Feature Selection in Proton Magnetic Resonance Spectroscopy Dada of Brain Tumors

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¹ H-MRS Spectroscopy oo	Class-Separability Feature Selection	Experimental Settings	Results 000	Conclusions

Outline

- 1 ¹H-MRS Spectroscopy
 - ¹H-MRS Proton Magnetic Resonance Spectroscopy
- 2 Class-Separability Feature Selection
 - A distinctive aspect
 - The Algorithm
- 3 Experimental Settings
 - The Data Set
 - The Addressed Problem
 - Experimental Conditions
- 4 Results
 - Feature Selection XVAL
 - Visualization
- 5 Conclusions
 - Conclusions

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Is a non-invasive technique that provides information about the biochemical profile of brain tissue



Figure 1: ¹H-MRS Fundamentals. Image source:

http://www.chem.ucalgary.ca/courses/351/Carey/Carey.html

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Figure 2: ¹H-MRS example.

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A distinctive aspect				

Metabolites

- Meningiomas NAA = \emptyset , Choline = \uparrow
- Metastases Creatine =↓
- High–Grade tumors Lipids =↑

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The Algorithm				

The Class-Separability Feature Selection Algorithm (CSFS)

1 Calculate distance value for each metabolite.



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The Algorithm				

The Class-Separability Feature Selection Algorithm (cont.)

2 Separability degree for each metabolite.

$$DS_i = \sum_{j
eq k} |ar{x}_{j,i} - ar{x}_{k,i}|$$

3 Sort DS_i in descending order.

- 4 DS_i feeds a Forward-Backward Search.
- 5 All computations are bootstrap averages.

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¹ H-MRS	Spectroscopy

The Data Set

Single voxel ¹H-MR spectra acquired *in vivo* from brain tumor patients



LTE (PRESS 135–144 ms): 195 cases with 55 meningiomas 78 glioblastomas, 31 metastases, 20 astrocytomas grade II 6 oligoastrocytomas grade II and 5 oligodendrogliomas grade II

STE (PRESS 30–32 ms): 217 cases with 58 meningiomas 86 glioblastomas, 38 metastases, 22 astrocytomas grade II 6 oligoastrocytomas grade II, and 7 oligodendrogliomas grade II

LSTE: the merged LET and SET data, with 195 cases

195 frequency intensity values, from 4.21 ppm \rightarrow 0.51 ppm

International Network for Pattern Recognition of Tumors Using Magnetic Resonance *INTERPRET*

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The Addressed Problem				

Three Super-classes

- 1 High-grade Gliomas.
- 2 Low-grade Gliomas.
- 3 Meningiomas.

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Experimental Conditions				

- The LTE, STE and LSTE data. The three super-classes.
- The median metric is used.
- Forward-Backward selection in wrapper mode
- Trained Six classifiers: NN, LDC, QDC, LR, ISVM, rSVM by 10x10 cross validation on the original data sets.

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Feature Selection - XVAL				

	NN	LDC	QDC	LR	ISVM	rSVM
LTE	[11] 89.70	[15] 93.51	[9] 89.09	[7] 91.48	[9] 91.82	[10] 93.88
STE	[8] 92.21	[16] 93.34	[6] 87.40	[8] 90.48	[12] 93.14	[8] 94.48
LSTE	[17] 96.14	[26] 98.27	[8] 92.83	[7] 92.07	[14] 94.83	[12] 94.77

 Table 1: CSFS Feature selection results and final performance. The number in square brackets is the final Best Spectral Subset (BSS) size. The right number is the averaged 10x10 CV accuracy in the original (continuous) ¹H-MRS datasets.

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Feature Selection - XVAL				



Figure 3: Best Spectral Subset from LSTE-LDC model as positioned in the whole spectrum.

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Visualization				



Figure 4: Projection of the dataset (using the final *selected* feature subset of the best LSTE-LDC model) onto the first two eigenvectors of the scatter matrices as coordinate system. Circles represent low-grade *gliomas*; filled squares high-grade *malignant tumors* and stars *meningiomas*.

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Conclusions				

- The proposed algorithm takes advantage of the differential presence of certain metabolites.
- It also accounts for possible redundancies.
- A competitive model w.r.t. other solutions in the literature.

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Conclusions				

- The "Best" Subset: It is extremely unlikely that it is found by a search process.
- This study confirmed that the LSTE combination renders better subsets in classification accuracy.
- Linear models are among the best suited for the task.

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Conclusions				

- Most of the identified metabolites are positively defined by the medical literature.
- Some concordances are found with successful recent machine learning works.

