Knowledge Discovery from Structured Mammography Reports Using Inductive Logic Programming

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Joint work with

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Objectives

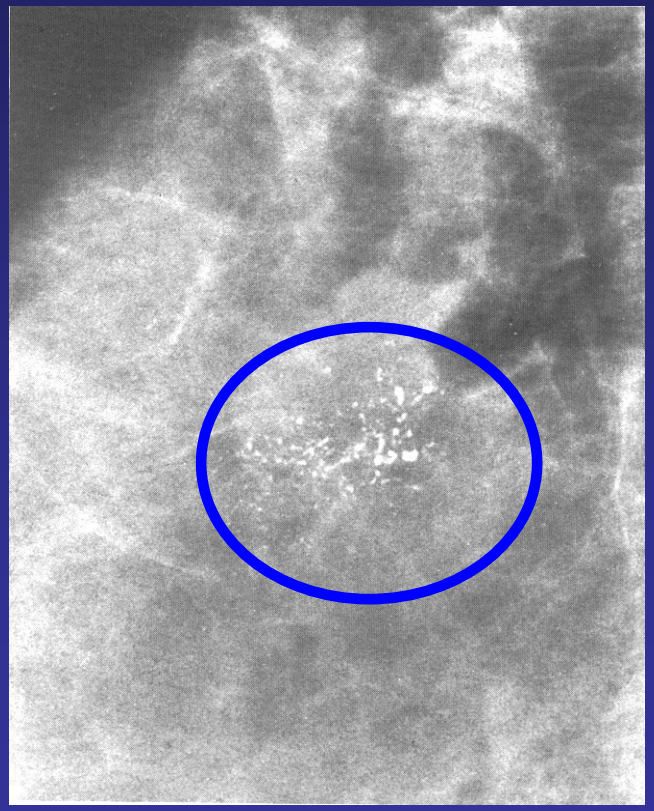
- Knowledge discovery using
  - Demographic information
  - Mammography findings
  - Inductive logic programming (ILP)
- Discuss domain of breast cancer imaging
- Describe Data
- ILP
- Unique features of data discovery in this domain
- Results
- Conclusions

Background

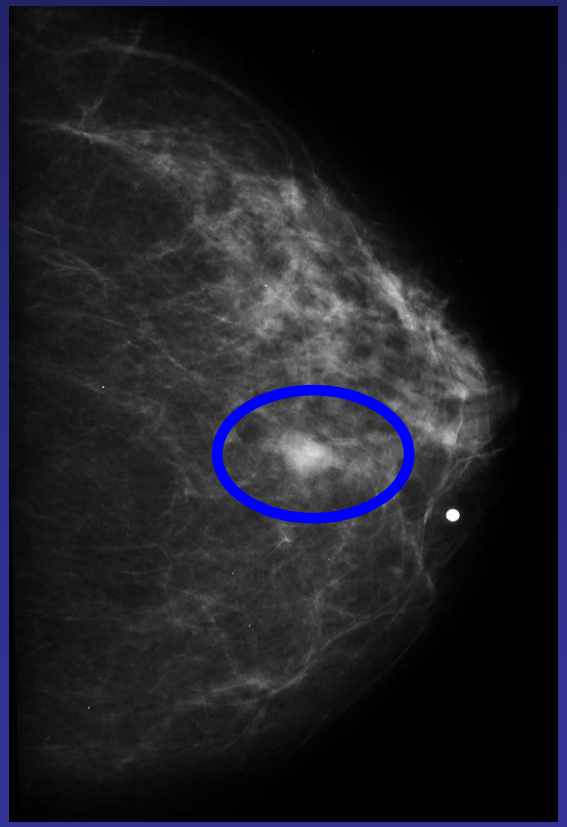
- Breast cancer is the most common cancer
- Mammography is the only proven screening test demonstrated in RCT to improve survival from breast cancer (also the cheapest)
- 20 million mammograms every 2 years

Common Mammogram Findings

Calcifications

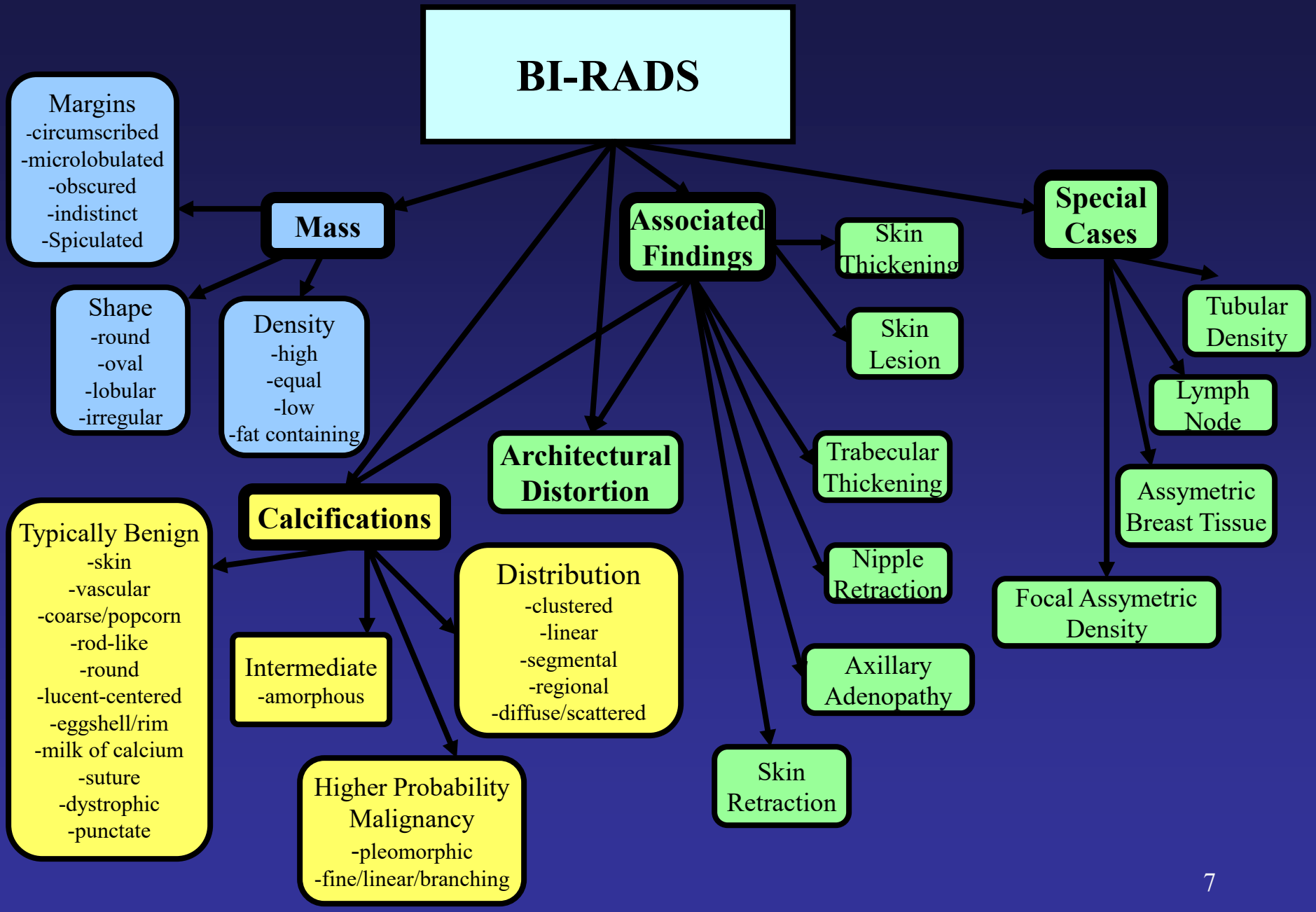


Masses



Mammography Lexicon

- BI-RADS
- A controlled terminology for mammography reporting
- A hierarchy of terms describing features of findings seen on mammograms
- Terms were selected among those most predictive of benign and malignant diseases


BI-RADS
Margins
-circumscribed
-microlobulated
-obscured
-indistinct
-Spiculated
Mass
Shape
-round
-oval
-lobular
-irregular
Density
-high
-equal
-low
-fat containing
Associated Findings
Skin Thickening
Skin Lesion
Special Cases
Tubular Density
Lymph Node
Assymetric Breast Tissue
Focal Assymetric Density
Architectural Distortion
Trabecular Thickening
Nipple Retraction
Axillary Adenopathy
Skin Retraction
Calcifications
Typically Benign
-skin
-vascular
-coarse/popcorn
-rod-like
-round
-lucent-centered
-eggshell/rim
-milk of calcium
-suture
-dystrophic
-punctate
Intermediate
-amorphous
Distribution
-clustered
-linear
-segmental
-regional
-diffuse/scattered
Higher Probability Malignancy
-pleomorphic
-fine/linear/branching

BI-RADS Category

- Decisions are based on category:
  - BI-RADS 0: “Needs Additional Imaging”
  - BI-RADS 1: “Negative”
  - BI-RADS 2: “Benign”
  - BI-RADS 3: “Probably Benign”
  - BI-RADS 4: “Suspicious for malignancy”
  - BI-RADS 5: “Highly suggestive of malignancy”

Data

- National Mammography Database
- Defines a standard for reporting
  - Observed abnormalities on mammograms
  - Structured data that facilitates the use of computer technologies
- Our dataset contains
  - All abnormalities from 1999-2004 at MCW
  - 435 malignancies
  - 65,365 benign abnormalities

Data

Patient information	Abnormality location	Mass descriptors	Calcification descriptors
Age	Side	Shape	Shape
Hormone therapy	Depth	Density	Distribution
Family medical history	Clock location	Margins	Stability
Personal medical history	Quadrant location	Stability	

Mammography Database

Patient	Finding	Date	Calcification Fine/Linear	…	Mass Size	Loc	Benign/ Malignant
P1	1	5/02	No		0.03	RU4	B
P1	2	5/04	Yes		0.05	RU4	M
P1	3	5/04	No		0.04	LL3	B
P2	4	6/00	No		0.02	RL2	B
…	…	…	…		…	…	…

Important Change Over Time

Patient	Finding	Date	Calcification Fine/Linear	…	Mass Size	Loc	Benign/ Malignant
P1	1	5/02	No		0.03	RU4	B
P1	2	5/04	Yes		0.05	RU4	M
P1	3	5/04	No		0.04	LL3	B
P2	4	6/00	No		0.02	RL2	B
…	…	…	…		…	…	…

Inductive Logic Programming (ILP)

- Learn set of rules in 1st order logic
- Rules distinguish between positive and negative examples
- ILP algorithms: **Aleph** (Srinivasan), Progol (Muggleton), FOIL (Quinlan), etc.

Inductive Logic Programming (ILP)

- Assumption 1
  - Background knowledge B
  - Form of a Prolog program

Inductive Logic Programming (ILP)

- Assumption 2
  - Language specification
  - Clause representation

```
is_malignant(A) :-
    'Age'(A,age6570),
    'MassesShape'(A,spiculated),
    'BIRADS_category'(A,b5)
```

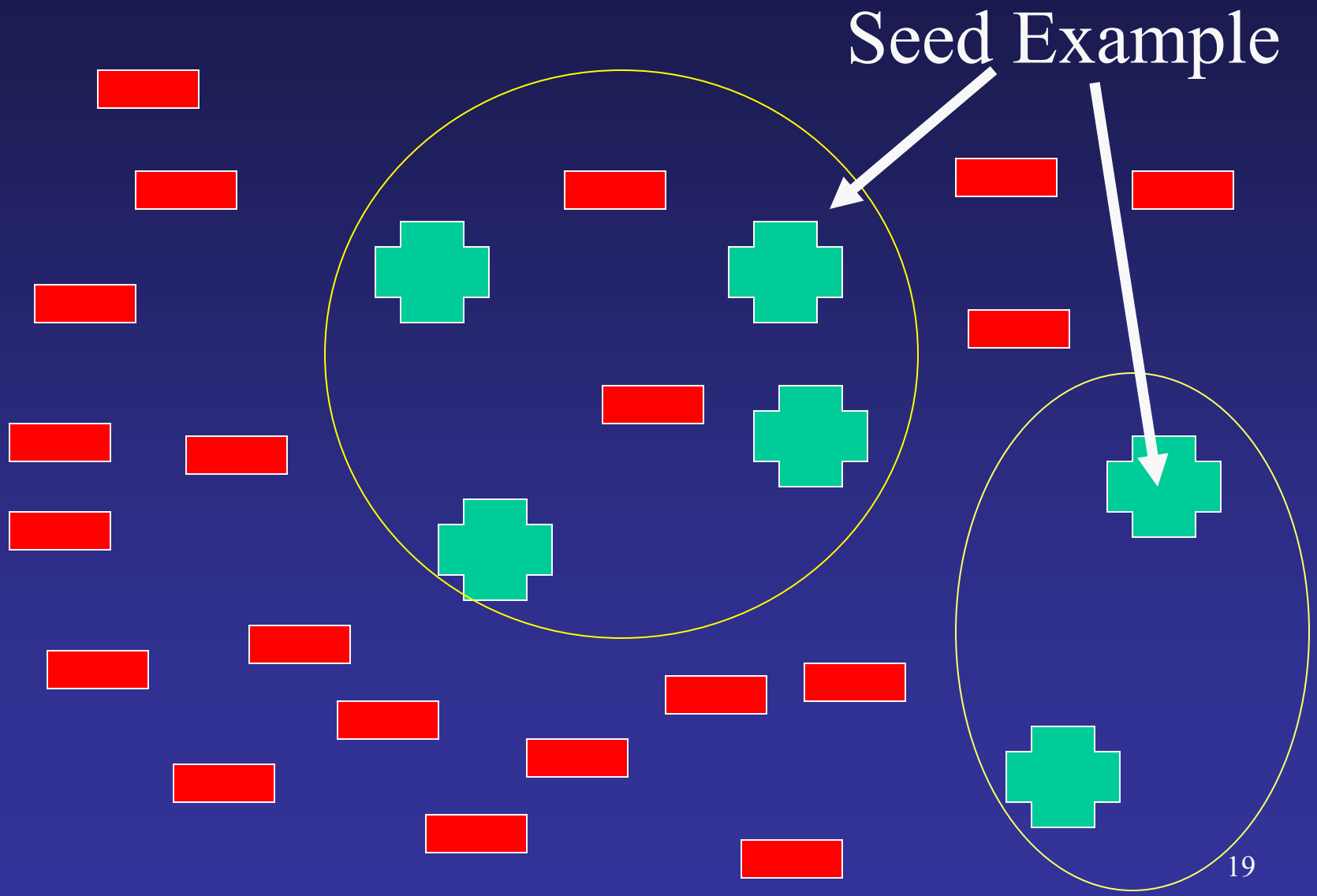
Inductive Logic Programming (ILP)

- Assumption 3
  - Constraints on acceptable clauses
  - Example:
    clause cannot have more than six literals

Inductive Logic Programming (ILP)

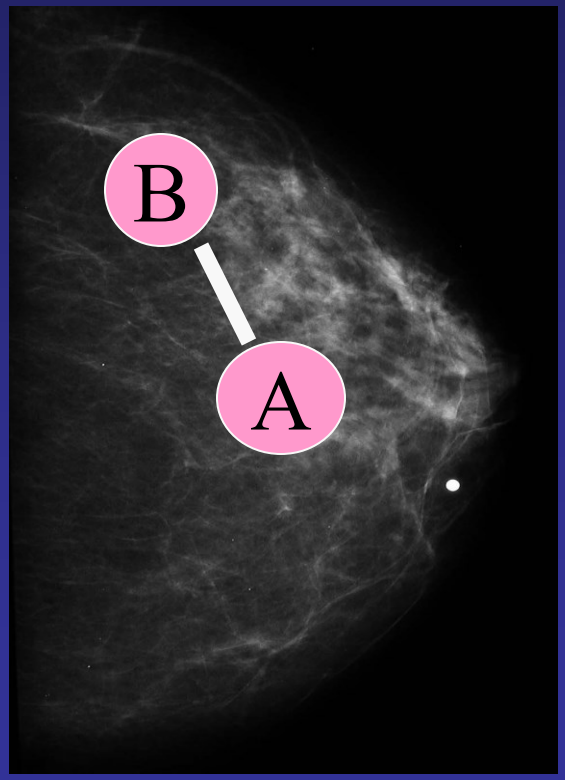
- Assumption 4
  - Finite set of examples
    - E+ are positive examples (malignant)
    - E- are negative examples (benign)

ILP as in Aleph



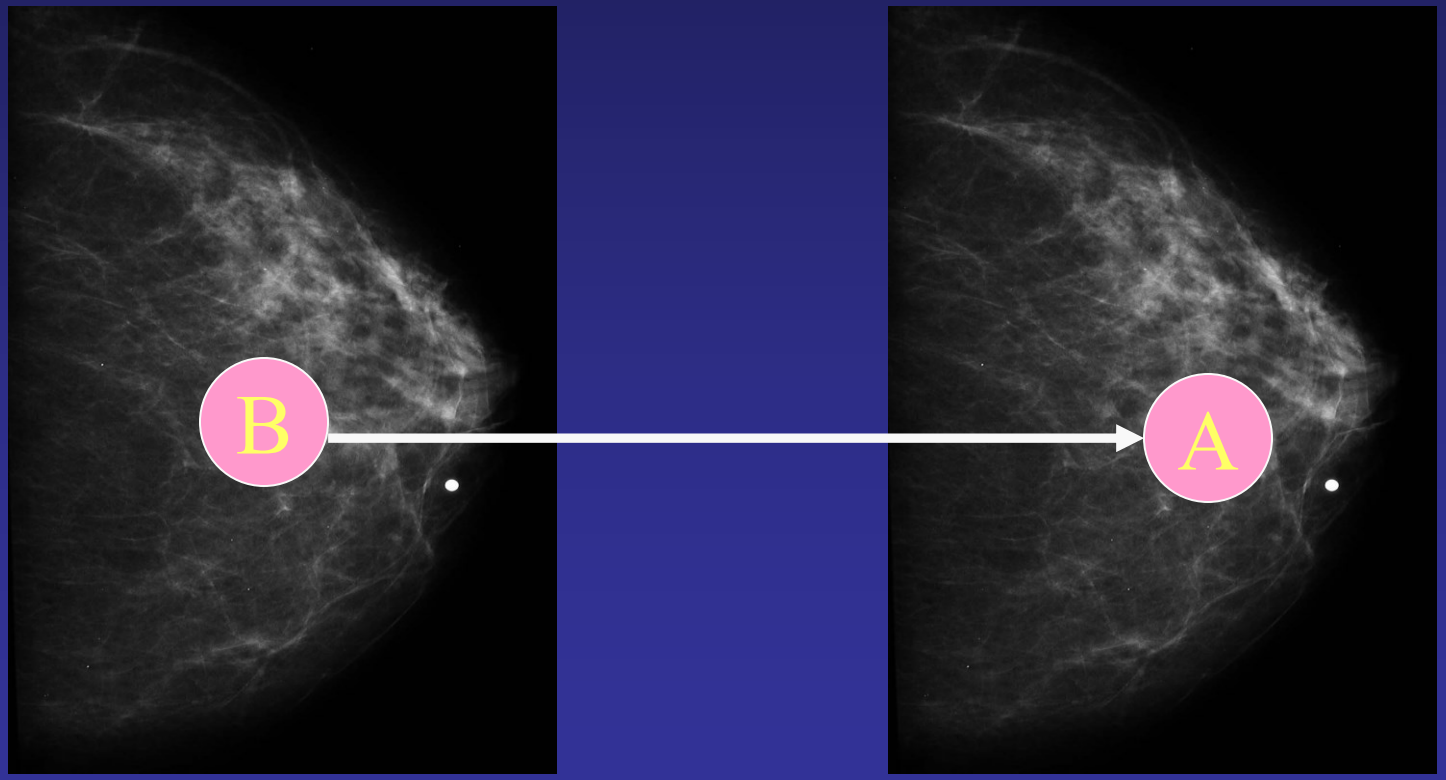
Incorporating related information

in_same_mammogram(A,B)



Incorporating related information

prior_mammogram(A,B)



Results

- Aleph discovered millions of rules
- Evaluated each rule by how well it covered E+ and not E-
- We quantify performance using the m-estimate, a smoothed ratio between the number of positive E+ covered and the total E covered
- Selected the top 130 rules

Review of Results

- Radiologist reviewed these rules
- Found 2 to be interesting
- Significance of these rules was validated using the data

Rule #1

```
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).
```

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```
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    'MassesDensity'(A,high),
    'HO_BreastCA'(A,hxDCorLC),
    in_same_mammogram(A,B),
    'Calc_Pleomorphic'(B,notPresent),
    'Calc_Punctate'(B,notPresent).
```

42 malignant and 11 benign findings

Significance of Rule #1

Mass density has not previously been significantly associated with breast cancer

Jackson VP, Dines KA, Bassett LW, Gold RH, Reynolds HE, Diagnostic importance of the radiographic density of noncalcified breast masses: analysis of 91 lesions. Am J Roentgenol. 1991 Jul;157(1):25-8.

Validity of Result #1

Mass Density	Malignant (%)		Total
Fat-density	0	(0)	493
Low	2	(.1)	3408
Equal	17	(3.3)	513
High	103	(31.7)	324
Total	122	(2.6)	4738

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Rule #2

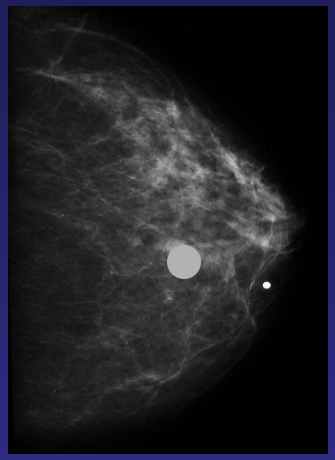
```
is_malignant(A) :-
    'BIRADS_category'(A,b5),
    'Mass'(A,present),
    'Age'(A,age6570),
    previous_finding(A,B),
    'Calc_Punctate'(B,notPresent),
    'BIRADS_category'(B,b3).
```

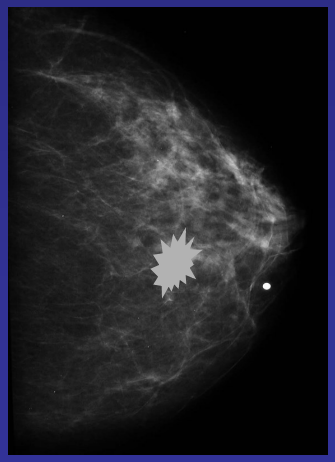
Rule #2

```
is_malignant(A) :-
    'BIRADS_category'(A,b5),
    'Mass'(A,present),
    'Age'(A,age6570),
    previous_finding(A,B),
    'Calc_Punctate'(B,notPresent),
    'BIRADS_category'(B,b3).
```

7 malignant and 0 benign findings

Significance of Rule #2

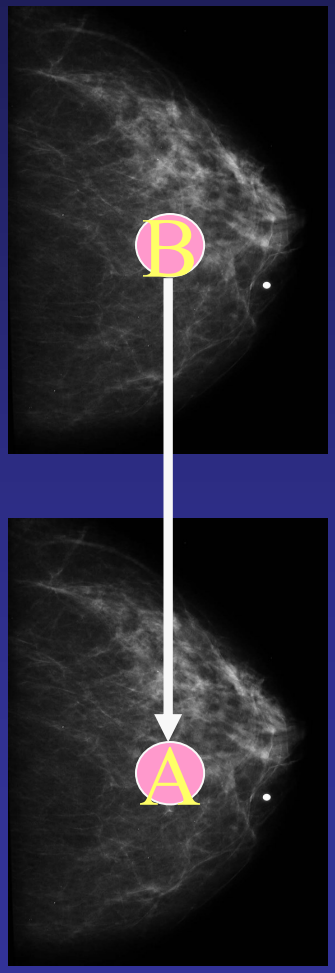




BI-RADS 3:
Probably Benign

BI-RADS 5: Highly Suggestive of Malignancy

Significance of Rule #2



BI-RADS 3:
Probably Benign

Delay in Diagnosis!!

BI-RADS 5: Highly Suggestive of Malignancy

Validity of Result #2

Analysing all cases labeled as BI-RADS 3 and later diagnosed with cancer

BI-RADS 3 abnormality					BI-RADS 5 abnormality					
abnormality	side	clock	depth	quad	abnormality	side	clock	depth	quad	match
Clustered calcifications	L	12	M	UO	High density spiculated mass	L	C	M	*	possible
Ill-defined oval mass	R	11	M	UO	High density spiculated mass	R	11	M	UO	**yes**
Oval circumscribed mass	R	12	A	UI	Oval spiculated mass	R	5	P	UI	no
*	R	4	M	*	Round spiculated mass	R	4	M	LI	**yes**
Oval mass	R	12	P	UO	Irregular spiculated mass	R	12	P	UO	**yes**
Ill-defined oval mass	R	2	P	LI	Irregular high density mass	R	2	P	LI	**yes**
*	L	12	M	UO	Irregular spiculated mass	L	1	M	UO	possible

Important: location!

Conclusion

- With large amounts of data, ILP holds significant promise in the domain of mammography to discover novel hypothesis and provide quality assurance.

Thank you!

Connecting Abnormalities

May 2002 Patient 1 May 2004