Computer Assisted Reading of Chest Radiographs

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Outline

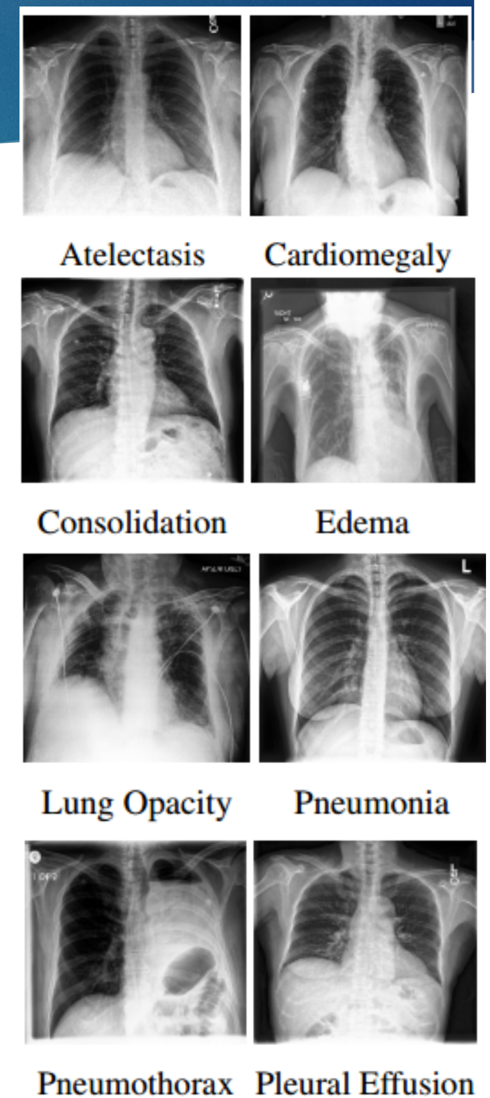
- Motivation
- Dataset
- Method
  - Framework to classify common thoracic diseases
  - Framework to retrieve similar images for diagnosis
- Results
- Conclusion

Motivation

- Radiographs or X-ray images are a common diagnostic tool to identify different thoracic diseases and other abnormal cardiopulmonary conditions
- With the increasing amount of radiology examinations ordered, there is increase in radiologists' workloads resulting in an increase in the total radiology turnaround time
- A computer-assisted system to analyse radiographs for primary screening and retrieve similar images for diagnosis have the potential to accelerate the radiologists' workflow and thereby improving the overall quality of healthcare

Dataset

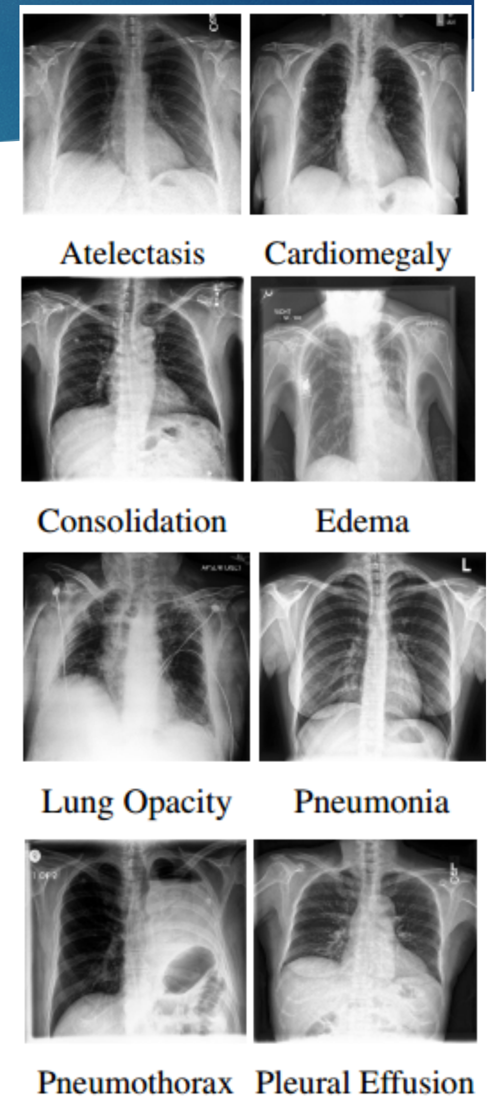
- 223,648 chest X-ray images from 64,740 patients
  - 191,229 frontal chest X-rays
  - 32,419 lateral X-rays.
  - 35,917 male
  - 28,822 female
- Disease labels generated from associated radiology reports using automatic rule-based labeler



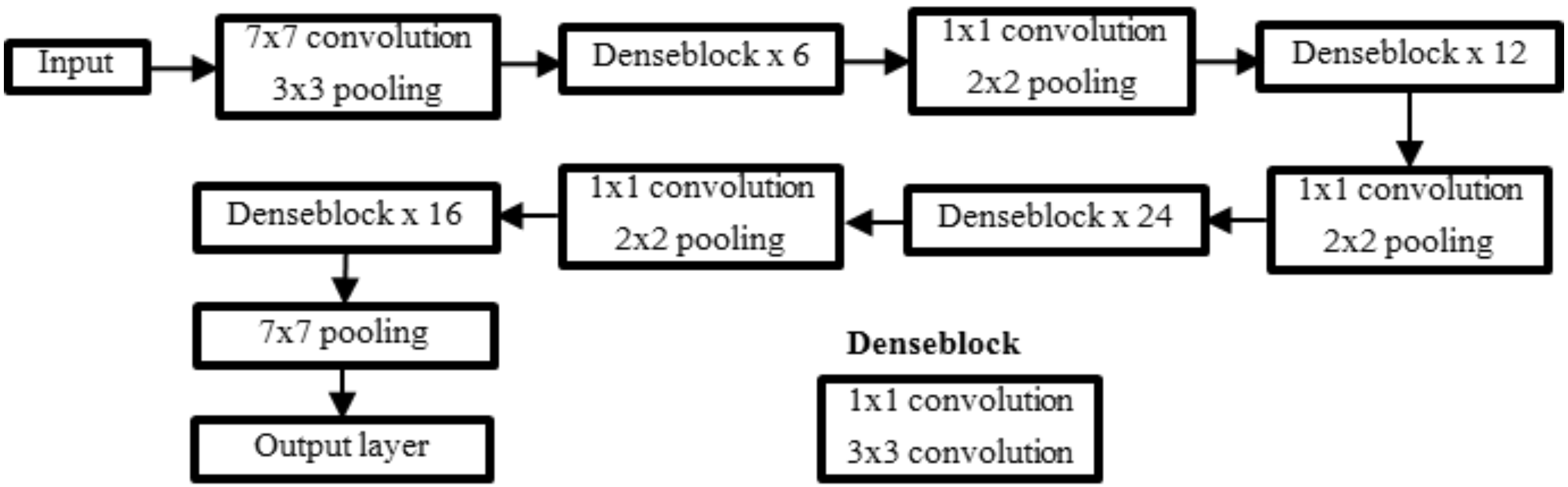
Dataset

Table 1: Number of cases from different disease types with positive, negative and uncertain labels.

Disease label	Positive	Negative	Uncertain
Atelectasis	33,456	156,453	33,739
Cardiomegaly	27,068	188,493	8,087
Consolidation	14,816	181,090	27,742
Edema	52,291	158,373	12,984
Lung Opacity	105,707	112,343	5,598
Pneumonia	6,047	198,831	18,770
Pneumothorax	19,456	201,047	3,145
Pleural Effusion	86,254	125,766	11,628



Deep Network Architechture



Training

- **Dataset is multilabel**
  - sigmoid function as the activation function
- **Dataset has uncertain labels**
  - All samples included in training ignoring uncertain labels while updating the gradient
- **Dataset is highly-imbalanced**
  - Weighted cross-entropy as the loss function

$$\mathcal{L}_{X|y} = \sum_{y \in \{0,1\}}^{i} -w_{i+} \times y_i log(\bar{y}_i) - w_{i-} \times (1-y_i) log(1-\bar{y}_i)$$

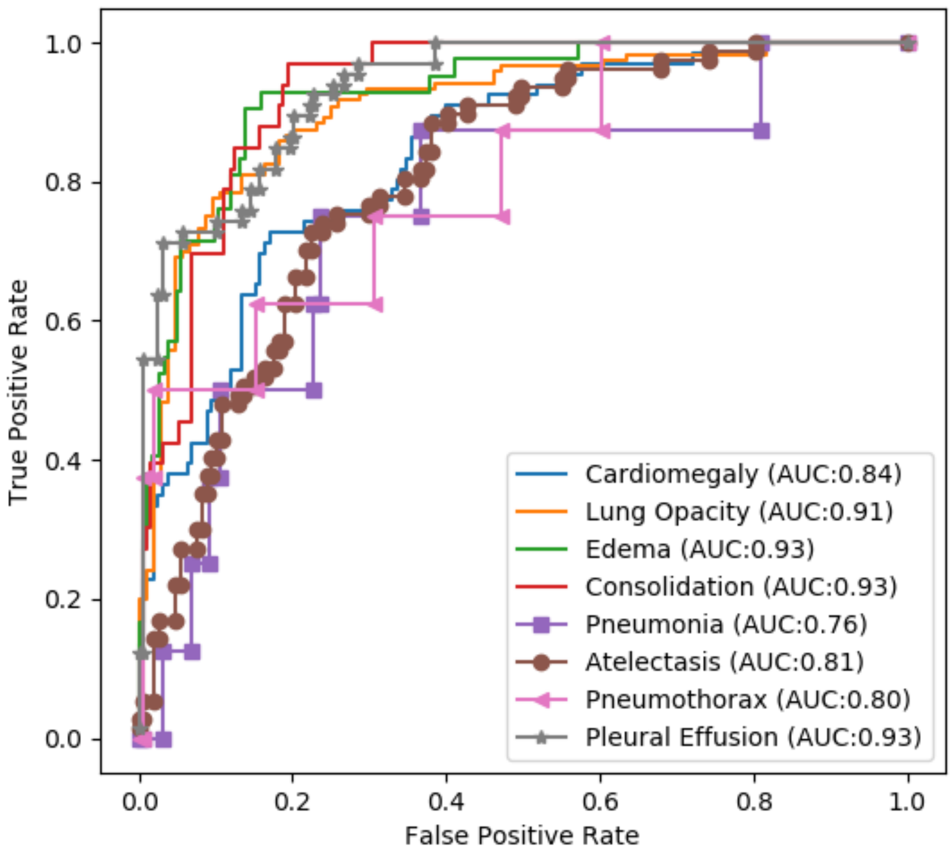
$$where, \quad w_{i+} = \frac{|n_{i-}|}{N}; \quad w_{i-} = \frac{|n_{i+}|}{N}$$

where $\mathcal{L}_{X|y}$ is the loss term for sample X with the label y, y_i is the ground truth label for disease class-i and $\bar{y}_i$ is the predicted likelihood. $|n_{i+}|$ and $|n_{i-}|$ are the total number of positive and negative samples respectively for class-i and N is the total number of samples.

Training

- Model pre-trained on ImageNet dataset
- Epochs = 20
- Batch size = 32
- Learning rate = 10^{-4} reduced by a factor of 10 at plateau
- Adam with $\beta_1 = 0.9$, $\beta_2 = 0.999$

Receiver Operating Characteristics Curve



- Mean AUC = 0.86
- Best performing labels:
  - Consolidation: 0.93
  - Pleural Effusion: 0.93
  - Edema: 0.93
  - Opacity: 0.91

Comparison

Table : Comparison with the state-of-art method on CheX-pert dataset.

Disease label	Allaouzi *et al.**	Our Implementation
Atelectasis	0.72	**0.81**
Cardiomegaly	0.88	**0.84**
Consolidation	0.77	**0.93**
Edema	0.87	**0.93**
Lung Opacity	0.76	**0.91**
Pneumonia	0.79	**0.76**
Pneumothorax	0.86	**0.80**
Pleural Effusion	0.90	**0.93**

* Allaouzi I. *et al.*, IEEE Access, vol. 7, pp. 64279–64288, 2019.

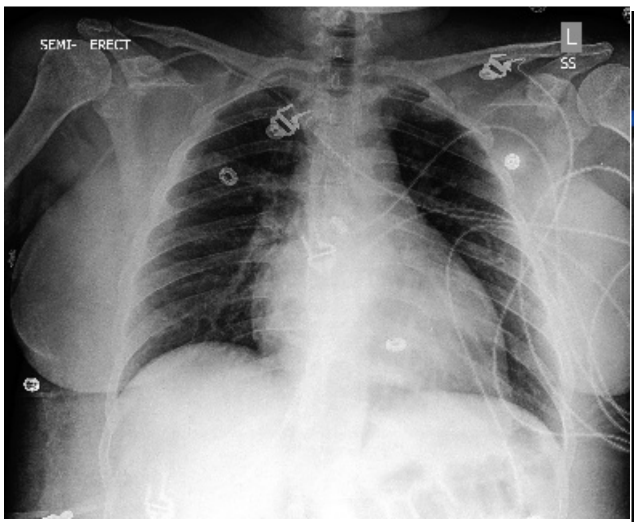
Disease Level Colormaps

- Disease-level colormaps generated to visualize the location of predicted diseases

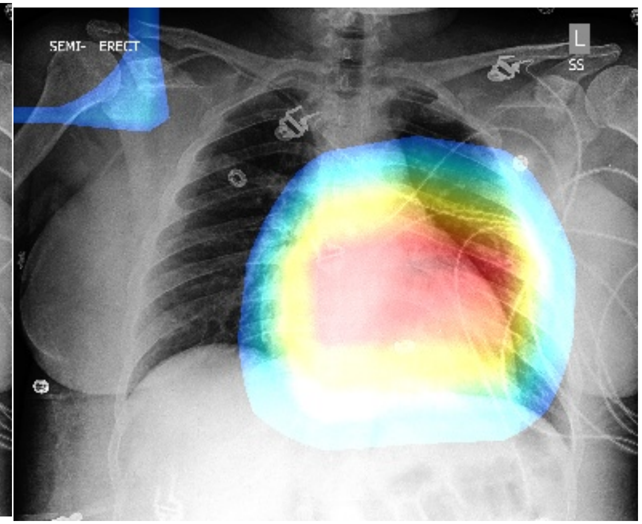
$$\mathcal{C}_{i|I(x,y)} = \sum_{m} \omega_i^m \times \mathcal{X}_m(x,y)$$

  - $C_{i\,|\,I(x,y)}$ = i^{th} disease-level colormap for image *I(x, y)*
  - $X_m(x,y)$ = m-th feature map of the last convolutional layer
  - w_i^m = weight term corresponding to class-i for the m-th feature map at the last classification layer

Disease Level Colormaps

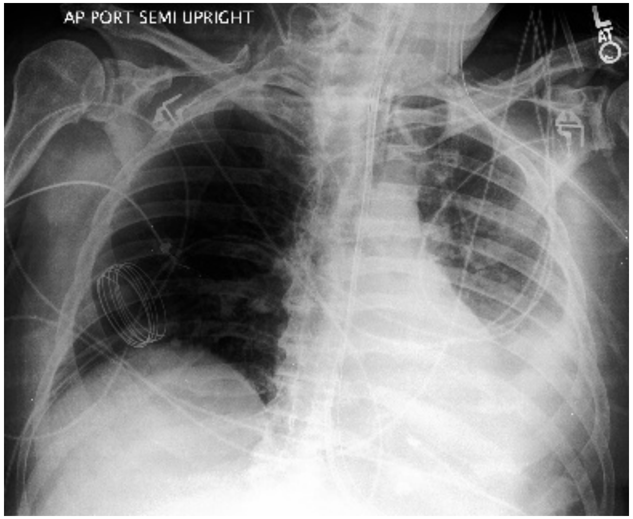


The original X-ray image for a patient with ground truth label of Cardiomegaly

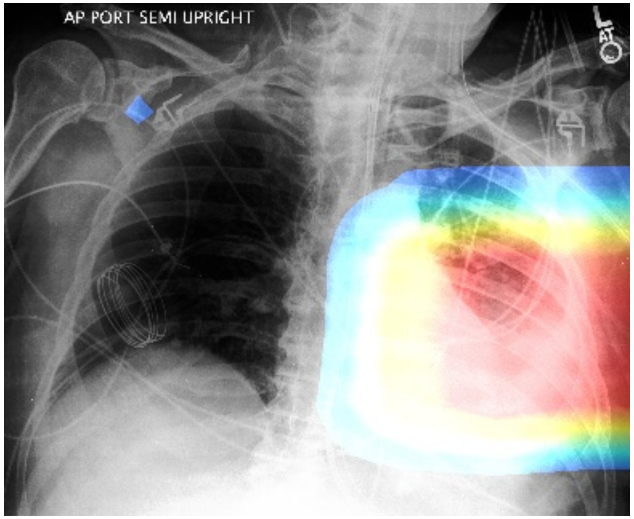


Generated Cardiomegaly colormap showing area indicative of the disease.

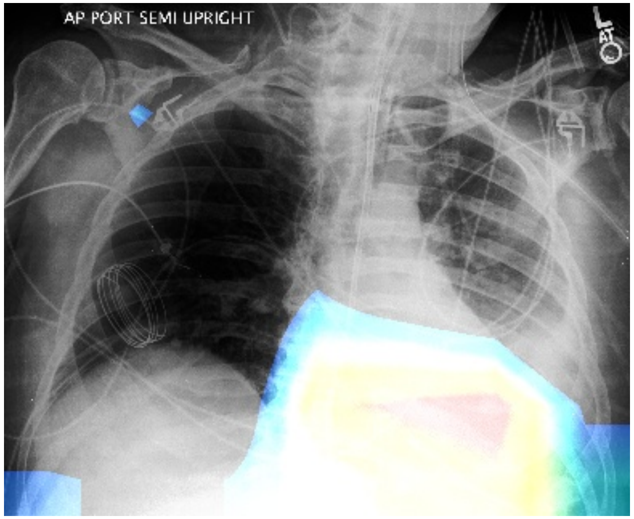
Disease Level Colormaps



The original X-ray image for a patient with ground truth label of pleural effusion and lung opacity

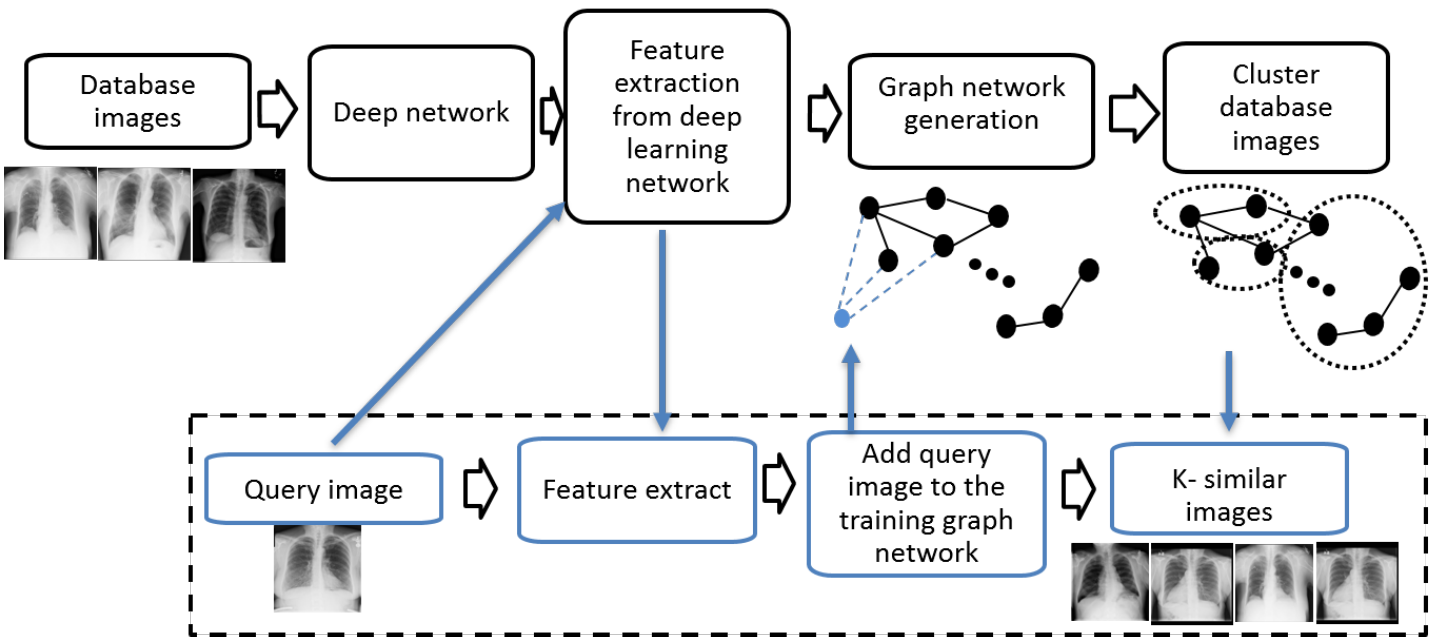


Generated Pleural Effusion colormap showing area indicative of the disease.



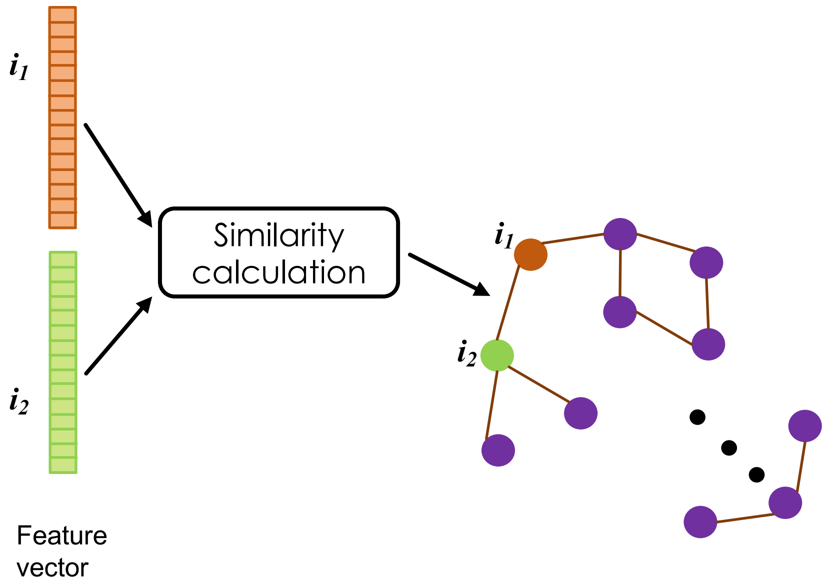
Generated Lung Opacity colormap showing area indicative of the disease.

Large Scale Image Retrieval : Framework



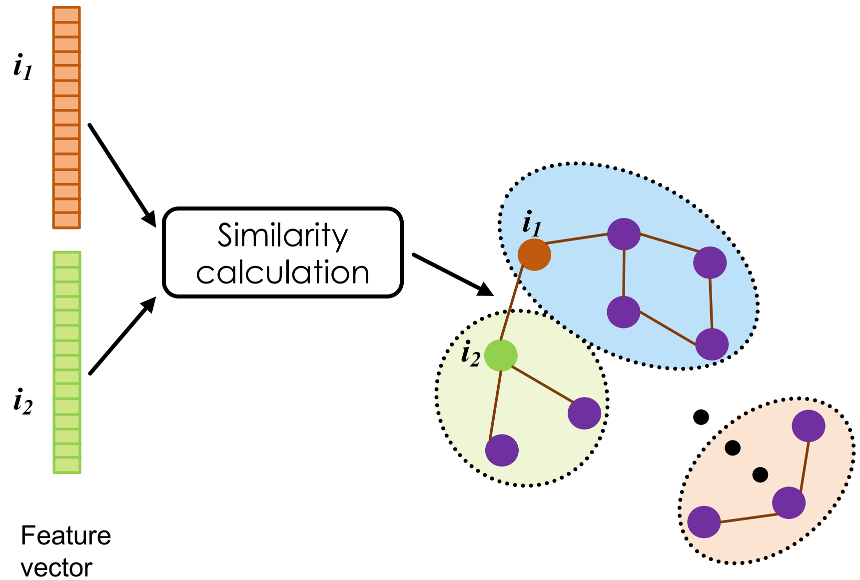
Large Scale Image Retrieval : Graph Generation

- 1024-dimensional features from the deep learning network
- Graph generation by defining images as *nodes*
- *Edge* generation by cosine similarity between image-representative features



Large Scale Image Retrieval : Image Community Formation

- Image community formation with a modularity-based approach
- Maximizing modularity for large graphs* to find optimum partition



Blondel, V.D.., *et al.* Journal of statistical mechanics.10 (2008): P10008.

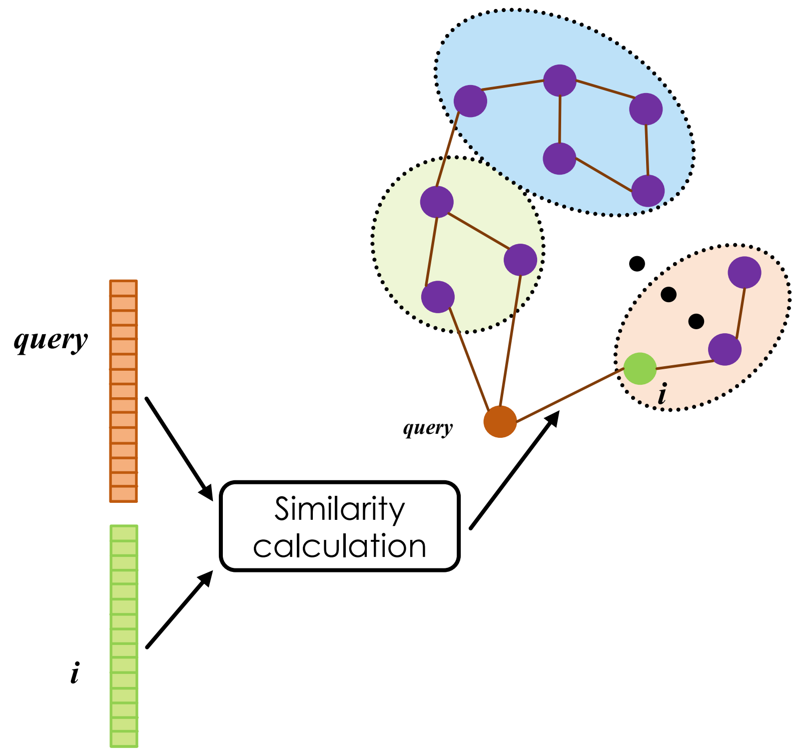
Large Scale Image Retrieval : Top-N Image Retrieval Given A Query Image

- Query Image placement in the network as a node
- Edge generation by similarity
- Region growing approach by maximizing weighted modularity* to find top-N most similar images

$$Q_w = \sum_{i=1}^{c} \lambda_i q_i = \sum_{i=1}^{c} \lambda_i (e_{ii} - a_i^2)$$

$$where \ \ \lambda_i = 1 + \frac{2l_i}{n_i(n_i - 1)}$$

e_{ii} is the fraction of edges within community i
a_i is the fraction of edges with at least one end in community-i
l_i is total number of edges within community-i
n_i is the total number of nodes within community-i



Haq, N.F., *et al.* Pattern Recognition Letters (2019).122:14-22.

Retrieval Performance

DataSet	ACG	Precision
CXR- five most prevalent disease labels (atelectasis, cardiomegaly, edema, consolidation, pleural effusion)	0.65	78%
CXR- all labels	0.65	73%

- Precision = $\frac{\#relevant\ images}{\#retrieved\ images}$
- ACG = $\frac{sum\ of\ graded\ relevance}{\#retrieved\ images}$

Conclusion

- Implemented a framework to predict common thoracis diseases from their radiographs
- Generated disease-level colormaps overlapped on chest radiographs to highlight the area that should be paid more attention to while generating the radiology reports
- Implemented a large-scale image retrieval framework based solely on the radiographs combining a graph-clustering technique to the deep learning network

Questions?