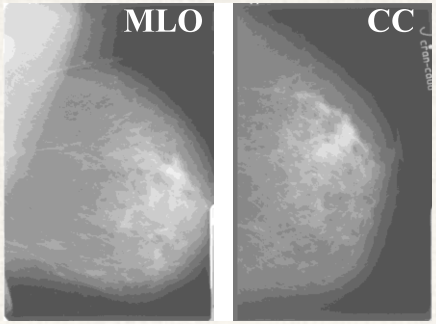

Probabilistic multi-view detection of mammographic findings

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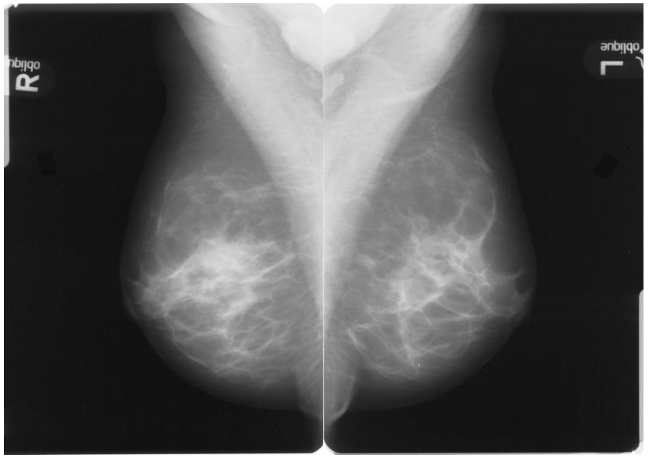
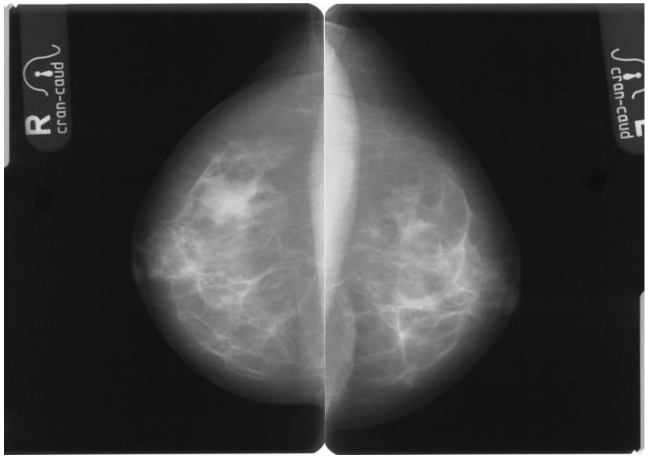
Screening mammograms

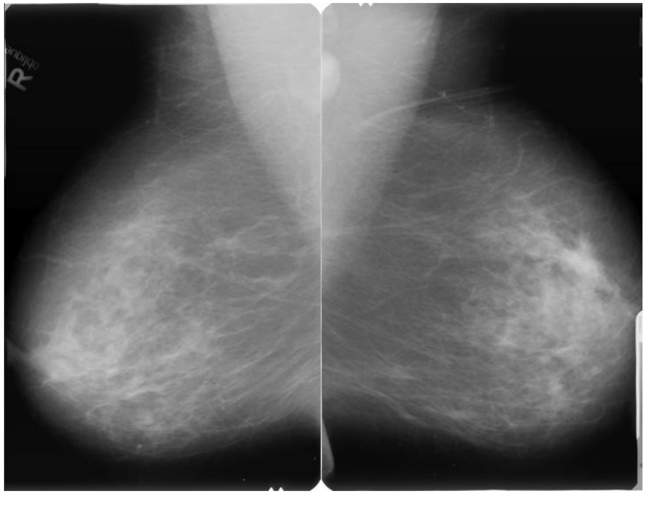
Mediolateral-oblique (MLO) | **Craniocaudal (CC)**

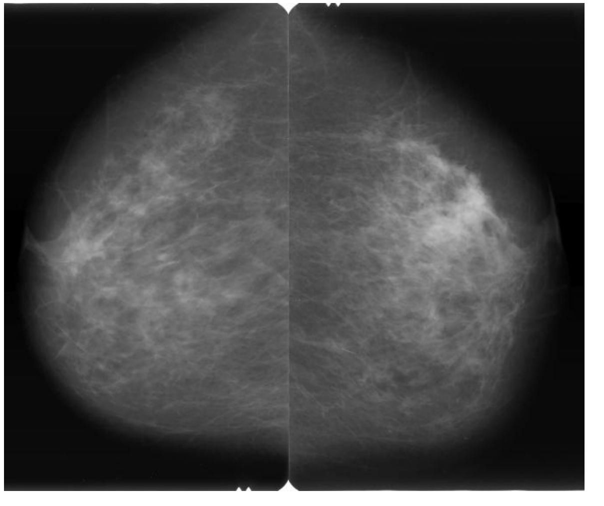
case A





case B



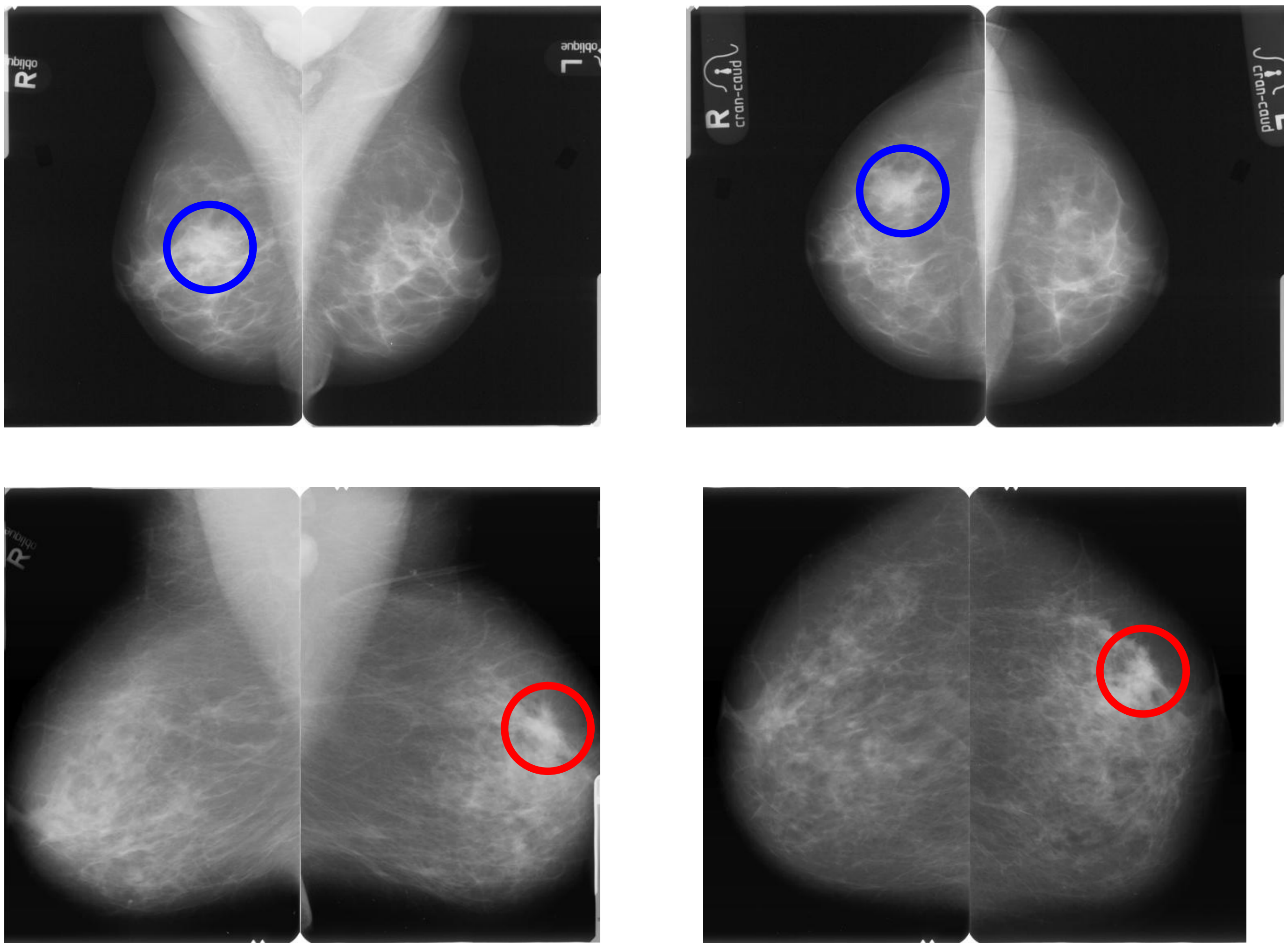


Screening mammograms: Diagnosis

Mediolateral-oblique (MLO) | Craniocaudal (CC)

Benign case A

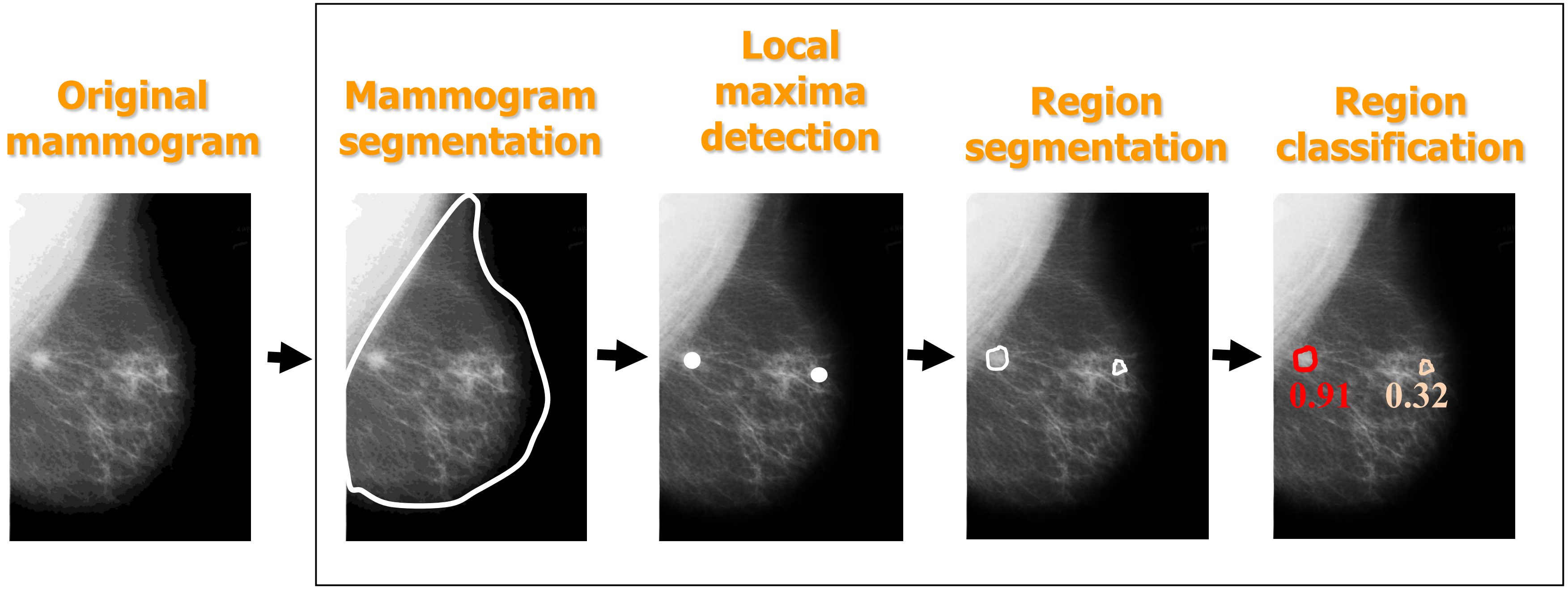
Malignant case B



Screening challenges

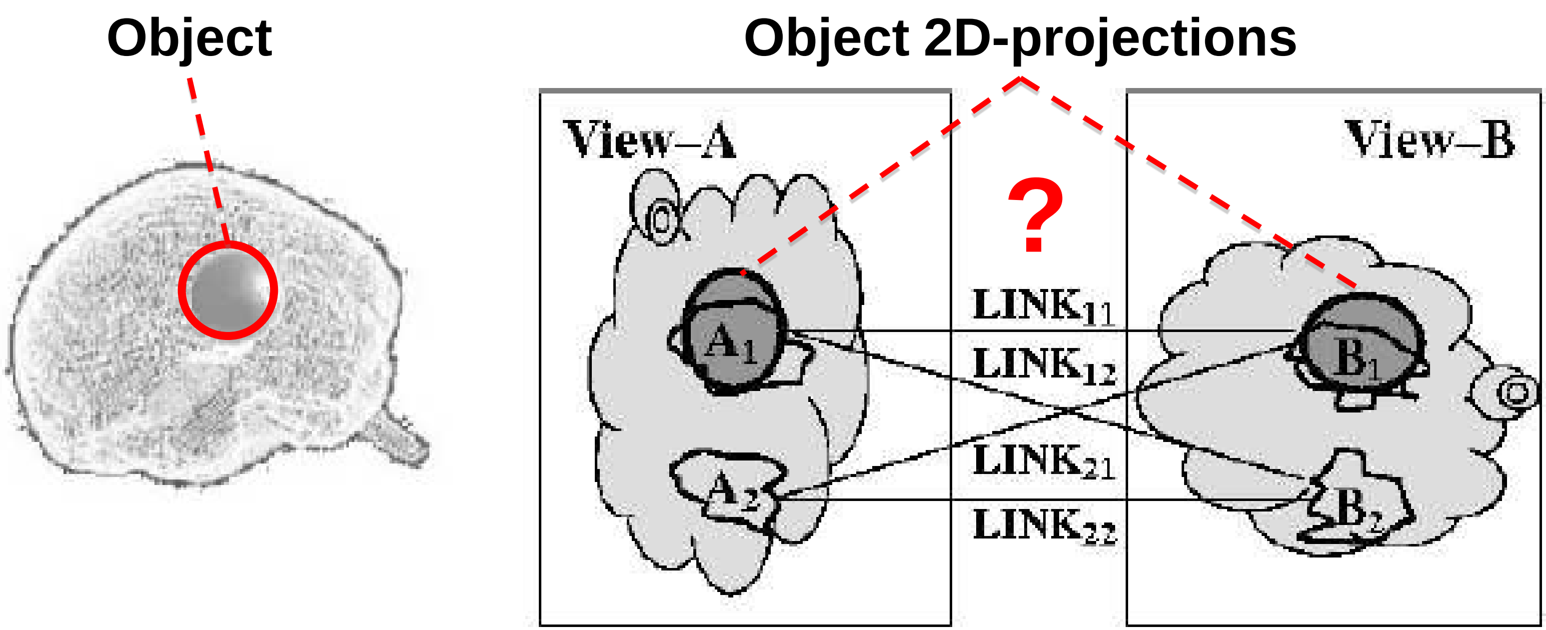
- Complex image interpretation
- High volume and short viewing time
- Extremely low incidence (3-10/1,000)
- **Overlooking**
  - Missed diagnoses (False negatives)
- **Misinterpretation** (more problematic!): abnormalities are seen but their significance is misinterpreted
  - Excessive follow-ups (False positives)
  - Missed diagnoses (False negatives)

Single-view CAD system



- **Region features**: contrast, size, location, margin, etc.
- **Advantage**: a good detection rate per image
- **Shortcoming**: unsatisfactory performance at a patient level – views are treated *independently*

Multi-view image analysis



- A_i, B_j – regions detected from a single-view CAD system
- Class $\mathrm{LINK}_{ij} = \ell_{ij}$ **?**

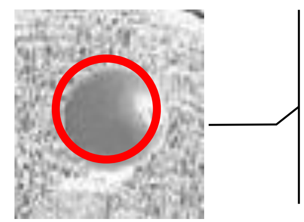
① $\ell_{ij} \in \{\mathrm{TPTP}, \mathrm{TPFP}, \mathrm{FPTP}, \mathrm{FPFP}\}$

② $$\ell_{ij} = \begin{cases} \mathit{true} & \text{if } A_i \textbf{ OR } B_j \text{ are } \textbf{TP}, \\ \mathit{false} & \text{otherwise.} \end{cases}$$

Knowledge & Representation

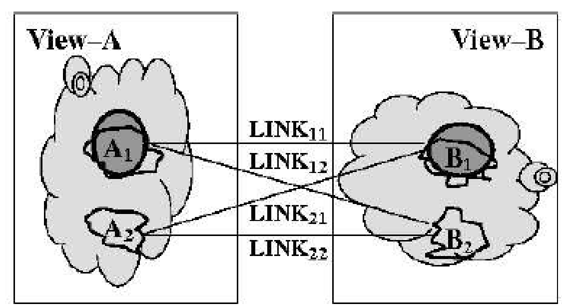
- Uncertainty ➜ **Probability**
- Causal relationships ➜ **Graphical model (Bayesian networks)**
- Two representation approaches:

① Object-feature (**descriptive**)
(as present in the real world)



Size
Margin
Location

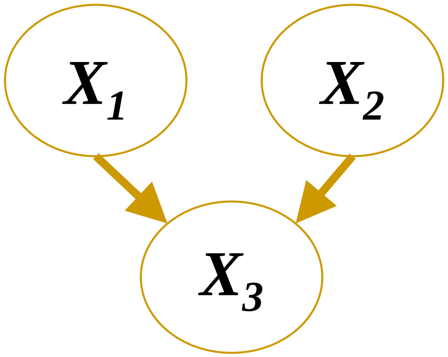
② Region-based (**discriminative**)
(as detected by a CAD system)



Bayesian networks

- A compact specification of full joint distributions
- Syntax:
  - a set of nodes, one per variable
  - a directed, acyclic graph (→ ≈ "direct influences")
  - a conditional distribution for each node X_i given its parents π:

$$P(X_i \mid \pi(X_i))$$



Discrete case: conditional probability table (CPT)

CPT of X_3

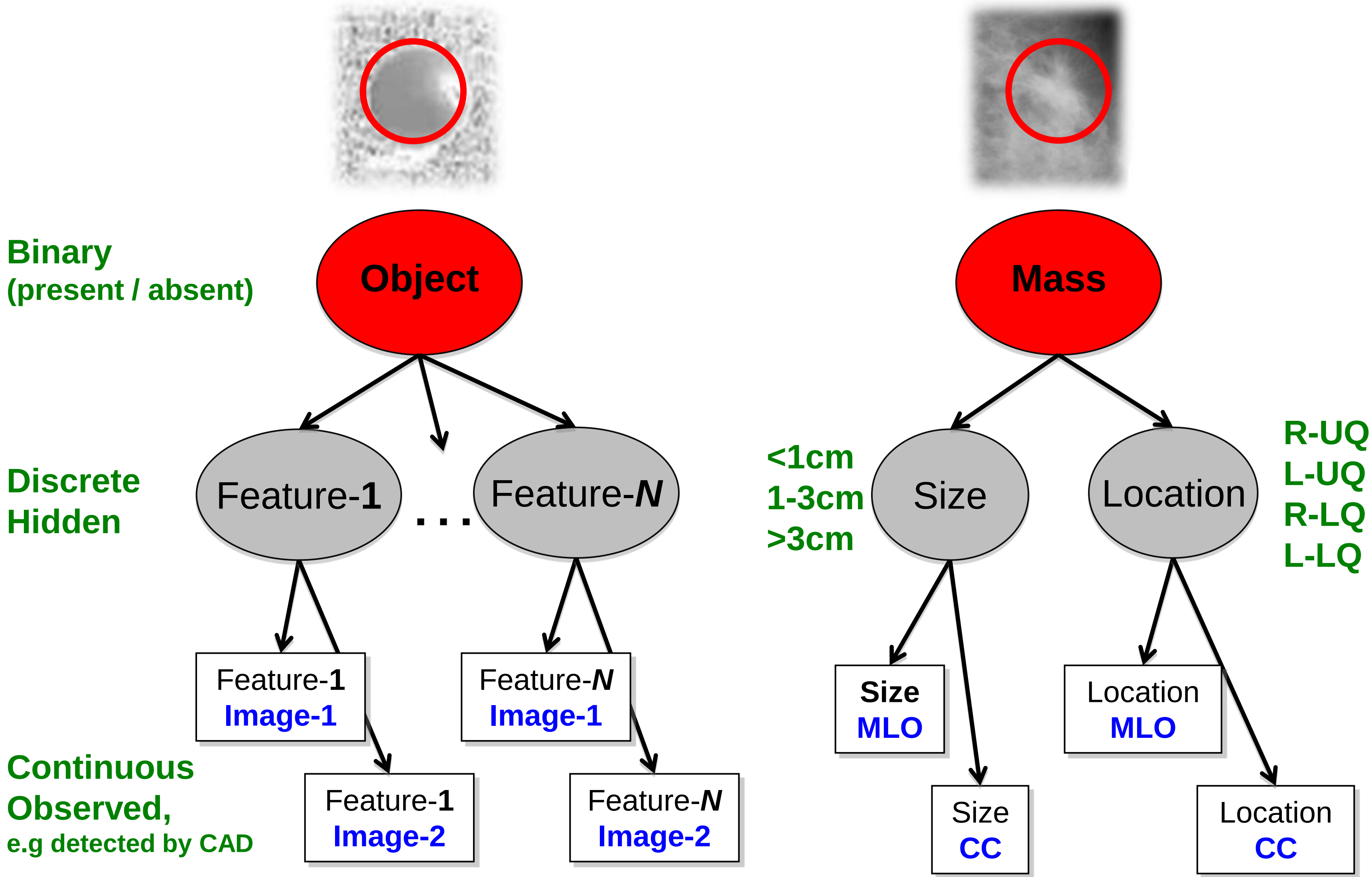
X_1	X_2	$P(X_3 = t \mid X_1, X_2)$
f	*f*	0.03
f	*t*	0.25
t	*f*	0.48
t	*t*	0.76

- Joint distribution:

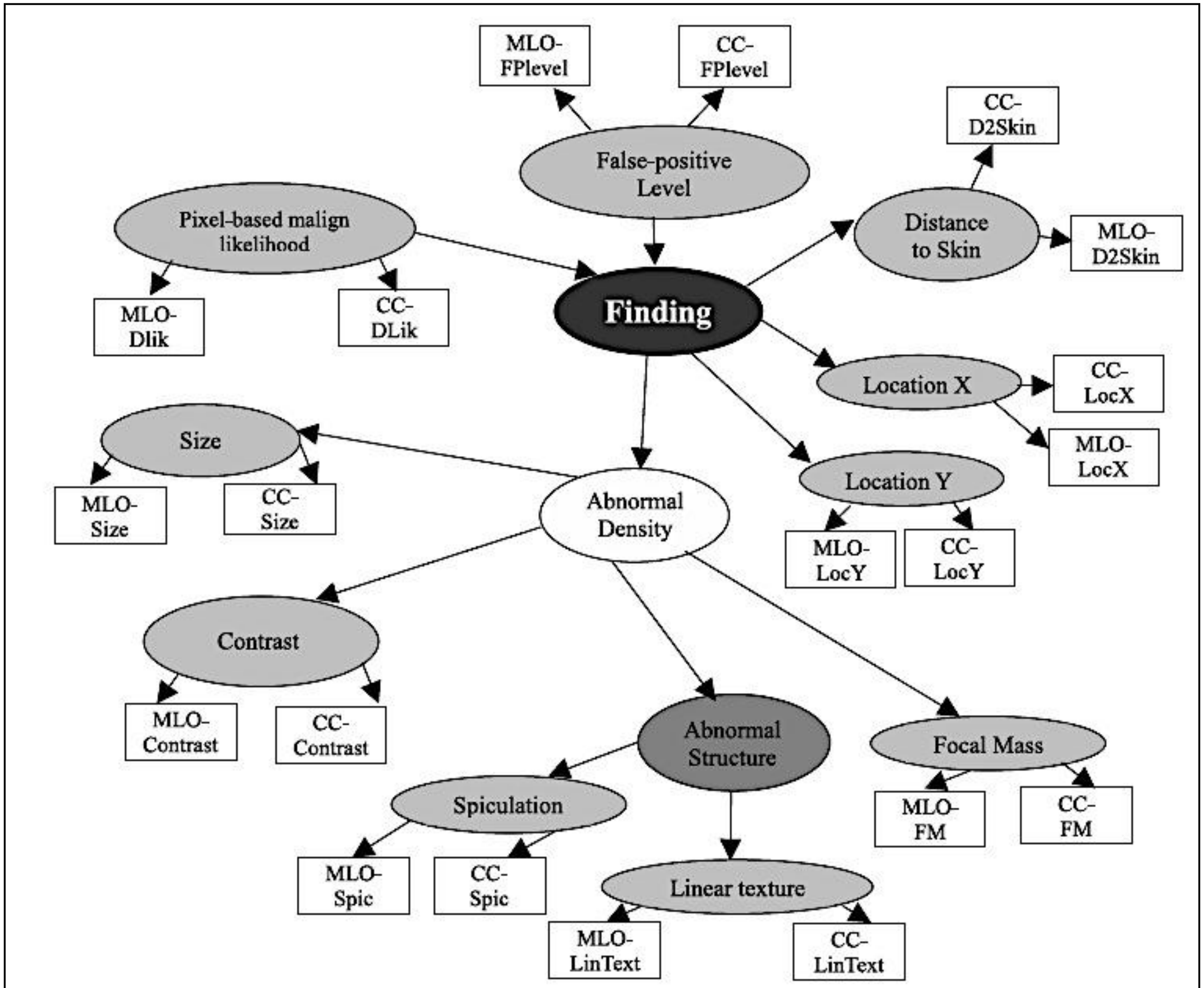
$$P(X) = \prod_{i=1}^{n} P\left(X_i \middle| \pi\left(X_i\right)\right)$$

$$P(X_1 X_2 X_3) = P(X_3 | X_1 X_2) \times P(X_1) \times P(X_2)$$

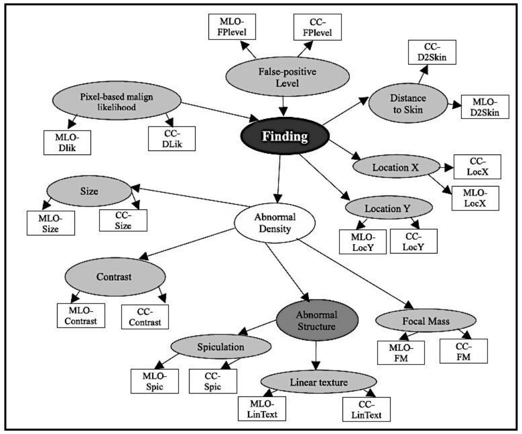
① Object-feature representation



① Multi-view mammographic model



① Multi-view mammographic model



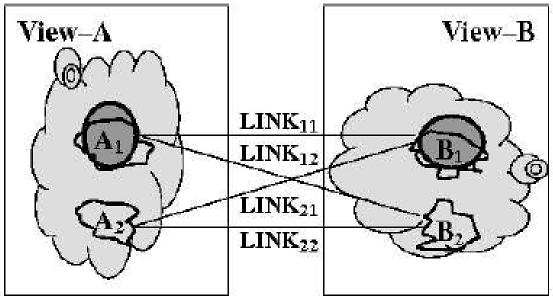
- Performance: **not optimal**
  - Object (finding) features vs. low-level image features - the causal relationship is not clear
  - Object features are not observed so their prior probabilities are unknown
  - Possible relationships between the image features may not be represented

- Critique: understand and improve knowledge representation by learning from real mammographic data:
  - We discretized the low-level image features
    - Increase in the detected cancers of up to 11.7%
    - Improved interpretation capabilities of the network
  - We learned Bayesian network structures
    - More dependencies between the image features were discovered

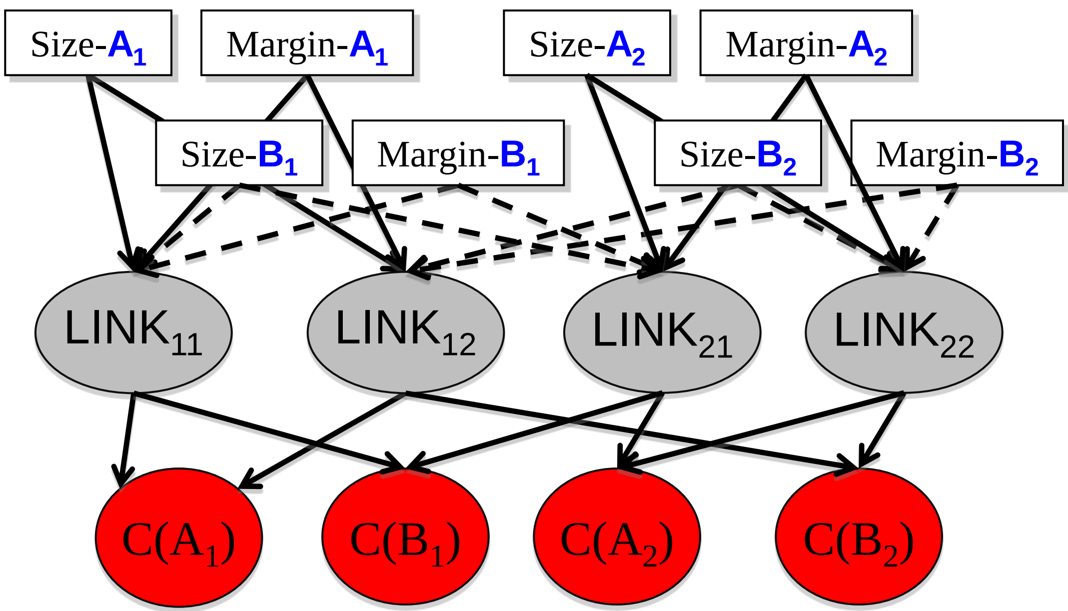
Results published in:

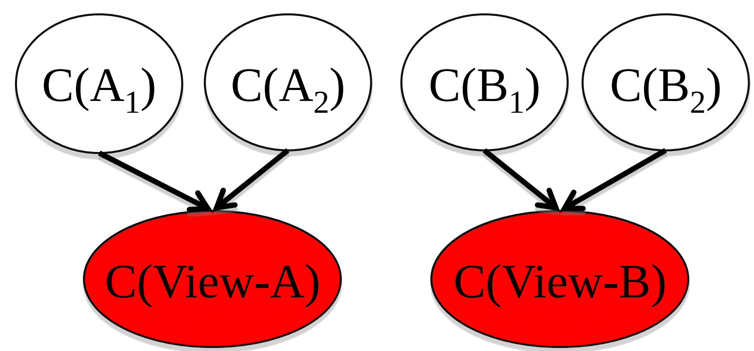
"*On the interplay of machine learning and background knowledge in image interpretation by Bayesian networks*"
Velikova, Lucas, Samulski and Karssemeijer, Artificial Intelligence In Medicine, 57:1, pp. 73-86, 2013

② Region-based representation



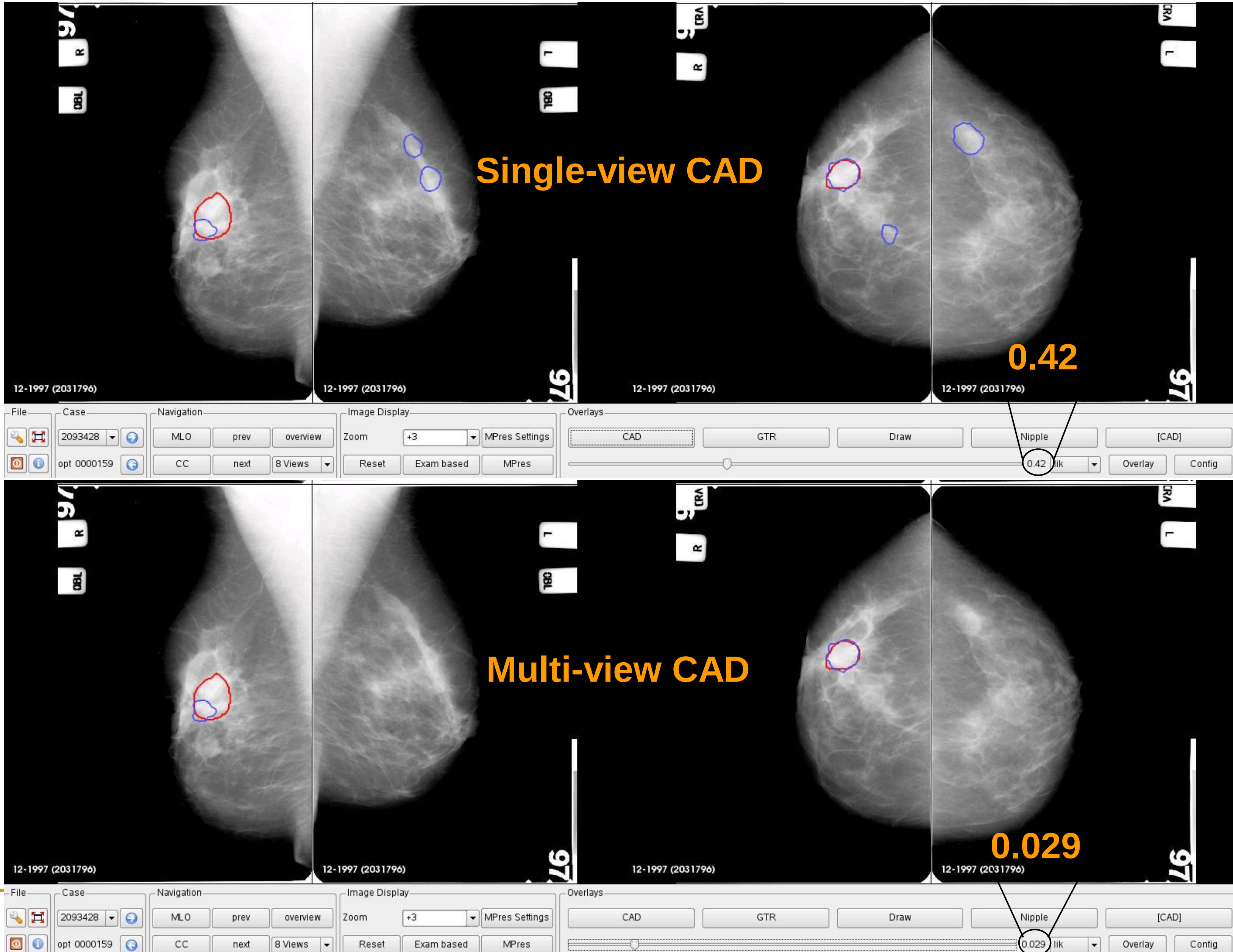
- Reg = {A_i, B_j}
- r∈Reg, r = {x_1, x_2, …, x_M}, M image features
- **C(r) / C(View)**: region / view class = {positive, negative}





"*Improved mammographic CAD performance using multi-view information: A Bayesian network framework*"
Velikova, Samulski, Lucas and Karssemeijer, *Physics in Medicine and Biology, 54, pp. 1131-1147, 2009*

Single- vs. Multi-view CAD system



Summary

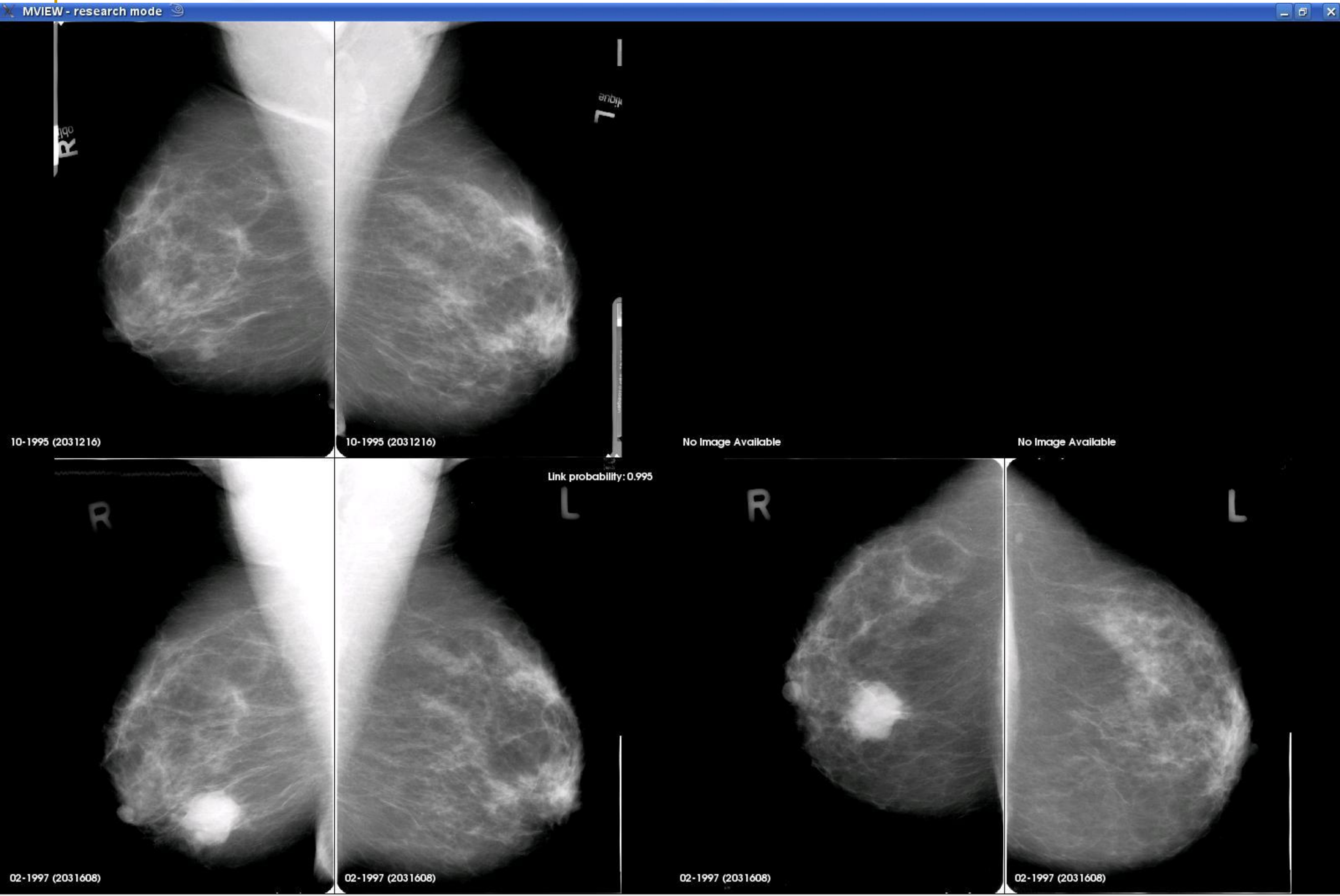
- Two types of Bayesian network models – object-feature oriented and region-based – for multi-view detection of mammographic findings
  - Manual construction of the network structure
  - Parameter learning from real mammographic data

- Experiments showed improvement in the breast cancer detection rate in comparison with a single-view CAD system

Open questions

- Unified representation language for various levels of image analysis (region, view, breast, patient)
  - Risk factors, e.g., age, (family) history of breast cancer
  - Spatial resoning
  - Temporal reasoning

Temporal reasoning



Temporal reasoning

Open questions

- Unified representation language for various levels of image analysis (region, view, breast, patient)
  - Risk factors, e.g., age, (family) history of breast cancer
  - Spatial resoning
  - Temporal reasoning

- Personalized models, i.e., Bayesian updating of parameters, based on learning from data per patient