CLINICAL INTERPRETATION OF OMICS CLUSTERING RESULTS

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Supervisor: Milena Kraus

Ajay Kesar



AGENDA

- ► Task
- ► Data
- Feature Selection Models

Filter / Wrapper (DT) / Embedded

- Decision Tree Baseline
- Regularized Tree Model
- ► Future Work







Α	В	С	D	E	F	G	Н
	PatientID	Category	ParameterName	Event	Value	Unit	Unnamed: 6
0	SM 01	Demographics / Clinical Parameters	Gender	General	female		
1	SM 01	Demographics / Clinical Parameters	Study group	General	No cardiac	medication	
2	SM 01	General	Time between VISIT 1 and VISIT 2	General	223		
3	SM 01	General	Time between VISIT 1 and surgery	General	3		
4	SM 01	General	Time between surgery and VISIT 2	General	220		
5	SM 01	Surgery Parameters	Age at Surgery	Surgery	69	years	
6	SM 01	Surgery Parameters	Aortic Valve Replacement	Surgery	yes		
7	SM 01	Surgery Parameters	MIC	Surgery	yes		
8	SM 01	Surgery Parameters	Additional Surgery	Surgery	no		
9	SM 01	Surgery Parameters	CABG Surgery	Surgery	no		
10	SM 01	Surgery Parameters	Other Surgery	Surgery	no		
11	SM 01	Surgery Parameters	Aortic Valve Size	Surgery	23	mm	
12	SM 01	Surgery Parameters	Biological Aortic Valve?	Surgery	yes		
13	SM 01	Surgery Parameters	Modell of Aortic Valve	Surgery	CE Perimou	unt Magna Ease	e 23mm, 3300 TFX
14	SM 01	Surgery Parameters	Aortic Clamping Time	Surgery	87	min	
15	SM 01	Surgery Parameters	Perfusion Time	Surgery	122	min	
16	SM 01	Surgery Parameters	Reperfusion Time	Surgery	18	min	
17	SM 01	Surgery Parameters	Cardiac Arrest Time	Surgery	87	min	
18	SM 01	Surgery Parameters	Biopsy	Surgery	yes		
19	SM 01	Surgery Parameters	Postoperative Pacemaker	Surgery	no		
20	SM 01	Catheter Measurement	Left ventricular systolic pressure	General	230	mm[Hg]	2015-03-18
21	SM 01	Catheter Measurement	Left ventricular end diastolic pressure	General	15	mm[Hg]	2015-03-18
22	SM 01	Catheter Measurement	Pressure in the ascending aorta	General	180	mm[Hg]	2015-03-18
23	SM 01	Demographics / Clinical Parameters	Height	VISIT 1	164	cm	
24	SM 01	Demographics / Clinical Parameters	Weight	VISIT 1	71	kg	
25	SM 01	Demographics / Clinical Parameters	NYHA stage	VISIT 1	2		
26	SM 01	Demographics / Clinical Parameters	Blood pressure systolic right arm	VISIT 1	164	mm[Hg]	
27	SM 01	Demographics / Clinical Parameters	Blood pressure diastolic right arm	VISIT 1	80	mm[Hg]	
28	SM 01	Demographics / Clinical Parameters	Blood pressure mean right arm	VISIT 1	122	mm[Hg]	
29	SM 01	Demographics / Clinical Parameters	Blood pressure systolic left arm	VISIT 1	164	mm[Hg]	
30	SM 01	Demographics / Clinical Parameters	Blood pressure diastolic left arm	VISIT 1	80	mm[Hg]	
31	SM 01	Demographics / Clinical Parameters	Blood pressure mean left arm	VISIT 1	122	mm[Hg]	
32	SM 01	Demographics / Clinical Parameters	Time of blood pressure	VISIT 1	5	pm	
33	SM 01	Demographics / Clinical Parameters	Heart rate	VISIT 1	76	per minute	
45	SM 01	Diagnoses	Diagnoses		AS III		
46	SM 01	Diagnoses	Diagnoses		Hyperchole	esterinemia, (fa	am.)
47	SM 01	Diagnoses	Diagnoses		Gastritis (Autoimmune)		
48	SM 01	Diagnoses	Diagnoses		Hysterectomy 1990		
49	SM 01	Diagnoses	Diagnoses		Ovarectomy 2010		
50	SM 01	Diagnoses	Diagnoses		Vitamin B 1	12 anemia	_
51	SM 01	Diagnoses	Diagnoses		hypertensi	on	
52	SM 01	Diagnoses	Diagnoses		Arterial hy	pertension	
53	SM 01	Diagnoses	Diagnoses		Bicuspid ac	ortic valve	

DATA

> 29 Patients

- ► 33 common features
- ► 199 different features in total
- Feature selection for heterogeneous data



FEATURE SELECTION MODELS

- 1. Filter
- 2. Wrapper (DT)
- 3. Embedded



FEATURE SELECTION MODELS - FILTER

- Filters select features based on criteria independent of any supervised learner, performance of filters may not be optimal for a chosen learner
 - Pearson's Correlation
 - LDA: Linear discriminant analysis
 - ANOVA: Analysis of variance
 - Chi-Square







FEATURE SELECTION MODELS - WRAPPER

- Wrappers use learner as black box to evaluate relative usefulness of a feature computationally expensive
 - Forward Selection
 - Backward Elimination
 - Recursive Feature Elimination



subset, search the best feature subset for given supervised learner, tend to be



FEATURE SELECTION MODELS - EMBEDDED

- information gained from training a learner
 - Lasso regression (L1 regularization)
 - Ridge regression (L2 regularization)



Instead of treating learner as black box, embedded methods select features using the



DECISION TREE APPROACH - INNER JOIN

33 CATEGORIES

gini = 0.0samples = 21value = [21, 0] class = group1





DECISION TREE APPROACH - INNER JOIN & MAX. TREE DEPTH=1

33 CATEGORIES



DECISION TREE APPROACH - INNER JOIN & SPLIT-CRITERIA=ENTROPY $MRI_SV_VISIT 1_ml \le 20.5$ entropy = 0.797samples = 29value = [22, 7]class = group1rue False **33 CATEGORIES**







DECISION TREE APPROACH - OUTER JOIN

199 CATEGORIES







DECISION TREE APPROACH - OUTER JOIN & SPLIT_CRITERIA=ENTROPY

199 CATEGORIES





DECISION TREE APPROACH - STEPS

- Data Preparation
 - ► 33 common categories in 29 files
 - 199 different categories
 - ► <u>170</u> categories ignored
- Different imputation strategy
 - mean, median, most frequent value in category, regression

DECISION TREE APPROACH - REDUNDANCY

(a) A decision tree may use both X_1 and X_2 to (b) X_2 alone can perfectly separate the two classes. split.

REGULARIZED TREE MODEL

- > Split a decision tree node only if information gain increases significantly
- Lower redundancy
- Higher efficiency
- Apply to regularized bagged random forest

FUTURE WORK

- Implement normal Random Forest classifier for comparison
- Apply other two feature selection models: Filter & Embedded
- Imputation strategy
- Evaluation of results with clinician

Implement Regularized Bagged Random Forest (RRF) (<u>https://goo.gl/BqMSMr</u>)

