An optimization approach to segment breast lesions in ultra-sound images using clinically validated visual cues

Doctoral Day
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Université de Bourgogne


Features
Training
CostFunction
ComputerAidedDiagnosisCAD
Data
I2CVB
InterIntraObserver
Lesion
ModelLearning
SearchSpace
Segmentation
OpenResearch
Optimization
Modeling
SuperPixel
AreaOverlap
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
GraphCuts
Ultrasound
MachineLearning


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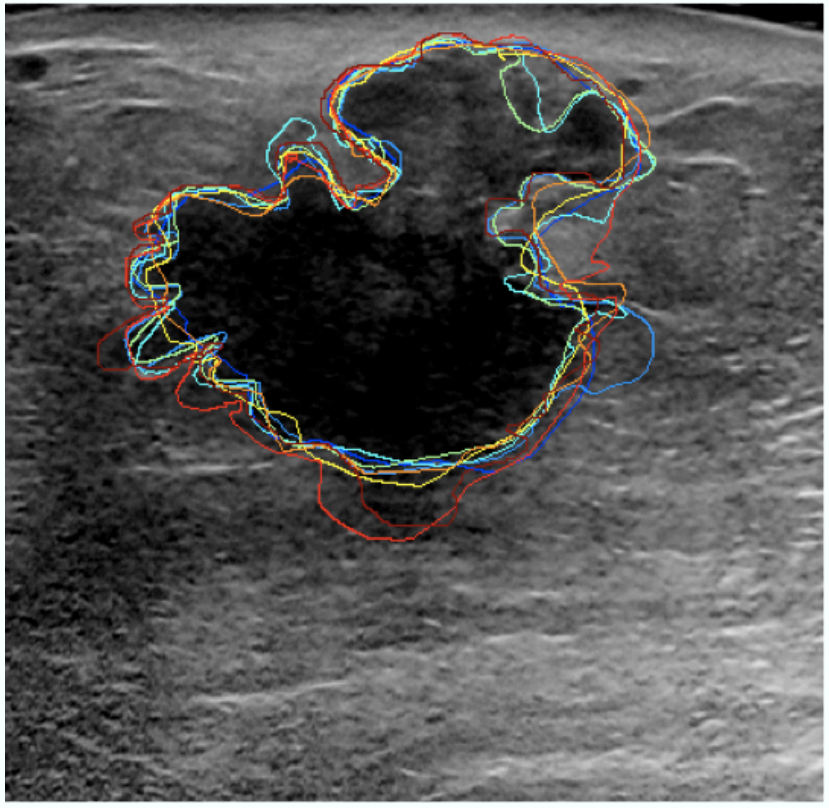
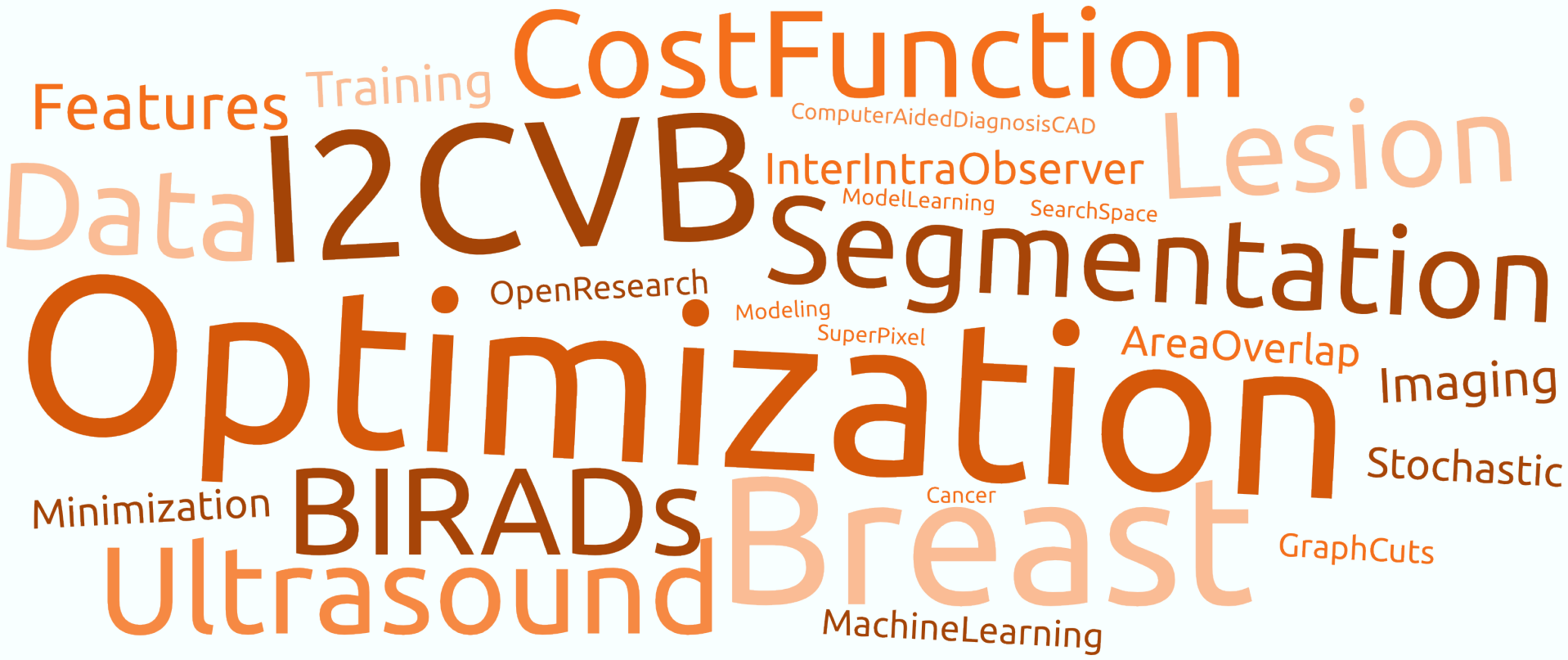
Breast Lesion Segmentation in US images

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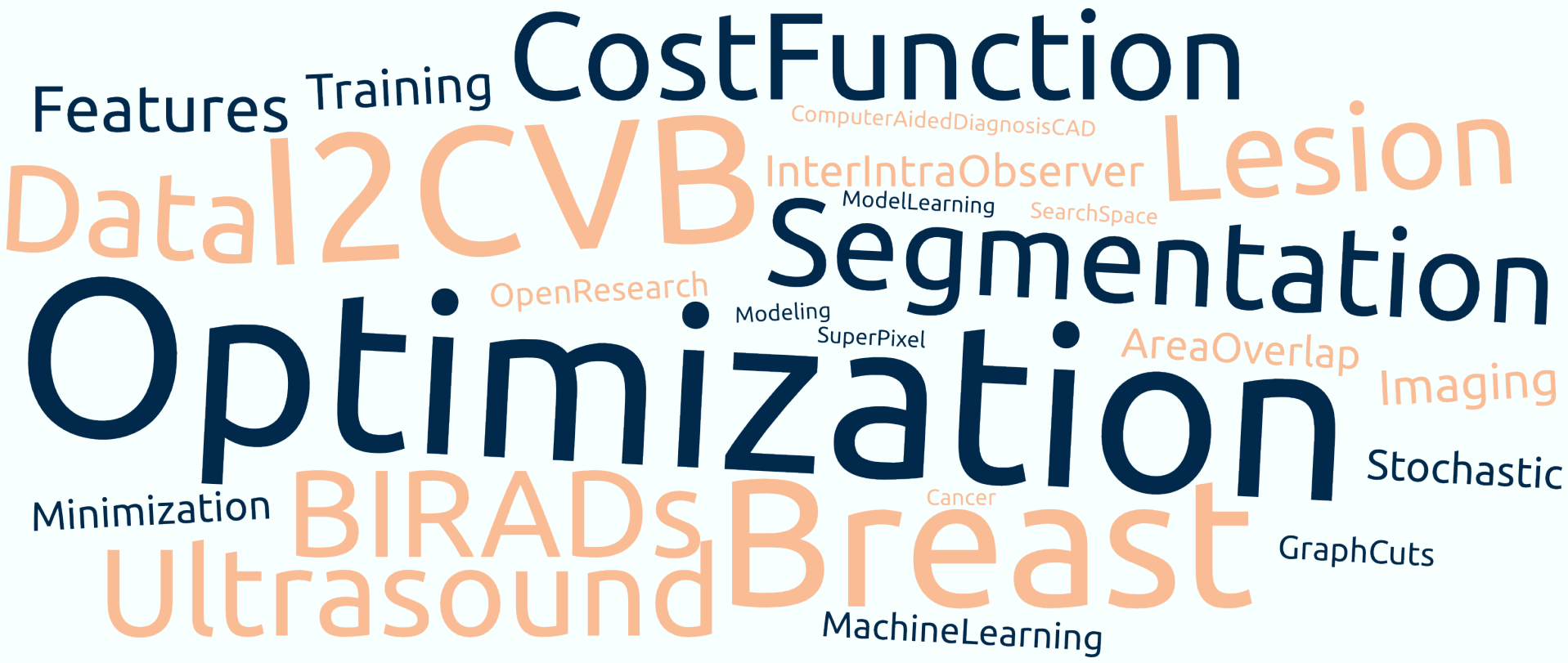
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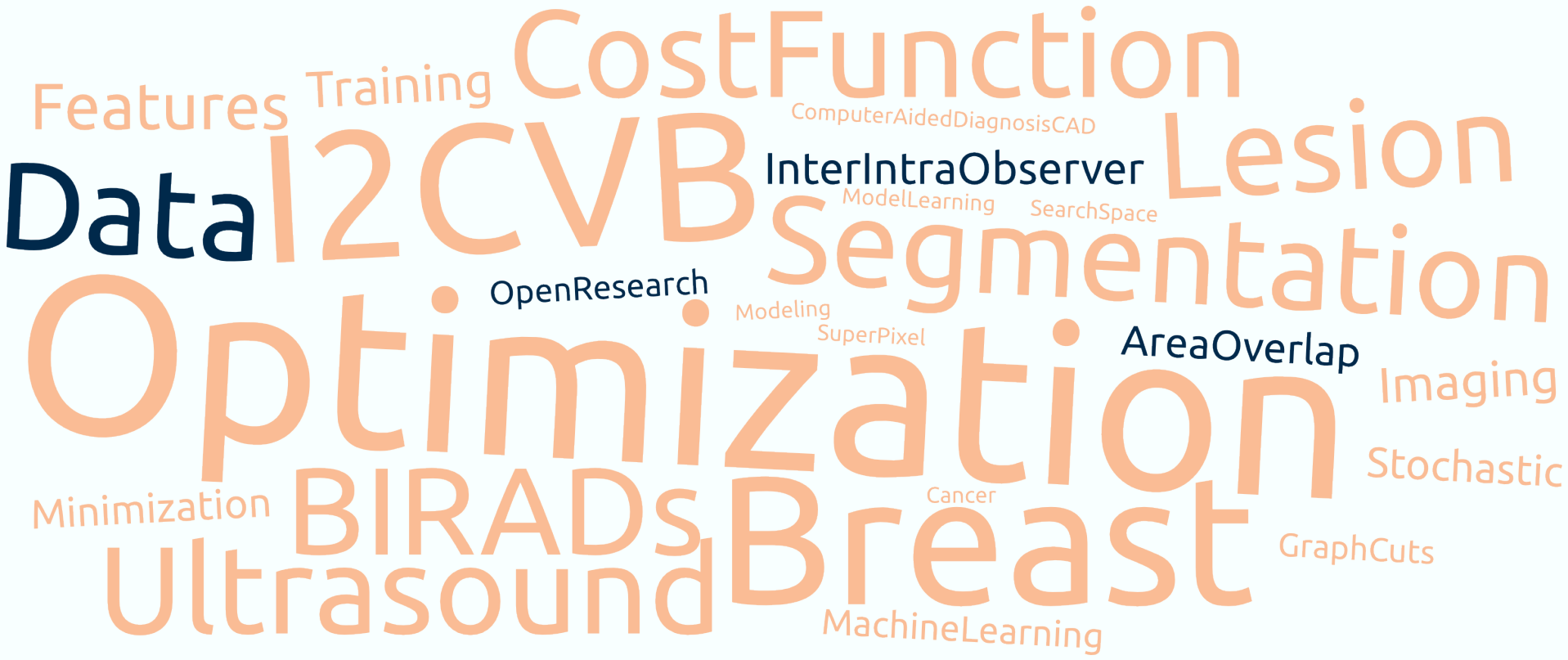
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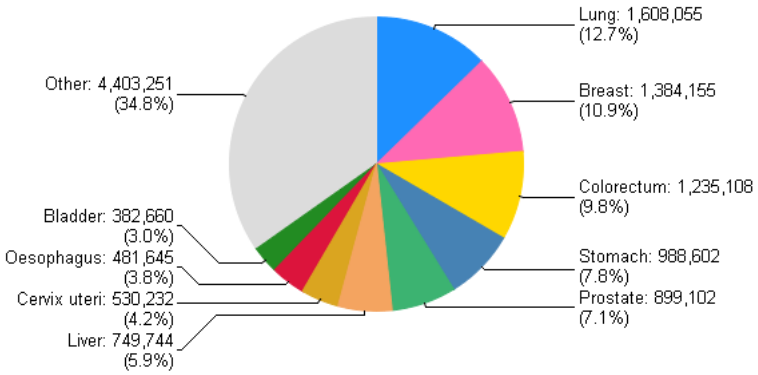
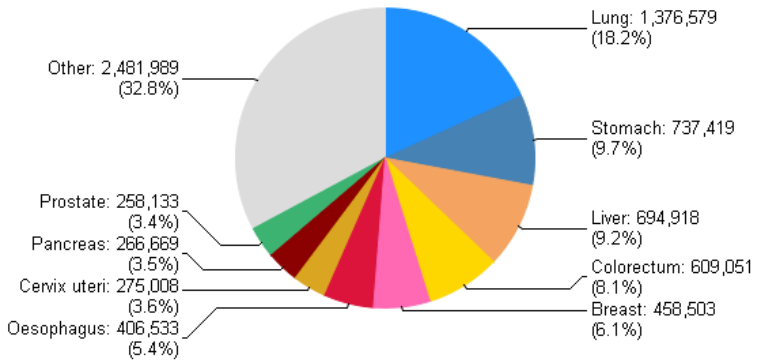
Motivations

Statistics



(a) # of cancer cases



(b) # of cancer deaths

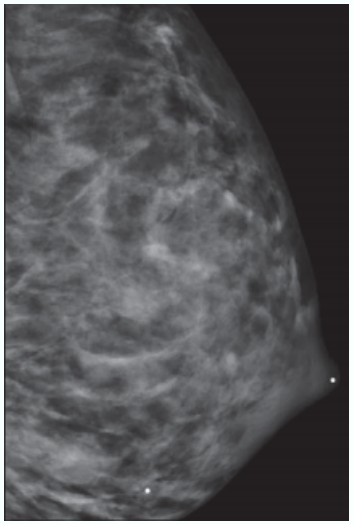
Implications

- 1.4 million cases per year
- 10.9% of diagnosed cancers
- 5^{th} cause of cancer death (1^{th} females)

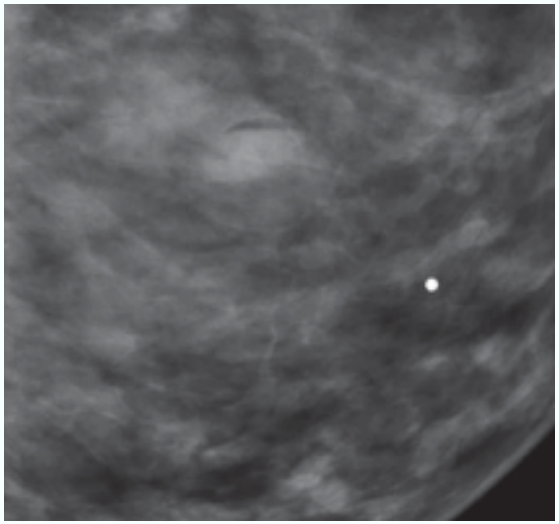
Breast Imaging

Ultra-Sound(US) imaging, the most common adjunct modality

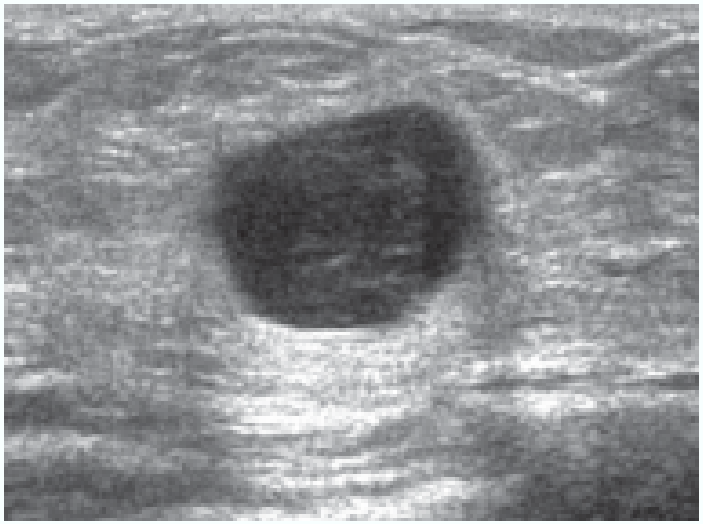
- Ability to discern solid lesions typologies
- Lesions shielded by dense breast in Digital Mammography(DM) are distinguishable in US



(c) DM



(d) DM, Region of Interest (ROI)



(e) Breast Ultra-Sound(BUS), ROI

Breast structures under US screening

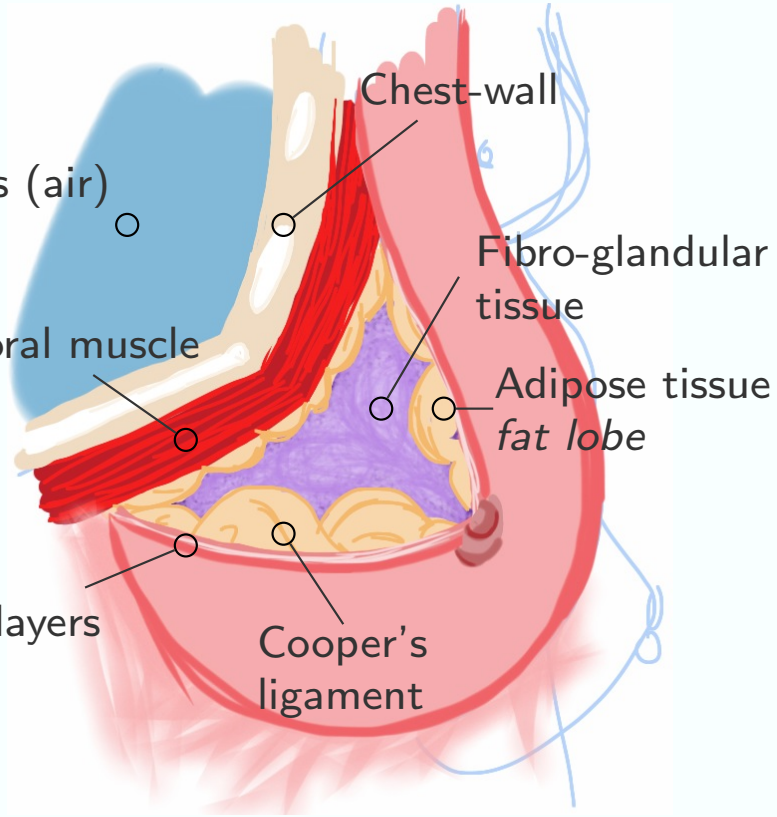


Figure: Breast structure elements.

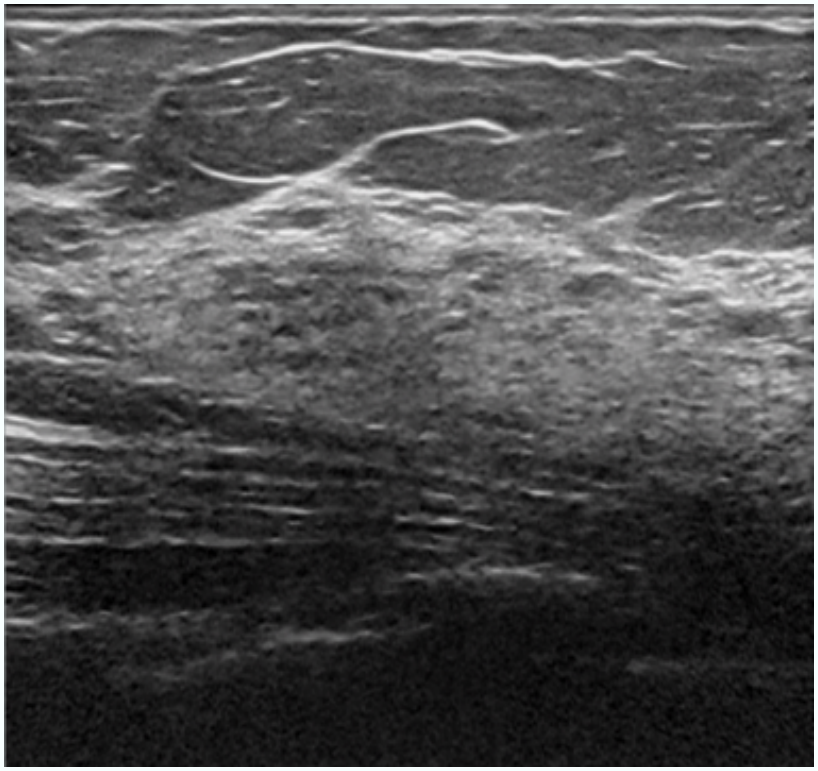


Figure: Breast US image example.

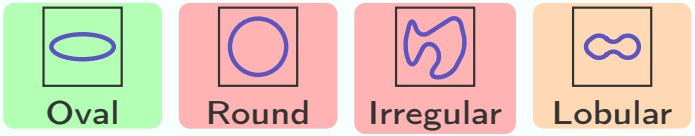
State of health from image visual Inspection

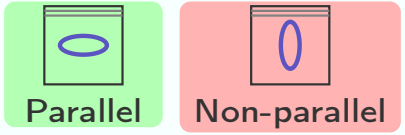
Radiologic diagnosis error rates are similar to any other human visual inspection

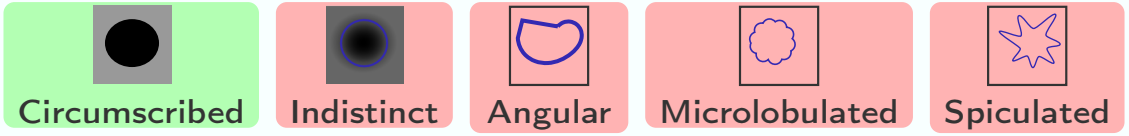
- Quality of the images.
- Ability to interpret the physical properties of the images.

1. Double readings.
2. Computer Aided Diagnosis(CAD).

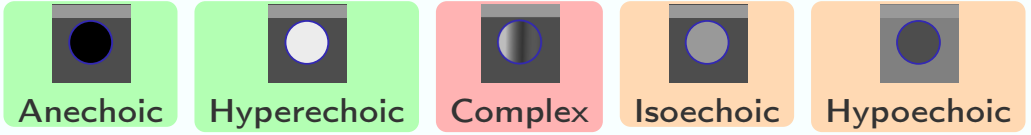
BI-RADs Lexicon
A standardized toolkit tested for diagnosis

- BKGD Echotexture : adipose, fibro-glandular, heterogeneous
- Mass shape : 

- Mass orientation : 

- Mass margin : 

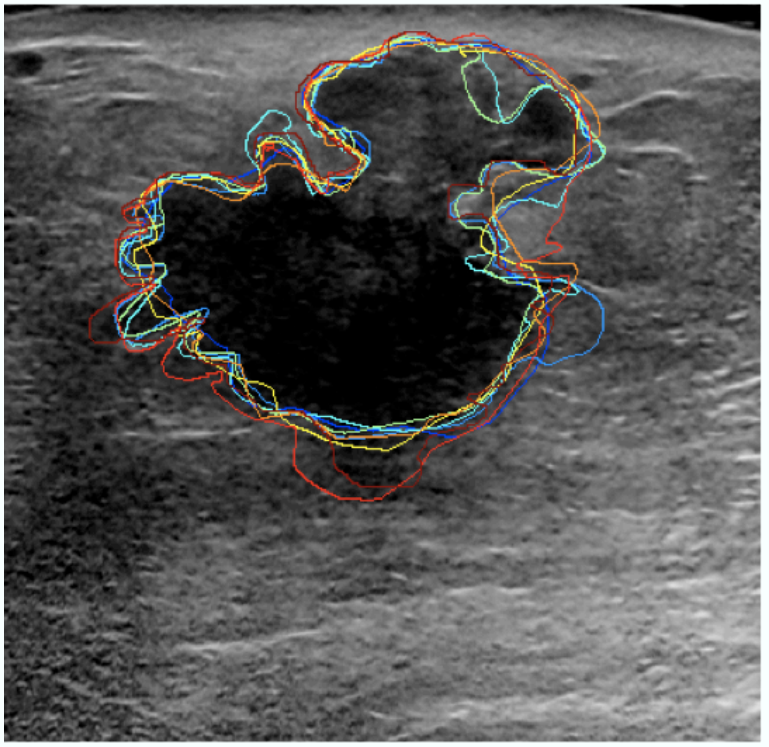
- Lesion boundary : 

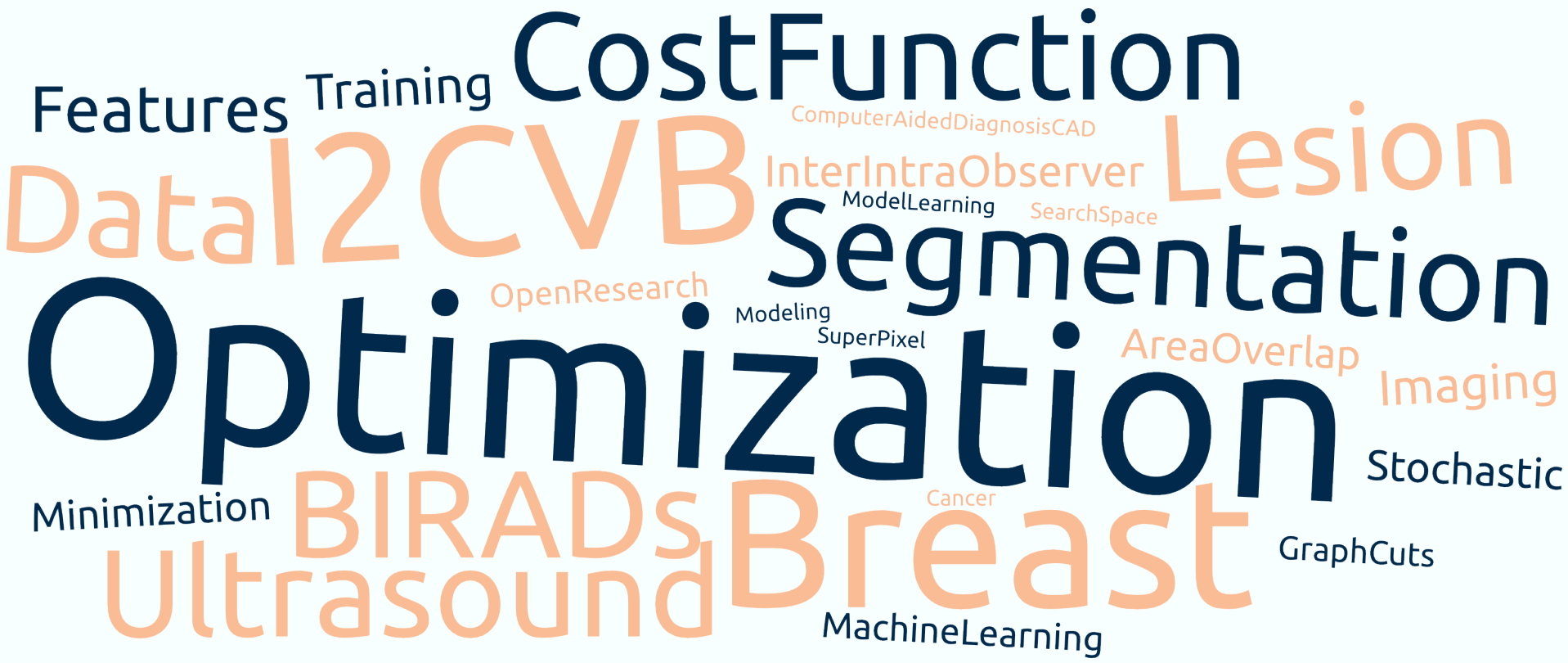
- Echo pattern : 

- Posterior acoustic pattern : 

[0] benign, malignant and undetermined

Take away
Accurate delineations to develop CAD systems for BUS

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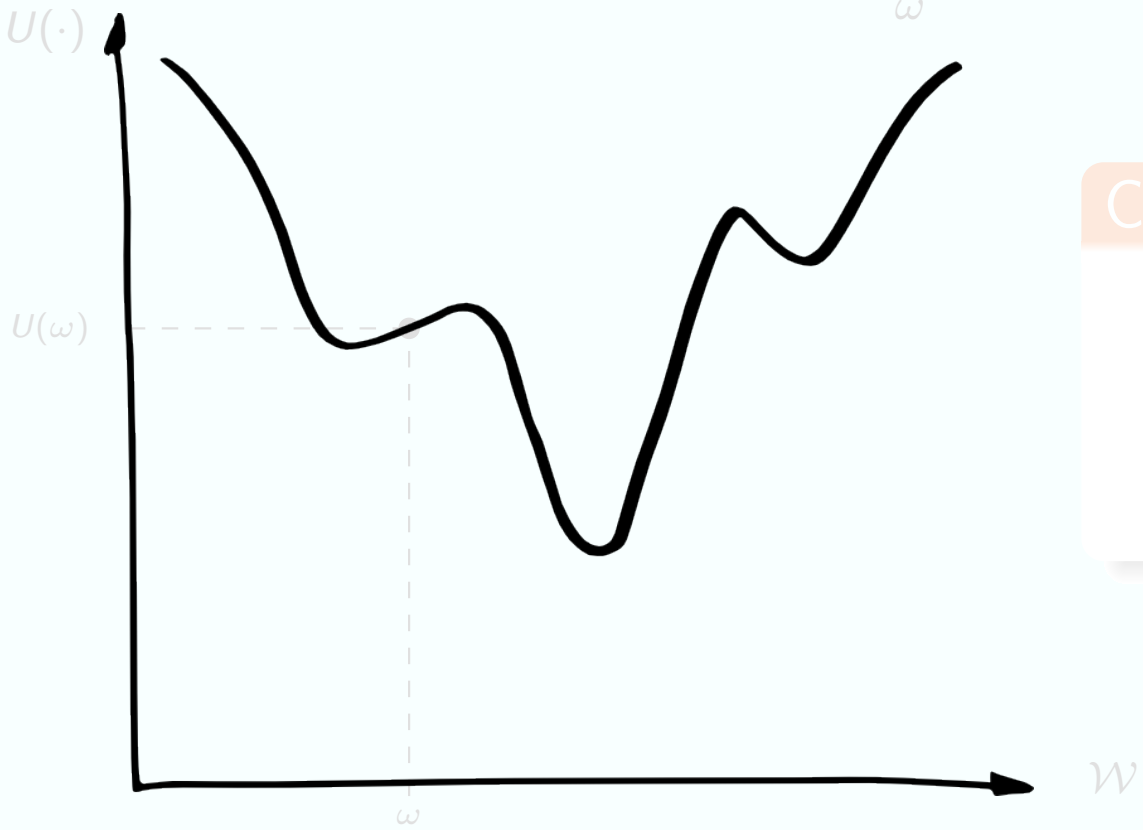
Optimization
For image segmentation

$$\hat{\omega} = \arg\min_{\omega} U(\omega)$$

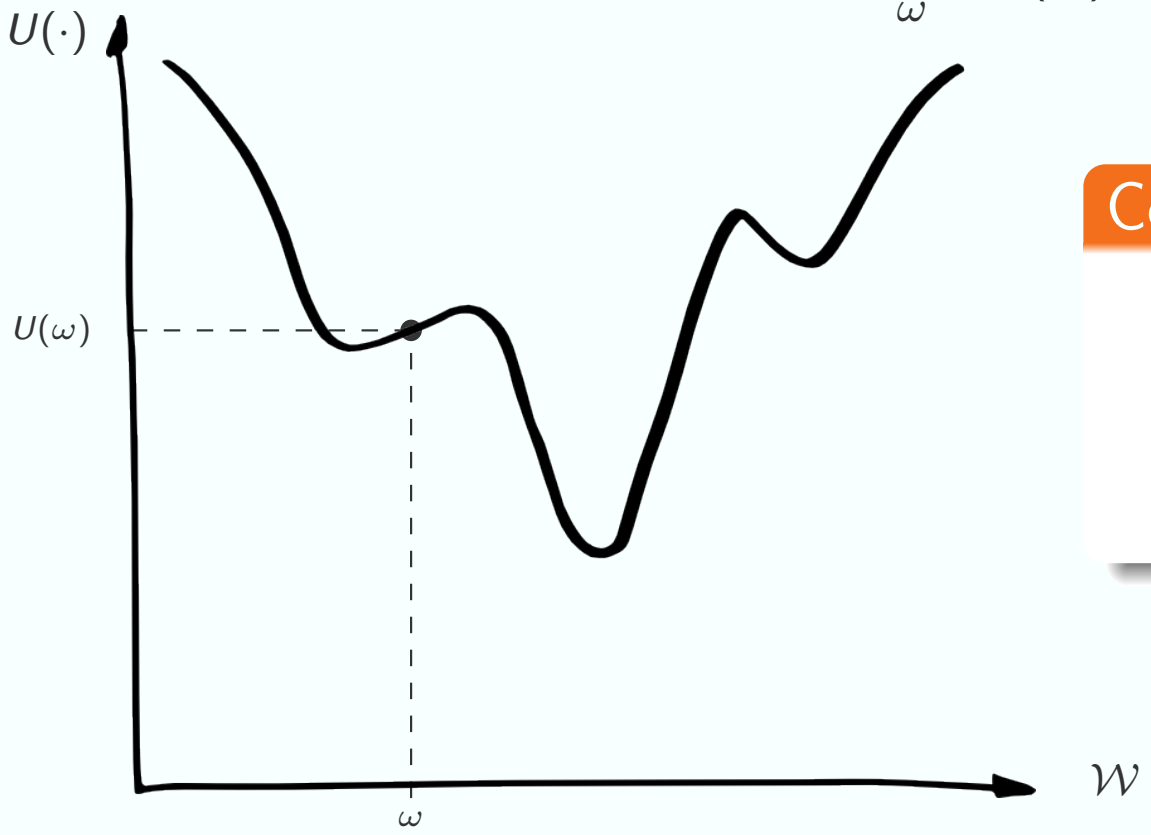


Considerations

- Search Space $\mathcal{W}$
- Cost Function $U(\cdot)$
- Minimization Strategy

Optimization
For image segmentation

$$\hat{\omega} = \arg\min_{\omega} U(\omega)$$

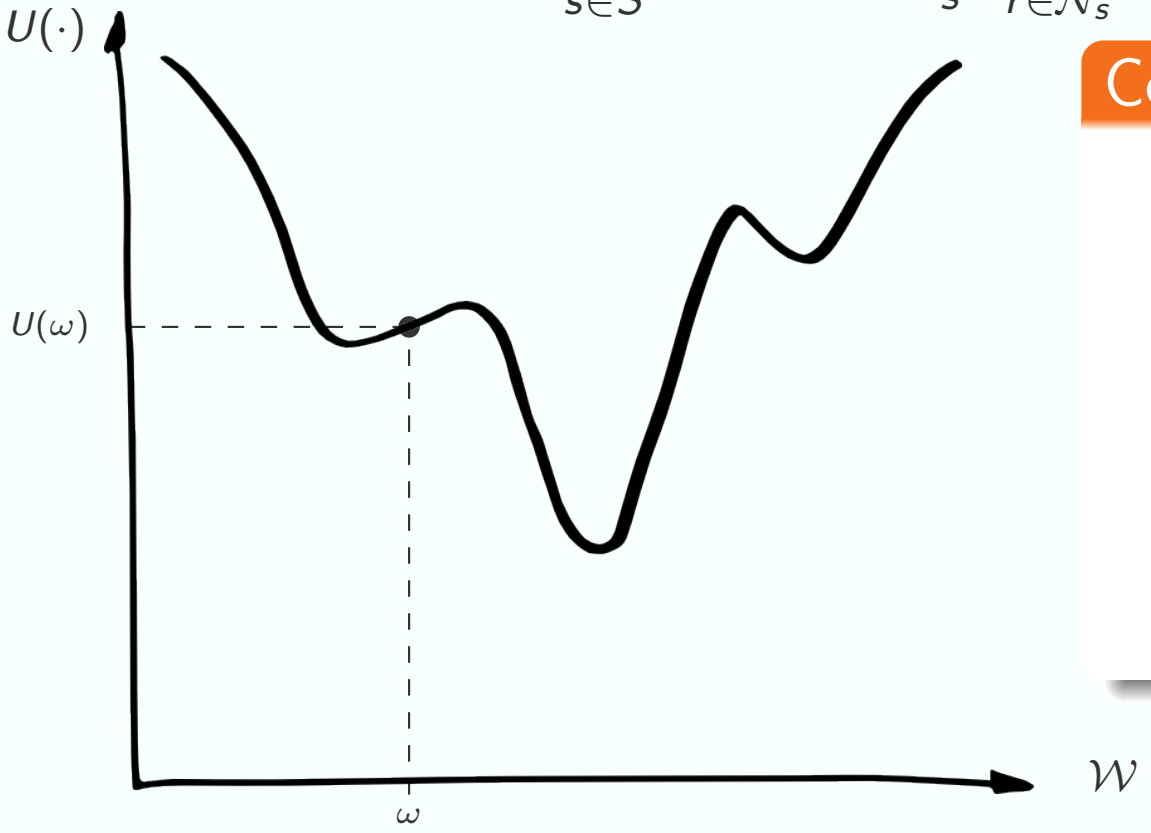


Considerations

- Search Space $\mathcal{W}$
- Cost Function $U(\cdot)$
- Minimization Strategy

Image Segmentation by Optimization
The Metric Labeling Problem

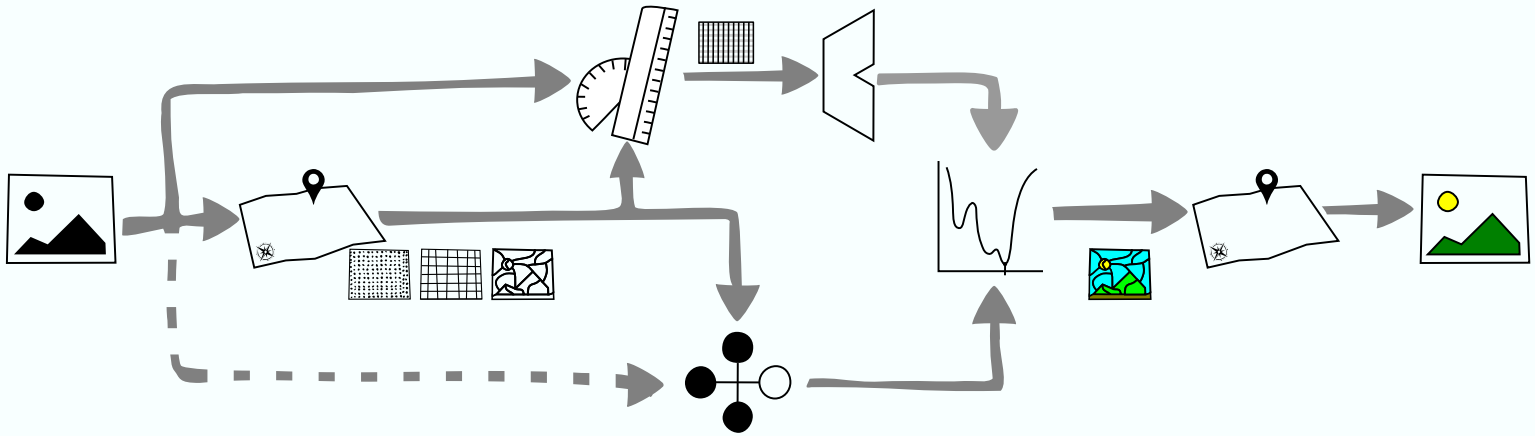
$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_{s} \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$$



Considerations

- Image as a discrete set $\mathcal{S}$
- Search Space $\mathcal{W}$ $(\omega_s = l)$, $l \in \mathcal{L}$, $\forall s \in \mathcal{S}$
- Cost Function
- Minimization Strategy

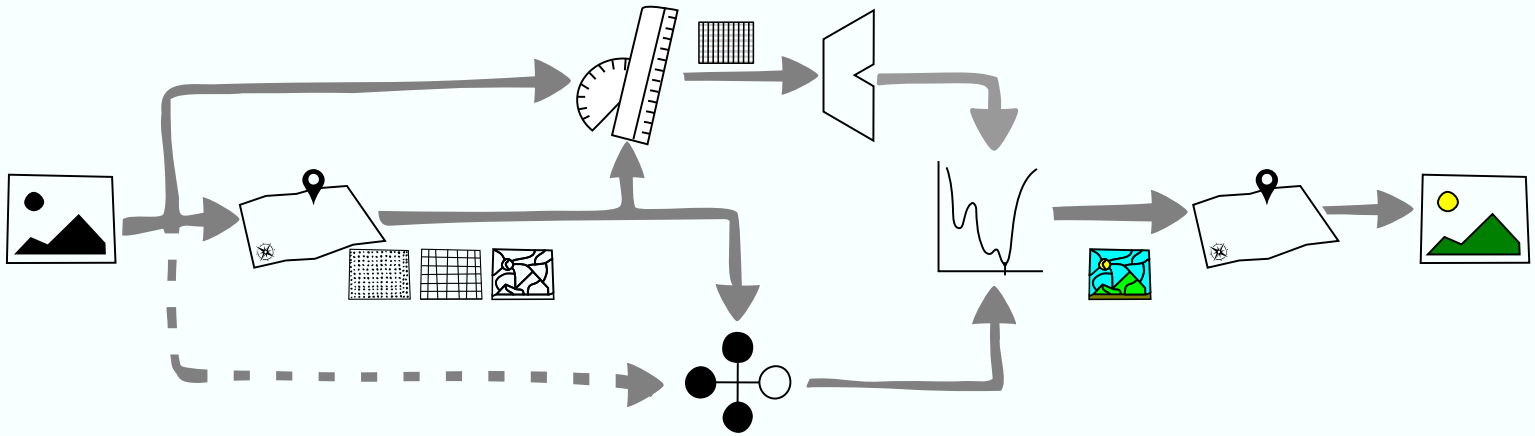
The Metric Labeling Problem
Conceptual schema



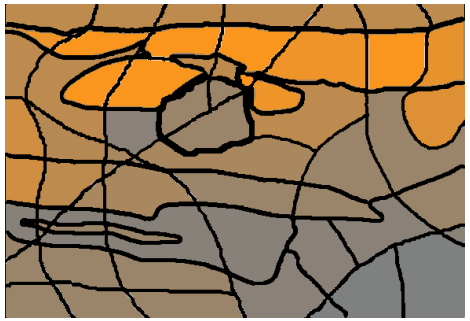
$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_s \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$$

- $D_s(\omega_s = l_{\checkmark}) << D_s(\omega_s = l_{\times})$
- $$V_{s,r}(\omega_s, \omega_r) = \begin{cases} \beta, & \text{if } \omega_s \neq \omega_r \\ 0, & \text{otherwise} \end{cases}$$
- $|\mathcal{W}| = |\mathcal{L}|^{|S|}$

The Metric Labeling Problem
Conceptual scheme

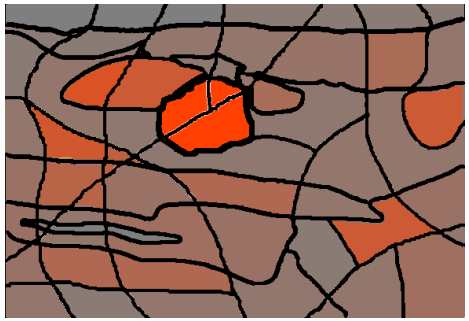


$D_s(\omega_s = l)$ Interpretation



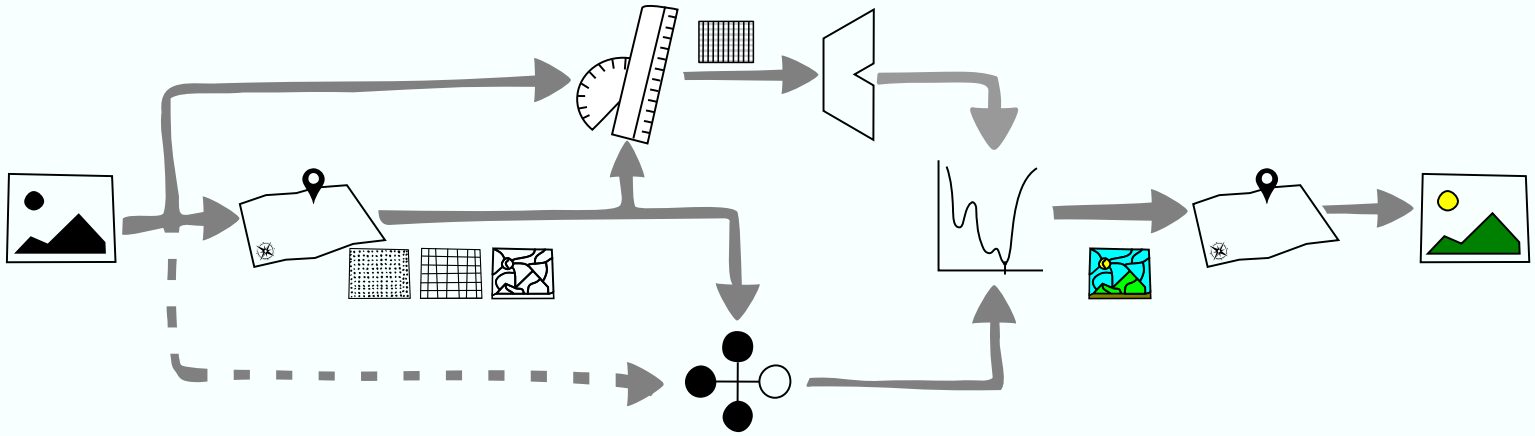
(a) l is fat

(b) l is lungs

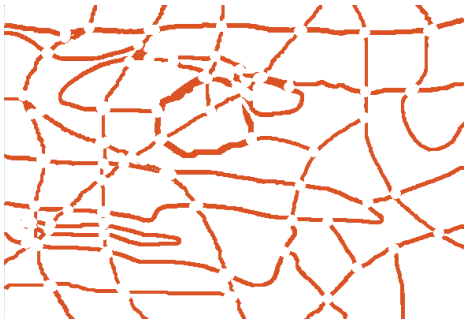


(c) l is lesion

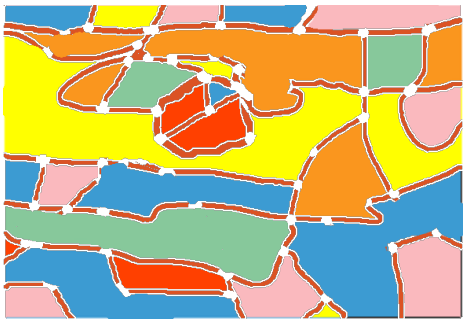
The Metric Labeling Problem
Conceptual schema



$V_{s,r}(\omega_s, \omega_r)$ Interpretation



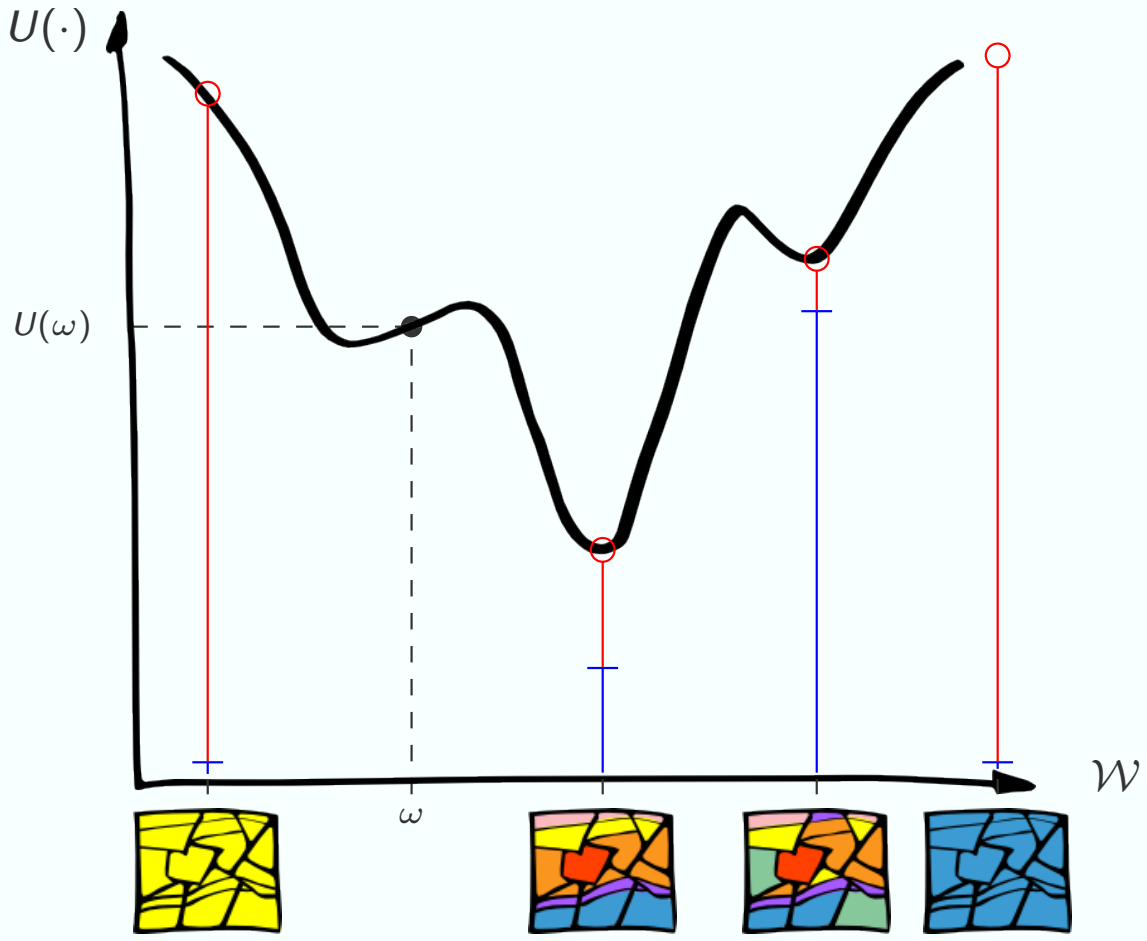
(d)



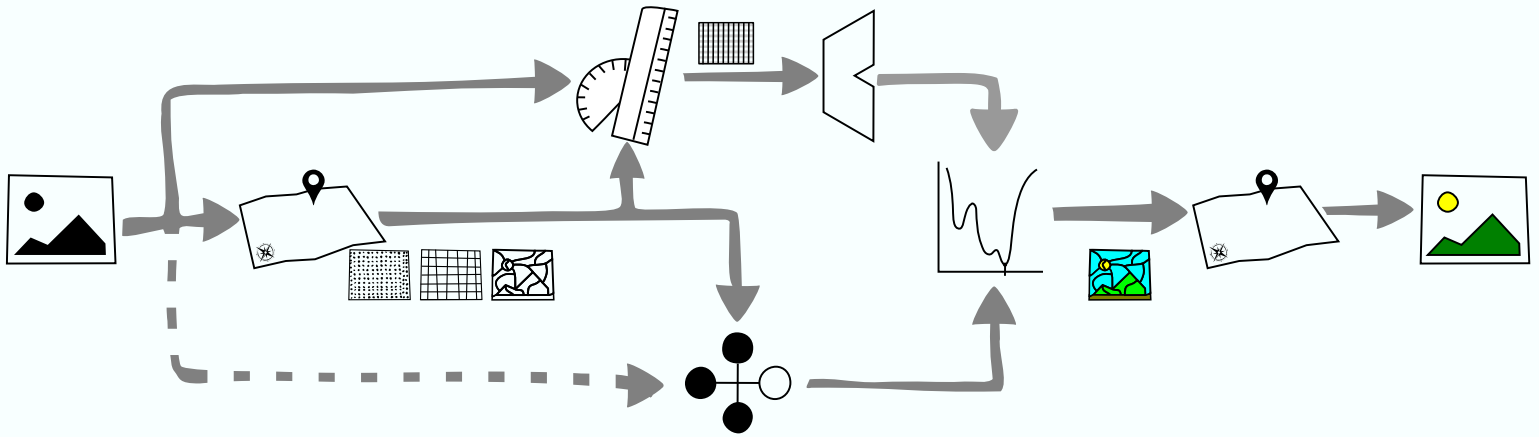
(e)

(f)

Interpretation of the Minimization Stage



Take Away



$V_{s,r}(\omega_s, \omega_r)$ Interpretation

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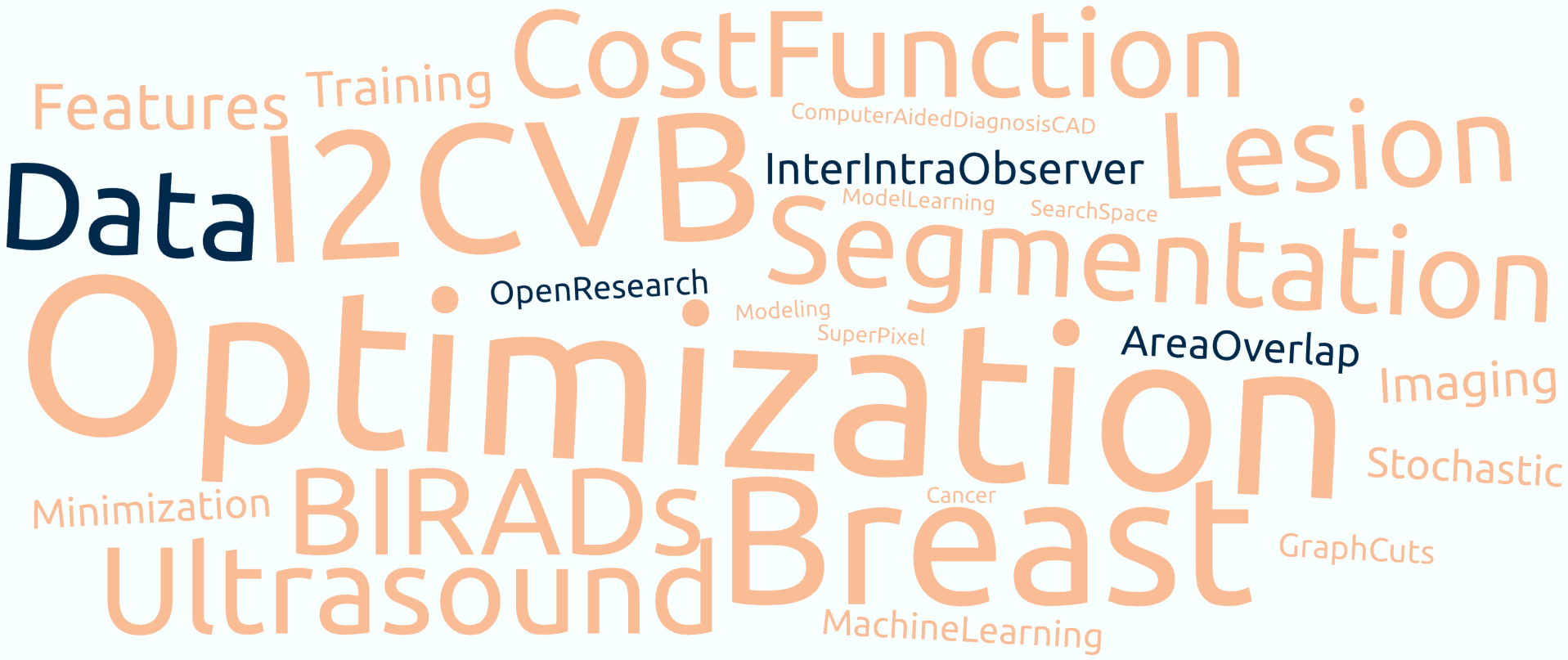
$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_{s} \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$$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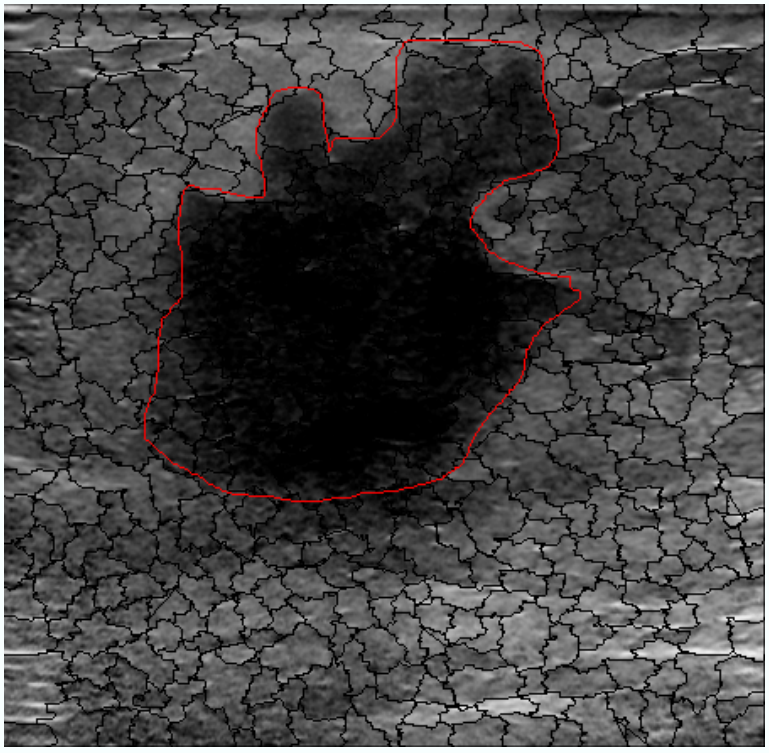
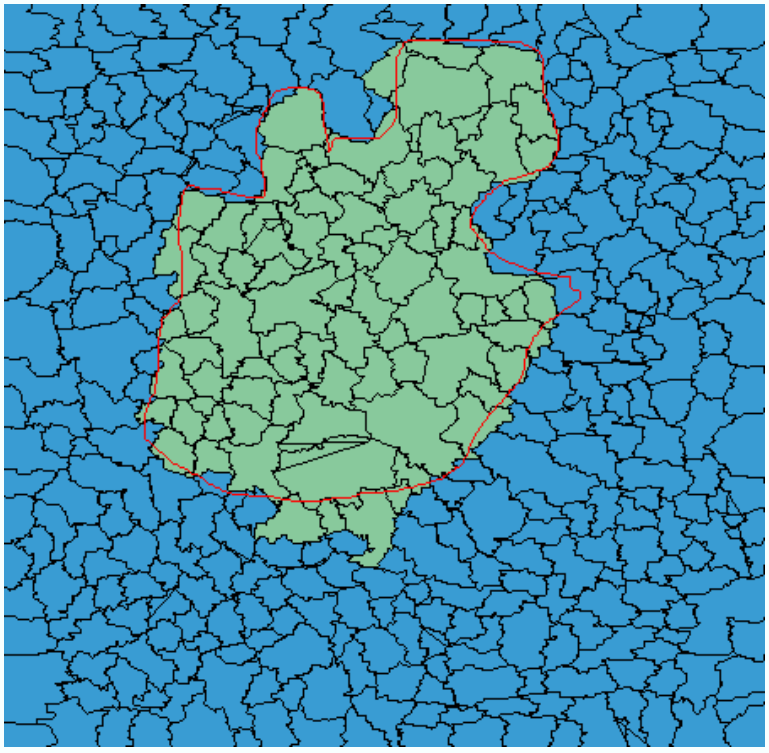
Qualitative results
Super-pixel classification vs Area-Overlap

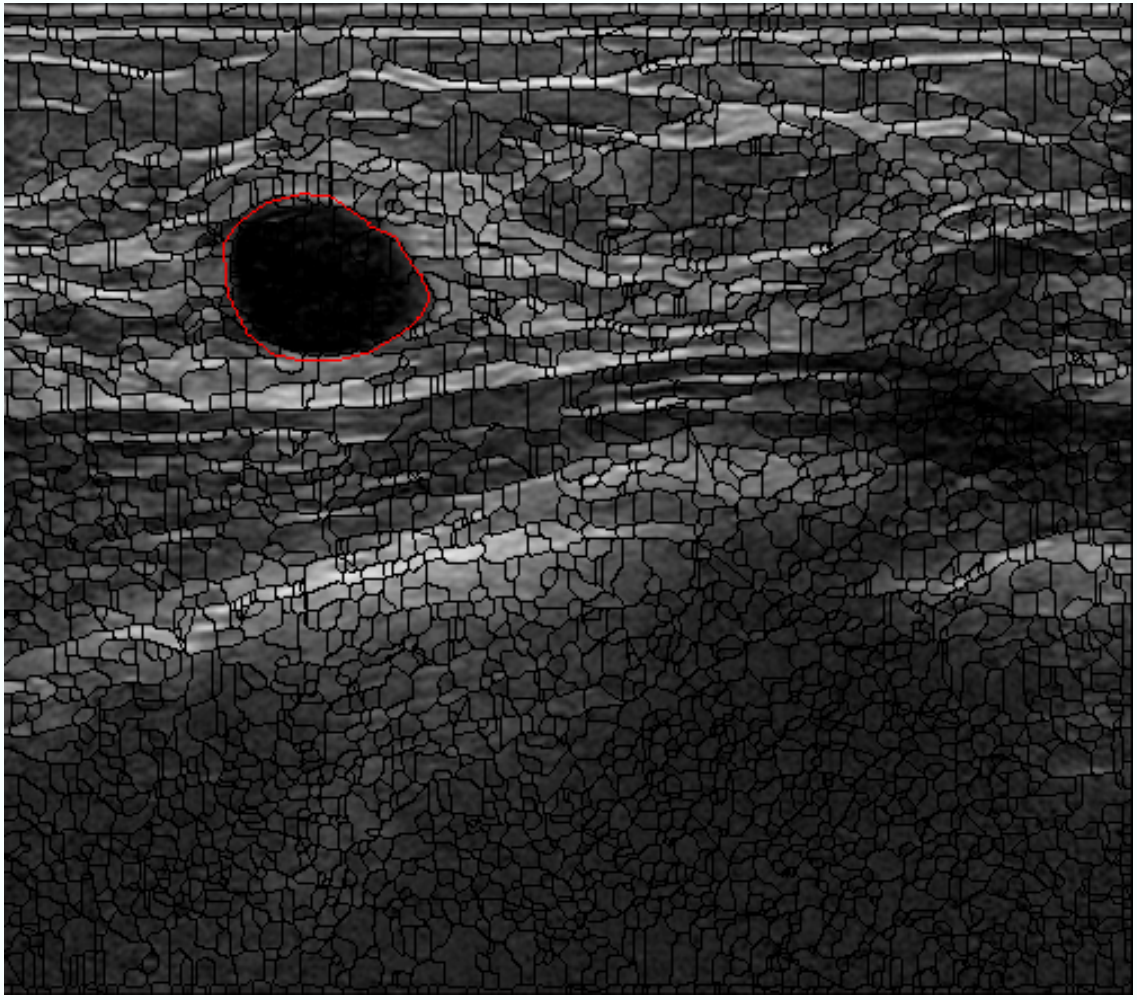


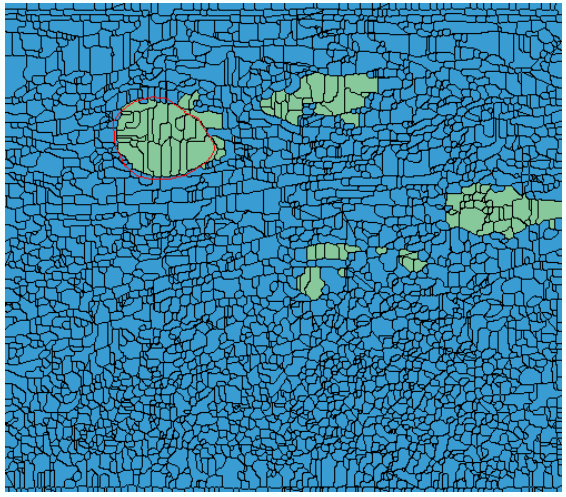
(g) Original Image, Ground Truth and Super-Pixels delineation.

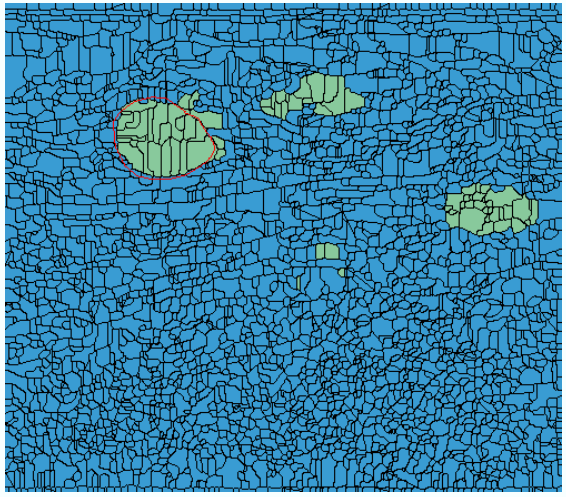


(h) $\{\text{lesion}, \overline{\text{lesion}}\}$ labeling results, GT and SP delineation.

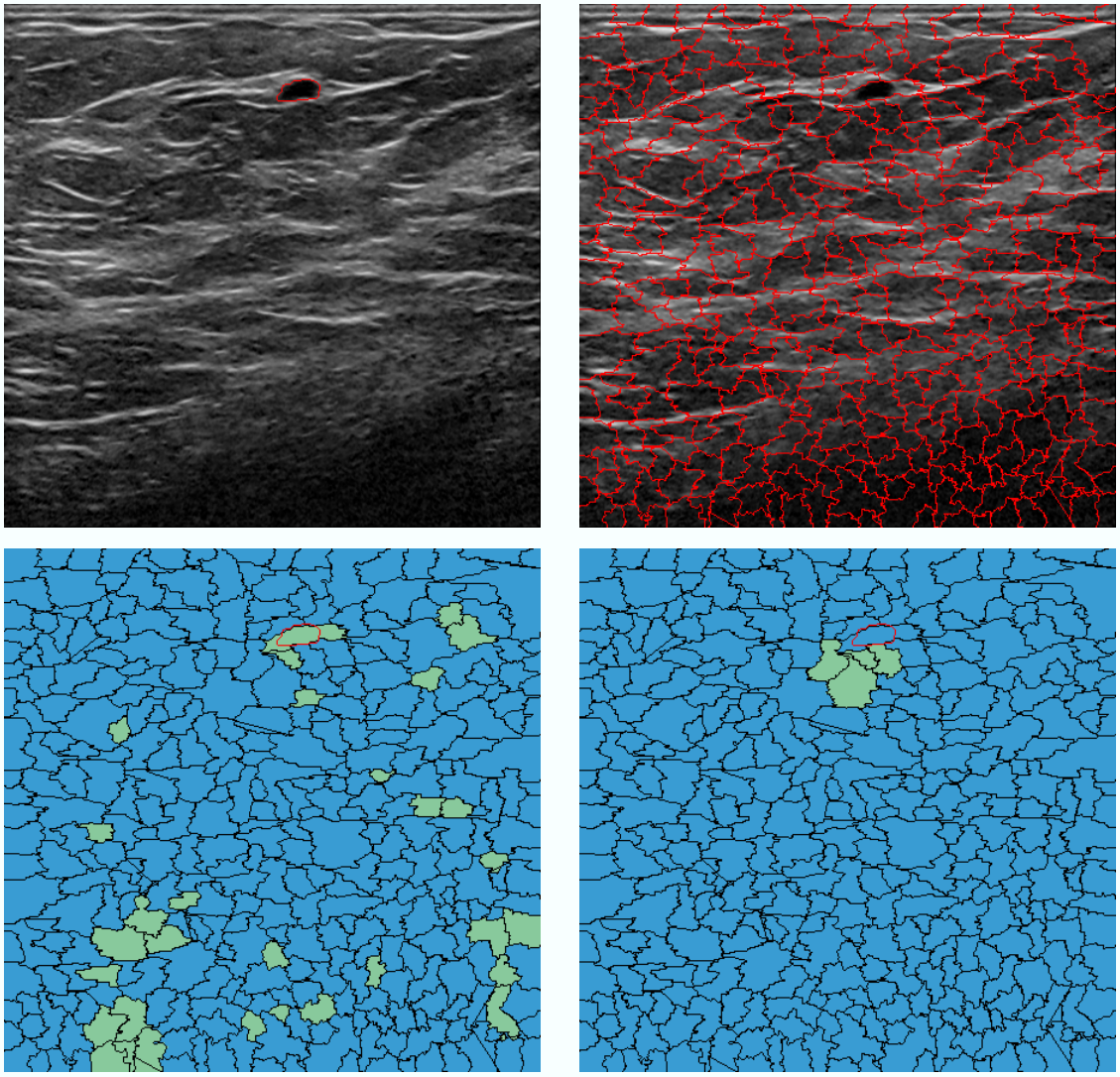
Qualitative results
Influence of the Smoothing Term to False Positive Ratio





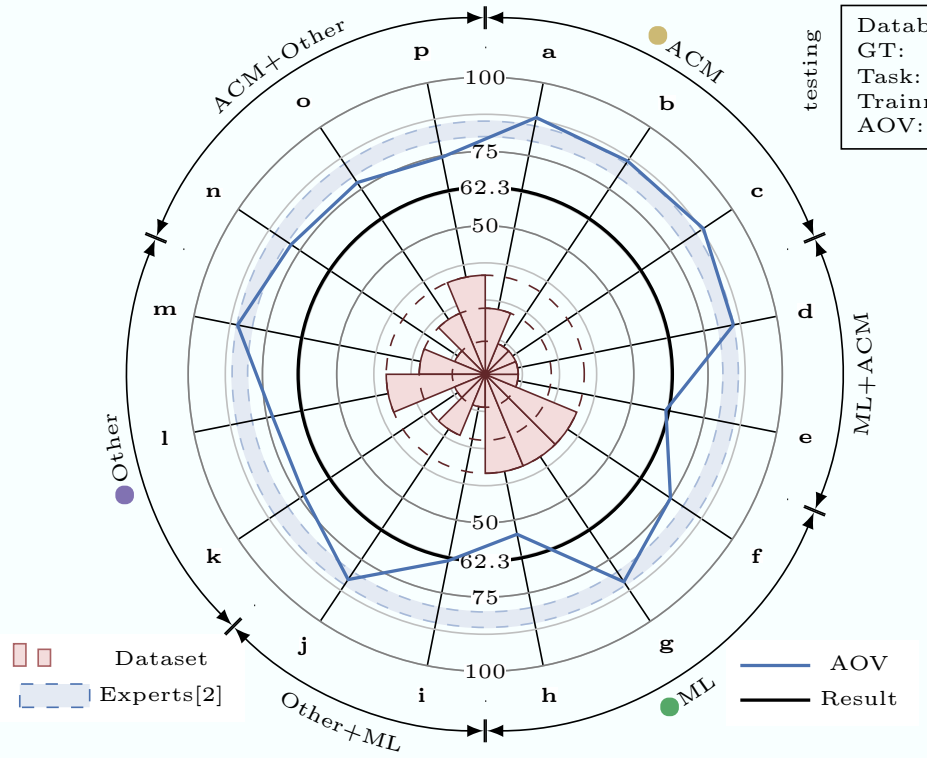


Qualitative results
When False Negative Emerge



Quantitative Results

Method Id:	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p
Dataset size:	76	20	32	20	42	480	347	352	25	120	6	400	50	20	118	488
techonlogy used for:																
detection																
segmetnation																
post-processing																
AOV (in %):	88.1	86.3	88.3	85.2	62.0	75.0	84.0	54.9	64.0	83.1	73.3	73.0	85.0	78.6	77.6	74.5



Database size:	16
GT:	multi-label
Task:	$\mathcal{L} = \{\text{lesion}, \overline{\text{lesion}}\}$
Trainning:	Leave-one-Patient-Out
AOV: .623	FPR: .4 FNR: .008