

# Predicting Malignancy from Mammography Findings and Surgical Biopsies

BIBM 2011 – November 13<sup>th</sup> 2011 – Atlanta, USA



FC FACULDADE DE CIÊNCIAS  
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# Outline

- Breast Cancer
- Objectives
- Data
- Methodology
- Results and Analysis
- *MammoClass* (online application)
- Conclusions and Future Work

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- **Breast Cancer**
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# Breast Cancer



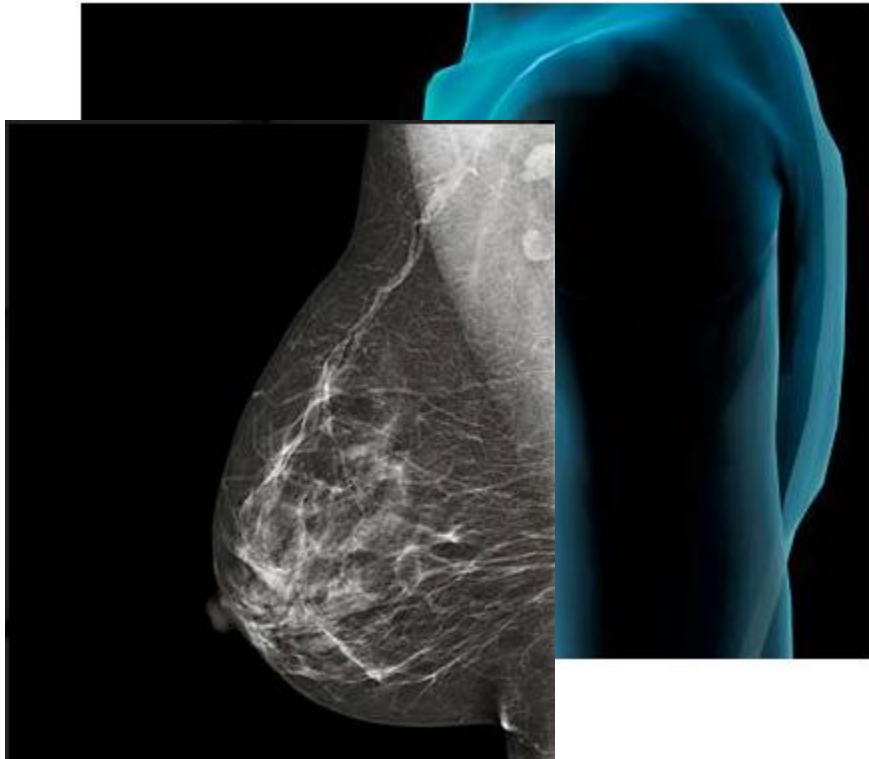
- USA:
  - 1 woman dies of breast cancer every 13 minutes
  - In 2011:
    - 230.480 invasive cancers
    - 39.520 ( $\approx 17\%$ ) expected to die

Source: *U. S. Breast Cancer Statistics* –  
October 2011

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

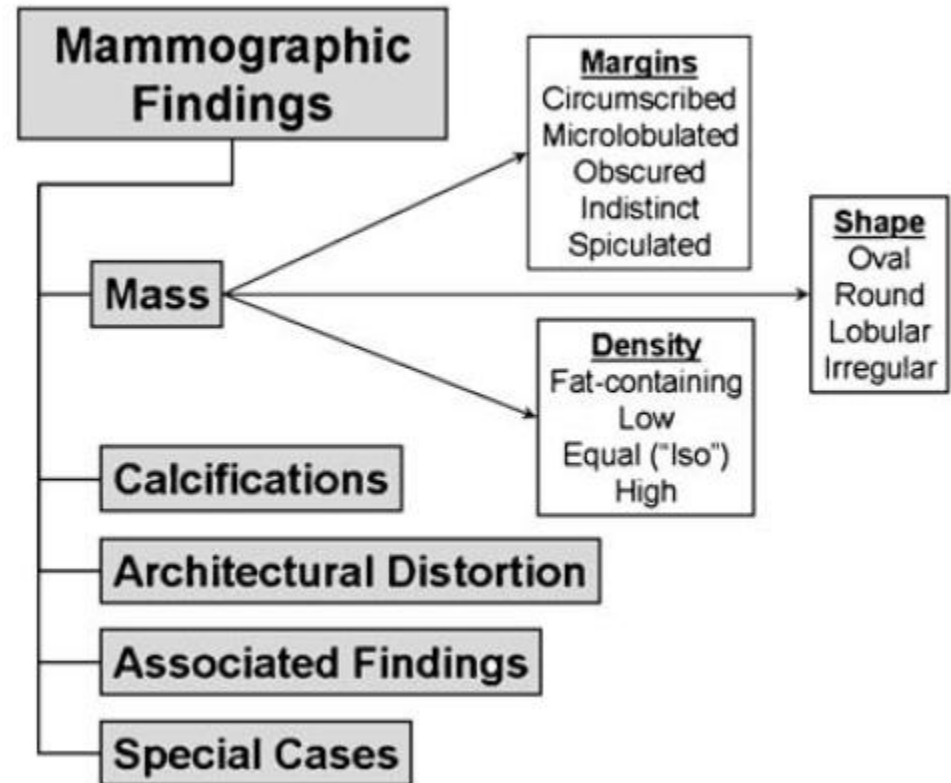
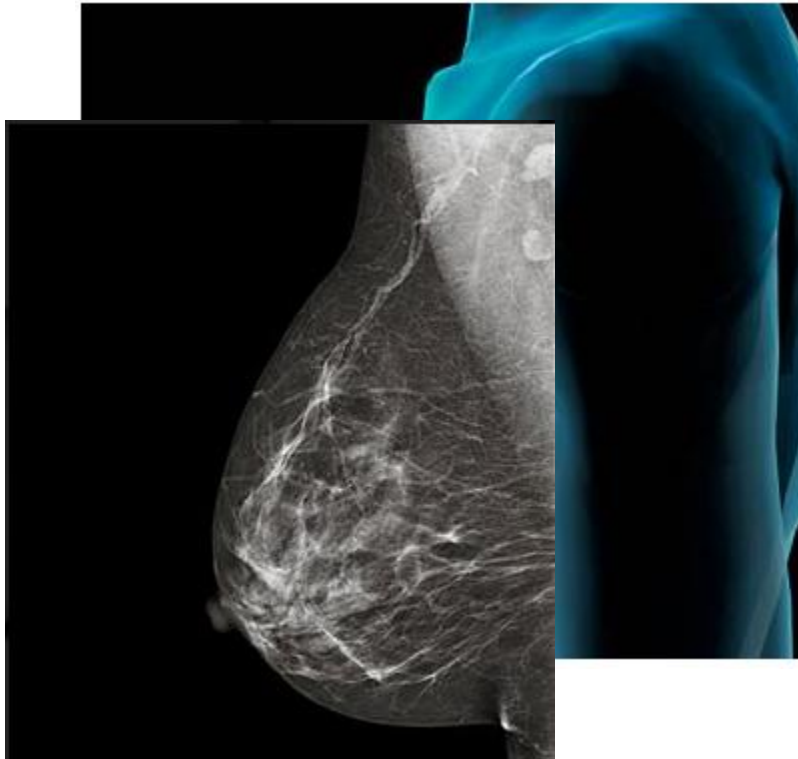
Source: *Liga Portuguesa Contra o Cancro* –  
November 2011

# Breast Screening Programs



- Reduction of death rate in 30%
- **Mammography:**  
The cheapest and most efficient method to detect cancer in a preclinical stage

# Mammography



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in *Studying the relevance of Breast Imaging Features* – HEALTHINF 2011

# Objectives



- Build classifiers capable of predicting **mass density** and **malignancy** from a reduced set of mammography findings



- Reduce the number of unnecessary biopsies



# Outline

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# Data



- Source:
  - Ryan Woods (M.D.)
  - Elizabeth Burnside (M.D.)



- 348 cases
- Each case refers to a breast nodule **retrospectively** classified according to BI-RADS® system
- From mammographies results
- Collected between October 2005 and December 2007

# Attributes

age\_at\_mammo

CLOCKFACE\_LOCATION\_OR\_REGION

MASS\_SHAPE

MASS\_MARGINS

SIDE

DEPTH

MASS\_MARGINS\_worst

QUADRANT\_LOCATION\_def

SIZE

OVERALL\_BREAST\_COMPOSITION

Density\_num

retro\_density

outcome\_num

# Masses classification

## Prospective

- **Classification** of feature **mass density** for **180** cases **just by one radiologist**:
  - low density;
  - iso-dense;
  - high density;
- **Brief** and superficial medical **report** (at the time of imaging);
- **Classification under stress**.



mass density

***density\_num***

## Retrospective

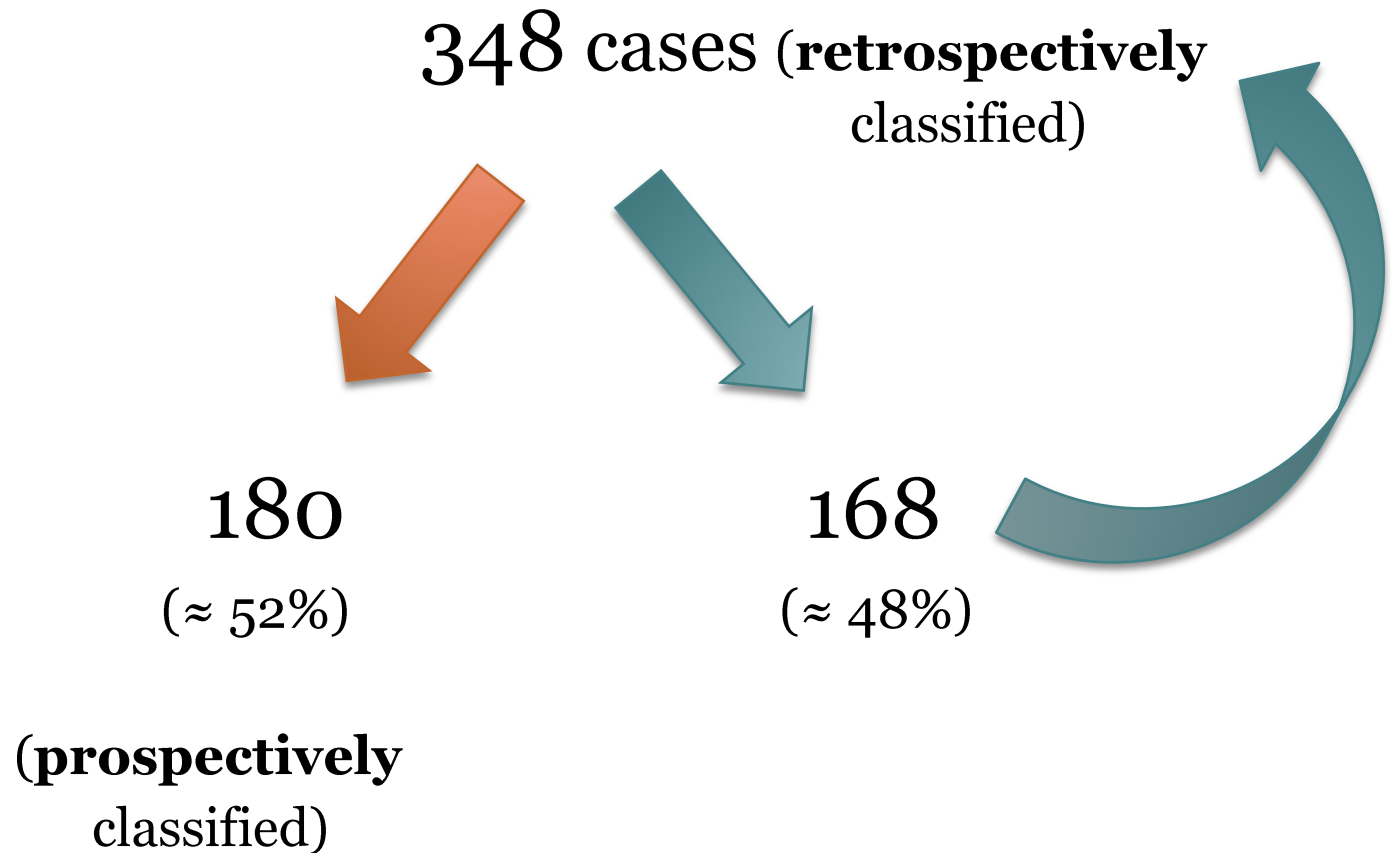
- **Classification** by a **group of experienced physicians** that **re-assess** all exams (**348**);
- **Review of mass density classification** made by radiologist (prospective study);
- **Classification without stress**;
- **Reference standard** for **mass density**.



mass density

***retro\_density***

# Masses classification



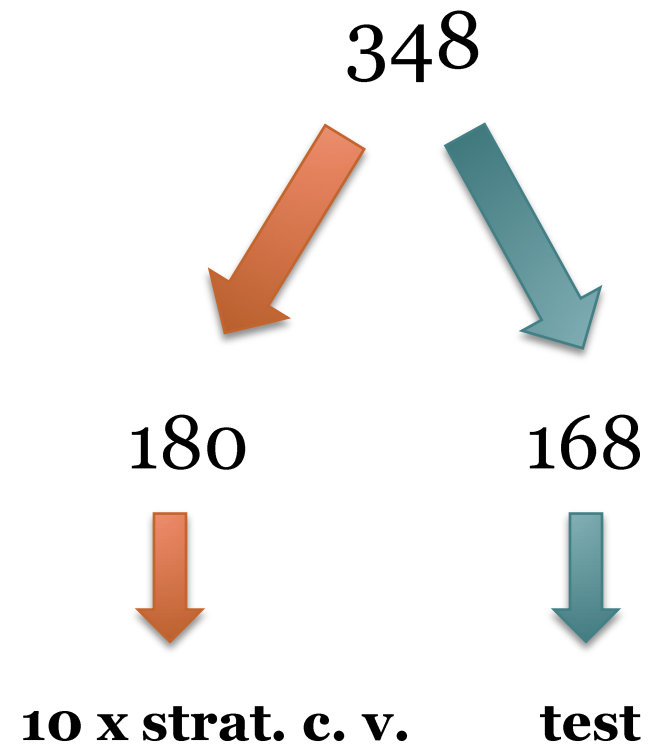
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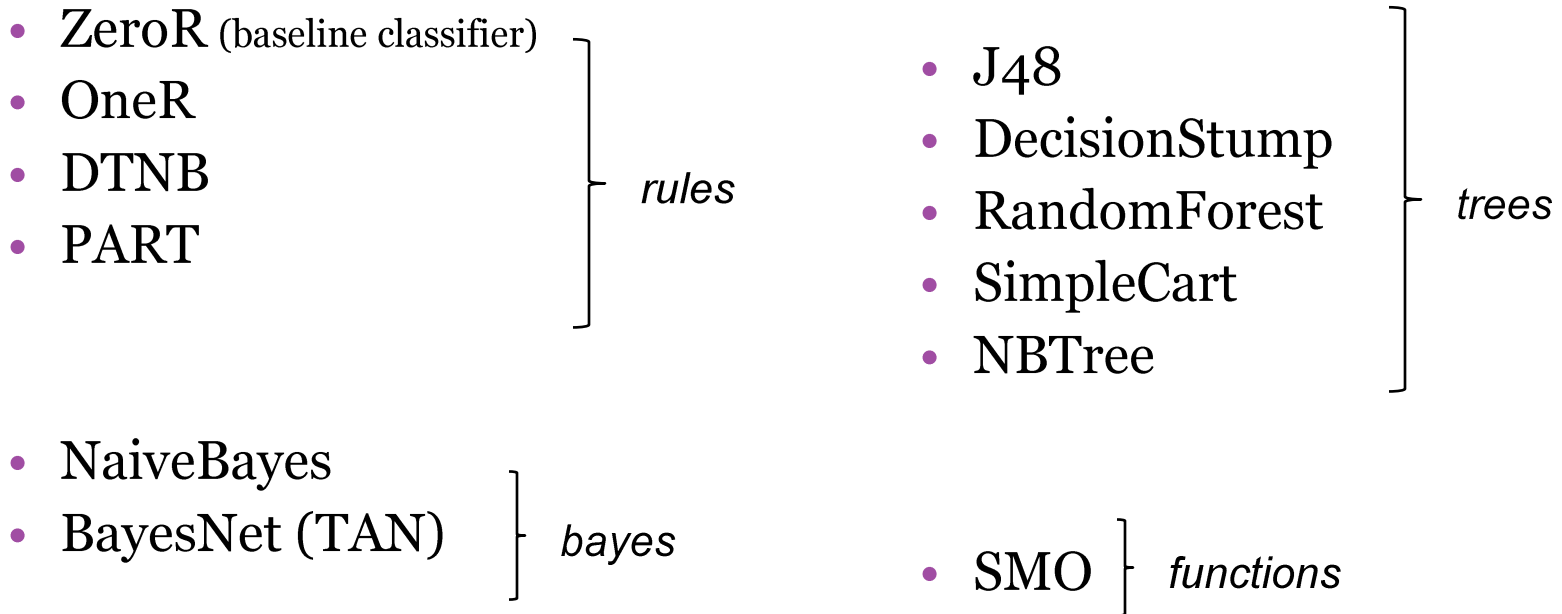
# Methodology



- WEKA
- Paired Corrected T-Tester
  - **Significance level: 0.05**



# Methodology - Algorithms applied



**internal parameter variation**



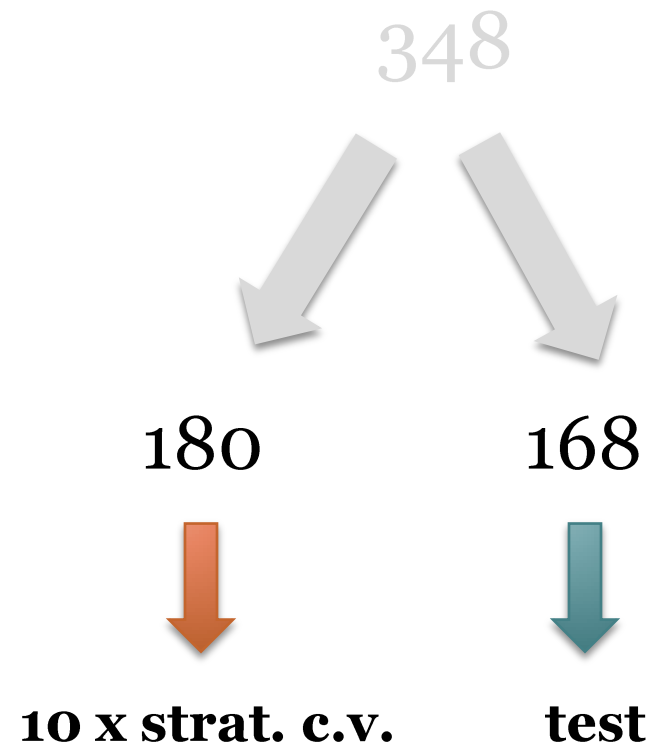
# Methodology - Experiments

**10 x stratified. c. v.**

180

- $E_1$  – Predicting malignancy with *retro\_density*
- $E_2$  – Predicting malignancy with *density\_num*
- $E_3$  – Predicting malignancy without mass density
  
- $E_4$  – Predicting *retro\_density*
- $E_5$  – Predicting *density\_num*

# Results



# Results - Experiments

**10 x stratified. c. v.**

180

Exp.	Algorithm	CCI	K	F	AUROC
E1	SMO	85.6 $\pm$ 7.3	0.69 $\pm$ 0.16	0.80 $\pm$ 0.11	0.84 $\pm$ 0.08
E1	DTNB	81.6 $\pm$ 8.2	0.60 $\pm$ 0.18	0.74 $\pm$ 0.13	0.88 $\pm$ 0.07
E1	NaiveBayes	81.3 $\pm$ 9.5	0.61 $\pm$ 0.20	0.76 $\pm$ 0.12	0.88 $\pm$ 0.08
E1	J48	80.7 $\pm$ 9.3	0.59 $\pm$ 0.20	0.75 $\pm$ 0.13	0.79 $\pm$ 0.11
E2	SMO	83.9 $\pm$ 7.7	0.66 $\pm$ 0.17	0.78 $\pm$ 0.11	0.82 $\pm$ 0.08
E2	NaiveBayes	80.3 $\pm$ 9.3	0.59 $\pm$ 0.19	0.75 $\pm$ 0.12	0.87 $\pm$ 0.09
E2	DTNB	79.8 $\pm$ 9.5	0.56 $\pm$ 0.21	0.72 $\pm$ 0.15	0.86 $\pm$ 0.09
E2	J48	75.4 $\pm$ 9.5	0.47 $\pm$ 0.21	0.65 $\pm$ 0.15	0.73 $\pm$ 0.12
E3	SMO	83.8 $\pm$ 7.7	0.65 $\pm$ 0.17	0.78 $\pm$ 0.11	0.82 $\pm$ 0.09
E3	J48	76.3 $\pm$ 9.9	0.49 $\pm$ 0.22	0.67 $\pm$ 0.15	0.76 $\pm$ 0.13
E3	NaiveBayes	76.2 $\pm$ 9.9	0.51 $\pm$ 0.20	0.71 $\pm$ 0.13	0.85 $\pm$ 0.09
E3	DTNB	75.7 $\pm$ 9.0	0.48 $\pm$ 0.19	0.67 $\pm$ 0.13	0.81 $\pm$ 0.10
E4	SMO	81.3 $\pm$ 8.2	0.52 $\pm$ 0.21	0.64 $\pm$ 0.17	0.75 $\pm$ 0.11
E4	J48	74.4 $\pm$ 8.8	0.32 $\pm$ 0.24	0.47 $\pm$ 0.21	0.67 $\pm$ 0.15
E4	DTNB	73.5 $\pm$ 10.0	0.34 $\pm$ 0.24	0.51 $\pm$ 0.19	0.76 $\pm$ 0.12
E4	NaiveBayes	72.8 $\pm$ 9.9	0.37 $\pm$ 0.23	0.56 $\pm$ 0.18	0.77 $\pm$ 0.11
E5	NaiveBayes	67.2 $\pm$ 12.1	0.33 $\pm$ 0.25	0.62 $\pm$ 0.15	0.72 $\pm$ 0.14
E5	SMO	66.8 $\pm$ 10.7	0.31 $\pm$ 0.22	0.55 $\pm$ 0.16	0.65 $\pm$ 0.11
E5	J48	63.6 $\pm$ 10.1	0.26 $\pm$ 0.21	0.56 $\pm$ 0.15	0.62 $\pm$ 0.13
E5	DTNB	62.1 $\pm$ 11.9	0.22 $\pm$ 0.24	0.54 $\pm$ 0.16	0.64 $\pm$ 0.14

# Results - Experiments

## Predicting density

180

# Results - Experiments

10 x stratified. c. v.

- $E_4$  – Predicting *retro\_density*

SVM's

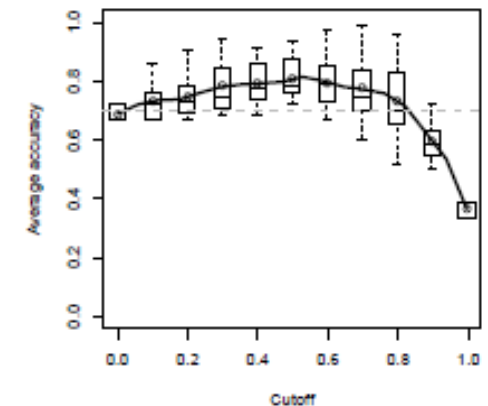
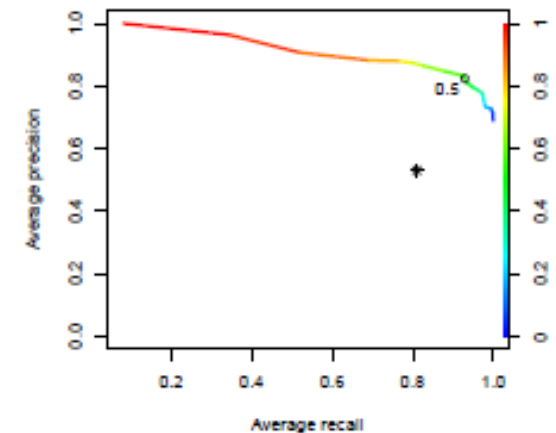
CCI: 81.3% (+/-8.2)

K: 0.52 (+/- 0.21)

F: 0.64 (+/- 0.17)

**Radiologist's accuracy = 70 %**

**Our classifier  $\approx$  81 %**



# Results - Experiments

## TEST

- $E_6$  – Predicting *retro\_density*  
(model  $E_4$  applied)

SVM's

CCI: 84.5%

K: 0.46

F: 0.91

180

SVM's

CCI: 81.3% (+/- 8.2)

K: 0.52 (+/- 0.21)

F: 0.64 (+/- 0.17)

# Results - Experiments

## Predicting malignancy

180

# Results - Experiments

10 x stratified. c. v.

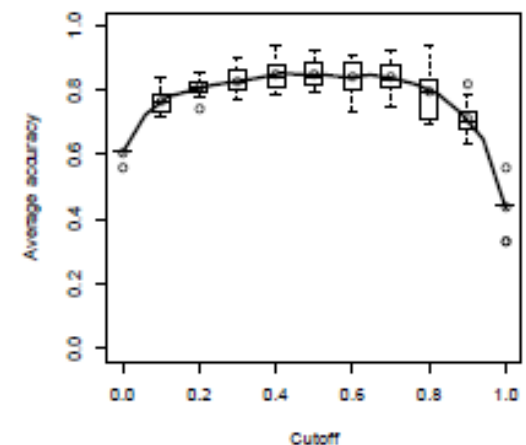
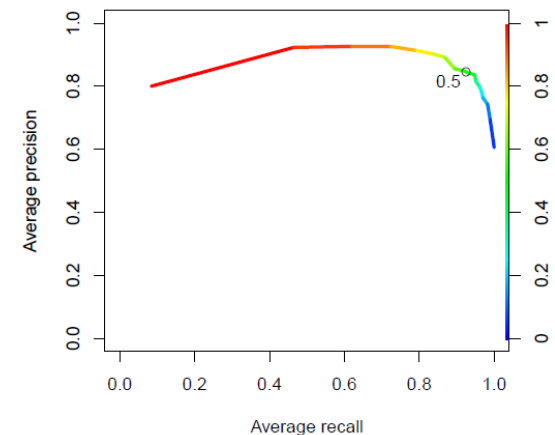
- $E_1$  – Predicting malignancy with *retro\_density*

SVM's

CCI: 85.6% (+/-7.3)

K: 0.69 (+/- 0.16)

F: 0.80 (+/- 0.11)





168

# Results - Experiments

## TEST

180

SVM's

CCI: 85.6% (+/- 7.3)

K: 0.69 (+/- 0.16)

F: 0.80 (+/- 0.11)

- $E_8$  – Predicting malignancy with *retro\_density*  
(model  $E_1$  applied)

SVM's

CCI: 81.0%

K: 0.50

F: 0.87

with **real** values  
of **retro\_density**

SVM's

CCI: 78.0%

K: 0.45

F: 0.85

with **predicted**  
values of  
**retro\_density**  
by classifier  $E_6$

# MammoClass

- Online application freely available at:

□ <http://cracs.fc.up.pt/mammoclass/>



## 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

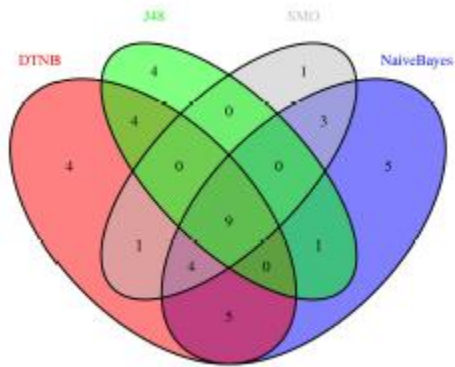
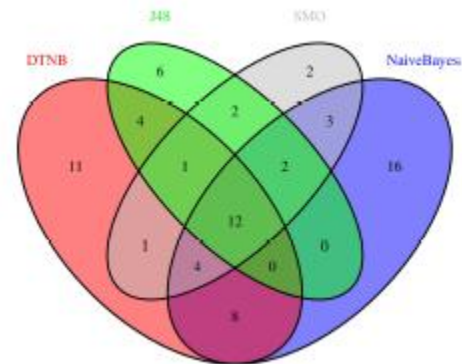
Mass shape

Mass clockface location

Mass margins (1)

Mass margins (2)

# Misclassified Instances


 $E_1$ 

 $E_4$

# Conclusions and Future Work

- a) **Automatic classification** of a mammography can reach **equal or better results** than the classification performed by a **radiologist**;
- b) Machine learning **classifiers** can **predict mass density** with **higher quality** than the one obtained by radiologists
  - a) our classifier can **predict malignancy** in the absence of mass density, since we can **fill up** this **attribute** using our **mass density predictor**.

# Conclusions and Future Work

- a) Apply other machine learning techniques based on statistical relational learning;
- b) Investigate how other features can affect malignancy or are related to the other attributes;
- c) Study why the **parameter variation** on **WEKA algorithms** has a strong **impact** on the **performance** of **classifiers**;
- d) Investigate with the radiologist why some **instances** are **consistently misclassified** by all algorithms.

# Thank you!



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# Appendices

# Methodology

## 10-fold stratified cross-validation

Iteration

1



2



3



4



5



(...)

(...)

Training

Test





# Data distribution

- 348

348	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	59 (70.2%)	59 (22.3%)	<b>118 (33.9%)</b>
<i>benign</i>	25 (29.8%)	205 (77.7%)	<b>230 (66.1%)</b>
Total	<b>84 (24.1%)</b>	<b>264 (75.9%)</b>	

# Data distribution

- 180

180	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	42 (75.0%)	29 (23.4%)	<b>71 (39.4%)</b>
<i>benign</i>	14 (25.0%)	95 (76.6%)	<b>109 (60.6%)</b>
<b>Total</b>	<b>56 (31.1%)</b>	<b>124 (68.9%)</b>	

180	<i>density_num</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	51 (63.0%)	20 (20.2%)	<b>71 (39.4%)</b>
<i>benign</i>	30 (37.0%)	79 (79.8%)	<b>109 (60.6%)</b>
<b>Total</b>	<b>81 (45.0%)</b>	<b>99 (55.0%)</b>	

# Data distribution

- 168

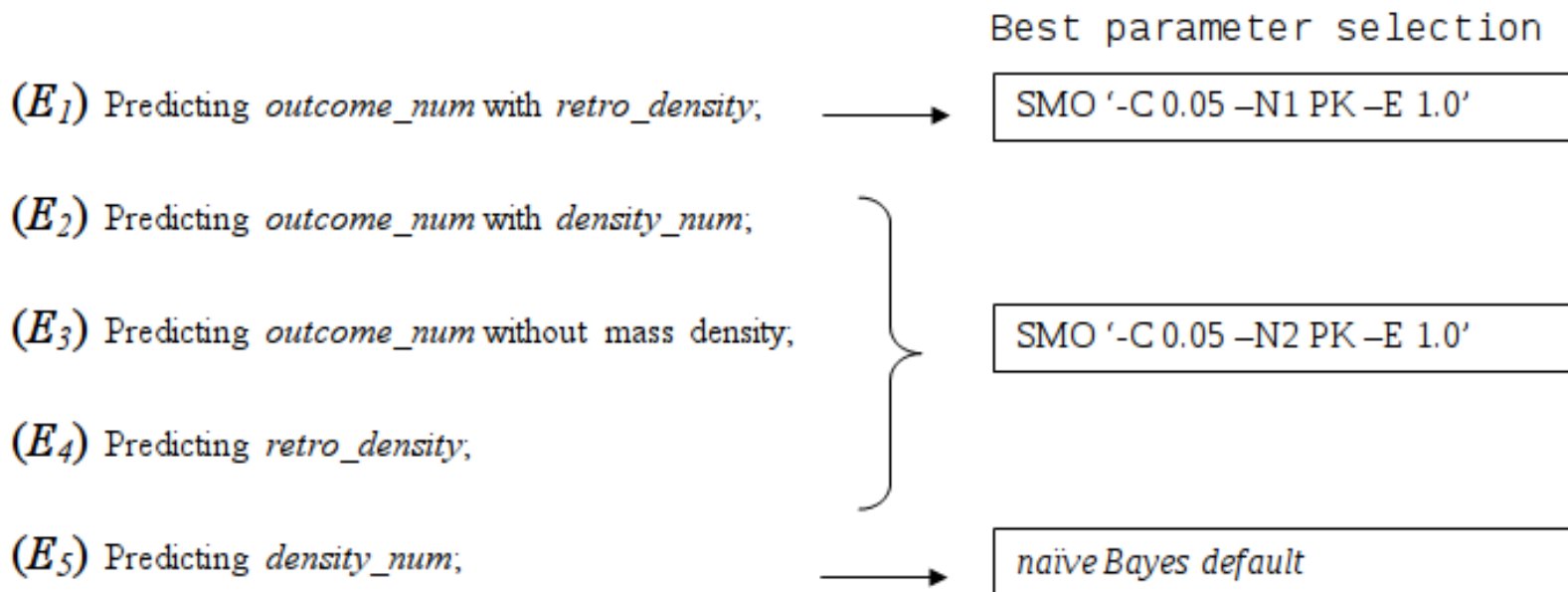
168	<i>retro_density</i>		Total
<i>outcome_num</i>	<i>high</i>	<i>iso</i>	
<i>malignant</i>	17 (60.7%)	30 (21.4%)	<b>47 (28.0%)</b>
<i>benign</i>	11 (39.3%)	110 (78.6%)	<b>121 (72.0%)</b>
Total	<b>28 (16.7%)</b>	<b>140 (83.3%)</b>	

# WEKA algorithms used

CLASSIFIERS' PERFORMANCE FOR EACH TASK. VALUES NOT IN BOLD ARE STATISTICALLY SIGNIFICANTLY WORSE THAN THE CLASSIFIER WITH HIGHEST ACCURACY (USING PAIRED T-TEST WITH  $\alpha = 0.05$ ).

Exp.	Algorithm	CCI	K	F	AUROC
E1	SMO	<b>85.6</b> $\pm 7.3$	<b>0.69</b> $\pm 0.16$	<b>0.80</b> $\pm 0.11$	<b>0.84</b> $\pm 0.08$
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E3	DTNB	75.7 $\pm 9.0$	0.48 $\pm 0.19$	0.67 $\pm 0.13$	<b>0.81</b> $\pm 0.10$
E4	SMO	<b>81.3</b> $\pm 8.2$	<b>0.52</b> $\pm 0.21$	<b>0.64</b> $\pm 0.17$	<b>0.75</b> $\pm 0.11$
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# Parameter variation in WEKA algorithms



## Parameters Selection:

### SMO:

- C (complexity parameter)
- N (filterType)
  - 0 - Normalize training data
  - 1 - Standardize training data
  - 2 - No normalization/standardization
- PK (Poly Kernel)
- E (exponent value)

debug	False
displayModelInOldFormat	False
useKernelEstimator	False
useSupervisedDiscretization	False