Streaming Feature Selection

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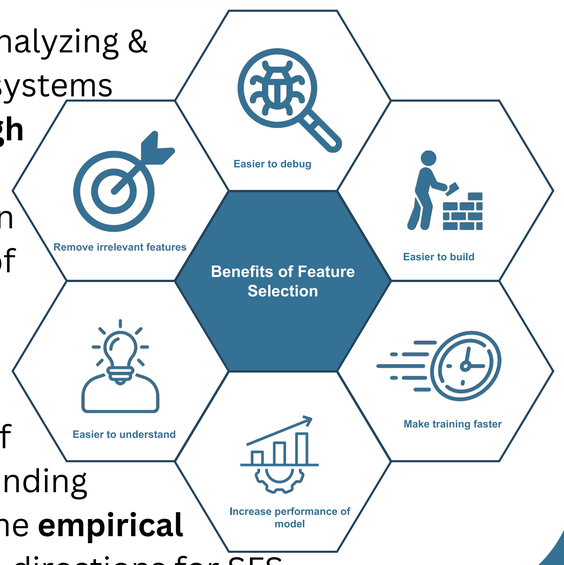
Introduction

Feature Selection is an important task in analyzing & predicting the outcome. But for real-time systems where features are **dynamic**, **velocity is high** and **domain knowledge is limited**. It is not efficient to use traditional feature selection techniques because of streaming fashion of real-time datasets. In this article, we are presenting the methodology (**redundancy** and **relevancy** analysis) of streaming feature selection (SFS) and the evolution of algorithms employing innovative ways of finding **optimal** no. of features. We also discuss the **empirical analysis** of SFS algorithms and future directions for SFS.



Traditional vs Streaming

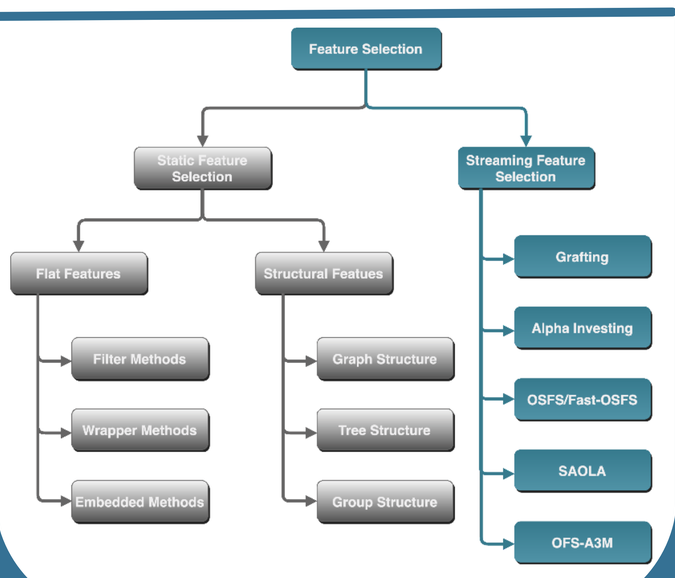
Traditional Feature Selection

1. Assumes the entire dataset is available at once, and aims to select a subset of features most relevant for the learning task.
2. **Offline Processing**: Operates on static data, whole dataset is available before hand.
3. **Batch Computation**: Computes feature relevance based on the entire datase
4. Fixed Feature Set

Streaming Feature Selection

1. Data arrives sequentially or in a streaming fashion. This approach is designed **to adapt** to changing data distributions and evolving feature relevance.
2. **Online Processing**: Operates on data as it arrives, often in real-time.
3. **Incremental Computation**: Updates feature relevance on-the-fly.
4. Dynamic Feature Set

Taxonomy



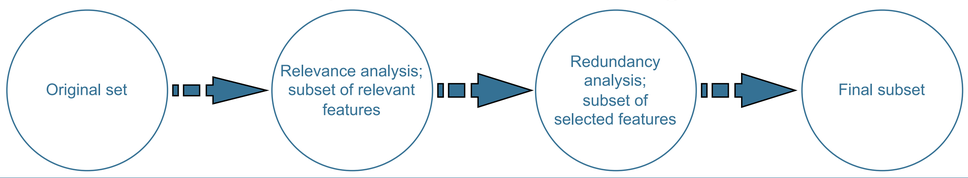
Methodology

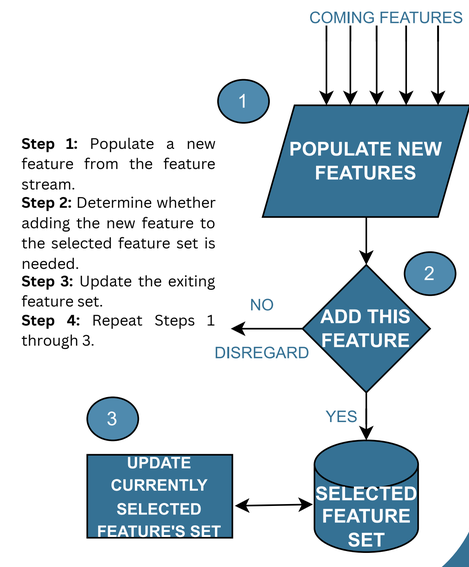
OnLine Relveance Analysis

During this stage, features are categorised into three groups: strong relevance, weak relevance, and irrelevance. If the feature is **strongly or weakly relevant**, it is included in the feature subset. However, if the feature is deemed **irrelevant**, it is **disregarded**.

OnLine RedunDancY Analysis

Identifies and **removes redundant features** by checking subsets of the **Best Candidate Features (BCF)** and ensures that newly added features are optimal by examining if they create conditional independence with existing features and the class attribute.





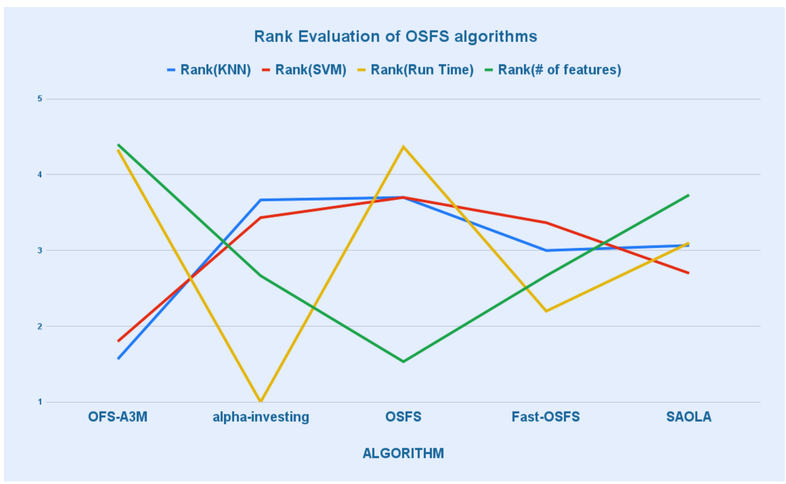
Step 1: Populate a new feature from the feature stream.
Step 2: Determine whether adding the new feature to the selected feature set is needed.
Step 3: Update the exiting feature set.
Step 4: Repeat Steps 1 through 3.

Evolution of Algorithms

Result Analysis

The graph shows the rank of performance for OFS algorithm on **15 classification** datasets. It shows:

- OFS-A3M has the **best** predictive **accuracy** for KNN
- Alpha-Investing is the **fastest algorithm** in term of running time
- OSFS selects the **least** number of **feature** and potentially misses critical information
- SAOLA has comparable performance but is **sensitive** to **noisy** datasets



Conclusion

Existing approaches to streaming feature selection typically involve testing **individual features** to select an optimal subset, which may not be effective for extremely high-dimensional big data, necessitating the development of more innovative approaches. In real life, feature may not arrive individually but in **group fashion** as well. Latest SFS algorithms usually suffer from high time complexity. The **scalability** challenge presents a future research direction for online feature-selection algorithms, considering the difficulty of loading the entirety of big data into memory during a **single scan** and obtaining reliable relevance scores for features without sufficient **density** around each sample.

References

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