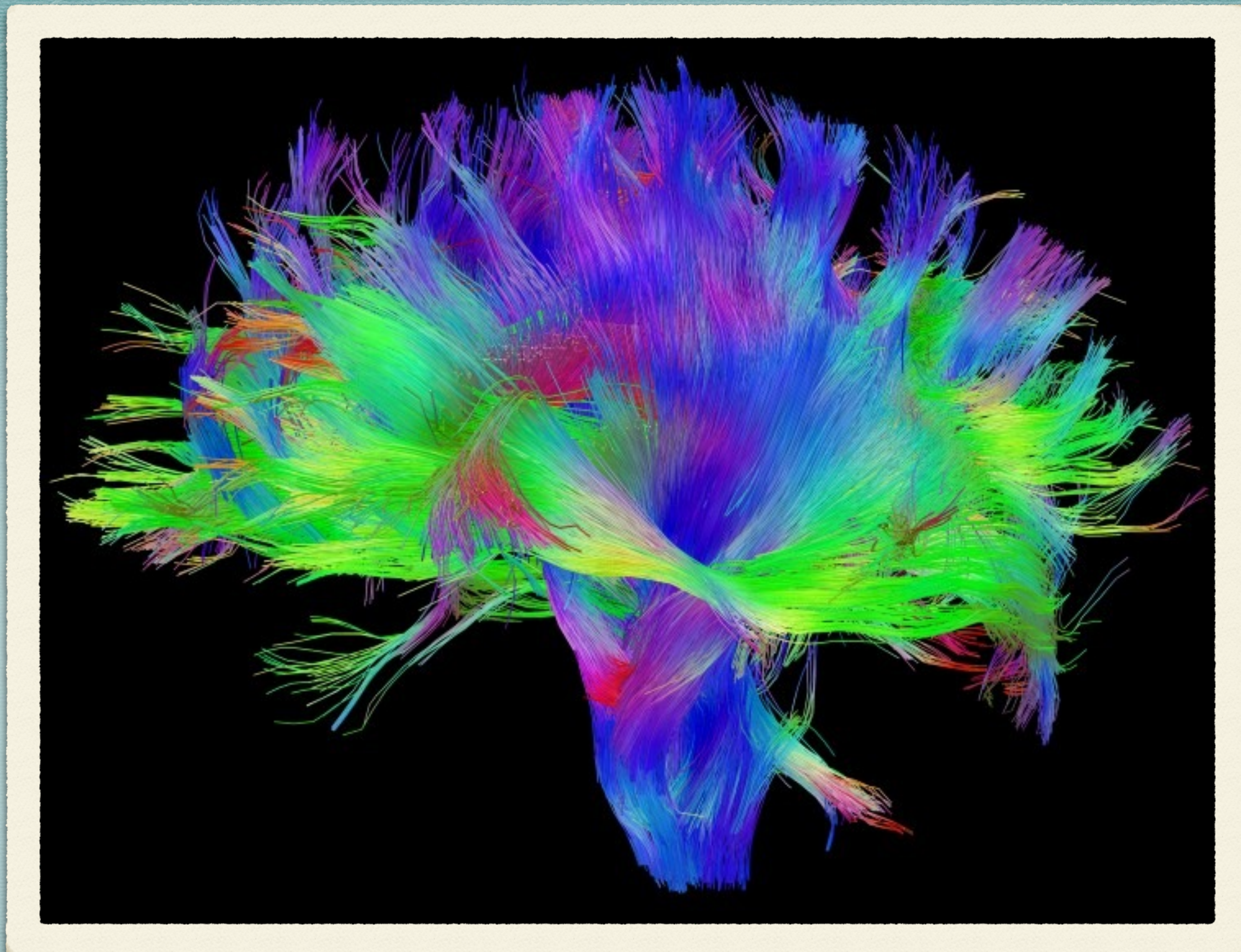


Artificial Intelligence in Medical Imaging

André M. Carrington, PhD, MMath, PEng

A diffusion spectral image of a brain's white matter fibers, from the Human Connectome Project.

Agenda

* Introduction
* Some examples of my work
* Research interests

Artificial intelligence (AI) and machine learning

* Acquiring "structural descriptions from examples" [1][2]
* "for prediction, explanation, and understanding." [2]
* Away from rules and substantive (parametric) models, i.e. statistics, toward patterns and empirical models [3]

Tasks for AI in medical imaging

Segment
Register
Denoise
Extract Features
Measure
Inpaint
Reconstruct
Create Atlas
Remove Artifacts/Bias

Annotate
Index
Deidentify

Screen
Detect
Classify
Identify ROIs and Slices
Content Based Information Retrieval
Detect Anomalies
Estimate Prognostic Risk
Identify Subgroups in Data
Surgical Path Planning
Assist Surgery (VR)
Model Organs
Generate Synthetic Data (deep fakes)

Some examples of my work

* Melanoma classification
* Lung tumor segmentation (CT)
* Lung tumor features
* Brain tissue classification (multimodal MRI)
* Filtered back projection (CT)
* Lung tissue simulation
* Deep ROC analysis for screening and detection

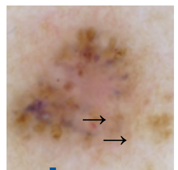
Melanoma classification

Patient

52	F

age

gender



dermoscopic photo

arms

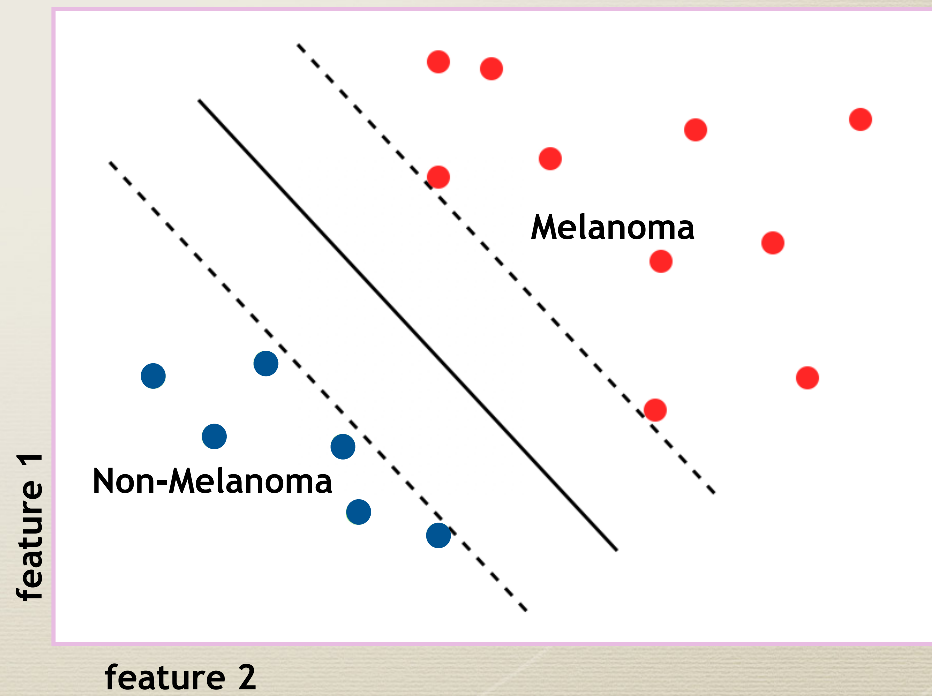
body region

blue ovoid nest, maple leaf-like areas, structureless area

observations

Zernicke moments
SIFT
contour sphericity

[52 1 2000...400...2200 3 112]



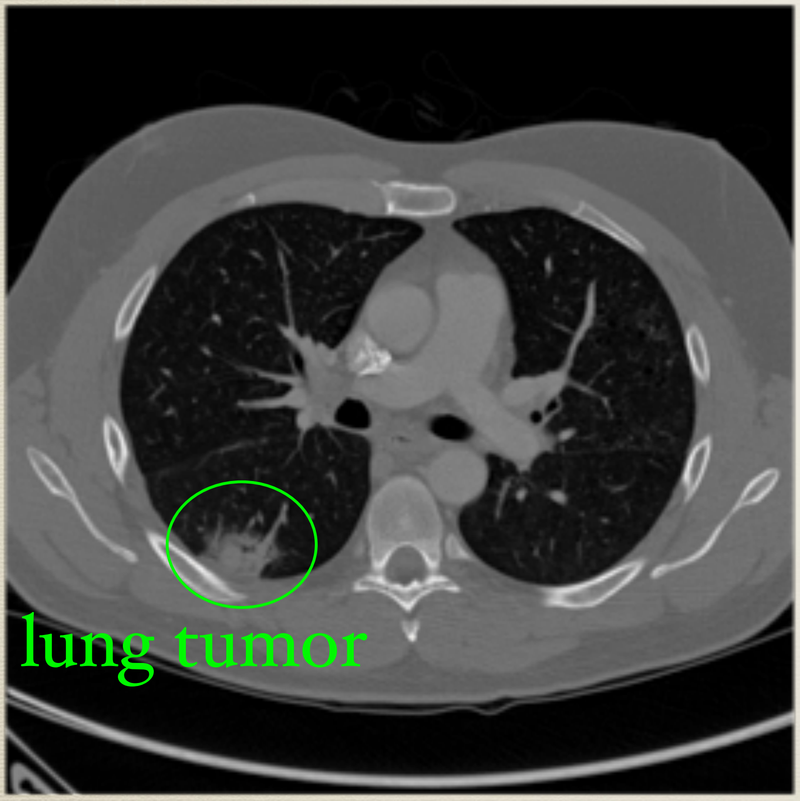
Melanoma classification accuracy[4]

Mean accuracy of support vector machines with various kernels

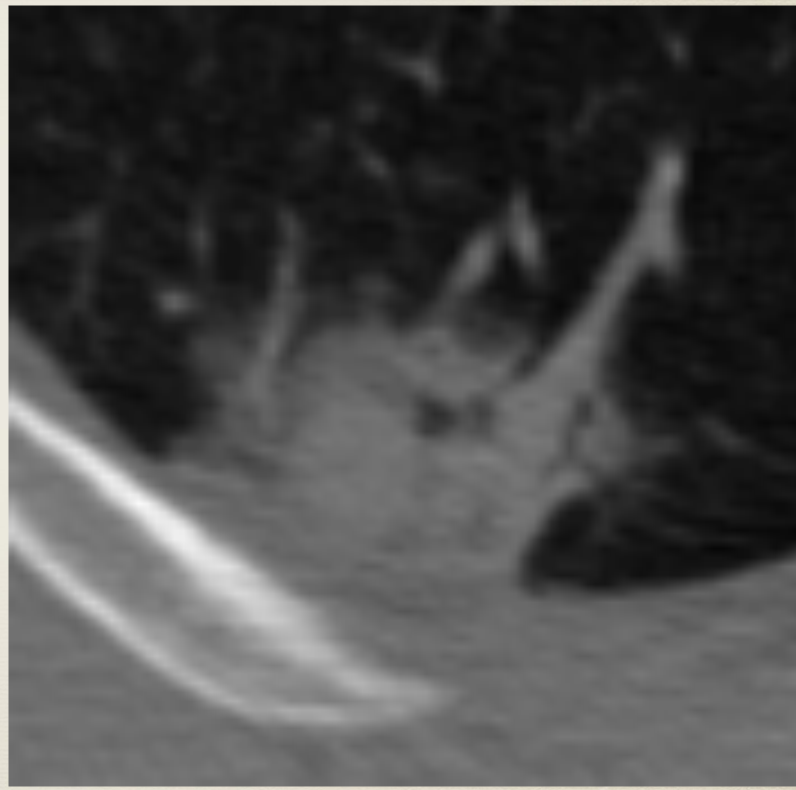
	Linear	Polynomial	Gaussian RBF	Sigmoid	Normalized Sigmoid	Mercer Sigmoid
Mean Accuracy	84.1	n/a	87.6	86.8	87.1	88.4
Standard Dev	0.42	n/a	0.52	0.76	1.0	0.66

29 experiments, 60 hyperparameter sets (random search) in 5 iterations of 10-fold cross-validation

Lung tumors in CT scans



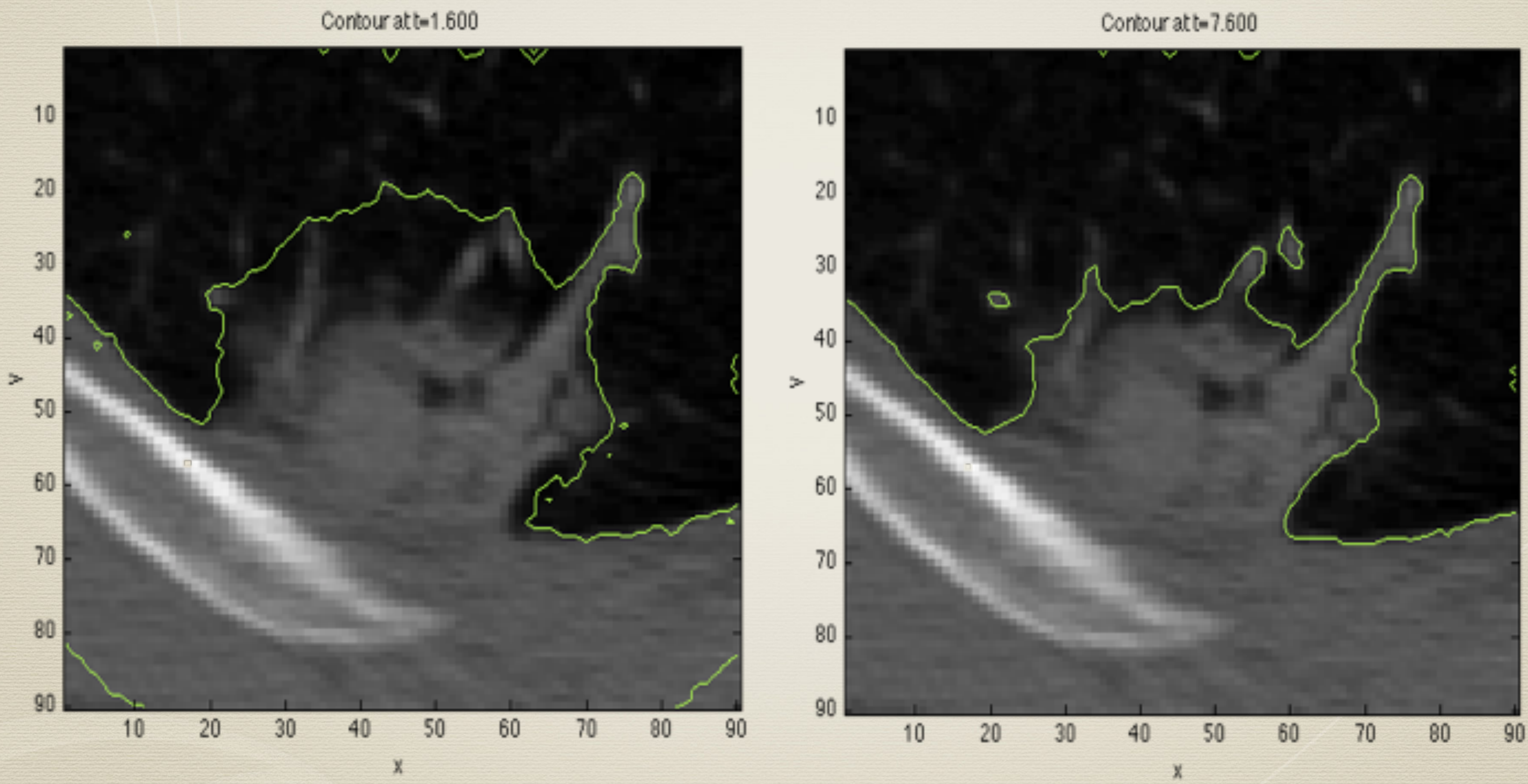
Region of Interest



Computed Tomography images (from The Cancer Imaging Archive) are slices of 3-dimensional data reconstructed from radon transforms using filtered back projection.

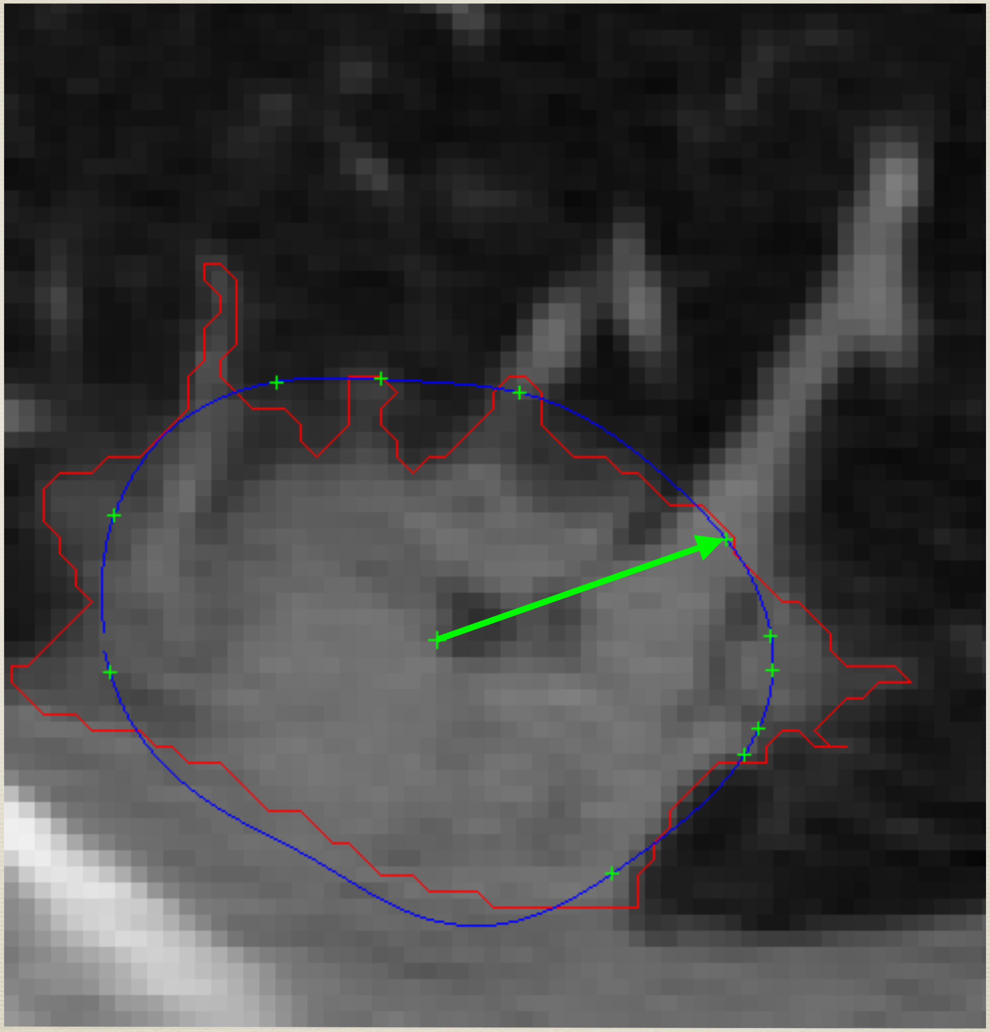
Segmentation with a Sobel edge filter yields broken contours

Chan and Vese's active contours without edges [5] using level sets



Written from scratch in Matlab based on Chan and Vese's paper using level sets.

Lung tumor features

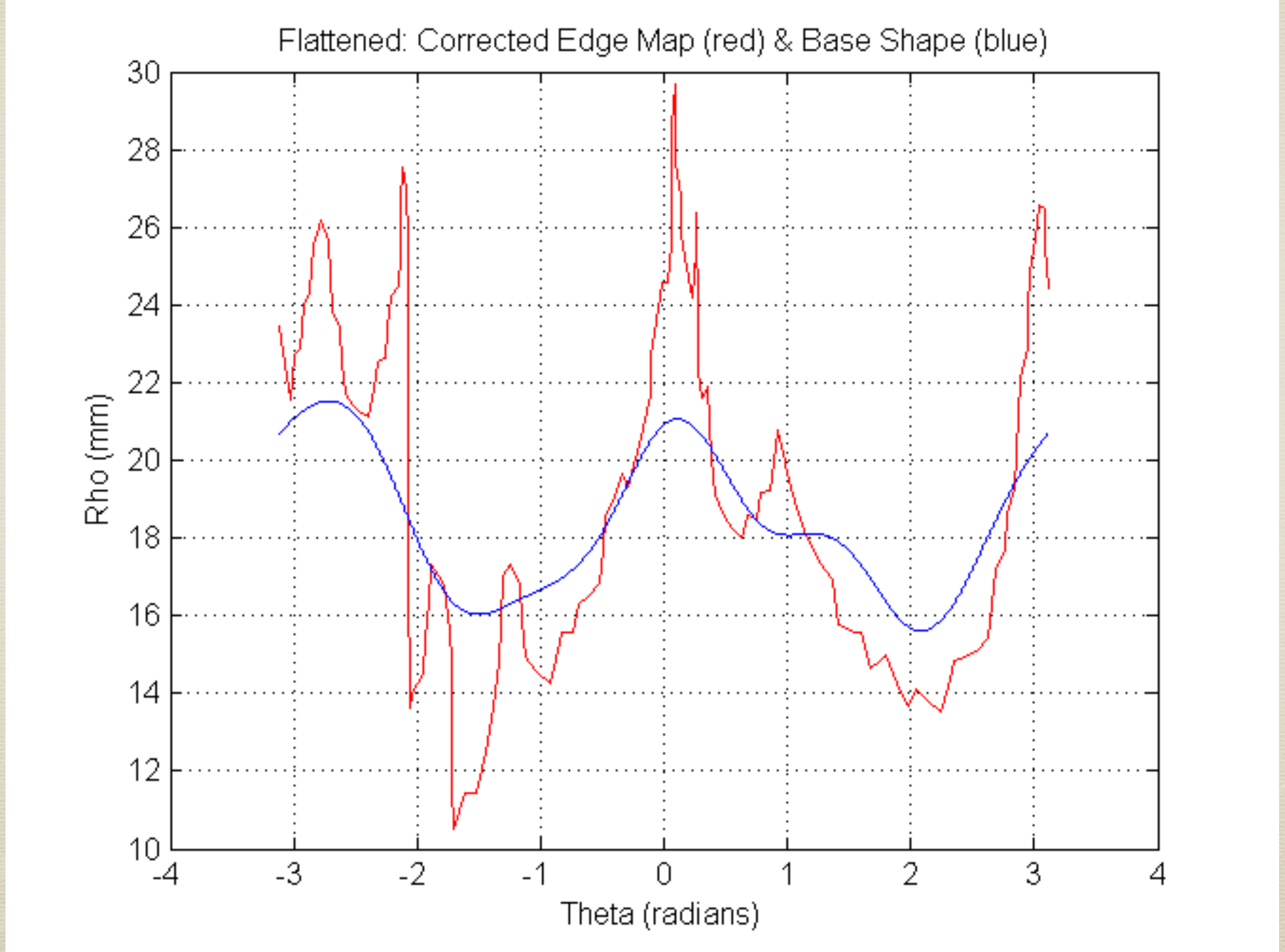


Red contour: radiologist

Blue contour: the extracted "base" (smooth) shape from the red contour

Uses my invention: polar Fourier descriptors

My invention unwraps the polar contour into a horizontal signal



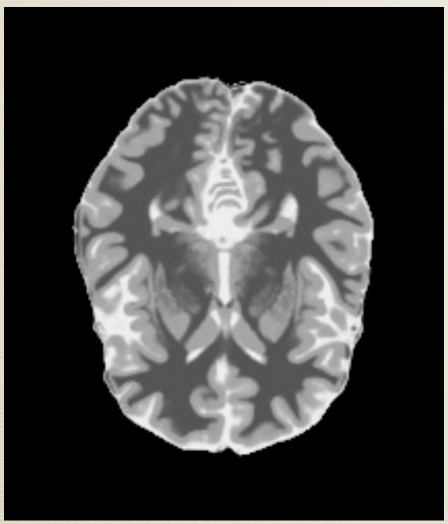
Other lung tumor features

* Subjective measures from LIDC [6]:
  * lobulation, an ordinal
  * spiculation, an ordinal
  * radiographic solidity, a nominal
  * calcification, an ordinal

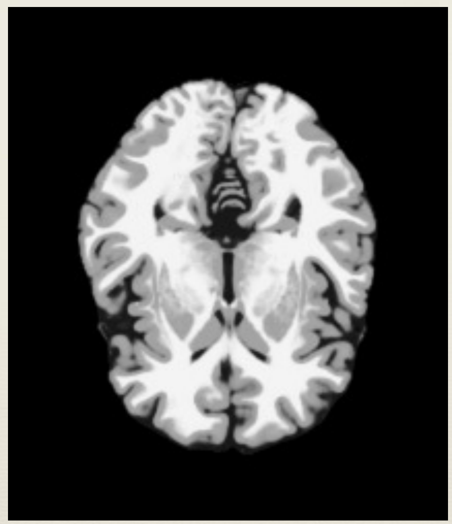
* Objective measures:
  * Sphericity [7]
  * Boyce-clarke shape index [8]
  * Spherical disproportion [9]
  * Spherical density [9]
  * Elongation [9]
  * Pondered radial distance [9]
  * Volume [10]
  * Radius of equiv. sphere [10]
  * Max. Compactness [10]
  * Max. Circularity [10]
  * Max. Eccentricity [10]
  * Mean Gray Level [10]

MRI scans of a brain

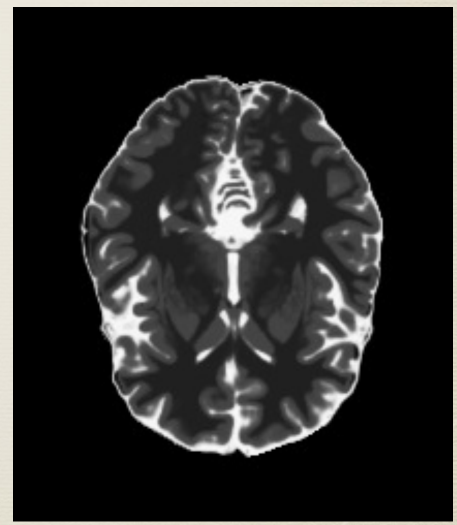
* Find the white matter, gray matter, cerebrospinal fluid and fat from multimodal MRI data.



PD weighted



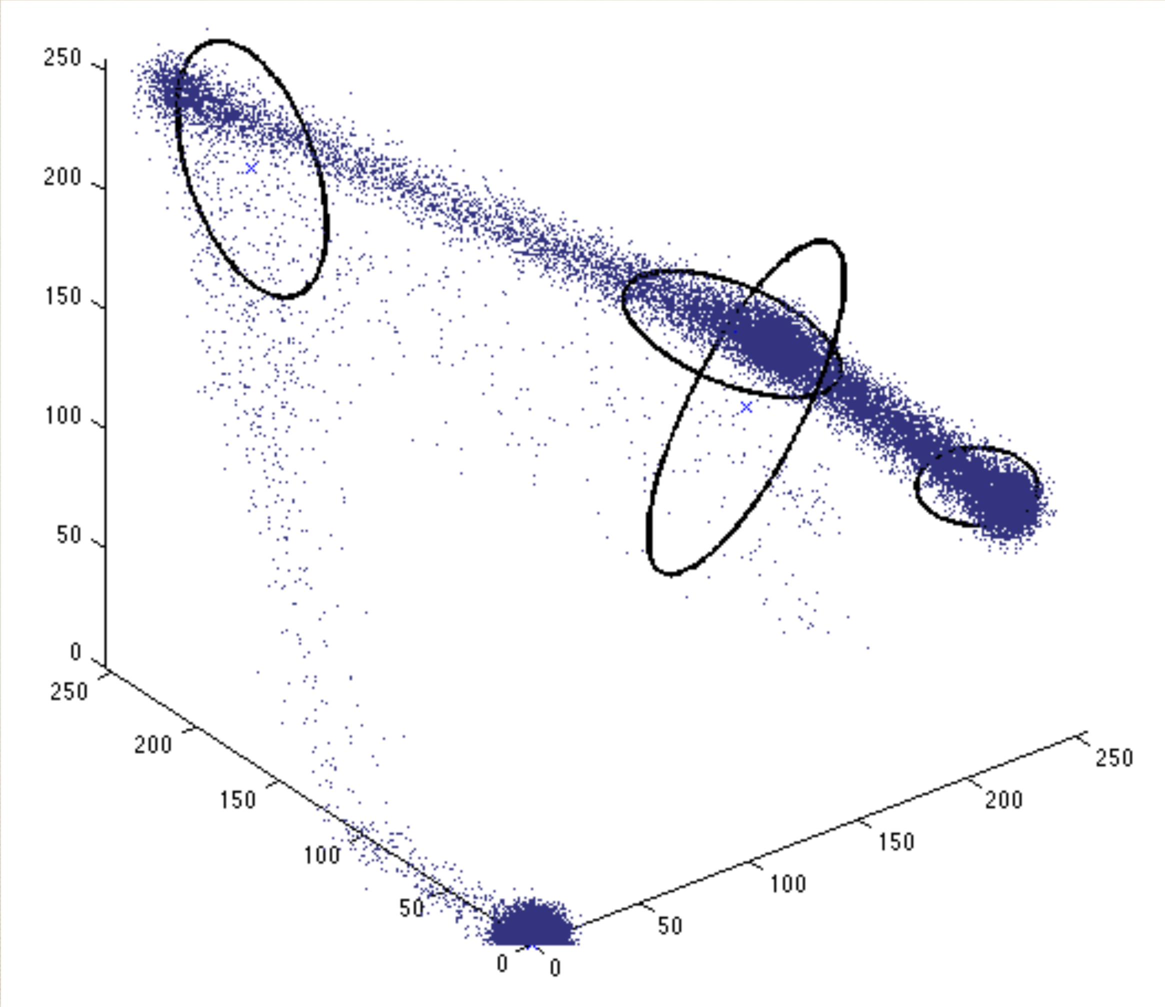
T1 weighted



T2 weighted

PD=proton density, T1=longitudinal relaxation time, T2=transverse relaxation time.

Plot the intensities from each modality then classify* tissues



*Wrote Gaussian mixture models with expectation maximization in Matlab (no built-ins)

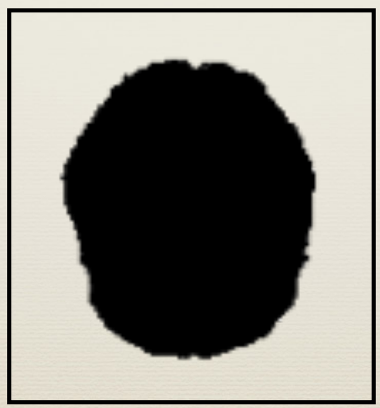
Classification results


white matter

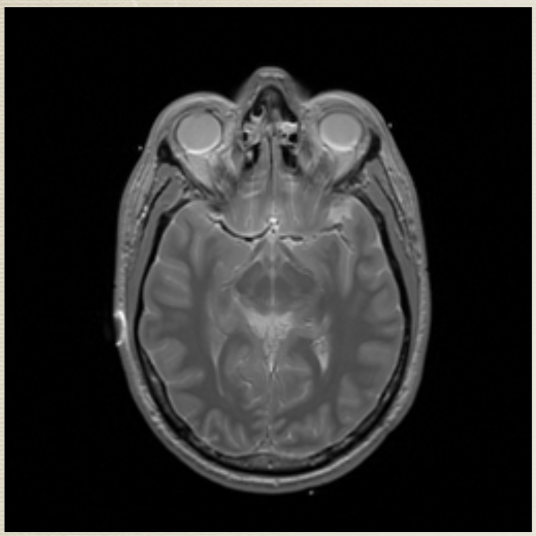

gray matter

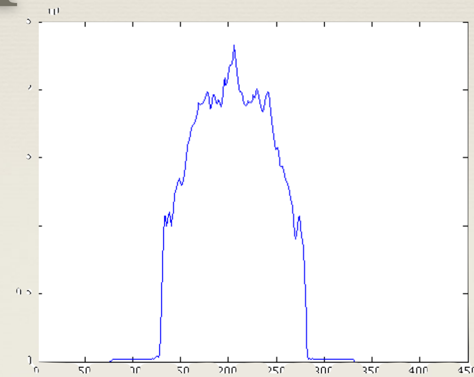

cerebrospinal fluid


fat tissue

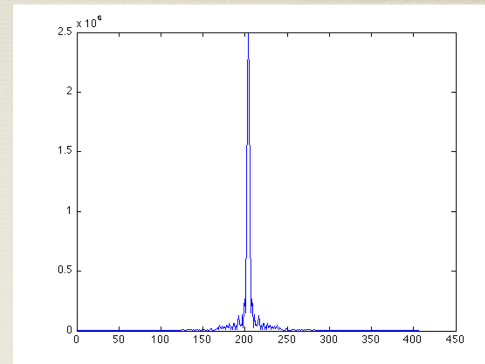

background

Filtered back-projection experiments



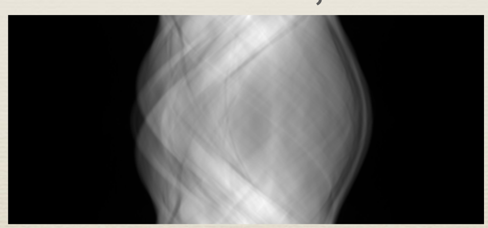


1D radon, θ_1

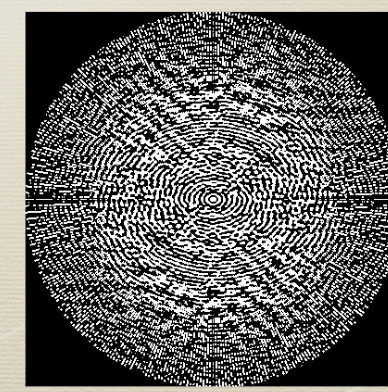


1D Fourier, θ_1

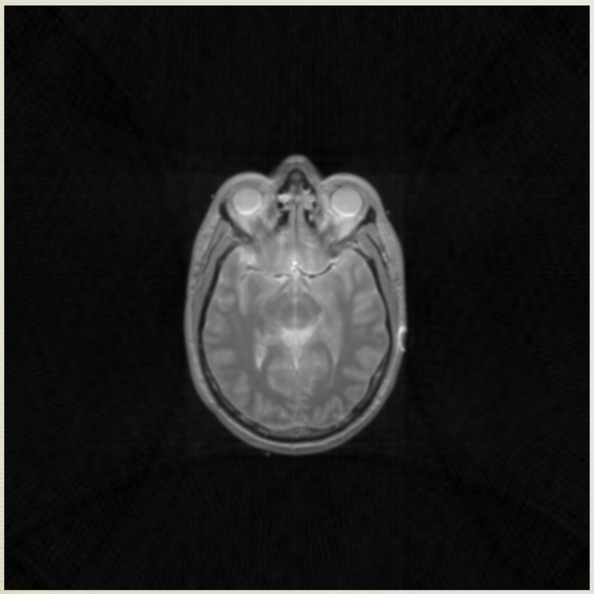
superposition of 1D radons, all θ



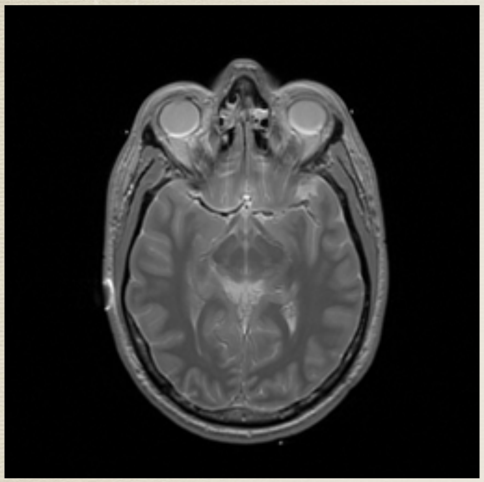
superposition of 1D Fouriers = 2D Fourier

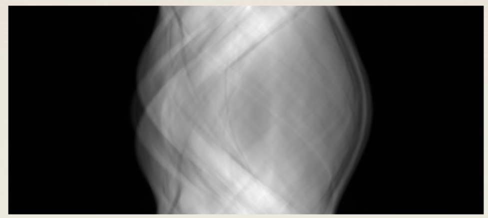


Reconstruction #1: a simple back-projection sanity check

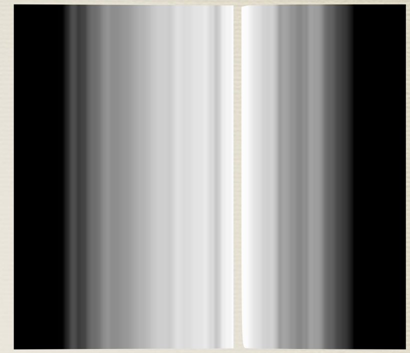


Reconstruction #2 with a 2D-cone filter: real back-projection



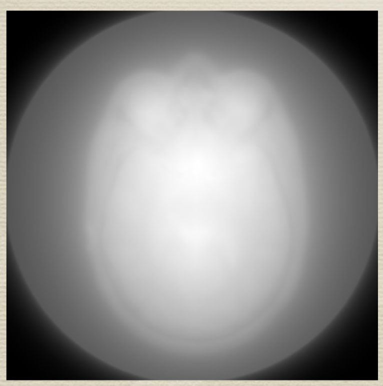


superposition of 1D radons, all θ

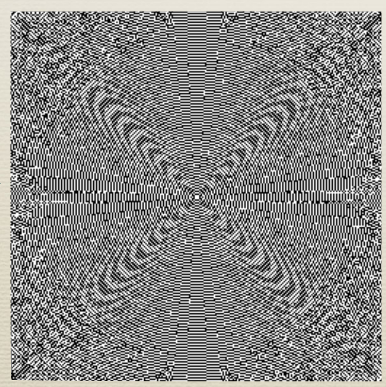


Extrude (back project) each radon

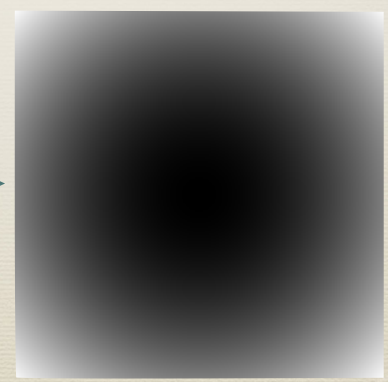
Reconstruct



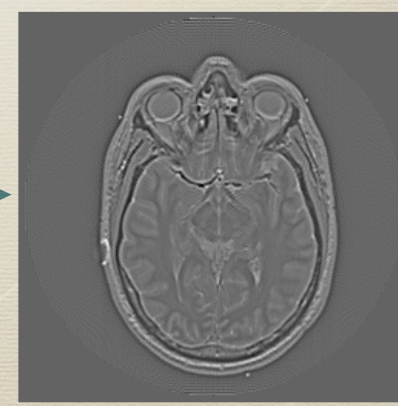
Apply 2D FFT



Apply 2D cone

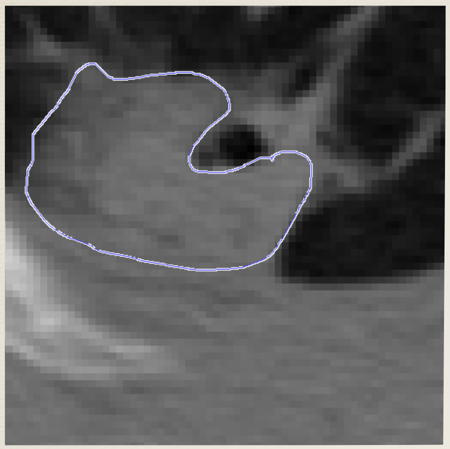


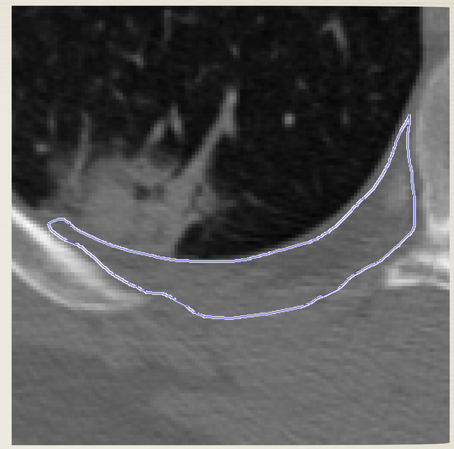
Deblur, contrast



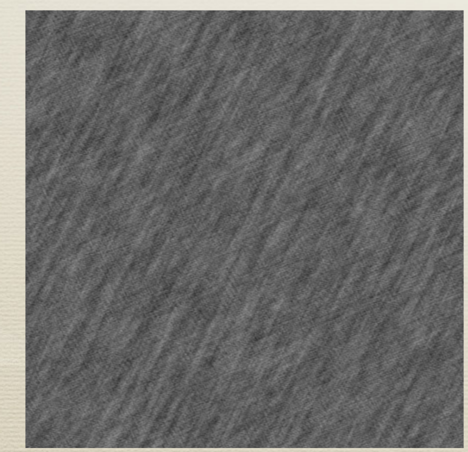
Skipping steps like padding and cropping.

Texture sampling of a tumor and the pleura (lung wall)

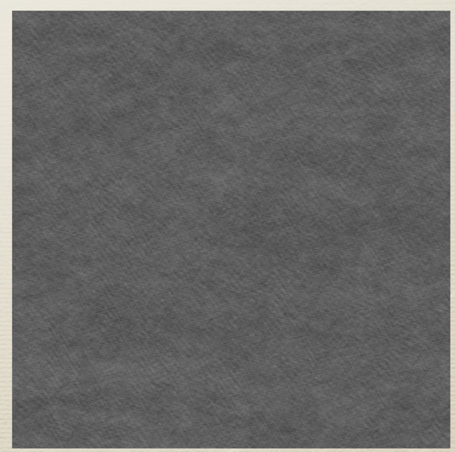




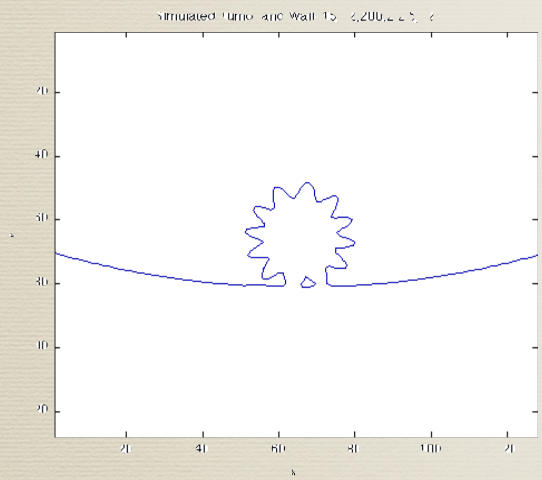
Tumor texture

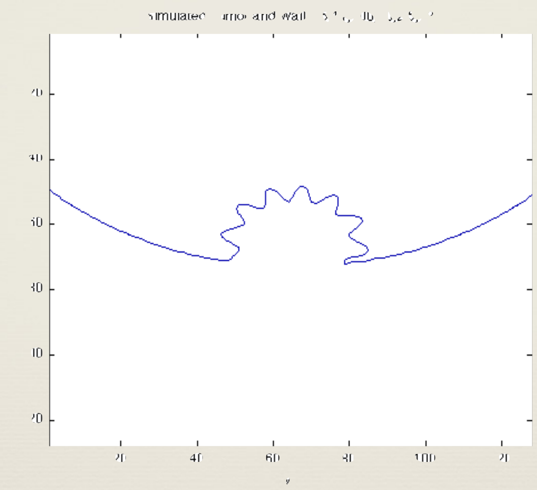


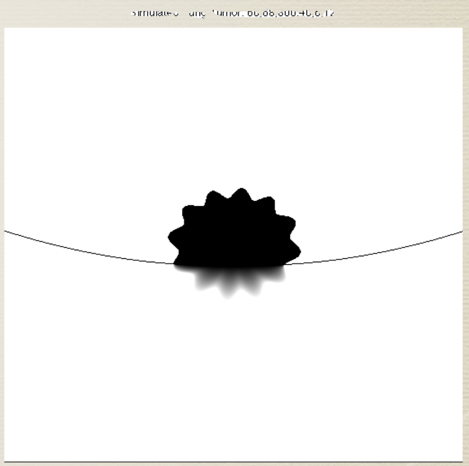
Wall texture



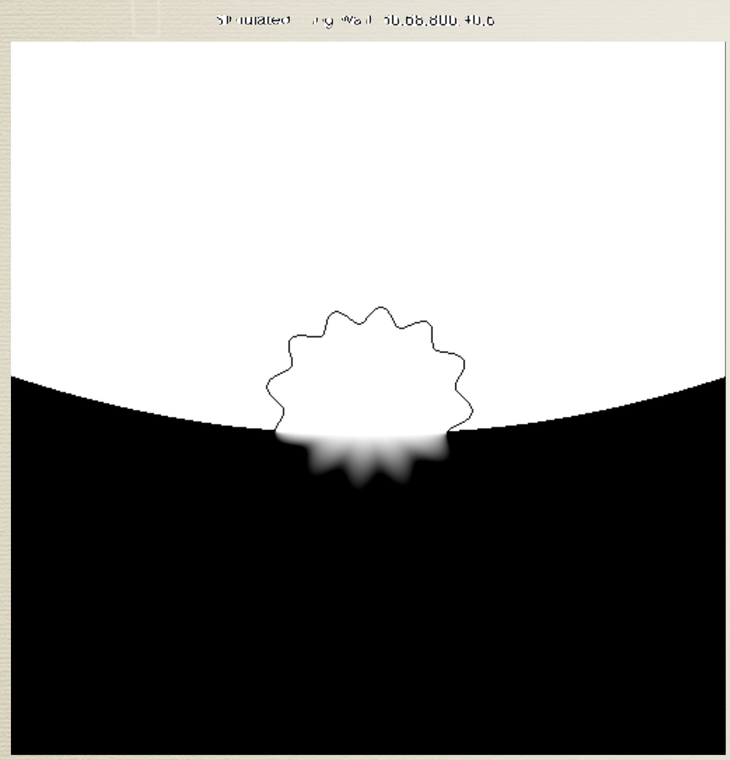
Simulated tumor, lung wall and gradient interaction

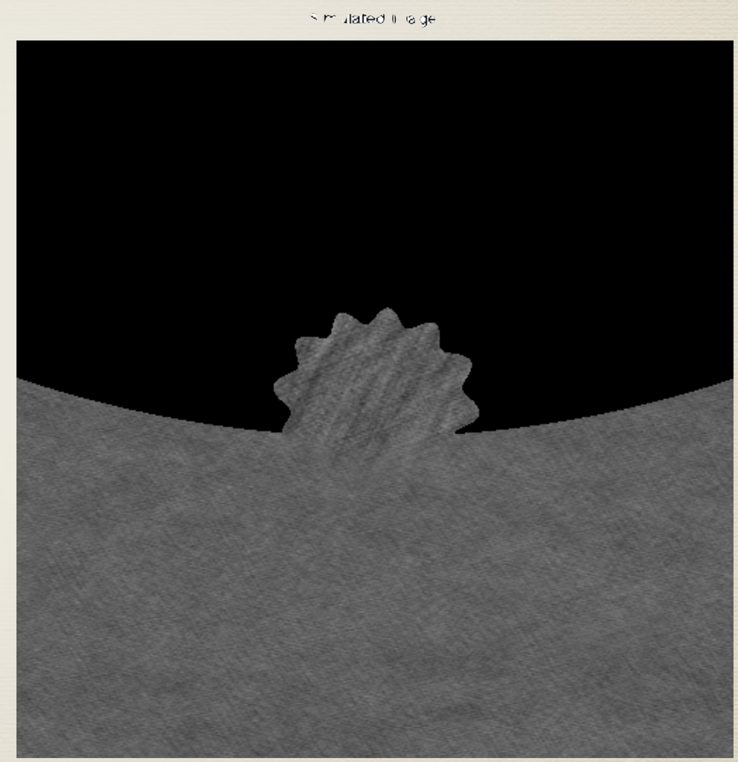




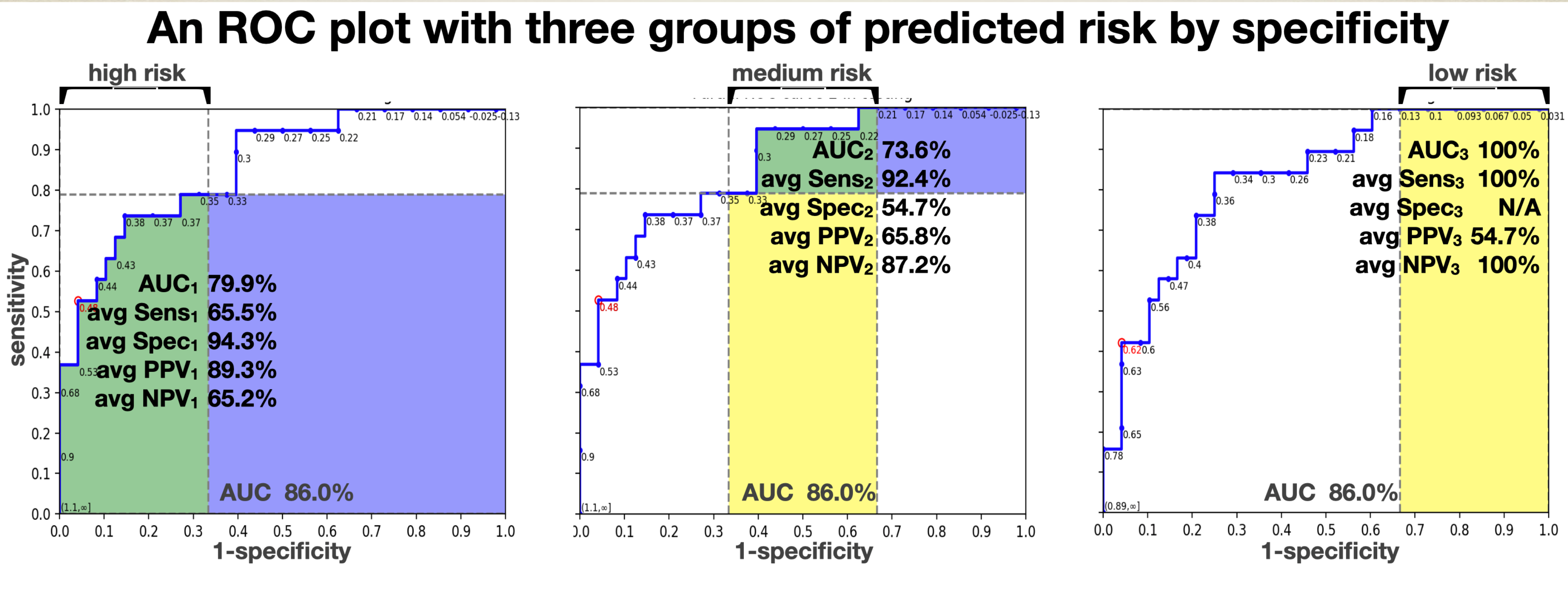


Application of texture to simulation





Deep ROC analysis to improve screening and detection



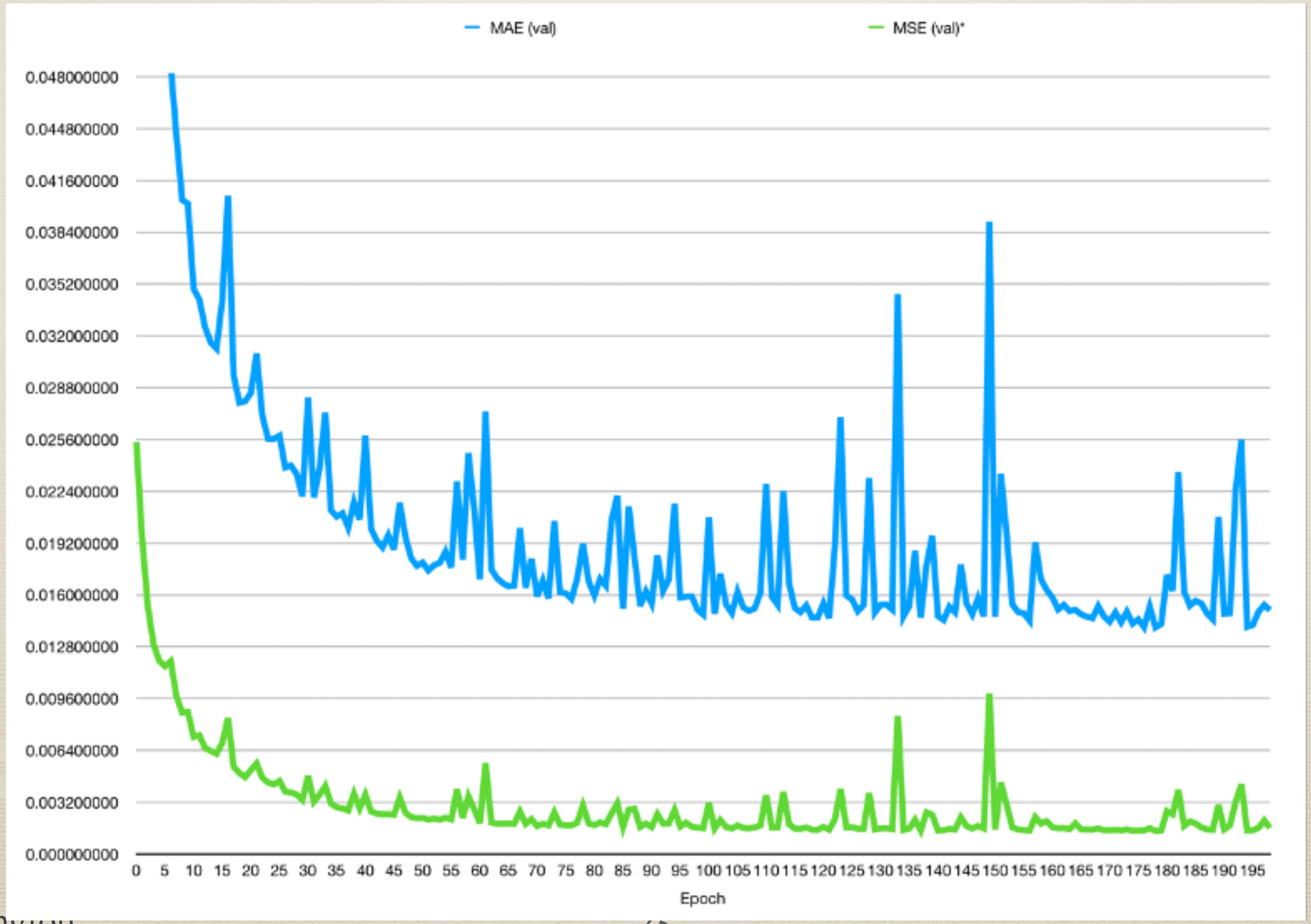
http://www.deeproc.org

Unsupervised methods

* Practical experience with:
    * Maximum variance unfolding
    * Non-negative matrix factorization
    * Kernel supervised principal components analysis
    * Probabilistic latent components analysis
    * Principal components analysis

Deep autoencoders can help reduce the dimensionality of data

Using public use Canadian Community Health Survey data, 613 features for 130,880 patients were reduced to 60 features with 1.40% maximum absolute error using my own 8 layer denoising autoencoder with the Nadam optimizer.



Research interests

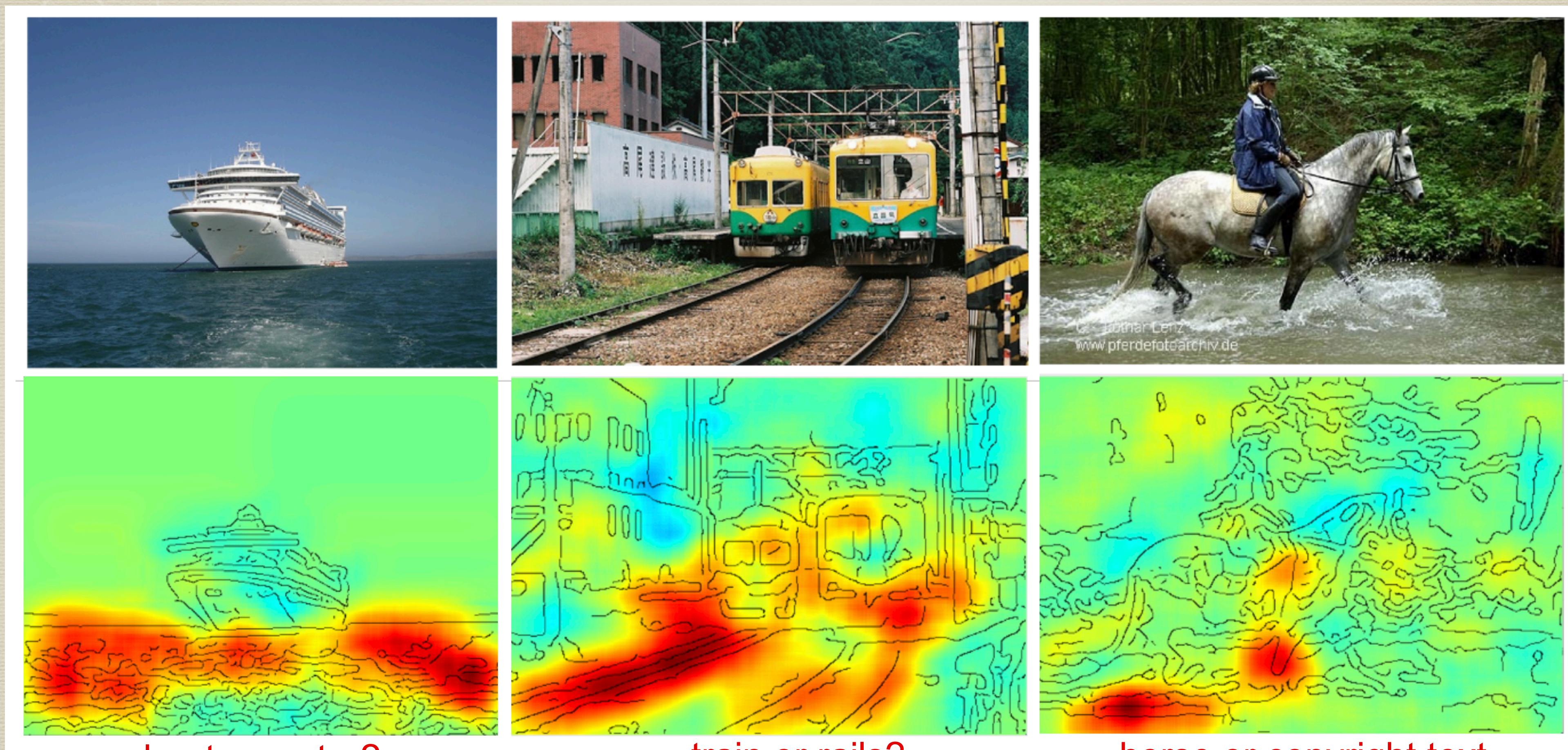
* Explainable AI
* Data set quality
* Performance measures and clinical utility
* Recent applications of AI in medical imaging

eXplainable AI in imaging

- Unsupervised learning extracts features that **are sometimes intuitive**
    - e.g. Maximum variance unfolding can extract or measure the amount of smiling on a face [11]
    - e.g. Local linear embedding can extract or measure the angle of a face [12,13]

- Saliency maps **are sometimes intuitive** explanations, but sometimes not (see next slide)

Unstable/improper features



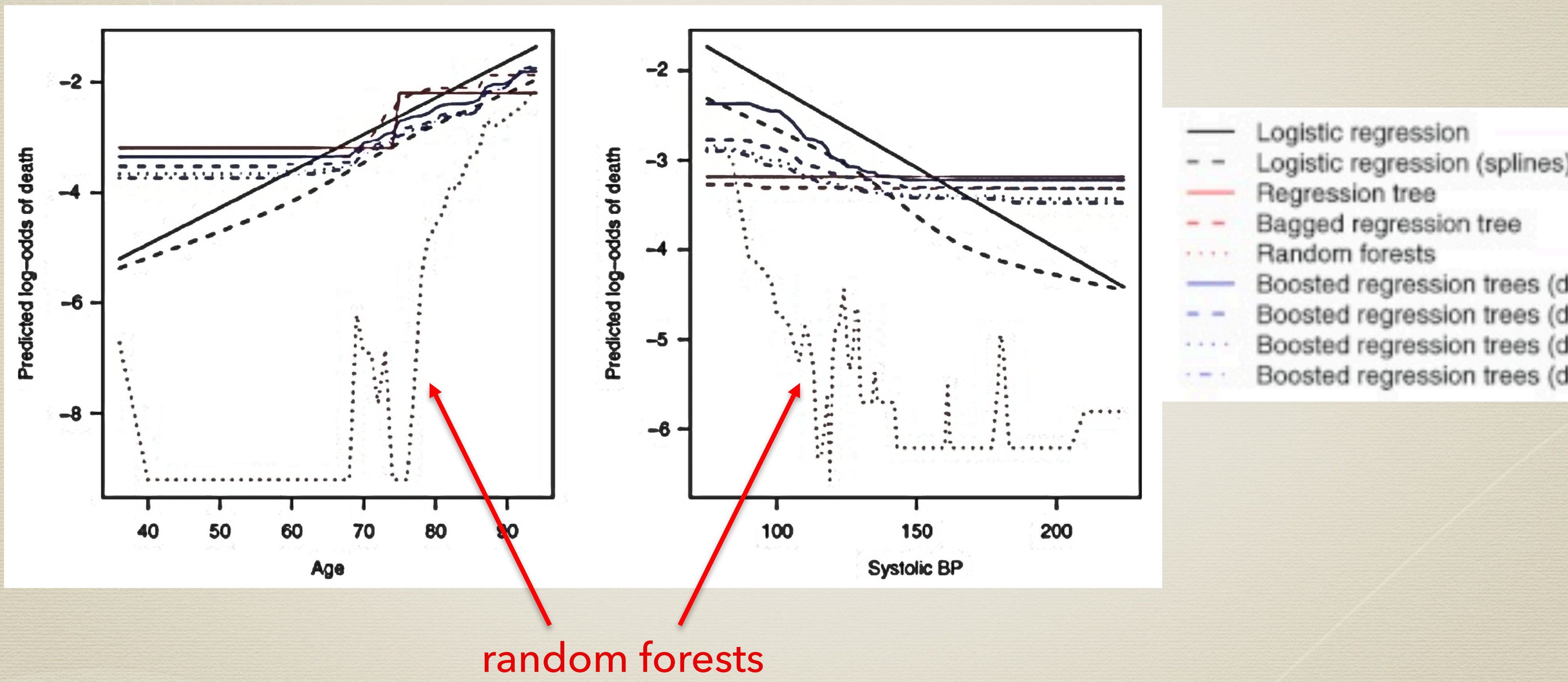
boat or water?
by color? arrangement?

train or rails?
straight parallel?

horse or copyright text
only in horse images?

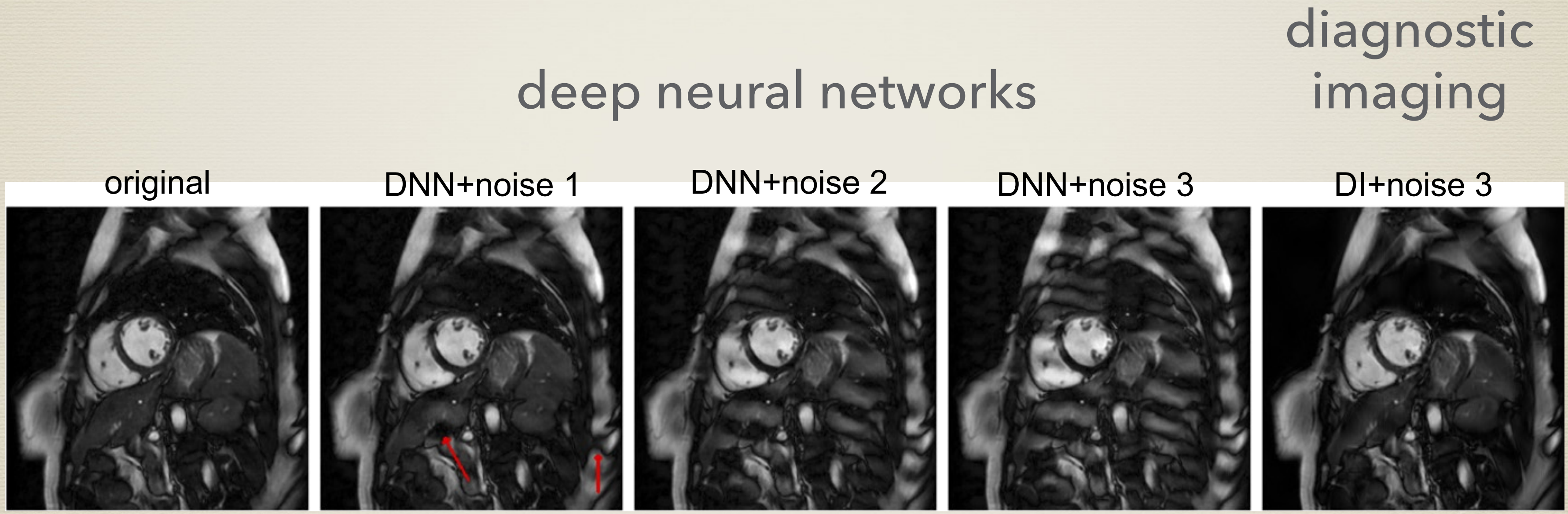
Lapuschkin et al. Unmasking Clever Hans Predictors and
Assessing What Machines Really Learn. 2019

Unstable influence of a feature!



Austin et al. Regression trees for predicting mortality in patients with cardiovascular disease: What improvement...2012

Deep learning is often non-local: bad for image reconstruction [14]



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The End

acarrington@toh.ca