Streaming Machine Learning (SML)

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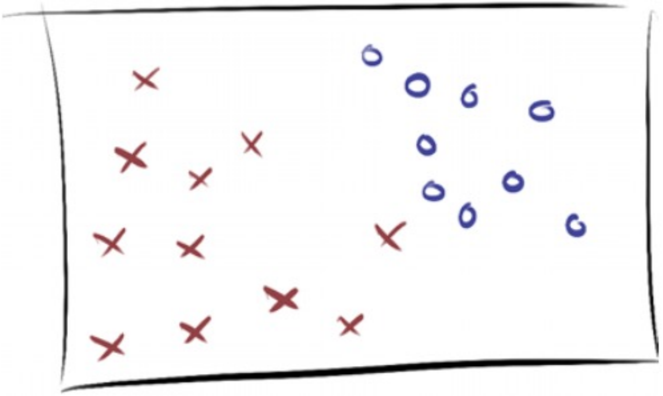
Part III

Classification

Credits

- Albert Bifet DATA STREAM MINING 2020-2021 course at Telecom Paris
- Alessio Bernardo & Emanuele Della Valle

SML Classification models



Naïve Bayes

- Based on Bayes Theorem, where c is the class and d is the instance to classify:

$$P(c|d) = \frac{P(c) * P(d|c)}{P(d)}$$

- Estimate the probability of observing attribute a and the prior probability $P(c)$:

$$P(c|d) = \frac{P(c) * \prod_{a \in d} P(a|c)}{P(d)}$$

John, G. H., & Langley, P. **Estimating continuous distributions in Bayesian classifiers**. arXiv preprint 2013.

Naïve Bayes

Mean and Variance with a batch of *n* samples

$$\hat{x} = \frac{1}{n} * \sum_{i=1}^{n} x_i \qquad \sigma^2 = \frac{1}{n-1} * \sum_{i=1}^{n} (x_i - \widehat{x})^2$$

Mean and Variance with a stream $\boldsymbol{x_1, \dots, x_i, \dots, x_n}$

$$s_i = s_{i-1} + x_i \qquad q_i = q_{n-1} + {x_i}^2$$

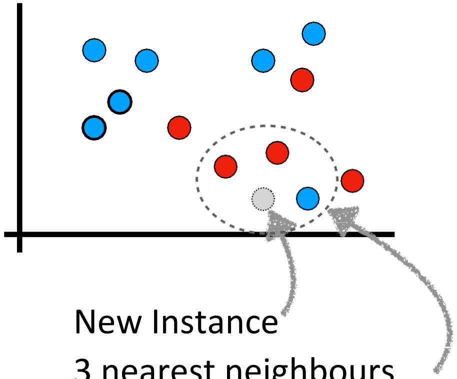
$$\hat{x}_i = \frac{s_i}{i} \qquad {\sigma_i}^2 = \frac{1}{i-1} * \left(q_i - \frac{{s_i}^2}{i}\right)$$

John, G. H., & Langley, P. **Estimating continuous distributions in Bayesian classifiers**. arXiv preprint 2013.

K-Nearest Neighbours (KNN)

- The most common label of the *k* instances closer to a new instance determines its label
- The distance between instances is calculated (commonly) using the Euclidean Distance:

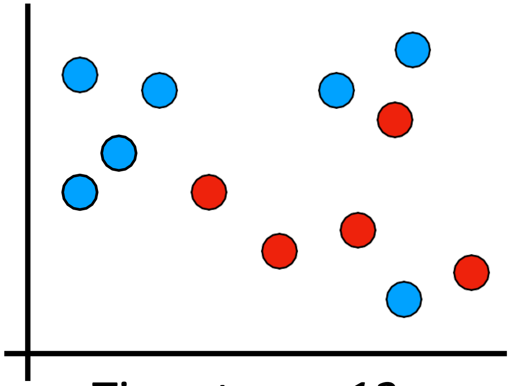
$$d(a,b) = \sqrt{\sum_{i=1}^{m}(a_i - b_i)^2}$$



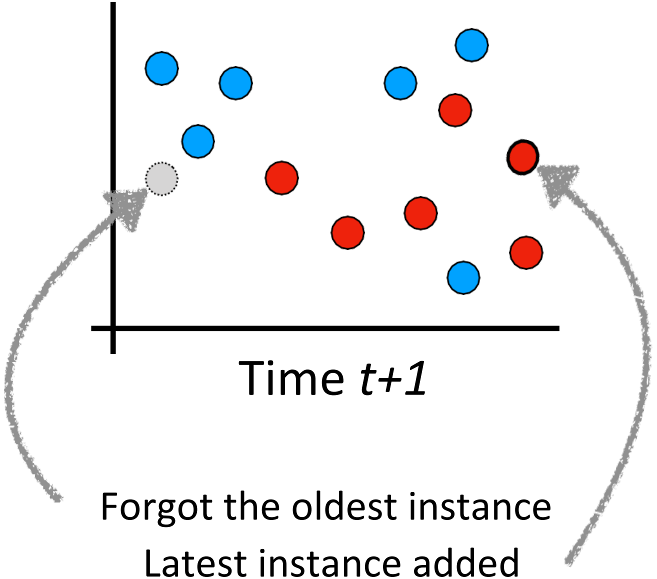
Bifet, A., Pfahringer, B., Read, J., & Holmes, G. **Efficient data stream classification via probabilistic adaptive windows**. 28th ACM symposium on applied computing (2013).

K-Nearest Neighbours (KNN)

- Use a *sliding window* to save the instances



Time *t, w = 12*



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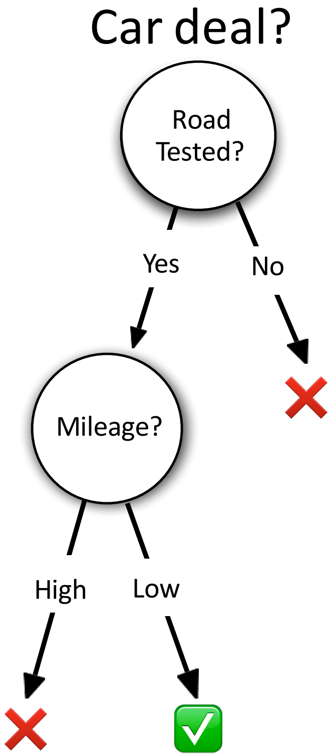
Decision Trees

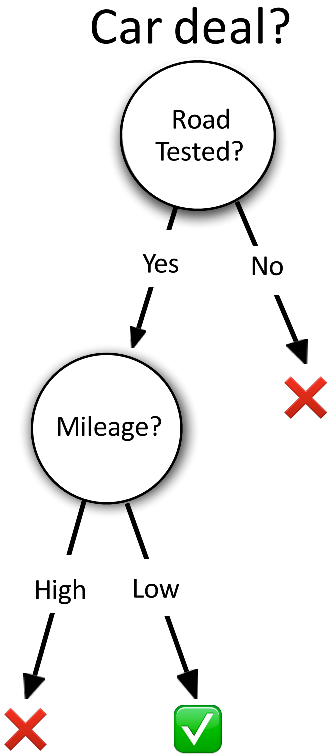
- Each node tests a features
- Each branch represents a value
- Each leaf assigns a class
- Greedy recursive induction:
  - ➢ Sort all examples through tree
  - ➢ X_i = most discriminative attribute using the Information Gain
  - ➢ New node for X_i, new branch for each value, leaf assigns majority class
  - ➢ Stop if no error or limit on #instances



https://en.wikipedia.org/wiki/Decision_tree_learning

Hoeffding Trees (VFDT)

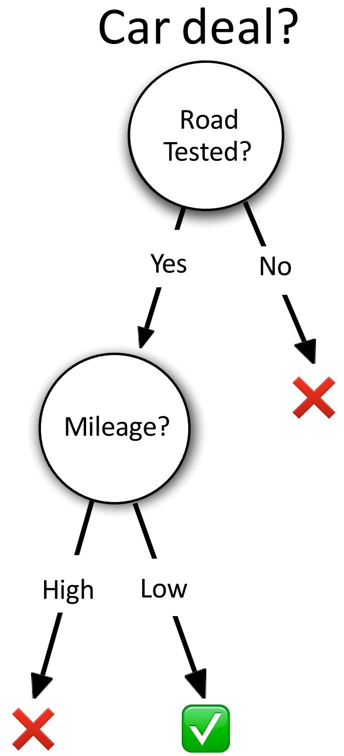
- Build the decision tree incrementally
- The final tree must be identical (with high probability) to a tree built using a batch decision tree algorithm
- With theoretical guarantees on the error rate



Pedro Domingos and Geoff Hulten**. Mining high-speed data streams**. 2000

Hoeffding Trees (VFDT)

- Which attribute to choose at each splitting node?
- A small sample can often be enough to choose the optimal splitting attribute
  - ➢ Collect sufficient statistics from a small set of examples
  - ➢ Estimate the merit of each attribute
- How large should be the sample?
  - ➢ **Fixed size**: defined *apriori* without looking for the data



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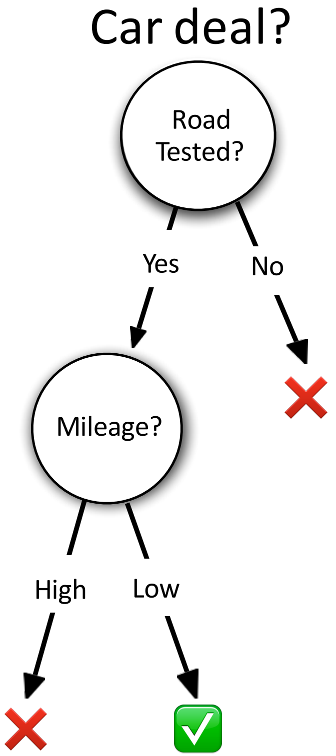
❌ ➢ **Fixed size**: defined *apriori* without looking for the data

✅ ➢ **Moving size**: Choose the sample size that allow to differentiate between the alternatives.



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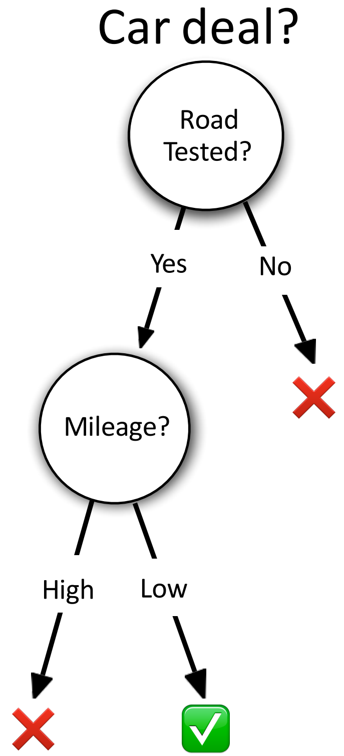
Hoeffding Trees (VFDT)

- **Moving size:** Use Hoeffding bound to guarantee that the best attribute is really the *best*:
  - ➢ Let X_1 and X_2 be, respectively, the two most informative attribute
  - ➢ Split if: $G(x_1) - G(x_2) > \varepsilon = \sqrt{\frac{R^2 * \log(1/\delta)}{2N}}$,

    where R is the G range, δ is the confidence bound and N is the number of instances seen by that node



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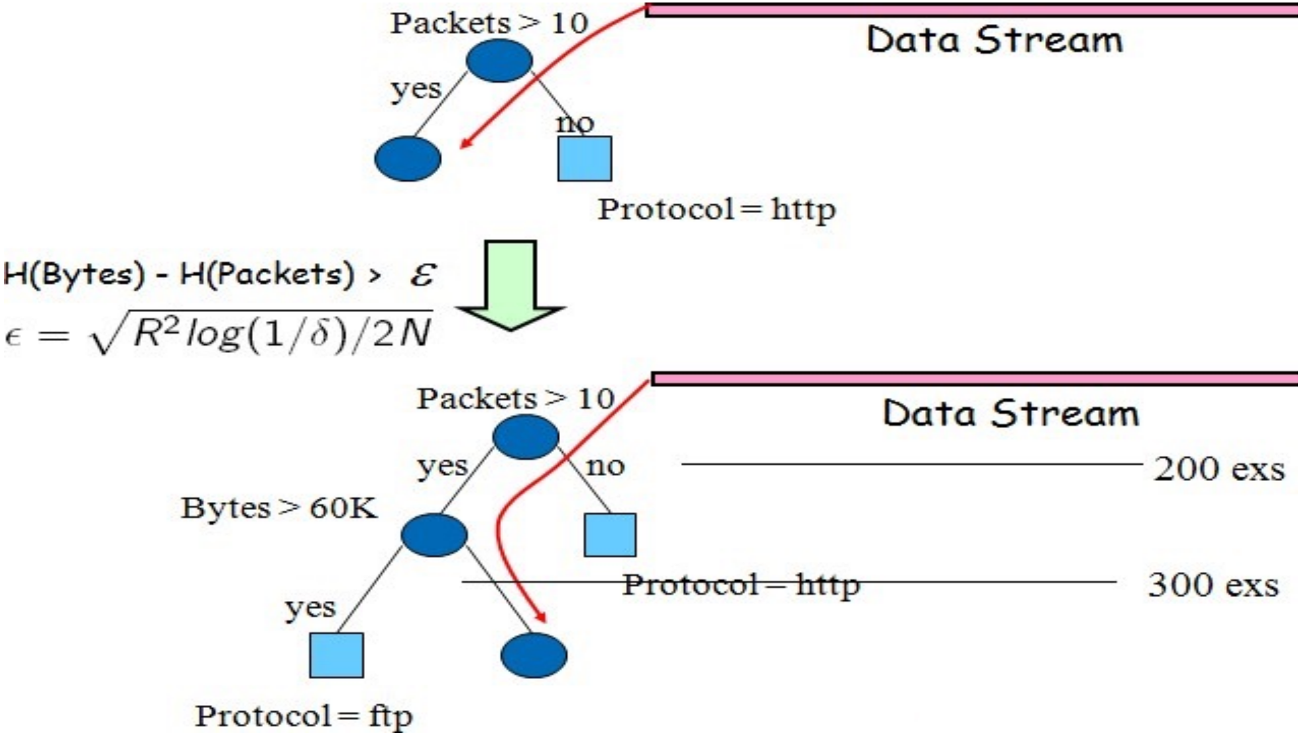
Hoeffding Trees (VFDT)

Attributes:
- **Packets**
- **Bytes**

Label: **Protocol**
- http
- ftp



From Gehrke's SIGMOD tutorial

Concept Adapting VFDT (CVFDT)

- What happens when a **concept drift** occurs?
  - ➢ The nodes are no longer representative of the current concept

- CVFDT keeps its model consistent with a sliding window of *w* samples
- It constructs “alternative branches” as preparation for changes
- If the alternative branch becomes more accurate, switch of tree branches

Cons:

➢ No theoretical guarantees on the error rate of CVFDT

➢ *W* is fixed

G. Hulten, L. Spencer, and P. Domingos. **Mining time-changing data streams.** 2001

Hoeffding Adaptive Tree (HAT)

- Replace frequency statistics counters by estimators
  - ➢ Don’t need a window to store examples, due to the fact that we maintain the statistics data needed with estimators

- Change the way of checking the substitution of alternate subtrees, using a change detector with theoretical guarantees (ADWIN)
  - ➢ Keeps sliding window consistent with the *no-change hypothesis*

Pro:

- ➢ Theoretical guarantees
- ➢ No Parameters

A. Bifet, R. Gavald`a: **Adaptive Parameter-free Learning from Evolving Data Streams.** IDA, 2009

QUIZ

1. How does the SML version of KNN work?
    a. By saving all the instances and finding the neighbors among them
    b. By saving the last *w* instances in a sliding window and finding the neighbors among them
    c. Without saving any instances
2. Why is Hoeffding Bound used in SML to build a decision tree?
    a. To find the best attribute for which make a split
    b. To make a prediction
    c. To check any statistical evidences that the number of samples seen by a node are enough to make a split

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EXERCISE 3: Stream Classification