# Machine Learning - Day 2

# Data modelling

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# Libraries

```
library(dplyr)
library(ggplot2)
library(here)
```

# **DATA IMPORT**

```
dc <- file.path(here(), "data", "dc-wikia-data.csv") %>%
  read.csv(na.strings = "")

max_year <- max(dc$YEAR, na.rm =T)

dc <- dc %>%
  mutate(active_years = max_year - YEAR)
```

## DATA MODELING

## LINEAR REGRESSION

Simple linear regression

## Easy ex

```
ggplot(data = cars, aes(x = dist, y = speed)) +
   geom_point() +
   geom_smooth(method='lm',formula=y~x)

m1 <- lm(data = cars, speed ~ dist)

summary(m1)

residuals(m1)
predict(m1)</pre>
```

#### Comics example

```
dc_small <- dc %>%
  filter(APPEARANCES >20)

dc %>%
  ggplot(aes(x = active_years, y = APPEARANCES)) +
  geom_point()

dc_small %>%
  ggplot(aes(x = active_years, y = APPEARANCES, col = ID)) +
  geom_point()

m1 <- lm(data=dc_small, APPEARANCES ~ active_years)

summary(m1)

plot(m1)</pre>
```

## Multiple linear regression

```
m3 <- lm(data=dc, APPEARANCES ~ active_years + ALIGN)
summary(m3)
plot(m3)
m4 <- lm(data=dc, APPEARANCES ~ active_years + ALIGN + active_years*ALIGN)
summary(m4)
plot(m4)
```

## Log-level regression

http://www.cazaar.com/ta/econ113/interpreting-beta

```
dc %>%
  ggplot(aes(x = APPEARANCES)) +
  geom_density()

dc %>%
  ggplot(aes(x = log(APPEARANCES))) +
  geom_density()

dc %>%
  ggplot(aes(x = active_years, y = log(APPEARANCES), col = ID)) +
  geom_point()

m2_1 <- lm(data=dc, log(APPEARANCES) ~ active_years)

summary(m2_1)

plot(m2_1)</pre>
```

Se aggiungiamo un altro anno di attività, ci aspettiamo che il numero di apparizioni cresca del 3%

```
m3 <- lm(data=dc, log(APPEARANCES) ~ active_years + ALIGN)
summary(m3)
plot(m3)</pre>
```

Se aggiungiamo un altro anno di attività, ci aspettiamo che il numero di apparizioni cresca del 3%. Se il personaggio è cattivo, però, ci aspettiamo un decremento del numero di apparizioni del 17%, mentre se è buono un incremento del 47%.

```
https://www.youtube.com/watch?v=wXC2kViEGz8
m4 <- lm(data=dc, log(APPEARANCES) ~ active_years + ALIGN + active_years*ALIGN)
summary(m4)
plot(m4)</pre>
```

## LOGISTIC REGRESSION

https://datascienceplus.com/perform-logistic-regression-in-r/

```
dc_class <- dc %>%
  filter((ALIGN == "Bad Characters" | ALIGN == "Good Characters") &
           (SEX == "Female Characters" | SEX == "Male Characters")) %>%
  select(name, ALIGN, SEX, APPEARANCES, active_years) %>%
  na.omit
11 <- glm(data = dc_class, ALIGN ~ SEX, family = "binomial")</pre>
summary(11)
post_l1 <- predict(l1, type = "response")</pre>
ALIGN_pred <- ifelse(post_l1>0.5, "Good Characters", "Bad Characters")
misClasificError <- mean(ALIGN_pred != dc_class$ALIGN)
print(paste('Accuracy',1-misClasificError))
table(dc_class$ALIGN)
table(ALIGN_pred)
table(dc_class$ALIGN, ALIGN_pred)
ggp <- ggplot(data = dc_class, mapping = aes(x = active_years, y = ALIGN)) +</pre>
  geom_point(colour="blue") +
  \#geom\_line(mapping = aes(x = active\_years, y = ALIGN), colour="red") +
  facet_wrap(facets = ~SEX)
print(ggp)
12 <- glm(data = dc_class, ALIGN ~ SEX + active_years, family = "binomial")
```

## DECISION TREE

https://gormanalysis.com/decision-trees-in-r-using-rpart/
library(rpart)

table(iris\$Species)

iris\_tree <- rpart(Species ~ ., method = "class", data = iris)

print(iris\_tree)

summary(iris\_tree)

plot(iris\_tree, compress = T, margin = 0.2, branch = 0.3)
text(iris\_tree, use.n = T, digits = 3, cex = 0.8)

printcp(iris\_tree)

iris\_pred <- predict(iris\_tree, type = "class")

table(iris\_pred, iris\$Species)

misClasificError <- mean(iris\_pred != iris\$Species)</pre>

```
print(paste('Accuracy',1-misClasificError))

align_tree <- rpart(ALIGN ~ SEX + active_years + APPEARANCES, method = "class", data = dc_class)
summary(align_tree)

plot(align_tree, uniform = T, compress = T, margin = 0.2, branch = 0.3)
text(align_tree, use.n = T, digits = 3, cex = 0.6)

align_pred_tree <- predict(align_tree, type = "class")

table(align_pred_tree, dc_class$ALIGN)

misClasificError <- mean(align_pred_tree != dc_class$ALIGN)
print(paste('Accuracy',1-misClasificError))</pre>
```

# Training and test dataset

```
train <- sample(nrow(dc_class), 4800)
dc_train <- dc_class[train,]
dc_test <- dc_class[-train,]</pre>
```

## CLUSTER

```
dc full <- dc %>%
  select(name, ALIGN, EYE, HAIR, SEX, ALIVE, APPEARANCES, active_years, YEAR) %>%
  na.omit()
dc_cluster <-dc_full %>%
  select(active_years, APPEARANCES) %>%
  scale() %>%
  as.data.frame()
# Finding cluster number through Within groups sum of squares
wss <- (nrow(dc_cluster)-1)*sum(apply(dc_cluster,2,var))
for (i in 2:15){
  wss[i] <- sum(kmeans(dc_cluster, centers=i)$withinss)</pre>
plot(1:15, wss, type="b", xlab="Number of Clusters", ylab="Within groups sum of squares")
# Let's try 4
set.seed(1234)
# K-Means Cluster Analysis
fit <- kmeans(dc_cluster, 4) # 4 cluster solution</pre>
# append cluster assignment
dc_full <- data.frame(dc_full, cluster = as.factor(fit$cluster))</pre>
```

```
# CLUSTERS MEANS
# Stats
cluster_stats <- dc_full %>%
 group_by(cluster) %>%
 summarise(count = n(),
           perc = paste0(round(n()/nrow(dc_full)*100,2),"%"),
           avg_appear = mean(APPEARANCES),
           avg_year = mean(active_years))
### LABELS MAY BE DIFFERENT!!
dc_full <- dc_full %>%
  mutate(label = case_when(
    cluster == 1 ~ "Stabili",
   cluster == 2 ~ "Star",
   cluster == 3 ~ "Comparse",
   cluster == 4 ~ "Secondari"
  ))
ggplot(data = dc_full, aes(x = active_years, y = APPEARANCES, col = label)) +
 geom_point()
star <- dc_full %>%
filter(label == "Star")
```