

# Medical Image Retrieval

## Challenges And Successful Approaches

René Donner

Co-Founder & CTO, [rene@contextflow.com](mailto:rene@contextflow.com)



contextflow

# **What do Radiologists do?**

## **Metric Learning**

### **contextflow Tech Stack**



**contextflow**



# What do radiologists do?

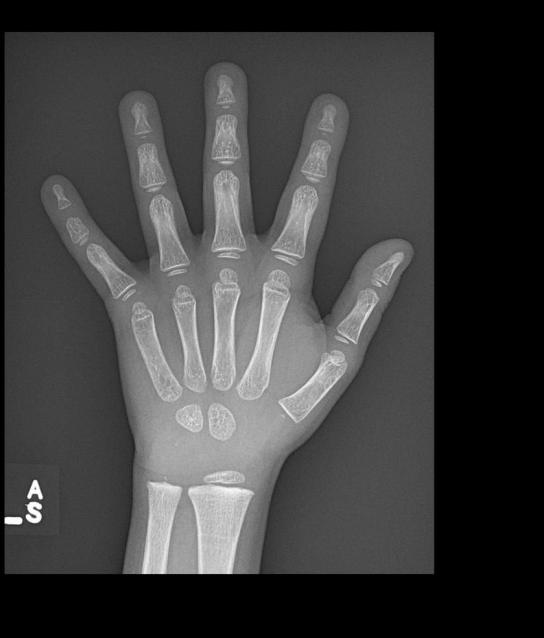


# X-Ray / Radiograph



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# X-Ray / Radiograph

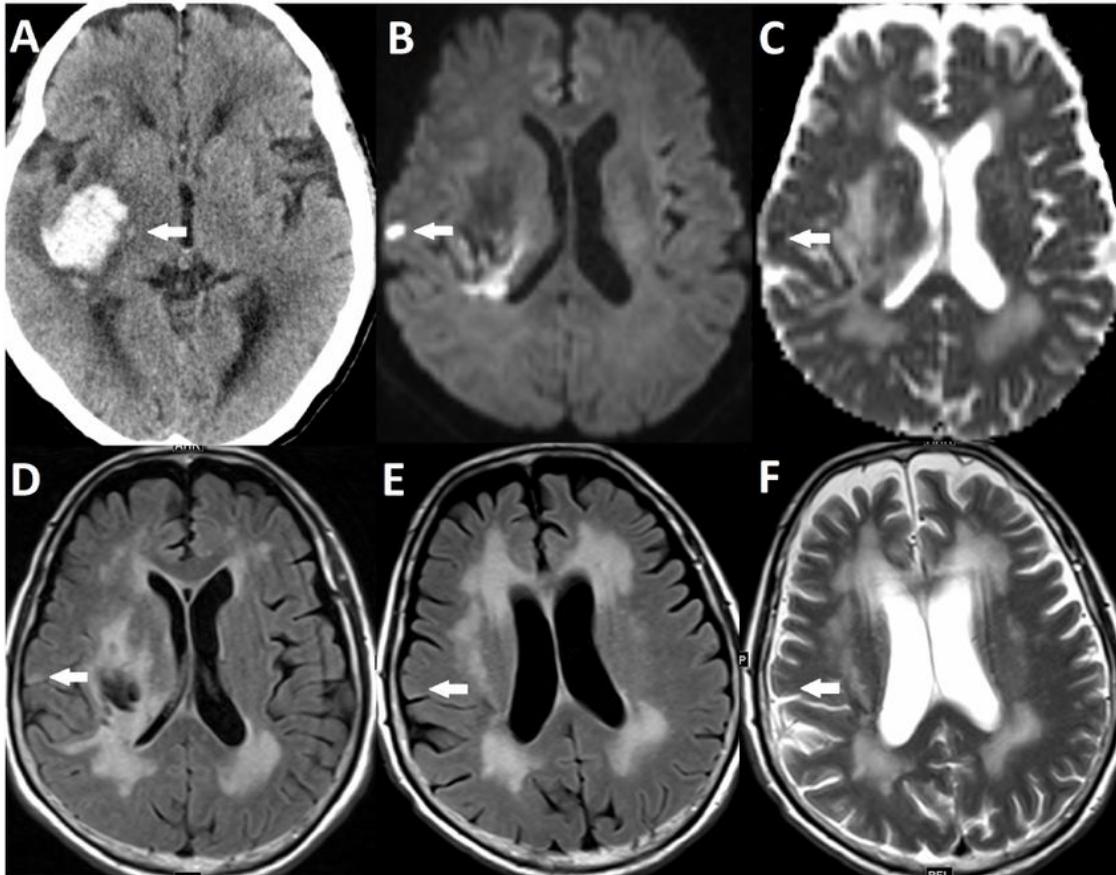


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# MRI



# MRI



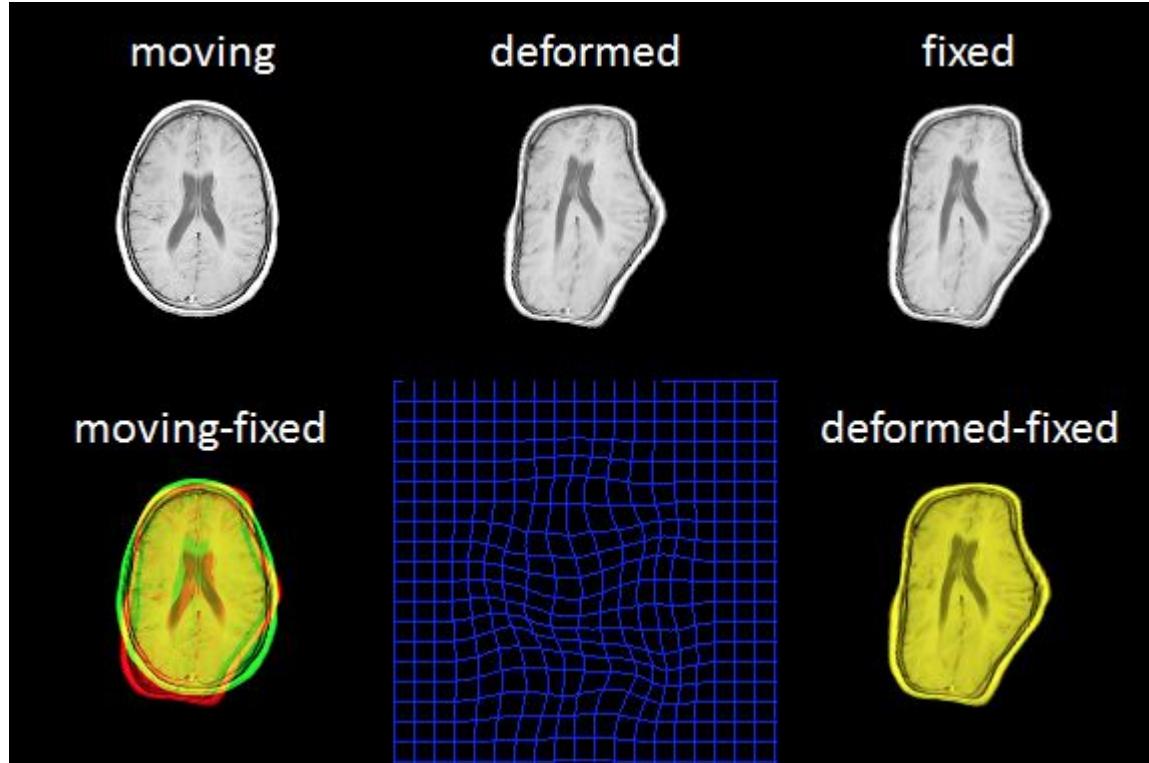
# CT / Volume Rendering



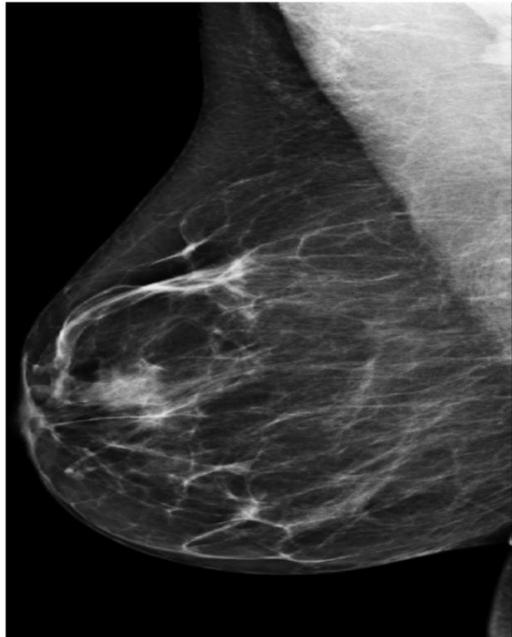
# **ML/DL Topics in Medical Imaging**



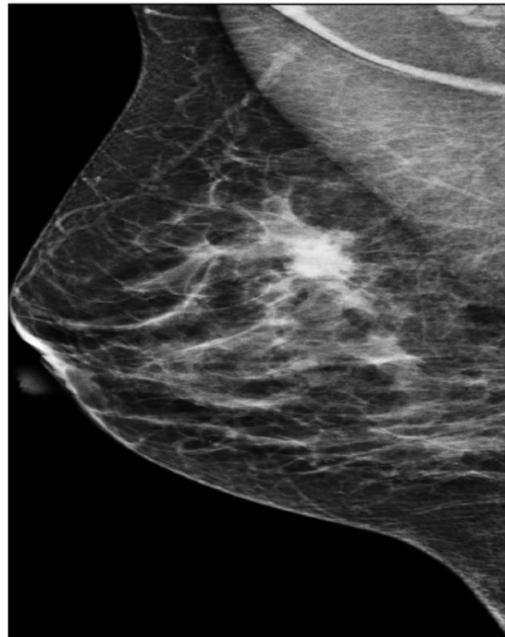
# Registration



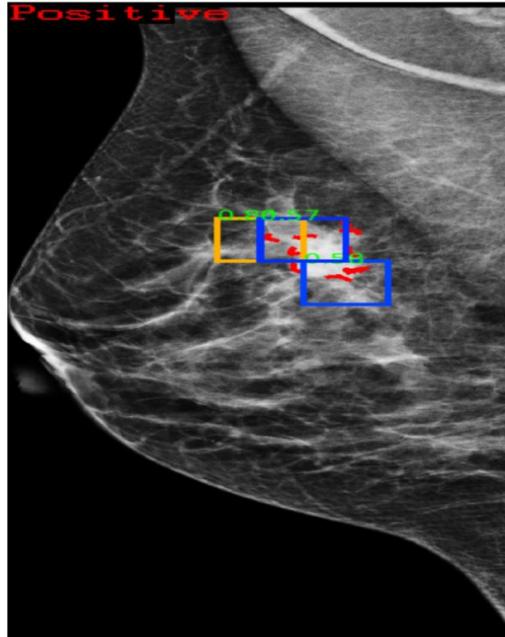
# Classification



(a) Negative-Normal

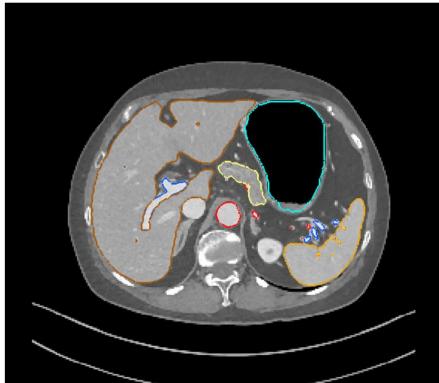


(b) Positive-Highly Suspicious as Malignant

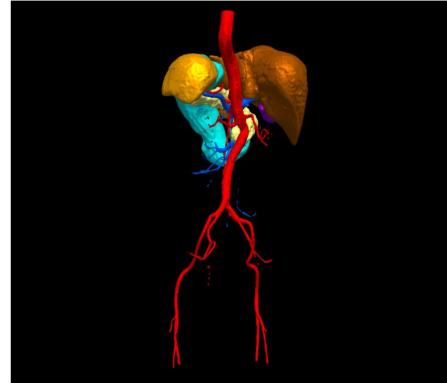


(c) Method Result

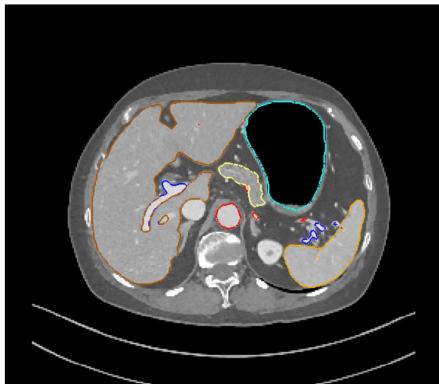
# Semantic Segmentation



(a) Ground truth (axial)



(b) Ground truth (3D)

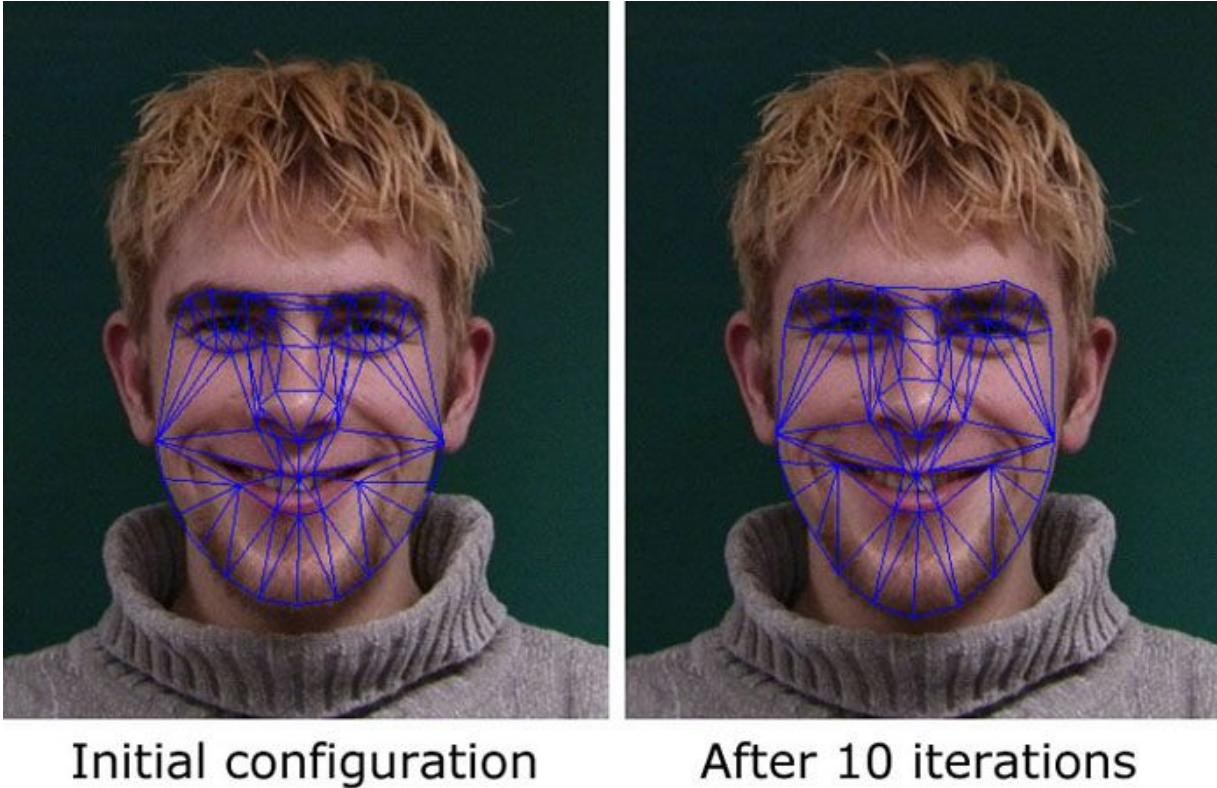


(c) Segmentation (axial)

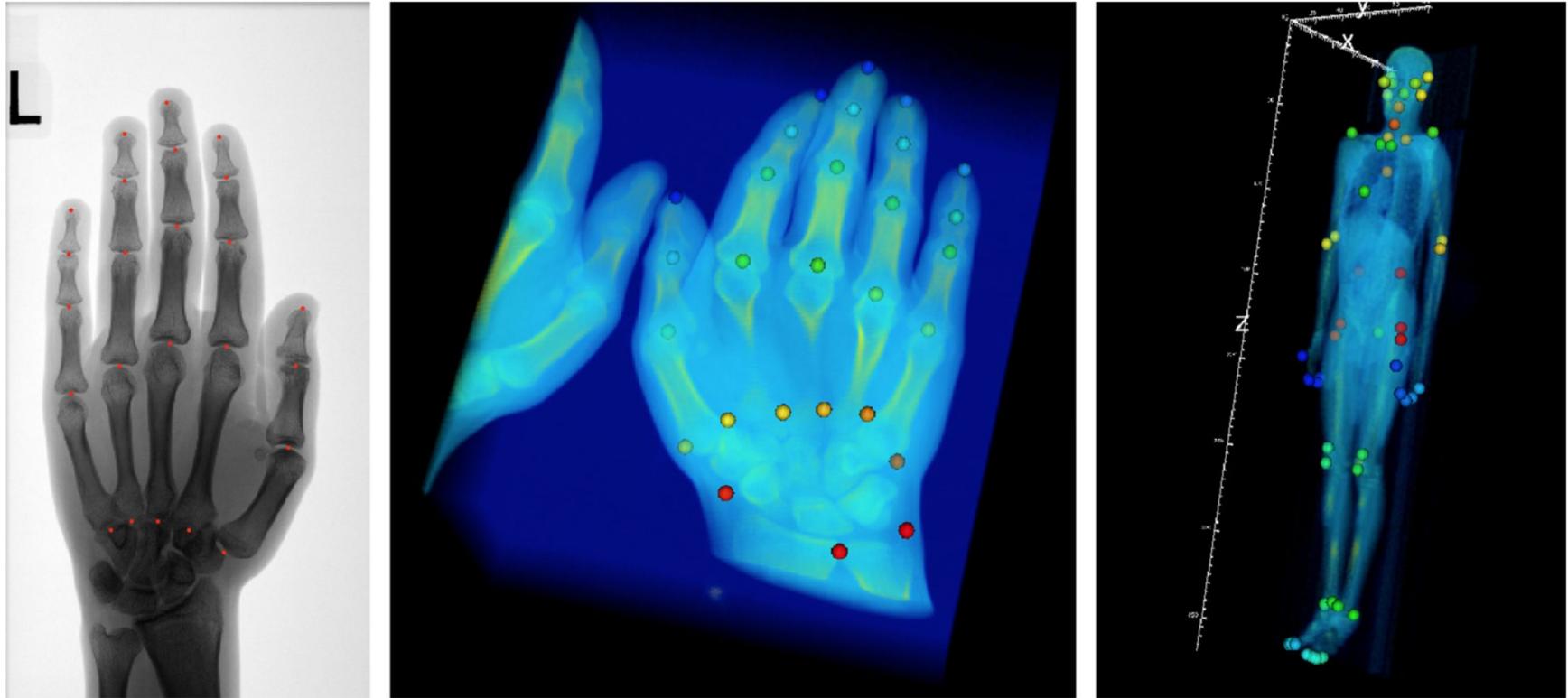


(d) Segmentation (3D)

# Segmentation

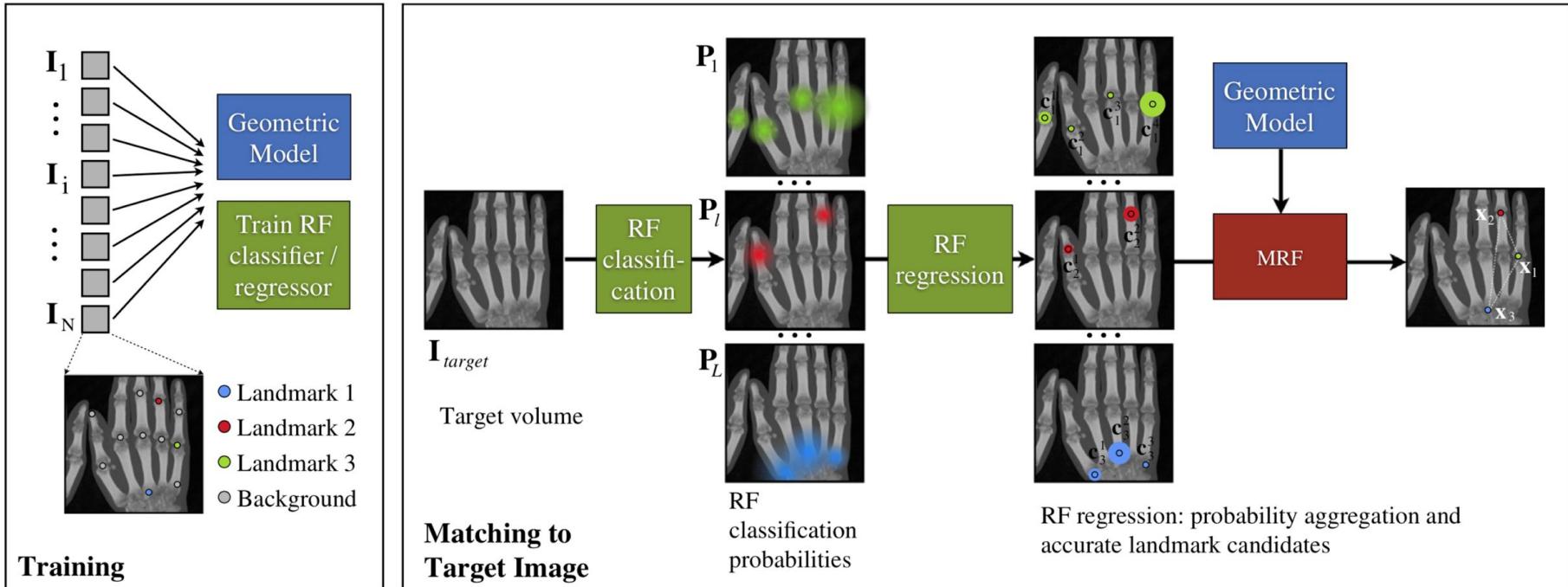


# Localization



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# Localization



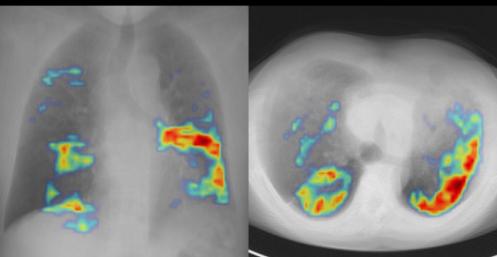
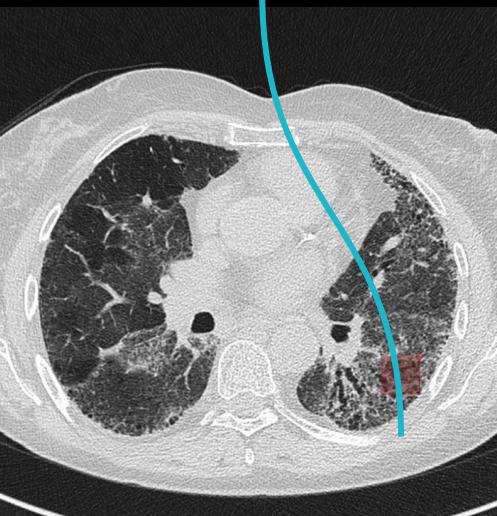
# Image Retrieval

Find matching cases

See relevant references

Mark region of interest

Patient



Matching Cases

Overview

Ground Glass  
Fibrosis  
Normal

Volumes

Details

References

Reference Cases

Ground Glass

- Anate: Infections or Edema (hydrostatics or permeability) or Hemorrhage
- Chronic hypersensitivity pneumonitis or nonspecific interstitial pneumonia - adenocarcinoma; rare: desquamative interstitial pneumonia, lymphoid interstitial pneumonia

Radiopaedia | Radiologyassistant | PubMed

Fibrosis

- Signs of fibrosis: loss of volume traction, honey-combing bronchiectasis
- Mid field distribution vs. upper lung field predominance
- Usual interstitial pneumonia, hypersensitivity pneumonitis or nonspecific interstitial pneumonia - adenocarcinoma; rare: desquamative interstitial pneumonia

Radiopaedia | Radiologyassistant | PubMed

Thieme Content

Ground Glass

Zysten und Milchglastrübungen bei Pneumocystis-jirovecii-Pneumoni

Article  
Search  
Media Search  
Thieme

Fibrosis

Silikose

Article  
Search  
Media Search  
Thieme

Healthy

Web & Literature  
Anatomy

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Statistics on findings

Reference cases with bullet point information

Publications and anatomical drawings

Professional Reference Content



# Challenges

# What it is a “similar” image?



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**What it is a “similar” image?**

**Many TBs of medical images**



**contextflow**

**What it is a “similar” image?**

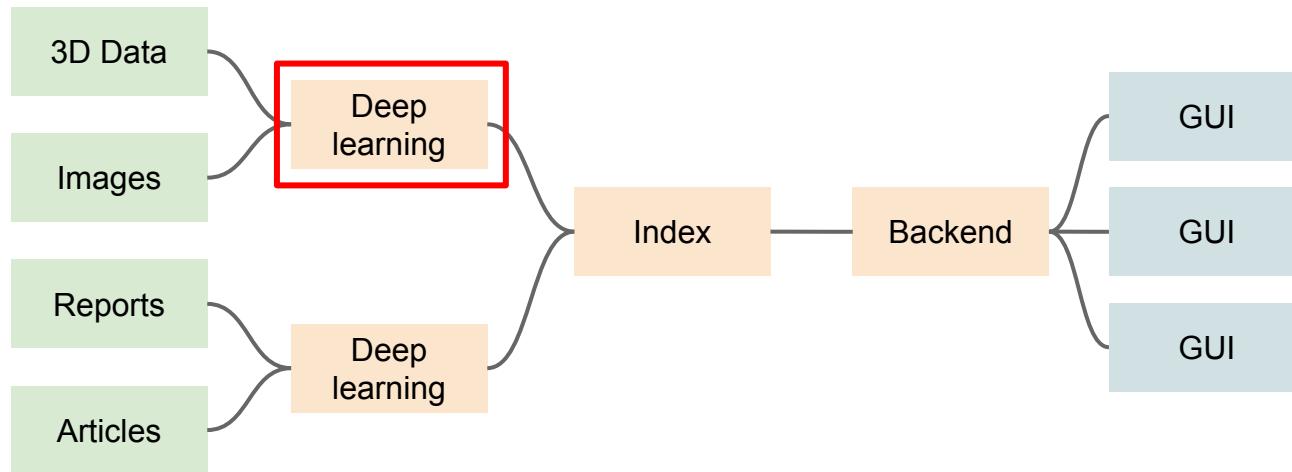
**Many TBs of medical images**

**Quick indexing / instant retrieval**



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# Architecture Overview



Data flow framework

Custom Data Structure

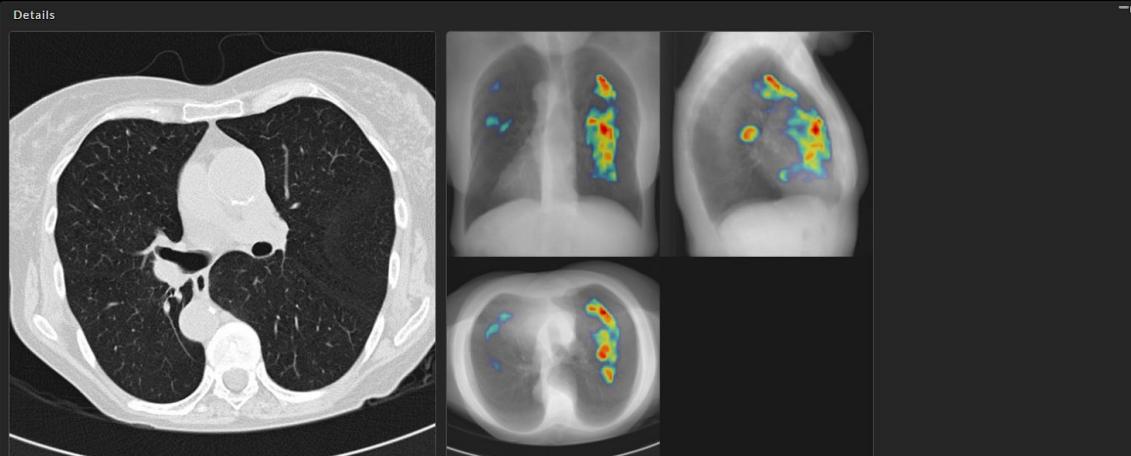
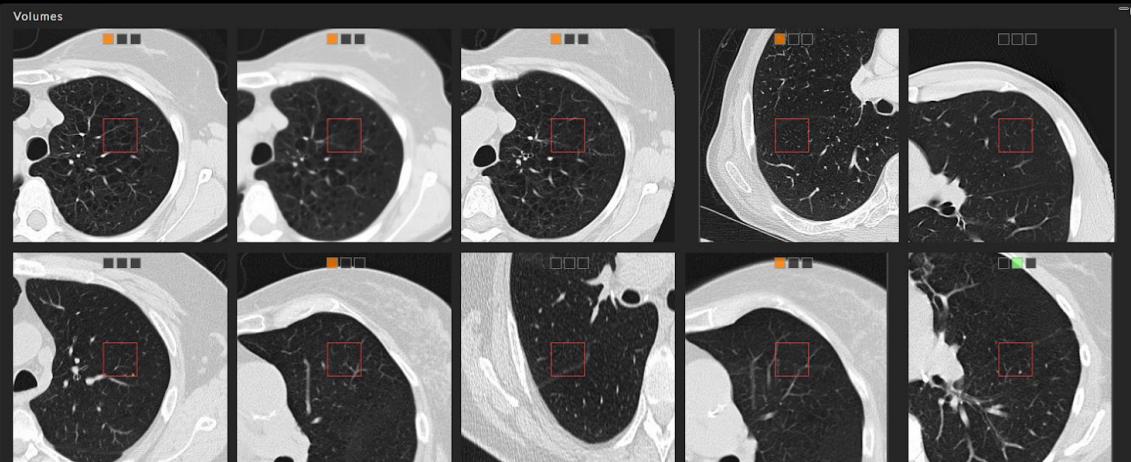
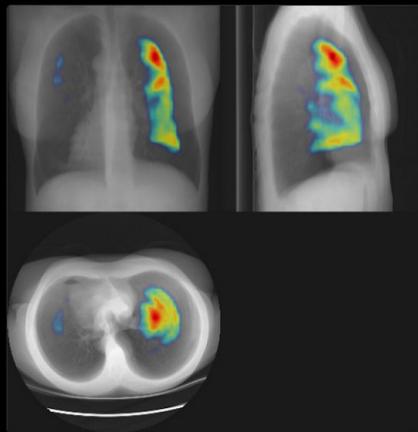
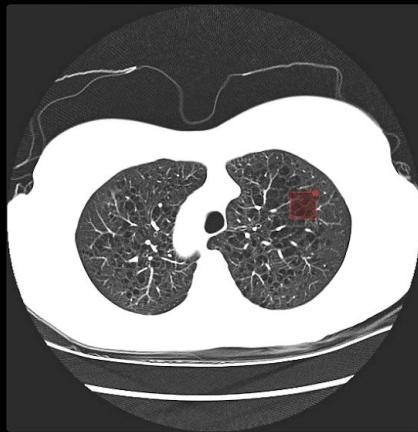
Go / GraphQL / Elm



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# Image Retrieval





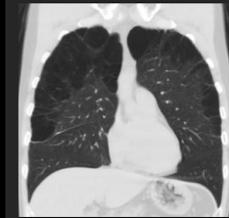
INVESTIGATIONAL - NOT AVAILABLE FOR COMMERCIAL SALE

#### Statistic



#### Reference Cases (Radiopaedia)

##### Emphysem



##### Pleural effusion



#### Web & Literature

##### Pleural effusion

- [Pleural effusion \(Radiopaedia\)](#)
- Pleural effusion tends to be used as a catch-all term denoting a collection of fluid within the pleural space. This can be further divided into exudates and transudates depending on the biochemical analysis of aspirated pleural fluid (see below). Essentially it represents any pathological process which overwhelms the pleura's ability to reabsorb fluid.

- [Diagnostic Tools of Pleural Effusion \(PubMed Central\)](#)

Moon Jun Na  
2014. *Tuberculosis & Respiratory Diseases*

##### Miliary Tuberculosis

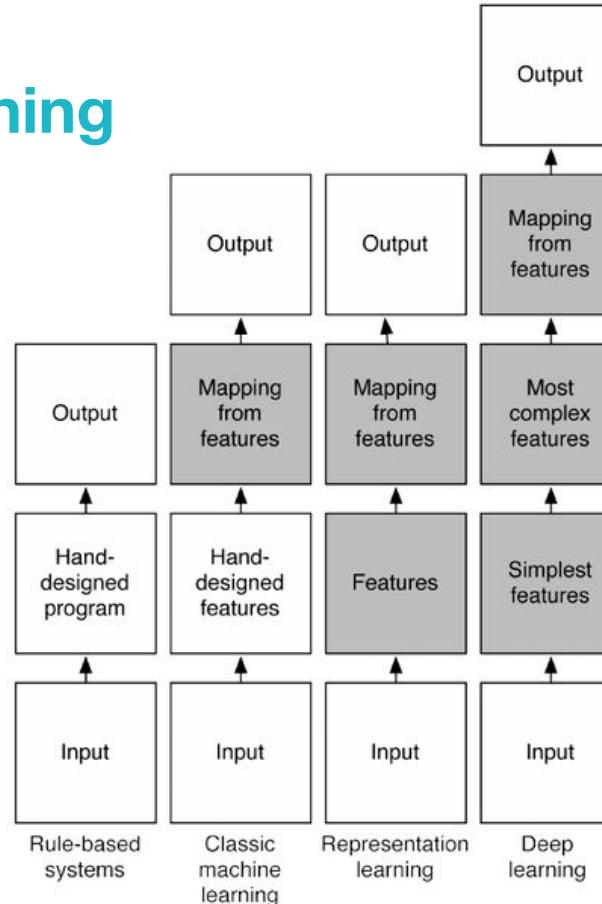
- [Miliary tuberculosis \(Radiopaedia\)](#)
- Miliary tuberculosis is an uncommon pulmonary manifestation of tuberculosis. It represents haemogenous dissemination of uncontrolled tuberculous infection and carries a relatively poor prognosis.

- [Tuberculosis: pulmonary manifestations \(Radiopaedia\)](#)

#### Anatomy



# Deep learning vs classical machine learning



# Image Retrieval before DL

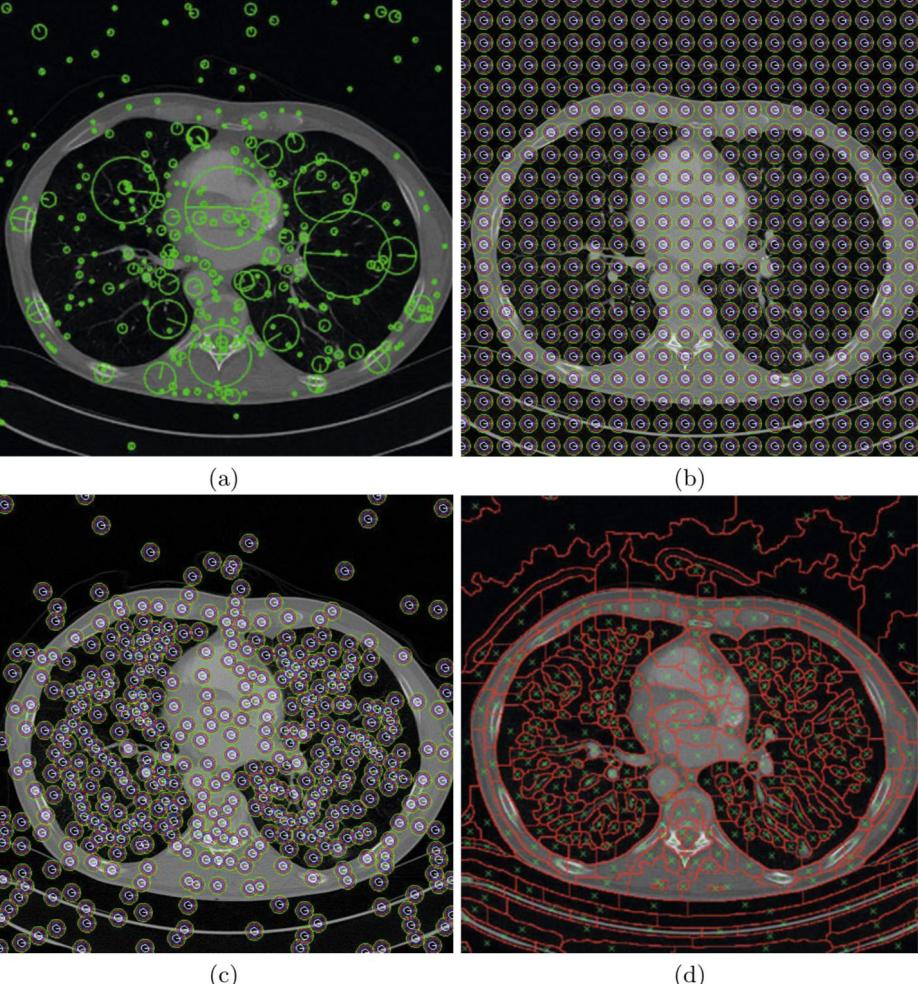
## Superpixel-Based Interest Points for Effective Bags of Visual Words Medical Image Retrieval

Sebastian Haas<sup>1,\*</sup>, René Donner<sup>1</sup>, Andreas Burner<sup>1</sup>, Markus Holzer<sup>1</sup>,  
and Georg Langs<sup>1,2</sup>

<sup>1</sup> Computational Image Analysis and Radiology Lab, Department of Radiology,  
Medical University of Vienna, Austria

[sebastian.haas@meduniwien.ac.at](mailto:sebastian.haas@meduniwien.ac.at)

<sup>2</sup> Computer Science and Artificial Intelligence Laboratory,  
Massachusetts Institute of Technology, Cambridge, MA, USA

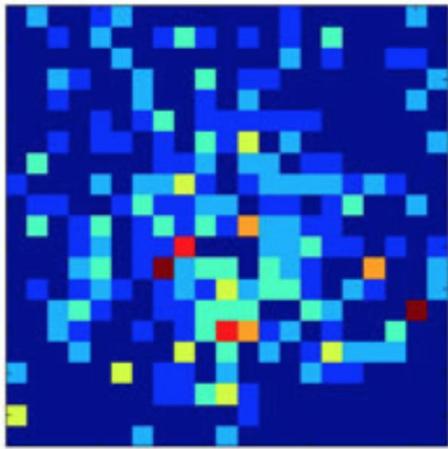


**Fig. 2.** An example lung image showing interest point position, orientation and scale for a) SIFT b) DENSE c) superpixel d) shows the the superpixel regions as well as the

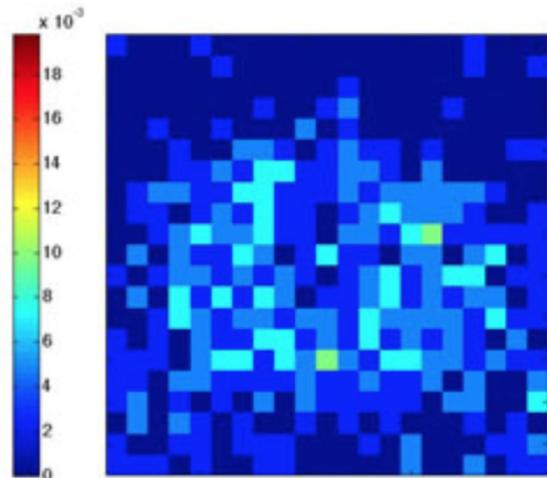
# Image Retrieval before DL



(a)



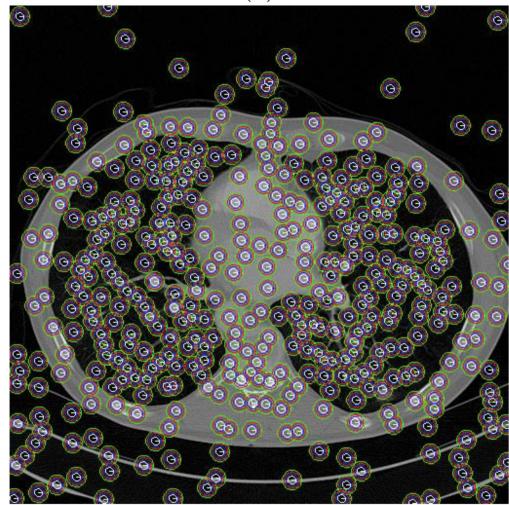
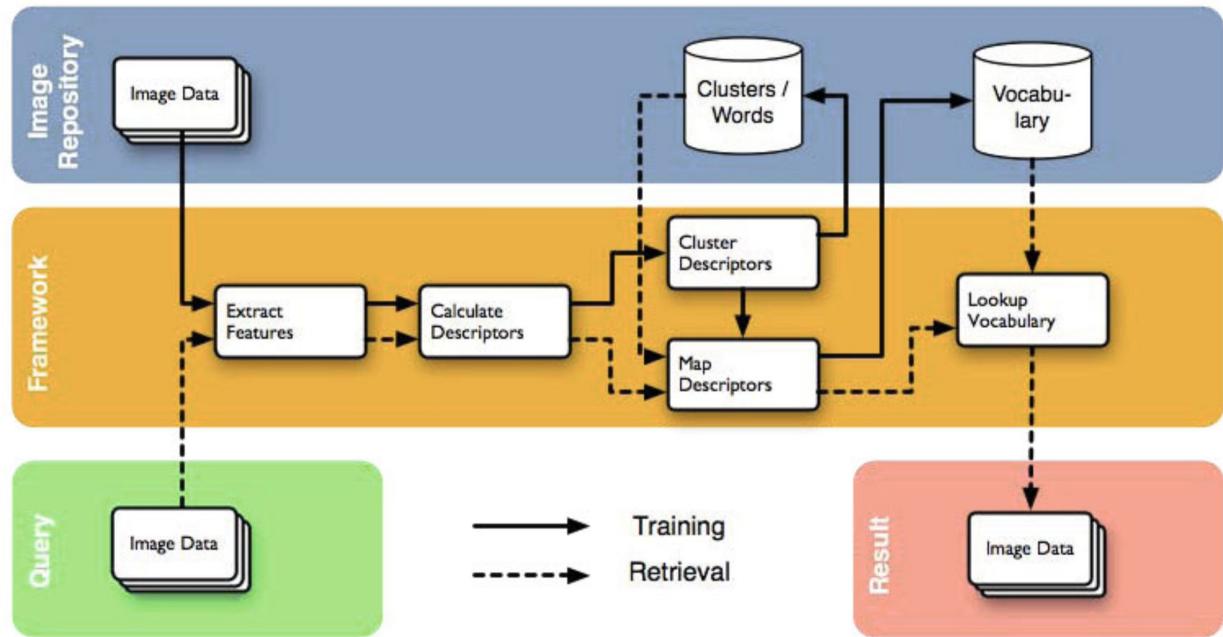
(b)



(c)

**Fig. 3.** Based on the image shown in a) the distribution of the SIFT and superpixel interest points are shown in b) and c), respectively. The number of interest points per type are normalized to obtain comparable heat maps. Note the more even and more concentrated distribution in the area of the medical object of interest.

# Image Retrieval before DL



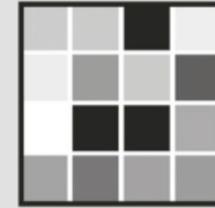
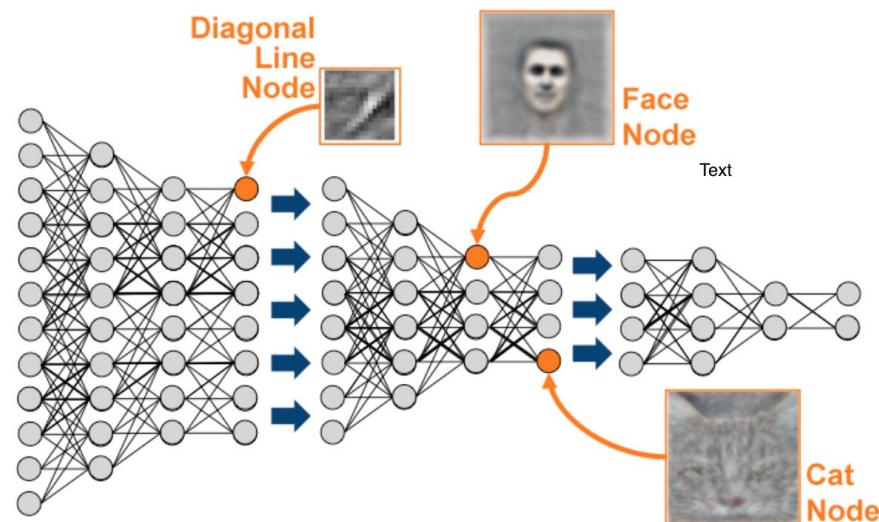
**Fig. 1.** Schematic overview of the Bag of Visual Words framework



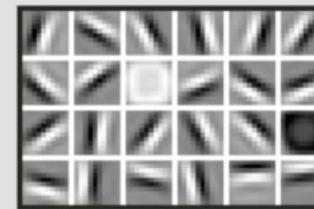
# Deep Learning Approach

## FACIAL RECOGNITION

Deep-learning neural networks use layers of increasingly complex rules to categorize complicated shapes such as faces.



Layer 1: The computer identifies pixels of light and dark.



Layer 2: The computer learns to identify edges and simple shapes.

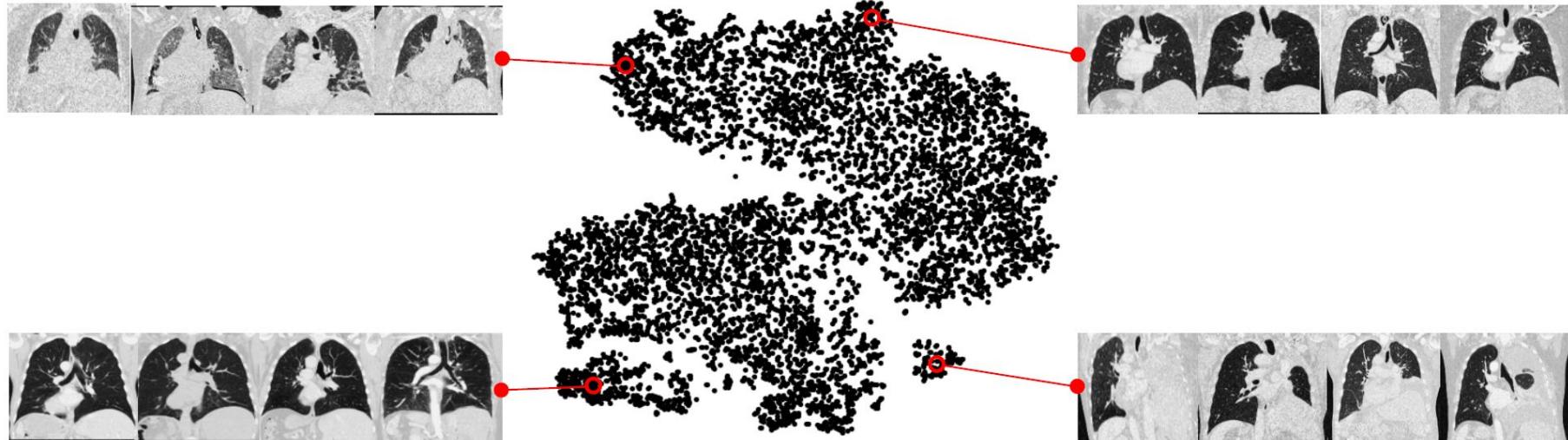


Layer 3: The computer learns to identify more complex shapes and objects.



Layer 4: The computer learns which shapes and objects can be used to define a human face.

# Medical Embeddings



Hofmanninger, MICCAI  
2016

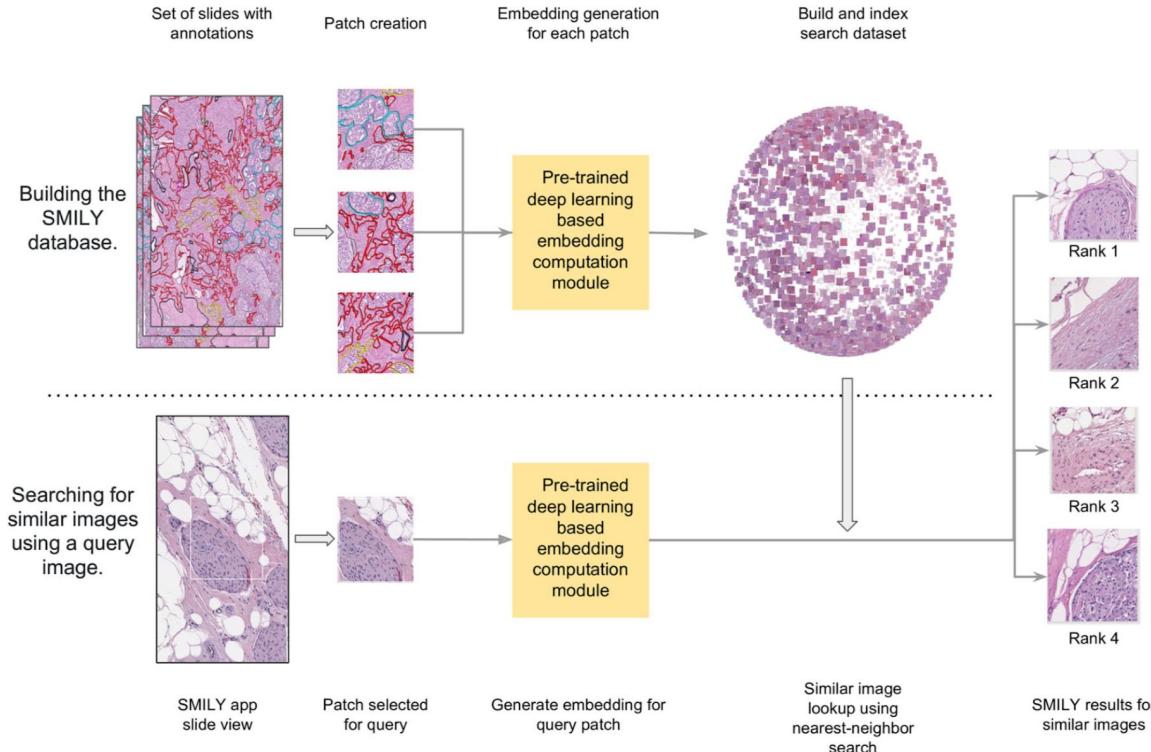
## Similar image search for histopathology: SMILY

Narayan Hegde<sup>1</sup>, Jason D. Hipp<sup>1</sup>, Yun Liu<sup>1</sup>, Michael Emmert-Buck<sup>2</sup>, Emily Reif<sup>1</sup>, Daniel Smilkov<sup>1</sup>, Michael Terry<sup>1</sup>, Carrie J. Cai<sup>1</sup>, Mahul B. Amin<sup>3</sup>, Craig H. Mermel<sup>1</sup>, Phil Q. Nelson<sup>1</sup>, Lily H. Peng<sup>1</sup>, Greg S. Corrado<sup>1</sup> and Martin C. Stumpe<sup>1,4</sup>

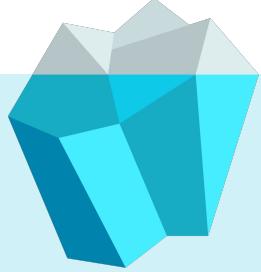
npj

N. Hegde et al.

2



# Metric Learning



# Metric Learning, distance learning, similarity learning

Classification, regression: CNNs, RNNs

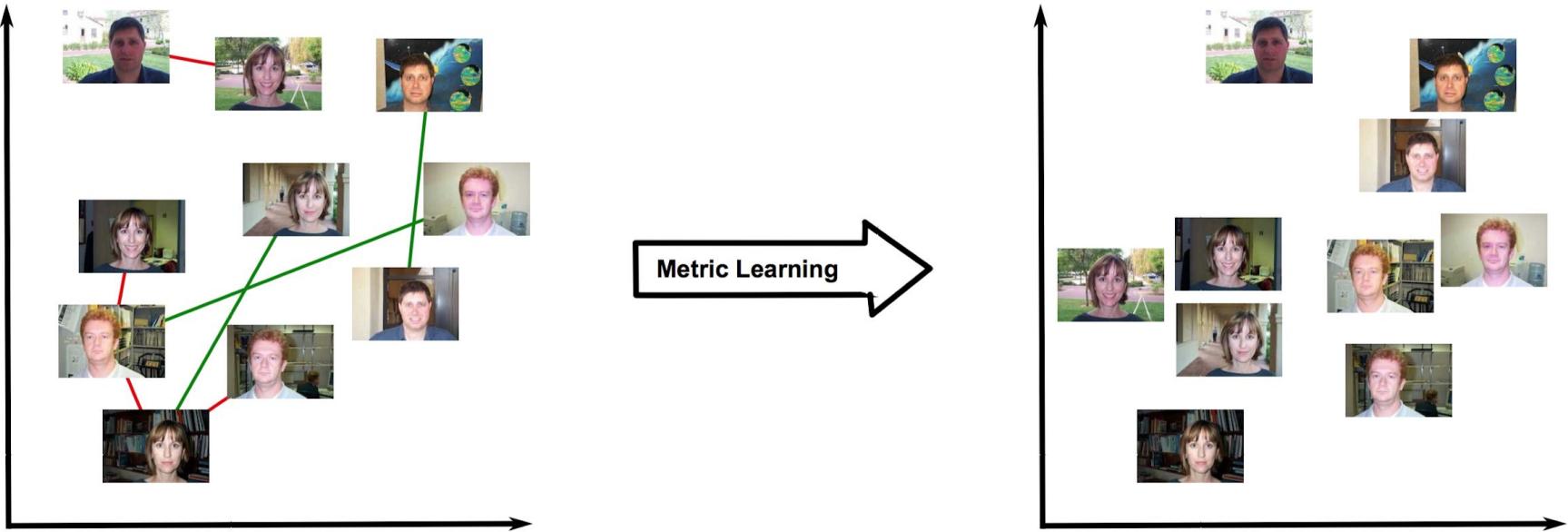
Generative Adversarial Networks (GANs)

Clustering, recommender systems,  
retrieval ...?



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# Metric Learning



<https://arxiv.org/abs/1306.6709v4>

# Siamese Networks

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## Signature Verification using a “Siamese” Time Delay Neural Network

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Jane Bromley, Isabelle Guyon, Yann LeCun,  
Eduard Säckinger and Roopak Shah  
AT&T Bell Laboratories  
Holmdel, NJ 07733  
[jbromley@big.att.com](mailto:jbromley@big.att.com)

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# Siamese Networks

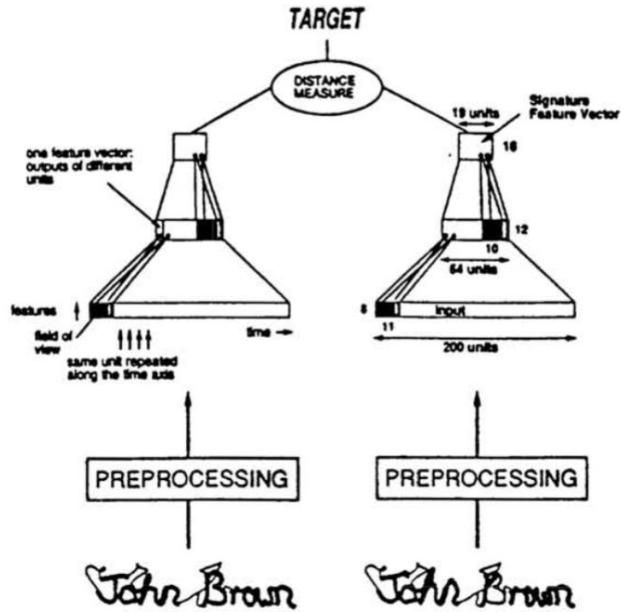
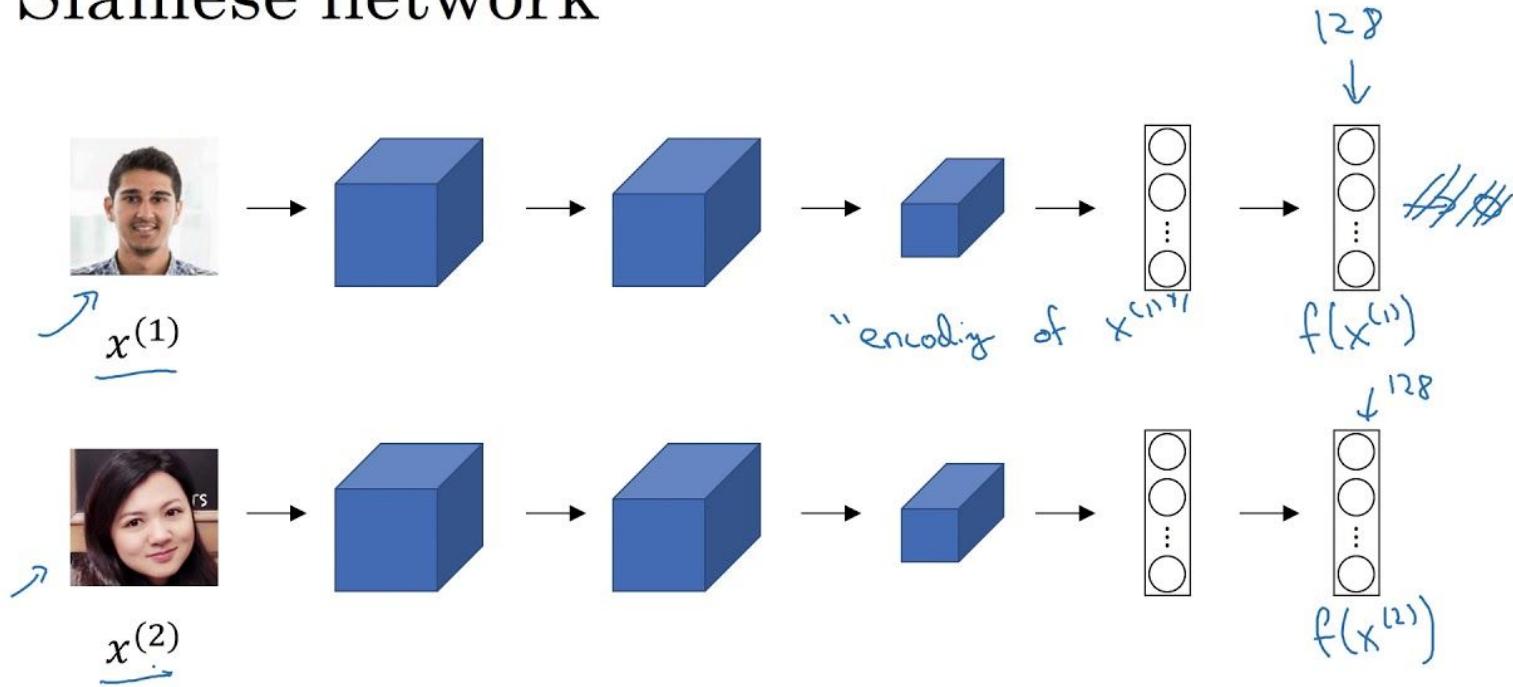


Figure 1: Architecture 1 consists of two identical time delay neural networks. Each network has an input of 8 by 200 units, first layer of 12 by 64 units with receptive fields for each unit being 8 by 11 and a second layer of 16 by 19 units with receptive fields 12 by 10.

# Siamese network

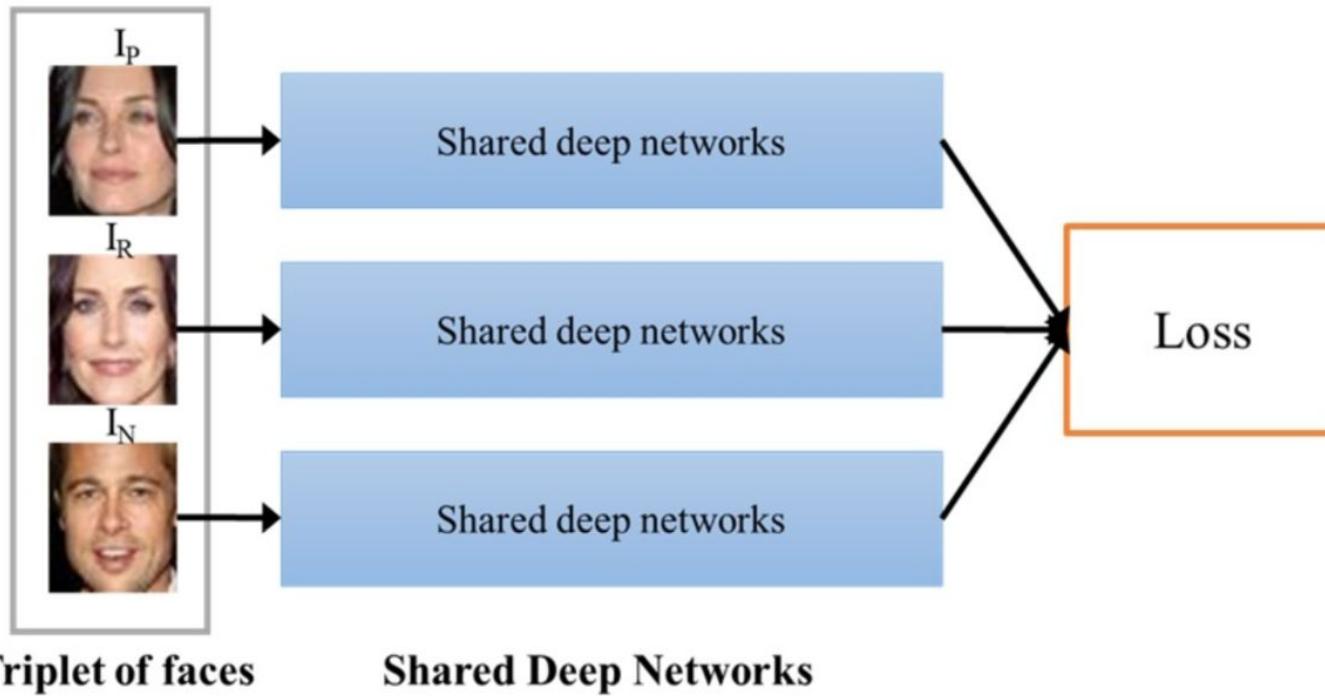


[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

Andrew Ng

<https://www.youtube.com/watch?v=6jfw8MuKwpI>

# Triplet Networks



# Triplet Networks

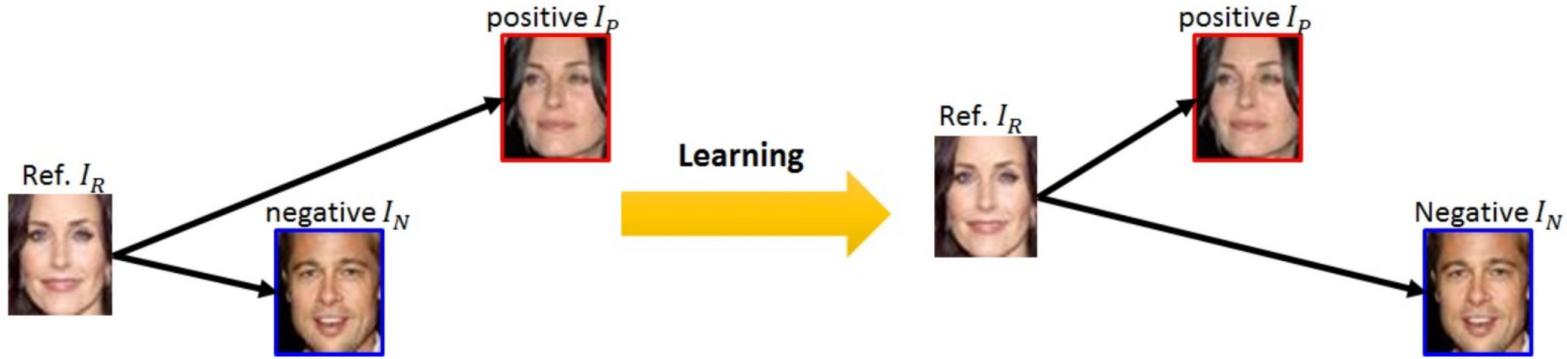
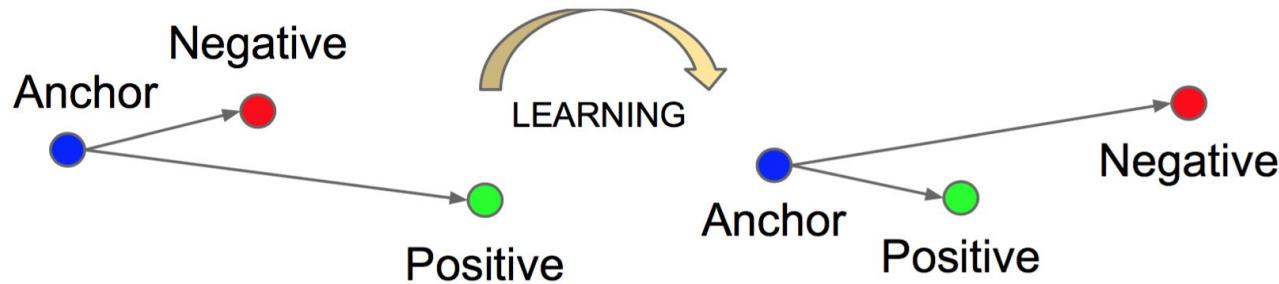


Fig. 3. The triplet loss minimize the distance between the given face image  $I_R$  and the positive face image  $I_P$  both of which have the same identity and maximize the distance between the given face image  $I_R$  and the negative face image  $I_N$  of the different identity.

# Triplet Networks - Hinge Loss

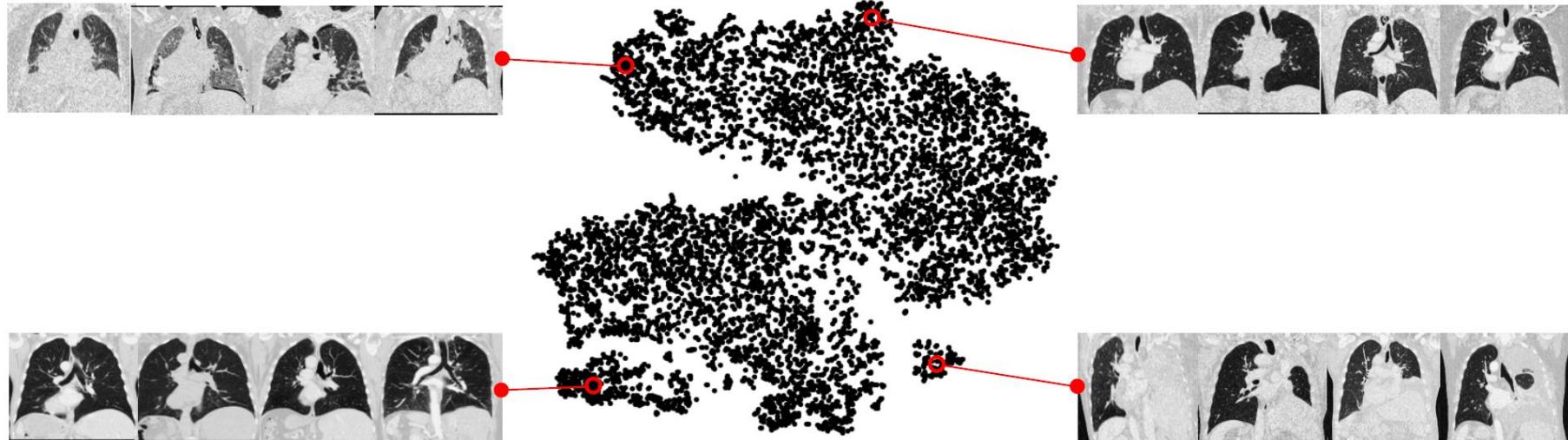


$$\sum_i^N \left[ \|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

# Metric Learning



# Medical Embeddings



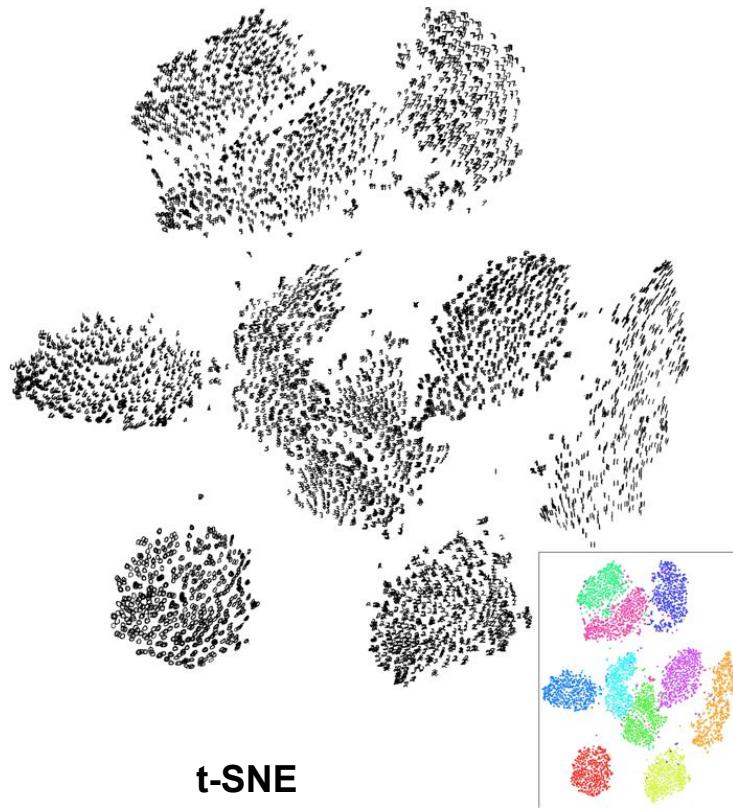
Hofmanninger, MICCAI  
2016

# Metric Learning - difference to dimensionality reduction

PCA

Kernel PCA

t-SNE

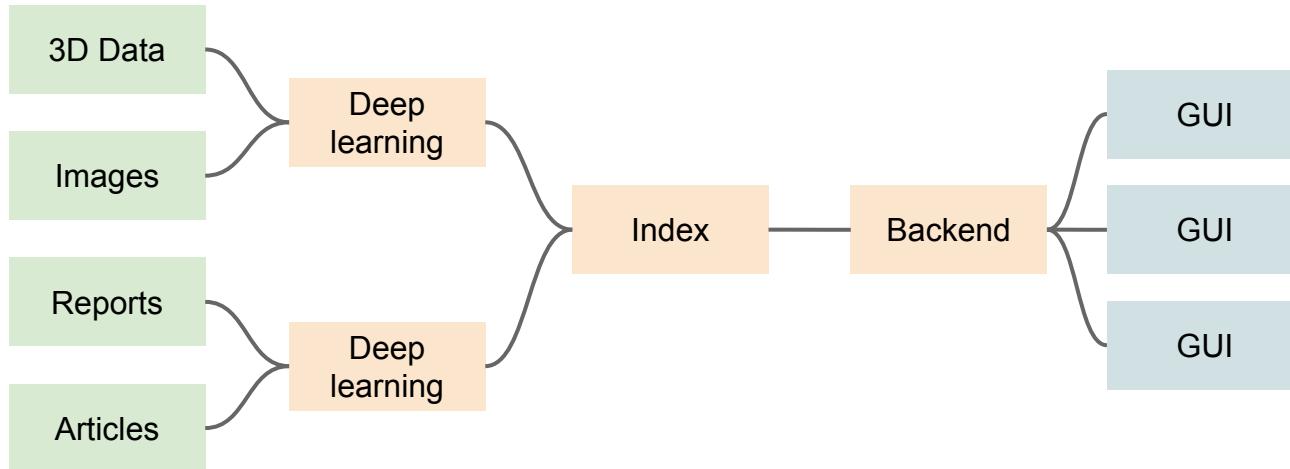


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# Tech Stack

# Overview

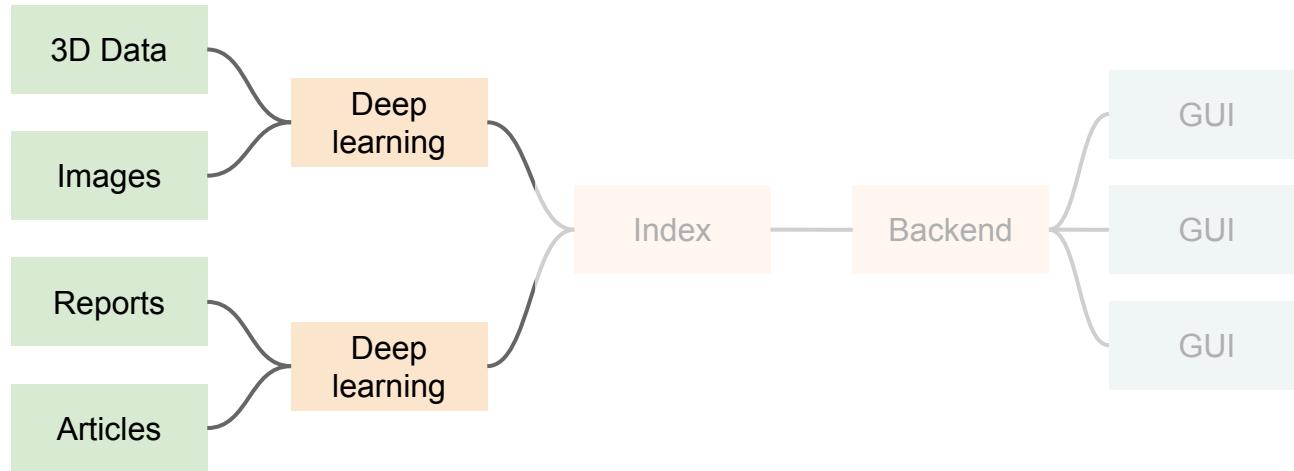


Data flow framework

Custom Data Structure

Go / GraphQL / Elm

# Data flow framework



Data flow framework

Custom Data  
Structure

Go / GraphQL / Elm



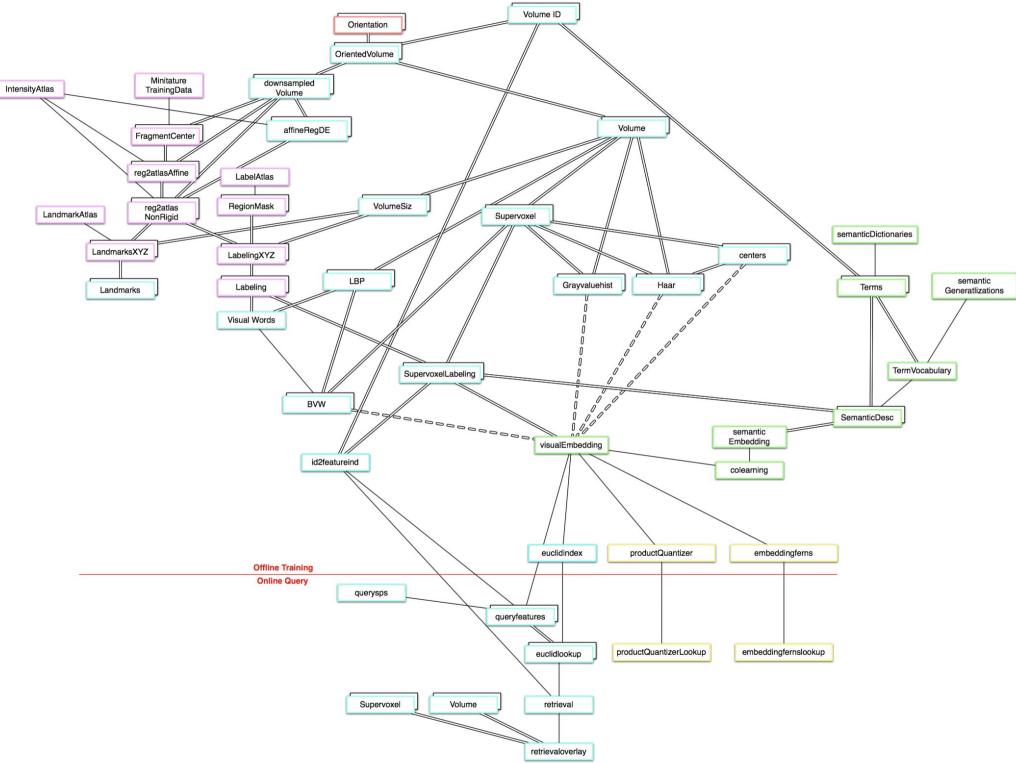
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# Data Flow Framework

**Scheduling**  
dependencies drive computation

**Storage**  
no explicit state

**Focus on algorithms**



# Julia Programming Language

## **Easy to code**

Like Python / Matlab

Focus on numerical computing and HPC

## **Fast**

Like C. JIT compiled.

Easy parallelization, control over memory layout

## **Deep learning**

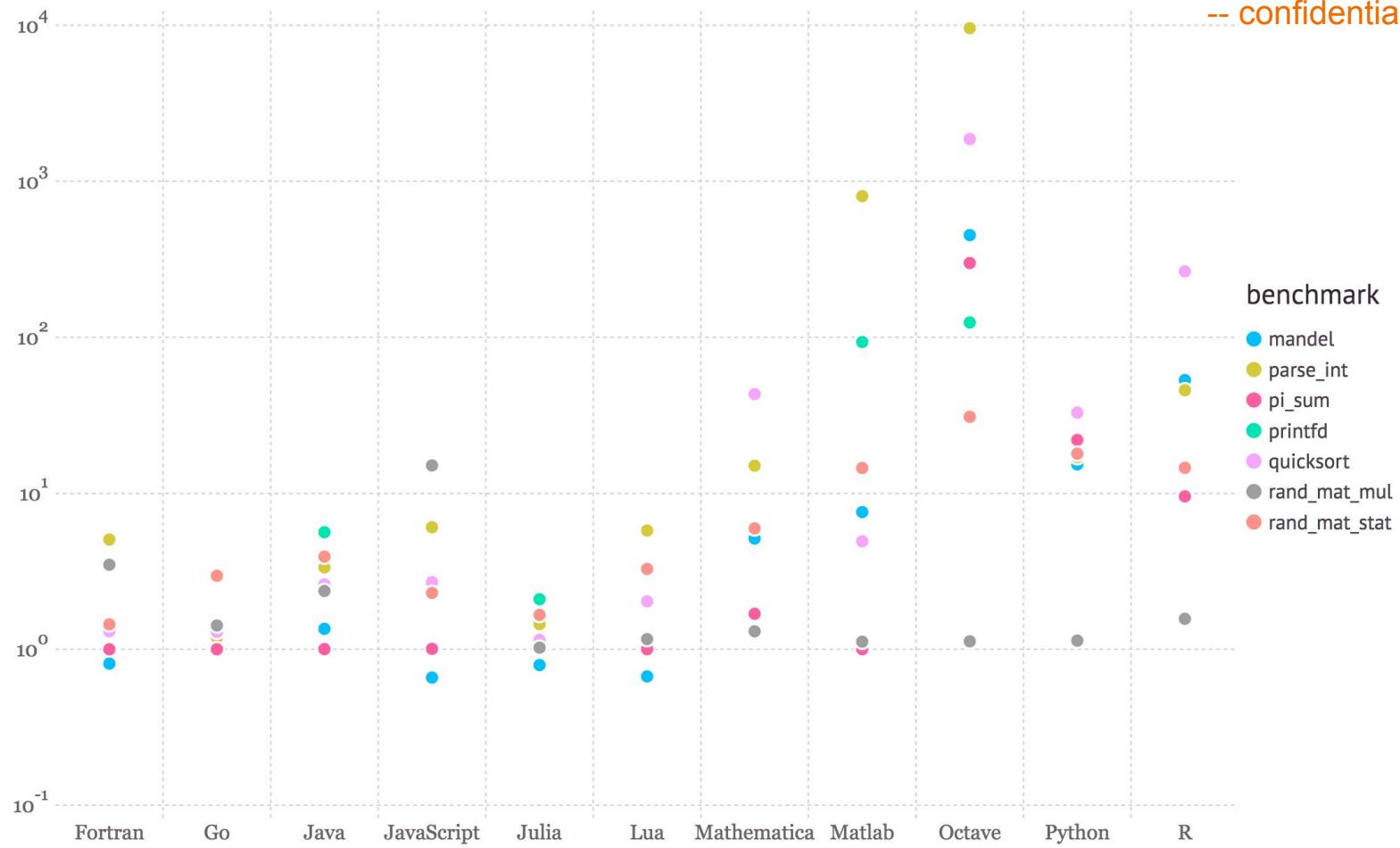
Tensorflow, MXNet, Knet

CUDA, CuDNN

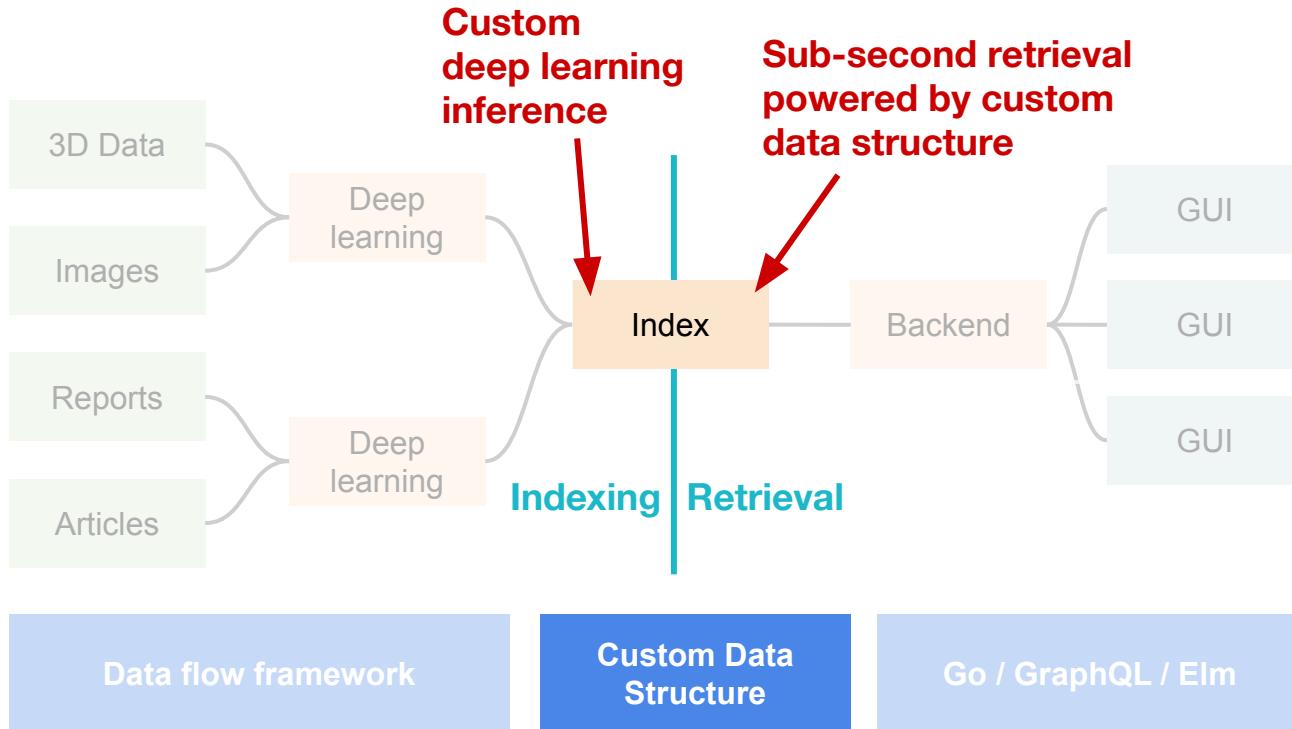


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# Julia

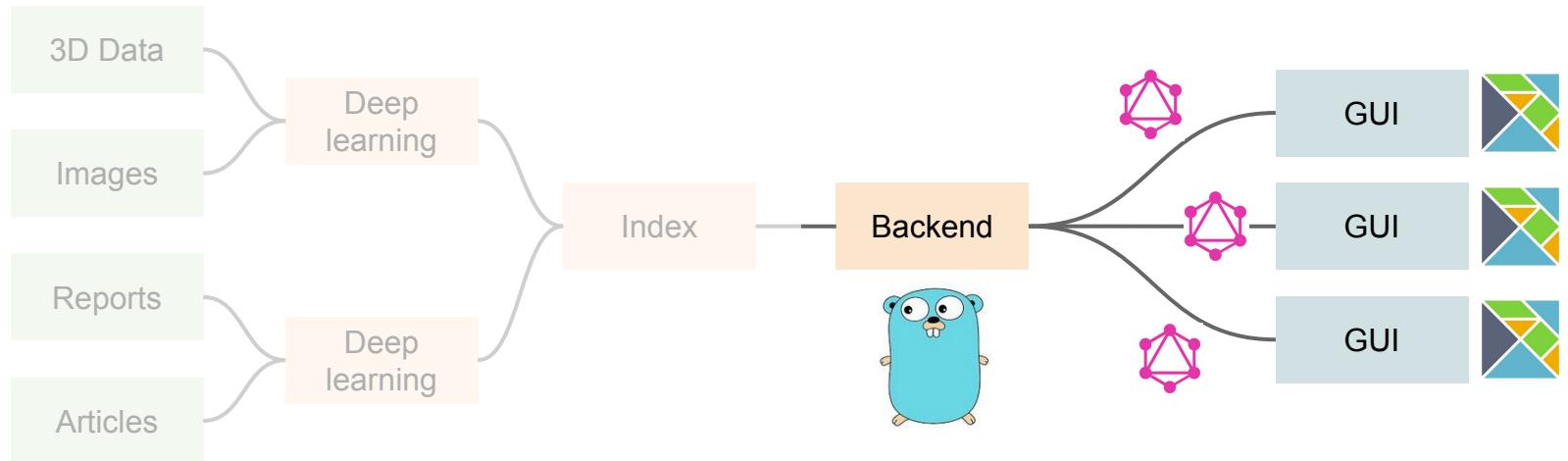


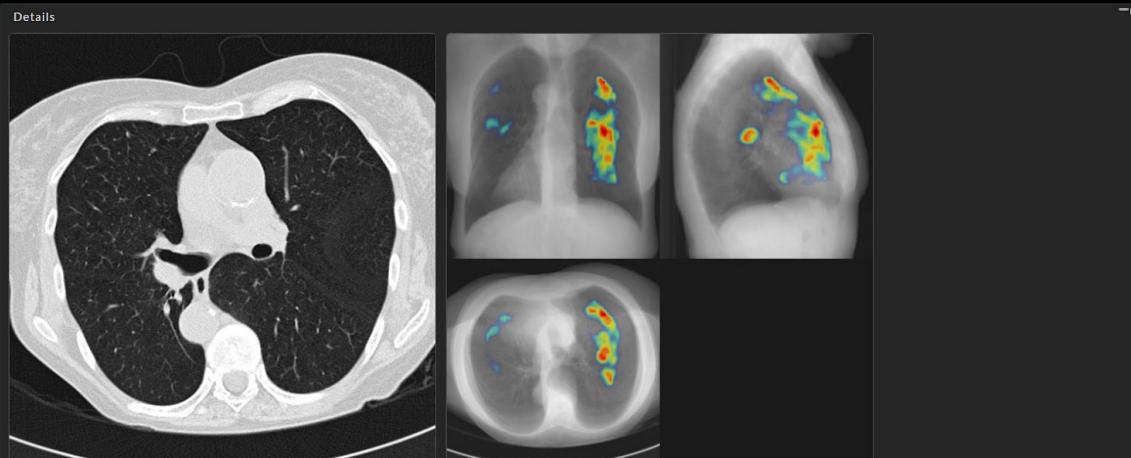
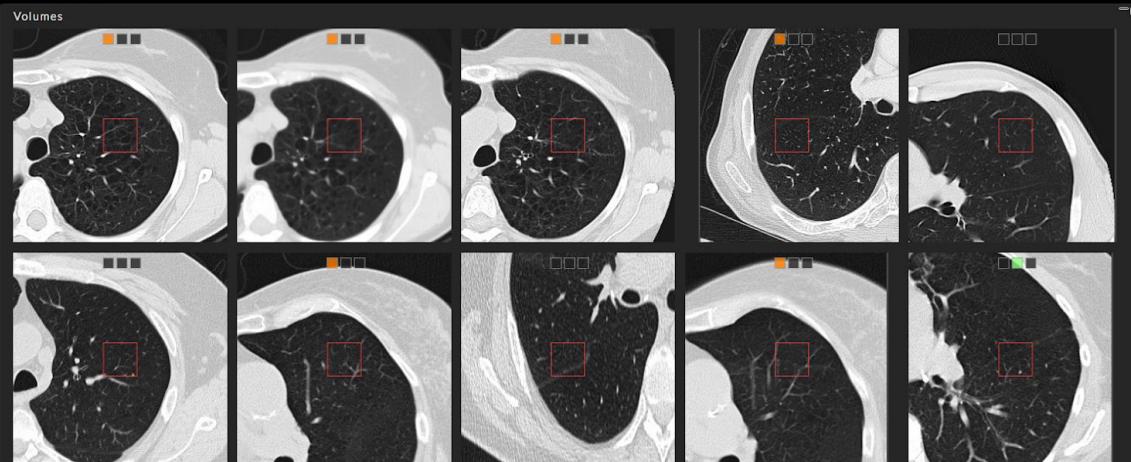
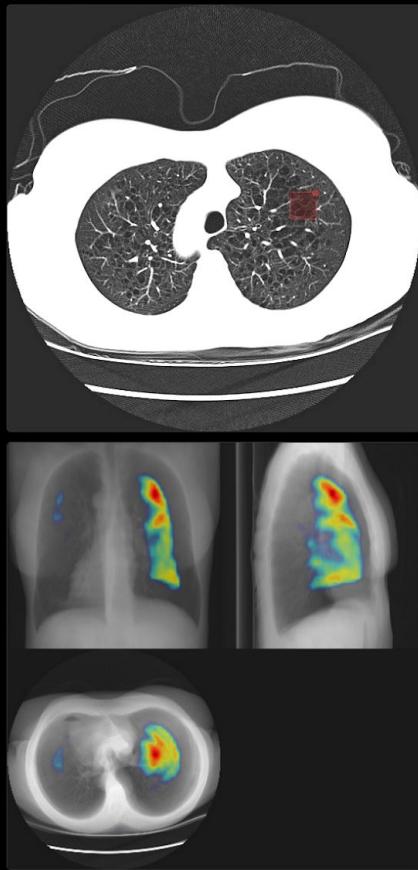
# Speed



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# Backend / Frontend





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#### Statistic



#### Reference Cases (Radiopaedia)

##### Emphysem



##### Pleural effusion



#### Web & Literature

##### Pleural effusion

- [Pleural effusion \(Radiopaedia\)](#)
- Pleural effusion tends to be used as a catch-all term denoting a collection of fluid within the pleural space. This can be further divided into exudates and transudates depending on the biochemical analysis of aspirated pleural fluid (see below). Essentially it represents any pathological process which overwhelms the pleura's ability to reabsorb fluid.

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- [Tuberculosis: pulmonary manifestations \(Radiopaedia\)](#)

#### Anatomy



# Public Data Sets

## Overview

### About VISCERAL

VISCERAL is an abbreviation for **Visual Concept Extraction Challenge in Radiology**.

The tasks and data can be used through the [continuously running Benchmarks](#). These are:

- [Anatomy3 Continuous](#)
- [Detection2](#)
- [Retrieval2](#)

The software tools, deliverables and publications arising from the VISCERAL project are available on the [Resources page](#).

The [VISCERAL Consortium](#) achieved [these objectives](#).



This project is supported by the European Commission under the Information and Communication Technologies (ICT) Theme of the 7th Framework Programme for Research and Technological Development.



Microsoft Research

The cloud infrastructure for the benchmarks is supported by Microsoft Research on the Microsoft Azure Cloud.

### Latest news

19/06/2017  
[VISCERAL cloud services suspended](#)

18/08/2015  
[VISCERAL Anatomy Silver Corpus now available](#)

17/08/2015  
[Segmentation Comparison Software and Publication](#)

30/06/2015  
[VISCERAL Anatomy3 Proceedings Online](#)

24/06/2015  
[Anatomy3, Retrieval2, Detection2 Benchmarks Open](#)

[>>All news](#)

### Next events

[>>All events](#)

# Public Data Sets

## Filters

Modality

Task type

Structure

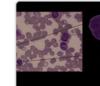
Displaying 174 of 174

## All Challenges

Here is an overview of all challenges that have been organized within the area of medical image analysis that we are aware of. If you know any study that would fit in this overview, or want to advertise your challenge, please send an email to support@grand-challenge.org and we will add the challenge to the list on this page.

Active filters: 0

### 2019



#### C-NMC 2019

Organized by ISBI

An effort to build an automated classifier for classification of normal vs malignant cells in B-ALL white blood cancer microscopic images that will overcome the problems associated with deploying sophisticated high-end machines with recurring reagent ...

Participants: 11

Workshop: April 8, 2019

Associated with: ISBI 2019

Hosted on: [grand-challenge.org](http://grand-challenge.org)



#### EAD2019

Organized by ISBI

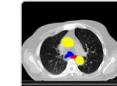
Endoscopic Artefact Detection (EAD) is a core problem and needed for realising robust computer-assisted tools. The EAD challenge has 3 tasks: 1) Multi-class artefact detection, 2) Region segmentation, 3) Detection generalisation.

Participants: 73

Workshop: April 8, 2019

Associated with: ISBI 2019

Hosted on: [grand-challenge.org](http://grand-challenge.org)

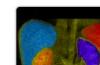


#### SegTHOR

Segmentation of Thoracic Organs at Risk in CT images



#### ANHIR



#### CHAOS



#### BreastPathQ

# Medical Image Retrieval

## Challenges And Successful Approaches

René Donner

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