AI for Genomics: from CNNs and LSTMs to Transformers

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Session content

Topics we'll cover in this session:

1) Basics of artificial neural networks: gradient descent

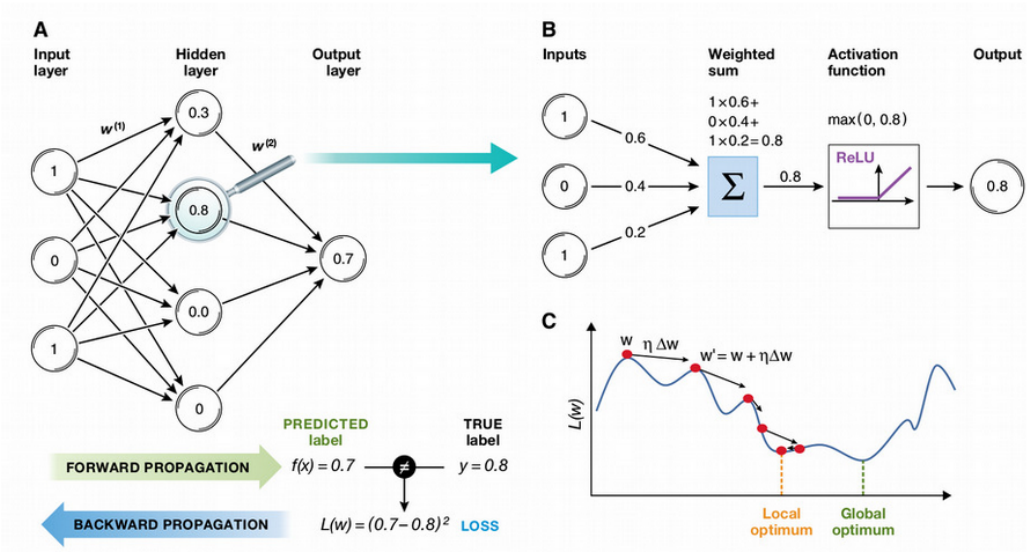
2) Universal Approximation Theorem (UAT)

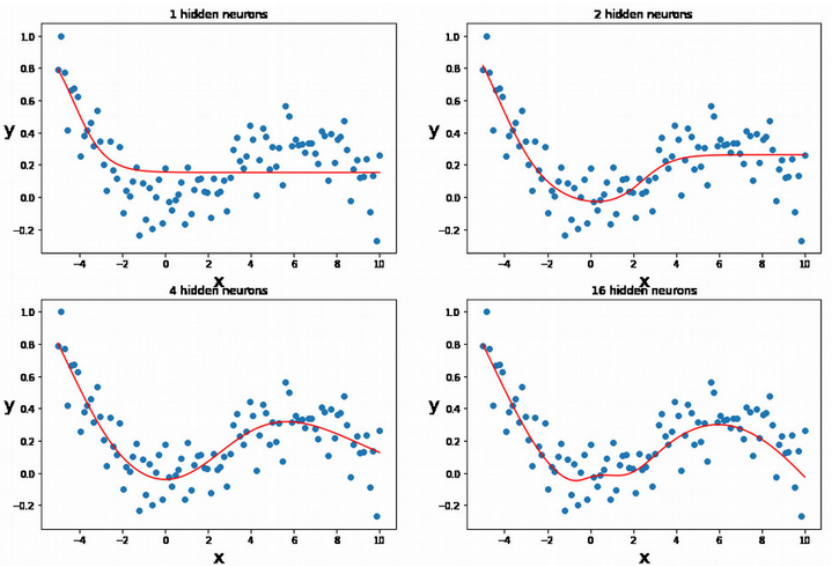
3) Coding vanilla neural network from scratch in R and Python

Basics of artificial neural networks: gradient descent and neural network from scratch

From linear models to artificial neural networks (ANNs)

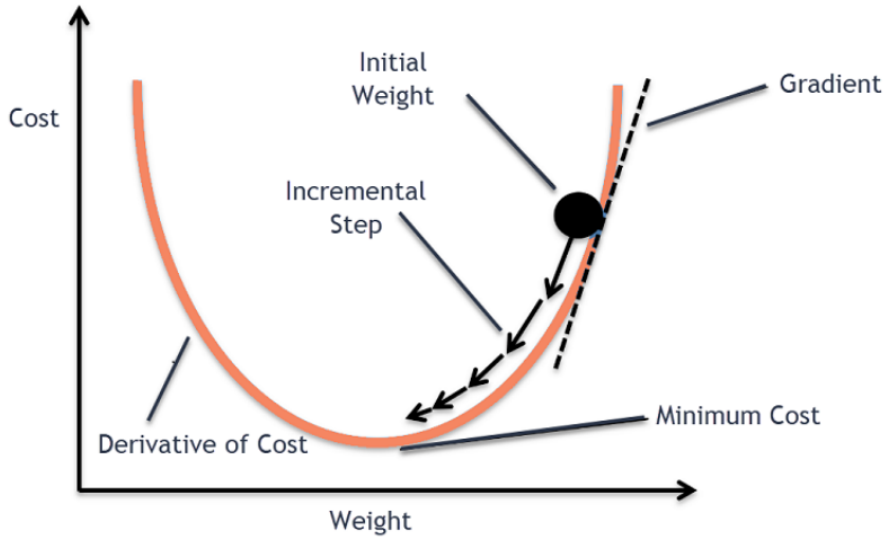
- ANN: a mathematical function Y = f(X) with a special architecture
- Can be **non-linear** depending on **activation function**
- Backward propagation (**gradient descent**) for minimizing error
- Universal Approximation Theorem





Angermueller et al., Molecular Systems Biology 2016

Gradient descent



$$\hat{\alpha}, \hat{\beta} = \operatorname{argmin} \mathrm{E}(\alpha, \beta)$$

$$\frac{\partial E(\alpha,\beta)}{\partial \alpha} = -\frac{2}{n}\sum_{i=1}^{n}(y_i - \alpha - \beta x_i)$$

$$\frac{\partial E(\alpha,\beta)}{\partial \beta} = -\frac{2}{n}\sum_{i=1}^{n} x_i(y_i - \alpha - \beta x_i)$$

Numeric implementation of gradient descent:

$$y_i = \alpha + \beta x_i + \epsilon,\ \ i = 1 \ldots n$$

$$E(\alpha,\beta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \alpha - \beta x_i)^2$$

$$\alpha_{i+1} = \alpha_i - \eta \frac{\partial E(\alpha,\beta)}{\partial \alpha}\bigg|_{\alpha=\alpha_i,\beta=\beta_i}$$

$$\beta_{i+1} = \beta_i - \eta \frac{\partial E(\alpha,\beta)}{\partial \beta}\bigg|_{\alpha=\alpha_i,\beta=\beta_i}$$

Coding gradient descent from scratch in R

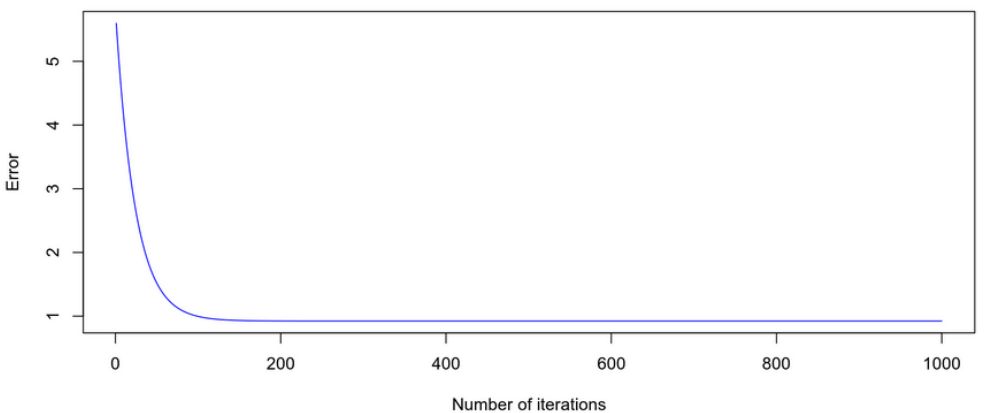
```r
n <- 100 # sample size
x <- rnorm(n) # simulated expanatory variable
y <- 3 + 2 * x + rnorm(n) # simulated response variable
summary(lm(y ~ x))
```

```
Call:
lm(formula = y ~ x)

Residuals:
    Min      1Q  Median      3Q     Max
-1.9073 -0.6835 -0.0875  0.5806  3.2904

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.89720    0.09755   29.70   <2e-16 ***
x            1.94753    0.10688   18.22   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9707 on 98 degrees of freedom
Multiple R-squared:  0.7721,    Adjusted R-squared:  0.7698
F-statistic:   332 on 1 and 98 DF,  p-value: < 2.2e-16
```

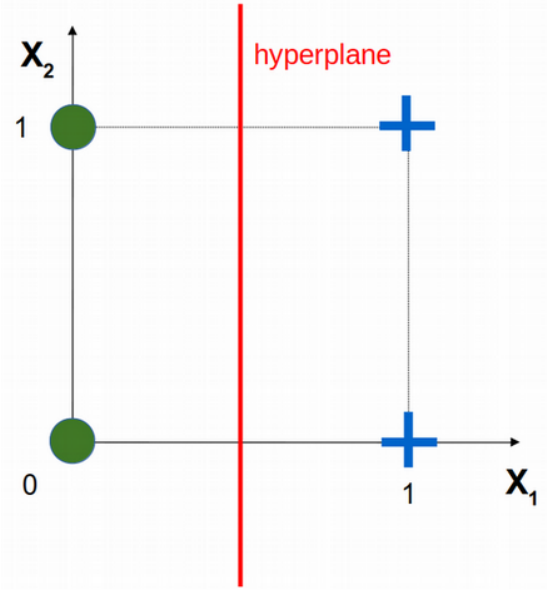
Let us now reconstruct the intercept and slope from gradient descent

```r
alpha <- vector(); beta <- vector()
E <- vector(); dEdalpha <- vector(); dEdbeta <- vector()
eta <- 0.01; alpha[1] <- 1; beta[1] <- 1 # initialize alpha and beta
for(i in 1:1000)
{
  E[i] <- (1/n) * sum((y - alpha[i] - beta[i] * x)^2)
  dEdalpha[i] <- - sum(2 * (y - alpha[i] - beta[i] * x)) / n
  dEdbeta[i] <- - sum(2 * x * (y - alpha[i] - beta[i] * x)) / n

  alpha[i+1] <- alpha[i] - eta * dEdalpha[i]
  beta[i+1] <- beta[i] - eta * dEdbeta[i]
}
print(paste0("alpha = ", tail(alpha, 1),", beta = ", tail(beta, 1)))
```

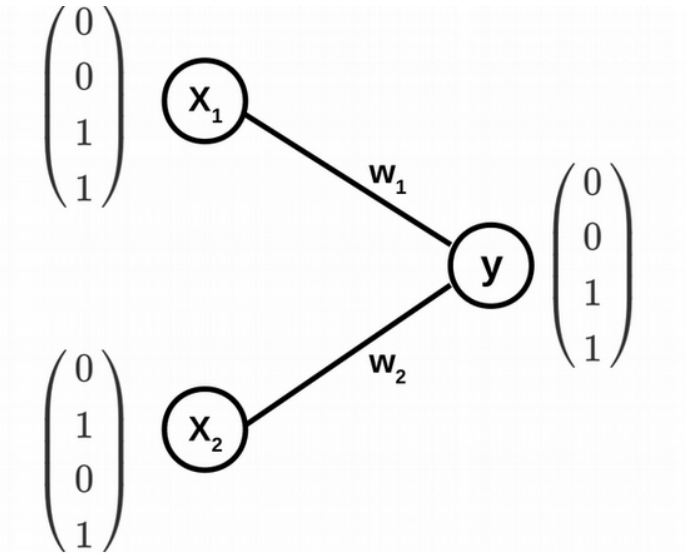
```
[1] "alpha = 2.89719694937354, beta = 1.94752837381973"
```



ANN from scratch in R: problem formulation



X_1	X_2	d (true) y (pred)
0	0	0 - circle
0	1	0 - circle
1	0	1 - cross
1	1	1 - cross




```r
d <- c(0, 0, 1, 1)  # true labels
x1 <- c(0, 0, 1, 1) # input variable x1
x2 <- c(0, 1, 0, 1) # input variable x2

data.frame(x1 = x1, x2 = x2, d = d)
```

x1	x2	d
0	0	0
0	1	0
1	0	1
1	1	1

$$y(w_1, w_2) = \phi(w_1 x_1 + w_2 x_2)$$

$$\phi(s) = \frac{1}{1 + e^{-s}} - \text{sigmoid}$$

$$\phi'(s) = \phi(s)\,(1 - \phi(s))$$

ANN from scratch in R: implementation in code

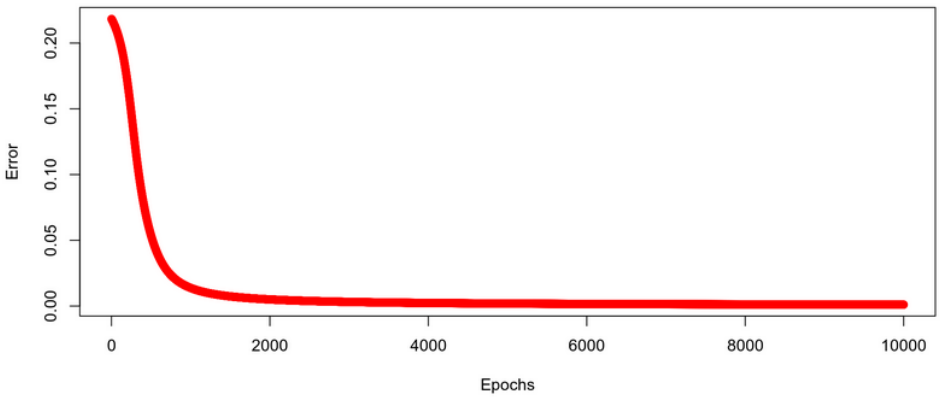
$$E(w_1, w_2) = \frac{1}{2N} \sum_{i=1}^{N} (d_i - y_i(w_1, w_2))^2$$

$$w_{1,2} = w_{1,2} - \mu \frac{\partial E(w_1, w_2)}{\partial w_{1,2}}$$

$$\frac{\partial E}{\partial w_1} = -\frac{1}{N} \sum_{i=1}^{N} (d_i - y_i) * y_i * (1 - y_i) * x_{1i}$$

$$\frac{\partial E}{\partial w_2} = -\frac{1}{N} \sum_{i=1}^{N} (d_i - y_i) * y_i * (1 - y_i) * x_{2i}$$

```r
phi <- function(x){return(1/(1 + exp(-x)))} # activation function

mu <- 0.1; N_epochs <- 10000
w1 <- 0.1; w2 <- 0.5; E <- vector()
for(epochs in 1:N_epochs)
{
  #Forward propagation
  y <- phi(w1 * x1 + w2 * x2 - 3) # we use a fixed bias -3

  #Backward propagation
  E[epochs] <- (1 / (2 * length(d))) * sum((d - y)^2)
  dE_dw1 <- - (1 / length(d)) * sum((d - y) * y * (1 - y) * x1)
  dE_dw2 <- - (1 / length(d)) * sum((d - y) * y * (1 - y) * x2)
  w1 <- w1 - mu * dE_dw1
  w2 <- w2 - mu * dE_dw2
}
plot(E ~ seq(1:N_epochs), xlab="Epochs", ylab="Error", col="red")
```




```r
y
```

```
[1] 0.04742587 0.05752359 0.95730271 0.96489475
```

We nearly reconstruct true labels d = (0, 0, 1, 1)

Session summary

Take home messages of the session:

1) Artificial neural networks are based on computing derivatives

2) Gradient descent (backward propagation) is the engine of ANNs

3) Universal Approximation Theorem allows fitting any function

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