

It is obvious that the running times of Alpha-investing, Fast-OSFS, OSFS and SAOLA algorithms are shorter than that of OFS-A3M, OFS-Gapknn and RHOFs algorithms. This is mainly because the first four algorithms mostly perform statistical comparison methods with low time complexity to calculate the relevance between features

(Run time)

- 1- By exploring the class separability in the boundary region of rough hypercuboid approach, an integrated feature evaluation criterion is proposed by examining not only the explicit patterns contained in the positive region but also the useful implicit patterns derived from the negative region
- 2- Consider the explicit patterns of classification while ignoring the use of implicit patterns. The discriminating ability of a feature or a subset of features. The ignorance of implicit patterns in these methods may cause the absence of useful information which may lead to degraded prediction performance.
- 3- Don't need pre-knowledge of dataset
- 4- Handles scale and variety
- 5- Get better with more dataset present. But it will also get slow as it will more data as required for further analysis
- 6- Handles slowness by distributed computing on spark
- 7- Based on the information provided in the context, it does not seem like the RHDOFS algorithm requires prior knowledge of the dataset. The algorithm is designed to handle streaming data in a dynamic environment, where the full feature space is unknown in advance and features arrive in streams. The algorithm uses an incremental iterative approach to select relevant and remove redundant features in an online fashion. Therefore, it is designed to work without prior knowledge of the dataset.
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- 9- the proposed RHOFS method is inferior to Fast-OSFS and OSFS algorithms, but outperforms investing, SAOLA and OFS-A3M algorithms in terms of the average cardinality of feature subsets and the average rank.
- 10- Compared with OFS-Gapknn, RHOFS can achieve more compact subsets on most of the datasets, although the average number of features of RHOFS is larger.

Working on the Rough Hypercuboid Approach based Online Feature Selection (RHOFS) involves implementing the methodology described earlier to perform dynamic feature selection for online learning tasks. The process starts with initializing a seed set of features and gradually adding or removing features based on their contribution to the hypercuboids constructed around training instances. The RHOFS algorithm continuously updates the feature set as new data arrives to maintain a concise and relevant feature representation.

However, it's important to note that RHOFS does have its complexity and drawbacks. One major drawback arises from the evaluation of feature contributions to the hypercuboids, which can be computationally intensive, especially when dealing with high-dimensional datasets. Additionally, the online nature of RHOFS requires constant monitoring and updating, which can add computational overhead.

Another drawback of RHOFS is the sensitivity to the initial seed set. Depending on the initial seed set, the algorithm may converge to different feature subsets, leading to potential variations in performance. This sensitivity makes the initialization process critical and may require domain knowledge or preprocessing steps to ensure a suitable seed set.

Furthermore, RHOFS assumes that the hypercuboids accurately represent the data distribution. If the data contains complex patterns or non-linear relationships, the hypercuboids might not capture these nuances effectively, potentially leading to suboptimal feature selection.

Lastly, RHOFS may face challenges when dealing with highly imbalanced datasets or when new instances introduce concept drift. The algorithm's ability to adapt to evolving data may be limited, and the selected feature set might not adequately represent the changing characteristics of the data.

Considering these complexities and drawbacks, it is important to carefully assess the suitability of RHOFS for specific applications and datasets. Alternative feature selection methods and complementary techniques, such as dimensionality reduction or ensemble approaches, can be considered to address the limitations and enhance the performance of RHOFS in practical scenarios.

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