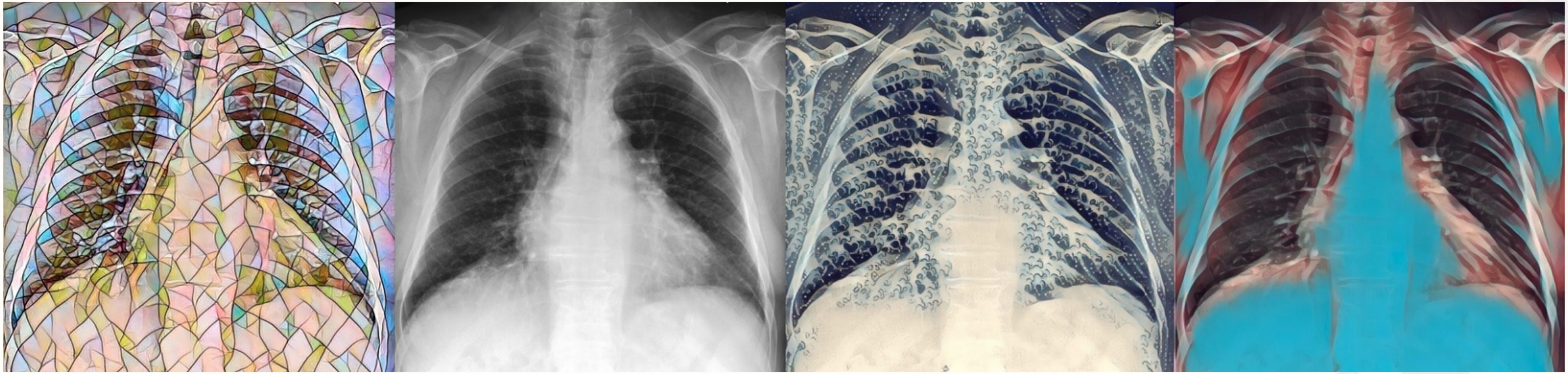
Deep learning and CXRs



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June 20th, 2021

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Lessons from this tutorial

1. Learn about the domain you are working in
2. Understand the data generation process
3. Ask yourself: what data **<u>don’t</u>** I have?

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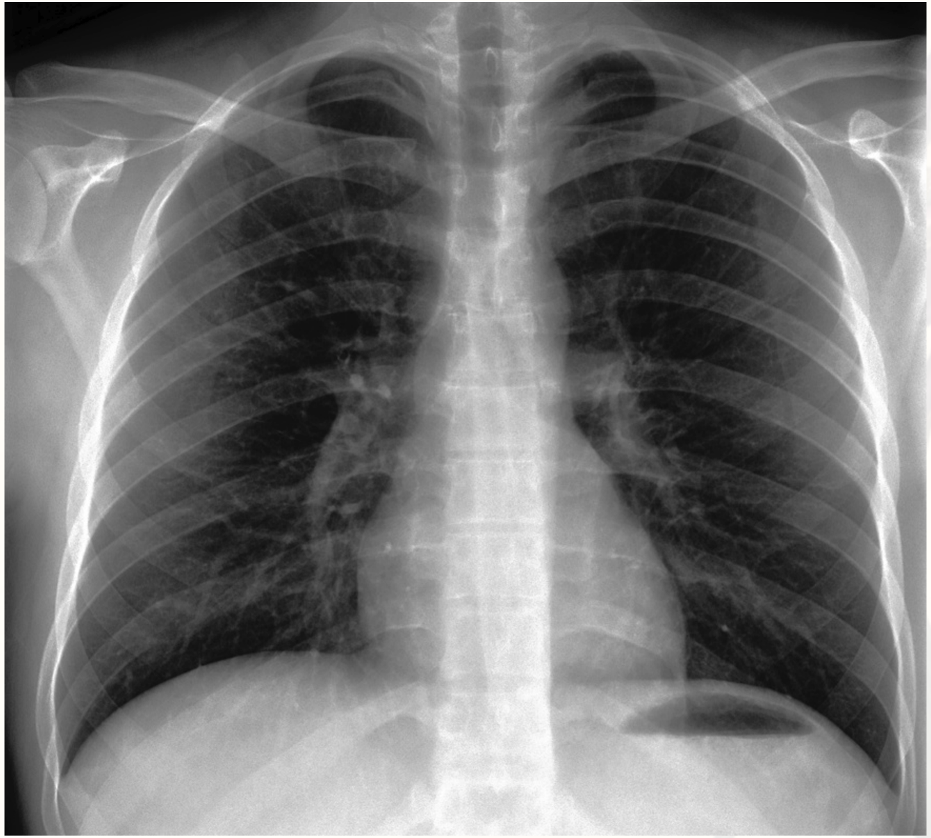
Chest radiographs

- Commonly called X-rays
    - (“X” stands for “I have no idea what this thing is but look I see through people’s skin”)
- Visualizes the lungs
- Visualizes the heart

What do radiologists look for in these x-rays?



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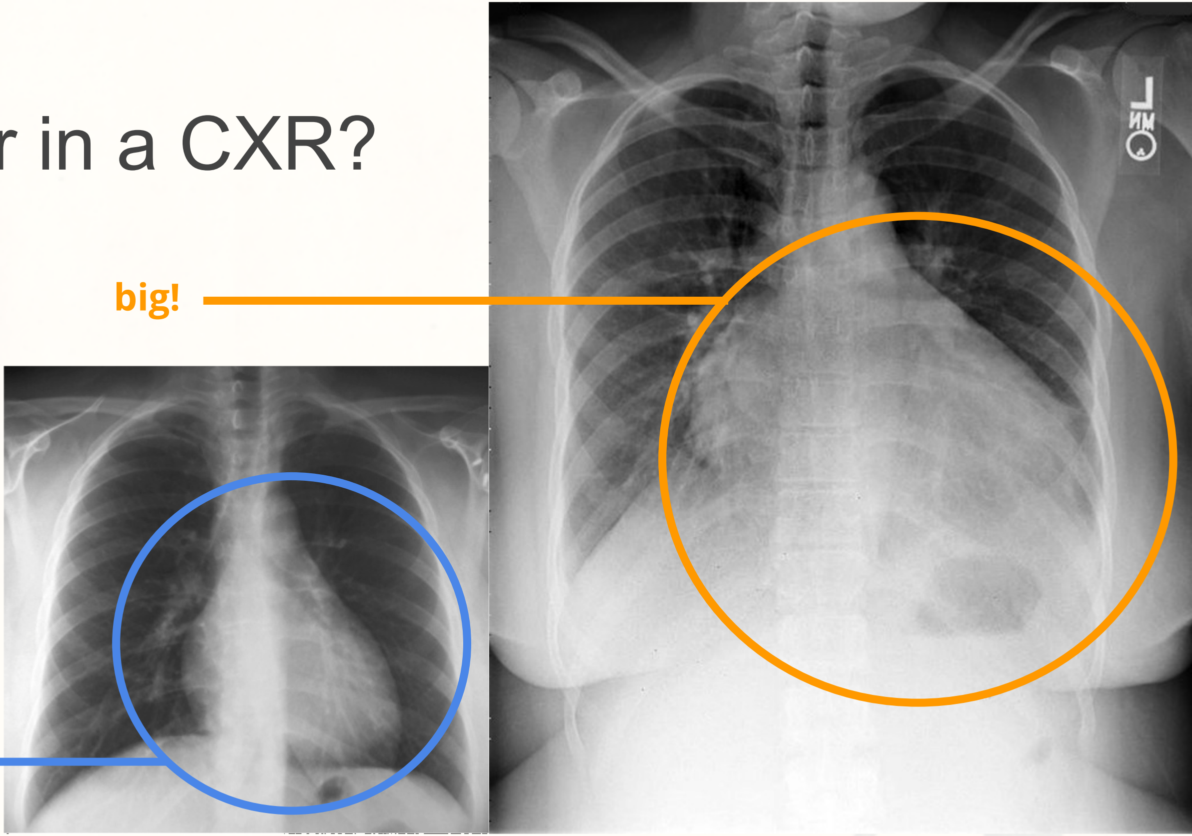
What do we look for in a CXR?

A big heart, “cardiomegaly”

(and not in a good way!)



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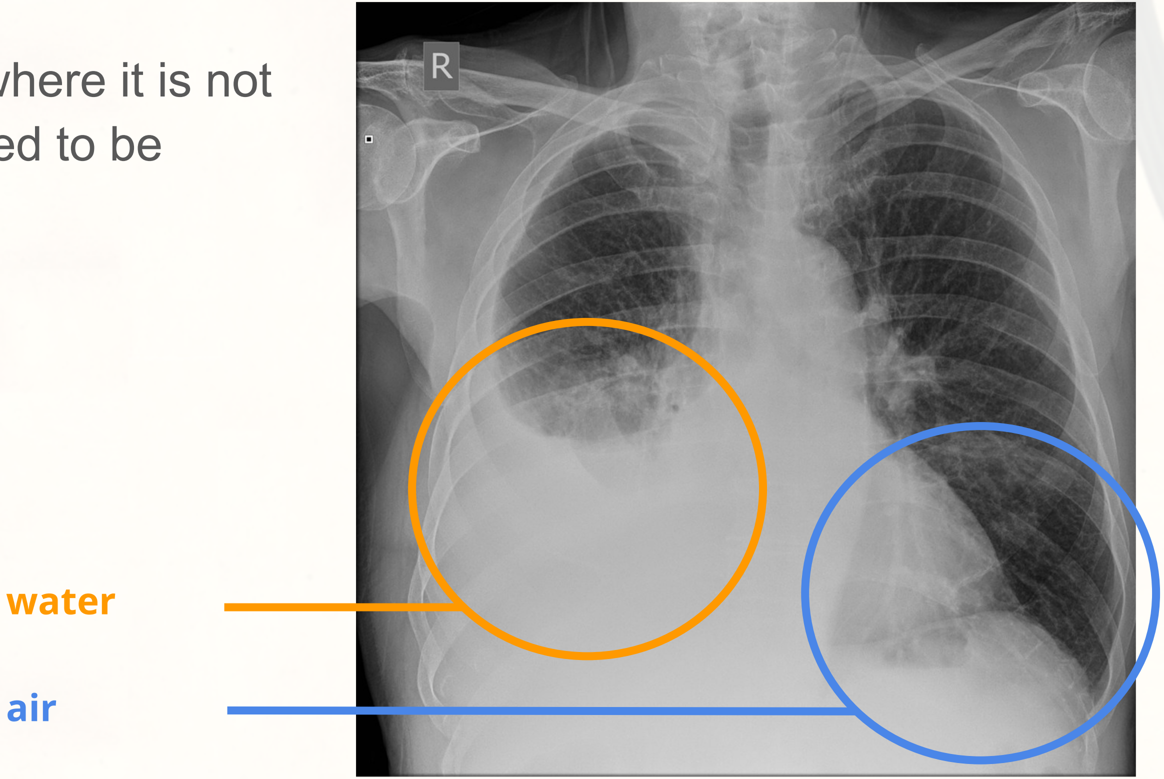
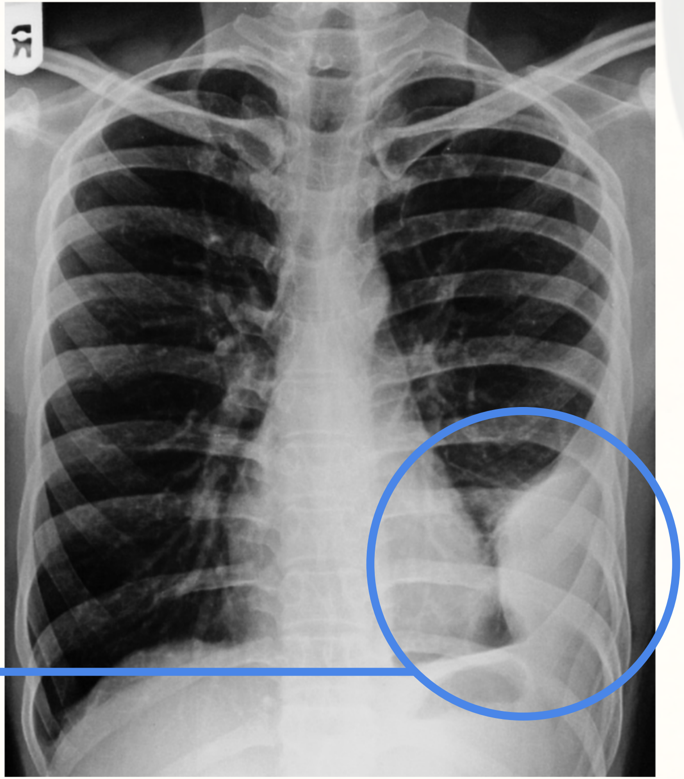
What do we look for in a chest x-ray?

- Water where it is not supposed to be



What do we look for in a chest x-ray?

- ~~Water~~ Fluid where it is not supposed to be



Blood? Water? Pus?

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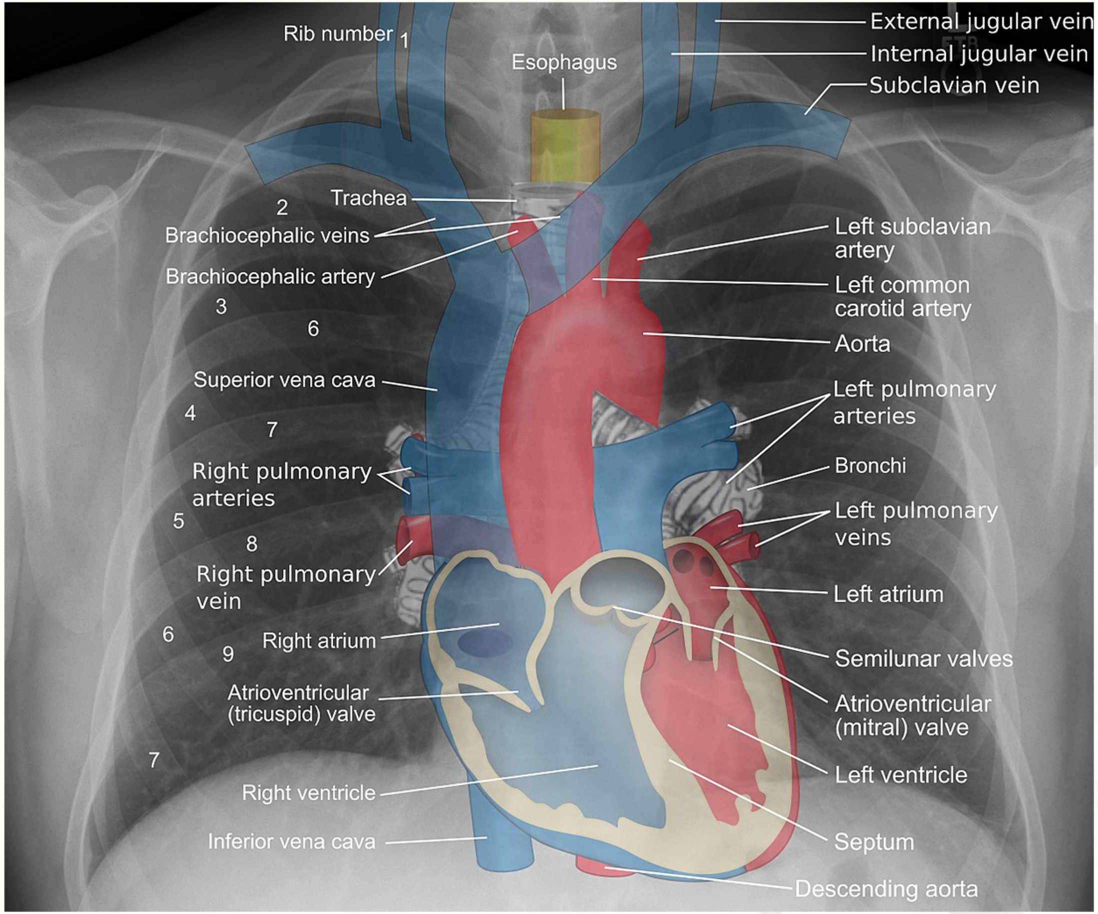
Chest radiographs

Radiologists have a strong mental model of what a CXR **should look like**



Mikael Häggström, M.D. "A pictorial essay: Radiology of lines and tubes in the intensive care unit". Indian Journal of Radiology and Imaging 21 (3): 182.

Why should we automate x-ray interpretation?

"My mom is a radiologist! Don't take her job!"

- 12 million people in Rwanda, 11 radiologists [1]
- 4 million people in Libya, 2 radiologists [1]
- Most radiologists are in urban settings [2]
- Delays in medical image interpretation are <u>*bad*</u>

[1] Abi Rimmer. Radiologist shortage leaves patient care at risk, warns royal college. BMJ: British Medical Journal.

[2] Cook PS. The challenges of providing interventional radiology services to rural and smaller community hospitals. American Journal of Roentgenology. 2018 Oct;211(4):744-7.

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What do we need to train a CXR model?

1. Data
2. Models
3. A lot of free time

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NIH to the rescue!

- 30,000+ patients
- 100,000+ images
- Each associated with 14 labels
  - Derived automatically from the free-text report
- Freely, publicly available

Media Advisory

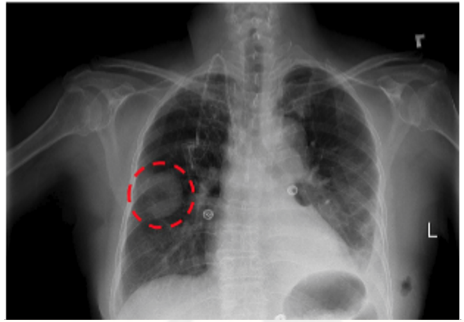
Wednesday, September 27, 2017

NIH Clinical Center provides one of the largest publicly available chest x-ray datasets to scientific community

The dataset of scans is from more than 30,000 patients, including many with advanced lung disease.

What

The NIH Clinical Center recently released over 100,000 anonymized chest x-ray images and their corresponding data to the scientific community. The release will allow researchers across the country and around the world to freely access the datasets and increase their ability to teach computers how to detect and diagnose disease. Ultimately, this artificial intelligence mechanism can lead to clinicians making better diagnostic decisions for patients.



https://www.nih.gov/news-events/news-releases/nih-clinical-center-provides-one-largest-publicly-available-chest-x-ray-datasets-scientific-community

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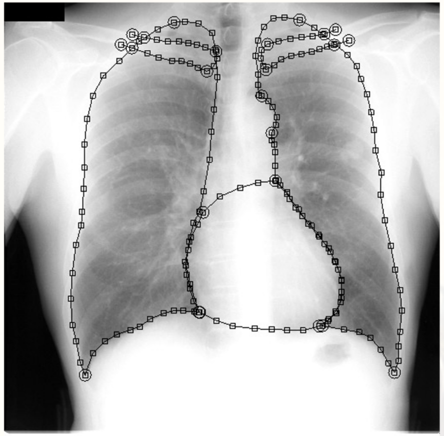
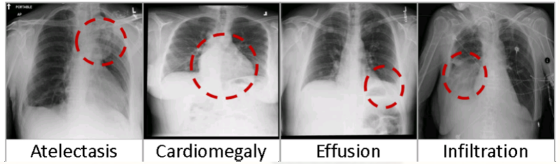
Others join in the data sharing craze





Currently available chest x-ray datasets

- **JSRT Database** - 247 DICOMs, have heart + lung segmentation
- **Open-I Indiana University CXR** - 8121 DICOMs, 3996 reports
- **ChestXray14 (ChestXray8)** - 112,120 PNGs, 14 labels
- **MIMIC-CXR-JPG** - 369,188 JPGs, 14 labels
- **MIMIC-CXR** - same as above, full resolution DICOMs + actual text
- **VinDr-CXR** - 18,000 PA views, 28 labels
  - 22 labels are bounding boxes
- **CheXpert** - 224,316 JPGs, 14 labels
- **PadChest** - 160,000 PNGs
  - 174 findings / 19 dx / 104 anatomy
  - UMLS coded
- **RSNA + Kaggle** - too many to list!
  - Warning: may overlap with other datasets

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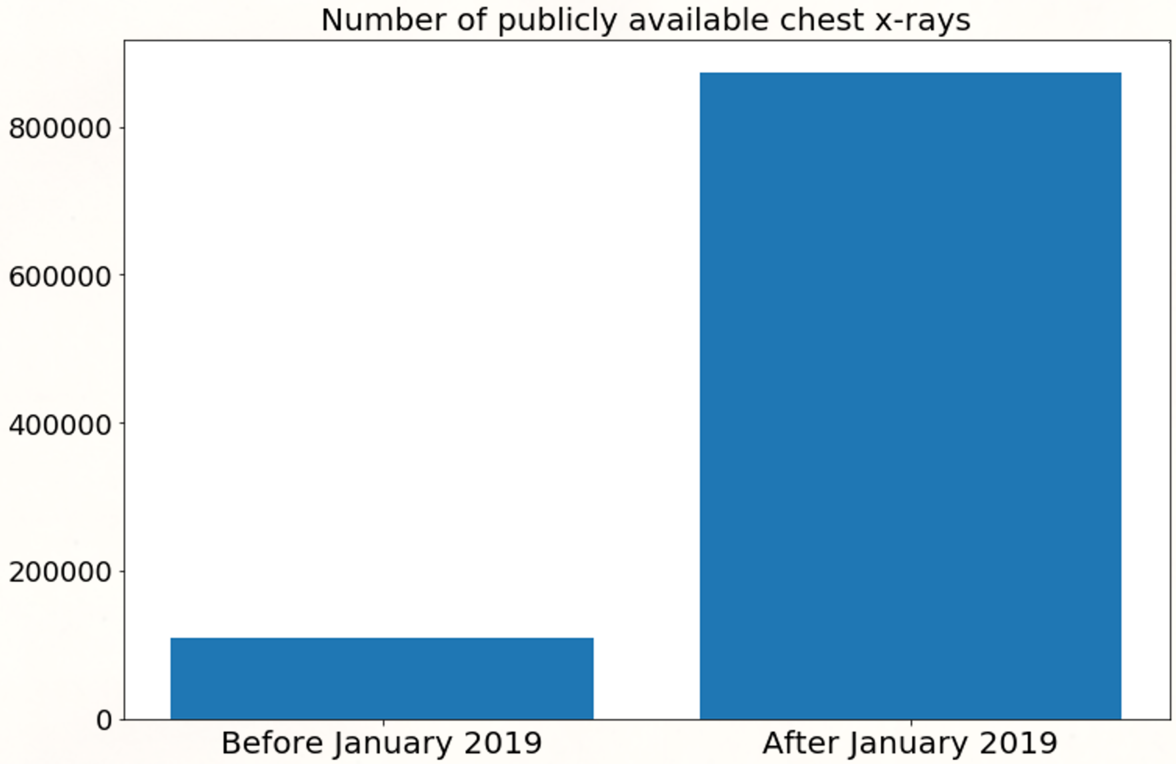
We live in exciting times!



We have data.

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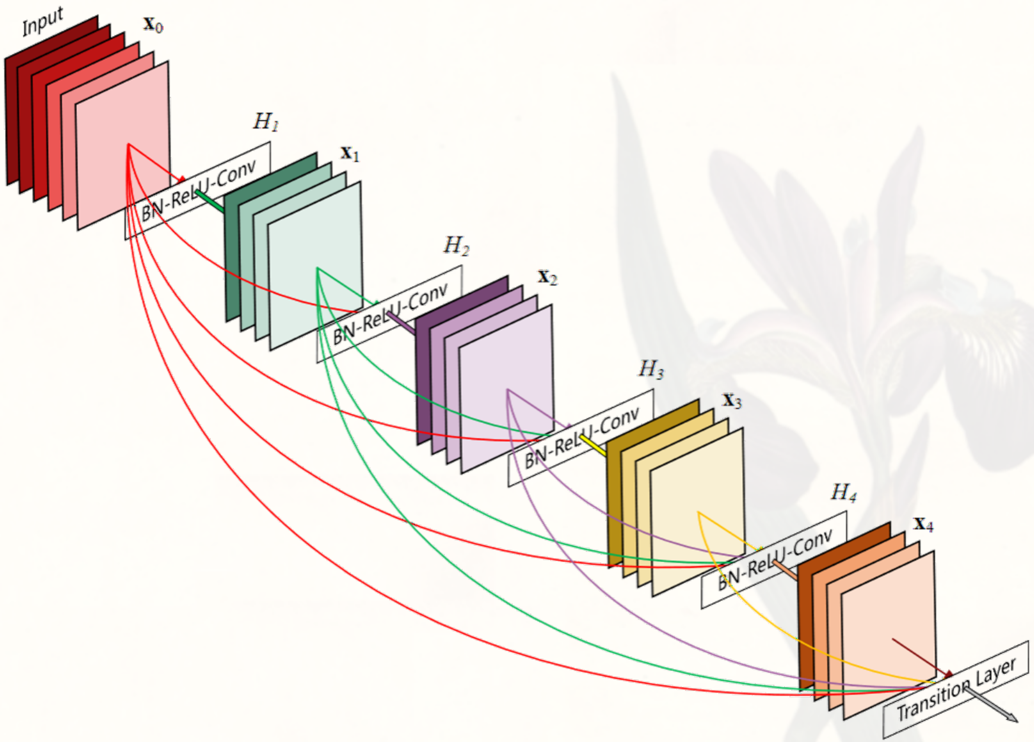
Model

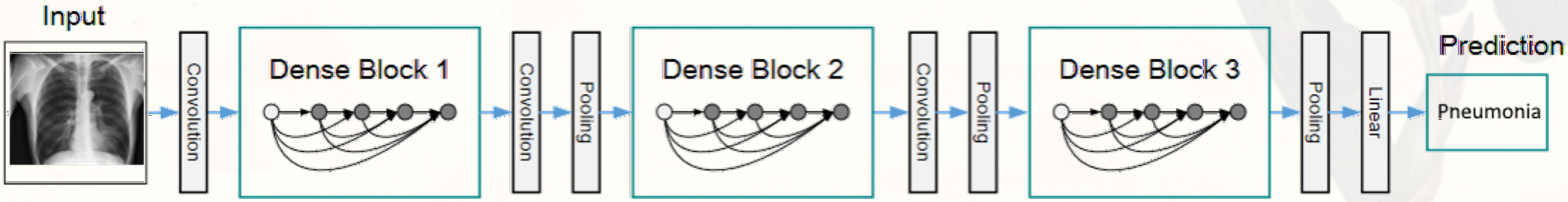
- DenseNet-121
- Chosen as it performed well in past publications



Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition 2017 (pp. 4700-4708).

CheXNet - Classify Pneumonia

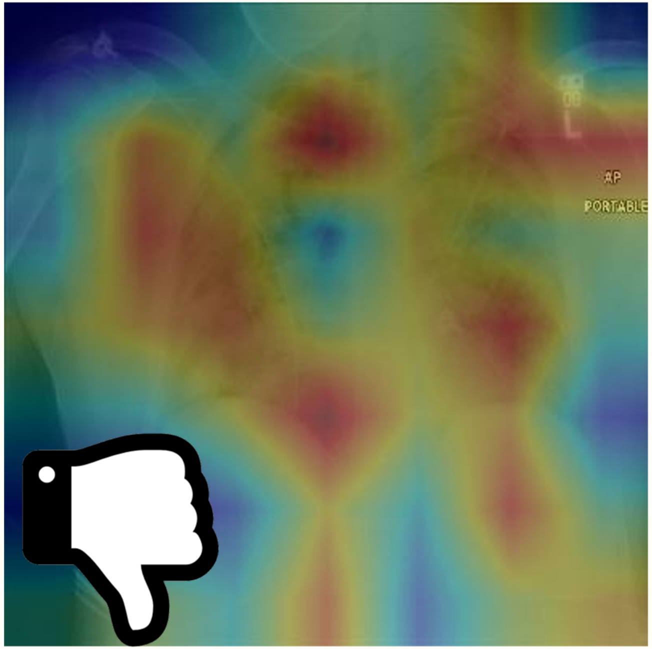
- Classify chest x-rays using a large labeled dataset
- Compare to domain experts (radiologists)



Rajpurkar P, Irvin J, Zhu K, Yang B, Mehta H, Duan T, Ding D, Bagul A, Langlotz C, Shpanskaya K, Lungren MP. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225. 2017 Nov 14.

Also worth a read: Bálint Botz, “A Few Thoughts About CheXNet—And The Way Human Performance Should (And Should Not) Be Measured”

CheXNet - Classify Pneumonia



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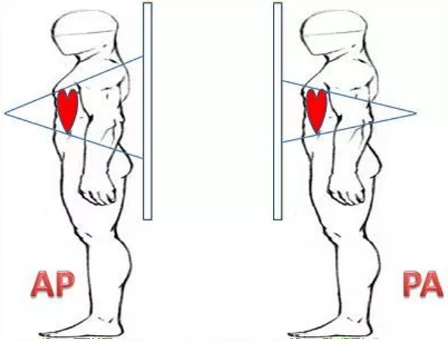
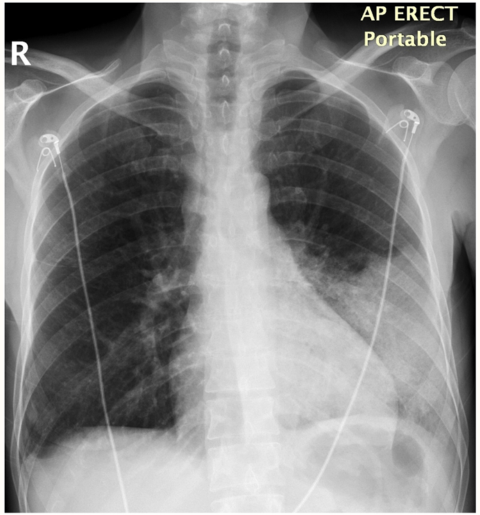
Understand the data generating process





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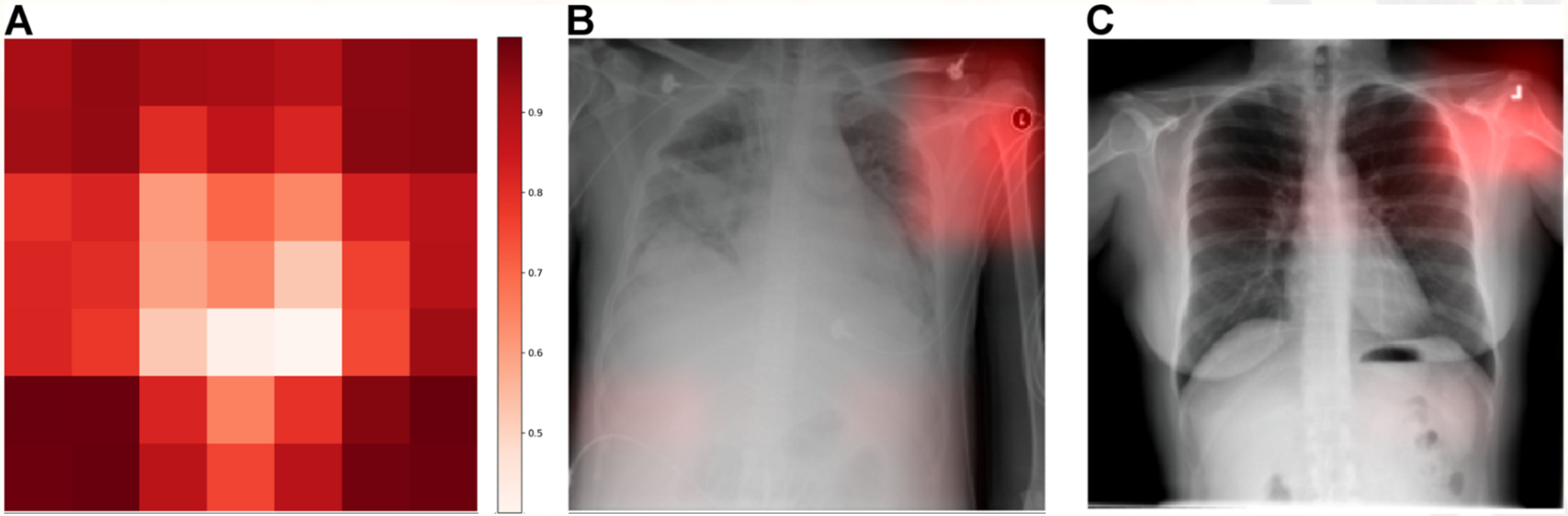
Issue #1: we are using non-causal features

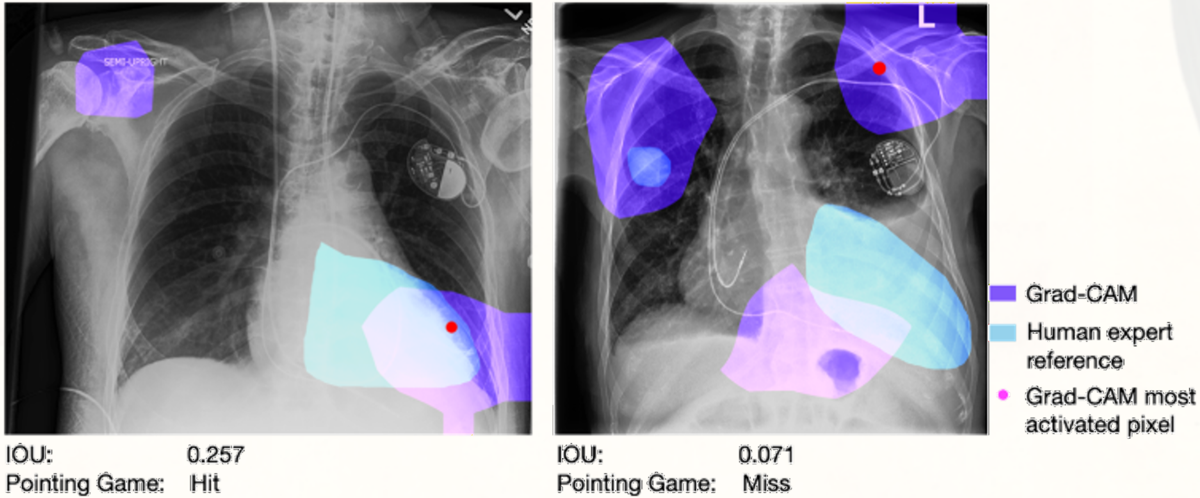


Average Grad-CAM

Classifying hospital A from hospital B

Zech JR, Badgeley MA, Liu M, Costa AB, Titano JJ, Oermann EK. Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: a cross-sectional study. PLoS medicine. 2018 Nov 6;15(11):e1002683.

Issue #1: we are using non-causal features

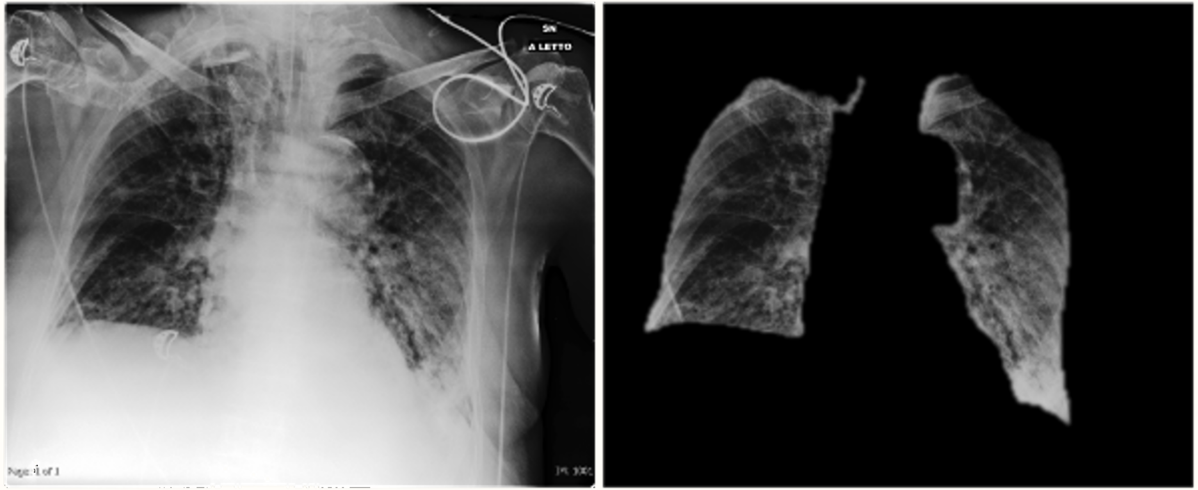


Good saliency

Bad saliency

Saporta A, Gui X, Agrawal A, Pareek A, Truong SQ, Nguyen CD, Ngo VD, Seekins J, Blankenberg FG, Ng A, Lungren MP. Deep learning saliency maps do not accurately highlight diagnostically relevant regions for medical image interpretation. medRxiv. 2021 Jan 1.

Solution: block out the non-causal factors



(a) (b)

Figure 2. Original image (a) and extracted lung segmented image (b). Many possible bias sources like all the writings and medical equipment is naturally removed.

Tartaglione E, Barbano CA, Berzovini C, Calandri M, Grangetto M. Unveiling covid-19 from chest x-ray with deep learning: a hurdles race with small data. International Journal of Environmental Research and Public Health. 2020 Jan;17(18):6933.

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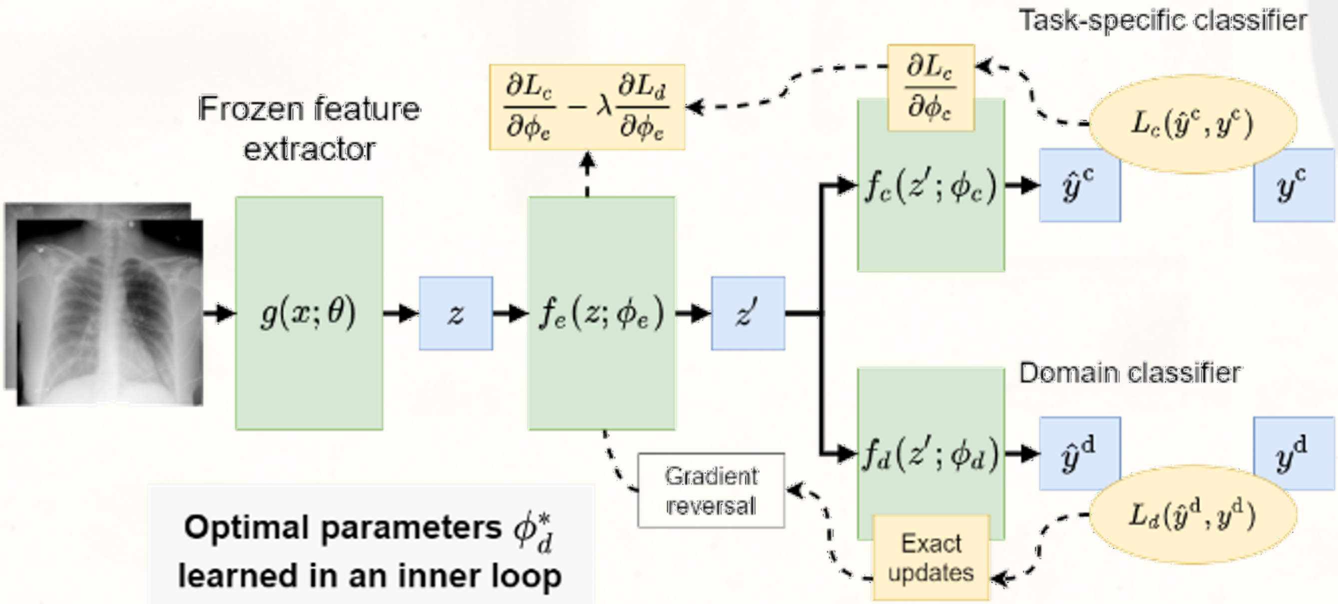
Solution: explicitly model the non-causal factors



Optimal parameters ϕ_d^* learned in an inner loop

Robinson C, Trivedi A, Blazes M, Ortiz A, Desbiens J, Gupta S, Dodhia R, Bhatraju PK, Liles WC, Lee A, Kalpathy-Cramer J. Deep learning models for COVID-19 chest x-ray classification: Preventing shortcut learning using feature disentanglement. medRxiv. 2021 Jan 1.

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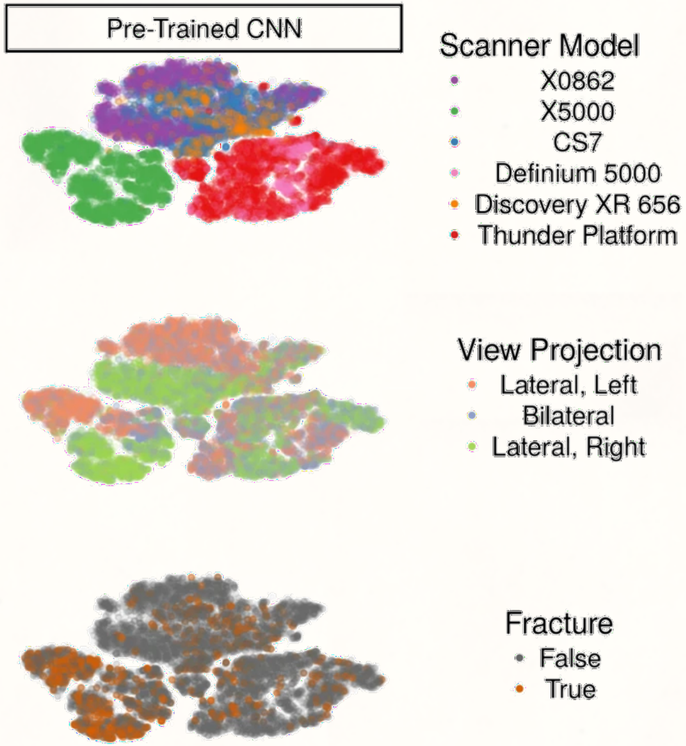
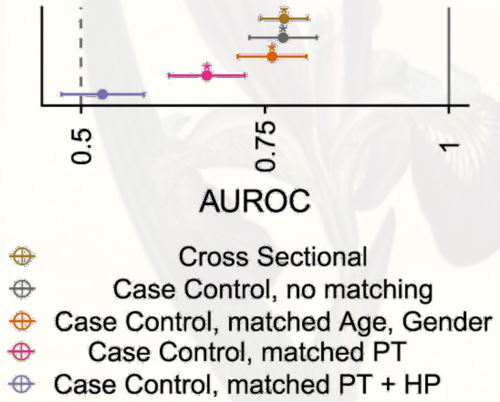
Solution: stratify the patient population

Models adjusted for demographic and process factors have significantly weakened performance





Badgeley MA, Zech JR, Oakden-Rayner L, Glicksberg BS, Liu M, Gale W, McConnell MV, Percha B, Snyder TM, Dudley JT. Deep learning predicts hip fracture using confounding patient and healthcare variables. NPJ digital medicine. 2019 Apr 30;2(1):1-0.

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Issue #2: we are using noisy labels

FINDINGS:

Coarse bilateral interstitial opacities are consistent with patient's known interstitial lung disease. There is minimally increased prominence of pulmonary vasculature and heart size compared to prior, possibly secondary to slightly lower lung volumes and/or interval hydration/fluid overload. Mild congestive heart failure cannot be excluded. No pleural effusion or pneumothorax is seen. **Underlying interstitial lung disease slightly limits evaluation for pneumonia, but no new large opacities are detected.** Aortic calcification is again seen. A nasogastric tube traverses below the diaphragm, distal tip not well seen.

> Labeled as *Positive* for Pneumonia

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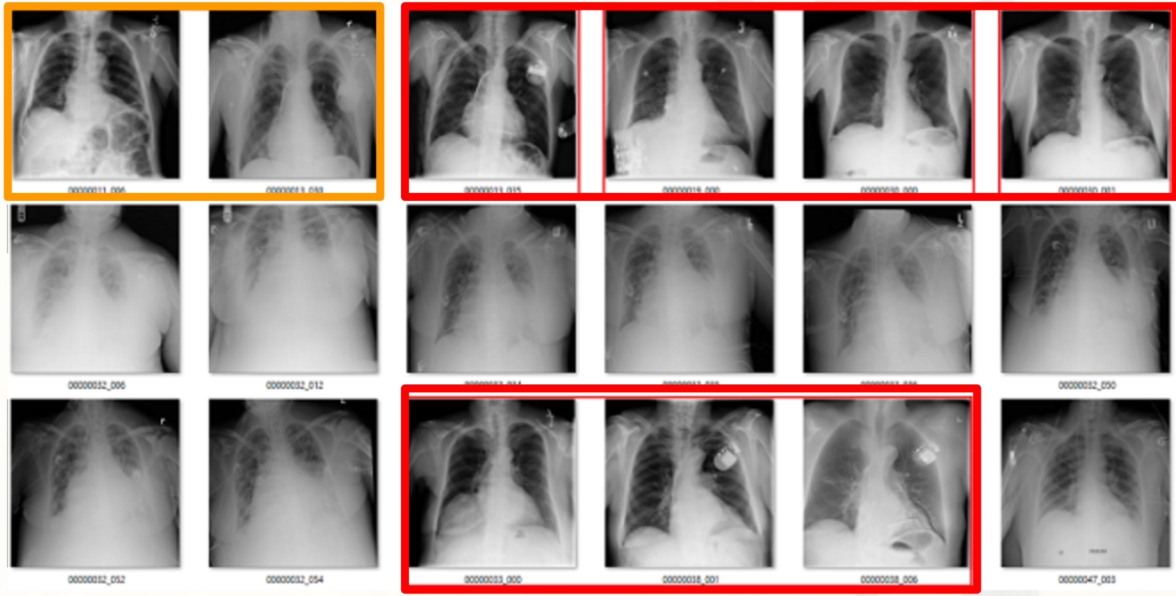
Issue #2: we are using noisy labels

- All of these were supposed to be *atelectasis*
- But many clearly aren't
- Consistent across labels

Label	PPV (visual)
Consolidation	35%
Cardiomegaly	80%
Pneumothorax	60%
Pneumonia	35%
Fibrosis	24%
No finding	60%



Red = I disagree

Orange = eh, I'm not sure

Oakden-Rayner L. Exploring large-scale public medical image datasets. Academic radiology. 2020 Jan 1;27(1):106-12.

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Solution: improve processing of the notes

NegBio / CheXPert algorithms parse free-text notes to identify negations and uncertainty - not easy

Later sessions will talk recent developments!

1. *unremarkable* cardiomediastinal silhouette

2. diffuse reticular pattern, which can be seen with an atypical infection **or** chronic fibrotic change. *no* focal consolidation.

3. *no* pleural effusion or pneumothorax

4. mild degenerative changes in the lumbar spine and old right rib fractures.

Observation	Labeler Output
No Finding	
Enlarged Cardiom.	0
Cardiomegaly	
Lung Opacity	1
Lung Lesion	
Edema	
Consolidation	0
Pneumonia	u
Atelectasis	
Pneumothorax	0
Pleural Effusion	0
Pleural Other	
Fracture	1
Support Devices	

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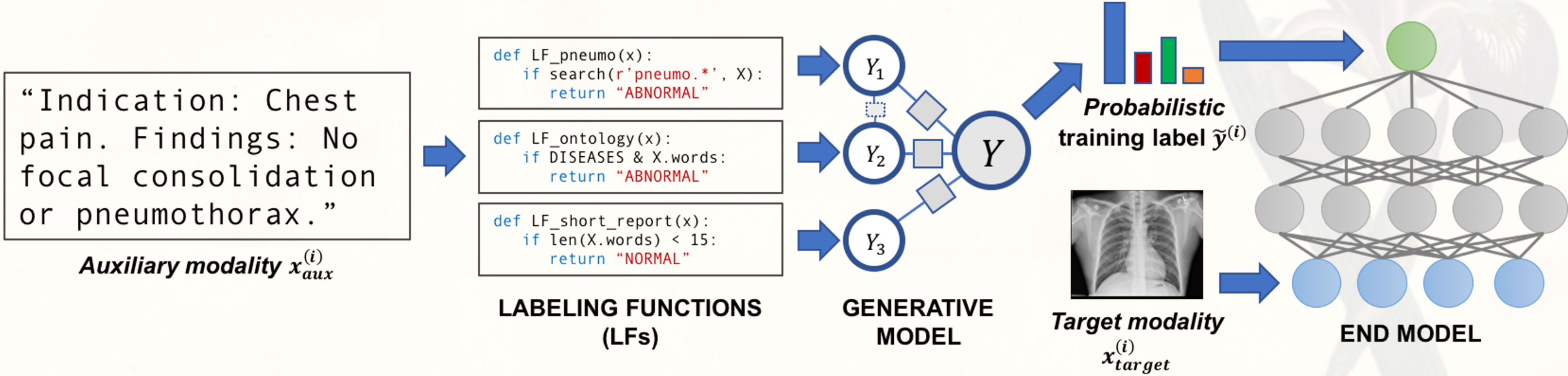
Solution: learn with noisy labels

Iteratively build labeling functions, and use "unlabeled" data



Dunnmon JA, Ratner AJ, Saab K, Khandwala N, Markert M, Sagreiya H, Goldman R, Lee-Messer C, Lungren MP, Rubin DL, Ré C. Cross-modal data programming enables rapid medical machine learning. Patterns. 2020 May 8;1(2):100019.

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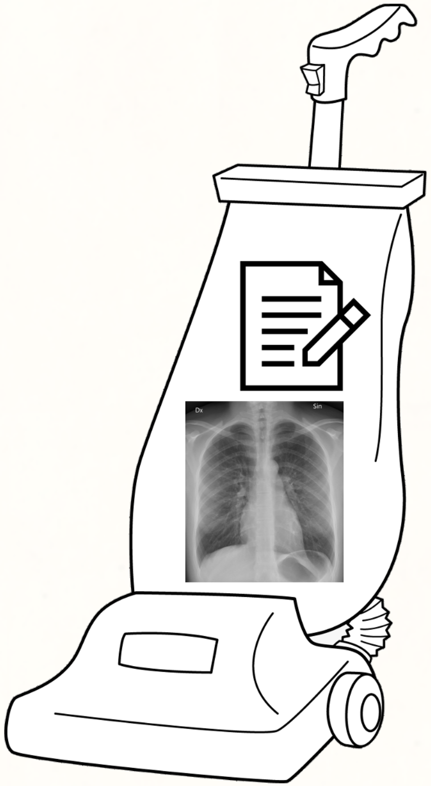
Issue #3: we are not incorporating clinical context



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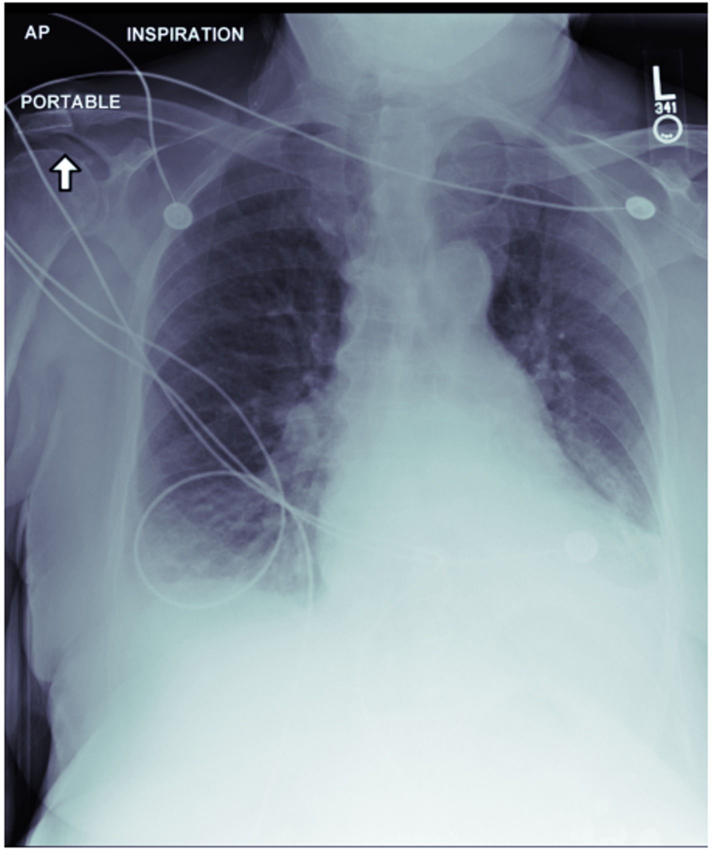
Radiologist reports...



CLINICAL INFO: 78 year old female.

FINDINGS:

Let's write this section together!

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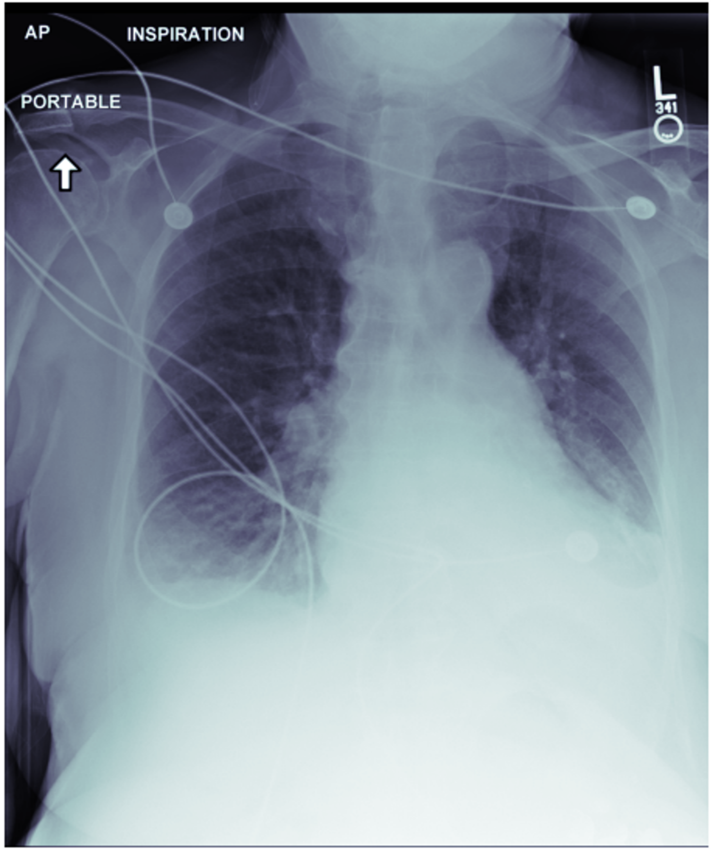
Radiologist reports...

CLINICAL INFO: 78 year old female.

FINDINGS:

Let’s write this section together!

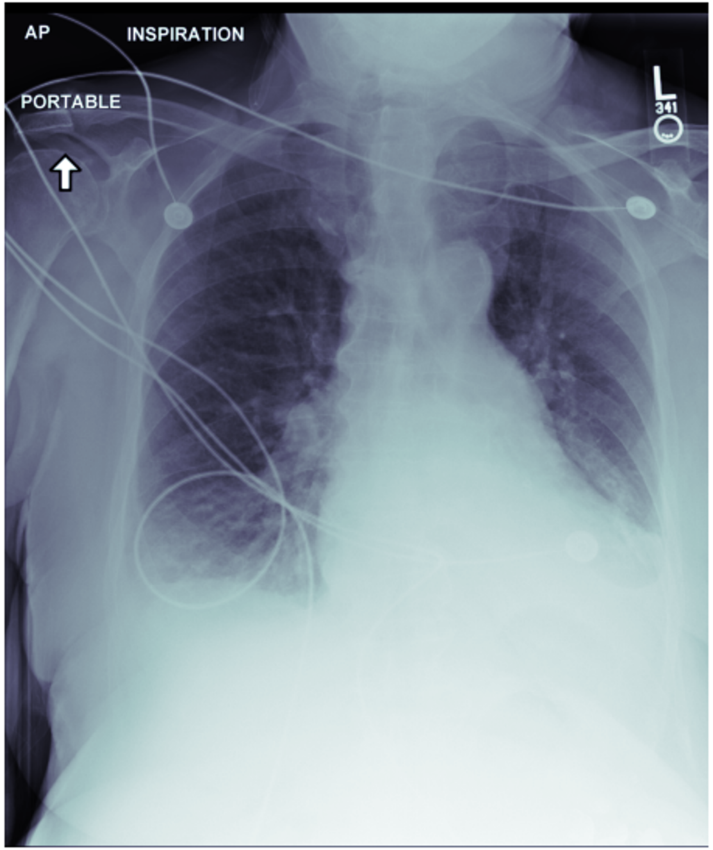


Radiologist reports...

CLINICAL INFO: 78 year old female.

FINDINGS:

Patient has twelve pairs of ribs, and two clavicle bones. They have both of their lungs, and their heart is located between their two lungs. Both clavicle bones are in place and no fractures there. I can see one humerus but the other is out of view..



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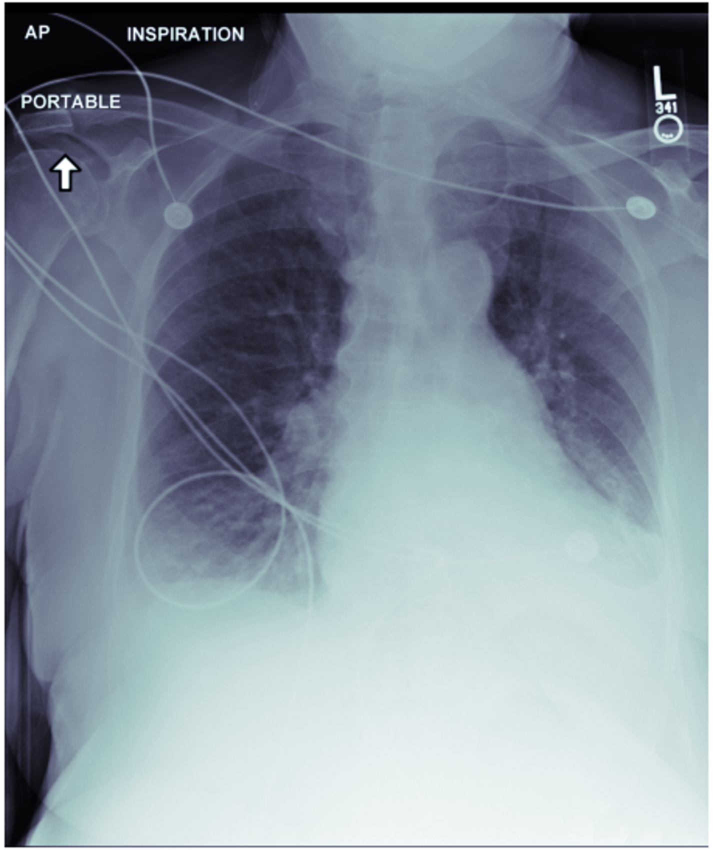
RRs are not the whole story!

CLINICAL INFO: 78 year old female.

INDICATION: ___ year old woman with large goiter and hypercapnic acute on chronic respiratory failure. Please assess for diaphgramatic elevation or other intraparenchymal abnormality.

IMPRESSION: Moderate pulmonary congestion and mild interstitial edema is increased, moderate right pleural effusion is new, and moderate left basilar atelectasis is increased since ___, consistent with acute CHF exacerbation.



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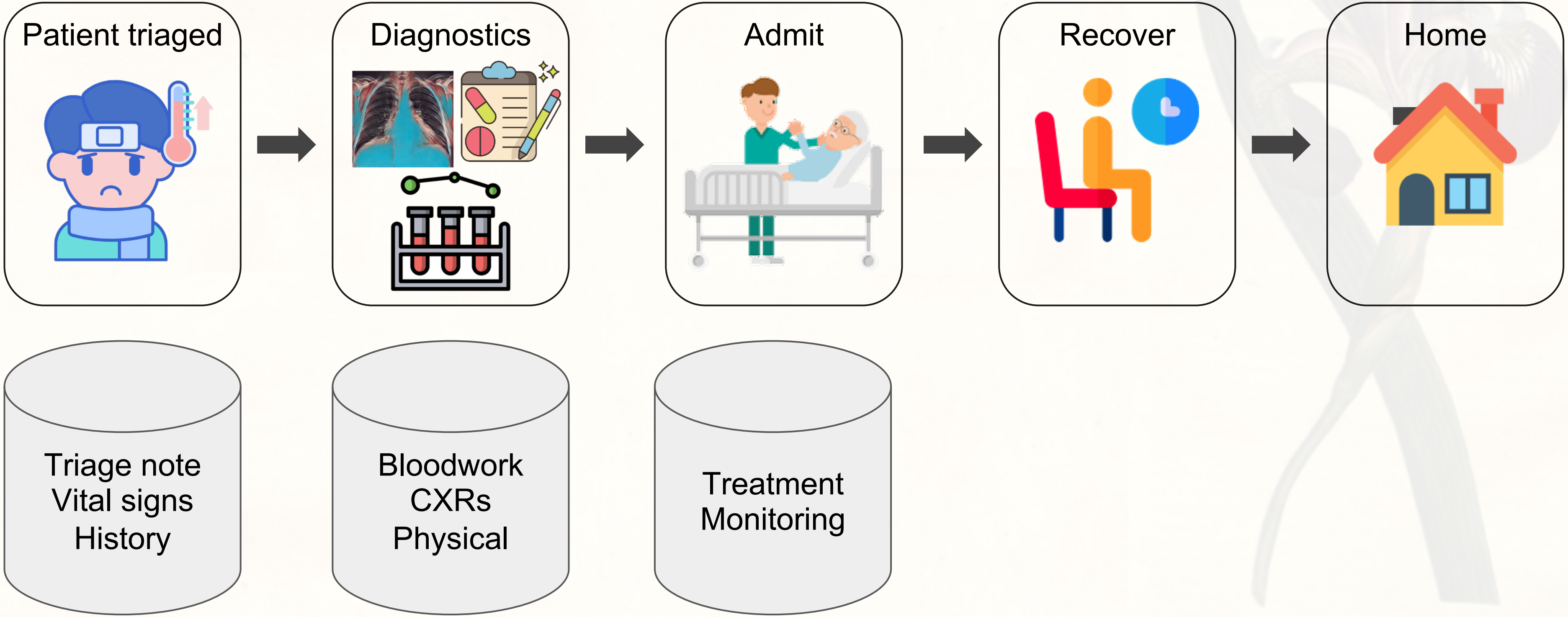
Workflow for an ED admission for pneumonia



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Thanks!

- CVPR tutorial site
  - https://bionlplab.github.io/cvpr2021tutorial/
- Train your own model and evaluate it using Google Colab
  - https://alistairewj.github.io/talk/2021-cvpr-cxr-tutorial/

… and thanks to all those who made data available!

Stanford HEALTH CARE

NIH National Institutes of Health

RSNA® Radiological Society of North America

Beth Israel Lahey Health
Beth Israel Deaconess Medical Center

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