Impact of filter feature selection on classification: an empirical study

Authors

Uchechukwu NJOKU, Alberto ABELLÓ

Besim BILALLI, Gianluca BONTEMPI (Université Libre de Bruxelles)

DOLAP 2022

29th March, 2022

Feature selection (FS)

The process of finding a subset of features in a dataset that are more relevant based on a **defined criteria**

Classification

- **Filter methods:** model independent

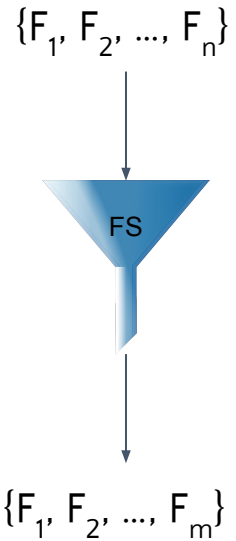
E.g: Gini, ReliefF, SPEC, CMIM, MRMR, JMI, RFS, CFS

- Wrapper methods: model dependent

E.g: Sequential forward(backward) selection

- Embedded methods: included in model

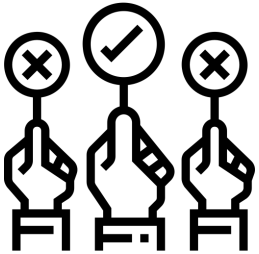
E.g: Tree based algorithms



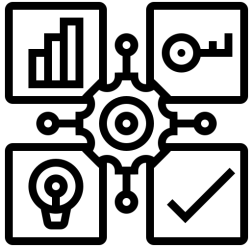
Why feature selection?

- Data understanding
- Data visualization
- Training time
- Storage

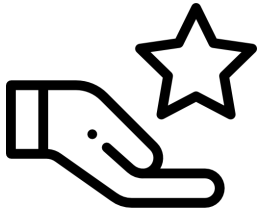
Contributions



Propose a systematic method to select representative datasets



Study and highlight the different effects of FS on the accuracy and training time of **binary and multiclass** classification models



Recommendations for choice of FS

Data selection

Why?

many more datasets than needed

Systematic approach steps:

1. Retrieve metadata: to gain insights into available data
2. Normalize metadata: for uniformity of values
3. Discretize metadata: to create clusters of similar datasets for selection

Data selection: OpenML Use Case

Over 21,000 datasets

Filter Factors

- Numerical types
- No missing values
- Single target variable
- Number of classes: [2, 19]
- Number of features: [max. 1,000]
- Number of instances: [max. 10,000]

380 candidate datasets

Data selection: OpenML Use Case

380 candidate datasets

Step 1: Retrieve metadata (Using OpenML API)

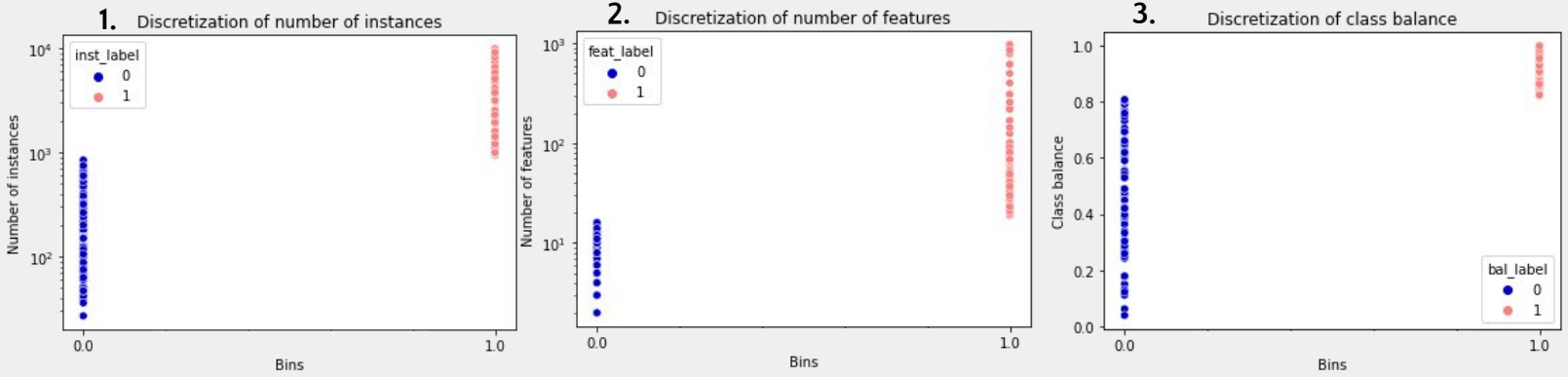
- Number of classes
- Number of features
- Number of instances
- Class balance (derived from the number of classes and instances)

Step 2: Normalize metadata (Using log)

- Number of features
- Number of instances

Data selection: OpenML Use Case

Step 3: Discretize metadata (using agglomerative clustering)



4. Number of classes discretized into 0:binary (2 classes) and 1:multiclass (>2 classes)

- All datasets fall under one of 16 (2^4) possible factor combinations
- Two representatives chosen randomly

Datasets: OpenML Use Case

- **Number of features:**

0: [2, 16] 205 datasets
1: [19, 971] 175 datasets

- **Number of Instances**

0: [27, 846] 246 datasets
1: [937, 9.989] 134 datasets

- **Classes**

0 – Binary 262 datasets
1 – Multiclass 118 datasets

- **Class balance**

0: [0,0385, 0,8083] 84 datasets
1: [0,8232, 1,0] 296 datasets

CFIB

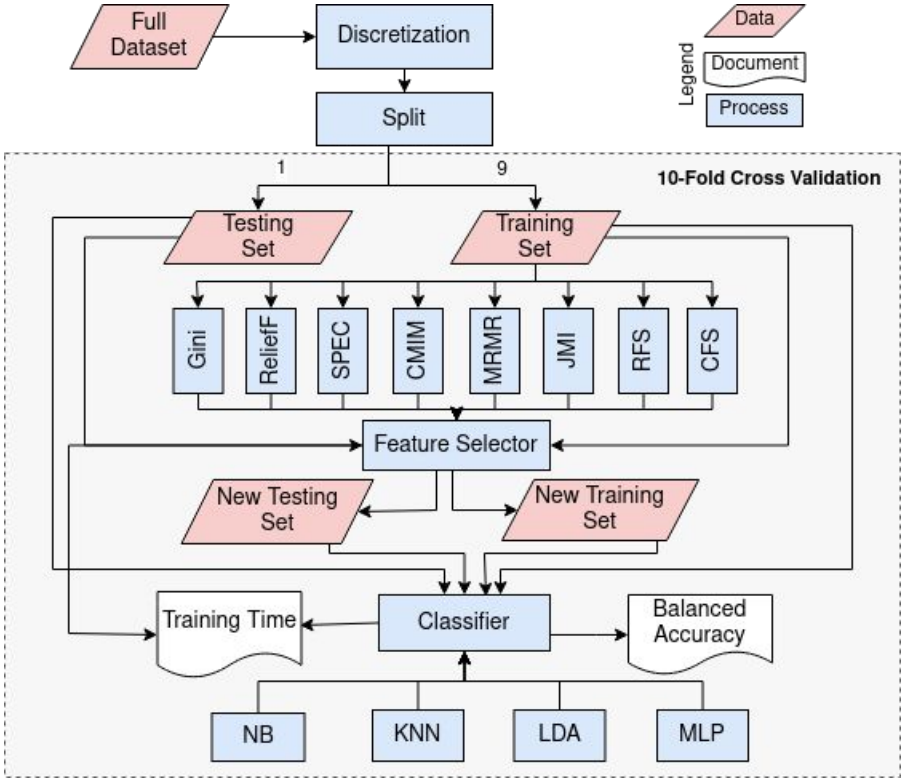
0000: 4
0001: 98
0010: 6
0011: 24
0100: 23
0101: 55
0110: 21
0111: 31

C F I B

1000: 4
1001: 46
1010: 18
1011: 5
1100: 5
1101: 11
1110: 3
1111: 26

- **All datasets fall under one of 16 (2^4) possible factor combinations**
- **Two representatives chosen randomly**

Methodology



Work Load

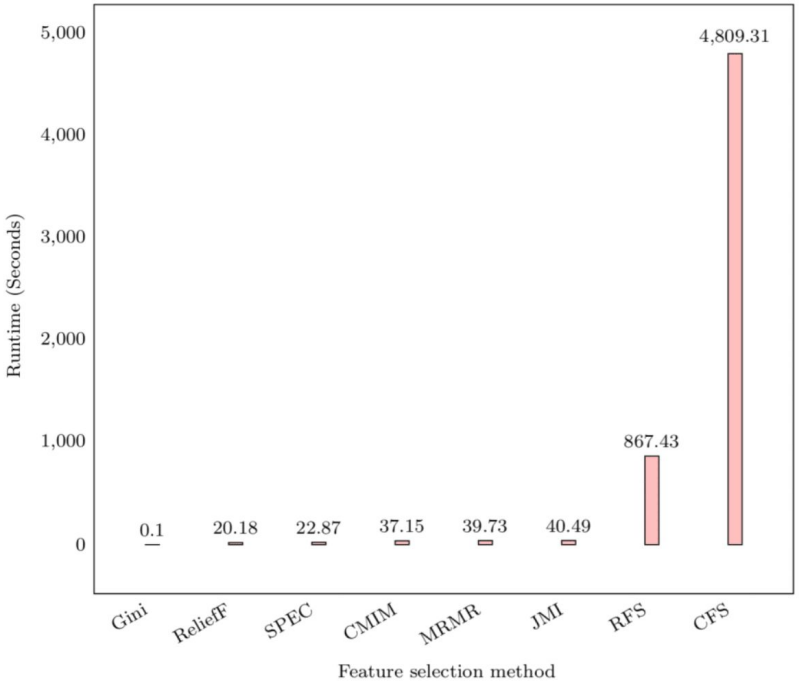
- 32 datasets
- 8 feature selection methods
- 4 classification algorithms
- 5 feature subset sizes [#features^(0.5,0.6,0.7,0.8,0.9)]

Metrics

- Feature selection runtime
- Classifier accuracy change
- Classifier runtime change

Results

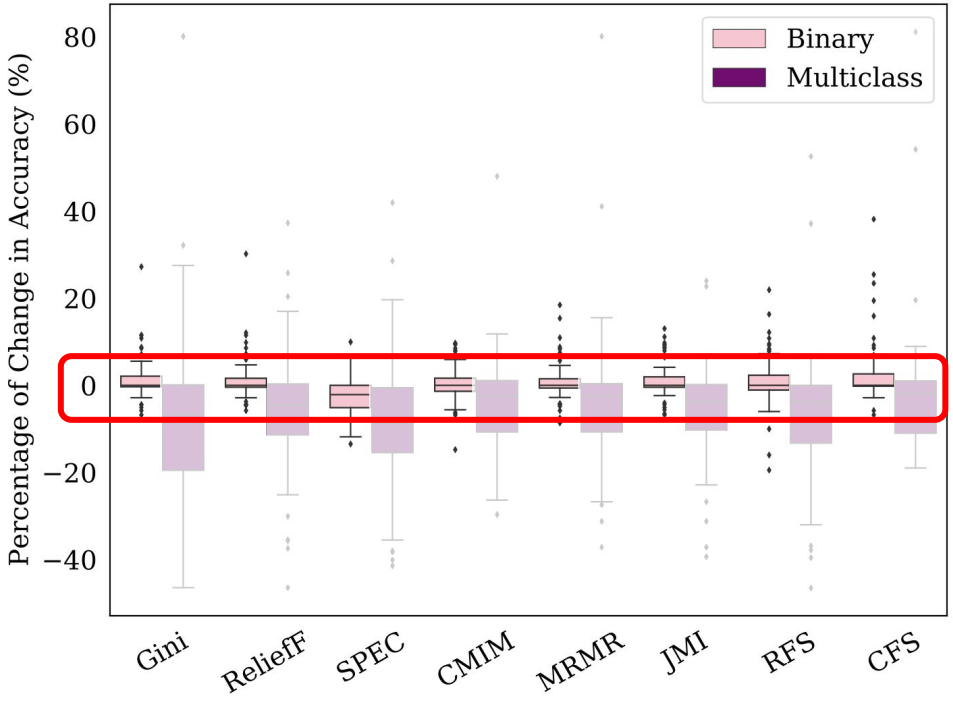
FS runtime



- Determined by various factors (number of instances, features, class, ...)
- Gini method (less than one second) is most time efficient
- CFS (over 80 minutes) is the least efficient method timewise due to the required computation of pairwise correlations between features
- Selected features can be re-used for model selection

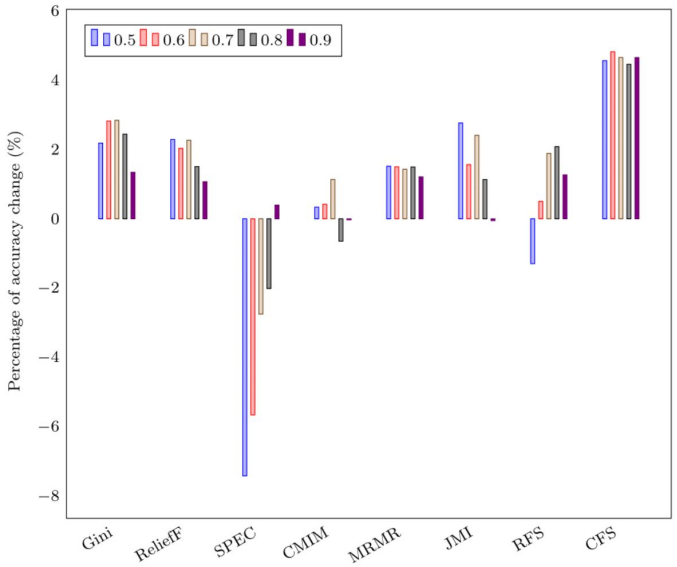
Classifier accuracy

The improvement in accuracy after feature selection is different for binary and multiclass classifications



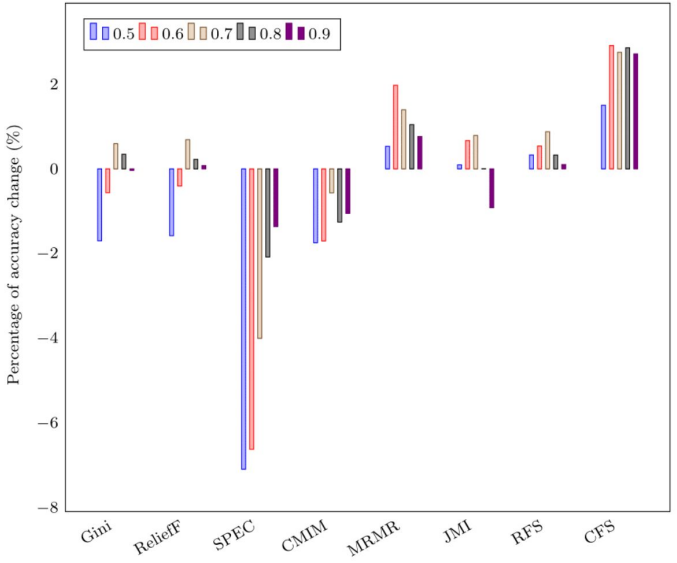
Binary classification

K-Nearest neighbour



K-Nearest Neighbour accuracy change for binary classification.

Naive Bayes

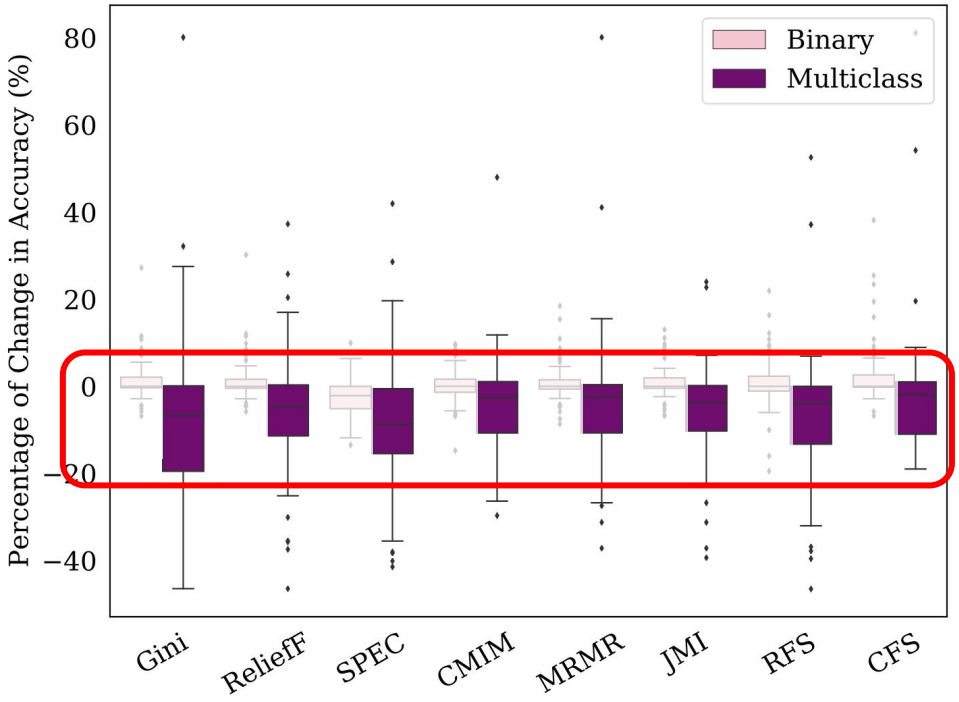


Naive Bayes accuracy change for binary classification.

Up to 5% accuracy improvement for binary classific

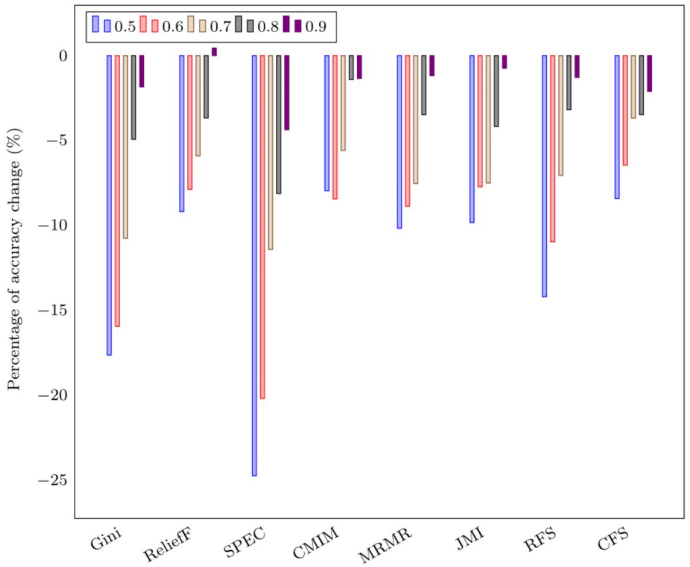
Classifier accuracy

The improvement in accuracy after feature selection is different for binary and multiclass classifications



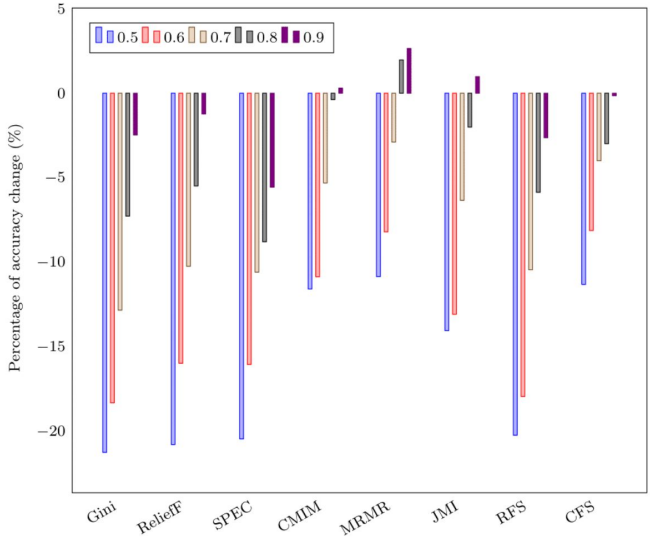
Multiclass classification

K-Nearest neighbour



K-Nearest Neighbour accuracy change for multi-class classification.

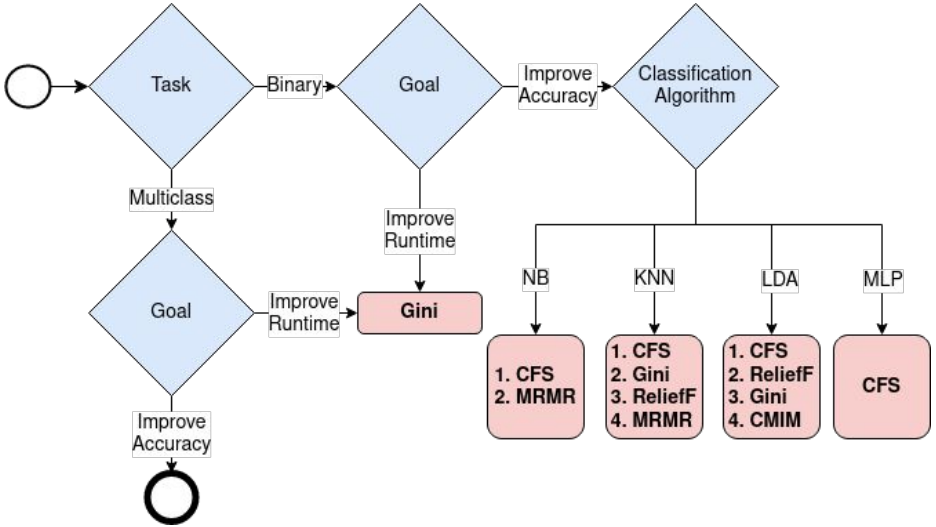
Naive Bayes



aive Bayes accuracy change for multi-class classification.

Feature selection mostly leads to accuracy degradation for multiclass classification

Recommendation



Recommendation based on:

- Goal
- Task
- Classification algorithm

No one size fits all FS method

Further work

- Extend work to larger datasets with more clusters of dataset factors and repositories
- Investigate the dependence of multiclass classification performance degradation after FS on the multiclass classification strategy
- Extend work to regression and clustering tasks
- Propose more efficient implementations of FS methods aiming for faster runtime

Thank You!

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

DTIM Database Technologies and Information Management

Contact

Email: unjoku@essi.upc.edu

Website: https://www.essi.upc.edu/dtim

Github: https://github.com/F-U-Njoku/filter-fs-impact-on-classification