# 4.1 Linear Regression

## Regression

Some Examples:

- Predicting future stock price
- Predicting if someones going to drop out of college or not
- Estimating the income price for banks

#### What are Linear Models?

An approximation method that we can use to describe behavior within data and predict its attributes in a timeframe.

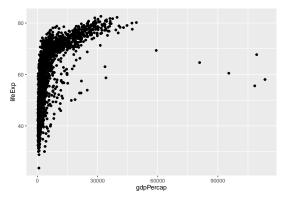
```
library(ggplot2)
```

```
## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'tibble'

## Warning: replacing previous import 'lifecycle::last_warnings' by
## 'rlang::last_warnings' when loading 'pillar'

library(gapminder)
# Model fitting in R, the Basics:

ggplot(gapminder, aes(x = gdpPercap, y = lifeExp )) +
    geom_point()
```



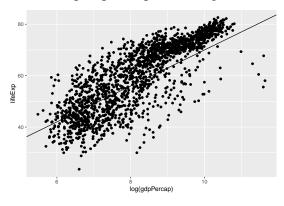
Note: Given that a column has large numbers, we can use logarithm to reduce the values. And make the data easier to understand.

```
# Make the same chart, but look at the log of gdp per capita instead
ggplot(gapminder, aes(log(gdpPercap), lifeExp ) ) +
  geom_point()
```

```
40 - 6 8 8 log(gdpPercap)
```

```
# Use geom_abline to guess the relationship
ggplot(gapminder, aes(log(gdpPercap), lifeExp ) ) +
  geom_point() +
  geom_abline(incercept = 0, slope = 7)
```

#### ## Warning: Ignoring unknown parameters: incercept



#### Manually creating a model with 1 x variable

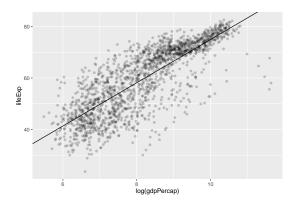
```
y <- gapminder$lifeExp
x <- log(gapminder$gdpPercap)

x_bar <- mean(x)
y_bar <- mean(y)

x_diff <- x - x_bar
y_diff <- y - y_bar

beta_1 <- sum(y_diff * x_diff/sum(x_diff^2))
beta_0 <- y_bar - (beta_1 * x_bar)

ggplot(gapminder, aes(x=log(gdpPercap), y=lifeExp )) +
    geom_point(alpha = .2) +
    geom_abline(intercept = beta_0, slope = beta_1 )</pre>
```



### Model fitting in R syntax

"Formula syntax" takes the form:  $lm(y var \sim x var, data = dataset)$ 

The formula syntax is more commonly used and we will focus on that today

### Predicting gdpPerCap

In order to illustrate linear models, models with different features are ran.

- a. lifeExp is used solely to get the gdpPercap.
- b. pop is used solely to get the gdpPercap.
- c. [year, pop, gdpPercap] are used to get the gdpPercap.

```
# a. x = lifeExp
model1 <- lm( gdpPercap ~ lifeExp, data = gapminder)

# b. x = pop
model2 <- lm( gdpPercap ~ pop, data = gapminder)

# b. x = [year, pop, gdpPercap]
model3 <- lm(gdpPercap ~ pop + year + lifeExp, data = gapminder)</pre>
```

#### Making predictions

In order to make predictions, we use the predict function.

```
predictions <- predict(model1, gapminder)</pre>
```

#### Validating models

In order to decide which features should be used, we run the loss functions to see which model has a high accuracy and lower error.

```
# Getting the predictions
model1_pred <- predict(model1, gapminder)
model2_pred <- predict(model2, gapminder)
model3_pred <- predict(model3, gapminder)

# Loss functions

# MAE
mae <- function(y_true, y_pred) { sum(abs(y_true - y_pred)) / NROW(y_true) }</pre>
```

```
# MSE
mse <- function(y_true, y_pred) { sum((y_true - y_pred) ** 2 / NROW(y_true)) }</pre>
# RMSE
rmse <- function(y_true, y_pred) { sqrt(sum((y_true - y_pred) ** 2 / NROW(y_true)) ) }</pre>
error <- c("MAE", "RMSE", "MSE")</pre>
error_model1 <- c(mae(model1_pred, gapminder$gdpPercap), rmse(model1_pred, gapminder$gdpPercap), mse(model1_pred, gapminder$gdpPercap), mse(model1_pred, gapminder$gdpPercap)
error_model2 <- c(mae(model2_pred, gapminder$gdpPercap), rmse(model2_pred, gapminder$gdpPercap), mse(model2_pred, gapminder$gdpPercap)
error_model3 <- c(mae(model3_pred, gapminder$gdpPercap), rmse(model3_pred, gapminder$gdpPercap), mse(model3_pred, gapminder$gdpPercap), mse(model3_pred, gapminder$gdpPercap)
errors <- data.frame(error, error_model1, error_model2, error_model3)</pre>
head(errors)
      error error_model1 error_model2 error_model3
## 1
      MAE
                   4801.936
                                   6535.112
                                                    4763.591
                   8001.558
                                   9851.332
                                                    7972.770
## 2 RMSE
```

## 3

MSE 64024938.216 97048744.296 63565055.580