Drift anticipation with forgetting to improve evolving fuzzy system

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Abstract

Data stream learning problem has become a new topic of interest that breaks with classical batch learning model:

- **One-shot learning**
- **Concept drift**
- **Real time** constraints

To satisfy these constraints, the analysis system have to **evolve its model** over time and have to **forget obsolete knowledge**.

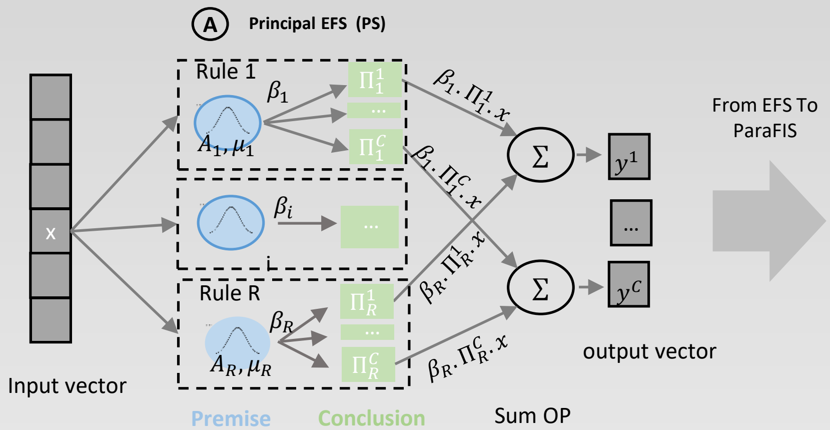
Based on a set of inference rules, **Evolving Fuzzy Systems** - EFS - have proven to be effective in solving the data stream learning problem. However, the forgetting is subjected to the **stability-plasticity dilemma**, that is, increasing forgetting improve reactivity of adapting to the new data while reducing the robustness of the system. Tackling the stability-plasticity dilemma is still an open question.

This paper proposes a coherent method to integrate forgetting in EFS, based on the recently introduced notion of concept drift anticipation. The forgetting is applied only in an anticipation module to keep stability of the main system while the anticipation module allow a better reactivity in case of drift detection.

Key words: Data stream learning, Evolving fuzzy system - EFS, drift adaptation and anticipation.

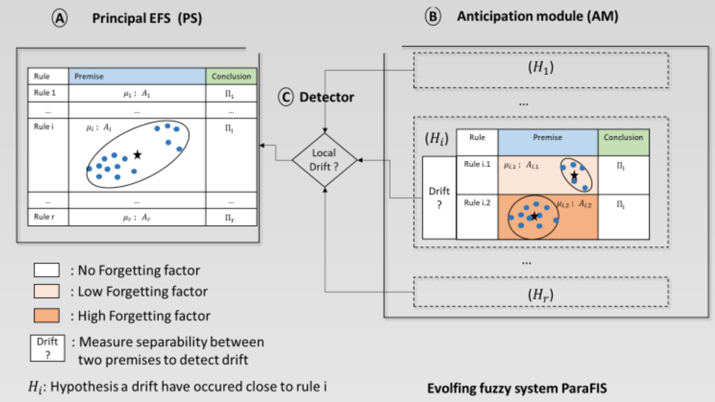
Model Proposition ParaFIS Forget AM

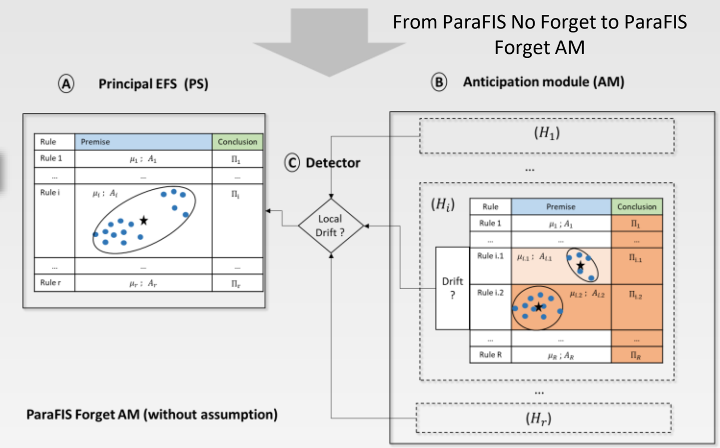
Building blocks of the ParaFIS Forget AM model



Evolving fuzzy system – EFS - learns incrementally over each new data point
Premise fits the data distribution while conclusion discriminates between classes

Anticipate a drift occurrence to faster react in case of drift detection. Only premise have forgetting capacity here





Consistent forgetting between premise and conclusion thanks to the **differed directional forgetting** - DDF

Take care of dependency of each conclusions with all premises
Use **assumptions** (**Naïve** or **Global**) to deal with time complexity for real time learning purpose

Results

The proposed method have been evaluated on **several benchmark** from online community with different typologies (different kind of drifts and distributions) with a **statistical significance test**. Results Tables I shows that integrate forgetting in the conclusion from the anticipation module is often a better solution.

TABLE I: Final Results - Mean Accuracy Score

Model		Electricity Pricing	Hyperplane	Iris+	Car	10dplane	Weather	Sea	SinH	Line	Sin	Mean
ParaFIS	No Forget	**77±15**	91±03	82±14	8±11	68±34	78±03	94±04	67±09	85±15	85±13	81
	Forget PS	**77±15**	**93±02**	**85±12**	79±12	63±16	78±03	97±01	71±07	93±06	**94±06**	83
	Forget AM Naive	**77±15**	**93±02**	82±14	**82±09**	70±31	79±03	96±03	70±07	92±10	93±09	83
	Forget AM Global	**77±15**	**93±02**	**85±15**	81±10	77±34	78±03	**98±01**	70±07	**94±06**	**94±08**	**85**
Learn++	CDE	69±08	90±00	**85±14**	68±30	71±13	73±02	93±02	**75±50**	89±14	80±13	79
Learn++	NSE	69±08	91±02	84±17	67±30	72±14	75±03	93±02	73±22	88±13	80±15	79
pENsemble	AxisParallel	75±16	92±02	78±15	79±10	78±20	**80±02**	97±02	71±06	90±07	78±26	82
pENsemble	Multivariate	75±16	92±02	75±17	79±10	**80±20**	78±02	97±02	71±06	90±07	78±30	82
pClass		68±10	91±02	73±18	77±10	63±26	68±04	89±10	71±09	91±07	72±20	76