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### Improved interpretability with DNetPRO classifier applied to radiomics data

with

<u>Nico Curti</u>, Sara Dalmonte, Riccardo Biondi, Daniel Remondini

27/09/2024

Dept. of Physics and Astronomy, University of Bologna

## **Big BioMedical Data**





# DNetPRO: A network approach for low-dimensional signatures from high-throughput data

- <u>High-throughput</u> data (10<sup>3</sup> 10<sup>5</sup> variables)
- Looking for <u>low</u>-dimensional set of observables
- Gene or Protein expression by an <u>up/down</u> regulation
- Features selection is a critical step
- Exploration of all feature space is an <u>NP-hard</u> problem
- Few samples available
- <u>III-posed</u> problem

Curti et al., Scientific Report, 2022



Methods that select variables for multi-dimensional signatures based on single-variable performance can have limits in predicting higherdimensional signature performance. As shown in the Fig. a, in which both variables taken singularly perform poorly, but their performance becomes optimal in a 2-dimensional combination, in terms of linear separation of the two classes.

## **Big BioMedical Data**





# DNetPRO: A network approach for low-dimensional signatures from high-throughput data















2019 Cytokin Alzheimer Di

KNN 0.721 0.579 0.607 0.617 KNN-0.582 KNN-0.683 0.643 0.595 0.677 0.713 0.589 0,710 0,640 DA 0.605 0.667 0.620 0.575 DA DA 0.657 LR 0.697 0.589 0.668 0.604 LR 0.594 LR 0.652 0.645 0.618 0.670 0.670 NC-0.594 0.615 0.612 NC-0.584 0.707 0.671 0.599 NC PLS-0.713 0.589 0.671 0.640 PLS-0.677 0.605 0.667 0.620 0.589 PLS-0.692 RF 0.633 0.619 RF 0.589 0.643 RF 0.664 SVM 0.725 0.608 0.658 0.626 SVM 0.621 0,625 SVM-0.721 0,696 0.625 DNetPRO DNetPRC DNetPRO 0.739 0.666 0.641 0.589 0.738 0.620 0.598 0.609 0,734 0.615 0,660 (procedure A) (procedure A) (procedure A) DNetPRO DNetPRO DNetPRO 0.724 0.637 0.616 0.586 0.700 0.599 0.628 0.620 (procedure B) (procedure B) (procedure B LUSC USC URC RC BM 04 GBM 6 ć, LRC . USC

2022

miRNA

0.586

0.682

DDA

2018 No Med App Traffic scientific reports

mRNA

0.658

0.618

0.673

DDA-

mR

Check for updates

**RPPA** 

0.671

0.714

DDA

0.8

0.7

0.6

)24

iomic

**T** samples

0.578

### OPEN A network approach for low dimensional signatures from high throughput data

Nico Curti<sup>1,2,4</sup>, Giuseppe Levi<sup>1,2,4</sup>, Enrico Giampieri<sup>2,3⊠</sup>, Gastone Castellani<sup>2,3</sup> & Daniel Remondini<sup>1,2</sup>

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#### 2019 Cytokine Alzheimer Di

mR



#### Docs » Welcome to DNetPRO algorithm's documentation!

2022

G Edit on GitHub

#### Welcome to DNetPRO algorithm's documentation!

Official implementation of the DNetPRO algorithm published on BioRXiv by Curti et al. The *DNetPRO* algorithm produces multivariate signatures starting from all the couples of variables analyzed by a Discriminant Analysis. The method is particularly designed to gene-expression data analysis and it was tested against the most common feature selection techniques. In the current implementation the *DNetPRO* object is totally equivalent to a *scikit-learn* feature-selection method and thus it provides the member functions *fit* (to train your model) and *predict* (to test a trained model on new samples). The combinatorial evaluation is performed using a *C++* version of the code wrapped using *Cython*.

2018 No Med App Traffic

### scientific reports

Check for updates

### OPEN A network approach for low dimensional signatures from high throughput data

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)24 iomic T samples

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### **Radiomic Analysis**



Radiomic Analysis is becoming a standard practice in many medical applications

Number of publications per year since 1967.

1990

Year

2000

2010

Huang et al., *Nature Reviews*, **2023** 

الاليتيتينييناللالية

1980

1970

#### Pros

2020

- Multiple features
- Easy to use
- Integration with other software
- Use of Anatomical image information
- Easy extraction of the results

#### Cons

Vs

- Multi-dimensional analyses
- <u>Ill-posed problems</u>
- Large noise sources
- Biases and batch effects in multi-center studies
- <u>Hard interpretation of</u> <u>the results</u>

3,000

2,000

1,000

## **PET/CT Recurrent Rectal Cancer**





1 hospital – IRCCS Sant'Orsola – Malpighi Bologna



44 patients – radial resection – primary rectal adenocarcinoma



PET/CT dataset – manual segmentation of lesions performed by expert radiologists

Full set of radiomic features – Original, Wavelet, and LoG



Classification pipeline – Locally Recurrent Rectal Cancer (LRRC) vs NO LRRC





### PET/CT LRRC - DNetPRO





#### СТ

Signature 1 = {Entropy, LargeDependenceEmphasis}

Signature 2 = {Entropy, Kurtosis, Mean, Range, LargeDependenceEmphasis}

Signature 3 = {Entropy, Mean}

Signature 4 = {Entropy}

Signature 1 = {RunVariance, Strength, Maximum3DDiameter, SurfaceVolumeRatio} Signature 2 = {Strength}

Signature 3 = {ShortRunEmphasis, Strength}

Signature 4 = {RunEntropy, ShortRunHighGrayLevelEmphasis}

Signature 5 = {Entropy, Kurtosis, Mean, Range, TotalEnergy, SumAverage, SumEntropy, SumSquares, GrayLevelVariance, LargeDependenceEmphasis} Signature 6 = {GrayLevelVariance}

### PET/CT LRRC - DNetPRO







Identification of PET/CT radiomic signature for locally recurrent rectal cancer classification

Heliyon

Under Review

Sara Dalmonte<sup>a,b,\*</sup>, Maria Adriana Cocozza<sup>c,\*</sup>, Dajana Cuicchi<sup>d</sup>, Daniel Remondini<sup>e</sup>, Lorenzo Faggioni<sup>k,1</sup>, Paolo Castellucci<sup>f,1</sup>, Andrea Farolfi<sup>f</sup>, Emilia Fortunati<sup>f</sup>, Alberta Cappelli<sup>c</sup>, Riccardo Biondi<sup>g</sup>, Arrigo Cattabriga<sup>c</sup>, Gilberto Poggioli<sup>d</sup>, Stefano Fanti<sup>f</sup>, Gastone Castellani<sup>h,\*\*</sup>, Francesca

Features	Sensitivity	Specificity	BAS	MCC
CT	0.80	0.82	0.81	0.61
$\operatorname{PET}$	0.93	0.61	0.77	0.52
CT + PET	0.80	0.75	0.77	0.53

Table 2: Results of the SVC model trained in a 10-fold cross-validation with selected CT, PET, and CT+PET features.

## **MRI Sinonasal tumors**





Ground Truth Tumor mask overlay







2 hospitals – Como & Varese centres **New collaborations** !!



145 patients – sinonasal tumor – multiple tumor classes grouped as Malignant vs Benign



T1w & T2w – manual segmentation of lesions performed by expert radiologists



Full set of radiomic features – Original, Wavelet, and LoG



Classification pipeline – Malignant vs Benign Tumors







### **Preliminary Results & Conclusions**

- **DNetPRO** as **Novel** approach to feature selection in AIM
- Publicly available code in multiple languages
- Applicability to different kind of samples (new in Radiomics!)
- Computationally efficient on ill-posed like problems
- Possibility to extract multiple (or just one) signatures
- Easy Explainability of the results for biomedical (and clinical) applications
- We are currently developing **web (server) interface** for public usages





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# Thank you for Your attention

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