Lecture 7. Data Stream Mining. Building decision trees

Ricard Gavaldà

MIRI Seminar on Data Streams, Spring 2015

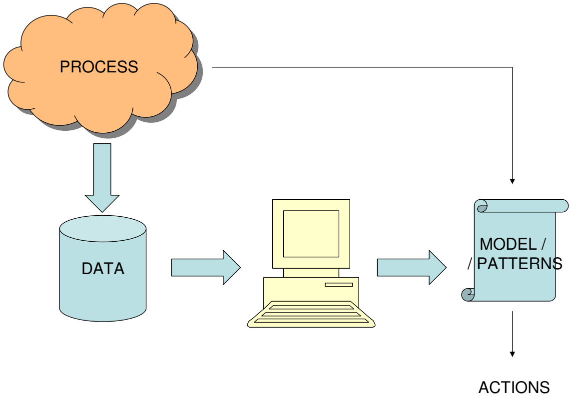
Contents

Data Stream Mining

Background: Learning and mining

- Finding in what sense data is not random
- For example: frequently repeated patterns, correlations among attributes, one attribute being predictable from others, ...
- Fix a description language a priori, and show that data has a description more concise than the data itself

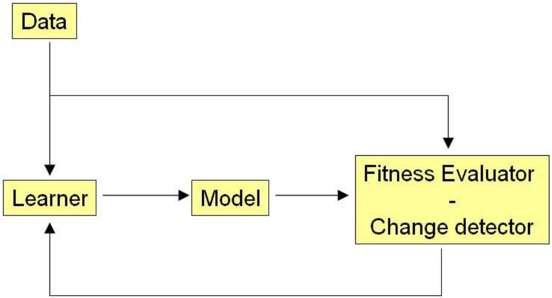
Background: Learning and mining



Mining in Data Streams: What's new?

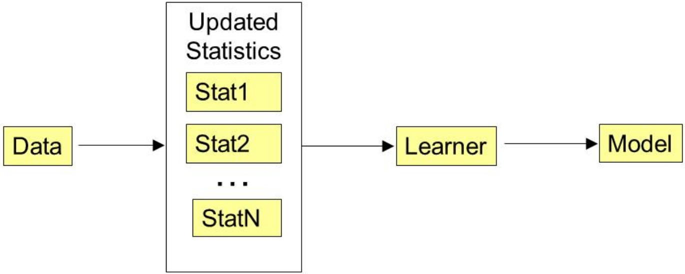
- Make one pass on the data
- Use low memory
  - Certainly sublinear in data size
  - In practice, that fits in main memory – no disk accesses
- Use low processing time per item
- Data evolves over time - nonstationary distribution

Two main approaches



- Learner builds model, perhaps batch style
- When change detected, revise or rebuild from scratch

Two approaches



- Keep accurate statistics of recent / relevant data
- e.g. with “intelligent counters”
- Learner keeps model in sync with these statistics

Decision Tree Learning

Background: Decision Trees

- Powerful, intuitive classifiers
- Good induction algorithms since mid 80's (C4.5, CART)
- Many many algorithms and variants now

Top-down Induction, C4.5 Style

Induct(Dataset S) returns Tree T

  if (not_expandable(S)) then

    return Build_Leaf(S)

  else

    choose "best" attribute $a \in A$

    split S into $S_1, \ldots S_v$ using a

    for $i = 1..v$, $T_i = \text{Induct}(S_i)$

    return Tree(root=$a, T_1, \ldots, T_v$))

Top-down Induction, C4.5 Style

To have a full algorithm one must specify:

- not_expandable(S)
- Build_Leaf(S)
- notion of "best" attribute
  - usually, maximize some gain function $G(A, S)$
  - information gain, Gini index, ...
  - relation of A to the class attribute, C
- Postprocessing (pruning?)

Time, memory: reasonable polynomial in $|S|$, $|A|$, $|V|$

Extension to continuous attributes: choose attribute *and* cutpoints

VFDT

P. Domingos and G. Hulten: “Mining high-speed data streams” KDD’2000.

- Very influential paper
- Very Fast induction of Decision Trees, a.k.a. Hoeffding trees
- Algorithm for inducing decision trees in data stream way
- Does not deal with time change
- Does not store examples - memory independent of data size

VFDT

Crucial observation [DH00]

An almost-best attribute can be pinpointed quickly:
Evaluate gain function $G(A, S)$ on examples seen so far S, then use Hoeffding bound

Criterion

If A_i satisfies

$$G(A_i, S) > G(A_j, S) + \varepsilon(|S|, \delta) \text{ for every } j \neq i$$

conclude "A_i is best" with probability $1 - \delta$

VFDT-like Algorithm

T := Leaf with empty statistics;
For $t = 1, 2, \ldots$ do VFDT_Grow(T,x_t)

VFDT_Grow (Tree T, example x)
    run x from the root of T to a leaf L
    update statistics on attribute values at L using x
    evaluate $G(A_i, S_L)$ for all i from statistics at L
    if there is an i such that, for all j,
        $G(A_i, S_L) > G(A_j, S_L) + \varepsilon(S_L, \delta)$ then
            turn leaf L to a node labelled with A_i
            create children of L for all values of A_i
            make each child a leaf with empty statistics

Extensions of VFDT

- IADEM [G. Ramos, J. del Campo, R. Morales-Bueno 2006]
  - Better splitting and expanding criteria
  - Margin-driven growth
- VFDT$_c$ [J. Gama, R. Fernandes, R. Rocha 2006], UFFT [J. Gama, P. Medas 2005]
  - Continuous attributes
  - Naive Bayes at inner nodes and leaves
  - Short term memory window for detecting concept drift
  - Converts inner nodes back to leaves, fill them with window data
  - Different splitting and expanding criteria
- CVFDT [G. Hulten, L. Spencer, P. Domingos 2001]

CVFDT

G. Hulten, L. Spencer, P. Domingos, “Mining time-changing data streams”, KDD 2001

- Concept-adapting VFDT
- Update statistics at leaves *and* inner nodes
- Main idea: when change is detected at a subtree, grow candidate subtree
- Eventually, either current subtree or candidate subtree is dropped
- Classification at leaves based on most frequent class in a window of examples
- Decisions at leaf use a window of recent examples

CVFDT

VFDT:

- No concept drift
- No example memory
- No parameters but δ
- Rigorous performance guarantees

CVFDT:

- Concept drift
- Window of examples
- Several parameters besides δ
- No performance guarantees

CVFDT

Parameters related to time-change [default]:

1. W: example window size [100,000]
2. T_1: time between checks of splitting attributes [20,000]
3. T_2: # examples to decide whether best splitting attribute is another [2,000]
4. T_3: time to build alternate trees [10,000]
5. T_4: # examples to decide if alternate tree better [1,000]

Enter ADWIN

[Bifet, G. 09] Adaptive Hoeffding Trees

Recall: the ADWIN algorithm

- detects change in the mean of a data stream of numbers
- keeps a window W whose mean approximates current mean
- memory, time $O(\log W)$

Adaptive Hoeffding Trees

- Replace counters at nodes with ADWIN's (AHT-EST), or
- Add an ADWIN to monitor the error of each subtree (AHT-DET)
- Also for alternate trees
- Drop the example memory window

AHT have no parameters!

- When to start growing alternate trees?

  When ADWIN says "error reate is increasing", or

  When ADWIN for a counter says "attribute statistics are changing"
- How to start growing new tree?

  Use accurate estimates from ADWIN's at parent - no window
- When to tell alternate tree is better?

  Use the estimation of error by ADWIN to decide
- How to answer at leaves?

  Use accurate estimates from ADWIN's at leaf - no window

Memory

CVFDT's Memory is dominated by example window, if large

CVFDT	AHT-Est	AHT-DET
$TAVC + AW$	$TAVC \log W$	$TAVC + T \log W$

T = Tree size
V = Values per attribute
C = Number of classes
A = # attributes
W = Size of example window

Experiments

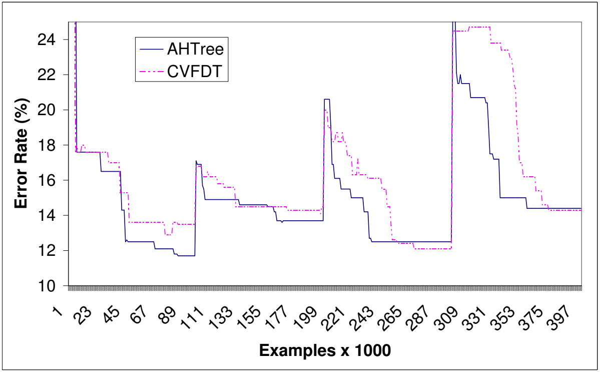


Figure: Learning curve of SEA concepts using continuous attributes

Adaptive Hoeffding Trees: Summary

- No “magic” parameters. Self-adapts to change
- Always as accurate as CVFDT, and sometimes much better
- Less memory - no example window
- Moderate overhead in time ($<$50%). Working on it
- Rigorous guarantees possible

Exercise

Exercise 1

- Design a streaming version of the Naive Bayes classifier for stationary streams
- Now use ADWIN or some other change detection / tracking mechanism for making it work on evolving data streams

Recall that the NB classifier uses memory proportional to the product of #attributes x #number of values per attribute x #classes. Expect an additional log factor in the adaptive version. Update time should be small (log, if not constant).