

# Linear regression

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# Let's do some actual analysis!

Now that we've got the hang of some R commands, let's do some real analysis

# Linear regression

- ▶ explains the relationship between dependent (Y) and independent (X) variables
- ▶ “line of best fit” to data
- ▶ a “simple” linear regression is equivalent to a correlation
- ▶ is a *supervised* machine learning technique
- ▶ the model learns from known data, and can be used to predict
- ▶ sometimes we are looking for trends and don't care about predictions

# Linear regression

linear regression takes the linear equation of:

$$Y = mX + b$$

But we're going to use it more like:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + \epsilon_i$$

where:

$\hat{y}_i$  = predicted response for experimental unit  $i$

$x_i$  = predictor (or independent variable) of experimental unit  $i$

$\hat{\beta}_0$  = is expected value when  $x_i = 0$  (intercept)

$\hat{\beta}_1$  = slope

$\epsilon$  = some error, because models are never perfect!

## $\beta_0$ and $\beta_1$

$\beta_0$  and  $\beta_1$  are unknown.

We will estimate these coefficients from known data. To do this, we need to estimate a line of best fit than minimizes error

## An example: Does head size predict brain size?

```
library(data.table)
# we've already loaded this package...
head_brain <- fread('http://www.stat.ufl.edu/~winner/data/brainhead.dat')
head(head_brain)
```

```
##      V1 V2   V3   V4
## 1:    1  1 4512 1530
## 2:    1  1 3738 1297
## 3:    1  1 4261 1335
## 4:    1  1 3777 1282
## 5:    1  1 4177 1590
## 6:    1  1 3585 1300
```

# Brain and head size data

Columns are:

1. gender (1 = male, 2 = female)
2. age (1 = 20-46, 2 = 46+)
3. head size ( $cm^3$ )
4. brain weight (g)

```
# name columns to reflect what they are  
colnames(head_brain) = c("gender", "age", "head", "brain")
```

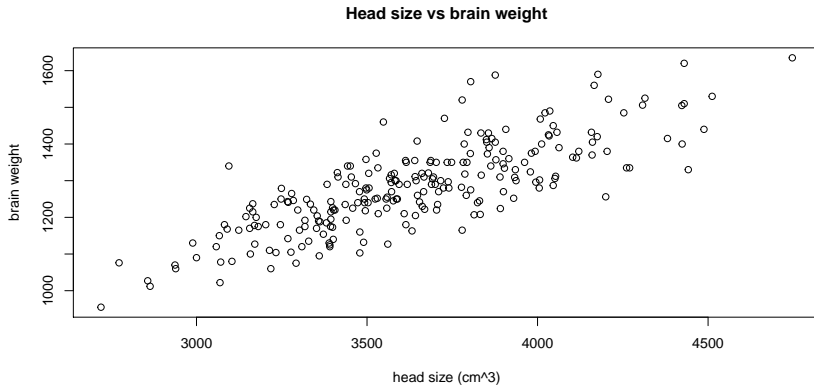
## Change data type

```
head_brain$gender <- as.factor(head_brain$gender)
head_brain$age <- as.factor(head_brain$age)
head_brain$head <- as.numeric(head_brain$head)
head_brain$brain <- as.numeric(head_brain$brain)
```



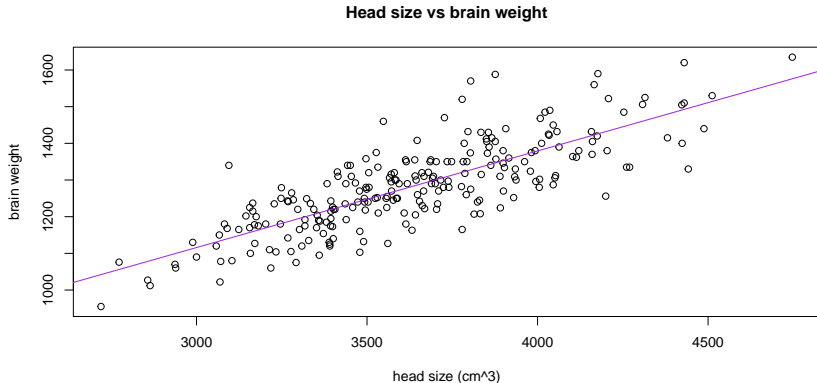
# Plot data

```
#attach(head_brain)  
plot(head_brain$head, head_brain$brain,  
      main="Head size vs brain weight",  
      xlab = "head size (cm^3)", ylab = "brain weight")
```



# How to do a linear regression

```
set.seed(519)
lm1 = lm(brain ~ head, data=head_brain)
plot(head_brain$head, head_brain$brain,
     main="Head size vs brain weight",
     xlab = "head size (cm^3)", ylab = "brain weight")
abline(lm1, col="purple")
```



# Summary of the linear regression

Here's a good explanation of the summary in MUCH more detail.

```
summary(lm1)
```

```
##
## Call:
## lm(formula = brain ~ head, data = head_brain)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -175.98  -49.76   -1.76    46.60   242.34
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 325.57342   47.14085    6.906 4.61e-11 ***
## head         0.26343    0.01291   20.409 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 72.43 on 235 degrees of freedom
## Multiple R-squared:  0.6393, Adjusted R-squared:  0.6378
## F-statistic: 416.5 on 1 and 235 DF,  p-value: < 2.2e-16
```

# Summary output gives a lot of information

1. Info about distribution of residuals (errors)
2. The estimates of our coefficients
3. Standard error of coefficient estimates
  - ▶ square root of the variance
  - ▶  $\sqrt{\sigma^2}$
4. t-values (coefficient estimates/standard error)
5.  $R^2$  = (want closer to 1)
6. p-values (yuck!)
  - ▶ testing if your coefficient = 0

# Quick residual check

What is a residual?

Residuals

Min	1Q	Median	3Q	Max	-175.98	-49.76
-1.76	46.60	242.34				

- ▶ Median should be around 0
- ▶ 1Q and 3Q should be roughly of same absolute magnitude

# Linear equation with coefficients

- ▶  $\beta_0 = \text{intercept} = 325.57$
- ▶  $\beta_1 = \text{head size coefficient} = 0.26$

$$\hat{y}_i = 325.57 + 0.26x_i + \epsilon_i$$

What does this mean in actual words?

# Use confidence intervals instead of p-values

```
confint(lm1, level=0.95) #95% confidence interval
```

```
##                2.5 %      97.5 %  
## (Intercept) 232.7007553 418.4460868  
## head        0.2380003   0.2888584
```

# We have more information than just head size!

We also have age range and sex!

We can use this information to potentially improve our regression by using a multiple linear regression model.

Here's a good tutorial.



# Multiple linear regression

First, let's change out age and sex categories into 0s and 1s.  
(This is the convention in programming)

```
head_brain$gender = as.factor(ifelse(head_brain$gender == 1, 1, 0))  
# if head_brain$gender[i] == 1  
#   head_brain$gender[i] == 1  
# else  
#   head_brain$gender[i] == 0  
head_brain$age = as.factor(ifelse(head_brain$age == 1, 1, 0))
```

# Does age have an effect on brain size?

We have some options on possible formulas for the linear regression:

►  $\text{brain} \sim \text{head} + \text{age}$

►  $\hat{\text{brain}}_i = \hat{\beta}_0 + \hat{\beta}_1 \text{head}_i + \hat{\beta}_2 \text{age}_i + \epsilon_i$

►  $\text{brain} \sim \text{head}:\text{age}$

►  $\hat{\text{brain}}_i = \hat{\beta}_0 + \hat{\beta}_2 \text{age}_i \text{head}_i + \epsilon_i$

►  $\text{brain} \sim \text{head} * \text{age} = \text{brain} \sim \text{head} + \text{age} + \text{head} \times \text{age}$

►  $\hat{\text{brain}}_i = \hat{\beta}_0 + \hat{\beta}_1 \text{head}_i + \hat{\beta}_2 \text{age}_i + \hat{\beta}_3 \text{age}_i \text{head}_i + \epsilon_i$

```
lm2 = lm(brain ~ head + age, data=head_brain)
lm3 = lm(brain ~ head:age, data=head_brain)
lm4 = lm(brain ~ head * age, data=head_brain)
```

# How can we interpret this?

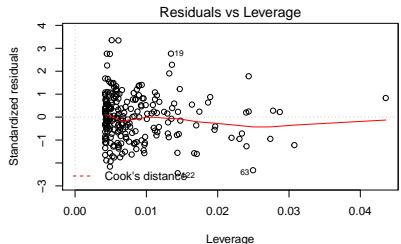
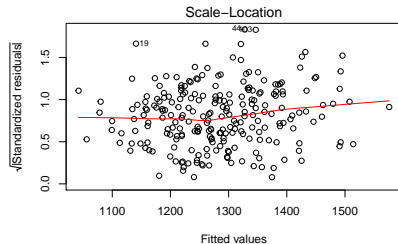
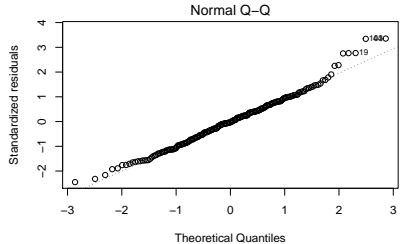
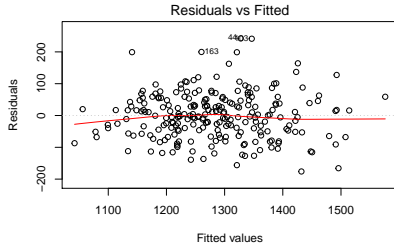
Interactions mean that slopes is different for each age category and each head size.

# Evaluate

How can we evaluate these models?

# Do these models meet the assumptions of linear models?

```
par(mfrow=c(2,2))  
plot(lm1)
```



# Diagnostic plot

- ▶ Residuals vs. Fitted
  - ▶ look for residuals randomly distributed around 0.
- ▶ Q-Q plot
  - ▶ used to look for normality of residuals
  - ▶ want the points to follow the diagonal line.
- ▶ Scale-Location plot
  - ▶ Similar to residuals vs fitted.
- ▶ Residuals vs. Leverage plot
  - ▶ Was our model driven by outliers?
    - ▶ Cook's distance lines would be visible (they aren't right now)
    - ▶ Data points driving the model would be labeled
    - ▶ If this happens, try removing the outliers.

PS. <http://data.library.virginia.edu/diagnostic-plots/> is helpful for interpreting these plots.

# Predictions

What if we are given new data, and want to make predictions from our models?

```
new_data = data.frame(gender = as.factor(c(1,1,0,0)), age = as.factor(c(0,1,0,1))  
print(new_data)
```

```
##   gender age head  
## 1      1   0 2265  
## 2      1   1   999  
## 3      0   0 2775  
## 4      0   1 9275
```

# Predictions

```
lm1_pred <- predict(lm1,newdata=new_data,  
                    interval="confidence", level=.95)  
lm2_pred <- predict(lm2,newdata=new_data,  
                    interval="confidence", level=.95)  
lm3_pred <- predict(lm3,newdata=new_data,  
                    interval="confidence", level=.95)  
lm4_pred<- predict(lm4,newdata=new_data,  
                    interval="confidence", level=.95)
```



# Predictions

To see our predictions...

How do they compare?

```
print(lm1_pred)
print(lm2_pred)
print(lm3_pred)
print(lm4_pred)
```

Can we test which model has the best predictions?

How can we do this?

# Acknowledgements

This document was inspired by: [this tutorial](#)