SCIENCE CHINA
Information Sciences

• LETTER •

March 2026, Vol. 69, Iss. 3, 139101:1–139101:2
https://doi.org/10.1007/s11432-025-4673-5

An accurate and efficient online broad learning system for data stream classification

Chunyu LEI[1,3,4], Guang-Ze CHEN[2], C. L. Philip CHEN[1,3,4] & Tong ZHANG[1,3,4*]

[1]School of Computer Science & Engineering, South China University of Technology, Guangzhou 510006, China;
[2]Faculty of Science and Technology, University of Macau, Macao 999078, China
[3]Research Center for AI Large Models and Intelligent Cognition, Pazhou Lab, Guangzhou 510335, China
[4]Engineering Research Center of the Ministry of Education on Health Intelligent Perception and Paralleled Digital-Human, Guangzhou 510006, China

Received 6 May 2025/Revised 9 September 2025/Accepted 7 November 2025/Published online 20 January 2026

Citation Lei C Y, Chen G-Z, Chen C L P, et al. An accurate and efficient online broad learning system for data stream classification. Sci China Inf Sci, 2026, 69(3): 139101, https://doi.org/10.1007/s11432-025-4673-5

Online learning (OL) [1] offers an effective solution for acquiring knowledge from various real-world data streams, such as weather, call records, and stock market transactions. The general OL pipeline proceeds as follows. (1) The initial model comes with zero or random weights because no samples have been received. (2) When a new sample arrives, its model weights are rapidly updated to provide a more accurate prediction for subsequent arrivals. Thus, a brilliant OL model for data stream learning must be both efficient and accurate. Although appealing, existing state-of-the-art (SOTA) OL models are generally optimized based on gradient descent algorithms [2]. To be specific, when a new sample arrives, these models execute the error backpropagation and weight update only once in sequence. Thus, none of them can achieve an optimal solution for model weights.

Broad learning system (BLS) [3] has recently been proposed as an efficient and effective machine learning model. Importantly, its closed-form solution ensures optimal weights, while its data incremental learning algorithm enables it to continuously learn from data streams, thereby avoiding expensive model retraining. Thus, it sheds light on tackling the above OL issue. Since several data incremental BLS algorithms [3–5] have been proposed, we first consider using them to solve online machine learning tasks via setting the number of training samples for each increment to one and making minor modifications. Thanks to their closed-form solutions, these methods can rigorously guarantee the optimality for each online update. Despite their straightforwardness, they still encounter challenges in handling data stream tasks. The most critical issue is that all of them rely on matrix inversion, which results in high computational complexity and reduced numerical stability. It means that substantial errors are incurred when solving for online model weights. In other words, their accuracy and efficiency remain to be improved.

Unlike the above methods, we develop a native online broad learning system (Online-BLS) framework to address the suboptimality issue of OL model weights in data stream learning tasks. To our knowledge, this study clarifies this issue for the first time and succeeds in solving it using our Online-BLS framework. The technical contributions of our study are summarized as follows.

(1) We deduce an effective weight estimation algorithm (EWEA) based on Cholesky factorization and forward-backward substitution, which substantially enhances the accuracy of Online-BLS and provides excellent theoretical error bounds.

(2) An efficient online updating strategy (EOUS) is designed based on the rank-one update algorithm of the Cholesky factor to improve the efficiency of Online-BLS. The time complexity analysis shows a significant reduction in computational overhead.

(3) We propose a simple yet effective extension to achieve non-stationary data stream classification. The accuracy, efficiency, and versatility of Online-BLS are empirically confirmed through comprehensive comparisons with baselines.

Method. The Online-BLS architecture consists of three parts: the feature layer, the enhancement layer, and the output layer. Its online learning process is illustrated in Figure 1. Initially, the parameters of the feature and enhancement layers are randomly initialized and then frozen. The weight matrix of the output layer $\mathbf{\Theta}^{(0)}$ is initialized as $\mathbf{0}$, and the Cholesky factor $\mathbf{L}^{(0)}$ is set to $\mathrm{Chol}(\lambda\mathbf{I})$, where $\mathrm{Chol}(\cdot)$ calculates a lower triangular matrix using Cholesky decomposition. Then, our algorithm follows four main steps.

First, when a sample $\mathbf{x}_k$ arrives, the feature and enhancement nodes are obtained through feeding $\mathbf{x}_k$ into the feature and enhancement layers, respectively. Since we apply a linear and nonlinear activation function at the feature and enhancement layers, respectively, the feature and enhancement nodes represent the linear and nonlinear features of $\mathbf{x}_k$. By cascading them, the broad feature $\mathbf{a}_k$ is obtained. Second, to avoid expensive Cholesky decompositions at each online update, we propose an EOUS, which incrementally computes $\mathbf{L}^{(k)}$ from $\mathbf{L}^{(k-1)}$ and $\mathbf{a}_k$. Specifically, we cascade $\mathbf{a}_k$ and $\mathbf{L}^{(k-1)}$ as an augmented matrix $[\mathbf{a}_k, \mathbf{L}^{(k-1)}]$. Through constructing and performing an orthogonal Givens rotation $\mathbf{G}_i$ on the above augmented matrix, the i-th element of the broad feature $\mathbf{a}_k$ is eliminated. After applying a series of Givens transformations $\mathbf{G} = \mathbf{G}_m\mathbf{G}_{m-1}\cdots\mathbf{G}_1$, the broad feature $\mathbf{a}_k$ becomes a zero vector. At this point, $\mathbf{L}^{(k-1)}$ also becomes $\mathbf{L}^{(k)}$ accordingly. This

* Corresponding author (email: tony@scut.edu.cn)

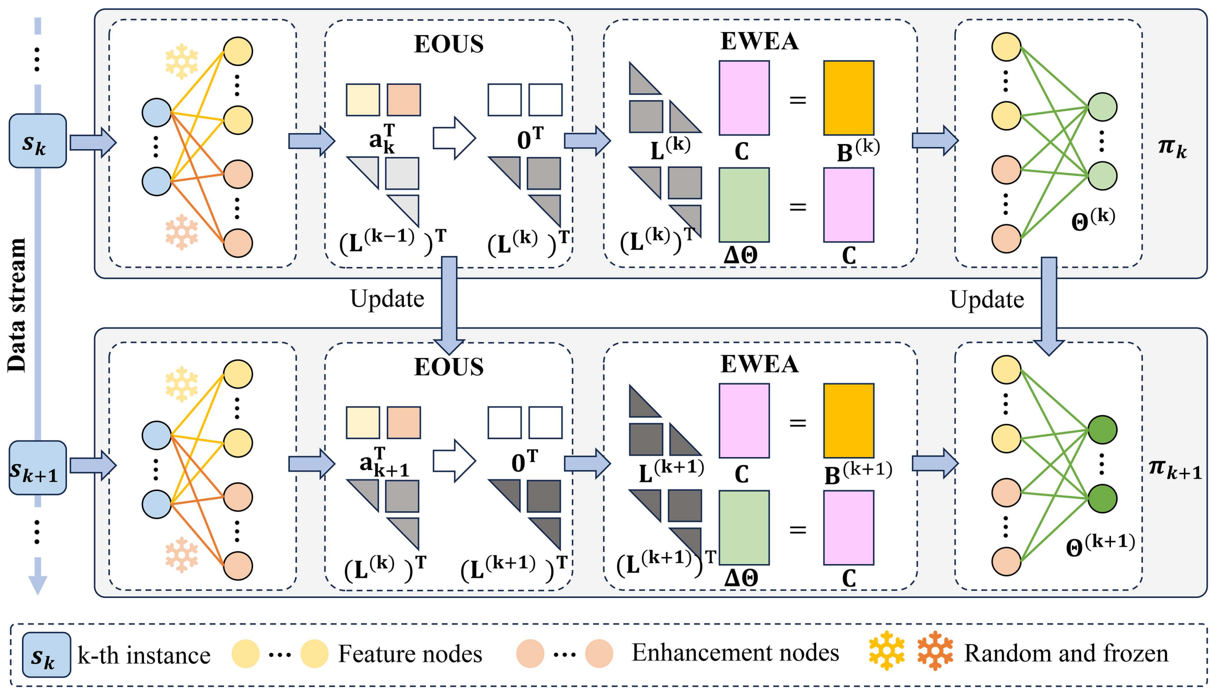

Figure 1 (Color online) The online learning process of Online-BLS. The instance $\mathbf{s}_k$ contains a sample $\mathbf{x}_k$ and a label $\mathbf{y}_k$, and $\mathbf{y}_k$ generally arrives later than $\mathbf{x}_k$. For simplicity, this delay is ignored when we draw. $\boldsymbol{\pi}_k$ represents our model after k updates.

method reduces the time complexity of solving $\mathbf{L}^{(k)}$ from $\mathcal{O}(m^3)$ to $\mathcal{O}(m^2)$, where m denotes the dimension of the square matrix $\mathbf{L}^{(k)}$. Third, we devise an EWEA based on Cholesky factorization and forward-backward substitution. To solve $\boldsymbol{\Delta\Theta}^{(k)}$ accurately, we calculate $\mathbf{B}^{(k)} = \mathbf{a}_k \left(\mathbf{y}_k^\top - \mathbf{a}_k^\top \boldsymbol{\Theta}^{(k-1)}\right)$, where $\mathbf{y}_k$ is the label vector associated with $\mathbf{a}_k$. Then, with the aid of an intermediate variable $\mathbf{C}$, we calculate $\boldsymbol{\Delta\Theta}^{(k)}$ through one forward substitution and one backward substitution. This method ingeniously evades matrix inversion, thus avoiding its notorious instability. Lastly, our output layer weights are updated via $\boldsymbol{\Theta}^{(k)} = \boldsymbol{\Theta}^{(k-1)} + \boldsymbol{\Delta\Theta}^{(k)}$.

Moreover, concept drift is a common challenge in data streams. Thanks to the flexibility of our Online-BLS framework, we present a simple solution to handle this problem. The core idea is that learning the time-varying concept with new data is better than with old one. Technically, more attention to new data is encouraged by multiplying history by a decay factor μ. For a more detailed description of our method, please refer to Appendix B.

Experiments. To verify the superiority of Online-BLS, experiments were conducted from three aspects. First, we compared Online-BLS with SOTA incremental BLS methods and matrix decomposition-based OL algorithms on stationary datasets. Second, we adapted our proposed OL algorithm to other random neural networks to prove its generality. Finally, when evaluated on non-stationary datasets against SOTA online deep learning models, our method achieved higher accuracy and time efficiency. Detailed experimental results are provided in Appendix C.

Conclusion and future work. This study presented an accurate and efficient Online-BLS framework to solve the suboptimal model weights problem. On the one hand, an EWEA was proposed to improve model accuracy. By replacing matrix inversion with Cholesky factorization and forward-backward substitution, our proposed Online-BLS becomes accurate. On the other hand, an EOUS was developed to improve the efficiency of our method. Through the integration of EWEA and EOUS, our Online-BLS framework attains both accuracy and efficiency. Theoretical analysis also proves that Online-BLS has excellent error bounds and favorable time complexity. In addition, this study proposed a simple solution for the concept drift problem. Experiments on stationary and nonstationary datasets demonstrate the superiority of our Online-BLS and its universality to other random neural networks. This work is the first significant attempt to tailor BLS to online learning tasks. In the future, we will consider the issue of class imbalance in online data streams to improve the model performance further.

Acknowledgements This work was funded in part by National Natural Science Foundation of China (Grant Nos. 62222603, 62536004), Key-Area Research and Development Program of Guangdong Province (Grant No. 2023B0303030001), Science and Technology Program of Guangzhou (Grant No. 2024A04J6310), and Fundamental Research Funds for the Central Universities (Grant No. 2025ZYGXZR021).

Supporting information Appendixes A–C. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Hoi S C H, Sahoo D, Lu J, et al. Online learning: a comprehensive survey. Neurocomputing, 2021, 459: 249–289
2 Su R, Guo H, Wang W. Elastic online deep learning for dynamic streaming data. Inf Sci, 2024, 676: 120799
3 Chen C L P, Liu Z. Broad learning system: an effective and efficient incremental learning system without the need for deep architecture. IEEE Trans Neural Netw Learn Syst, 2017, 29: 10–24
4 Du J, Liu P, Vong C M, et al. Class-incremental learning method with fast update and high retainability based on broad learning system. IEEE Trans Neural Netw Learn Syst, 2023, 35: 11332–11345
5 Zhong L, Chen C L P, Guo J, et al. Robust incremental broad learning system for data streams of uncertain scale. IEEE Trans Neural Netw Learn Syst, 2025, 36: 7580–7593