

**SUPSI**

# Machine Learning

## Introduction

Dario Piga

SUPSI - Scuola Universitaria Professionale della Svizzera Italiana

IDSIA – Dalle Molle Institute for Artificial Intelligence

dario.piga@supsi.ch

Machine Learning

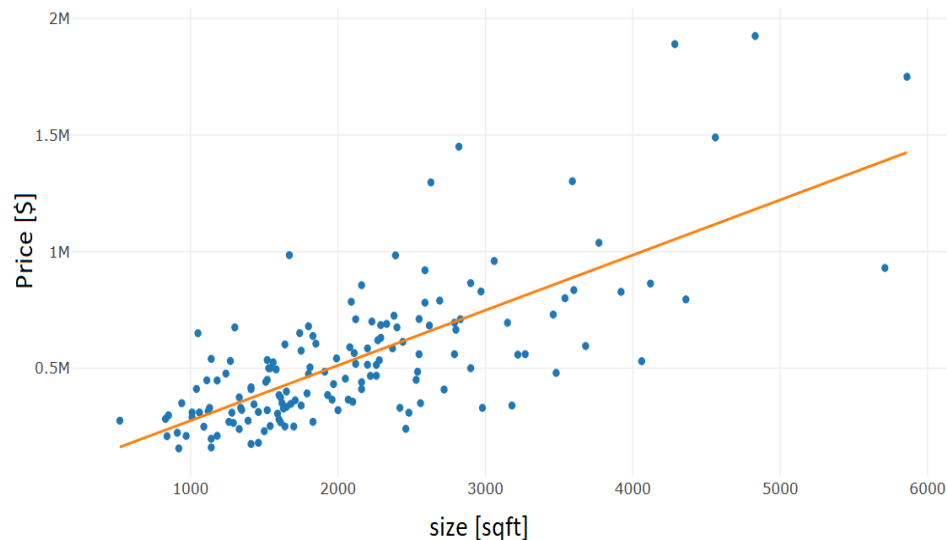
# Artificial Intelligence

- Artificial Intelligence (AI) is “the science and engineering of making intelligent machines” (John McCarthy, 1956)
- Development of computer systems able to perform tasks that normally require human intelligence (e.g., game playing, driving a car, walking, recognize a face, a digit or a sound, detect an anomalous behaviour, etc.)
- Two main approaches for AI:
  - program the machine to perform a specific task
  - let the machine learn from experience (machine learning)

# Supervised learning

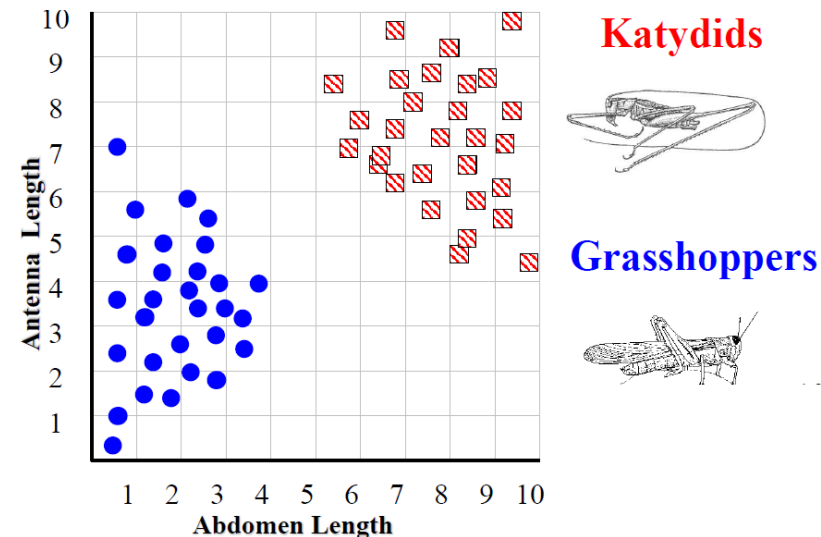
- Information: set of **input-output data** is given
- Goal: **discover relation** between input and output
- Utility: given a new input, **predict** the output

## Regression



Continuous-value output

## Classification



Discrete-value output

## Examples of classification

- Image recognition
- Predicting tumor cells as benign or malignant (extract features from cells images)
- Detecting faults (unbalanced problem)
- Predicting level of affinity (low/high) between a protein and a ligand

## Classification: notation

- We are given  $N$  training input-output data  $\{x_i, y_i\}_{i=1}^N$ :
- $x_i \in \mathbb{R}^D$
  - $y_i \in \{True, False\}, \{0, 1, 2, \dots\}, \{Cat, Dog, Rat\}, \dots$

x: image, y:rat



D=64x64x3=12'288

# Classification: parametric approach

x: image, y:rat



Unknown weights

$f(x, W)$

Score for each possible class

$D=64 \times 64 \times 3=12'288$

$$s=f(x, W) = Wx + b$$

$12'288 \times 1$

$3 \times 1$

Assume 3 classes

## Classification: parametric approach

$x$ : image,  $y$ :rat



$D=64 \times 64 \times 3=12'288$

$$\longrightarrow f(\mathbf{x}, \mathbf{W}) \longrightarrow$$

-10	cat
9.1	dog
4.2	rat

Are the chosen values of the weights  $\mathbf{W}$  good or bad?

How to choose  $\mathbf{W}$ ?

# Loss function

How to quantify goodness of  $W$ ?

Suppose 4 training examples  $\{x_i, y_i\}_{i=1}^{N=4}$  and 3 classes (cat, dog, rat)



cat	-10	1	-0.2	1
dog	9.1	15	3	2
rat	4.2	3	2.9	10

Loss for each sample

$$L = \frac{1}{N} \sum_{i=1}^N L_i(f(x_i, W), y_i)$$

Loss



## SVM loss

$$L_i(f(\mathbf{x}_i, \mathbf{W}), \mathbf{y}_i) = \sum_{j \neq y_i} \begin{cases} 0 & \text{if } s_{y_i} \geq s_j + 1 \\ s_j - s_{y_i} + 1 & \text{o.w.} \end{cases}$$



cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$L_1(f(\mathbf{x}_1, \mathbf{W}), \mathbf{y}_1) = 0 + (9.1 - 4.2 + 1) = 5.9$$

$$L_2(f(\mathbf{x}_2, \mathbf{W}), \mathbf{y}_2) = 0 + 0 = 0$$





$$L_3(f(\mathbf{x}_3, \mathbf{W}), \mathbf{y}_3) = 0 + (2.9 - 3 + 1) = 0.9$$

$$L_4(f(\mathbf{x}_4, \mathbf{W}), \mathbf{y}_4) = (2 - 1 + 1) + (10 - 1 + 1) = 12$$

## Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k | X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$





				
cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$P(Y = cat | X = \mathbf{x}_1) = \frac{e^{s_{cat}}}{\sum_j e^{s_j}} = \frac{e^{-10}}{e^{-10} + e^{9.1} + e^{4.2}} \cong 0$$

# Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k|X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$





				
cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$P(Y = \text{dog}|X = \mathbf{x}_1) = \frac{e^{s_{\text{dog}}}}{\sum_j e^{s_j}} = \frac{e^{9.1}}{e^{-10} + e^{9.1} + e^{4.2}} \cong 0.9926$$

## Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k|X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

				
cat	-10	1	-0.2	1
dog	9.1	15	3	2
rat	4.2	3	2.9	10

$$P(Y = rat|X = \mathbf{x}_1) = \frac{e^{s_{rat}}}{\sum_j e^{s_j}} = \frac{e^{4.2}}{e^{-10} + e^{9.1} + e^{4.2}} \cong 0.0074$$

## Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k|X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$







cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$P(Y = cat|X = \mathbf{x}_1) = \frac{e^{s_{cat}}}{\sum_j e^{s_j}} = \frac{e^{-0.2}}{e^{-0.2} + e^3 + e^{2.9}} \cong 0.021$$

## Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k | X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

				
cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$P(Y = \text{dog} | X = \mathbf{x}_1) = \frac{e^{s_{\text{dog}}}}{\sum_j e^{s_j}} = \frac{e^3}{e^{-0.2} + e^3 + e^{2.9}} \cong 0.514$$

## Softmax classifier

Use scores to define probabilities of the classes

$$P(Y = k|X = \mathbf{x}_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$



cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$P(Y = rat|X = \mathbf{x}_1) = \frac{e^{s_{rat}}}{\sum_j e^{s_j}} = \frac{e^{2.9}}{e^{-0.2} + e^3 + e^{2.9}} \cong 0.4651$$

# Softmax classifier: loss function

$$L_i(f(\mathbf{x}_i, \mathbf{W}), \mathbf{y}_i) = -\log(P(Y = \mathbf{y}_i | X = \mathbf{x}_i)) = -\log\left(\frac{e^{s_{\mathbf{y}_i}}}{\sum_j e^{s_j}}\right)$$



cat	-10	1	-0.2	1
dog	9.1	<b>15</b>	<b>3</b>	2
rat	<b>4.2</b>	3	2.9	10

$$L_1(f(\mathbf{x}_1, \mathbf{W}), \mathbf{y}_1) = -\log\left(\frac{e^{4.2}}{e^{-10} + e^{9.1} + e^{4.2}}\right) = 4.9074$$

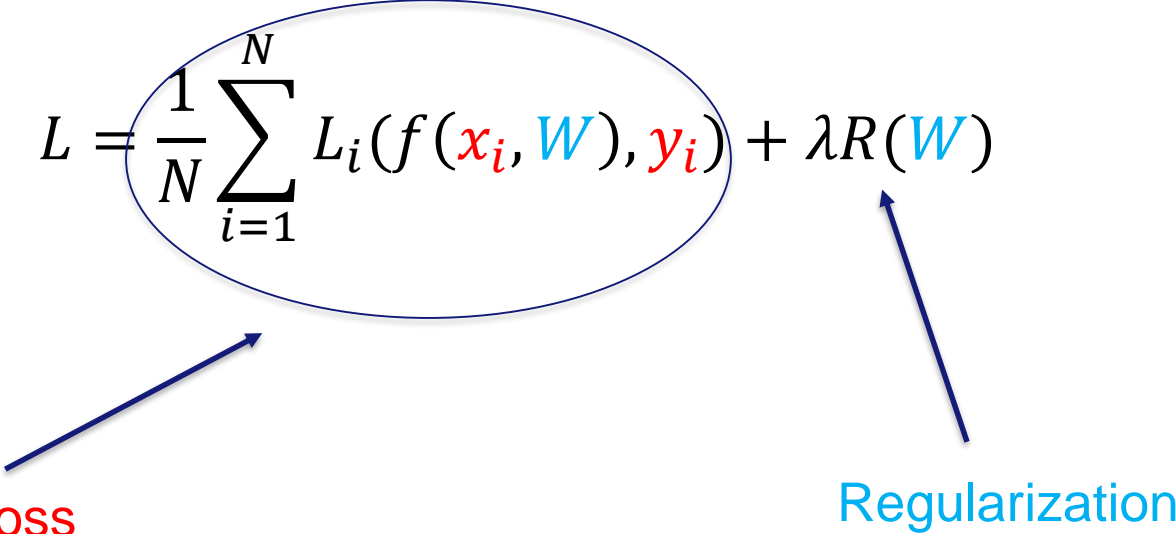
$$L_2(f(\mathbf{x}_2, \mathbf{W}), \mathbf{y}_2) = -\log\left(\frac{e^{15}}{e^1 + e^{15} + e^3}\right) \cong 0$$

$$L_3(f(\mathbf{x}_3, \mathbf{W}), \mathbf{y}_3) = -\log\left(\frac{e^3}{e^{-0.2} + e^3 + e^{2.9}}\right) = 0.6656$$

$$L_4(f(\mathbf{x}_4, \mathbf{W}), \mathbf{y}_4) = -\log\left(\frac{e^1}{e^1 + e^2 + e^{10}}\right) = 9.0005$$



# Classifier: regularization

$$L = \frac{1}{N} \sum_{i=1}^N L_i(f(\mathbf{x}_i, \mathbf{W}), \mathbf{y}_i) + \lambda R(\mathbf{W})$$


Data loss

Regularization

$$R(\mathbf{W}) = \sum_{i,j} \mathbf{W}_{i,j}^2$$

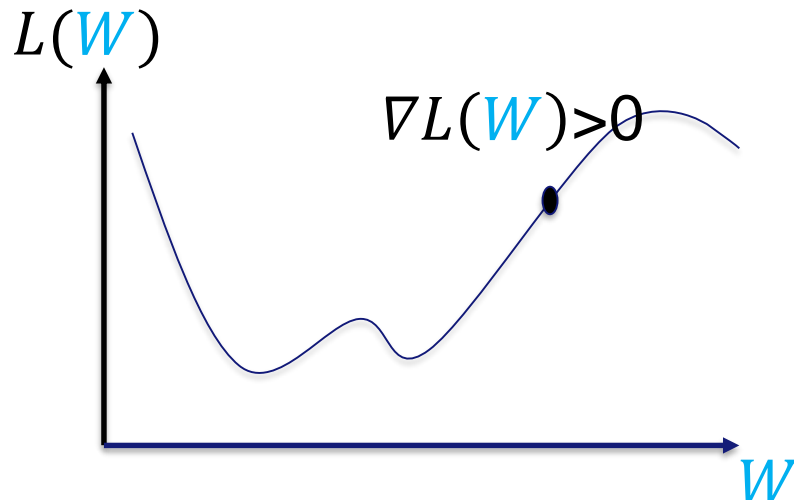
$$R(\mathbf{W}) = \sum_{i,j} |\mathbf{W}_{i,j}|$$

# Optimization

How to find the parameters  $W$  minimizing the loss  $L(W)$ ?

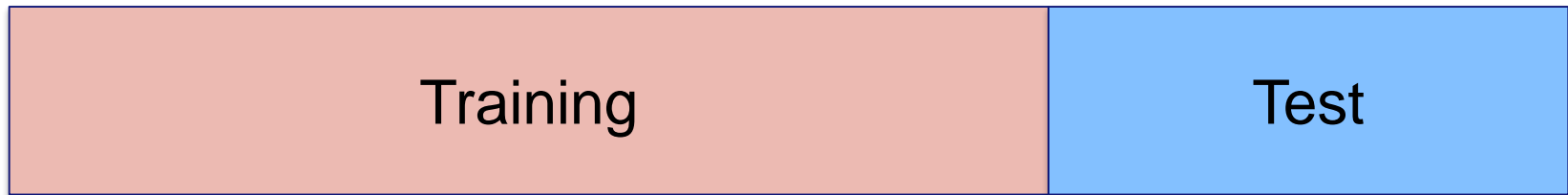
$$L(W) = \frac{1}{N} \sum_{i=1}^N L_i(f(x_i, W), y_i) + \lambda R(W)$$

Gradient descent algorithm: go in the opposite direction of the gradient



1. Start with initial value of  $W$
2. Iterate until convergence:
  - 2.1  $W = W - \gamma \nabla L(W)$

# Assessing performance



Use training data to find optimal  
parameters

Test performance on fresh data

## Assessing performance: accuracy

$$\text{accuracy: } \frac{\text{\#correctly classified samples}}{\text{\# samples}}$$

- If in the test set you have 50 images with dogs and 50 images with cats, are you satisfied if your classifier gives you an accuracy of 95%?
- If in the test set you have 95 images with dogs and 5 images with cats, are you satisfied if your classifier gives you an accuracy of 95%?
- You are training a classifier to detect if a patient is affected or not by COVID 19? In your test set there are 5 COVID-positive patients and 95 COVID-negative patients. Are you satisfied if your classifier gives you an accuracy of 86%?

# Assessing performance: confusion matrix

		Actual class	
		Positive	Negative
Predicted class	Positive	TP	FP
	Negative	FN	TN

		Actual class	
		Positive	Negative
Predicted class	Positive	98	25
	Negative	2	75

acc: 86%

sens: 98%

		Actual class	
		Positive	Negative
Predicted class	Positive	90	10
	Negative	10	90

acc: 90%

sens: 90%

# Classification pipeline

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
my_classifier = my_SMV_classifier() # create an object of class my_SMV_classifier
my_classifier.fit(X_train, y_train) #train classifier
y_test_pred = my_classifier.predict(X_test) #apply trained classifier to test data
accuracy = accuracy_score(y_test, y_test_pred) # compute accuracy
CM = confusion_matrix(y_test, y_test_pred) # compute confusion matrix
```