ETH zürich

K-Nearest Neighbour Classifier

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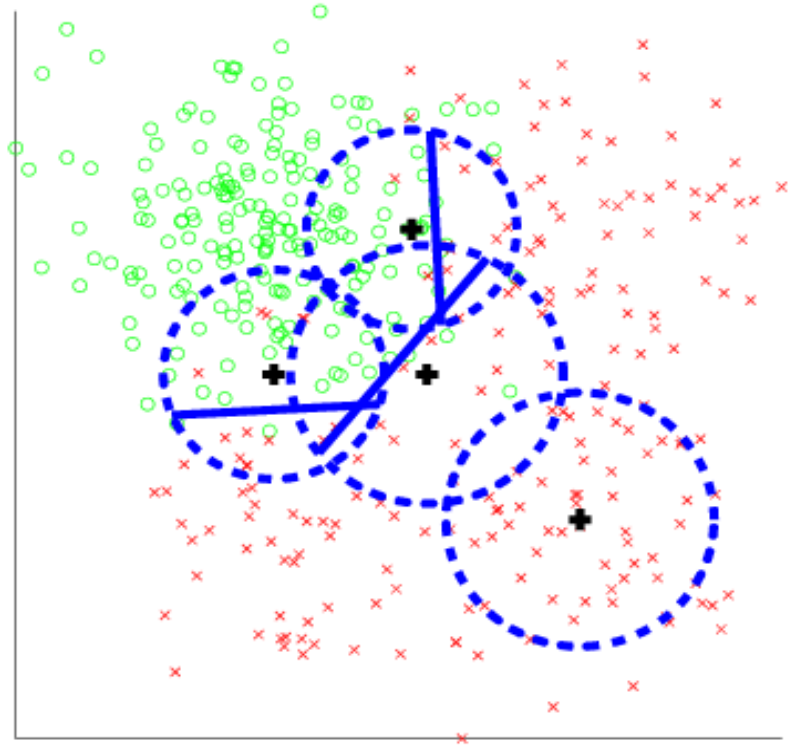
Reminder

Supervised data mining

✓ Classification

→ Decision Trees

K-Nearest Neighbour (kNN) Classifier



Classification steps

1. **Training** phase: a model is constructed from the training instances.
   - $\rightarrow$ classification algorithm finds relationships between predictors and targets
   - $\rightarrow$ relationships are summarised in a *model*
2. **Testing** phase: test the model on a test sample whose class labels are known but not used for training the model
3. **Usage** phase: use the model for classification on new data whose class labels are unknown

Instance-based Classification

Main idea:

Similar instances have similar classification

- no clear separation between the three phases of classification
- also called *lazy* classification, as opposed to *eager* classification

Eager vs Lazy Classification

Eager

- Model is computed before classification
- Model is independent of the test instance
- Test instance is not included in the training data
- Avoids too much work at classification time
- Model is not accurate for each instance

Lazy

- Model is computed during classification
- Model is dependent on the test instance
- Test instance is included in the training data
- High accuracy for models at each instance level

k-Nearest Neighbor (kNN)

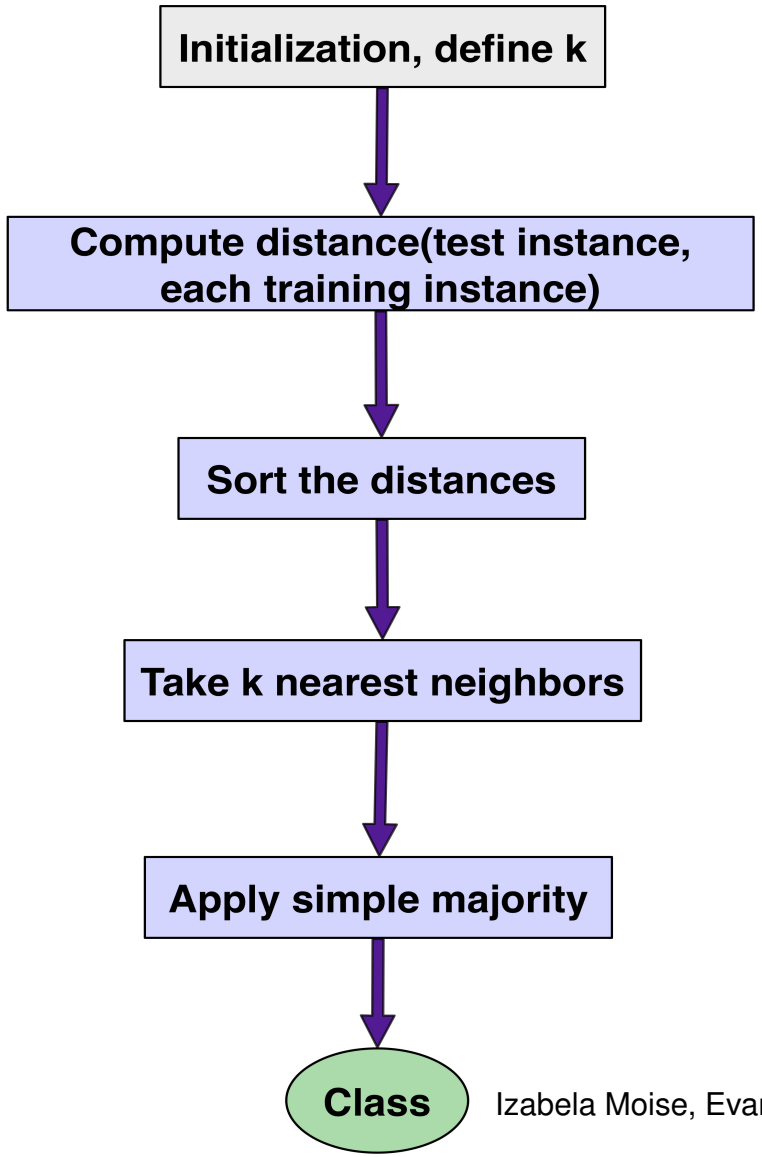
Learning by analogy:

Tell me who your friends are and I'll tell you who you are

$\rightarrow$ an instance is assigned to the **most common** class among the instances **similar** to it

1. how to measure similarity between instances
2. how to choose the most common class

How does it work?



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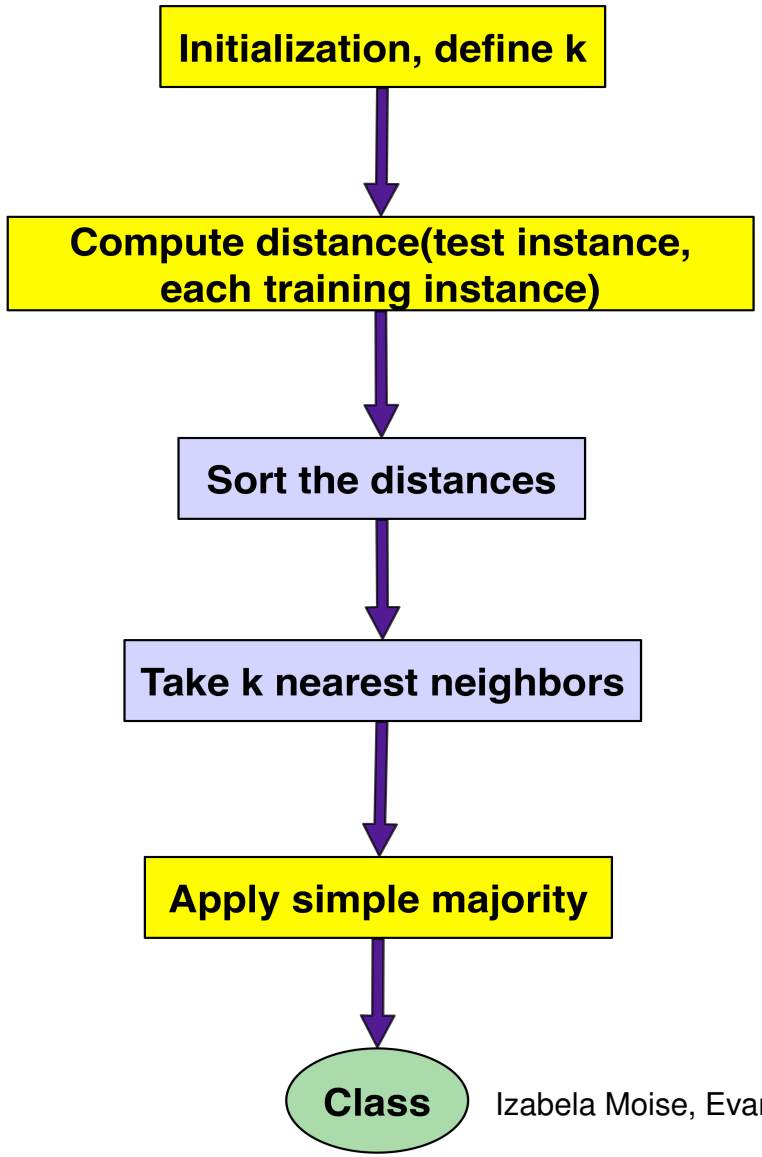

Comparing Objects

→ *Problem :* measure similarity between instances

- different types of data: numbers colours, geolocation, booleans etc.

✓ *Solution :* convert all features of the instances into numerical values

- represent instances as vectors of features in an n-dimensional space

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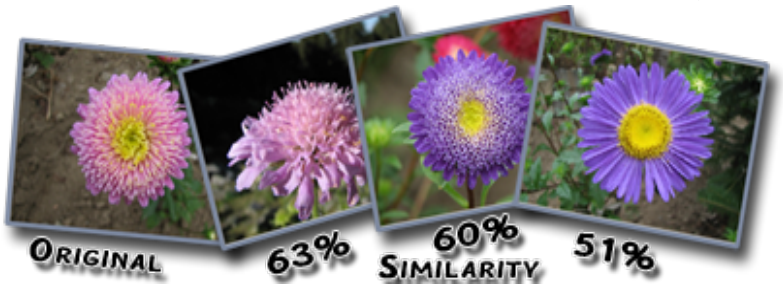

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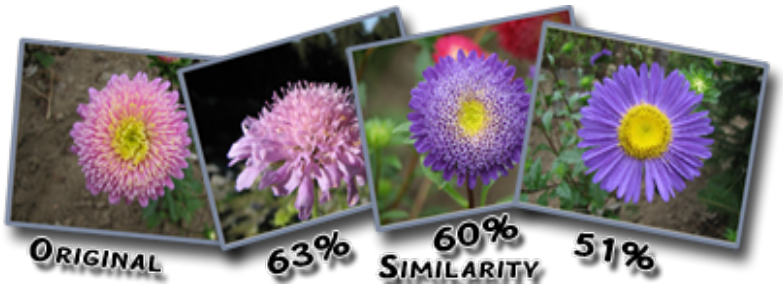

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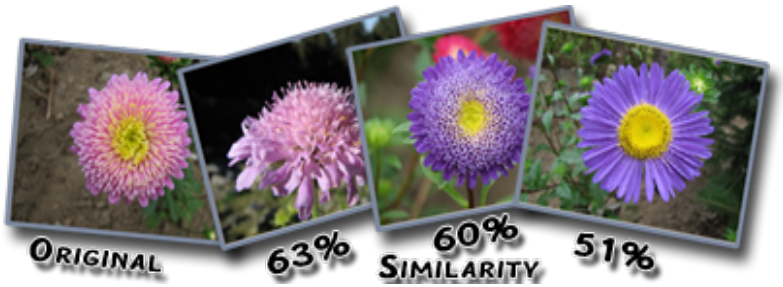

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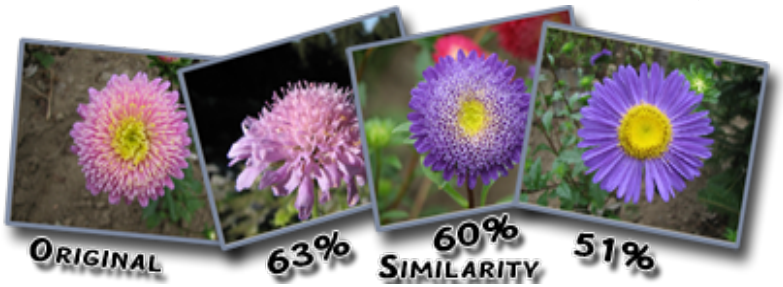

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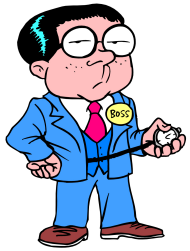
An Example:



John:
Age=35
Income=95K
No. of credit cards=3

Rachel:
Age=41
Income=215K
No. of credit cards=2

- Closeness" is defined in terms of the *Euclidean* distance between two examples.
  - The Euclidean distance between $X=(x_1, x_2, x_3,...x_n)$ and $Y=(y_1,y_2, y_3,...y_n)$ is defined as:

$$D(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

- Distance (John, Rachel)=sqrt $[(35-41)^2+(95K-215K)^2+(3-2)^2]$

Distance Metrics

1. Euclidean Distance

$$D(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

2. Manhattan Distance

$$D = \sum_{i=1}^{n} |x_i - y_i|$$

3. Minkowski Distance

$$D = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{1/p}$$

Choosing k

- Classification is sensitive to the correct selection of k
- if k is too small $\Rightarrow$ overfitting
  - $\rightarrow$ algorithm performs too good on the training set, compared to its true performance on unseen test data

small k?

larger k?

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small k? $\rightarrow$ less stable, influenced by noise

larger k? $\rightarrow$ less precise, higher bias

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k= $\sqrt[2]{n}$

Pros and Cons

Pros:

- ✓ simple to implement and use
- ✓ robust to noisy data by averaging k-nearest neighbours
- ✓ kNN classification is based solely on local information
- ✓ the decision boundaries can be of arbitrary shapes

Pros and Cons

Cons:

- ✗ curse of dimensionality: distance can be dominated by irrelevant attributes
- ✗ $O(n)$ for each instance to be classified
- ✗ more expensive to classify a new instance than with a model