

Sapienza University of Rome

Master in Artificial Intelligence and Robotics

# Machine Learning

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10. Instance based learning

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Sapienza University of Rome, Italy - Machine Learning (2024/2025)

we not compute a  
model  
↑

## 10. Instance based learning

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# Summary

- Non-parametric models
- K-NN for classification
- Locally weighted regression

## References

C. Bishop. Pattern Recognition and Machine Learning. Sect. 2.5

## Parametric and non-parametric models

*fixed respect nite of data*

*Parametric model:* Model has a fixed number of parameters

Examples:

- Linear regression
- Logistic regression
- Perceptron
- ...

*NO MODEL  
NO PARAMETER*

*Non-parametric model:* Number of parameters grows with amount of data

Simple non-parametric model: **instance-based learning**

# K-nearest neighbors

doesn't require training

↓  
but we need all data

Classification problem:  $f : X \mapsto C$  with data set  $D = \{(\mathbf{x}_n, t_n)_{n=1}^N\}$

Classification with K-NN,

hyperparameter

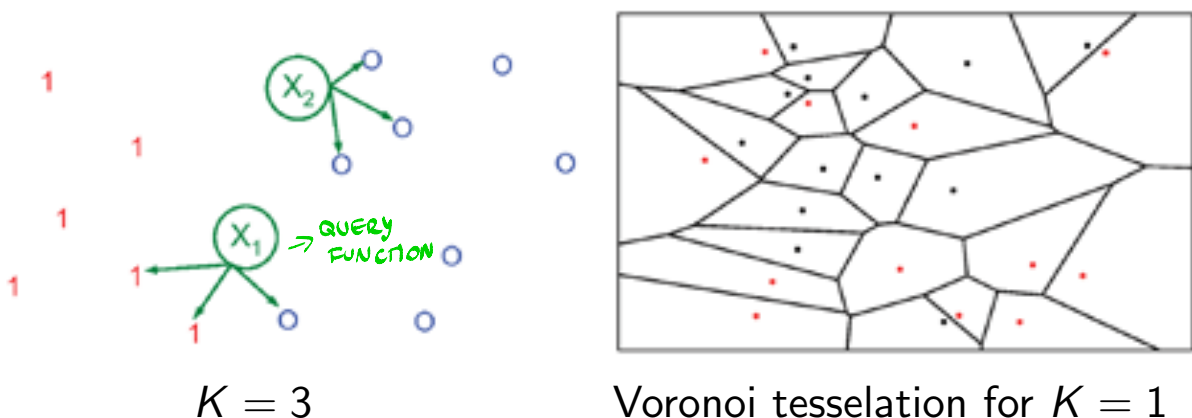
- 1 Find  $K$  nearest neighbors of new instance  $\mathbf{x}$
- 2 Assign to  $\mathbf{x}$  the most common label among the majority of neighbors

Likelihood of class  $c$  for new instance  $\mathbf{x}$ :

$$p(c|\mathbf{x}, D, K) = \frac{1}{K} \sum_{\mathbf{x}_n \in N_K(\mathbf{x}, D)} \mathbb{I}(t_n = c),$$

with  $N_K(\mathbf{x}_n, D)$  the  $K$  nearest points to  $\mathbf{x}_n$  and  $\mathbb{I}(e) = \begin{cases} 1 & \text{if } e \text{ is true} \\ 0 & \text{if } e \text{ is false} \end{cases}$ .

## K-nearest neighbors examples



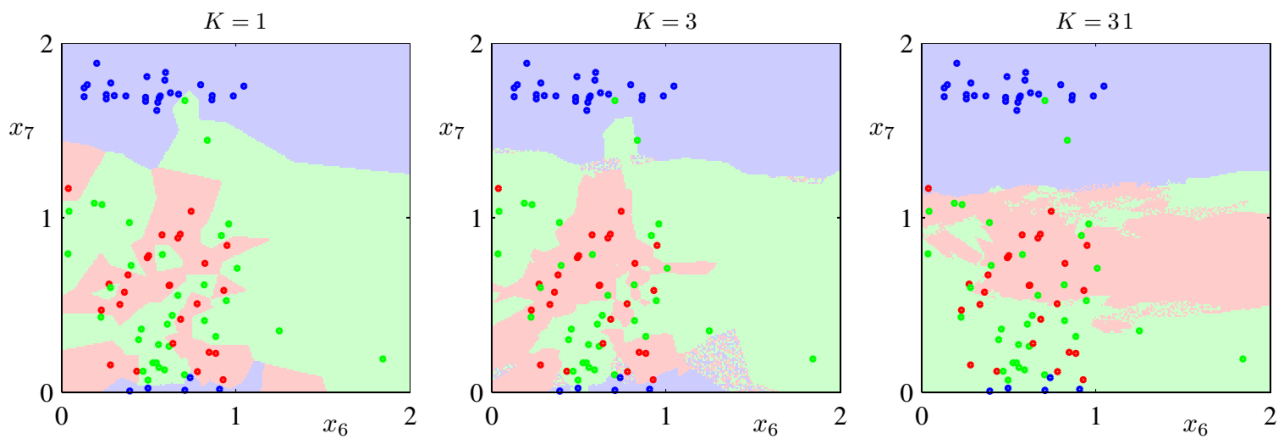
**Requires storage of all the data set!**

**Depends on a distance function!**

↓  
for some attributes is difficult to define a distance

# K-nearest neighbors

Increasing K brings to smoother regions (reducing overfitting)



## Kernelized nearest neighbors

Distance function in computing  $N_K(\mathbf{x}, D)$

$$\|\mathbf{x} - \mathbf{x}_n\|^2 = \mathbf{x}^T \mathbf{x} + \mathbf{x}_n^T \mathbf{x}_n - 2\mathbf{x}^T \mathbf{x}_n.$$

can be kernelized by using a kernel  $k(\mathbf{x}, \mathbf{x}_n)$

# Locally weighted regression

Regression problem  $f : X \mapsto \mathbb{R}$  with data set  $D = \{(x_n, t_n)_{n=1}^N\}$

Fit a local regression model around the query sample  $\mathbf{x}_q$

- ① Compute  $N_K(\mathbf{x}_q, D)$ : K-nearest neighbors of  $\mathbf{x}_q$
- ② Fit a regression model  $y(\mathbf{x}; \mathbf{w})$  on  $N_K(\mathbf{x}_q, D)$
- ③ Return  $y(\mathbf{x}_q; \mathbf{w})$

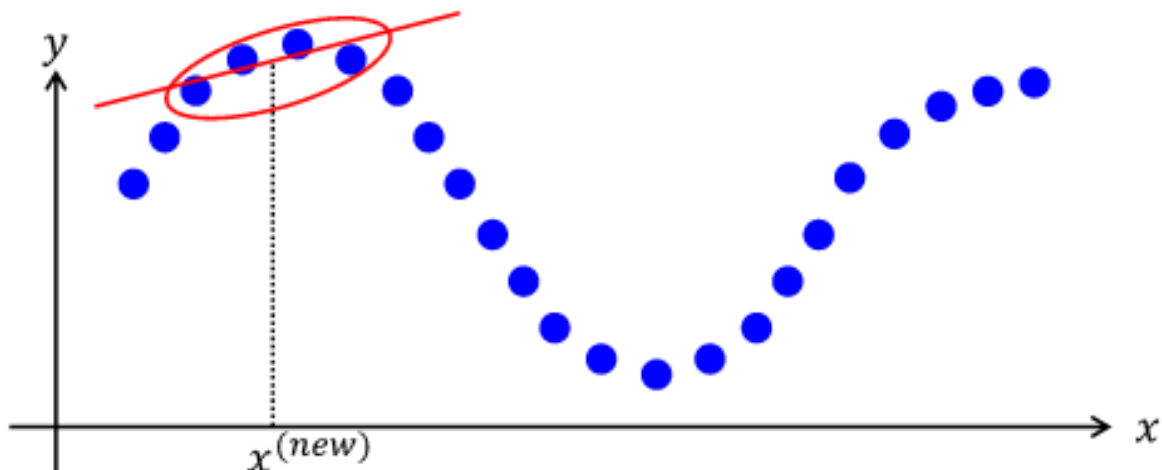
# Locally weighted regression

for the homework it will work pretty well  $\rightarrow$  a lot of action

$\hookrightarrow$  if we have different log is not guaranteed

$\hookrightarrow$  one for train one for test

Example with linear kernel



# Summary

- ① Non-parametric models based on storing data (lazy approaches)
- ② No explicit model
- ③ Sensitive to parameters and distance function
- ④ Require storage of all data