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Multilinear Weighted Regression (MWE) with Neural Networks for trend prediction

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HIGHLIGHTS

- The Authors provide a new idea of combining local optima based linear structures.
- This model bases his success in the weights of the structures that are used to predict a given trend.
- Weights are adjusted by a Neural Network with particle swarm (HydroPSO) to optimize the fitness function, final slope is calculated based on the number of the linear structures and its adjusted weights. This slope determines the trend.
- The conclusion establish that the accuracy improves in comparison with L.R and the method proves to be reliable and safe, in particular when predicting strong trends.

GRAPHICAL ABSTRACT

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ABSTRACT

The ability to define accurate linear models to find patterns or relationships between variables is one of the most challenging fields in Computer Science. In particular, extrapolative applications are widely used to predict values in Biological, Behavioral and Social Sciences. Analysts usually focus on reducing the approximation error in order to ensure fairly reliable predictions. Using pattern detection models such as Multilayer Artificial Neural Networks can offer good results in predicting possible outcomes, however they might not be the optimal fit for predicting evolutionary trends due to their inherent overfitting characteristics. Regression models, on the other hand are more often used to predict trending behaviors and therefore they can be more helpful when studying the evolution of a given instrument, symbol or series. However, a simple regression model can be very inaccurate with an unacceptable prediction error rate. This paper shows an automatic method to find trends in known instruments, by using a massive linear regression technique combined with a conventional machine learning proposal that works on optimizing the weights of the linear regressive structures. In this paper the authors show an application of the model in finance (stocks market instruments), however the proposal is designed to work for to any discipline that studies the trends of any evolutionary object.

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Table 4
Comparison between MWE and LR. Local optima are chosen in MWE at random, see Fig. 2.

Periods	Algorithm	SR	MAPE	LE	SD
150	L.R	0.66 (0.04)	0.0058	229	43.23
	MWE	0.62 (0.04)	0.0063	189	42.12
250	L.R	0.64 (0.04)	0.0058	256	43.23
	MWE	0.60 (0.04)	0.0062	178	41
350	L.R	0.72 (0.03)	0.0060	229	43.23
	MWE	0.69 (0.04)	0.0063	189	39.2
450	L.R	0.71 (0.03)	0.0058	129	43.4
	MWE	0.71 (0.03)	0.0055	192	42
550	L.R	0.73 (0.03)	0.0056	134	43.2
	MWE	0.71 (0.03)	0.0056	159	41
750	L.R	0.72 (0.03)	0.0052	201	44.3
	MWE	0.73 (0.03)	0.0054	187	42.12
1000	L.R	0.68 (0.03)	0.0052	292	43.22
	MWE	0.73 (0.03)	0.0053	156	42.33
1250	L.R	0.70 (0.03)	0.0053	193	43.21
	MWE	0.70 (0.03)	0.0063	189	42.11
1500	L.R	0.71 (0.03)	0.0058	201	43.23
	MWE	0.67 (0.04)	0.0063	175	42.11
1500	L.R	0.71 (0.03)	0.0058	202	43.23
	MWE	0.71 (0.03)	0.0063	164	42.33
1750	L.R	0.71 (0.03)	0.0058	187	43.23
	MWE	0.73 (0.03	0.0063	163	42.13
2000	L.R	0.72 (0.03)	0.0057	192	43.23
	MWE	0.73 (0.03)	0.0058	163	42.12
2250	L.R	0.69 (0.04)	0.0058	188	43.23
	MWE	0.76 (0.03)	0.0052	163	42.23
2500	L.R	0.73 (0.03)	0.0057	182	43.23
	MWE	0.73 (0.03)	0.0053	155	42.11
2750	L.R	0.74 (0.03)	0.0053	180	43.23
	MWE	0.73 (0.03)	0.0054	155	42.34
3000	L.R	0.73 (0.03)	0.0053	182	43.23
	MWE	0.76 (0.03)	0.0063	153	42.22
3250	L.R	0.72 (0.03)	0.0060	178	43.23
	MWE	0.77 (0.03)	0.0055	152	42.34
3500	L.R	0.73 (0.03)	0.0058	176	43.23
	MWE	0.80 (0.02)	0.0062	152	42.3
3650	L.R	0.74 (0.03)	0.0058	176	43.23
	MWE	0.77 (0.03)	0.0054	154	42.11

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2019.105555.

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