

# Loss functions

Linear regression and MSE:

$$L(w) = \frac{1}{\ell} \|Xw - y\|^2$$

Linear classification and cross-entropy:

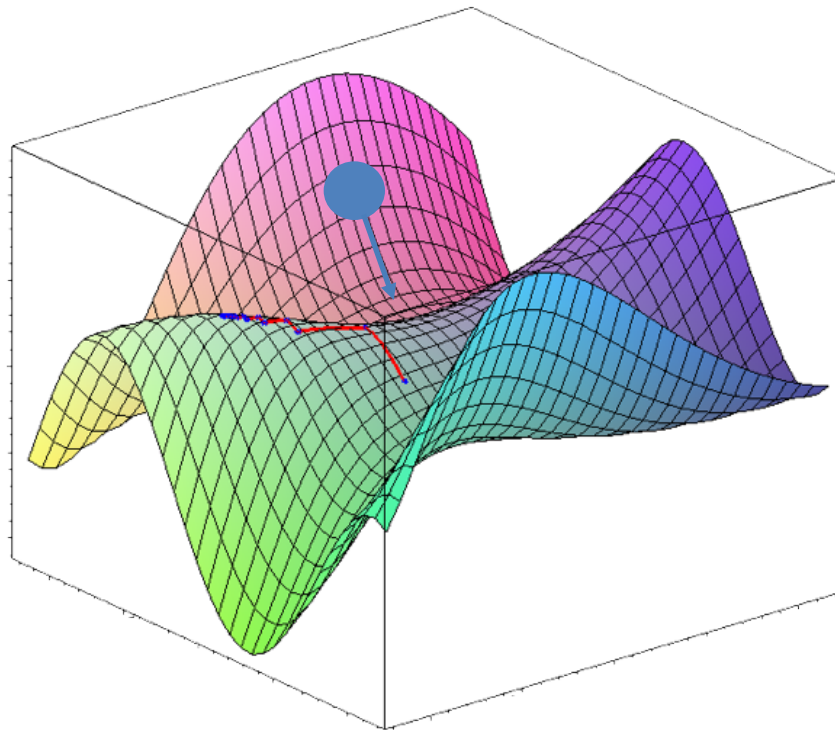
$$L(w) = - \sum_{i=1}^{\ell} \sum_{k=1}^K [y_i = k] \log \frac{e^{w_k^T x_i}}{\sum_{j=1}^K e^{w_j^T x_i}}$$

K is the number of classes, l is the number of training examples.  
So we take the crossentropy for each class k in K, and then sum them. Do this for each training sample i from 1 to l.

# Gradient descent

Optimization problem:  $L(w) \rightarrow \min_w$

Suppose we have some approximation  $w^0$  — how to refine it?



# Gradient descent

Optimization problem:  $L(w) \rightarrow \min_w$

$w^0$  — initialization

$\nabla L(w^0) = \left( \frac{\partial L(w^0)}{\partial w_1}, \dots, \frac{\partial L(w^0)}{\partial w_n} \right)$  — gradient vector

- Points in the direction of the steepest slope at  $w^0$
- The function has fastest decrease rate in the direction of negative gradient

# Gradient descent

Optimization problem:  $L(w) \rightarrow \min_w$

$w^0$  — initialization

$\nabla L(w^0) = \left( \frac{\partial L(w^0)}{\partial w_1}, \dots, \frac{\partial L(w^0)}{\partial w_n} \right)$  — gradient vector

$w^1 = w^0 - \eta_1 \nabla L(w^0)$  — gradient step

# Gradient descent

Optimization problem:  $L(w) \rightarrow \min_w$

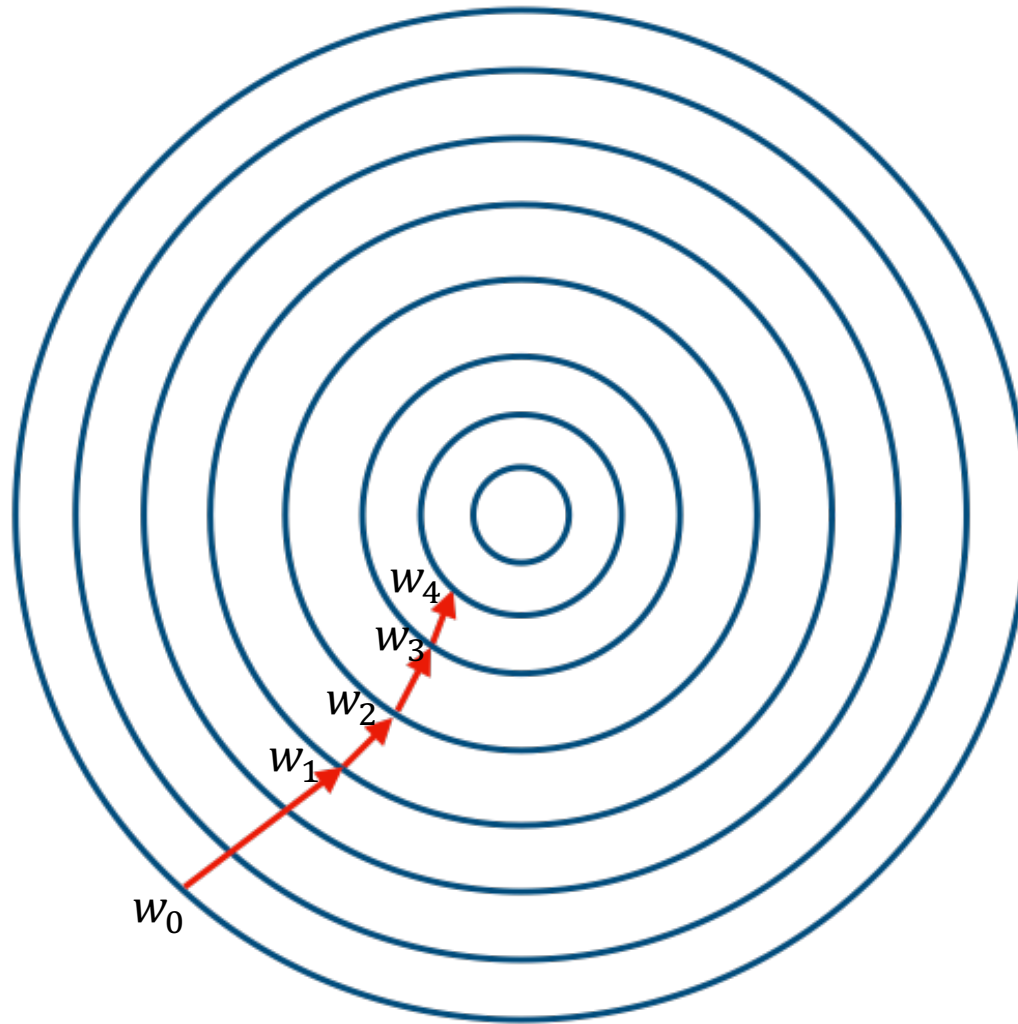
$w^0$  — initialization

while True:

$$w^t = w^{t-1} - \eta_t \nabla L(w^{t-1})$$

if  $\|w^t - w^{t-1}\| < \epsilon$  then break

# Gradient descent



# Gradient descent

Lots of heuristics:

- How to initialize  $w^0$
- How to select step size  $\eta_t$
- When to stop
- How to approximate gradient  $\nabla L(w^{t-1})$

# Gradient descent for MSE

Linear regression and MSE:

$$L(w) = \frac{1}{\ell} \|Xw - y\|^2$$

Derivatives:

$$\nabla L_w(w) = \frac{2}{\ell} X^T (Xw - y)$$



# Gradient descent vs analytical solution

Analytical solution for MSE:  $w = (X^T X)^{-1} X^T y$

Gradient descent:

- Easy to implement
- Very general, can be applied to any differentiable loss function
- Requires less memory and computations (for stochastic methods)

# Summary

- Gradient descent provides a general learning framework
- Can be used both for classification and regression tasks
- Advanced methods — in next lessons