Ministry of Higher Education and Scientific Research
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Faculty of Technology
Biomedical Engineering Laboratory (GBM)

Improvement of the learning environnement in the context of multi-label data

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Acknowledgements

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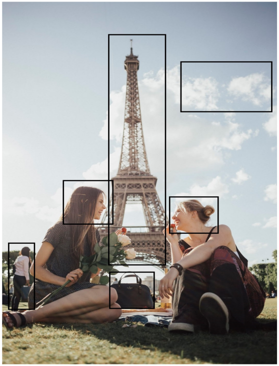
1. *Research background*
2. *Part1: Ensemble Methods for Multi-label Classification (MLC)*
3. *Part 2: MLC for Ambulatory Blood Pressure Monitoring*
4. *Part 3: Label Correlation for MLC based Decision Trees*
5. *Conclusions & Future Directions*

Introduction to Multi-label Classification

Some multi-label real-world applications (1/4)

Tags (labels):

- **Person 1**
- **Person 2**
- **Person 3**
- **Eiffel tour**
- **Friendship**
- **Sunny day**
- **Guccy bag**
- **Vacation**
- **Paris**
- **Etc**

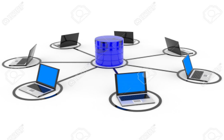


[1]

[1] designmosaique.com/best-things-to-do-in-paris.html

Introduction to Multi-label Classification

Some multi-label real-world applications (2/4)



	Features	Labels
Image 1		
Image 2		
………		
Image n		

Google Photos

Introduction to Multi-label Classification

Some multi-label real-world applications (3/4)

Data type	Application	Resource	References
Text	Categorization	News article Medical Report	[Schapire and Singer, 2000] [Moskovitch et al., 2006]
Image	Semantic annotation	Pictures	[Boutell et al., 2004]
Video	Semantic annotation	News Clip	[Qi et al., 2007]
Audio	Noise detection Emotion detection	Sound Clip Music Clip	[Streich and Buhmann, 2008] [Li and Ogihara, 2003]
Structured	Functional genomics Proteomics	Gene Protein	[Elisseef et al., 2002] [Rousu et al., 2006]

Introduction to Multi-label Classification

Some multi-label real-world applications (4/4)

Problem of polypathologies

- In medical field, a patient can be affected by multiple illnesses (labels) such as: Diabetes, Hypertension, Cardio-vascular risk and Renal faillure.

2

[2] www.chc.be/Services/Services-administratifs-et-logistiques/Direction-medicale.aspx

Existing Multi-label Approaches

Different forms of learning (1/2)

Different forms of learning

Mono label

	Features				Label 1	Label 2	Label 3	....
Example 1	*	*	*	*	1	0	1	
Example 2	*	*	*	*	0	1	1	
Example i	*	*	*	*	1	1	1	
....								

Multi-class

	Features				Output	Label 2	Label 3	....
Example 1	*	*	*	*	Classe 1	0	1	
Example 2	*	*	*	*	Classe 2	1	1	
Example i	*	*	*	*	Classe 3	1	1	
....								

Figure: Single label Vs. Multi-class classification

Existing Multi-label Approaches

Different forms of learning (2/2)

Different forms of learning

Multi-label

	Features				Label 1	Label 2	Label 3	....
Example 1	*	*	*	*	1	0	1	
Example 2	*	*	*	*	0	1	1	
Example i	*	*	*	*	1	1	1	
....								

Multi Dimensional

	Features				Label 1	Label 2	Label 3	....
Example 1	*	*	*	*	1	2	3	
Example 2	*	*	*	*	2	3	2	
Example i	*	*	*	*	2	3	1	
....								

Figure: Multi-label Vs. Multi-dimensional classification

Existing Multi-label Approaches

Different forms of learning

	Single Output		Multi Outputs					
	Binary	Multi-class	Multi-label			Multi-Dimensional		
	Diabete		Diabete	CVR	RF	Diabete	CVR	RF
Instance 1	P	Type 1	P	P	N	Type 1	VES	P
Instance 2	N	Type 2	N	N	N	N	N	N
………	………	………	………	………	………	………	………	………
Instance i	P	N	P	P	P	Type 2	AES	P

N: Normal
P: Pathological
CVR: CardioVascular Risk
RF: Renal Failure
VES: Ventricular ExtraSystole
AES: Atrial ExtraSystole

Figure: Single-label vs. Multi-label dataset.

Existing Multi-label Approaches

Learning from multi-label datasets

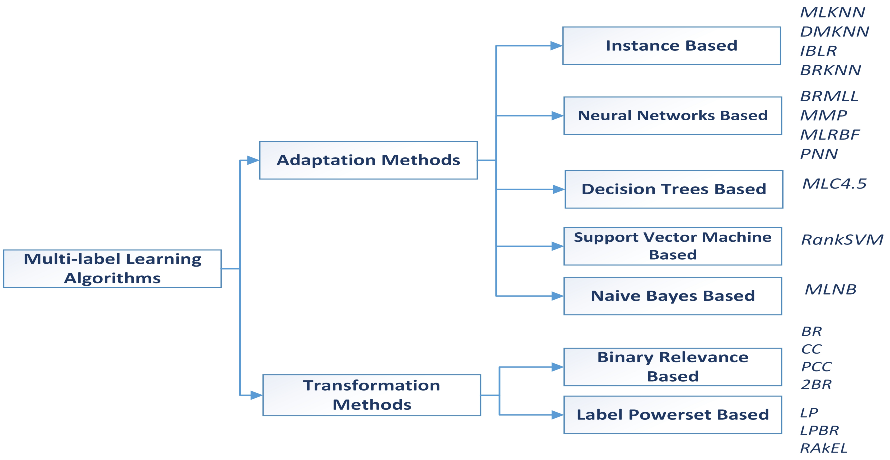


Figure: Categorization of Multi-label Algorithms.

Existing Multi-label Approaches

Multi-label approaches (Transformation) (1/2)

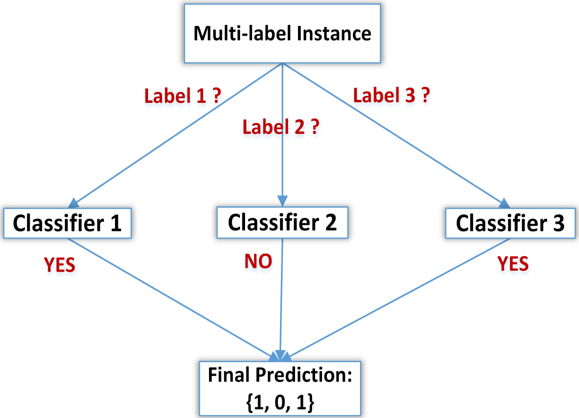


Figure: Binary Relevance (BR)

Existing Multi-label Approaches

Multi-label approaches (Transformation) (2/2)

Examples/ Labels	Label 1	Label 2	Label 3	Label 4
Example 1	0	1	1	0
Example 2	1	0	0	0
Example 3	0	1	1	0

↓ LP Transformation

Examples/ Labels	New Class
Example 1	0110
Example 2	1000
Example 3	0110

Figure: Label Powerset (LP)

Multi-label Evaluation Measures

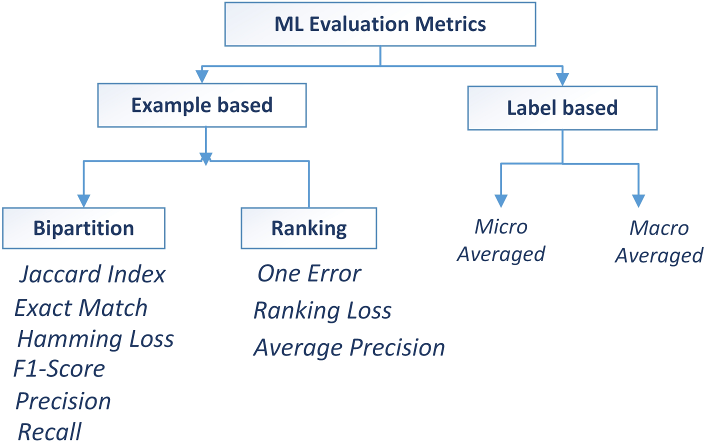


Figure: Categorization of Multi-label Evaluation Metrics.

Multi-label Toolboxes & Datasets Repository

How much the dataset is Multi-label?

- **Label Cardinality** [Tsoumakas et al., 2010] quantify the average number of the active labels per instance.
- **Label Density** [Tsoumakas et al., 2010]: it is the Label Cardinality divided by the number of labels.
- **Diversity** [Tsoumakas et al., 2010]: represents the total number of the labels in the dataset.
- **Distinct labelsets** [Tsoumakas et al., 2010] : the number of the possible combinations of labels in the dataset.
- **The Pmin**: is the percentage of instances in the dataset with only one active label [Herrera et al., 2016].

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Multi-label Toolboxes & Datasets Repository

Some available Multi-label datasets

Table: Characteristics of some Multi-label datasets.

Dataset	Domain	Instances	Attributes	Labels	Cardinality	Density	Distinct	Reference
Medical	Text	978	1449	45	1.245	0.028	94	[Crammer et al., 2007]
Bibtex	Text	7395	1836	159	2.402	0.015	2856	[Katakis and Vlahavas, 2008]
Enron	Text	1702	1001	53	3.378	0.064	753	[Klimt and Yang, 2004]
Mediamill	Media	43907	120	101	4.376	0.043	6555	[Snoek et al., 2006]
Emotions	Music	593	72	6	1.869	0.311	27	[Trohidis et al., 2008]
Scene	Media	2407	294	6	1.074	0.179	15	[Boutell et al., 2004]
Genbase	Biology	662	1185	27	1.252	0.046	32	[Diplaris et al., 2005]
Yeast	Biology	2417	103	14	4.237	0.303	198	[Elisseef et al., 2002]
Flags	Image	194	19	7	3.392	0.485	54	[Goncalves et al., 2013]
Birds	Sound	645	260	19	1.014	0.053	133	[Briggs et al., 2012]
Bookmarks	Text	87856	2150	208	2.028	0.010	18716	[Katakis and Vlahavas, 2008]
Delicious	Text	16105	500	983	19.017	0.019	15806	[Tsoumakas et al., 2008]
Reuters	Text	6000	500	103	1.462	0.014	811	[Read, 2010]

Multi-label Toolboxes & Datasets Repository

Some Multi-label toolboxes

Table: Some Multi-label Toolboxes

Toolbox	Language	Description	GUI	Reference
MULAN	Java	A Java library for MLL that provides a programming interface.	No	[Tsoumakas et al., 2011]
Meka	Java	A Multi-label/Multi-target extension to WEKA	YES	[Read et al., 2016]
Scikit-Multilearn	Python	A Python library for performing Multi-label Classification	NO	[Szymański and Kajdanowicz, 2017]
Scikit-learn	Python	Simple and efficient tools for data mining and data analysis.	NO	[Pedregosa et al., 2011]
RUMDR	R	R Ultimate Multi-label Datasets Repository	NO	[Charte et al., 2016]
LibSVM	Java, C++	software library for SVMs, it includes some Multi-label Classification algorithms	NO	[Chang and Lin, 2011]
KEEL	Java	Genral tool for data mining applications, it includes data repository for Multi-label.	YES	[Alcalá-Fdez et al., 2011]
MLC	Matlab/Octave	a MATLAB/OCTAVE library for Multi-label Classification	NO	[Mineichi, 2017]

Part1: Ensemble Methods for Multi-label Classification

Introduction (1/2)

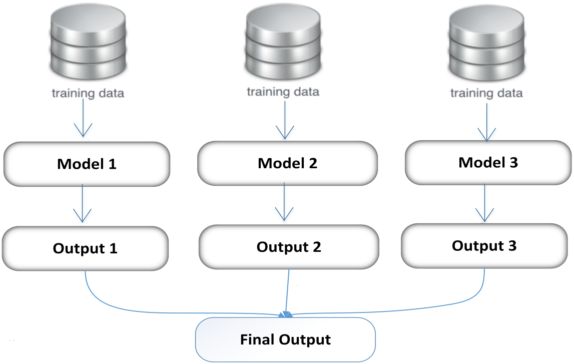

Figure: An illustration of Ensemble Methods principle using three models.

Part1: Ensemble Methods for Multi-label Classification

Introduction (2/2)

- Many approaches have been proposed to construct *Ensemble Methods*, one of the most useful is to manipulate the training examples to create diverse base learners.
- The two straightforward ways of manipulating the training set are *Bagging* and *Boosting* [Cornuéjols and Miclet, 2010].

Part1: Ensemble Methods for Multi-label Classification

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Part1: Ensemble Methods for Multi-label Classification

Related work

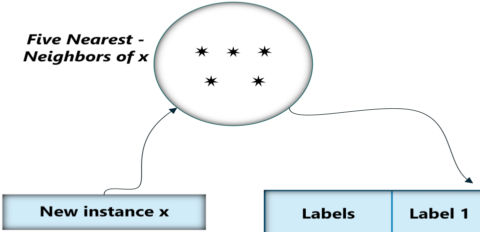
Table: Related Work of Multi-label Ensemble Methods.

Method	Summary	Reference
Boostexter	Boosting for text categorization	[Schapire and Singer, 2000]
RFPCT	Random Forest Predictive Clustering Tree	[Kocev et al., 2007]
EPS	Ensemble of Pruned Sets	[Read et al., 2008]
EBR	Ensemble of Binary Relevance classifiers,	[Read et al., 2009]
ECC	Ensemble Classifier Chain	[Read et al., 2011]
EnML	Multi-label Ensemble Learning	[Chuan et al., 2011]
RFMLC4.5	Random Forest of Multi-label-C4.5	[Gjorgji et al., 2012]

Part1: Ensemble Methods for Multi-label Classification

MLKNN algorithm [Zhang and Zhou, 2007]

- One of the most studied *ML* algorithm is *MLKNN*, is the adaptation of *K-Nearest-Neighbors* to *ML*.
- The improvement of its performance using *Bagging* [Breiman, 1996] and *Boosting* [Freund and Schapire, 1996].



Labels	Label 1	Label 2	Label 3	Label 4
MAP Probabilities, Threshold=0.5	0.6	0.4	0.9	0.8
Final labelset of x	1	0	1	1

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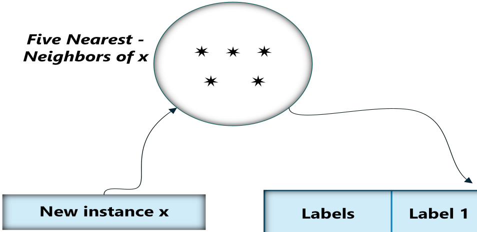

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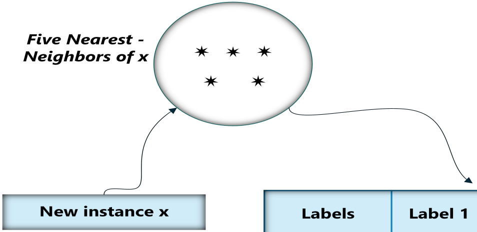

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Part1: Ensemble Methods for Multi-label Classification

Bootstrap and aggregating (Bagging) (1/2)

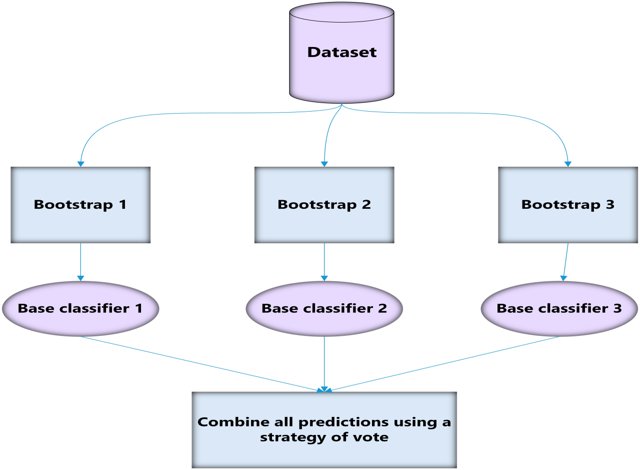

Figure: An illustration of Bagging using three base classifiers.

Part1: Ensemble Methods for Multi-label Classification

Bootstrap and aggregating (Bagging) (2/2)

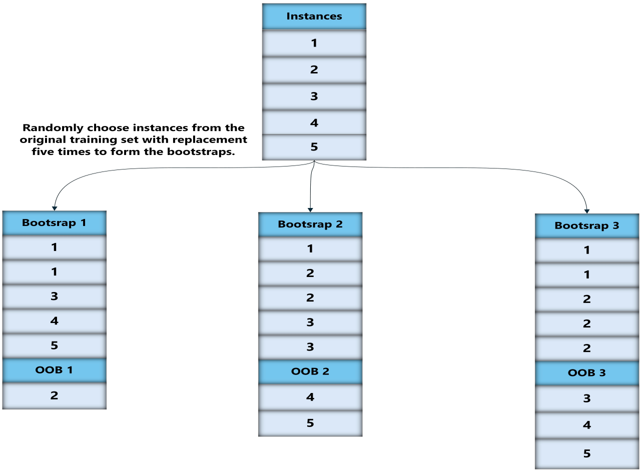

Figure: An example of Bootsrapping Sampling.

Part1: Ensemble Methods for Multi-label Classification

Proposed approach: Bagged MLKNN

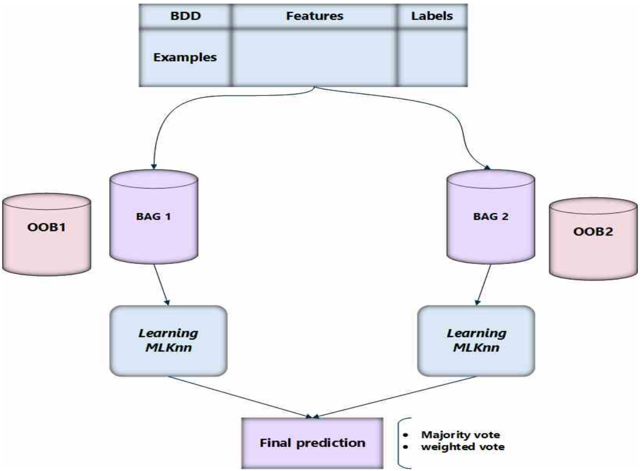

Figure: Classification process with *Bagged MLKNN*

Part1: Ensemble Methods for Multi-label Classification

Boosting

- In 1996, Shapire and Freund proposed *AdaBoost* (Adaptive *Boosting*) [Freund and Schapire, 1996].
- Change the distribution of samples available to train each expert, by overweighting misclassified examples in the preceding steps to force the learner to focus on the difficult examples of the sample learning.

Part1: Ensemble Methods for Multi-label Classification

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Part1: Ensemble Methods for Multi-label Classification

Proposed approach: AdaBoost MLKNN

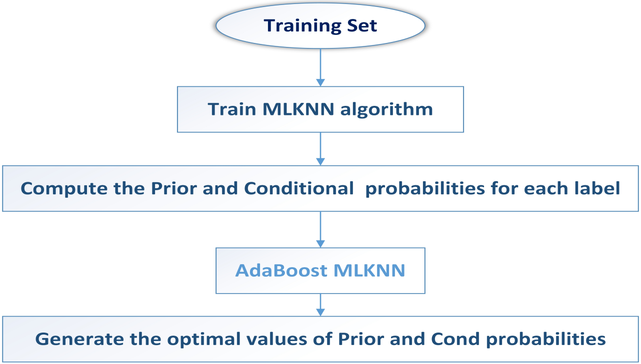

Figure: Major Steps of *AdaBoost MLKNN*

Part1: Ensemble Methods for Multi-label Classification

Results & Discussion

Dataset	Evaluation Metrics	MLKNN	Bagged MLKNN	AdaBoost MLKNN
Genbase	Accuracy	99,66 ±0	**99,72** ±0,0003	97,36 ±0,1989
	Subset Accuracy	0,93 ±0	**0,94** ±0	0,49 ±0,0098
	Fmeasure	96,3 ±0	**96,94** ±0,0385	60,08 ±0,0811
	Hamming Loss	**0** ±0	**0** ±0	0,03 ±0
Yeast	Accuracy	80,4 ±0	**80,61** ±0,0104	75,89 ±0,0843
	Subset Accuracy	0,17 ±0	**0,19** ±0	0,11 ±0,0007
	Fmeasure	63,17 ±0	**64,26** ±0,0639	57,09 ±0,0189
	Hamming Loss	0,2 ±0	**0,19** ±0	0,24 ±0
Scene	Accuracy	90,82 ±0	**91,17** ±0,0172	84,14 ±0,0107
	Subset Accuracy	**0,62** ±0	0,61 ±0	0,29 ±0,0057
	Fmeasure	71,64 ±0	**72,36** ±0	43,76 ±0,0686
	Hamming Loss	**0,09** ±0	**0,09** ±0	0,16±0,0001
Medical	Accuracy	98,27 ±0	**98,38** ±0.0014	97,38 ±0,0598
	Subset Accuracy	0,45 ±0	**0,47** ±0,0001	0,18 ±0,0018
	Fmeasure	62,7 ±0	**64,70** ±0,0080	32,74 ±0,0047
	Hamming Loss	**0,02** ±0	**0,02** ±0	0,03 ±0
Emotions	Accuracy	73,19 ±0	**73,93** ±0,0017	65,9 ±0,0963
	Subset Accuracy	0,12 ±0	**0,15**±0,0001	0,08 ±0,0009
	Fmeasure	46,72 ±0	**48,96** ±0,0083	39,2 ±0,0033
	Hamming Loss	0,27 ±0	**0,26** ±0	0,34 ±0

Part1: Ensemble Methods for Multi-label Classification

Contributions in Brief . . .

- The impact of using *homogeneous Ensemble Methods* (*Bagging* and *Boosting*) for *MLKNN* algorithm [Zhang and Zhou, 2007].
- The results are very competitive, the use of several *MLKNN* simultaneously improve the performance of the individual classifier.
- The replacement of 'majority vote' by the 'weighted vote' gives more efficient results.

- *The first work [Douibi et al., 2017b] was published in Proceeding ICCDA '17 Proceedings of the International Conference on Compute and Data Analysis. K. DOUIBI, N. SETTOUTI and MA. CHIKH. The homogeneous Ensemble Methods for MLKNN algorithm. Pages 197-201, Lakeland, FL, USA - May 19 - 23, 2017, ACM New York, NY, USA ©2017, DOI : 10.1145/3093241.3093262.*

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

Introduction: Machine Learning For Medecine

- Machine learning solutions are moving medical applications to a whole new level.
- **In medical imaging**, it helps to extract more accurate data from images and provides better interpretations to detect tumors.
- **Predictive medicine**, improve both the quality of patient care and working conditions of the practitioners by providing better information.

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

Statistics: Machine learning in medicine in the PubMed database

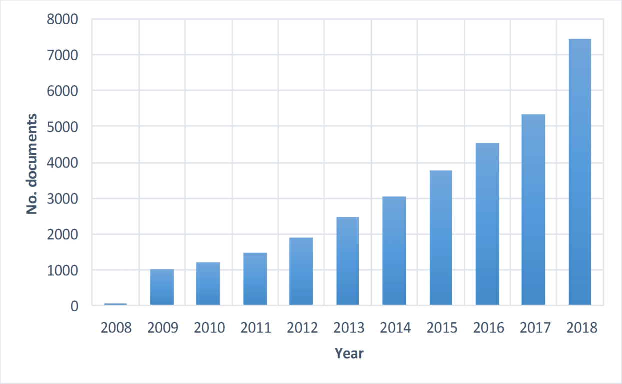

Figure: Number of PubMed publications for the query: (machine learning) and Medicine) from 2008 to 2018.

Part 2: MLC for Ambulatory Blood Pressure Monitoring

What is ABPM ? (1/4)

- Ambulatory Blood Pressure Monitoring is the record of the blood pressure for a duration of 24 hours, It is programmed to automatically measure *BP* every fifteen to twenty minutes a day and every thirty minutes during sleep.

Part 2: MLC for Ambulatory Blood Pressure Monitoring

What is ABPM ? (2/4)

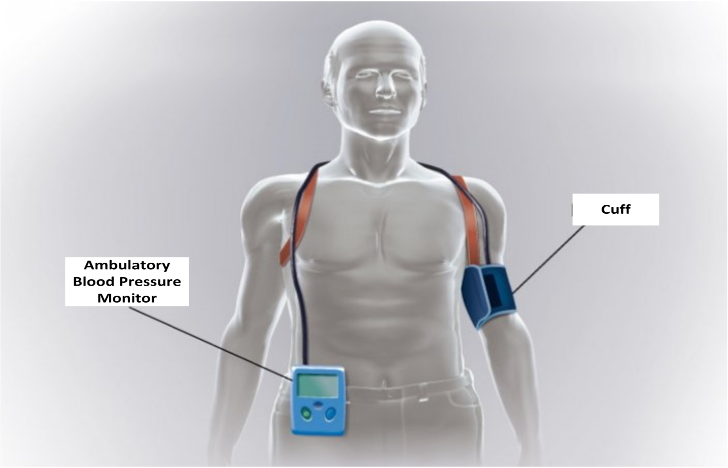

Figure: Ambulatory Blood Pressure Monitoring

Part 2: MLC for Ambulatory Blood Pressure Monitoring

What is ABPM ? (3/4)

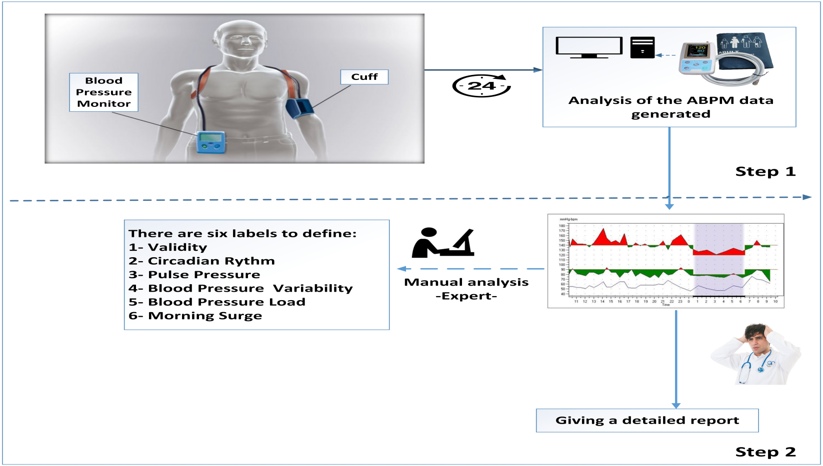

Figure: General process of ABPM

Part 2: MLC for Ambulatory Blood Pressure Monitoring

Related Work:

Table: Some Related Work.

Reference	Summary
[Copetti et al., 2009]	Presented a theoretical study of an intelligent surveillance system, for hypertensive patients at home by considering physiological variables, environment variables and behavior variables.
[Kanoun et al., 2010]	Evaluation of the Blood Pressure profile using *ABPM*
[Mena et al., 2012]	adressed the prognosis of fatal cardiovascular diseases based on ABPM data
[Ngendakumana and hattaoui, 2014]	Concluded that High Blood Pressure is frequently associated with diabetes, leading to an increase in the Cardiovascular risks
[Guo-Zheng et al., 2015]	Studied the impact of the traditional Chinese medicine, in the treatment based on Syndrome differentiation [3] by applying a MLC on clinical hypertension data

[3] Syndrome differentiation in Traditional Chinese Medicine (*TCM*) [Jiang et al., 2012] is the comprehensive analysis of clinical information gained by the four main diagnostic *TCM* procedures: observation, listening, questioning, and pulse analysis, and it is used to guide the choice of treatment either by acupuncture and/or *TCM* herbal formulae

Part 2: MLC for Ambulatory Blood Pressure Monitoring

Goals

The major aim of this work is twofold:

- The intelligent analysis of *ABPM* records using Multi-label Classification algorithms.
- A new *Multi-label* dataset with 40 *ABPM* features for 270 patients categorized into one or more out of 6 labels.
- The dataset is released to the public [Douibi et al., 2017a], to allow comparative experiments by other researchers while the publicly Multi-label medical datasets are very rare.

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

ABPM indications

- Search for High Blood Pressure.
- White Coat Effect.
- Affirm the *Resistant Hypertension*.
- Detect the *Masked Hypertension*.
- Search for a *HBP* in a pregnant woman, Parkinson's disease, diabetes, heart failure..

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

The medical ABPM analysis (1/6)

Validity

The *ABPM* record is reliable and interpretable if [Gobin et al., 2012]

- Two-thirds of the *BP* measures are valid and, equally distributed over periods of awakening and sleep.
- *ABPM* recording must be spread over the 24 hours without interruption of the recording more than 2 hours consecutive.

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The medical ABPM analysis (2/6)

Circadian Rhythm (BP Profile)

- The *ABPM* evaluates the Blood Pressure during sleep.
- **Dipper profile**: the decreasing physiologically from 10 % to 20 % at night.
- **Extreme Dipper**: If it exceeds 20 %.
- **Non Dipper**: this reduction is not sufficient, or even absent from 0 % to 10 %.
- **Reverse dipper**: *BP* may even be higher at night.

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

The medical ABPM analysis (3/6)

***Blood Pressure Variability** (BPV)*

- Pathological if it exceeds 12-15 mm Hg [Gobin et al., 2012].
- The *BPV* may occur during the *ABPM* in the following situations: Elderly patients, Diabetes, Primary neurological disorders (dysautonomia, Parkinson's disease).

Part 2: MLC for Ambulatory Blood Pressure Monitoring

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

The medical ABPM analysis (4/6)

Pulse Pressure *(PP)*

- Defined as the difference between *Systolic Blood Pressure* (SBP) and *Diastolic Blood Pressure* (*DBP*),
- The *PP* is a good predictor of Cardiovascular events in the elderly, especially compared to the *SBP*.

Part 2: MLC for Ambulatory Blood Pressure Monitoring

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

The medical ABPM analysis (5/6)

Blood Pressure Load *(BPL)*

The percentage of the *SBP* and the *DBP* values exceeding the upper limit of the standard. especially when it exceeds 40%.

Part 2: MLC for Ambulatory Blood Pressure Monitoring

The medical ABPM analysis (6/6)

Morning Surge (MS)

- The increase from the lowest *BP* during sleep to the average of the first two hours after waking,
- It is also a predictor of the occurrence of multiple pathologies as cerebral infarcts, stroke etc. Especially when it is greater than 55 mm Hg in the elderly.

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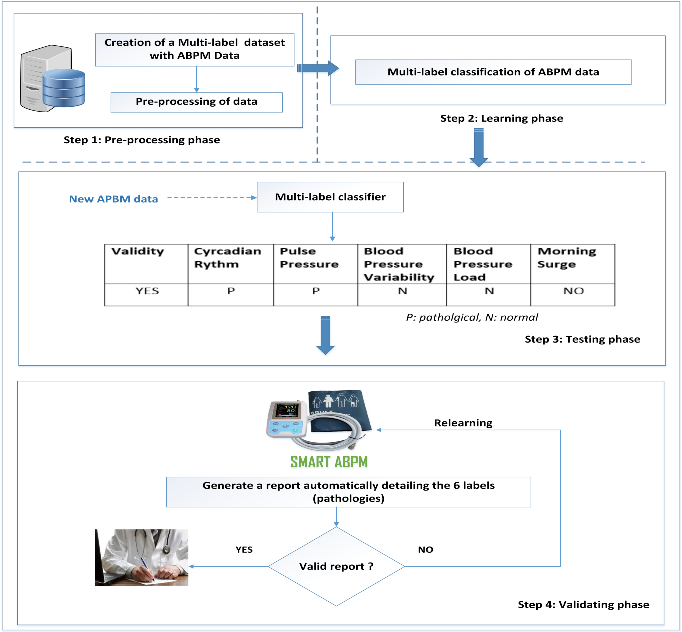

Creation of a Multi-label dataset with ABPM Data
Pre-processing of data
Step 1: Pre-processing phase
Multi-label classification of ABPM data
Step 2: Learning phase
New APBM data
Multi-label classifier
Validity
Cyrcadian Rythm
Pulse Pressure
Blood Pressure Variability
Blood Pressure Load
Morning Surge
YES
P
P
N
N
NO
P: patholgical, N: normal
Step 3: Testing phase
Relearning
SMART ABPM
Generate a report automatically detailing the 6 labels (pathologies)
YES
NO
Valid report ?
Step 4: Validating phase

Part 2: MLC for Ambulatory Blood Pressure Monitoring

Pre-processing phase and data gathering (1/2)

- Aims to prepare and clean the collected data [Douibi et al., 2017a] for training Multi-label classifiers.
- The study was performed on 270 patients (159 women and 101 men), aged between 14 and 92 years old.
- *ABPM* records were labeled by a cardiologist from *CHU SETIF cardiology* department.

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Part 2: MLC for Ambulatory Blood Pressure Monitoring

Pre-processing phase and data gathering (2/2)

Table: *ABPM* dataset statistics

Dataset	Domain	Instances	Attributes	Labels	Cardinality	Density	Distinct	Pmin
ABPM	Medical	270	40	6	4.4630	0.7438	26	0

Part 2: MLC for Ambulatory Blood Pressure Monitoring

Learning phase & Testing phase

- Search for the optimal Hypothesis *H*, which associate to each instance the correct labels.
- We conducted a comparative study of seven Multi-label algorithms commonly used under *MEKA* library [Read et al., 2016].
- All algorithms were evaluated using ML Evaluation Measures.

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Validating phase

- Once the best ML classifier is identified, the next goal is to study how can we integrate it with the Ambulatory Blood Pressure Monitor.
- The proposed Smart *ABPM* will be tested using a new data in real time.
- The expert verify if the report is valid. If not the system relearn to readjust its Classification, to improve the smart *ABPM* decisions for the future.

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Table: The predictive performance of seven competing algorithms based is DT

Algorithms / Evaluation Measure	BR	LP	RAkEL	MLKNN	BPMLL	CLR	PCC
Accuracy (Jaccard index)↑	**0.934**	0.889	0.920	0.815	0.83	0.878	0.922
Exact Match ↑	**0.756**	0.604	0.667	0.389	0.463	0.533	0.711
Hamming loss ↓	**0.051**	0.088	0.062	0.146	0.13	0.094	0.057
One Error ↓	0.022	0.067	**0**	0.007	0.007	**0**	0.015
Rank Loss ↓	0.061	0.131	0.048	0.058	0.051	**0.017**	0.077
Avg precision ↑	0.702	0.616	0.711	**0.831**	0.806	0.764	0.599
F1 (micro averaged) ↑	**0.962**	0.934	0.955	0.895	0.898	0.927	0.956

Table: Accuracy (Jaccard index) per label using the studied seven Multi-label classifiers.

Labels	*BR*	*LP*	*RAkEL*	*MLKNN*	*BPMLL*	*CLR*	*PCC*	Average
Validity	0,985	0,944	0,967	0,752	0.859	0.941	0.985	0.92 (2)
Circadian Rhythm	0,993	0,933	0,985	0,741	0.719	0.978	0.993	0.91 (3)
Pulse Pressure	0,985	0,789	0,856	0,859	0.822	0.659	0.785	0.82 (5)
Blood Pressure Load	0,985	0,970	0,985	0,907	0.963	0.985	0.985	0.97 (1)
Morning Surge	1	0,896	0.837	0,867	0.859	0.874	0.907	0.89 (4)

Label correlation Analysis for ABPM dataset

Analysis of labels-attributes dependencies for ABPM data (1/3)

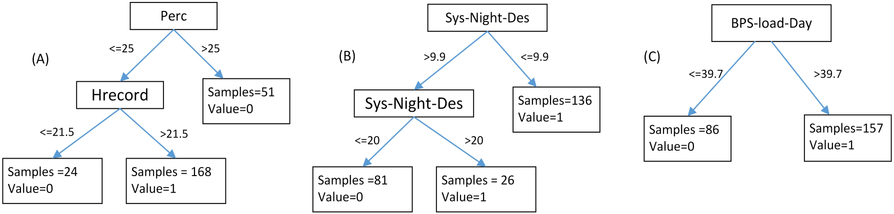

Figure: The Decision Trees for the Validity (Fig A), Circadian Rhythm (Fig B) and Blood Pressure Load (Fig C).

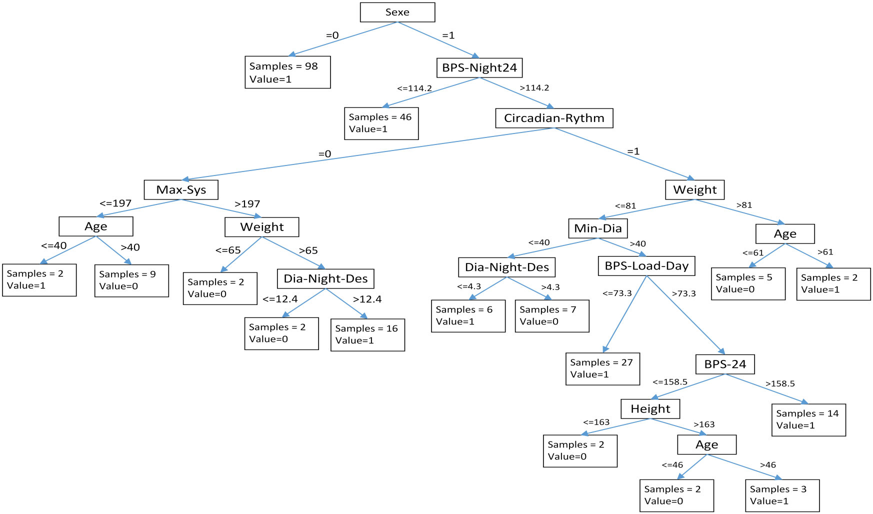

Figure: The Decision Tree for the Pulse Pressure label

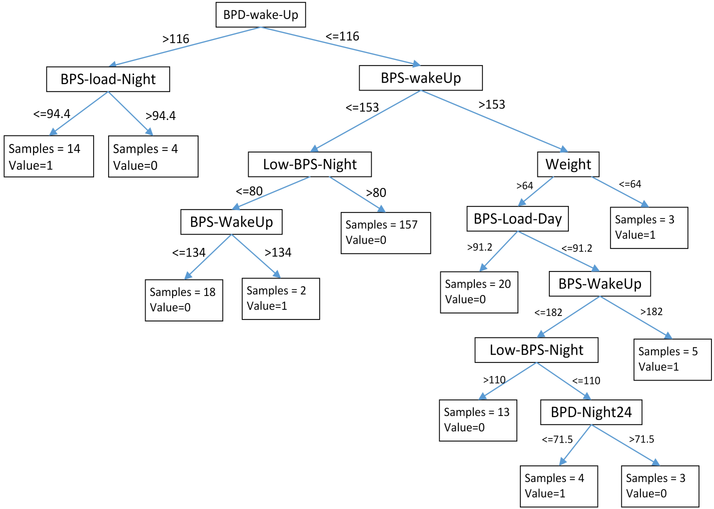

Figure: The Decision Tree for the Morning Surge label

Label correlation Analysis for ABPM dataset

Analysis of label dependencies for ABPM data (1/2)

- We analyze the dependencies between labels to draw conclusions on relationships between *ABPM* labels.
- We propose the idea of dividing the dataset into 15 subsets, for each one we study the Conditional dependence of labels two by two.
- Then, we apply two classifiers on each subset: the *BR* which predicts each label separately and the LP which takes into account the correlations between labels.

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Label correlation Analysis for ABPM dataset

Analysis of label dependencies for ABPM data (2/2)

Table: *Summary Table of the dependencies between the ABPM labels. NC: Not Correlated, PC: Probably Correlated, CCo: Conditionally Correlated, CI: Conditionally Independent.*

	Validity	Circadian Rhythm	BPV	PP	BPL	MS
Validity		NC	NC	NC	NC	NC
Circadian Rhythm			PC	PC	NC	NC
BPV				PC	PC	PC
PP					CI	CI
BPL						CCo
MS						

Part 2: MLC for Ambulatory Blood Pressure Monitoring

Contributions in Brief (1/2) . . .

- The *ABPM* data occupies a central place in the diagnosis and follow-up of the hypertensive patient.
- The traditional analysis is time-consuming.
- An automatic analysis of the *ABPM* data using MLC, to help the expert to exploit and to analyze them easily.

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The study consists of two major parts:

- A new collected dataset in cardiology department of CHU SETIF.
- A comparative study of seven algorithms and the analysis of dependencies labels-attributes and between labels of *ABPM* dataset.
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Part 3: Label Correlation for MLC based Decision Trees

Introduction

- Many researchers highlighted the importance of Label dependence for MLC [Alvares-Cherman et al., 2012].
- Extract new and implicit correlations between labels and features in Medical data.
- The proposed approach should be efficient but also interpretable.

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Introduction: Why Tree-based methods?

- Intuitive and interpretable, the structure can be captured by inexpert users easily.
- Selective, they select the most discriminative features from the data to construct the trees.
- However, they typically are not competitive with the best-supervised approaches in terms of prediction accuracy [James et al., 2013]
- We believe that modeling Label correlation during the Classification process can give an efficient and interpretable model.

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Related Work

Table: Some label correlation approaches based Decision Trees.

Method	Summary	Reference
MLC4.5	Adapt the decision trees C4.5 to multi-labels.	[Clare and King, 2001]
BR	For each label a single decision tree is build seperately.	[Boutell et al., 2004]
ERT	Extremely Randomized trees	[Geurts et al., 2006]
CC	Use a chain of classifiers to deal with label dependence.	[Read et al., 2009]
ML SVM DT	Build DT as ML C4.5 and use at leaves BR classifiers based on SVM.	[Gjorgjevikj et al., 2013]
ML Tree	Consider the tree as hierarchy and use SVM at each node for splitting.	[Wu et al., 2015]

Part 3: Label Correlation for MLC based Decision Trees

Label dependencies in litterature

- Two kinds of Label dependence were defined, namely Conditional and Unconditional (marginal) dependence [Krzysztof et al., 2012].
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The studied methods: BR [Boutell et al., 2004] (1/5)

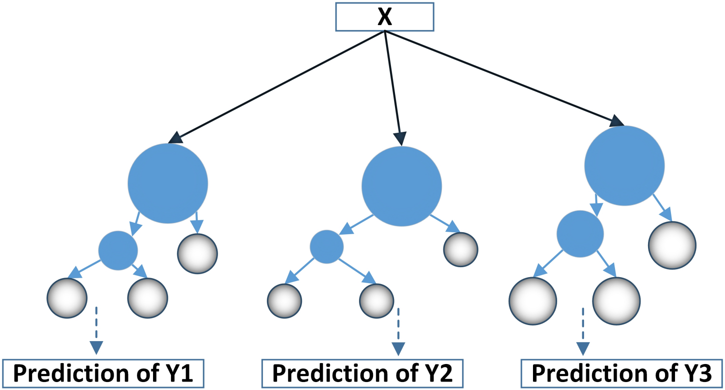

Figure: An illustration of Binary Relevance approach based DT.

Part 3: Label Correlation for MLC based Decision Trees

The studied methods: CC, ECC [Read et al., 2009] (2/5)

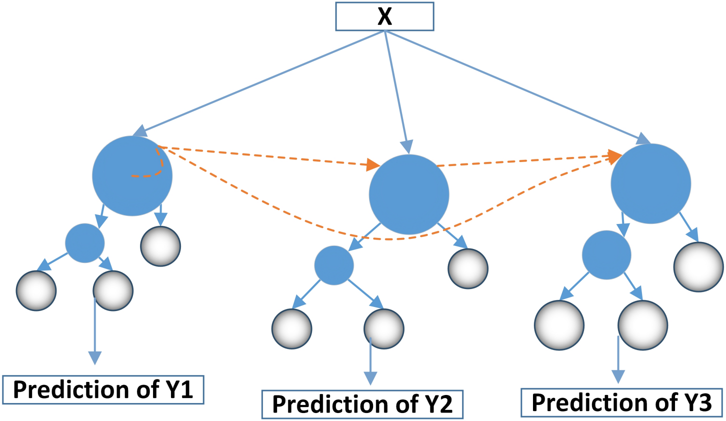

Figure: An illustration of Classifier Chain based DT.

Part 3: Label Correlation for MLC based Decision Trees

The studied methods: ERT (3/5) [Geurts et al., 2006]

- Extremely Randomized Trees (ERT) [Geurts et al., 2006] randomly choose both features and cut point while splitting a Tree node. The authors consider that the main strength of ERT is computational efficiency.

Part 3: Label Correlation for MLC based Decision Trees

The studied methods: MLC4.5 [Clare and King, 2001] (4/5)

- In [Clare and King, 2001] the authors adapted C4.5 to the Multi-label by computing separately the Entropy for each label, and then sums all Entropies to decide to split or not at each node of the Tree.
- The main advantage is the identification of relevant features to all labels at once, nevertheless, the splitting criterion does not consider any Label correlation.

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The studied methods: LaCova [Al-Otaibi et al., 2014] (5/5)

- **LaCova** is A tree-based multi-label classifier that use label covariance as splitting criterion.
- The key idea is a splitting criterion based on the label covariance matrix at that node, which allows to choose between a horizontal split (branching on a feature) and a vertical split (separating the labels).

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	Datasets/Algorithms	BR	CC	ECC	ERT	MLC4.5	LaCova
Accuracy↑	Yeast	0.449(2)	0.433(3)	0.494(1)	0.388(6)	0.391 (5)	0.393(4)
	Scene	0.407(4)	0.466(1)	0.408(3)	0.166(6)	0.299(5)	0.460(2)
	Emotions	0.456(4)	0.493(1)	0.485(2)	0.364(6)	0.462(3)	0.367(5)
	Genbase	0.983(1)	0.982(2)	0.983(1)	0.039(5)	0.190(4)	0.793(3)
	Medical	0.757(3)	0.771(2)	0.773(1)	0.131(5)	0.116(6)	0.714(4)
	ABPM	0.977(3)	0.978(2)	0.983(1)	0.748(6)	0.758(5)	0.785(4)
	Average Rank	2.83(3)	1.83(2)	1.5(1)	5.66(6)	4.66(5)	3.66(4)

	Datasets/Algorithms	BR	CC	ECC	ERT	MLC4.5	LaCova
Exact Match↑	Yeast	0.073(3)	0.141(2)	0.151(1)	0.062(4)	0.050 (5)	0.048(6)
	Scene	0.328(3)	0.396(1)	0.329(2)	0.161(6)	0.280(4)	0.260(5)
	Emotions	0.180(4)	0.222(2)	0.226(1)	0.156(5)	0.0254(6)	0.190(3)
	Genbase	0.965(1)	0.963(2)	0.965(1)	0.027(5)	0.176(4)	0.777(3)
	Medical	0.667(3)	0.696(1)	0.695(2)	0.105(5)	0.089(6)	0.634(4)
	ABPM	0.918(3)	0.922(2)	0.940(1)	0.244(6)	0.259(5)	0.303(4)
	Average Rank	2.83(3)	1.66(2)	1.33(1)	5.16(6)	5(5)	4.16(4)

	Datasets/Algorithms	BR	CC	ECC	ERT	MLC4.5	LaCova
Hamming Loss ↓	Yeast	0.220(1)	0.221(2)	0.229(5)	0.226(3)	0.239(6)	0.228(4)
	Scene	0.154(1)	0.171(3)	0.180(4)	0.165(2)	0.184(5)	0.235(6)
	Emotions	0.245(2)	0.241(1)	0.250(3)	0.267(5)	0.245(2)	0.261(4)
	Genbase	0.0018(2)	0.0019(3)	0.0016(1)	0.043(6)	0.040(5)	0.017(4)
	Medical	0.0105(3)	0.0102(2)	0.0101(1)	0.0259(6)	0.0252(5)	0.014(4)
	ABPM	0.0179(3)	0.0172(2)	0.013(1)	0.201(6)	0.196(5)	0.163(4)
	Average Rank	2(1)	2.16(2)	2.5(3)	4.66(5)	4.66(5)	4.33(4)

Part 3: Label Correlation for MLC based Decision Trees

Results & discussion

- We note that ECC and CC based Decision Trees outperform other algorithms.
- By comparing results from MLC4.5 and ERT, Information Gain as a splitting criterion is more interesting than the random choice of features for constructing the Tree.

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- Results from CC, ECC and BR that use a Gini index to grow the tree was better than those provided by MLC4.5 base Information gain.
- The choice between the two splitting criteria was widely discussed, many researchers concluded that testing both of them can help to choose the best one.
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Part 3: Label Correlation for MLC based Decision Trees

Contributions in Brief ...

- Two major types of label correlations were highlighted: Conditional and Marginal with their major differences.
- We reviewed recent works addressing this issue based *Transformation* and *Adaptation* algorithms.
- We focused on the use of DT as a base classifier and its main advantages.
- The studied algorithms were tested on ABPM dataset and the results are very promising.
- MLC4.5 and LaCova were developed under python and will be published soon.

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Conclusions & Future Directions (1/5)

Contribution 1

Conclusions

- The improvements of *MLKNN* algorithm [Zhang and Zhou, 2007] that adapts *KNN* to Multi-label data.
- The use of homogeneous Ensemble methods provide competitive results and improve greatly the performance of the individual classifier.

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- The improvement of *Bagged MLKNN* using variable selection methods, to identify relevant variables for each label.
- Evaluate the algorithm on ABPM dataset [Douibi et al., 2017a].

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- Expand ABPM dataset with more instances, by taking the case of Multi-dimensional for *Blood Pressure Load* and *Circadian Rhythm*.
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- Use semi-supervised approaches for the annotation since the manual annotation by the doctor is time and efforts consuming.
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Acknowledgements

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Acknowledgements

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Thank you for your attention !

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Multilabel Evaluation Measures:

Micro-average Vs. Macro-Average (1/2)

- Label-based strategy consists of computing a single label metric for each label based on the number of Tp, Tn, Fp and Fn and then obtaining an average value.
- Two possible averaging strategy known as Micro-average and Macro-average approaches.
- The first one consider predictions of all instances together (aggregating the Tp, Tn, Fp, and Fn values of all classes) and then calculates the measure across all labels.
- the second one computes one metric for each label and then the values are averaged over all the categories

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Multilabel Evaluation Measures:

Micro-average Vs. Macro-Average (2/2)

$B_{Micro} = B(\sum_{i=1}^{q} Tp_i, \sum_{i=1}^{q} Fp_i, \sum_{i=1}^{q} Tn_i, \sum_{i=1}^{q} Fp_i)$

$B_{Macro} = \frac{1}{q} \sum_{i=1}^{q} B(Tp_i, Fp_i, Tn_i, Fn_i)$

Example of Recall over the two approaches:

$Recall_{Micro} = \frac{\sum_{i=1}^{q} Tp_i}{\sum_{i=1}^{q} Tp_i + \sum_{i=1}^{q} Fn_i}$

$Recall_{Macro} = \frac{1}{q} \sum_{i=1}^{q} \frac{Tp_i}{Tp_i + Fn_i}$

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Part 3: Label Correlation for MLC based Decision Trees

The studied methods: LaCova [Al-Otaibi et al., 2014]

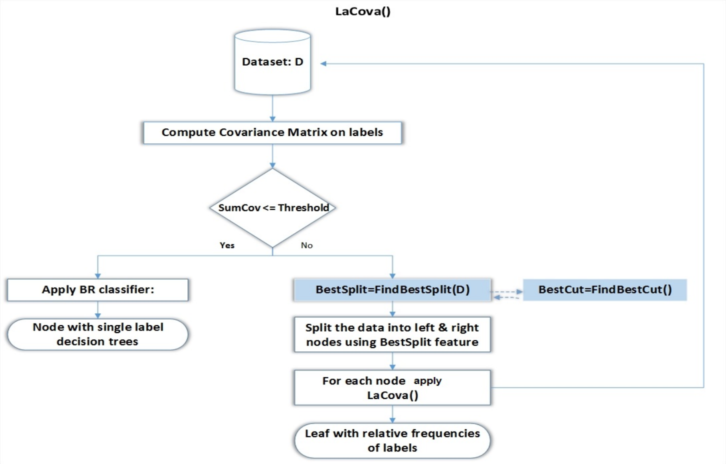

Figure: Steps of Lacova algorithm