

# Multi-Relational Learning with applications to Health

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FCT Fundação para a Ciência e a Tecnologia MINISTÉRIO DA EDUCAÇÃO E CIÊNCIA

# Agenda

- Motivation
- Data in Health x Healthy Data 😳
- Case studies:
  - Breast cancer
  - Heart Diseases in children
- Parallelisation
- Wrap up

### Motivation

is\_malignant(A) :-'BIRADS category'(A,b5), 'MassPAO'(A,present), 'MassesDensity'(A,high), 'HO BreastCA'(A,hxDCorLC), in\_same\_mammogram(A,B), 'Calc\_Pleomorphic'(B,notPresent), 'Calc Punctate'(B,notPresent).

### Motivation

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42 malignant and 11 benign findings (435 total malignant + 65,000 benign)

# Data (in Health)

- Unstructured x Structured
- Different sources of information
- Data from multiple tables
- Different formats

 $\textbf{Data} \rightarrow \textbf{Information} \rightarrow \textbf{Knowledge} \rightarrow \textbf{Understanding} \rightarrow \textbf{Wisdom}$ 

# Some data science principles

- (Medical) systems are complex
- Data is dirty: deal with it!
- SvOT = LoL!
- Data munging, taming and wrestling > 70% time
- Simplification. Reduction. Distillation.
- Curiosity. Empiricism. Skepticism.

(Somehano, DataScience London)

### Learning from data is tricky

Statistics	Vs.	Machine learning
Supervised	Vs.	Unsupervised
Induction	Vs.	Deduction
Correlation	Vs.	Causation
Sampling	&	Confidence intervals
Probability	&	Distribution
Deviation	&	Variance
Causation	&	Prediction

### **Case Studies**

- Breast Cancer Diagnosis
- Cardiac pathology detection



### Breast Cancer: General Scenario



• USA:

- 1 woman dies of breast cancer every 13 minutes
- In 2013:
  - 232.340 invasive cancers
  - 39.620 (≈ 17%) expected to die

Source: U. S. Breast Cancer Statistics – accessed January 2014

- Portugal:
  - Per year:
    - 4500 new cases
    - 1500 deaths (33%)

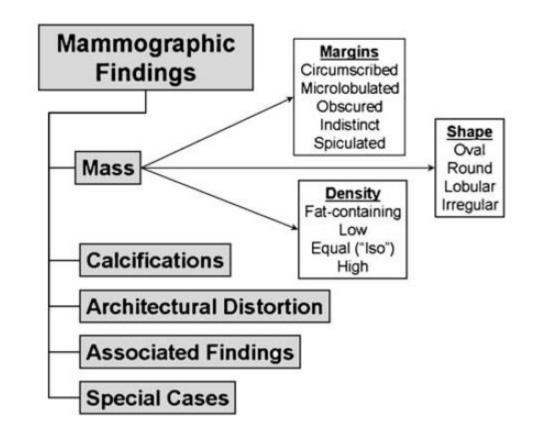
Source: *Liga Portuguesa Contra o Cancro* – accessed January 2014



# BI-RADS<sup>©</sup> Lexicon

Descriptors annotated by a specialist in mammography (X-Ray of the Breast)

- Breast screening
   Cheapest screening method to detect tumours at an early stage
- Image annotated according to the BI-RADS lexicon





### **BI-RADS**<sup>©</sup> categories

- Degree of malignancy of a finding:
  - B1, B2, B3: indicative of a **benign** finding
    B4, B5: indicative of high-risk **malignancy**
- Medical performance:

$$PPV = 0.67 (B5)$$
  
 $PPV = 0.06 (B4)$   
 $PPV = 0.09 (B3)$ 

• in G. Kennedy, et al., "**Predictive value of BI-RADS classification for breast** imaging in women under age **50**", in Breast Cancer Res Treat, 2011.



# What if something suspicious is found?

- Patients need to go through a biopsy
  - Invasive treatment
- Not all biopsies are conclusive!
- General practice: send every patient to excision
  - Less than 15% of patients that go through excision have, in fact, a malignant finding





# Goals

### • To improve:

- classification of malignant and benign tumors
  - MammoClass
  - ILP Rules
  - ExpertBayes
- classification of multiple diseases
  - Not yet approached
- BI-RADS<sup>©</sup> categorization
  - ongoing

# Goals

### • To be able to:

- deal with multiple tables
- correlate multiple exams of the same patient
  - T-SPPA
- reduce the number of patients that go to excision when results of biopsies are inconclusive
- extract BI-RADS<sup>©</sup> features from texts written in Portuguese
- integrate physician advice to the automatic learning process
  - ExpertBayes

# Other goals

- To study the value of information added by features obtained using image processing algorithms
- To produce interactive tools that can be used by specialists



# **Related Projects**

- ABLe: Advice-Based Learning applied to Health Care
  - FCT-funded



- Integrating Machine Learning and Physician Expertise for Breast Cancer Diagnosis
  - NLM-funded (National Library of Medicine)
- QREN (Project 38667) with NLPC
  - Interactive tool for data analysis and discovery







# Tools

- WEKA (Black-box classifiers)
  - Propositional classification algorithms
  - Feature selection
  - Filtering
- Aleph (White-box classifiers)
  - Inductive Logic Programming (ILP)
  - Multi-relational learning
  - First order-logic
  - Interpretable results
- YAP Prolog
  - Efficient implemention of Prolog
  - Several optimizations to ILP
- ExpertBayes (graphical model)
  - In-house implementation of Bayes networks refinements



### MammoClass

# • Online application freely available at:

<u>http://cracs.fc.up.pt/mammoclass/</u>

#### MammoClass

### Classification of a mammogram based in a reduced set of mammography findings

To obtain a prediction in terms of malignancy for a certain mass is only necessary to provide the values of the findings, annotated through the Breast Imaging Reporting and Data System (BIRADS), in the form bellow. It is also possible to get a prediction of the attribute *mass density* in case this feature is not known.

The output will indicate the probability of a certain mass being benign or malignant. In the latter case it is suggested that the patient should perform a biopsy. The probabilities are computed using machine learning models built as described in:

• P.Ferreira, N. A. Fonseca, I. Dutra, R. Woods, and E. Burnside, **Predicting Malignancy from Mammography Findings and Surgical Biopsies** 

#### Enter Data

Patient's age	
Mass size	
Breast Composition	Select a value
Mass shape	Select a value
Mass clockface location	Select a value
Mass margins (1)	Select a value
Mass margins (2)	Select a value

### First-order rules (ILP)

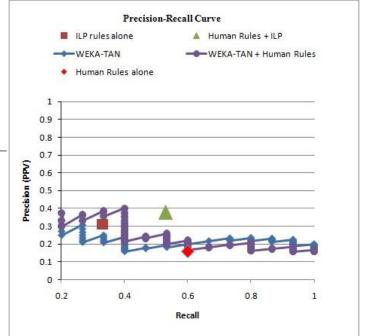
(1) Probability of upgrade increases for stereotactic biopsy if the finding is microcalcifications and biopsy results reveals atypical ductal hyperplasia (ADH)

upgrade(A) IF

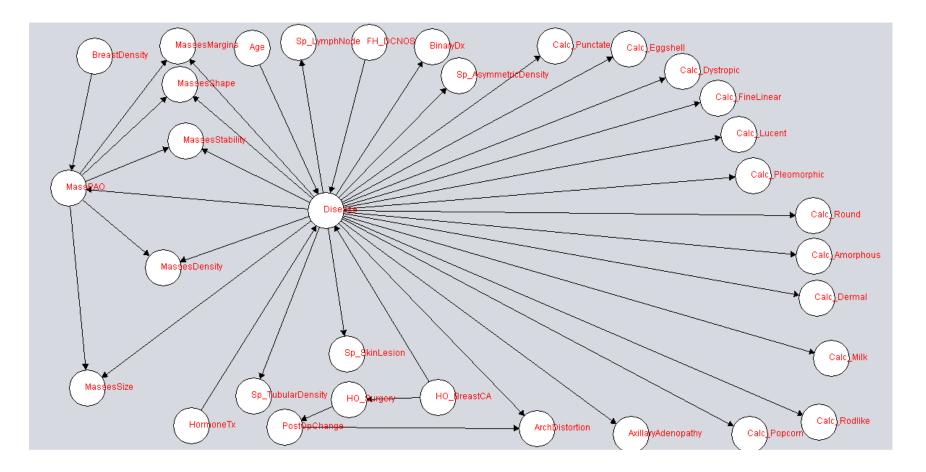
pathDx(A,atypical\_ductal\_hyperplasia), calcifications(A,'a,f') and biopsyProcedure(A, stereo)

(2) Probability of Upgrade increases for ultrasound (US) biopsy if the finding is a mass and biopsy results reveals benign breast tissue upgrade(A) IF

concordance(A,d), biopsyProcedure(A, US\_core) and pathDx(A,benign\_breast\_tissue)



### ExpertBayes





### People

Universidade do Porto	University of Wisconsin Madison	Radboud University Nijmegen
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Joana Côrte-Real		
Gustavo Augusto		
Ricardo Sousa		

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### Heart Diseases in Children



#### Sources:

1) European Society of Cardiology – June 2013

2) Api farma, Portuguese Association of the Pharmaceutical Industry-June 2013

3) Revista Brasileira de Cirurgia Cardiovascular– June 2013

4) Lucile Packard Children's Hospital at Stanford – June 2013

### • 6 million

 children worldwide suffer from heart disease <sup>1</sup>

### • 500

 cardiac surgeries in children per year in **Portugal**<sup>2</sup>

### • 8-10 out of 1000

 babies are born with a congenital heart disease in **Portugal**, **Brazil** and **USA**<sup>2,3,4</sup>



### State of the Art

- [1] D. Aha and D. Kibler, "Instance-based prediction of heart-disease presence with the Cleveland database", tech. rep., University of California, Mar. 1988.
  - Accuracy: 75.7%
- [2] S. M. Kamruzzaman, A. R. Hasan, A. B. Siddiquee, and M. E. H. Mazumder, "**Medical diagnosis using neural network**", in 3rd International Conference on Electrical & Computer Engineering (ICECE), pp. 28–30, Dec. 2004.
  - Accuracy: 87.5%
- [3] B. O'Hora, J. Perera, and A. Brabazon, "Designing radial basis function networks for classification using differential evolution", inProc. International Joint Conference on Neural Networks (IJCNN), pp. 2932 –2937, 2006.
  - Accuracy: 84%
- [4] J. Wu, J. Roy, and W. F. Stewart, **"Prediction modeling using EHR data: Challenges, strategies, and a comparison of machine learning approaches"**, Medical Care, vol. 48, pp. 106–113, Jun. 2010.
  - **detection of heart failure** more than **6 months before** the actual date of clinical **diagnosis**
  - **AUC: 0.77**



## Goals

- Study relations between demographic and physiological features
- Integrate clinical features with features extracted from the heart sounds
  - ongoing
- Build classifiers that, in an automatic way, distinguish between normal and pathological cases
  - ...to support decision during screening
- Create a database for cardiology



## Collaboration

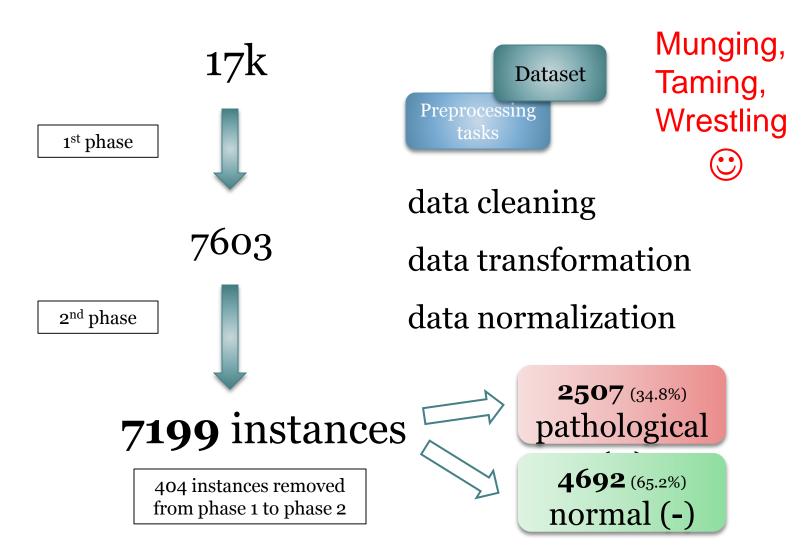




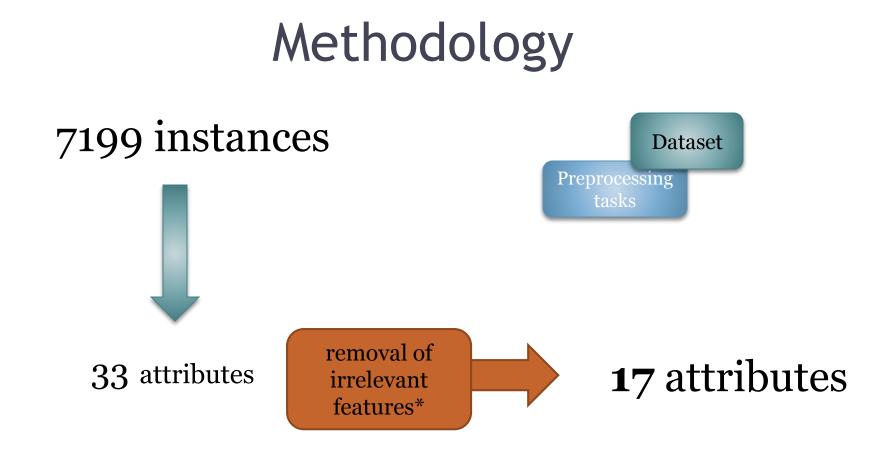
- Recife, Pernambuco Brazil
- Collected between October
   2003 and September
   2009
- [2-19] year old children
  Average age: 8.6 (year)



# Methodology







\* patient ID, name of the physician, health insurance information, etc.



### Methodology

#### Attribute

Height (cm)Weight (kg)SexAge RangeBody Mass Index PercentileSystolic Blood Pressure (SBP)Diastolic Blood Pressure (DBP)Result-SBP-DBPMurmurSecond Heart Sound (S2)

Pulses

Heart Rate (bpm)

Current Disease History 1 (CDH 1)

Current Disease History 2 (CDH 2)

**Primary Reason** 

**Secondary Reason** 

Pathology (class)



### 17 attributes

### Note:

Some of the attributes are **annotations provided by a cardiologist**, not features extracted from the sound wave files



### **Results: Feature Importance**

### All 7199 cases

Feature	Score
Murmur	0.6D
Secondary Reason	0.10
Weight	0.09
Primary Reason	0.05
HR	0.05



# Classification - Results Predicting abnormalities

7199       CCI (%)       93.31       93.32       Best algorithm in all folds: NaiveBayes         7199       Sensitivity       0.85       0.85       1000000000000000000000000000000000000		Metrics	Nested c.v.	internal test	
YI99     Sensitivity     0.85     0.85     folds: NaiveBayes       Specificity     0.98     0.98		CCI (%)	93.31	93.32	Best algorithm in all
	7199	Sensitivity	0.85		
		Specificity	0.98	0.98	
		AUC	0.93	0.93	

	Metrics	Nested c.v.	internal test
109	CCI (%)	91.56	90.53
	Sensitivity	0.72	0.70
	Specificity	0.98	0.97
	AUC	0.85	0.83

• [5] P. Ferreira et al., "**Detecting cardiac pathologies from annotated auscultations**", in Proc. International Symposium on Computer-Based Medical Systems (CBMS), 2012.

# **Related project**

DigiScope



### DigiScope

- Tools:
  - WEKA
  - Aleph
  - YAP Prolog
  - R
  - And yes...Excel!



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Ricardo Sousa		
Pedro Gomes		
Sergio Faria		
Fabio Hedayioglu		
Tiago Silva (past)		
Alípio Jorge		
André Fernandes		

We acknowledge the *Comissão de Ética da Universidade do Porto* and the Real Hospital Português

# Parallelisation

- Map-reduce construct for Prolog
  - Implemented in YAP Prolog
  - User level library
  - Useful to program many applications
  - Shared memory (thread-based)
  - Distributed memory (MPI)
  - Hybrid (ongoing)
  - Dynamic data scheduler

### Some Results: speedups

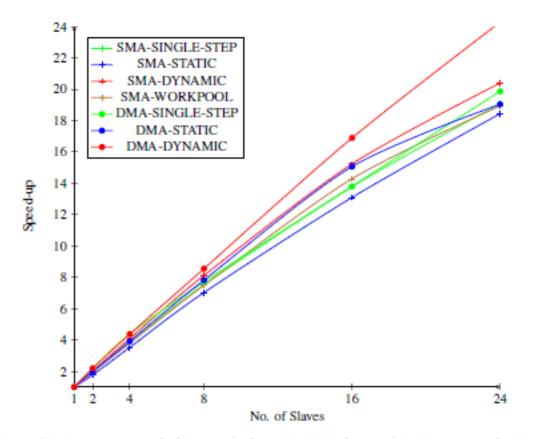


Figure 5.3: Comparison of scheduling methods for MAMMO dataset (600,000 queries and 1,000 elements per chunk)

### Parallelisation

- Datalog for GPUs
  - Implemented in CUDA
  - User level library
  - Conversion of Prolog terms to intermediate numeric representation (for GPU efficiency)
  - Join, select, and other database operations

### Some Results: Execution times

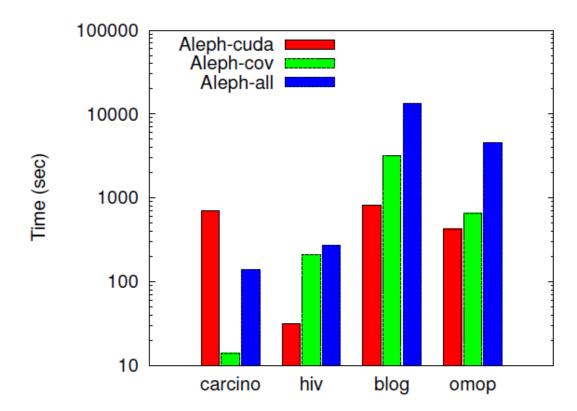


Fig. 5 Applications Total Execution Time for each Aleph version.



### People

Universidade do Porto	Cinvestav, Mexico	Universidade of Aizu
Joana Côrte-Real	Carlos Martínez-Angeles	Hitoshi Oi
Ricardo Rocha	Jorge Buenabad-Chávez	
Vítor Santos Costa		
Inês Dutra		
Alípio Jorge		
André Valente		

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# Parallelization: grid stuff

- Aleph in grids
- Scheduling algorithms and grid portal

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- People:
  - Odair Neves
  - Edgard Neto
  - João Rodrigues
  - Kiran Ali
  - Rafael Nunes
  - Hugo Figueiredo

# Wrap Up

- Various machine learning and statistical methods applied to two medical domains
   Focus on first-order models and graphical models
- Making machine learning efficient
   Parallelization for multicores and GPUs

### We are open to more adventures!

Thank you for your patience!