Cognition Inspired Diagnostic Image Quality Models

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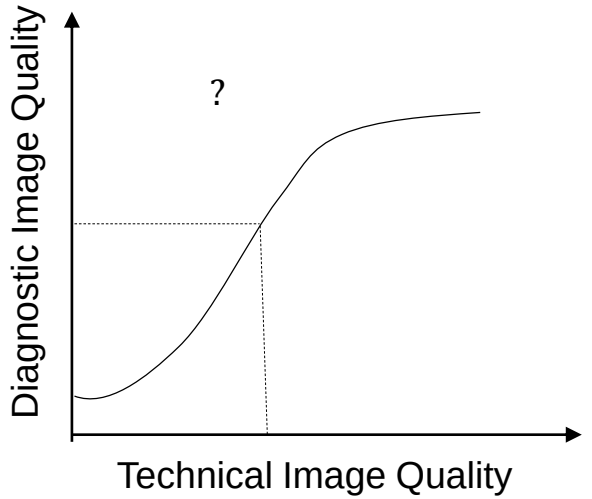
Summary

- Technical vs. diagnostic image quality
- Components of diagnostic image quality
- Subjective assessment
- Feature engineering
- Objective model
- Discussion

The Gap Between Technical and Diagnostic Image Quality

There is a qualitative assumption of monotonicity in the operating region. Little is understood about the actual variables except that they are complex functions of multiple components.



TIQ vs. DIQ

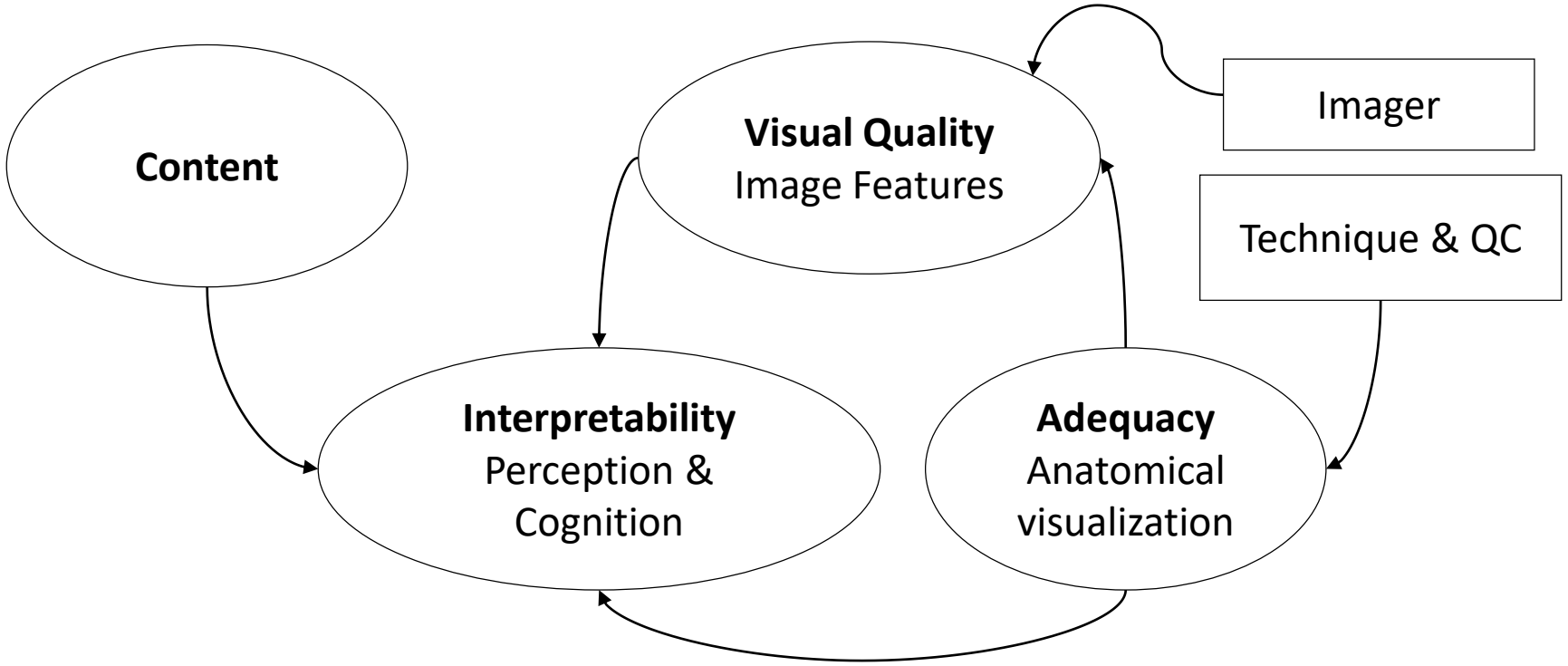
TIQ

- Imaging technology
- Quality assurance protocols
- HW & SW

DIQ

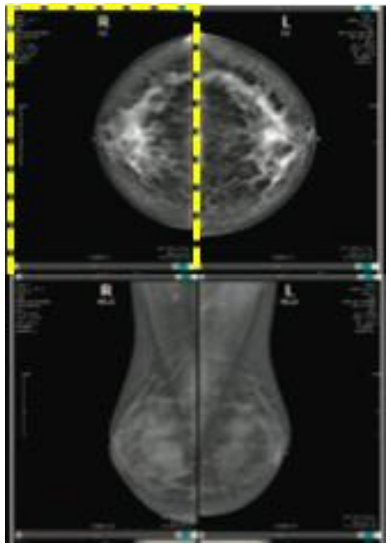
- Image interpretability is subject to perceptual constraints (contrast sensitivity, PSF of the human eye, visual system adaptation, workload) and content
- Image adequacy depends on radiation dose and technique to visualize anatomical structures (inc. 2D, 3D, etc).
- Visual quality is subject to imaging constraints including sensor physics, safety, and patient comfort.

Diagnostic Image Quality



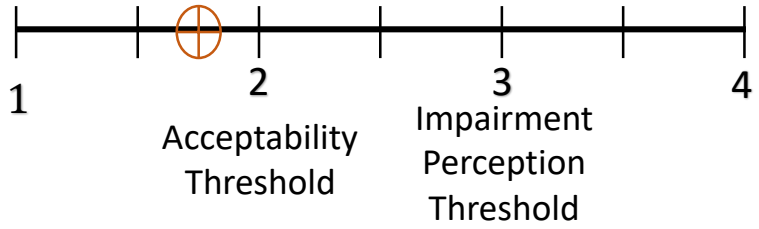
Subjective Diagnostic Image Quality -- Proposed

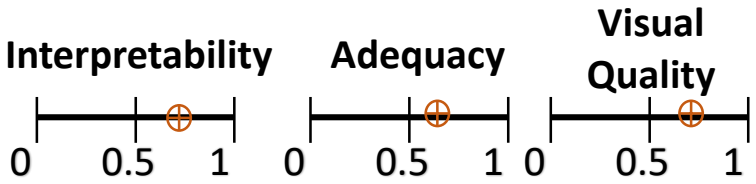
Case: A32
Image: **R-CC**



Diagnostic Image Quality

Poor → Good → Excellent





	Comments
DIQ	
I	
A	
V	

Not a radiological diagnosis!

Modeling DIQ

- A massive feature engineering challenge
- Besides visual features (e.g., brightness, contrast, sharpness, noise…) we need content dependent features (e.g., entropy, texture, structural complexity…) and high-level features dependent on modality & technique (e.g., ROI, size, density…)

Text Analysis and Concept Mapping: Background

NLP can be used to structure unstructured text by extracting concepts and their attributes

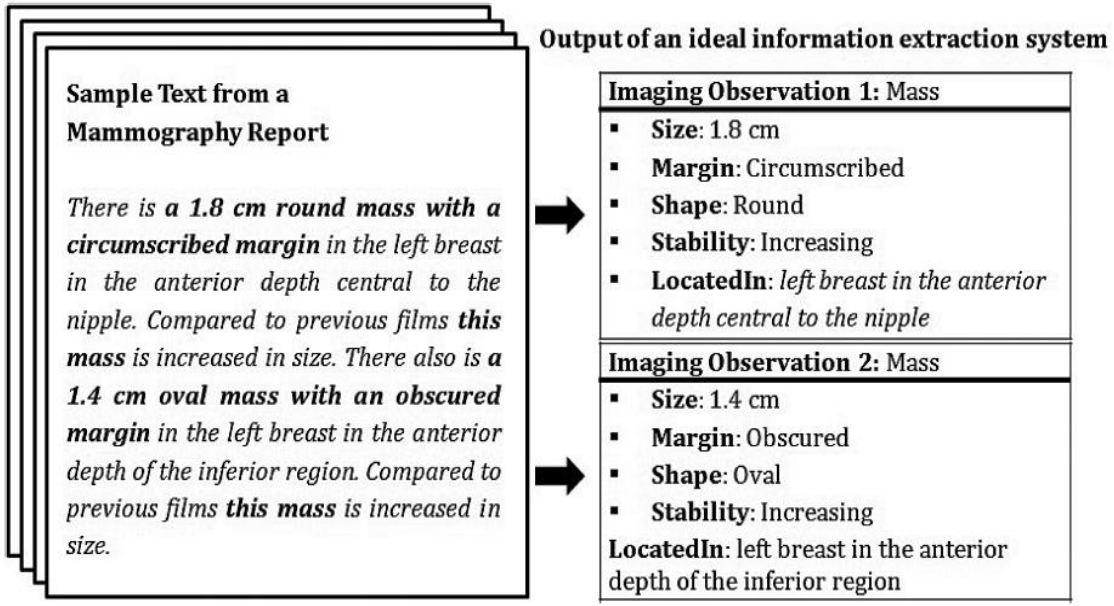


Figure 1 Example mammography report describing two different masses and the ideal output from a natural language processing system to extract the information suitable for input to a decision support system.

Selen Bozkurt, Jafi A Lipson, Utku Senol, Daniel L Rubin, Automatic abstraction of imaging observations with their characteristics from mammography reports, Journal of the American Medical Informatics Association, Volume 22, Issue e1, April 2015, Pages e81–e92, https://doi.org/10.1136/amiajnl-2014-003009

Comments Analysis and Concept Mapping: Linking Comments to Relevant Features

DIQ Comments

Interpretability score: 4

Description: the abnormal mass is highly visible and clearly distinguishable from the fatty tissue background without interference by obstructing tissue in front of it, its contour is well defined to allow a good segmentation and size estimation. Homogeneous and small irregular tissue structures are sufficiently visible to differentiate normal from abnormal anatomy.

Adequacy score: 5

Description: the images include full breast anatomy including well defined chest wall. The left and right images are symmetric, noise level is non-masking, no artifacts and no motion blur.

Visual quality score: 4

Description: Image brightness, contrast, and detail visibility are good in the region of interest. Smooth boundaries better visualized than irregular contours.

Image Feature Descriptions

Contrast: the difference in brightness that makes an object conspicuous over the background

Sharpness: an image's overall clarity in terms of contour definition and contrast, perception of sharpness depends on contrast and resolution, low sharpness is called blur

Structural complexity: image statistics that describe the richness of spatial content and its visibility

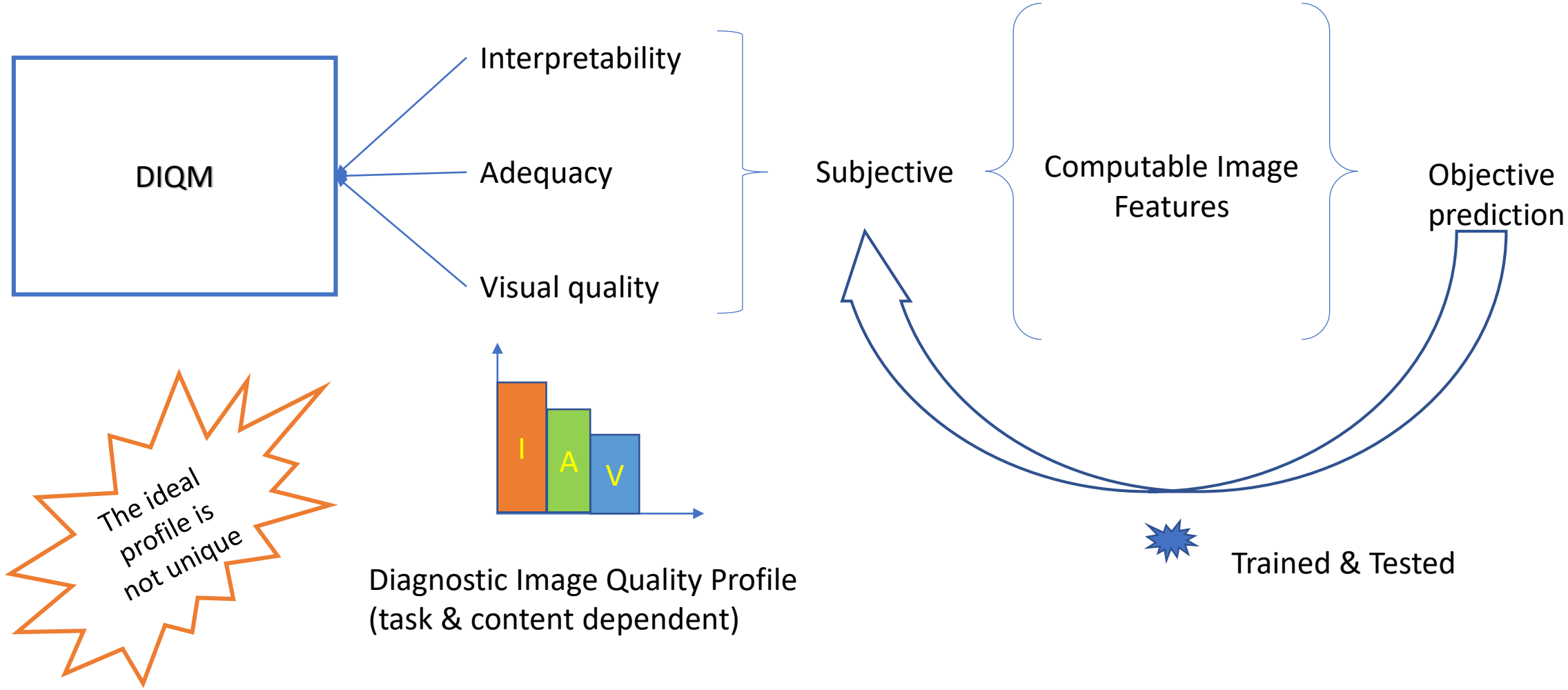
Entropy of corner distribution: related to the number and degree of spatial non-uniformity of corners (or singular points) in the image.

Fractal dimension: is a ratio providing a statistical index of complexity comparing how detail in a pattern changes with the scale at which it is measured. A measure of the space-filling capacity of a pattern.

Semantic Similarity: Vector Distance

- Relevant image features can be found by their feature vector distances to DIQ descriptions
- One approach may use the sum of the min conceptual distances from each concept in the DIQ description to the concepts in an image feature description.
- Conceptual distances can be computed in ontologies such as WordNet or a radiology lexicon
- Another approach may extract conceptual structures from DIQ descriptions (i.e. graph representation) and compute centroid distance to the conceptual structures in feature descriptions
- There are many distance metrics to choose from: cosine similarity, Euclidean, Minkowski, histogram similarity, etc.

DIQ Model


DIQM
Interpretability
Adequacy
Visual quality
Subjective
Computable Image Features
Objective prediction
I
A
V
The ideal profile is not unique
Diagnostic Image Quality Profile
(task & content dependent)
Trained & Tested

Discussion:

- We propose a move from unidimensional to tridimensional, cognition inspired DIQ models
- New techniques such as NLP based conceptual linking of diagnostic quality descriptions to image features can be integrated with traditional feature-based quality modeling
- Objective models can be made transparent by accounting for interpretability, adequacy and visual quality
- Operational models are possible by opening a window into the diagnostic quality components and making them available at quality control points of the diagnostic imaging chain
- DIQ models can be parametrized according to quality profiles

Collaboration:

- We are interested in joint work in any and all aspects of this topic
  - Radiologists to do subjective testing
  - Feature computation algorithms
  - Models (heuristic, regression based, DL)

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