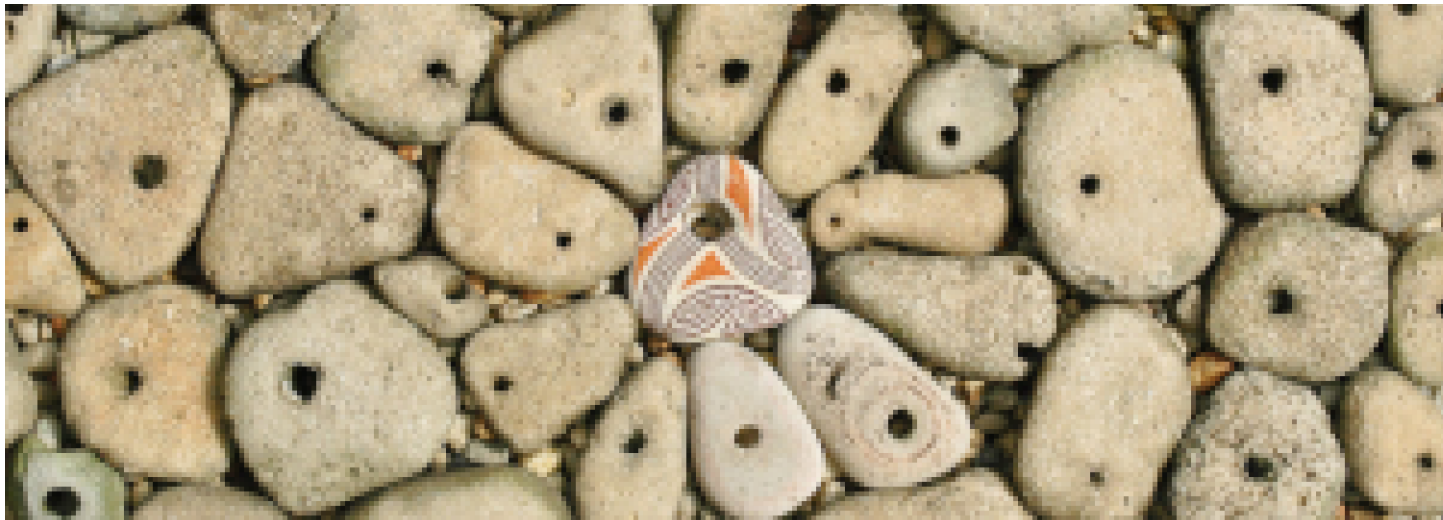


# REGRESSION & CLASSIFICATION



**Video Lectures**  
by Chris Emmery (MSc)

# GOALS OF DATA MINING

- Investigating, describing, and sanitizing data.
- Finding patterns in large data sets.
- Through the application and evaluation of algorithms: classification, clustering, regression, rule mining, outlier detection, etc.

# THIS LECTURE

Finding patterns through **prediction** using:

- Regression.
- Classification.

# WHAT MAKES PREDICTION POSSIBLE?

Associations between a **feature** ( $x$ ) and a **target** ( $y$ ).

If:

- Numerical: **correlation**.
- Categorical: **mutual information**.

*Given  $X$  and  $y \rightarrow$   
supervised learning.  
Given only  $X \rightarrow$   
unsupervised learning.*

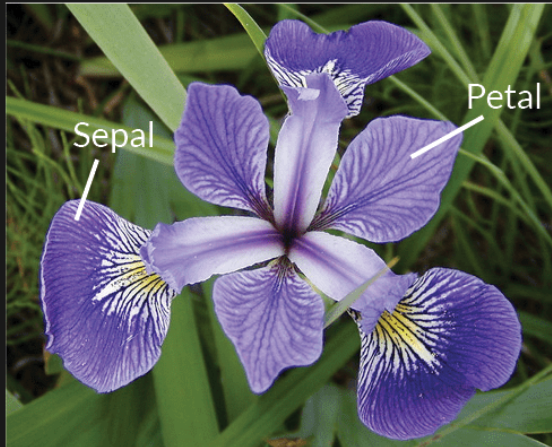
# CORRELATION

Pearson correlation:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

... where  $n$  is sample size,  $x$  a feature,  $y$  a target (or feature), indexed by  $i$ , and  $\bar{x}$  and  $\bar{y} = \frac{1}{n} \sum_{i=1}^n x_i$  or  $y_i$  (i.e. the mean).

# IRIS DATASET



**Iris Versicolor**



**Iris Setosa**



**Iris Virginica**

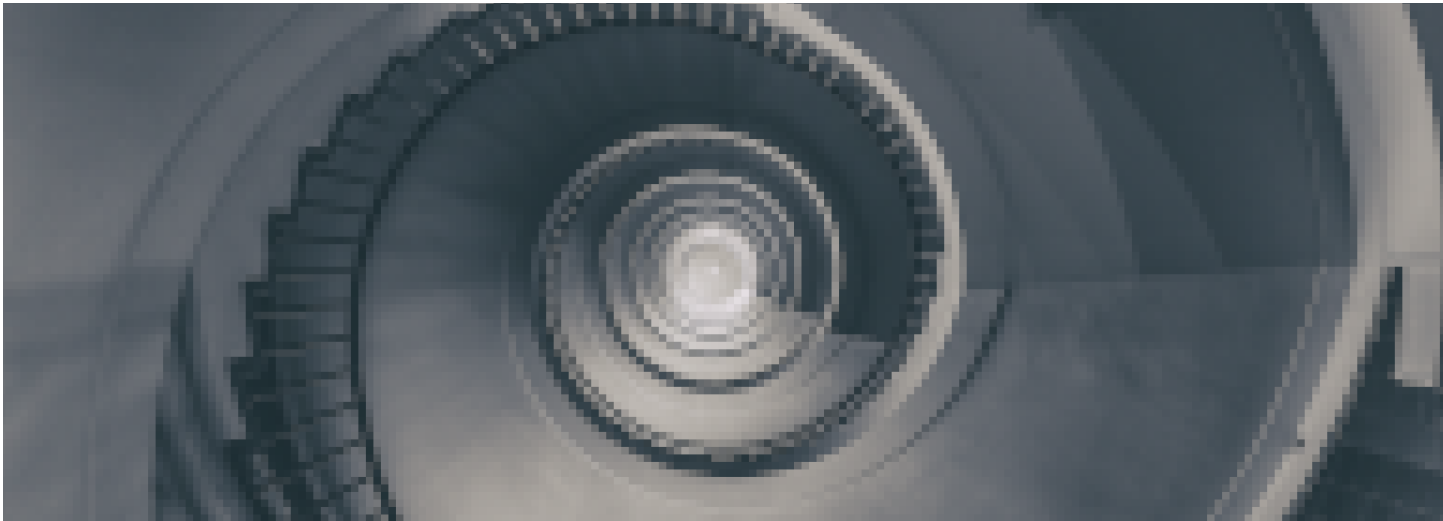
# IRIS CORRELATION

# IRIS CORRELATION II



# **EXPECTATIONS FROM CORRELATIONS**

# REGRESSION



# CAN WE MODEL THIS AS A FUNCTION?

$$f(X) = a \cdot x + b \text{ or } Y = \beta_0 + \beta_1 \cdot X$$

# EXAMPLE

city	students ( $X$ )	alcohol ( $Y$ )	$(X - \bar{X})^2$	$(X - \bar{X}) \cdot (Y - \bar{Y})$
Tilburg	26	41	$(26 - 18)^2 = 64$	$(26 - 18) \cdot (41 - 29) = 96$
Eindhoven	21	37	$(21 - 18)^2 = 9$	$(21 - 18) \cdot (37 - 29) = 24$
Wageningen	6	9	$(06 - 18)^2 = 144$	$(06 - 18) \cdot (09 - 29) = 240$
$\Sigma$	53	87	217	360

- $\bar{X} = 53/3 \approx 18, \bar{Y} = 87/3 = 29$
- $\beta_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{360}{217} \approx 1.66$
- $\beta_0 = \bar{Y} - \beta_1 \cdot \bar{X} = 29 - 1.66 \cdot 18 = -0.88$
- $\hat{y} = \beta_0 + \beta_1 \cdot X = -0.88 + 1.66 \cdot X$

*Sources: RIVM, infogram  
(2016, 2020)*

# RESULT

# EVALUATION

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}}$$

$$= \sqrt{((42.28 - 41)^2 + (33.98 - 37)^2 + (9.08 - 9)^2)} = 3.28$$

$$R^2 = 1 - \frac{MSE(f)}{MSE(\text{mean})} = 0.982$$

# CLASSIFICATION



# REGRESSION VS. CLASSIFICATION

- With regression our  $y$  is numerical.
- With classification our  $y$  is categorical.



# LOGISTIC REGRESSION

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot x)}}$$

$$g(p(x)) = \ln\left(\frac{p(x)}{1-p(x)}\right) = \beta_0 + \beta_1 \cdot x$$

# **LOGISTIC REGRESSION EXPLAINED**

# *k*-NEAREST NEIGHBORS





# DISTANCES

- Manhattan Distance:  $\sum_{i=1}^n |x_i - y_i|$
- Euclidean Distance:  $\sqrt{\sum_{i=1}^n (x_i - y_i)^2}$
- Minkowski Distance:  $(\sum_{i=1}^n |x_i - y_i|^p)^{\frac{1}{p}}$
- Hamming Distance: (1011101  $\rightarrow$  1001001 = 2)

More next video!