LOFS: A library of online streaming feature selection

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\section*{ABSTRACT}

As an emerging research direction, online streaming feature selection deals with sequentially added dimensions in a feature space while the number of data instances is fixed. Online streaming feature selection provides a new, complementary algorithmic methodology to enrich online feature selection, especially targets high dimensionality in big data analytics. This paper introduces the first comprehensive open-source library, called LOFS, for use in MATLAB and OCTAVE that implements the state-of-the-art algorithms of online streaming feature selection. The library is designed to facilitate the development of new algorithms in this research direction and make comparisons between the new methods and existing ones available. LOFS is available from https://github.com/kuiy/LOFS.

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\section*{1. Introduction}

Feature selection is to select a parsimonious feature subset to improve model interpretability and efficiency without degrading model accuracy [1]. Traditionally, online feature selection deals with the observations sequentially added while the total dimensionality is fixed [2]. However, in many real world applications, it is either impossible to acquire an entire feature set or impractical to wait for the complete set before feature selection starts. For instance, in Twitter, trending topics keep changing over time, and thus the dimensionality of data is changed dynamically. When a new top topic appears, it may come with a set of new keywords, which usually serve as key features to identify new hot topics. In bioinformatics, it is expensive for feature selection to acquire an entire set of features for each data observation due to the high cost in conducting wet lab experiments [2]. Many big data applications call for online streaming feature selection to consume sequentially added dimensions over time.

As an emerging research direction, online streaming feature selection provides a new, complementary algorithmic methodology to enrich online feature selection, especially addresses high dimensionality in big data analytics. But to the best of our knowledge, there is no comprehensive open-source packages existing for this problem. To facilitate research efforts on this research direction, we develop the open-source library called LOFS (Library of Online streaming Feature Selection).

The main contribution of the LOFS library lies on three aspects. (1) It is the first comprehensive open-source library for implementing algorithms of online streaming feature selection. (2) It provides the state-of-the-art algorithms of online streaming feature selection mainly developed by our research group. (3) It is written in MATLAB and OCTAVE respectively, easy to use, and completely open source. We hope it will facilitate the development of new online algorithms for tackling the grand challenges of high dimensionality in big data analytics, and encourage researchers to extend LOFS and share their algorithms through the LOFS framework.

\section*{2. Problems and background}

In general, assuming \(S\) is the feature set containing all features available till time \(t_{i-1}\), and \(C\) is the class attribute, then a training data set \(D\) is defined by \(D = \{S, C\}\), which is a sequence of features that is presented over time. As we process one dimension at a time, the research problem is that at any time \(t_i\), how to online maintain a minimum size of feature subset \(S_i^\ast\) of maximizing its predictive performance for classification. If \(F_i\) is a new coming feature at time \(t_i\), \(S_i^\ast \subset S\) is the selected feature set till time \(t_{i-1}\) and \(P(C|\mathcal{F})\) denotes the posterior probability of \(C\) conditioned on a subset \(\mathcal{F}\), the problem of online streaming feature selection is formulated as Eq. (1).
\[
S'_k = \arg\min_{S} |S| : S = \arg\max_{\xi \in \mathcal{G}_{k-1}} P(C_{\xi}). \tag{1}
\]

To solve Eq. (1), currently the state-of-the-art algorithms include Grafting [3], Alpha-investing [4], OSFS [5], Fast-OSFS [6], and SAOLA [7]. All of those algorithms only deal with one dimension at a time upon its arrival.

Group information sometimes is embedded in a feature space. For instance, in image analysis, features are generated in groups which represent color, texture and other visual information. If \(G_{k-1}\) is the set of all feature groups available till time \(t_{k-1}\), then at time \(t_k\), \(D\) is denoted by \(D = \{G_{k-1}, C\}\), which is a sequence of feature groups that is added sequentially. To consume grouped features sequentially added over time, online selection of dynamic groups is formulated as Eq. (2).

\[
G'_k = \arg\max_{G'_{k-1}, G_k \subseteq \mathcal{G}_{k-1}} P(C | G'_k)
\]

\[
\begin{align*}
(a) & \forall G_j \in G'_k, G_j \subseteq G'_{k-1}, \forall \xi, \eta \in \mathcal{G}_{k-1} \setminus \{\xi, \eta\}, P(C | G_j \setminus \{\xi, \eta\} \neq P(C | G_j \setminus \{\xi\}) \\
(b) & \forall G_j \in G'_k, P(C | G'_k \setminus G_j) \neq P(C | G'_k \setminus G_j). \\
\end{align*} \tag{2}
\]

In Eq. (2), \(G'_k\) is a new coming group at time \(t_k\), and \(G'_{k-1} \subseteq G_{k-1}\) is the set of selected groups till time \(t_{k-1}\). Eq. (2) attempts to yield a set of groups at time \(t_k\) that is as parsimonious as possible at the levels of both intra-groups (constraint (a)) and inter-groups (constraint (b)) simultaneously for maximizing its predictive performance for classification. To online utilize grouped features, the group-SAOLA algorithm was proposed [8].

3. Framework of LOFS

The LOFS architecture is based on a separation of three modules, that is, CM (Correlation Measure), Learning, and SC (Statistical Comparison), as shown in Fig. 1. The three modules in the LOFS architecture are designed independently, and all codes follow the MATLAB standards. The learning module consists of two submodules, LFI (Learning Features added Individually) and LGF (Learning Grouped Features added sequentially).

In the CM module, LOFS provides four measures to calculate correlations between features, Chi-square test, \(G^2\) test, Fisher’s \(Z\) test, and mutual information, where Chi-square test, \(G^2\) test, and mutual information for dealing with discrete data while Fisher’s \(Z\) test for handling continuous data.

With the measures above, the LFI module includes Alpha-investing [4], OSFS [5], Fast-OSFS [6], and SAOLA [7] to learn features added individually over time, while the LGF module provides the group-SAOLA algorithm [8] to online mine grouped features added sequentially.

Based on the learning module, the SC module provides a series of performance evaluation metrics (i.e., prediction accuracy, AUC, kappa statistic, and compactness, etc.). To conduct statistical com-
parisons of algorithms, the SC model further provides the Friedman test and the Nemenyi test [9].

4. Implementation of LOFS and empirical results

The LOFS library comes with detailed documentation. The documentation is available from https://github.com/kuiy/LOFS. This documentation describes the setup and usage of LOFS. All functions and related data structures are explained in detail. Fig. 2 gives an example to show how to implement the functions of the Fast-OSFS algorithm in LOFS, such as loading data, setting parameters, running algorithms, and evaluating performance.

In addition to the documentation, the extensive performance comparisons between online streaming feature selection and traditional online feature selection, and the empirical comparisons between online streaming feature selection and traditional feature selection can be found in [8].

5. Conclusion

This paper presents LOFS, an open-source package for online streaming feature selection to facilitate research efforts in machine learning and data mining. Through the LOFS framework, we hope that it will facilitate researchers to develop new online learning algorithms for big data analytics and share their algorithms.

Appendix. Required metadata

Current code version (Tables 1 and 2)

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