

Adaptive XML Tree Mining on Evolving Data Streams

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PASCAL2

Pattern Analysis, Statistical Modelling and
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Pattern Mining in Data Streams



Our setting

- Patterns: Objects where
 - “ p subpattern of q ”
 - makes sense (partial order)
- Sets, sequences, trees, graphs
- Mining frequent patterns
- Classifying patterns
- In a data stream that changes over time

XML Trees

```
<?xml version="1.0"?>
<?xml-stylesheet type="text/xsl" href="movie1.xsl"?>
<filmlibrary>
  <name>Classic Films</name>
  <movie>
    <title>The Bicycle Thief</title>
    <genre>Social Drama</genre>
    <language>Italian</language>
    <year>1948</year>
    <length>90 Min.</length>
    <filmtype>BW</filmtype>
    <credits>
      <director>Vittorio de Sica</director>
      <story>Gennarino Bartolini</story>
      <cinematography>Carlo Montuori</cinematography>
    </credits>
  </movie>
</filmlibrary>
```

Issues

Pattern Classification

- Mapping patterns \rightarrow features
- Frequent patterns, closed patterns, generators, ...

Data stream classification

- Highly sublinear memory (in #items seen)
- Low processing time per item
- Tolerate distribution & concept change

Our Work

- To our knowledge, first tree pattern classifier in data streams
- Builds features by mining frequent closed subtrees or maximal subtrees
 - Miner is interesting in itself / competitive with state-of-the art
- Uses recently proposed ensemble methods for classification
- Implementation over the MOA framework

Tree (Pattern) Mining

Task occurs in chemistry, computer vision, text retrieval bioinformatics, Web analysis, XML queries, ...

- A transaction *supports* a tree if the tree is a subtree of the transaction
- *Support* of a tree is the number of transactions that support it

Given a dataset of trees and value *min_support*, find

- Frequent Tree mining (FT):
all trees whose support is no less than *min_support*
- Closed Frequent Tree mining (CT):
+ no super-tree with the same support

Previous Work

- [Zaki-Agrawal] Classifier from frequent sets + Bayesian rules
- [Kudo et al.] Classifier from “significant” frequent trees + boosting
- [Collins et al., Kashima et al.] SVM's, tree kernels; feature space = frequent trees
- CMTreeMiner [Chi et al.], [Termier et al.] Dryade: Closed frequent tree miners *without* computing all frequent trees
- [Li et al 06] Frequent subtree miner for XML data streams
- [Bifet-G 08] Frequent closed pattern miner in data streams, unlabelled trees

Closure Operator on Trees

- \mathcal{D} : the finite input dataset of trees
- \mathcal{T} : the (infinite) set of all trees

Definition

We define the following Galois connection pair:

- For finite $A \subseteq \mathcal{D}$
 - $\sigma(A)$ is the set of subtrees of the A trees in \mathcal{T}

$$\sigma(A) = \{t \in \mathcal{T} \mid \forall t' \in A (t \preceq t')\}$$

- For finite $B \subset \mathcal{T}$
 - $\tau_{\mathcal{D}}(B)$ is the set of supertrees of the B trees in \mathcal{D}

$$\tau_{\mathcal{D}}(B) = \{t' \in \mathcal{D} \mid \forall t \in B (t \preceq t')\}$$

Closure Operator on Trees (2)

Closure Operator

The composition $\mathcal{C}_{\mathcal{D}} = \sigma \circ \tau_{\mathcal{D}}$ is a closure operator

Characterizing closed trees

A tree t is closed (no supertree with same support) in \mathcal{D}
iff

$$\mathcal{C}_{\mathcal{D}}(t) = \{t\}$$

Closure Operator on Trees (3)

Rules for adding and removing patterns to datasets [Bifet-G 08]:

Theorem

Let \mathcal{D}_1 and \mathcal{D}_2 be two datasets of patterns. A pattern t is closed for $\mathcal{D}_1 \cup \mathcal{D}_2$ if and only if

- *t is a closed pattern for \mathcal{D}_1 , or*
- *t is a closed pattern for \mathcal{D}_2 , or*
- *t is a subpattern of a closed pattern in \mathcal{D}_1 and of a closed pattern in \mathcal{D}_2 and $\mathcal{C}_{\mathcal{D}_1 \cup \mathcal{D}_2}(\{t\}) = \{t\}$.*

Theorem

Let \mathcal{D} be a pattern dataset. A pattern t is closed for \mathcal{D} if and only if the intersection of all its closed superpatterns is t .

Incremental Algorithm

Computing the lattice of frequent trees

Construct empty lattice L ;

Repeat

 Collect batch of B trees;

 Build closed tree lattice for B , L_2 ;

$L := \text{merge}(L, L_2)$ (using addition rule)

Memory & time depend on lattice size (number of closed trees)
not on DB size!

Efficient ops. using the representation for trees by
[Balcázar-Bifet-Lozano]

Dealing with time changes

- Keep a window on recent stream elements
 - Actually, just its lattice of closed sets!
- Keep track of number of closed trees in lattice, N
- Use some change detector on N
- When change is detected:
 - Drop stale part of the window
 - Update lattice to reflect this deletion, using deletion rule

Alternatively, sliding window of some fixed size

Miner is interesting in itself

Can also be used for static databases

For small number of labels:

- slightly *faster* than CMTreeMiner
- significantly *less memory* than CMTreeMiner
- (CMTreeMiner keeps all dataset in memory)

T8M synthetic dataset [Zaki02]:

100 labels, mother tree size 10,000, DBsize 8M

Maximal Trees

Maximal Trees

A tree is maximal if no supertree of t is frequent

All maximal trees are closed

- Non-maximal closed patterns can be derived from maximal ones
- ...but not their supports
- Are they still enough for classification?

XML Tree Classification on evolving data streams

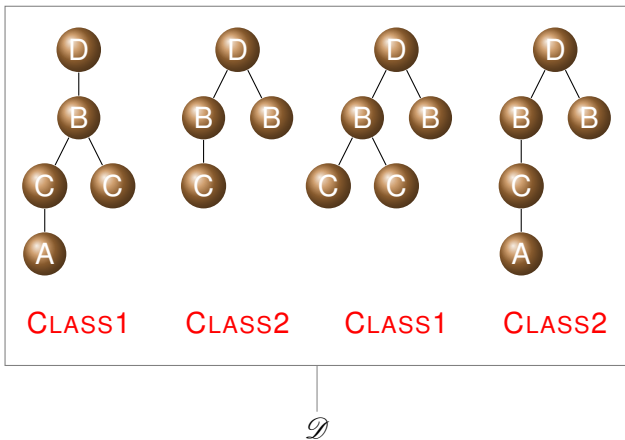


Figure: A dataset example

XML Tree Classification on evolving data streams

	Closed Trees				Maximal Trees			
Id Tree	c_1	c_2	c_3	c_4	c_1	c_2	c_3	Class
1	1	1	0	1	1	1	0	CLASS1
2	0	0	1	1	0	0	1	CLASS2
3	1	0	1	1	1	0	1	CLASS1
4	0	1	1	1	0	1	1	CLASS2

XML Tree Framework on evolving data streams

Two components:

- An XML closed frequent tree miner
- A Data stream classifier algorithm, which we will feed with tuples to be classified online.

Attributes in these tuples represent the occurrence of the current closed trees in the originating tree, although the classifier algorithm need not be aware of this.

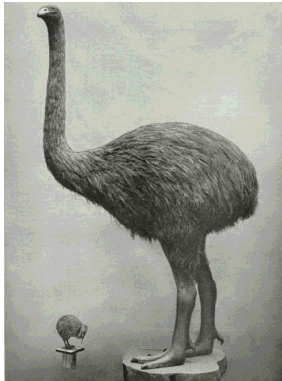


WEKA: the bird



MOA: the bird

The Moa (another native NZ bird) is not only flightless, like the Weka, but also extinct.



MOA: the software

{M}assive {O}nline {A}nalysis is a framework for online learning from data streams.

<http://www.cs.waikato.ac.nz/~abifet/MOA/>

- It is closely related to WEKA
- It includes a collection of offline and online algorithms and tools for evaluation:
 - Hoeffding Trees, Hoeffding option trees
 - Boosting and bagging. In particular:
 - Adaptive-Size Hoeffding Tree bagging & boosting [Bifet et al., KDD09]

with and without Naïve Bayes classifiers at the leaves.

Experiments: Synthetic datasets

- Zaki's tree dataset generator
- 2 mother trees, 2 classes, depth and fanout 10
- 1M samples, node labels change every 250,000 trees

Bagging	Time	Acc.	Mem.
AdaTreeMiner	161.61	80.06	4.93
IncTreeMiner	212.75	65.73	4.4

Experiments: Real dataset

LOGML files [Zaki 02]

describing 3 weeks of user sessions logs, each as XML file

classes = .edu vs. non-.edu visitors

		Maximal			Closed		
	# Trees	Att.	Acc.	Mem.	Att.	Acc.	Mem.
CSLOG12	15483	84	79.64	1.2	228	78.12	2.54
CSLOG23	15037	88	79.81	1.21	243	78.77	2.75
CSLOG31	15702	86	79.94	1.25	243	77.60	2.73
CSLOG123	23111	84	80.02	1.7	228	78.91	4.18

Conclusions

- A tree / XML tree stream classifier system
- Frequent closed / maximal trees as features
- Frequent closed tree miner based on closure operators
- That reacts quickly to distribution / label changes
- Maximal trees may suffice

Future Work

- More experiments for better understanding of behavior
- Especially, comparison with CMTreeMiner
- Deletion of obsolete attributes
- Use generators instead of closed / maximal
- XML mining in data streams when #labels is large