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# Ensemble methods and online learning for creation and update of prognostic scores in HF patients

Benoît Lalloué, Jean-Marie Monnez

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# Summary

- How to create a parsimonious event risk score with ensemble methods?
- How to update an ensemble score in the case of a data stream?
  - Tools for generalized linear regression: stochastic approximation processes.

# Parsimonious scores by an ensemble method

## Context

- Scores are mainly built using “classic” statistical methods : logistic regression, Cox regression...
- Another possibility: use ensemble methods.
- **Ensemble method**: collection of predictors (with different learning rules, samples, selection of variables, etc.) whose predictions are then aggregated.
- Often obtain better results than individual predictors.

# Parsimonious scores by an ensemble method

## Batch method – Duarte *et al.* 2018

Learning sample  
n observations, p variables

Choice of  $n_1$  classifiers

$n_2$  bootstrap samples

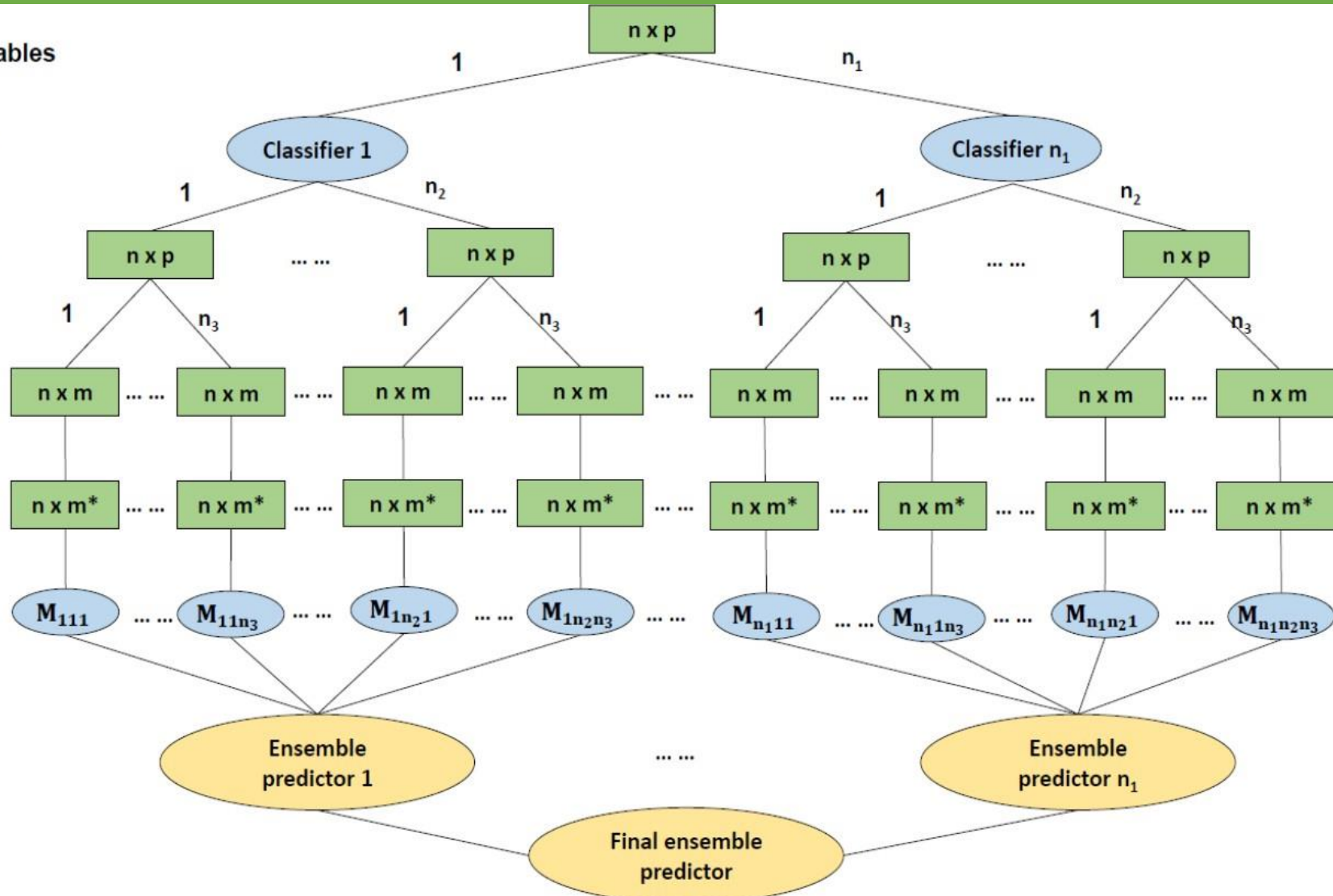
$n_3$  modalities of random selection of m variables

Selection of  $m^*$  variables

Construction of models

Aggregation by classifier

Final aggregation



Duarte K, Monnez JM, Albuissou E. Methodology for Constructing a Short Term Event Risk Score in Heart Failure Patients. *Appl Math.* 2018.

# Parsimonious scores by an ensemble method

## Context (2)

- Common difficulty in the construction of prognostic scores: **choose the variables** to include.
  - Balance between better statistical fit and practical application.
  - As we want to use an ensemble method, usual selection methods are not easily applicable.
- Methodology for constructing **parsimonious event scores** combining a stepwise preselection of variables and the use of ensemble scores

# Parsimonious scores by an ensemble method

## Selection methods

- We proposed several methods and compared them.
- Backward methods (need a score formula):
  - Build an ensemble score with a large number of variables
  - Backward selection of the variables, based on the coefficients in the score
- Forward methods (do not need a score formula):
  - Forward selection of the variables which maximize AUC
- A preselection of variables by classifier can precede the methods

# Parsimonious scores by an ensemble method

## Illustration for short-term predictions in chronic HF patients

- **Data:** subsample of the GISSI-HF trial
- **Data management:** couples patient-visit; winsorized and transformed variables; balancing of the sample (duplication of the cases)
- **Event:** hospitalization for aggravating HF or death from HF within 180 days of a visit
- 3 methods compared: similar selections of variables and performances
- 4 parsimonious scores using the fastest method:

Score's name	<b>S3.26</b>	<b>S3.15</b>	<b>S3.8</b>	<b>S3.2</b>
<b>Nb of variables used</b>	26	15	8	2
<b>AUC OOB final score</b>	0.8137	0.8002	0.7835	0.7523



# Online logistic regression

## Online learning & online standardization

### Online learning:

- Analysis of a data stream or of big data.
- **Update** the results in successive steps, taking into account new data at each step.
- A possibility: use **recursive stochastic algorithms**.

### Online standardization of the data:

- Data can be standardized to: avoid a numerical explosion or apply a shrinkage method (e.g. LASSO).
- Issue for data streams: means and variances are a priori unknown.
- A possibility: do an **online standardization**.
- Studied for the linear regression: better performance compared to raw data.
- We used a similar approach for the **logistic regression**.

# Online logistic regression

## Stochastic gradient processes

Stochastic approximation processes of this form were tested:

$$X_{n+1} = X_n - a_n \frac{1}{m_n} \sum_{j \in I_n} \tilde{Z}_j \left( h(\tilde{Z}_j' X_n) - S_j \right)$$

$$\bar{X}_{n+1} = \frac{1}{n+1} \sum_{i=1}^{n+1} X_i$$

Different variants exist:

- Classical ( $X_n$ ) or averaged ( $\bar{X}_n$ ).
- Raw data or online standardized data.
- Different numbers of new observations at each step ( $m_n$ ).
- Variable step-size or piecewise constant step-size ( $a_n$ ).

# Online logistic regression

## Datasets, datastream & comparison

- 24 processes tested on 5 datasets. Data streams simulated by randomly drawing successive data batches from the datasets.
- Usual logistic regression used as gold standard.
- Convergence criterion (norms ratio:  $\frac{\|\theta^c - \hat{\theta}_{n+1}\|}{\|\theta^c\|}$ ) recorded for fixed numbers of observations used and for fixed processing times.
- Processes ranked for each dataset and each recording point. Average rank across all datasets used to compare processes.

# Online logistic regression

Comparison for a fixed processing time (60s)

Process	Twonorm	Ringnorm	Quantum	Adult	HOSP30D	Mean rank
CR1V	0.055	0.019*	0.288	EXPL	EXPL	-
CR10V	0.061	0.005*	0.310	EXPL	EXPL	-
CR100V	0.073	0.002*	0.333	EXPL	EXPL	-
AR1P50	0.011*	0.019*	0.086	EXPL	EXPL	-
AR10P50	0.002*	0.002*	0.095	EXPL	EXPL	-
AR100P50	0.001*	0.001*	0.102	EXPL	EXPL	-
AR1P100	0.015*	0.029*	0.064	EXPL	EXPL	-
AR10P100	0.002*	0.003*	0.079	EXPL	EXPL	-
AR100P100	0.001*	0.001*	0.090	EXPL	EXPL	-
AR1P200	0.018*	0.052	0.040*	EXPL	EXPL	-
AR10P200	0.002*	0.005*	0.064	EXPL	EXPL	-
AR100P200	0.001*	0.001*	0.076	EXPL	EXPL	-
CS1V	0.139	0.023*	0.173	0.134	0.153	10.0
CS10V	0.182	0.011*	0.057	0.101	0.228	9.0
CS100V	0.227	0.004*	0.071	0.108	0.326	9.0
AS1P50	0.027*	0.025*	0.042*	0.389	0.095	8.6
AS10P50	0.006*	0.005*	0.014*	0.020*	0.053	4.8
AS100P50	0.009*	0.002*	0.007*	0.017*	0.014*	3.2
AS1P100	0.032*	0.037*	0.071	0.386	0.087	9.2
AS10P100	0.005*	0.006*	0.014*	0.025*	0.050*	4.8
AS100P100	0.004*	0.002*	0.007*	0.011*	0.011*	1.8
AS1P200	0.046*	0.060	0.121	0.498	0.112	10.6
AS10P200	0.005*	0.008*	0.017*	0.035*	0.049*	5.4
AS100P200	0.003*	0.002*	0.007*	0.009*	0.012*	1.6

\* Denotes a criterion value  $< 0.05$

**EXPL:** numerical explosion

- *Process type:* C for classical SGD, A for ASGD
- *Data type:* R for raw, S for online standardized
- *1<sup>st</sup> number:* number of new obs. per step
- *Step-size:* V for variable, P for piecewise constant (*2<sup>nd</sup> number:* levels size)

# Online ensemble score

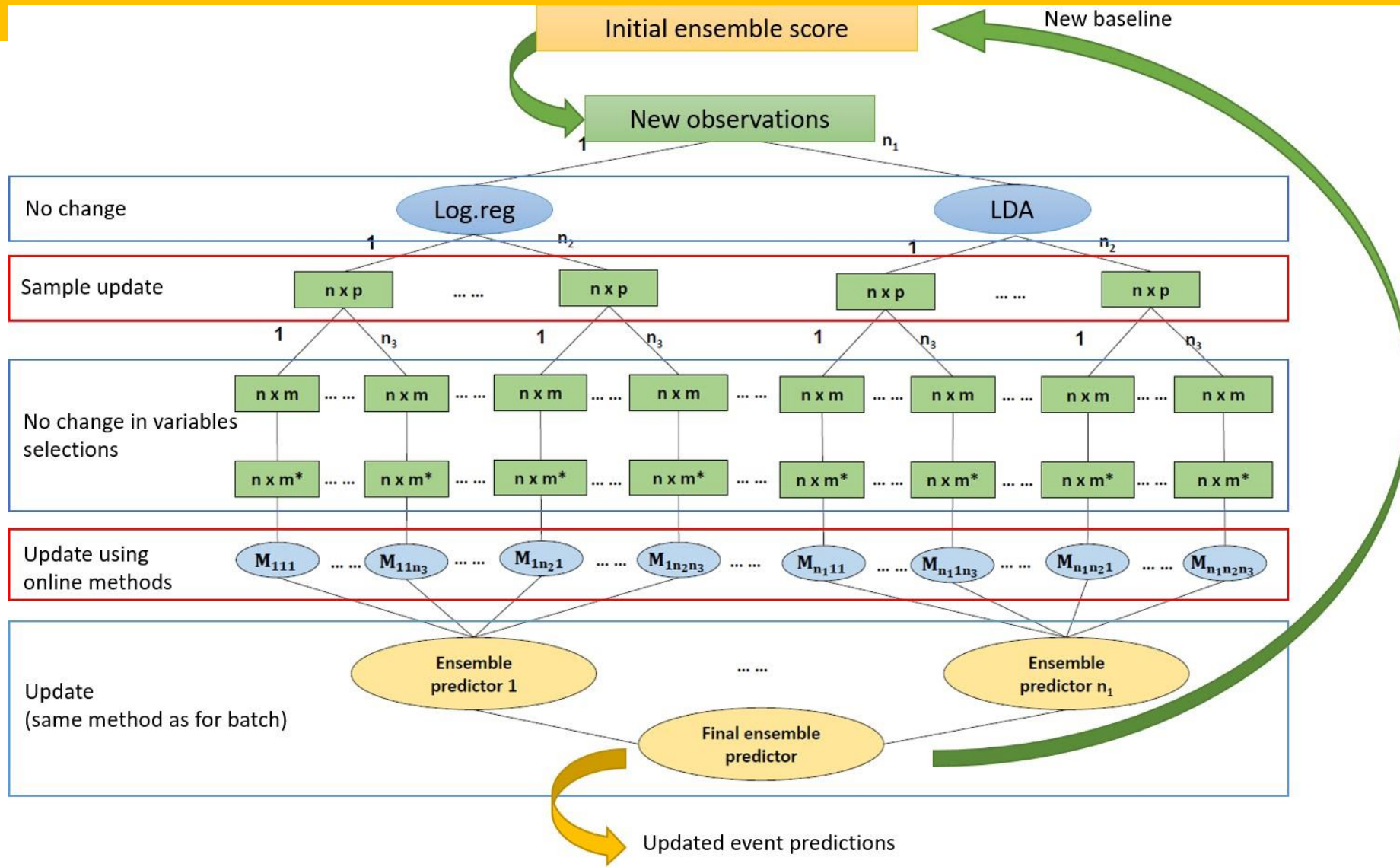
## Online method

How to update an ensemble score similar to Duarte et al. in the case of a data stream?

- Choice of classifiers: same as the initial ensemble score.
- Bootstrap samples: use **Poisson bootstrap**.
- Selection of variables: same as the initial ensemble score.
- Construction of models: use **online versions** (online linear regression, online logistic regression...).
- Aggregation: same as the initial ensemble score.

# Online ensemble score

## Online method (2)



# Online ensemble score

## Experiments

- Same datasets than previously. Data streams **simulated by randomly drawing** successive data batches from the datasets.
- A **batch score was created as reference** for each dataset:
  - 100 bootstrap samples.
  - 2 classifiers: logistic regression and linear discriminant analysis (linear regression).
  - 1 modality with all variables.
- 6 online scores using  $100N$  observations and the same parameters.
- Empirical study of convergence toward the reference score  $\left(\frac{\|\theta^c - \hat{\theta}_{n+1}\|}{\|\theta^c\|}\right)$ .



# Online ensemble score

Comparison with a fixed number of observations (100N)

Norms ratio between the batch score coefficients and the online scores coefficients:

Process		Twonorm	Ringnorm	Quantum	Adult	HOSPHF30D
CS100V_CS100V	<i>LDA</i>	0.0010*	0.0020*	0.0073*	0.0076*	0.0165*
	<i>Log. Reg.</i>	0.0033*	0.0009*	0.0168*	0.1002	0.0566
	<b><i>Final</i></b>	<b>0.0015*</b>	<b>0.0014*</b>	<b>0.0083*</b>	<b>0.0414*</b>	<b>0.0289*</b>
AS100P50_AS100P50	<i>LDA</i>	0.0006*	0.0007*	0.0027*	2.7560	0.0176*
	<i>Log. Reg.</i>	0.0006*	0.0007*	0.0032*	0.0346*	0.0203*
	<b><i>Final</i></b>	<b>0.0005*</b>	<b>0.0007*</b>	<b>0.0029*</b>	<b>1.6968</b>	<b>0.0192*</b>
AS100C_AS100P200	<i>LDA</i>	0.0006*	0.0007*	0.0028*	0.0066*	0.0165*
	<i>Log. Reg.</i>	0.0007*	0.0007*	0.0033*	0.0069*	0.0206*
	<b><i>Final</i></b>	<b>0.0006*</b>	<b>0.0007*</b>	<b>0.0030*</b>	<b>0.0067*</b>	<b>0.0190*</b>
CS100Vall_CS100V	<i>LDA</i>	0.0005*	0.0006*	0.0033*	0.0287*	0.0153*
	<i>Log. Reg.</i>	0.0033*	0.0009*	0.0168*	0.1002	0.0566
	<b><i>Final</i></b>	<b>0.0017*</b>	<b>0.0007*</b>	<b>0.0090*</b>	<b>0.0281*</b>	<b>0.0290*</b>
AS100P50all_AS100P50	<i>LDA</i>	0.0006*	0.0007*	0.0046*	0.0100*	0.0060*
	<i>Log. Reg.</i>	0.0006*	0.0007*	0.0032*	0.0346*	0.0203*
	<b><i>Final</i></b>	<b>0.0005*</b>	<b>0.0007*</b>	<b>0.0039*</b>	<b>0.0193*</b>	<b>0.0147*</b>
AS100Call_AS100P200	<i>LDA</i>	0.0006*	0.0007*	0.0046*	0.0153*	0.0060*
	<i>Log. Reg.</i>	0.0007*	0.0007*	0.0033*	0.0069*	0.0206*
	<b><i>Final</i></b>	<b>0.0005*</b>	<b>0.0007*</b>	<b>0.0039*</b>	<b>0.0120*</b>	<b>0.0149*</b>



# Conclusion

## Parsimonious scores:

- Methods which build a succession of scores from which **the user can choose according to its objectives**.
- In the application: **similar or better results** than other scores, with less variables.

## Online logistic regression:

- Online standardization of the data helps to avoid numerical explosion.
- Interest of **averaged processes with piecewise constant step-size and online standardized data**.

## Online ensemble score:

- Online ensemble scores converge empirically to the batch score (theoretical convergence already proven).

# Conclusion

## References

### Parsimonious ensemble score:

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