Incremental Generalized Eigenvalue Classification on Data Streams

Mario R. Guarracino, Salvatore Cuciniello, Davide Feminiano

High Performance and Networking Institute
National Research Council, Italy

Overview

- ✓What is supervised learning?
- ✓Classification on data streams
- ✓GEPSVM: Generalized Eigenvalue Problem Support Vector Machine
- ✓Problems
- ✓Incremental classification
- ✓SI-ReGEC: Stream Incremental Reguralized Eigenvalue Classifier
- ✓Numerical results
- ✓Conclusions

What is supervised learning?

- ✓ Supervised learning refers to the capability of a system to learn from examples
- ✓ The trained system is able to provide an answer for each new question
- ✓ Supervised means the desired output for the training set is provided by an external teacher
- ✓ Binary classification is among the most successful methods for supervised learning

Classification on data streams

Many applications:

- ✓ Computer network traffic (spam, intrusion detection,…)
- ✓ Bank transactions (fraud, credit cards,…)
- ✓ Web search (link rating)
- ✓ Video/Audio sensors (video surveillance, face identification,…)

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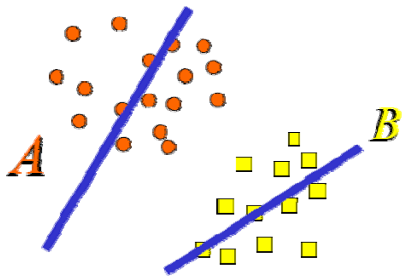
GEPSVM:Generalized Eigenvalue Problem Support Vector Machine

Binary classification problem can be formulated as a generalized eigenvalue problem (GEPSVM).

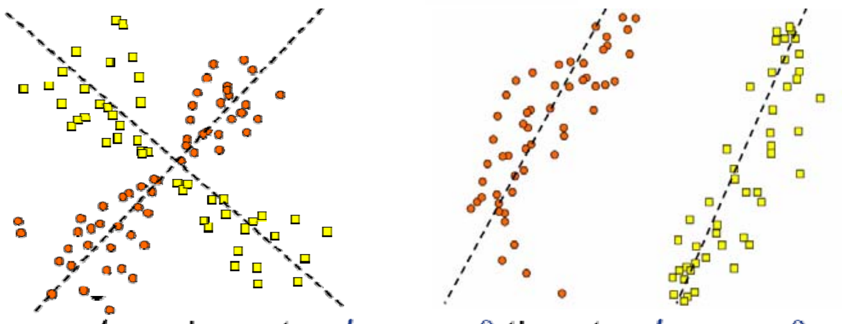
Find $x'w_1=\gamma_1$ the closest to A and the farthest from B



$$\min_{w,\gamma\neq 0} \frac{\|Aw-e\gamma\|^2}{\|Bw-e\gamma\|^2}$$

GEPSVM:Generalized Eigenvalue Problem Support Vector Machine

Let $[w_1\ \gamma_1]$ and $[w_m\ \gamma_m]$ be eigenvectors associated to min and max eigenvalues of $Gx=\lambda Hx$:



$a \in A \Leftrightarrow$ closer to $x'w_1 - \gamma_1 = 0$ than to $x'w_m - \gamma_m = 0$,

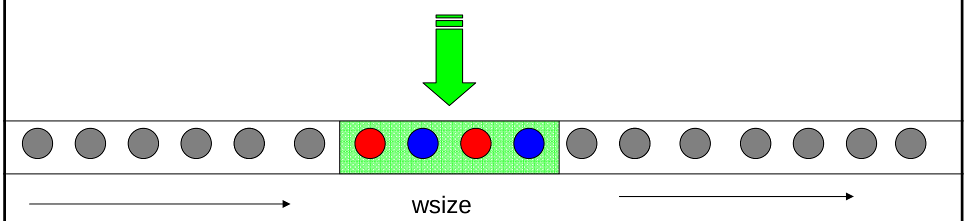
$b \in B \Leftrightarrow$ closer to $x'w_m - \gamma_m = 0$ than to $x'w_1 - \gamma_1 = 0$.

Problems

- ✓ Standard classification methods rely on the persistence of a complete training set
- ✓ Data not well represented by a persistent collection of items
- ✓ Data may be accessed but not completely loaded in main memory or stored

Incremental classification

A new approach consists in finding a small and robust subset of the training set while accessing data available in the window



When the window is full, all points within are processed by the classifier

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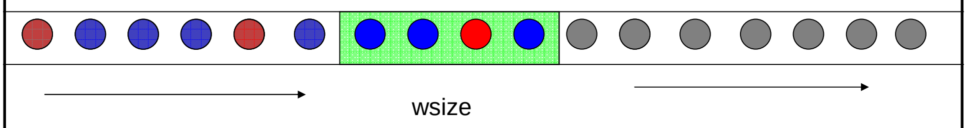
Incremental classification

It is possible to incrementaly train an algorithm using one point at time, analyzing its contribution of information.

Improvements:

- ✓A smaller set of points reduces the probabilty of overfitting the problem
- ✓It is computationally more efficient in predicting new points
- ✓As new points become available in the window, their influence is evaluated with respect to the existing classifier

SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier



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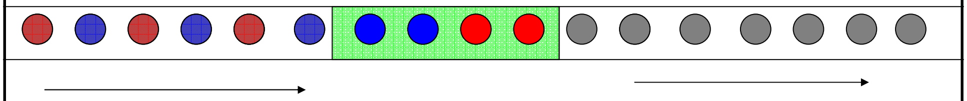
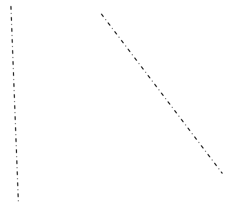
SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier



New data

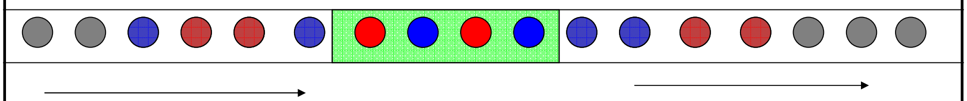
Old data



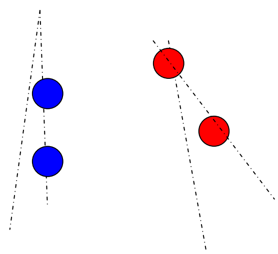
At each step, data in window are processed with the incremental learning classifier…

And hyperplanes are built

SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier

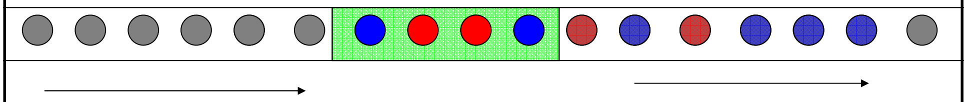


Step by step new points are processed



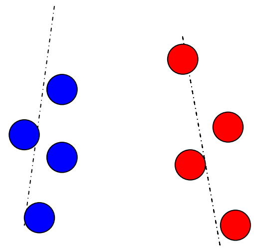
…and SI-ReGEC updates hyperplanes configuration

SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier

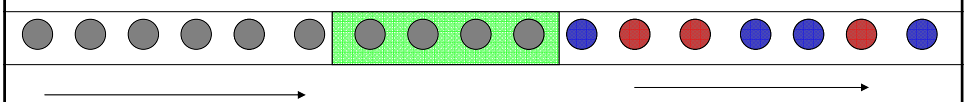


But not all points are considered…

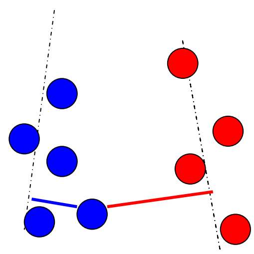
Some of them are discarted if their information contribution is useless



SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier



New unknown incoming points are classified by their distance from the hyperplanes



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SI-ReGEC:Stream Incremental Regularized Eigenvalue Classifier

An incremental learning technique based on GEPSVM that determines classification models based on a very small sample of data from the stream

$C = load(stream, wsize)$
$C_0 = kmean(C, km)$
$\Gamma_0 = C \setminus C_0$
$\{R_0, M_0\} = Classify(C, C_0)$
repeat
  $k = 1$
  while $|\Gamma_k| > 0$ **do**
    $x_k = x : \max_{x \in \{M_k \cap \Gamma_{k-1}\}} \{dist(x, P_{class(x)})\}$
    $\{R_k, M_k\} = Classify(C, \{C_{k-1} \cup \{x_k\}\})$
    if $R_k > R_{k-1}$ **then**
      $C_k = C_{k-1} \cup \{x_k\}$
    end if
    $\Gamma_k = \Gamma_{k-1} \setminus \{x_k\}$
    $k = k + 1$
  end while
  $C_0 = C_0 \cup C_k$
  $\Gamma_0 = load(stream, wsize)$
until $|\Gamma_0| = 0$

Numerical Results

Large-noisy-crossed-norm
Data set

200.000 points with 20 features
equal divided in 2 classes

100.000 train points

100.000 test points

Each class is drawn from a
multivariate normal distribution

Numerical Results

Parameter	B	ED	FP	EM	EM+E	SI-ReGEC
Error (%)	3.2	9.1	3.2	4.5	6.7	2.88
subset train	8321	4172	8452	1455	5308	413
window size	100000	500	500	500	500	500

SI-ReGEC has the lowest error and uses the smallest incremental set

B: Batch SVM
ED: Error-driven KNN
FP: Fixed partition SVM
EM: Exceeding-margin SVM
EM+E: Fixed margin + errors

Numerical Results

Larger windows lead to smaller train subset and execution time increases with window growth

Wsize	Acc.	Growth Rate	Avg. Time	Time
500	96.13%	15.75	4.25s	8.5e-4s
1000	96.92%	4.31	15.16s	1.5e-3s
2000	96.50%	2.63	61.79s	3.1e-3s
4000	97.45%	1.81	232.49s	7.0e-3s

Data is processed at 123.5 Gb/day on standard hardware

Conclusions

✓ SI-ReGEC:
1. achieves a classification accuracy well comparable with other methods
2. produces smaller incremental training sets

Future Work:
Investigate how to dinamically adapt window size to stream rate and nonstationary data streams

Thanks!