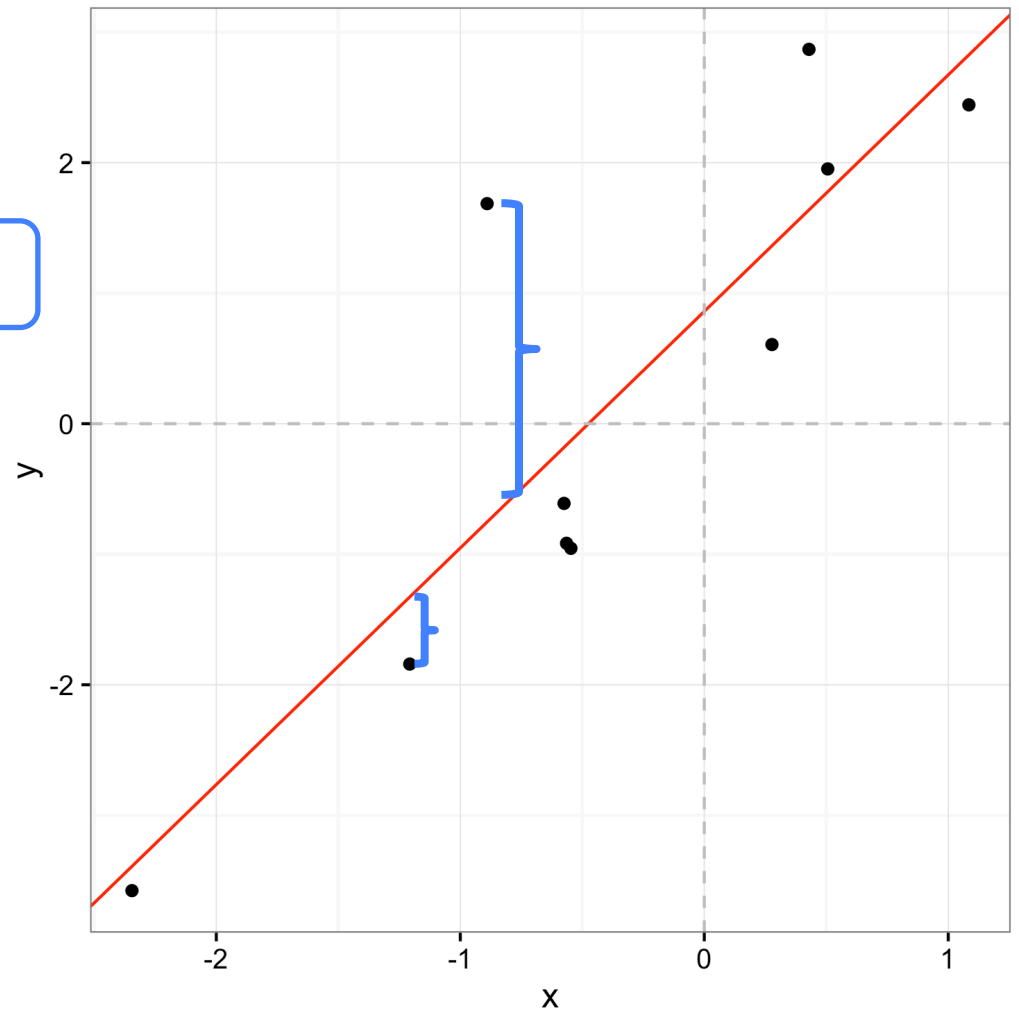
$$y = a + m * x$$

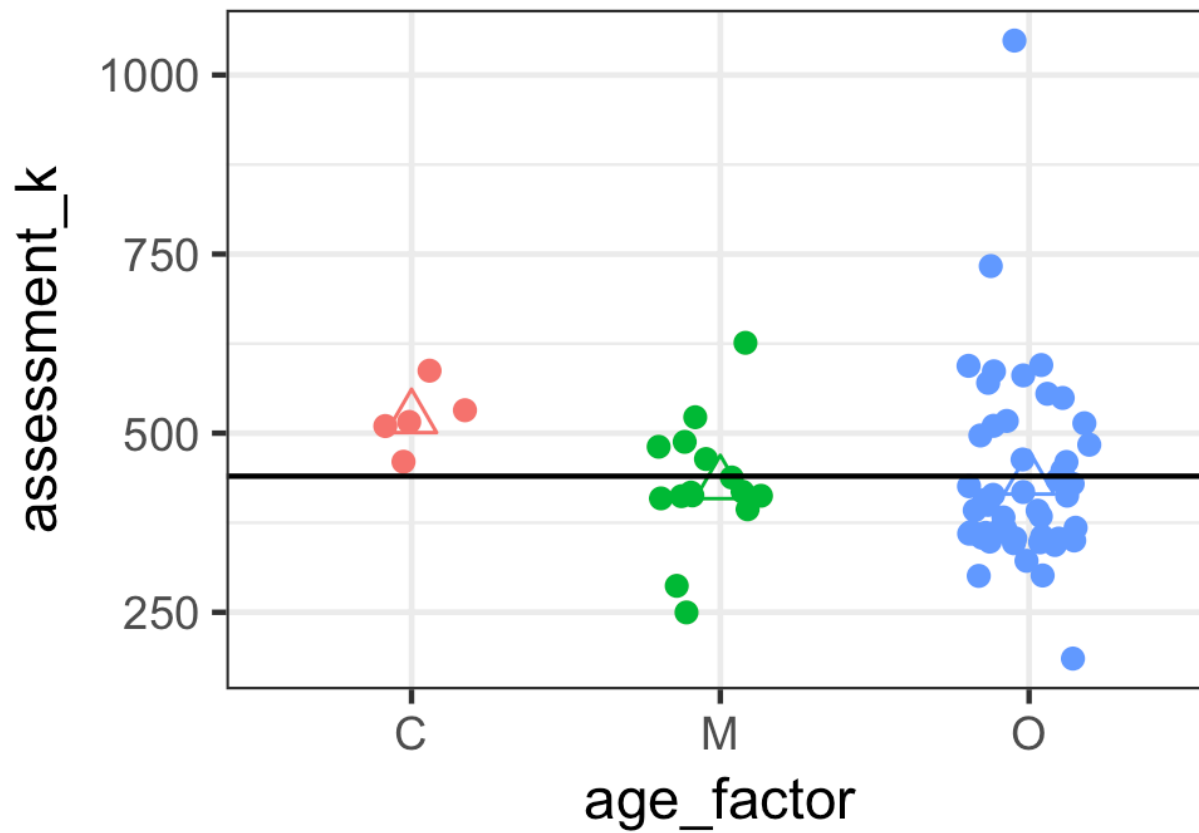


# A regression line

$$y_i = a + m * x_i + \varepsilon_i$$

error





**Where is the linear regression?**

YEAR_BUILT	age_factor	assessment_k
2013	C	510
2003	C	516
2002	C	460
2002	C	532
2005	C	587
1995	M	481
1989	M	409
1991	M	522
1998	M	413
1989	M	413
1988	M	394
1990	M	418
1998	M	464
1990	M	412
1989	M	488
1990	M	626
1984	M	417
1989	M	250
1997	M	438
1980	M	287

## Glance at the data

$$Y_C; Y_{C1}, \dots, Y_{C5}, n_C = 5$$

$$Y_M; Y_{M1}, \dots, Y_{M15}, n_M = 15$$

$$H_0 : \mu_C = \mu_M$$

## Call:

```
## lm(formula = assessment_k ~ age_factor, data = subset(dat.small,
##           age_factor %in% c("M", "C")))
```

...

$$Y_{ij} = \mu_j + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim F_j, E(\varepsilon_{ij}) = 0$$

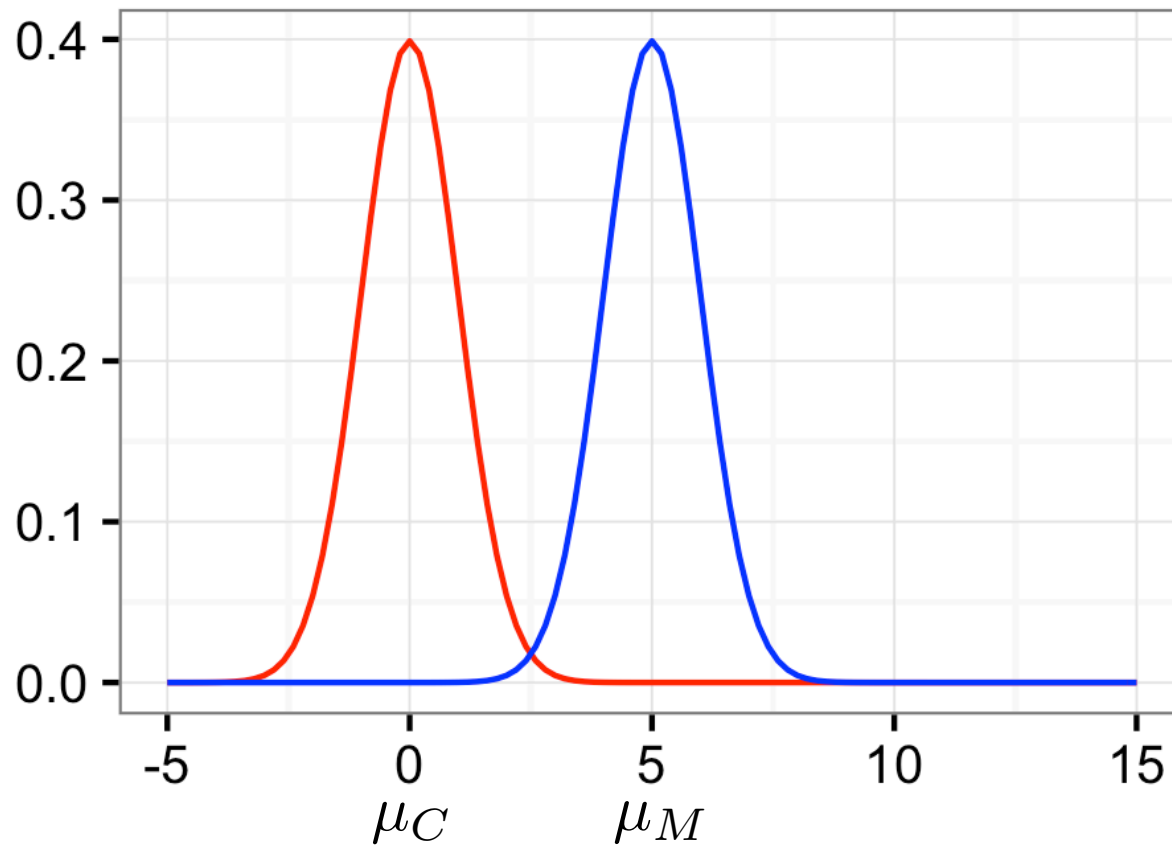
YEAR_BUILT	age_factor	assessment_k
2013	C	510
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2002	C	460
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1998	M	464
1990	M	412
1989	M	488
1990	M	626
1984	M	417
1989	M	250
1997	M	438
1980	M	287

$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{n_1 1} \\ Y_{12} \\ \vdots \\ Y_{n_2 2} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_1 \\ \mu_2 \\ \vdots \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$

$$H_0 : \mu_C = \mu_M$$

**Change in notation...**





$$Y_{ij} = \mu_j + \varepsilon_{ij}, \varepsilon_{ij} \sim F_j, E[\varepsilon_{ij}] = 0$$

$$Y_M \sim F_M; E[Y_M] = \mu_M$$

$$Y_C \sim F_C; E[Y_B] = \mu_C$$

$$H_0 : \mu_C = \mu_M$$

**We don't know or observe these curves and parameters**

$$Y_{ij} = \mu_j + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim F_j, E(\varepsilon_{ij}) = 0$$

$$\begin{bmatrix} \boxed{Y_{11}} \\ \vdots \\ \boxed{Y_{n_1 1}} \\ \boxed{Y_{12}} \\ \vdots \\ \boxed{Y_{n_2 2}} \end{bmatrix} = \begin{bmatrix} \boxed{\mu_1} \\ \vdots \\ \boxed{\mu_1} \\ \boxed{\mu_2} \\ \vdots \\ \boxed{\mu_2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$

$$Y_{ij} = \mu_j + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim F_j, E(\varepsilon_{ij}) = 0$$

$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{n_1 1} \\ Y_{12} \\ \vdots \\ Y_{n_2 2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_1 \\ \mu_2 \\ \vdots \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$

For example:

$$Y_{11} = 1 * \mu_1 + 0 * \mu_2 + \varepsilon_{11} = \mu_1 + \varepsilon_{11}$$

$$Y_{n_2 2} = 0 * \mu_1 + 1 * \mu_2 + \varepsilon_{n_2 2} = \mu_2 + \varepsilon_{n_2 2}$$

$$Y_{ij} = \mu_j + \varepsilon_{ij}, \text{ where } \varepsilon_{ij} \sim F_j, E(\varepsilon_{ij}) = 0$$

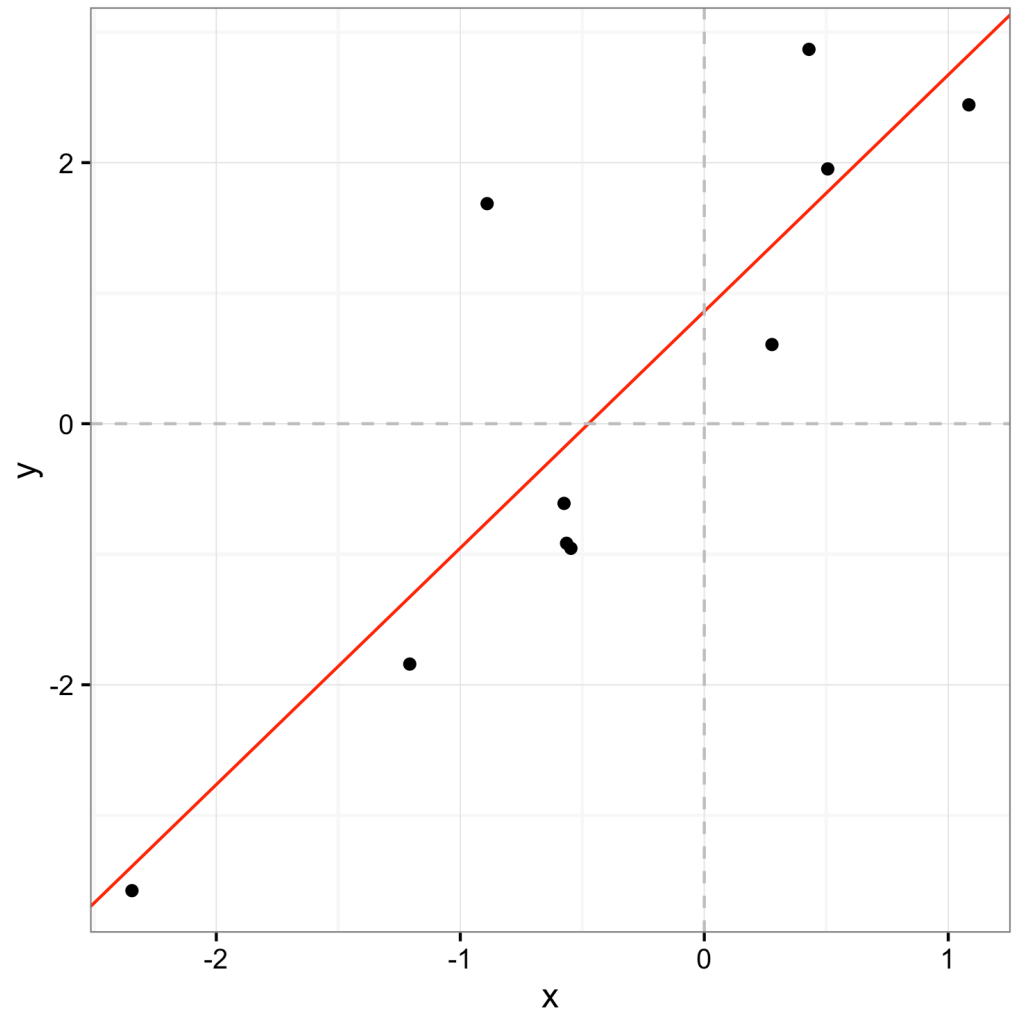
$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{n_1 1} \\ Y_{12} \\ \vdots \\ Y_{n_2 2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$



$$Y = X\alpha + \varepsilon$$

# A regression line

$$y_i = a + m * x_i + \varepsilon_i$$



the column vector of the responses  
one element per experimental unit

a column vector  
of the errors


$$Y = X\alpha + \varepsilon$$

a (design) matrix that represents covariate  
info, one row per experimental unit

a column vector of the parameters in the  
linear model

Generic linear model, using  
conventional matrix formulation

## Two groups

$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{n_1 1} \\ Y_{12} \\ \vdots \\ Y_{n_2 2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$

sample mean of C

```
summary(lm(assessment_k~age_factor,data=subset(dat.small,age_factor %in% c("M","C"))))
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    521.00      36.24  14.377 2.62e-11 ***
## age_factorM    -92.20      41.84  -2.203  0.0408 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 81.03 on 18 degrees of freedom
## Multiple R-squared:  0.2124, Adjusted R-squared:  0.1687
## F-statistic: 4.855 on 1 and 18 DF,  p-value: 0.04083
```

NOT the sample mean of M

$$\begin{bmatrix} Y_{11} \\ \vdots \\ Y_{n_1 1} \\ Y_{12} \\ \vdots \\ Y_{n_2 2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{n_1 1} \\ \varepsilon_{12} \\ \vdots \\ \varepsilon_{n_2 2} \end{bmatrix}$$

This is a one way of writing our problem as a linear regression

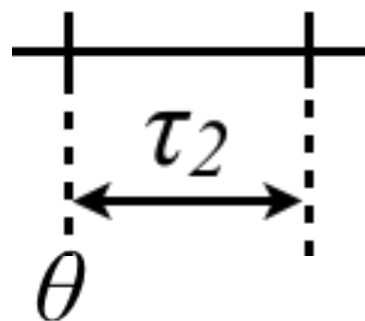
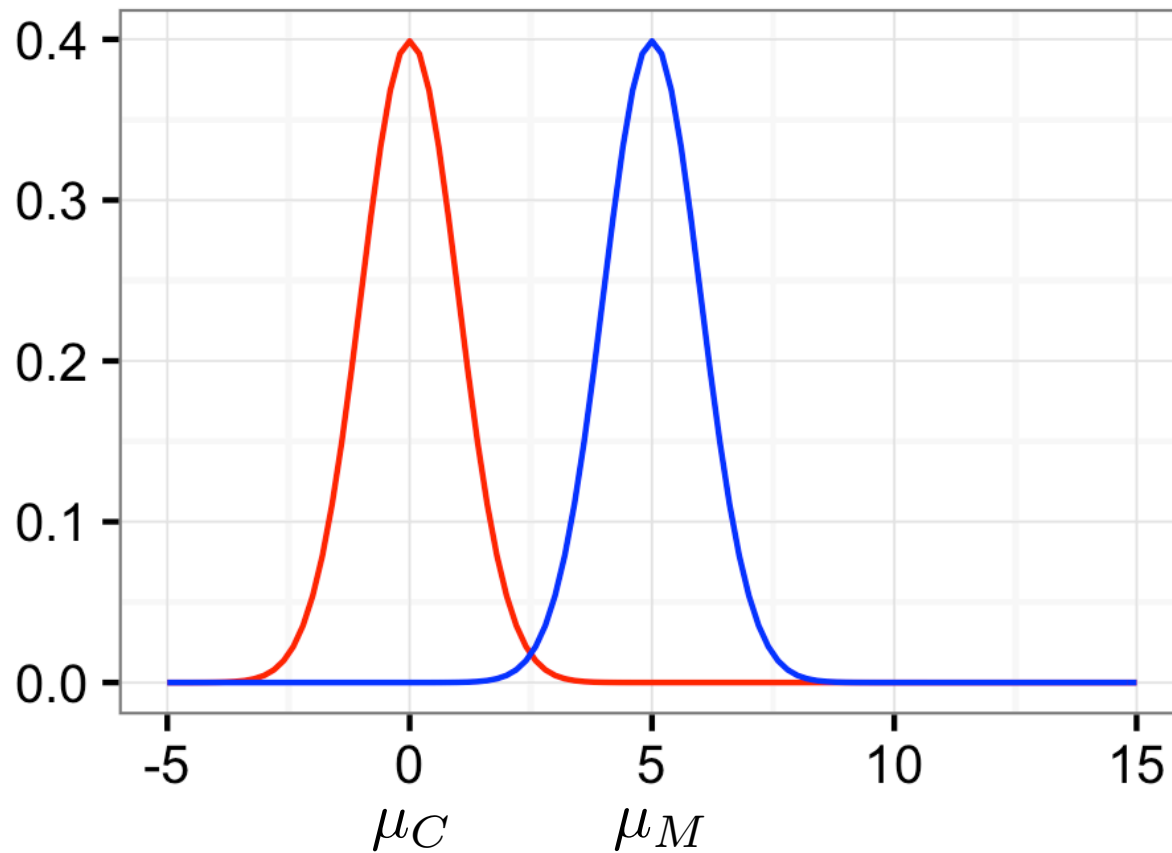
**“cell means”**  
parametrization

$$Y = X\alpha + \varepsilon$$

... but there are other ways!!

**By default, R does not estimate these parameters**





$$H_0 : \mu_M = \mu_C$$

$$H_0 : \tau_2 = 0$$

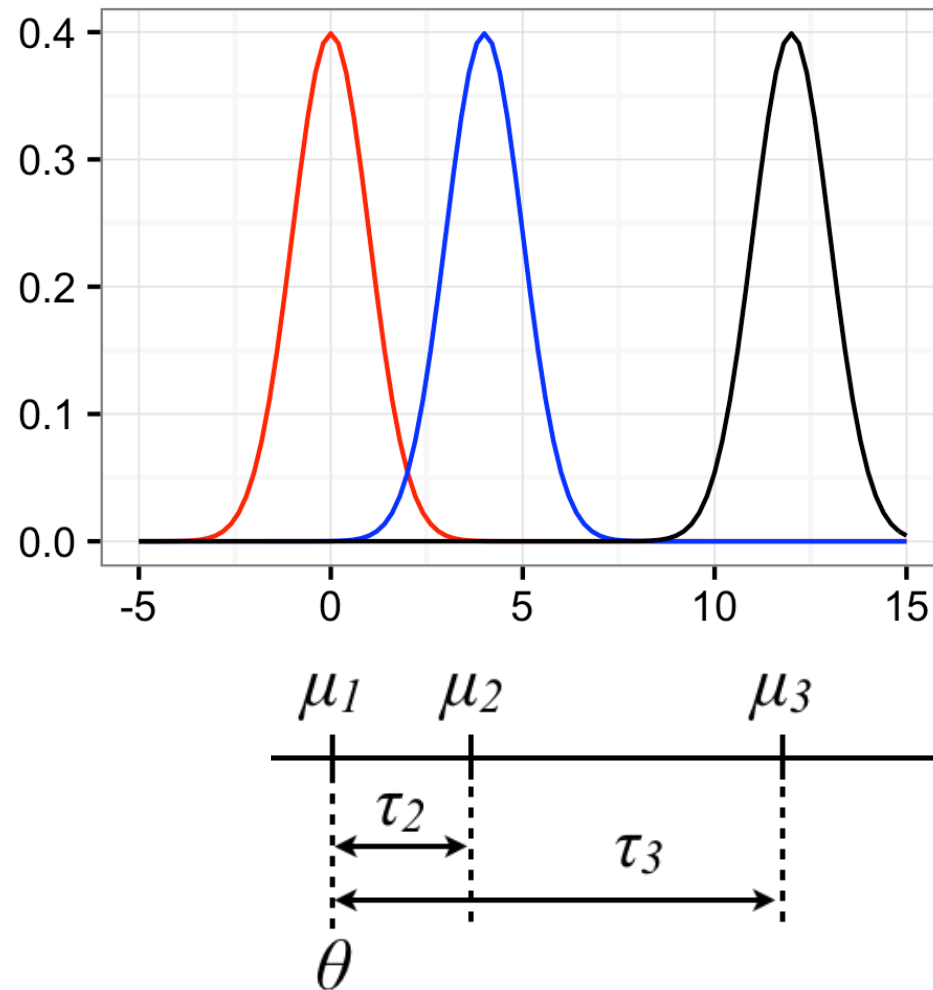
**A different parametrization: “reference-treatment effect”**

ANOVA-style, “cell means”

$$Y_{ij} = \mu_j + \varepsilon_{ij}$$

ANOVA-style, “ref + tx effects”

$$Y_{ij} = \theta + \tau_j + \varepsilon_{ij}, (\tau_1 = 0)$$



ANOVA-style, “cell means”


$$Y_{ij} = \mu_j + \varepsilon_{ij}$$

ANOVA-style, “ref + tx effects”

$$Y_{ij} = \theta + \tau_j + \varepsilon_{ij}, (\tau_1 = 0)$$

$$Y = X\alpha + \varepsilon$$

$$\begin{bmatrix} y_{11} \\ y_{21} \\ \vdots \\ y_{n_33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n_33} \end{bmatrix}$$

$$\begin{bmatrix} y_{11} \\ y_{21} \\ \vdots \\ y_{n_33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \theta \\ \tau_2 \\ \tau_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n_33} \end{bmatrix}$$


The design matrix specifies how the observed data relates to the regression parameters.


ANOVA-style, “cell means”

$$Y_{ij} = \mu_j + \varepsilon_{ij}$$

ANOVA-style, “ref + tx effects”

$$Y_{ij} = \theta + \tau_j + \varepsilon_{ij}, (\tau_1 = 0)$$

$$Y = X\alpha + \varepsilon$$



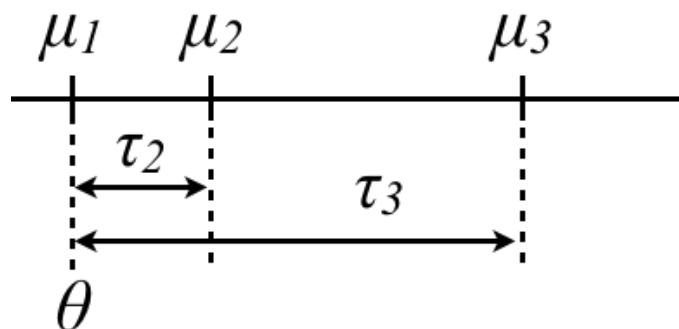
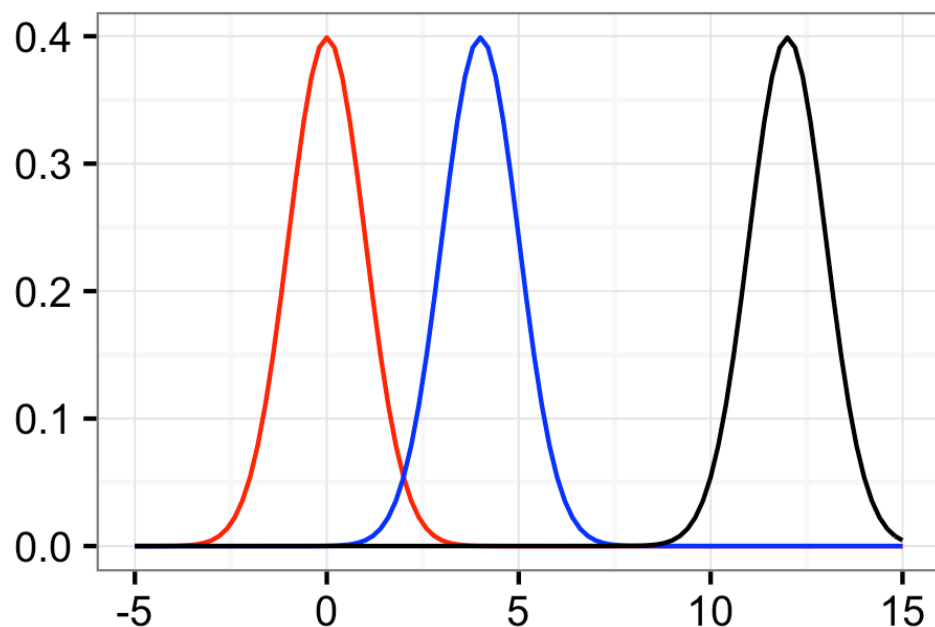
$$\begin{bmatrix} y_{11} \\ y_{21} \\ \vdots \\ y_{n_3 3} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n_3 3} \end{bmatrix}$$

$$\begin{bmatrix} y_{11} \\ y_{21} \\ \vdots \\ y_{n_3 3} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \theta \\ \tau_2 \\ \tau_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n_3 3} \end{bmatrix}$$

For example:

$$Y_{11} = 1 * \theta + 0 * \tau_2 + 0 * \tau_3 + \varepsilon_{11} = \theta + \varepsilon_{11} \implies E[Y_{11}] = \theta$$

$$Y_{13} = 1 * \theta + 0 * \tau_2 + 1 * \tau_3 + \varepsilon_{13} = \theta + \tau_3 + \varepsilon_{13} \implies E[Y_{13}] = \theta + \tau_3$$



$$H_0 : \mu_1 = \mu_2 = \mu_3$$

$$H_0 : \tau_2 = \tau_3 = 0$$

$$Y_{i1} \sim F_1; E[Y_{i1}] = \mu_1$$

$$Y_{i2} \sim F_2; E[Y_{i2}] = \mu_2$$

$$Y_{i3} \sim F_3; E[Y_{i3}] = \mu_3$$

$$E[Y_{i1}] = \theta$$

reference

treatment  
effect

$$E[Y_{i2}] = \theta + \tau_2 \implies E[Y_{i2}] - E[Y_{i1}] = \tau_2$$

$$E[Y_{i3}] = \theta + \tau_3 \implies E[Y_{i3}] - E[Y_{i1}] = \tau_3$$

$$Y = X\alpha + \varepsilon$$

$$\begin{bmatrix} Y_{11} \\ Y_{21} \\ \vdots \\ Y_{n_33} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 0 \\ 1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \theta \\ \tau_2 \\ \tau_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \vdots \\ \varepsilon_{n_33} \end{bmatrix}$$

Reference period: C

M vs C

O vs C

difference in **population** means