Real World Issues in Supervised Classification for data stream

European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (2013) […]
Workshop “Real-World Challenges for Data Stream Mining” […]

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Statistical learning provides numerous algorithms to build predictive models on past observations. These techniques proved their ability to deal with large scale realistic problems. However, new domains generate more and more data. This large amount of data (the buzz “big data”) can be dealt with using batch algorithms (parallelized . . . ) if the paradigm to store the data is realistic. But sometimes data are only visible once and need to be processed sequentially. These volatile data, known as data streams, come from telecommunication network management, social network, web mining, to name a few. The challenge is to build new algorithms able to learn under these constraints. The aim of this presentation will be to present several studies and research topics at Orange focusing on “supervised classification in data streams”, with the idea to stimulate a discussion on “the real issues”.

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Outline

1. Classification using Big Data versus Classification on Stream Mining
2. Different forms of learning
3. Stream: what changes?
4. Requirements for a good algorithm
5. Taxonomy of classifier for data stream
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7. Concept drift
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12. Alternative problem settings?
13. Just to do a small provocation… 😊
BIG DATA VERSUS STREAM MINING
Big Data – what does that mean?

- **Volume**
  - From: Internal (terabyte)
  - To: External (petabyte)

- **Velocity**
  - From: Batch
  - To: Real time

- **Variety**
  - From: Structured
  - To: Unstructured

- **Visualization**
  - From: Static
  - To: Dynamic

- **Value creation**
  - From: Reporting and compliance
  - To: Strategic asset / Competitive advantage

McKinsey & Company | 3
Big Data?

- Big Data = Large scale (data volume) analytics (lines & columns)
- Big Data = Emerging new data types (new multi-structured data types: web logs, sensor networks, social networks)
- Big Data = New (non-SQL) analytics (new Frameworks that provide parallel processing)
Big Data Analytics?

- Big Data Analytics: Extracting Meaningful and Actionable Data from a Massive Source

- Let’s avoid
  - Triviality, Tautology: a series of self-reinforcing statements that cannot be disproved because they depend on the assumption that they are already correct
  - Thinking that noise is an information

- Let’s try to have
  - Translation: capacity to transfer in concrete terms the discovery (actionable information)
  - TTM: Time To Market, ability to have quickly information on every customers (Who, What, Where, When)
Data Analytics - Orange Labs – team PROF

2000 - 2005:
Optimal Data Preparation
Automatic variable selection
Supervised Classification Models

2000 - 2005:
* Needs for datamining at France Telecom:
a great variety of contexts

2006 - 2010:
Scoring Factory & Khiops
Extending to various modelisation types
Extending volume capacities
Porting to Linux + 64bits

2011 - 2013:
* Studies diversification, Clients outside Orange

2011 - 2013:
Multi-tables
Automatic variable construction
Co-clustering, Clustering, Stream, …

CAP – Customer Analysis Platform
With Score Team (C. Riwan)
(CDRs from landlines)
Khiops – FT Scoring tool

PAC PUB – moving to Hadoop
With Orange Portail France
(Usage Data from DoubleClic)

Strengths

* Generic tool
* No user parameter
* Robustness
* Fineness
* Interpretability
* Efficient
STREAM MINING IS REQUIRED...  SOMETIMES
and...

Do not make the confusion!

Between Online Learning

and Online Deployment

A lot of advantages and drawback for both – but offline learning used 99% of the time
Machine Learning: What are the pros and cons of offline vs. online learning?

Try to find answers to:
(which is which)

• Computationally much faster and more space efficient
• Usually easier to implement
• A more general framework.
• More difficult to maintain in production.
• More difficult to evaluate online
• Usually more difficult to get "right".
• More difficult to evaluate in an offline setting, too.
• Faster and cheaper
• …
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DIFFERENT FORMS OF LEARNING
**Offline learning**

- Offline learning:
  - Examples are collected before learning starts
  - Distinct learning phase
    - It is then called “one shot learning”
  - Learning could be done:
    - Example by example
    - In batches of examples
Sequential learning

- Problems in batch learning
  - hard to control and easy to diverge
  - Can’t deal with data being available over time
  - The algorithm needs to remember all training data

- Sequential learning properties
  - Examples become available over time
  - Examples are received one-by-one or by chunks
  - The model discards examples after processing them
  - Doesn’t require retraining each time an example comes
  - The algorithm stops and returns a unique hypothesis when examples end, or when a certain condition is verified.
  - The algorithm stores only model’s parameters (e.g. weights)
  - Two distinct phases: learning and operation
Incremental learning

- properties
  - Inherits all properties of online learning
    - i.e. online learning is always incremental
  - But it is more general
    - It can be also offline
    - It can handle batches of data
  - Shares with sequential and online learning the obligation:
    - To Process new data and discard them later
    - Learn new information and retain old one’s
    - stability-plasticity dilemma
Properties

- Receives examples one-by-one
- Discards the example after processing it.
- Produce a hypothesis after each example is processed
  - i.e. produces a series of hypotheses
- No distinct phases for learning and operation
  - i.e. produced hypotheses can be used in classification
- Allowed to store other parameters besides model parameters (e.g. learning rate)
- Is a real time system
  - Constraints: time, memory, ...
  - What is affected: hypotheses prediction accuracy
- Can never stop
Focus today - Supervised classifier

- Try to find answers to:
  - Can the examples be stored in memory?
  - Which is the availability of the examples: any presents? In stream? Visible only once?
  - Is the concept stationary?
  - Does the algorithm have to be anytime?
  - What is the available time to update the model?
  - ...

- The answers to these questions will give indications to select the algorithms adapted to the situation and to know if one need an incremental algorithm, even a specific algorithm for data stream.
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STREAM: WHAT CHANGES?
Stream: what changes?

- Properties
  - Receives examples one-by-one
  - Discards the example after processing it.
  - Produce a hypothesis after each example is processed
    - I.e. produces a series of hypotheses
  - No distinct phases for learning and operation
    - I.e. produced hypotheses can be used in classification
  - Allowed to store other parameters than model parameters (e.g. learning rate)
  - Is a real time system
    - Constraints: time, memory, ...
    - What is affected: hypotheses prediction accuracy
  - Can never stop
  - No i. i. d
Why not use the classic algorithms?

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REQUIREMENTS
Properties of a efficient algorithm

- low and constant duration to learn from the examples;
- read only once the examples in their order of arrival;
- use of a quantity of memory fixed “a priori;”
- production of a model close to the “offline model”
- anytime
- concept drift management

(0) Domingos, P. et G. Hulten (2001). Catching up with the data : Research issues in mining data streams. In Workshop on Research Issues in Data Mining and Knowledge Discovery.
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TAXONOMY
Taxonomy (tentative)

**full example memory** Store *all* examples
- allows for efficient restructuring
- good accuracy
- huge storage needed
Examples: ID5, ID5R, ITI

**no example memory** Only store statistical information in the nodes
- loss of accuracy (depending on the information stored or again huge storage needed)
- relatively low storage space
Examples: ID4

**partial example memory** Only store *selected* examples
- trade of between storage space and accuracy
Examples: FLORA, AQ-PM
Taxonomy (Gama 2010)

Model Management

Full Memory
Weighting
Aging
Partial Memory
Windowing
Fixed Size Windows
Weighting
Aging
Adaptive Size Window
Weighting
Aging
"No memory"

Data Management

Detection

Monitoring of performances
Monitoring of properties of the classification model
Monitoring of properties of the data

Model Management

Number
Granularity
Weights

Adaptation

Blind methods
'Informed methods'

It is necessary to adapt the classifier to the application context
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LEADING CLASSIFIERS
Incremental Algorithm (no stream)

- Decision Tree
  - ID4 (Schlimmer - ML’86)
  - ID5/ITI (Utgoff – ML’97)
  - SPRINT (Shaffer - VLDB’96)
  - ...

- Naive Bayes
  - Incremental (for the standard NB)
  - Learn fastly with a low variance (Domingos – ML’97)
  - Can be combined with decision tree: NBTree (Kohavi – KDD’96)
Incremental Algorithm (no stream)

- Neural Networks
  - IOLIN (Cohen - TDM’04)
  - learn++ (Polikar - IJCNN’02), …

- Support Vector Machine
  - TSVM (Transductive SVM – Klinkenberg IJCAI’01),
  - PSVM (Proximal SVM – Mangasarian KDD’01), …
  - LASVM (Bordes 2005)

- Rules based systems
  - AQ15 (Michalski - AAAI’86), AQ-PM (Maloof/Michalski - ML’00)
  - STAGGER (Schlimmer - ML’86)
  - FLORA (Widmer - ML’96)
Incremental Algorithm (for stream)

- **Rules**
  - FACIL (Ferrer-Troyano – SAC’04,05,06)

- **Ensemble**
  - SEA (Street - KDD’01) based on C4.5

- **K-nn**
  - ANNCAD (Law – LNCS‘05).
  - IBLS-Stream (Shaker et al – Evolving Systems” journal 2012)

- **SVM**
  - CVM (Tsang – JMLR’06)
Incremental Algorithm (for stream)

- Decision Tree – the only ones used?
  - Domingos: VFDT (KDD’00), CVFDT (KDD’01)
  - Gama: VFDTc (KDD’03), UFFT (SAC’04)
  - Kirkby: Ensemble d’Hoeffding Trees (KDD’09)
  - del Campo-Avila: IADEM (LNCS’06)
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CONCEPT DRIFT
Concept drift

Concept shift

Gradual drift

Incremental shift

Reoccurring contexts
Context = Period of time without drift

Stream: sequence of context

Drift detection $\Leftrightarrow$ ? Manage drift

$P_1(x, y) = P_1(x)P_1(y|x)$

$P_2(x, y) = P_2(x)P_2(y|x)$

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$P_2(x, y) = P_2(x)P_1(y|x)$
Manage Drift?

- Either detect and:
  1) Retrain the model
  2) Adapt the current model
  3) Adapt statistics (summaries) on which the model is based
  4) Work with a sequence of
     • models
     • summaries
- or detect anything but train (learn) fastly
  • a single models
  • an ensemble of models
Parameters – The devil inside
No drift assumption?

Do not use online learning!
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EVALUATION
Prequential error – the only way?

Pessimistic

\[ S = \sum_{i=1}^{n} L( y_i, \hat{y}_i ) \quad M = \frac{S}{n} \]
But other ideas

  - Mystake-bound
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THE TWO STREAMS?
Supervised Classification

- Two streams exist
- Two drift detection have to be managed

![Diagram of supervised classification with labeled and unlabeled data streams]

Labeled Data stream

<table>
<thead>
<tr>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>$X_5$</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>...</td>
</tr>
</tbody>
</table>

Unlabeled data stream

<table>
<thead>
<tr>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_4$</th>
<th>$X_5$</th>
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</tr>
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</table>

models over the time $f:X \rightarrow C$

Predicted labels

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THE LABELED STREAM?

even for classic problem not easy to obtain…
Online Advertising
the problem: having the ‘label’ in a « correct » timing (and for the complete distribution)

\[ X_{\text{publicité}} + X_{\text{client}} \rightarrow \{\text{clic}, \neg\text{clic}\} \]
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LINK WITH

ACTIVE LEARNING

of course but in another talk?
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OTHER WAYS?
Alternative problem settings
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PROVOCATION
Make at simplest!
(the first thing to test, the baseline)

Model Management
- Full Memory
  - Weighting
  - Aging
- Partial Memory
  - Windowing
  - Fixed Size Windows
  - Weighting
  - Aging
  - Adaptive Size Window
- "No memory"

Data Management

Detection
- Monitoring of performances
- Monitoring of properties of the classification model
- Monitoring of properties of the data

Adaptation
- Blind methods
- 'Informed methods'

Number
Granularity
Weights
A classifier trained with few examples but often!

- Which classifier?
  - a random forest (based on "Learning with few examples: an empirical study on leading classifiers", Christophe Salperwyck and Vincent Lemaire, in International Joint Conference on Neural Networks (IJCNN July 2011))
  - using 4096 examples
Waveform
Outline

the end
Real issues - Discussion

- Different form of learning:
  - use online or very incremental algorithm only if needed
- Stream: the changes for a good algorithm
  - deal directly the tradeoff between memory used / precision / complexity
- Leading classifiers
  - tries to used fast learner
- Concept drift
  - no stream mining without the concept drift ‘management’
- Evaluation
  - use robust model and model selection (no validation) and prequential error
- The two streams?
  - not so easy to have a correct “labeled” stream, two different drifts have to be managed
- Others ways to pose the problem
  - do not forget
- Just to do a small provocation…
  - a lot of papers but not so many real applications – the parameters are the devil (and the life expectancy of the “system”)