

Some aspects of decision support systems: application to differential diagnosis of Parkinson's Disease and **feature selection**

Peter Drotár

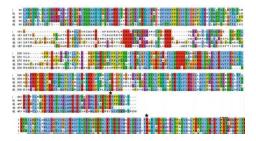


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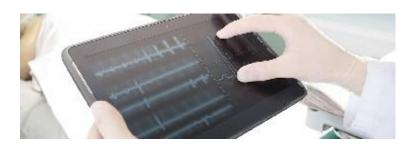
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Motivation



High dimensional data

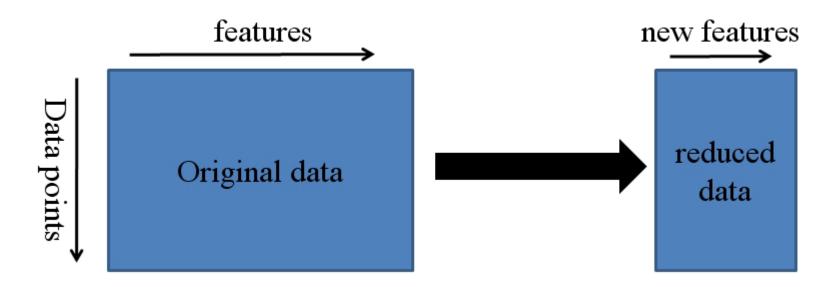




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Stability of FS algorithms

 Feature Selection techniques select a subset of features from the input which can efficiently describe the input data while reducing effects from noise or irrelevant features and still provide good prediction results.



problem of feature selection stability

• FS stability - the robustness of the feature preferences of FS algorithm to differences in training sets drawn from the same generating distribution [Kalousis et al, 2007]

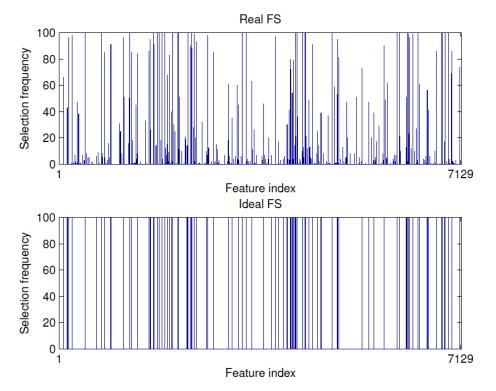


FIGURE: 100 runs of FS algorithm. FS selects 100 out of 7129 features in each run.

Stability of FS algorithms

Feature selection and stability of FS – simple example

Assume database of N samples and 10 features (f1, f2, f3, f4, f5, f6, f7, f8, f9, f10).

GOAL: Select 5 most significant features.

Run FS algorithm X with output : f1 f3 f4 f7 f9 Run FS algorithm X with output : f2 f3 f4 f6 f8 Run FS algorithm X with output : f1 f2 f4 f8 f9 Run FS algorithm X with output : f1 f3 f4 f7 f8 Run FS algorithm X with output : f2 f6 f7 f8 f9

Which features are really significant and how they influence prediction?

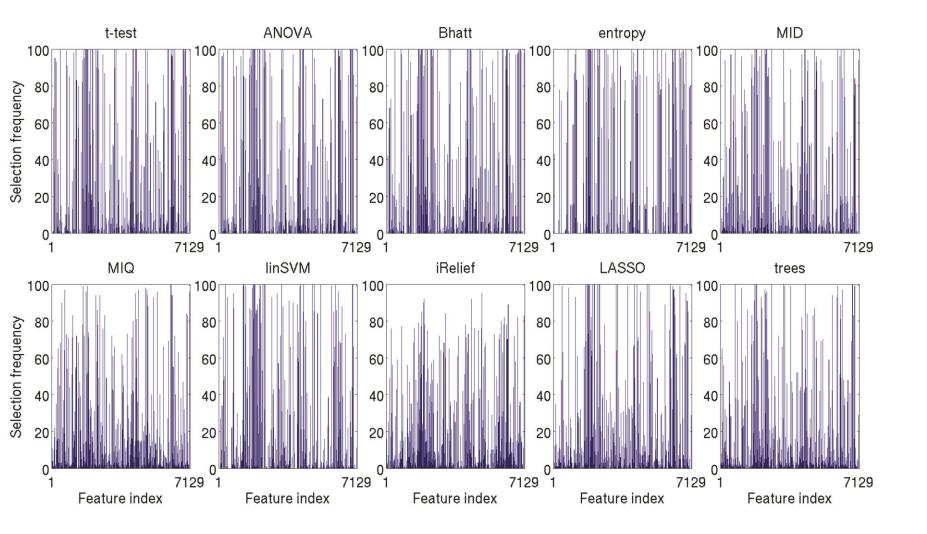
Feature selection techniques:

- t-test FS (univariate)
- ANOVA (univariate)
- Bhattacharyya distance (univariate)
- entropy (univariate)
- \circ MRMR MID
- \circ MRMR MIQ
- \circ linear SVM
- \circ iterative Relief
- o LASSO
- \circ tree

Stability of FS algorithms

Biomedical datasets:

Dataset name	source	# samples	# features
B2006	Burczynski [1]	127	22,283
C2006	Chowdary [2]	104	22,283
G1999	Golub [3]	72	7129
G2002	Gordon [4]	181	12,533
D2013	Drotar [5]	75	204
T2014	Tsanas [6]	126	309



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Stability of FS algorithms

• Stability measure:

- Kuncheva index [Kuncheva, 2007]
- Weighted Consistency index [Somol et al, 2010]

	Table 2: Stability for different FS methods measured by Kuncheva index κ									
dtb	t-test	ANOVA	Bhatt	entropy	MID	MIQ	linSVM	iRelief	LASSO	Tree
B2006	0.67	0.68	0.66	0.79	0.54	0.45	0.39	0.40	0.61	0.47
C2006a	0.71	0.71	0.68	0.65	0.48	0.37	0.34	0.46	0.48	0.51
C2006b	0.63	0.63	0.73	0.79	0.58	0.54	0.62	0.56	0.55	0.54
G1999	0.71	0.71	0.71	0.78	0.65	0.48	0.65	0.45	0.59	0.54
G2002	0.77	0.78	0.78	0.83	0.73	0.50	0.46	0.65	0.66	0.59
T2003	0.45	0.45	0.46	0.68	0.35	0.29	0.13	0.46	0.41	0.25
D2013	0.43	0.42	0.40	0.45	0.54	0.46	0.50	0.37	0.55	0.36
T2014	0.70	0.72	0.67	0.90	0.66	0.64	0.49	0.53	0.80	0.57
average	0.63	0.64	0.64	0.74	0.57	0.47	0.45	0.48	0.58	0.48

Table 2: Stability for different ES methods measured by Vuncheys index "

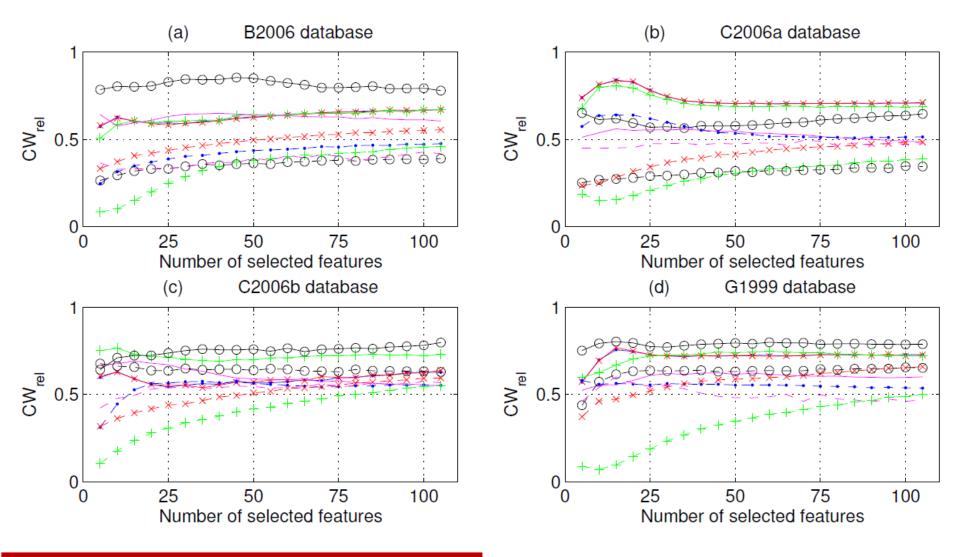
Stability of FS algorithms

	Table 3: Stability for different FS methods measured by weighted consistency CW									
dtb	t-test	ANOVA	Bhatt	entropy	MID	MIQ	linSVM	iRelief	LASSO	Tree
B2006	0.67	0.68	0.66	0.79	0.55	0.45	0.39	0.40	0.61	0.47
C2006a	0.71	0.72	0.68	0.65	0.48	0.37	0.34	0.46	0.48	0.51
C2006b	0.63	0.63	0.73	0.79	0.58	0.55	0.62	0.56	0.55	0.55
G1999	0.71	0.72	0.72	0.79	0.65	0.49	0.65	0.46	0.59	0.54
G2002	0.77	0.78	0.78	0.84	0.73	0.50	0.47	0.65	0.66	0.59
T2003	0.45	0.46	0.47	0.68	0.36	0.29	0.14	0.46	0.41	0.25
D2013	0.71	0.70	0.69	0.72	0.77	0.72	0.74	0.68	0.77	0.67
T2014	0.79	0.81	0.78	0.94	0.77	0.75	0.65	0.68	0.87	0.71
average	0.68	0.69	0.69	0.77	0.61	0.51	0.50	0.54	0.61	0.54

Stability of FS algorithms

Numerical results

- FS stability as a function of number of selected features
- Stability measure : relative weighted consistency index



Stability of FS algorithms

- FS similarity Ο
- Similarity measure : intersystem Kuncheva index Ο

	Table 4:	Similarity of	FS tech	niques expr	essed by	y intersy	stem Kunac	cheva index	х <i>Iк</i> . G1999	database
FS	t-test	ANOVA	Bhatt	entropy	MID	MIQ	linSVM	iRelief	LASSO	Tree
t-test		0.96	0.87	0.16	0.59	0.42	0.52	0.20	0.60	0.59
ANOVA	0.96		0.88	0.16	0.58	0.42	0.51	0.19	0.59	0.59
Bhatt	0.87	0.88		0.20	0.62	0.44	0.44	0.18	0.57	0.60
entropy	0.16	0.16	0.20		0.26	0.23	0.08	0.04	0.14	0.16
MID	0.59	0.58	0.62	0.26		0.71	0.35	0.20	0.44	0.49
MIQ	0.42	0.42	0.44	0.23	0.71		0.32	0.17	0.34	0.38
linSVM	0.52	0.51	0.44	0.08	0.35	0.32		0.36	0.42	0.36
iRelief	0.20	0.19	0.18	0.04	0.20	0.17	0.36		0.27	0.21
LASSO	0.60	0.59	0.57	0.14	0.44	0.34	0.42	0.27		0.51
Tree	0.59	0.59	0.60	0.16	0.49	0.38	0.36	0.21	0.51	

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Stability of FS algorithms

Numerical results

- FS influence on **prediction accuracy**
- Accuracy measure : Matthews correlation coefficient Ο

	Table 6: MCC performance										
dtb	classifier	t-test	ANOVA	Bhatt	entropy	MID	MIQ	linSVM	iRelief	LASSO	Tree
B2006	Ada	91.6	91.4	93.4	90.9	94.9	94.4	93.7	89.4	93.6	93.4
C2006a	Ada	78.0	78.5	79.5	78.1	93.8	81.3	78.1	67.8	76.5	80.7
C2006b	Ada	96.4	80.6	96.4	94.4	94.2	96.4	92.1	70.1	78.8	78.4
G1999	Ada	92.9	94.8	97.5	97.3	94.5	97.3	93.8	96.4	96.5	96.4
G2002	Ada	97.7	97.5	97.7	95.9	97.7	100.0	100.0	92.2	96.7	96.4
T2003	Ada	35.4	97.7	32.2	44.8	98.2	35.3	31.7	23.6	25.5	27.1
D2013	Ada	19.9	36.9	27.1	49.4	56.6	61.1	6.4	55.4	48.8	56.3
T2014	Ada	78.4	70.0	73.6	69.4	70.9	72.1	50.5	69.7	70.9	69.5

Table 6: MCC parformance

- \circ entropy based FS appears to be the most stable FS
- Features selected by mRMR techniques helps to achieve highest prediction accuracy
 - \circ however accuracies are comparable