

Multimodal Representation Learning for Medical Image Analysis

Ruizhi “Ray” Liao

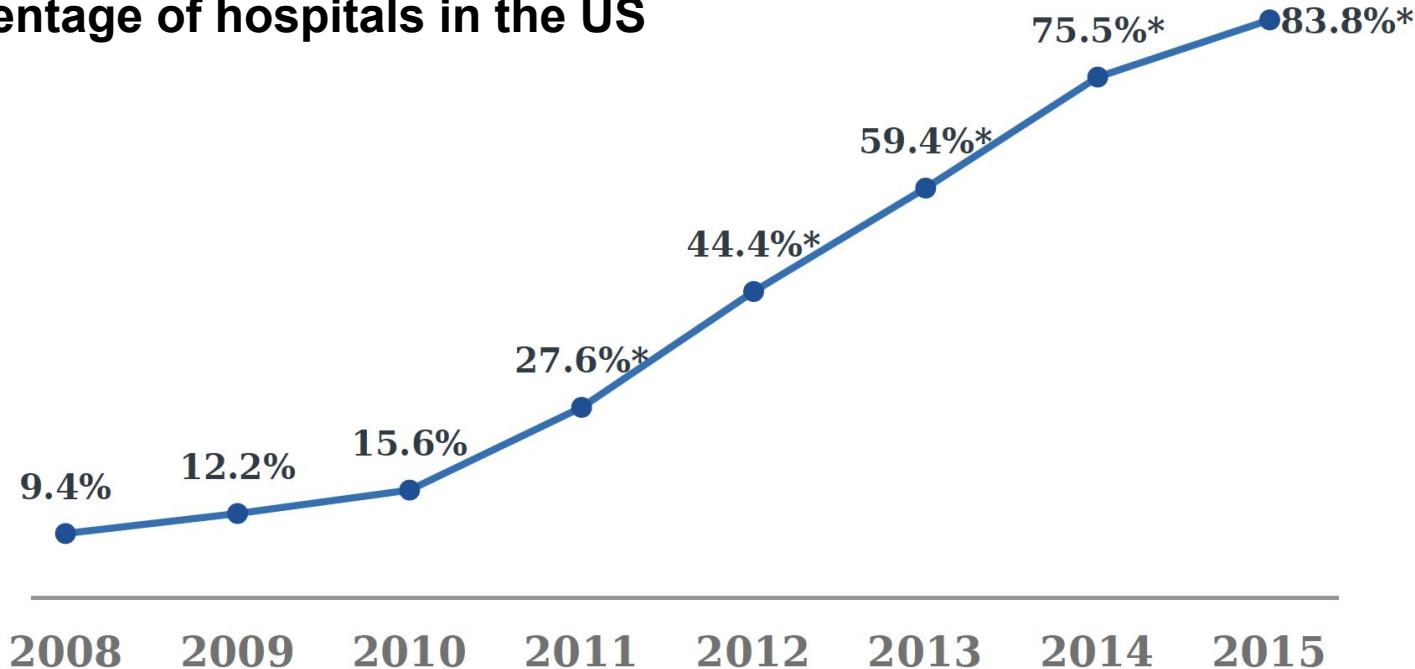
ruizhi@mit.edu

 @rayruizhiliao



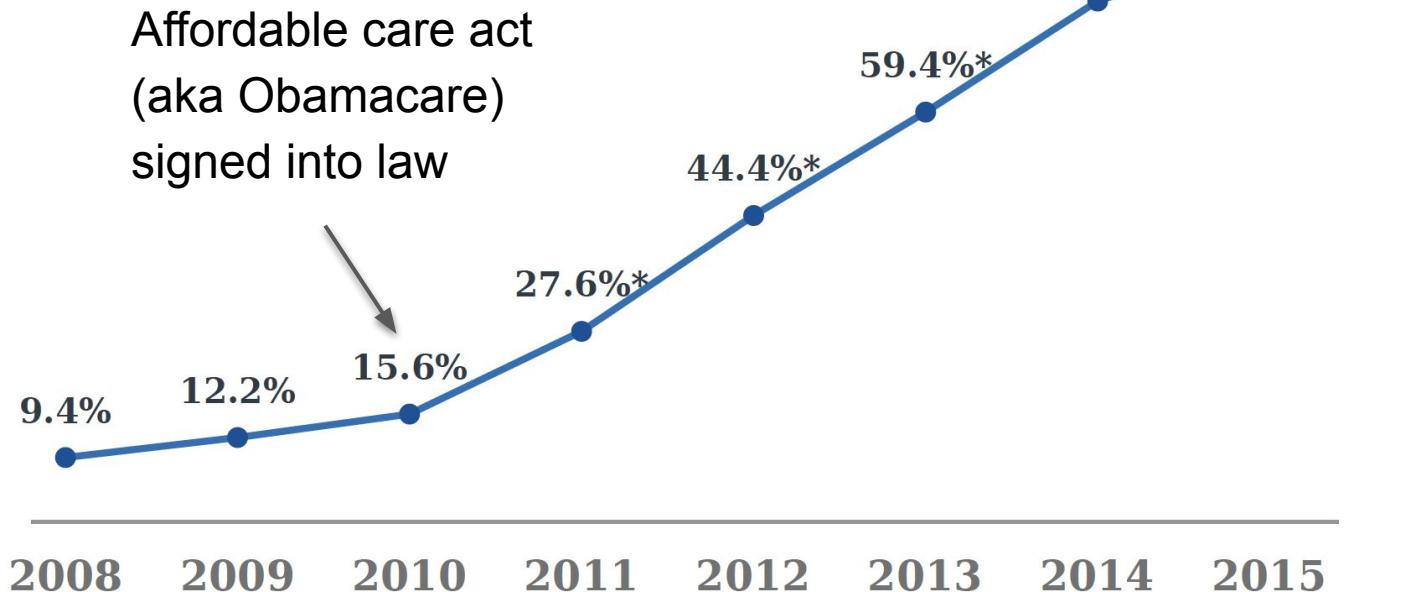
Adoption of electronic health records (EHR) has increased 9x in the US since 2008

Percentage of hospitals in the US



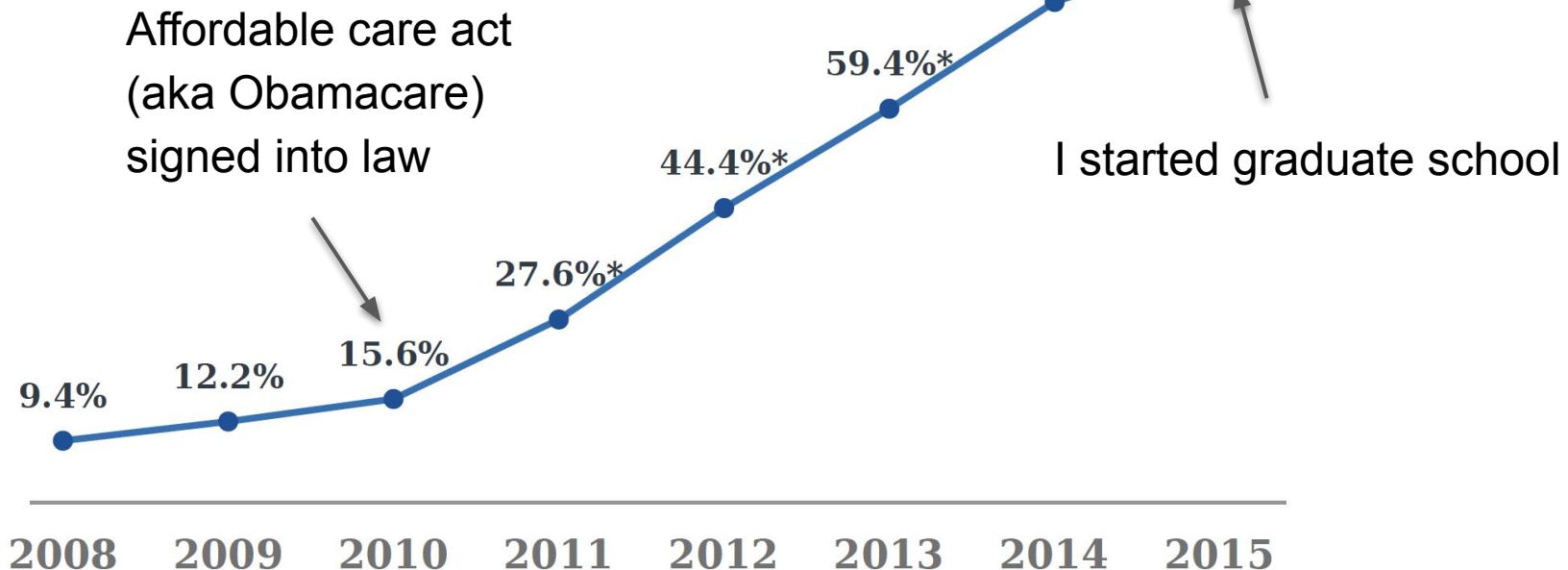
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Clinical data is multimodal



Images

$$x^I$$

FINAL REPORT
EXAMINATION: CHEST (PORTABLE AP)
INDICATION: ____ year old man with respiratory failure, ARDS // Volume overload?
TECHNIQUE: Single frontal view of the chest
COMPARISON: ____
IMPRESSION:
Moderate left pleural effusion decreased. Large right pleural effusion is probably unchanged. Tracheostomy tube is in unchanged position. Extensive bilateral alveolar opacities have improved, consistent with improve severe pulmonary edema. Cardiac size is obscured by the pleural parenchymal abnormalities



Text

$$x^R$$

Numerical signals

$$x^N$$

Multimodal clinical data reflect different yet correlated manifestations of a subject's underlying physiological processes



Images

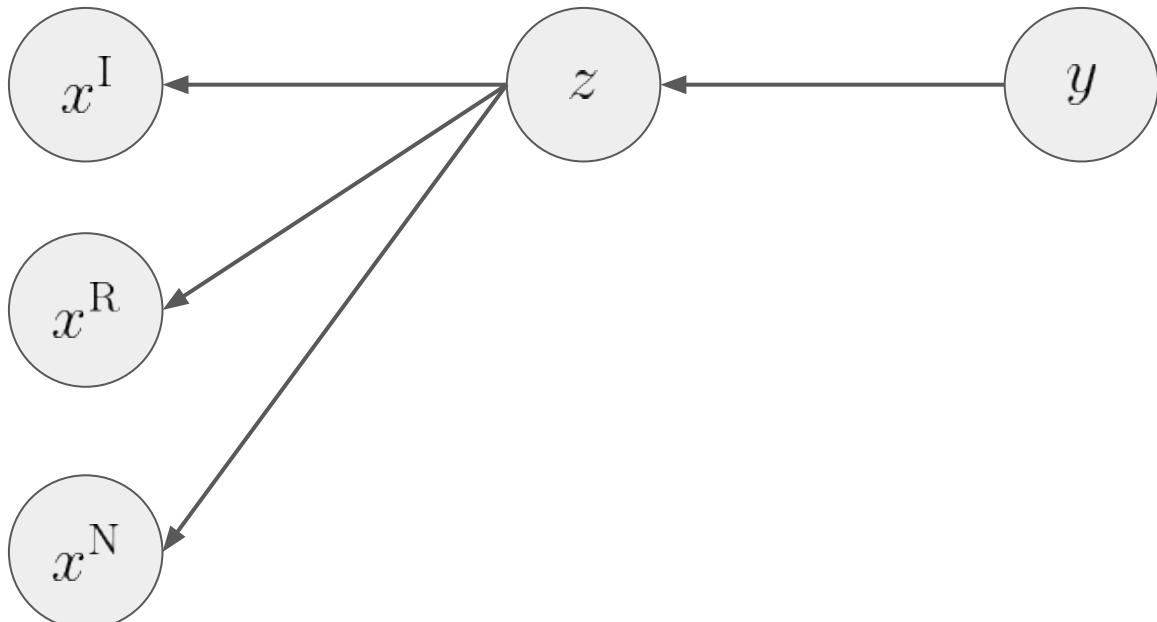
Text

Numerical
signals

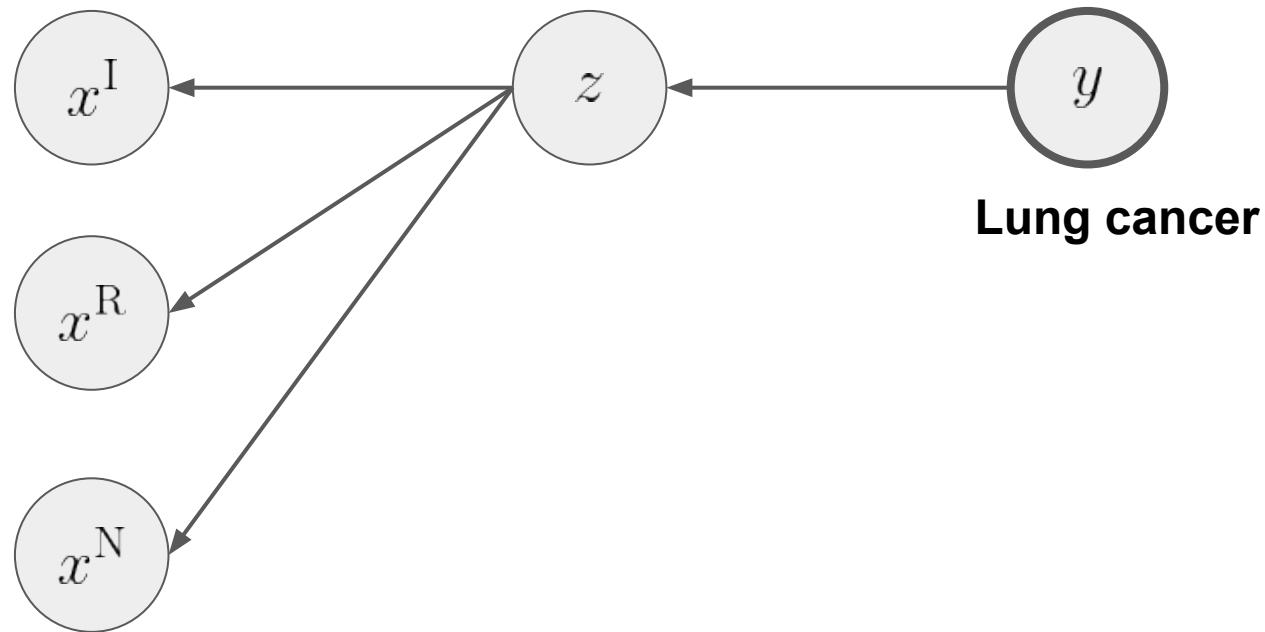
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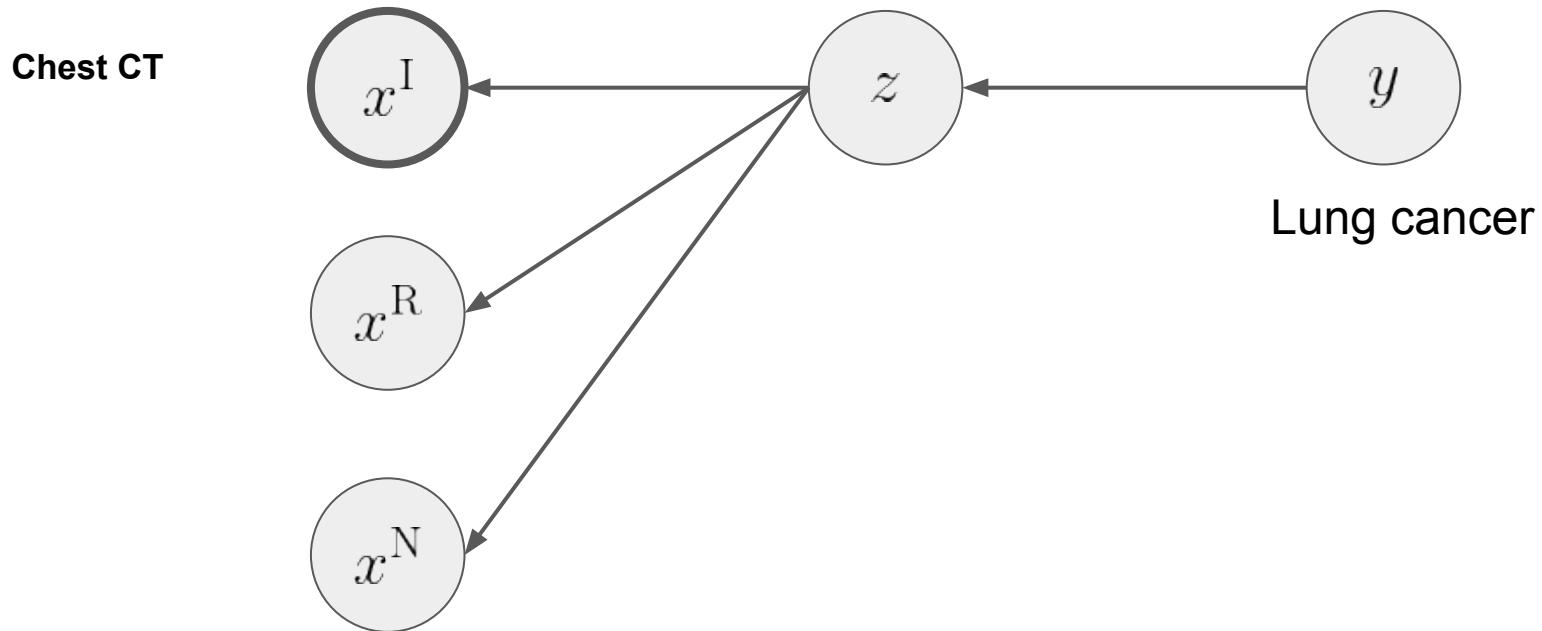
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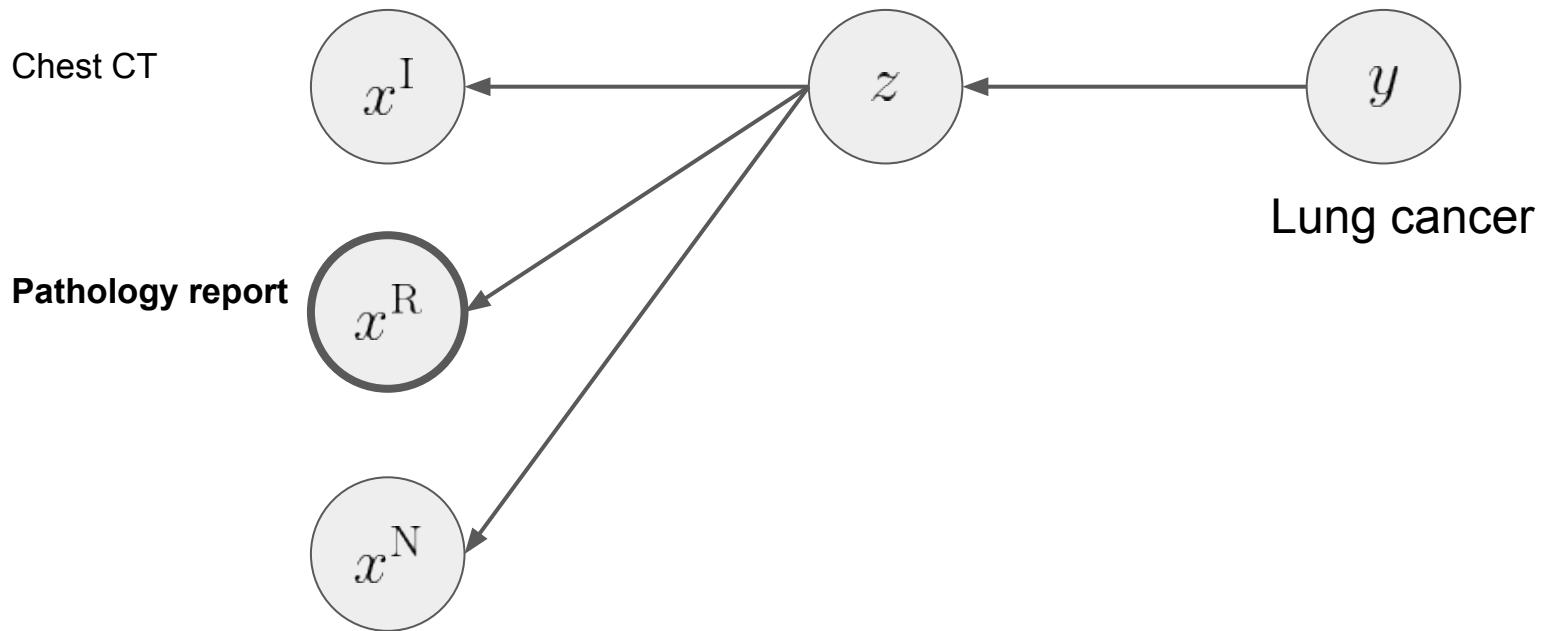
Multimodal clinical data reflect different yet correlated manifestations of a subject's underlying physiological processes



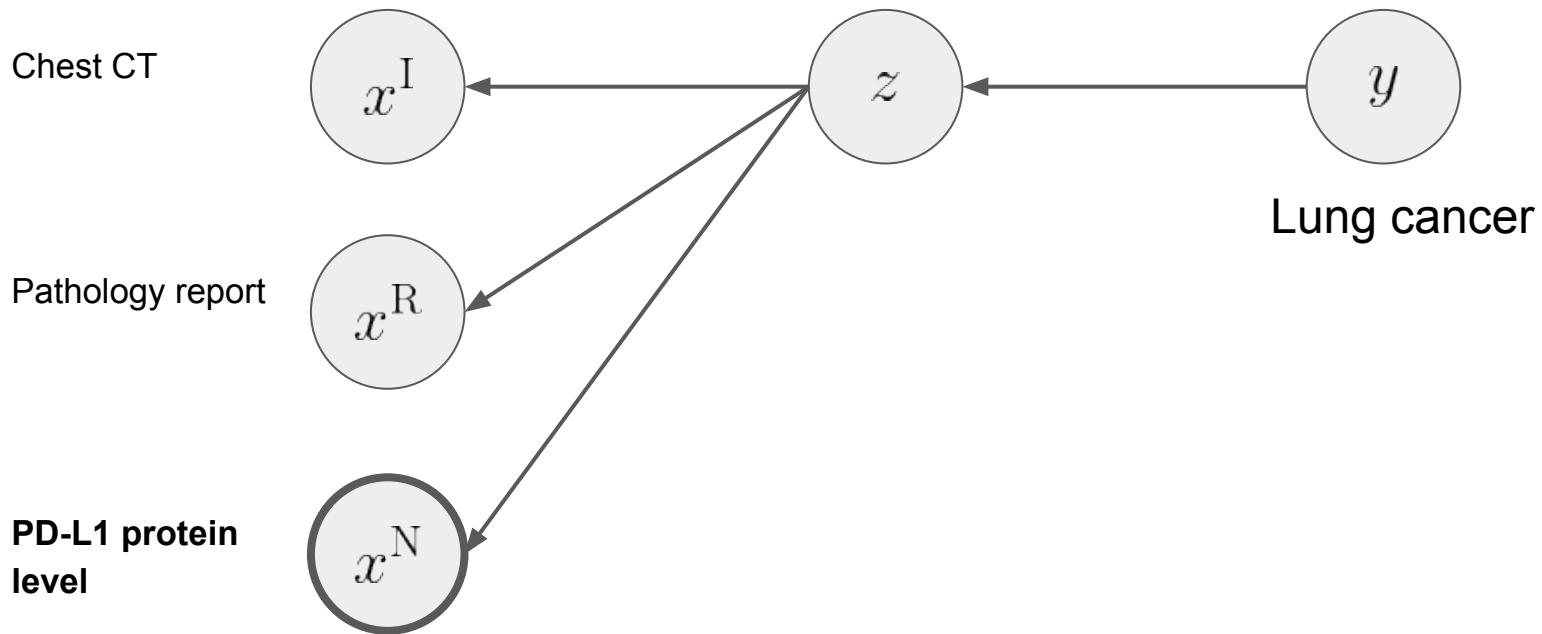
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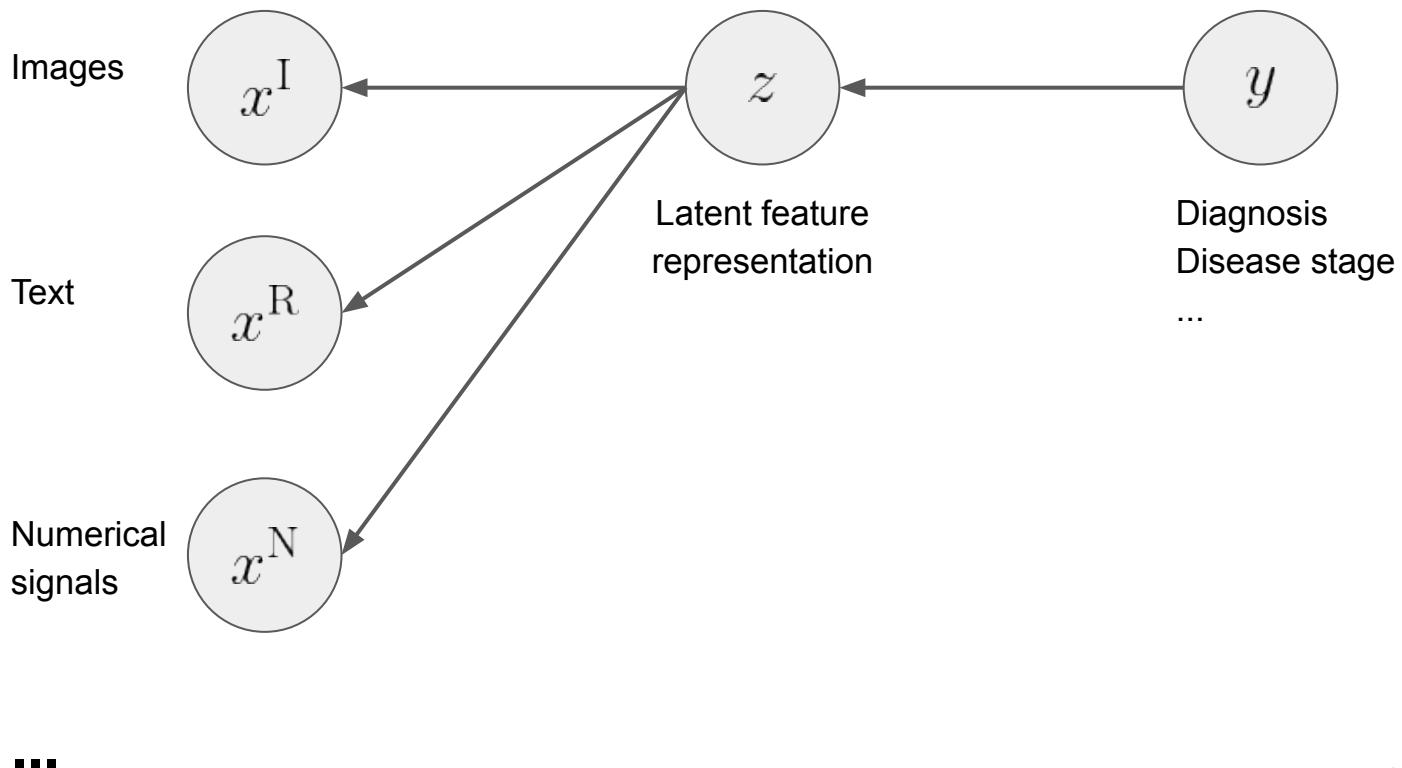
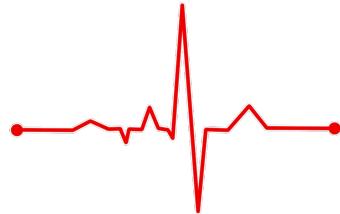
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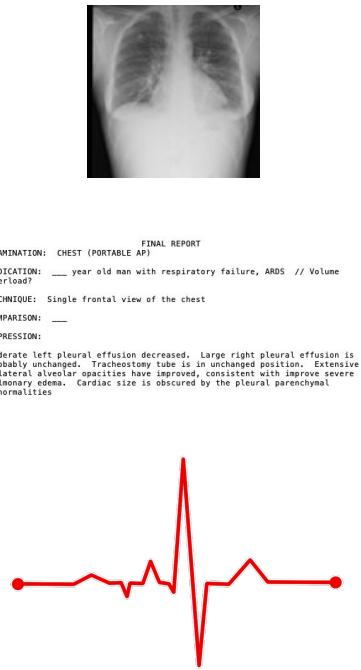
Multimodal representation learning for medical image analysis



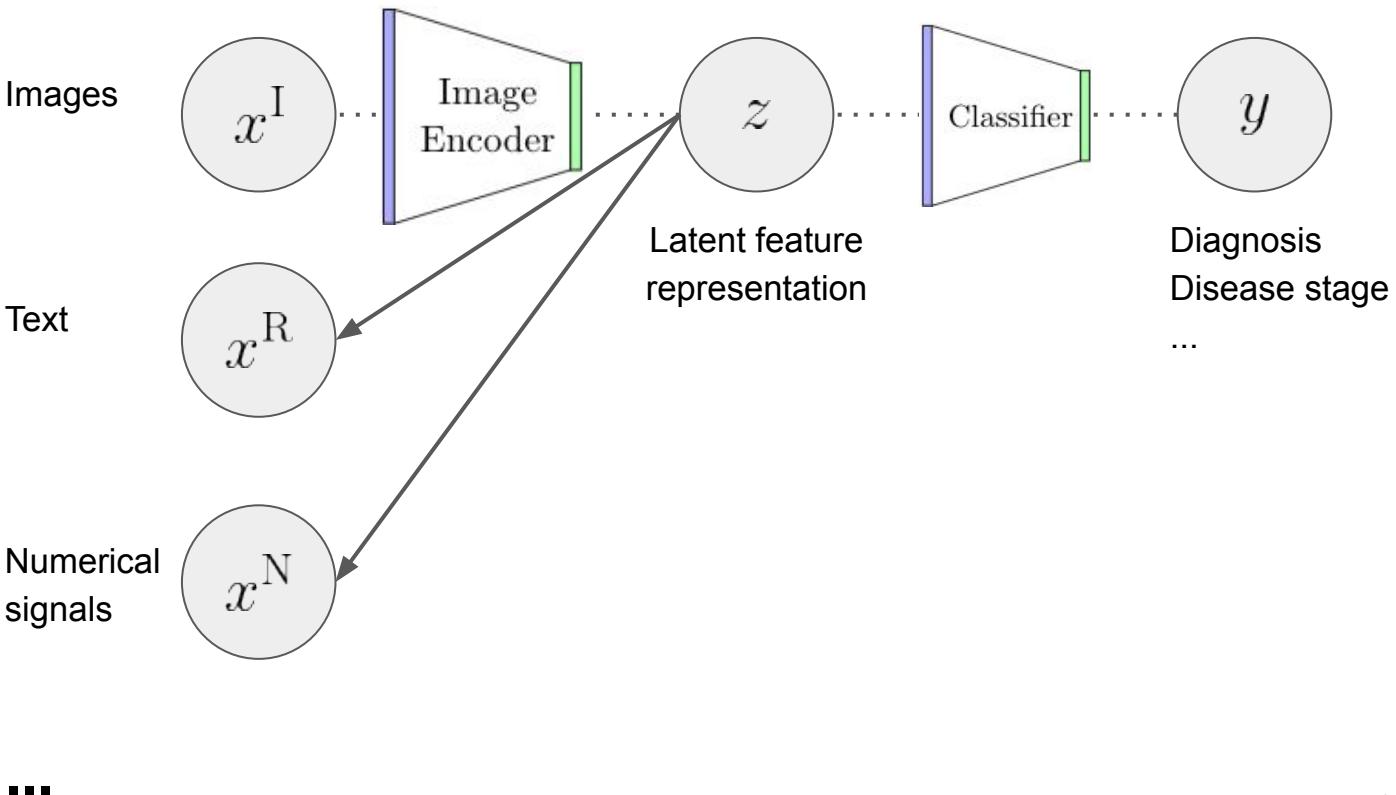
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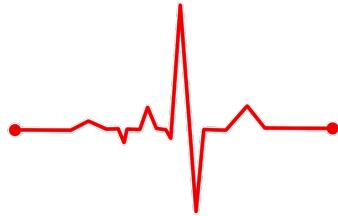
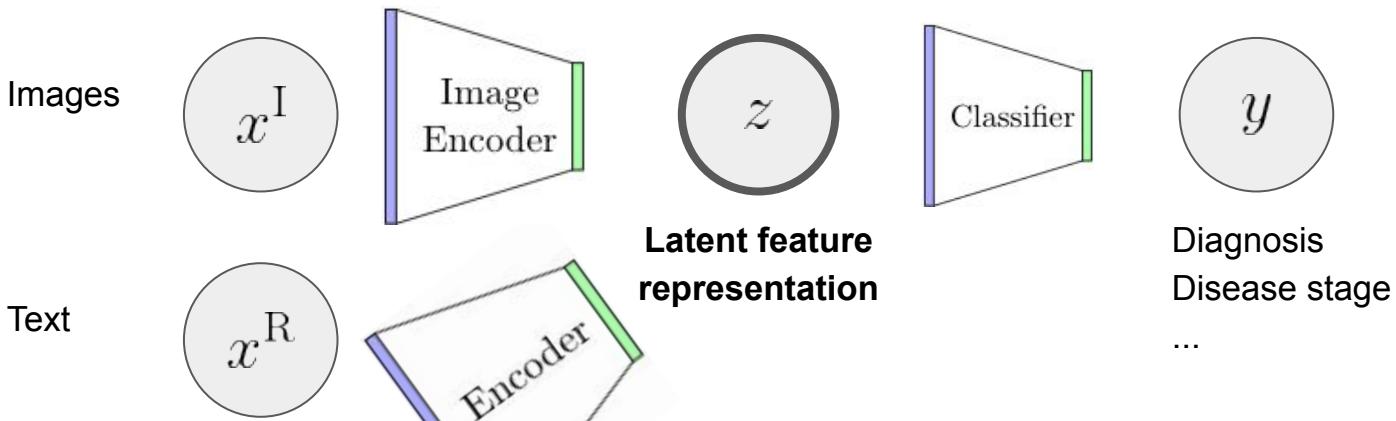
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Multimodal representation learning for medical image analysis



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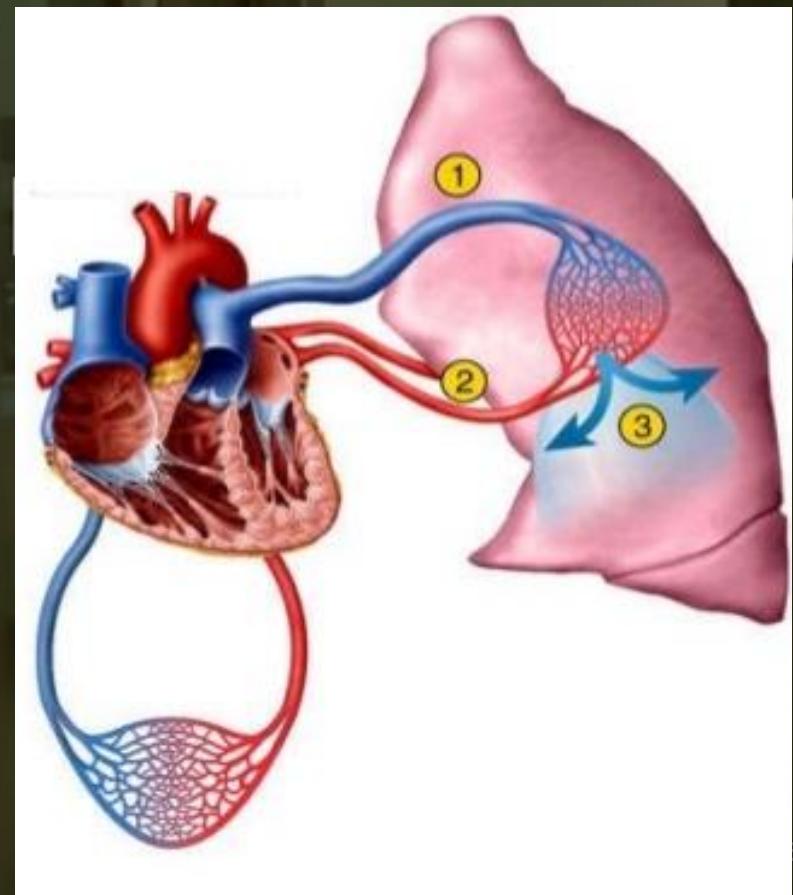
Outline

1. Motivating Clinical Problem
2. Image-based Model for Pulmonary Edema Assessment [Liao et al., 2019,
Horng*, Liao* et al., 2021]
3. Joint Image-text Modeling [Chauhan*, Liao* et al., 2020]
4. Mutual Information for Representation Learning [Liao et al., 2021]
5. Conclusions

Outline

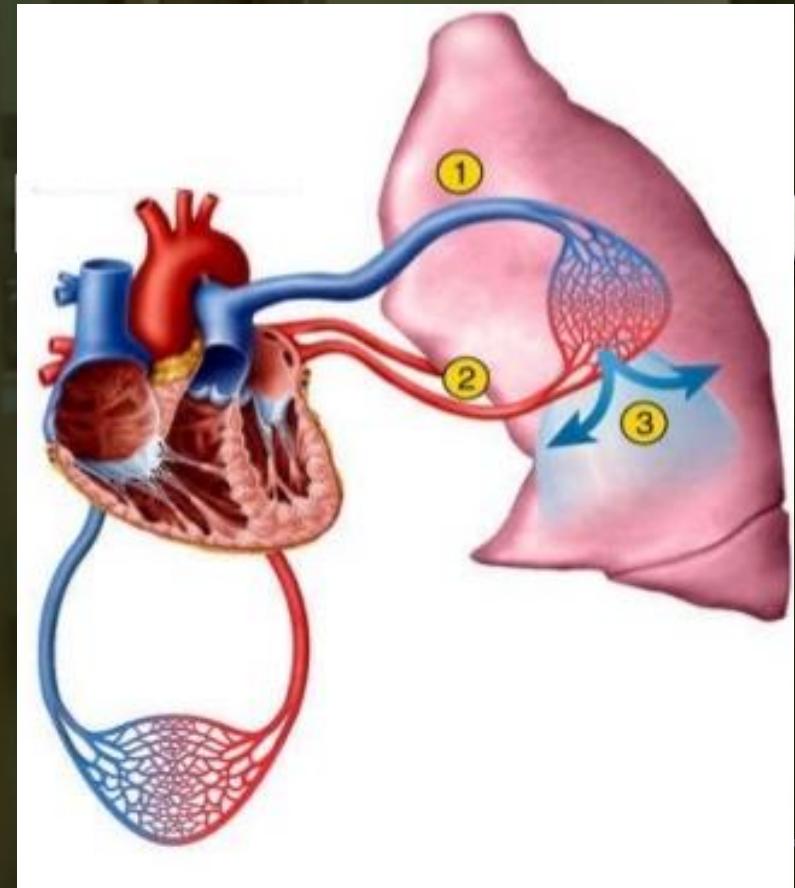
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5. Conclusions

Most common cause of heart failure hospitalizations: pulmonary edema



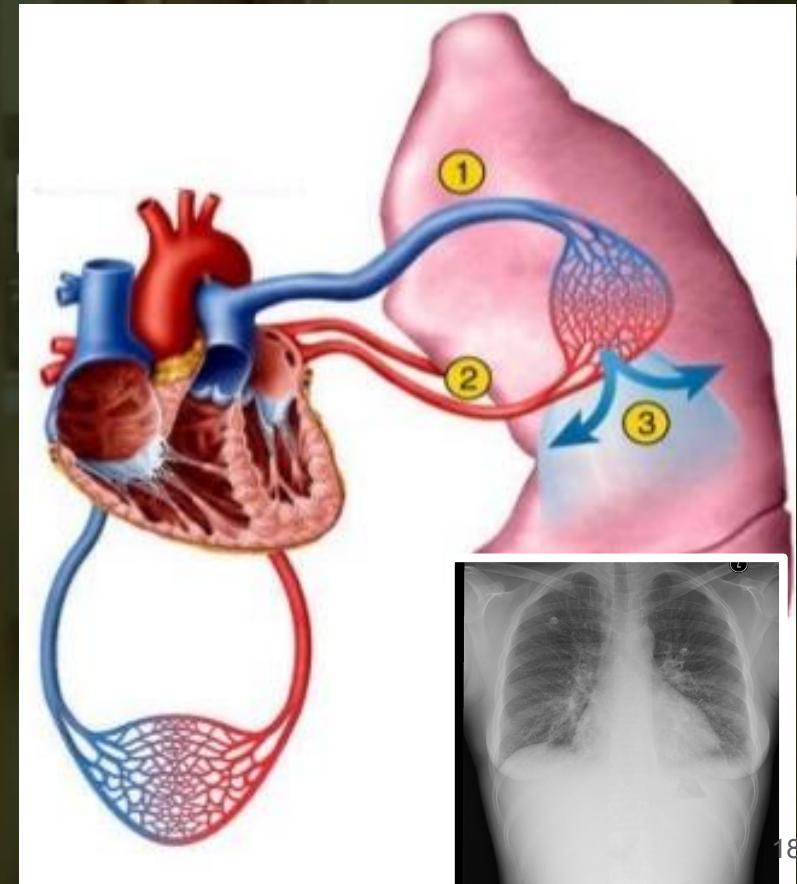
Heart failure is the leading cause of hospitalization in the US

- **1 million hospital stays** due to heart failure every year in the US (90% for pulmonary edema)
- **20% of heart failure patients readmitted** within 30 days of discharge
- **Roughly one out of eight US deaths** is caused at least in part by heart failure.

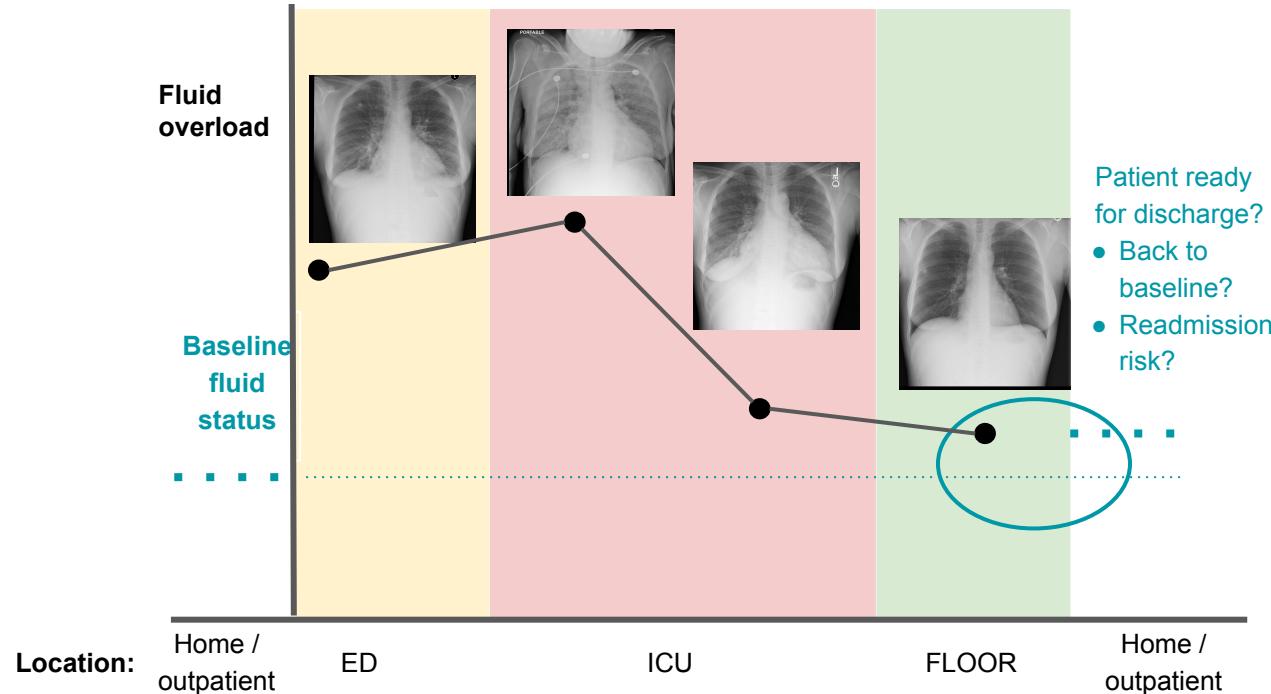


Chest x-ray is commonly performed to assess pulmonary edema

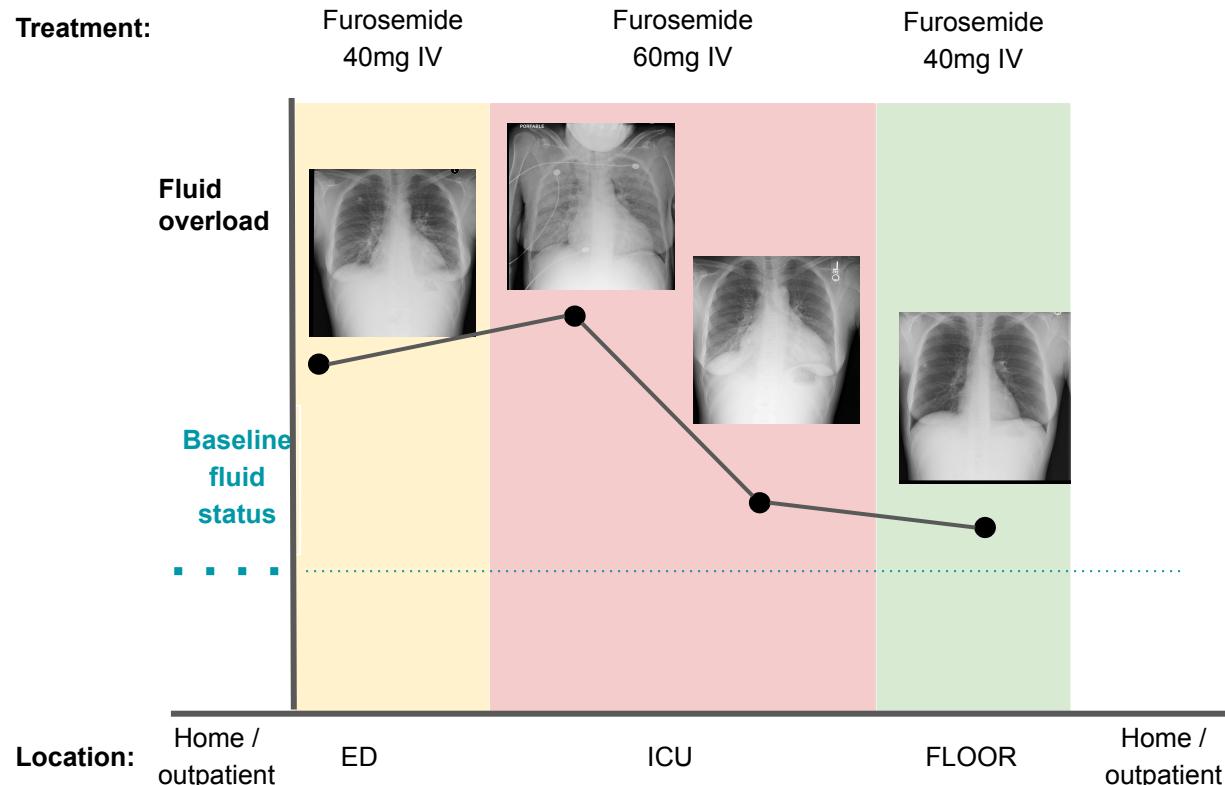
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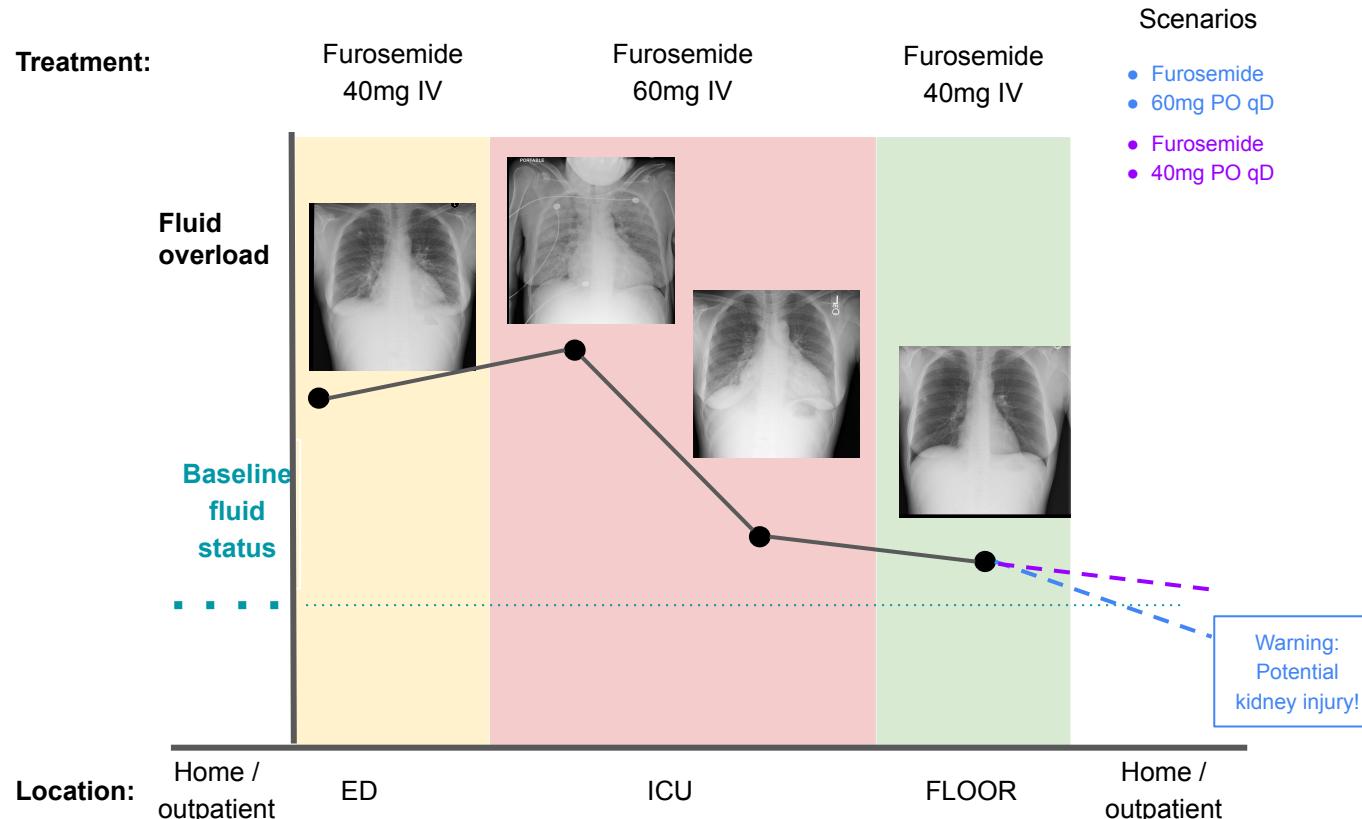
Retrospective clinical trajectory buried in the unstructured imaging data



Retrospective clinical trajectory buried in the unstructured imaging data



Retrospective clinical trajectory buried in the unstructured imaging data



I aim to develop computer vision models that assess pulmonary edema from chest x-rays



0: None



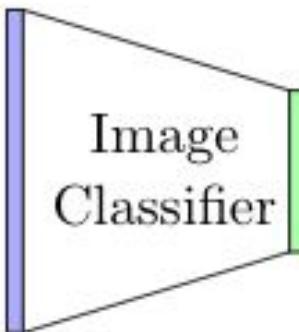
1: Vascular congestion
(mild)



2: Interstitial edema
(moderate)

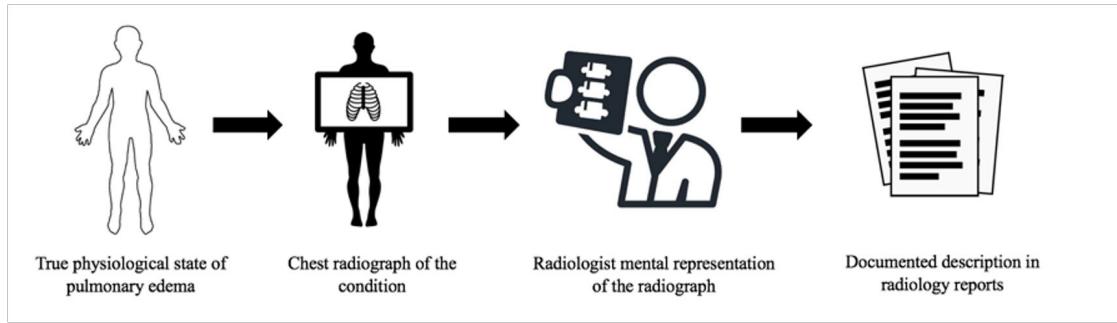


3: Alveolar edema
(severe)



2: Interstitial edema

MIMIC-CXR consists of 370K chest radiographs associated with radiology reports



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Labeling from radiology reports

- Regular expression (regex) labeled 6,710 reports. **[Training]**
- Three experts labeled 485 radiology reports. **[Validation/Test]**

FINAL REPORT
INDICATION: Evaluation for interval change in a patient status post core valve.
COMPARISON: ____ through ____.

FINDINGS: Portable AP semi-upright view of the chest is reviewed and compared to the prior study. An aortic core valve projects over the heart and a transvenous right internal jugular pacer follows the expected course and is unchanged in position. Interstitial abnormality is unchanged since ___, but increased since ___, probably due to edema, exaggerated by low post operative lung volumes. There is no significant pleural effusion or pneumothorax. The cardiomedastinal silhouette, reflecting mild cardiomegaly, are unchanged. Elevation of the left hemidiaphragm is chronic.

IMPRESSION:

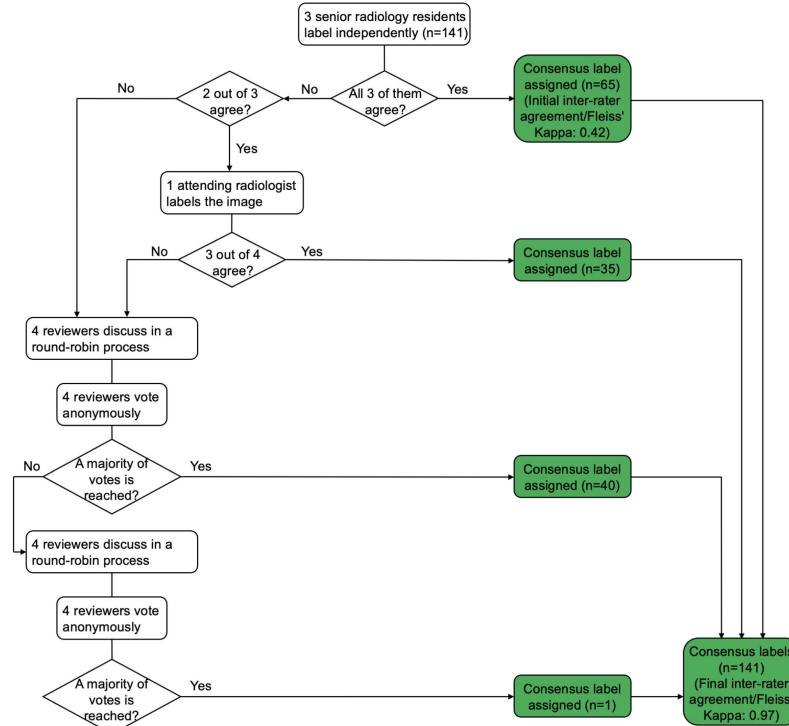
1. Mild interstitial edema stable since ___, increased since ___. 

Labeled as level 2: interstitial edema

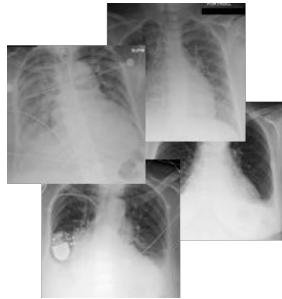
Consensus labeling (modified Delphi process) from chest x-ray images

- Regular expression (regex) labeled 6,710 reports. **[Training]**
- Three experts labeled 485 radiology reports. **[Validation/Test]**
- Four radiologists labeled 141 chest x-ray images. **[Test]**

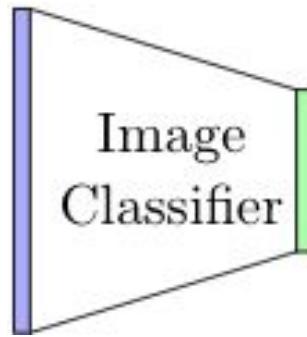
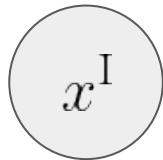
Labels released on PhysioNet!



We have limited numerical labels



(370K chest x-ray images)

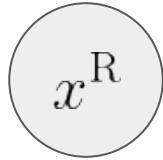


$y \in \{0, 1, 2, 3\}$

(7K labels for training,
<1K labels for evaluation)



(230K radiology reports)

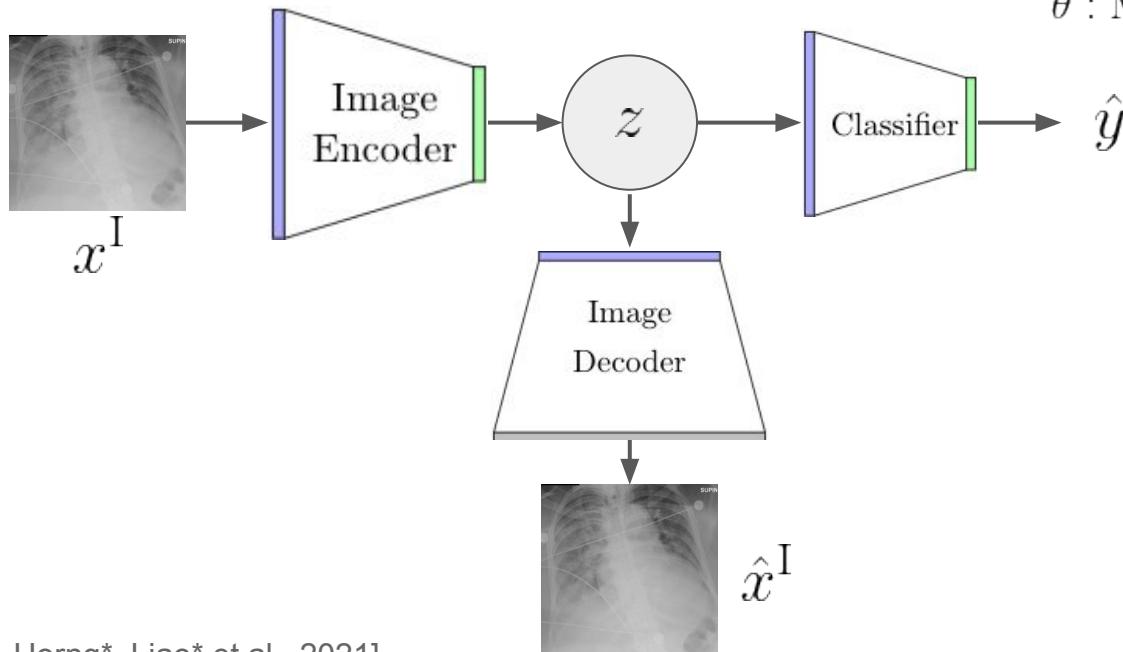


Semi-supervised learning to utilize unlabeled images

$$\max \log p(\mathbf{x}^I, \mathbf{y}; \theta) = \sum_{i=N_L+1}^N \log p(x_i^I; \theta) + \sum_{i=1}^{N_L} \log p(x_i^I, y_i; \theta)$$

N_L : Number of labeled images

θ : Model parameters

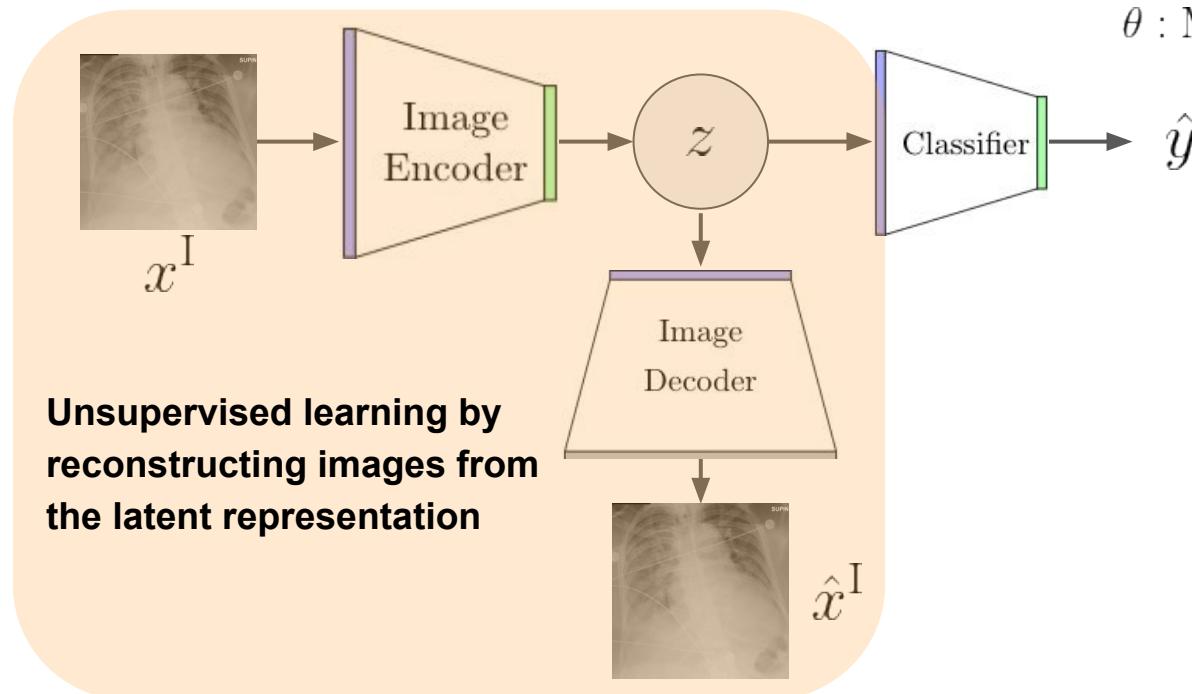


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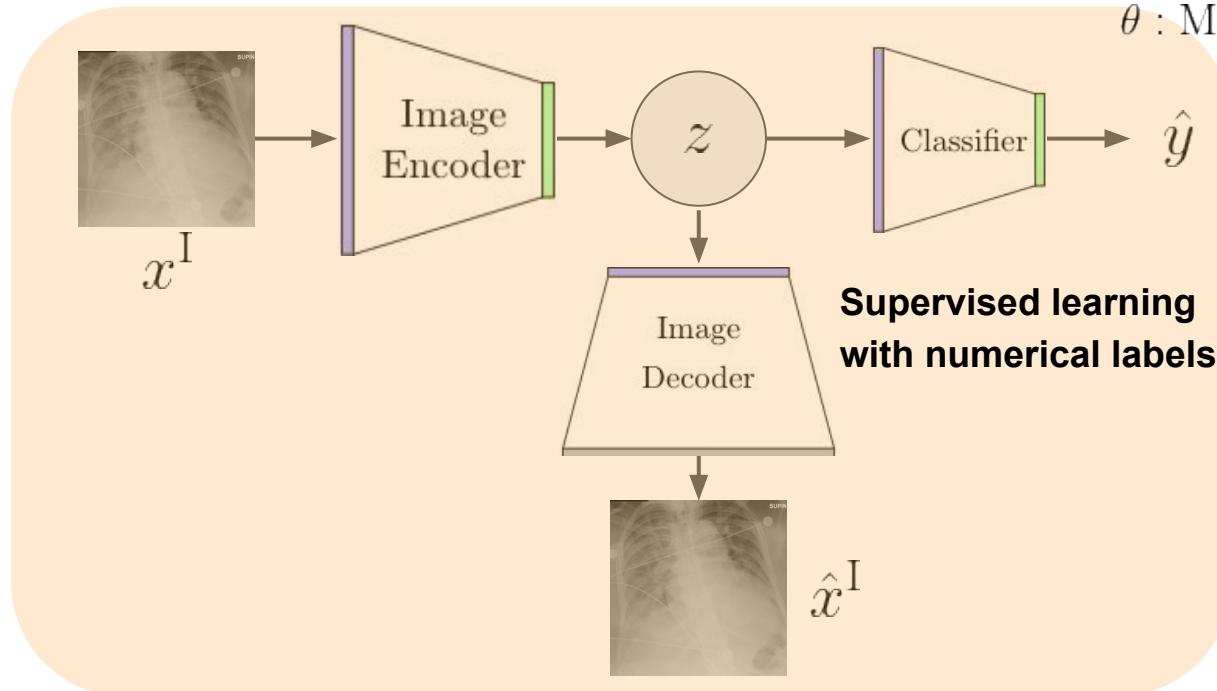


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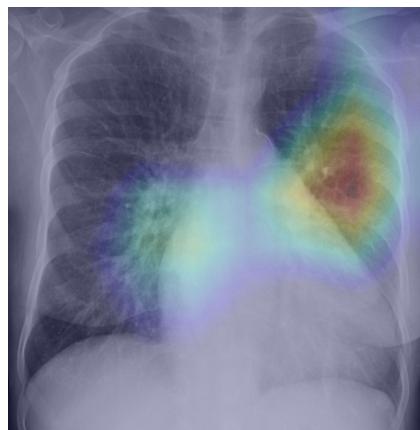
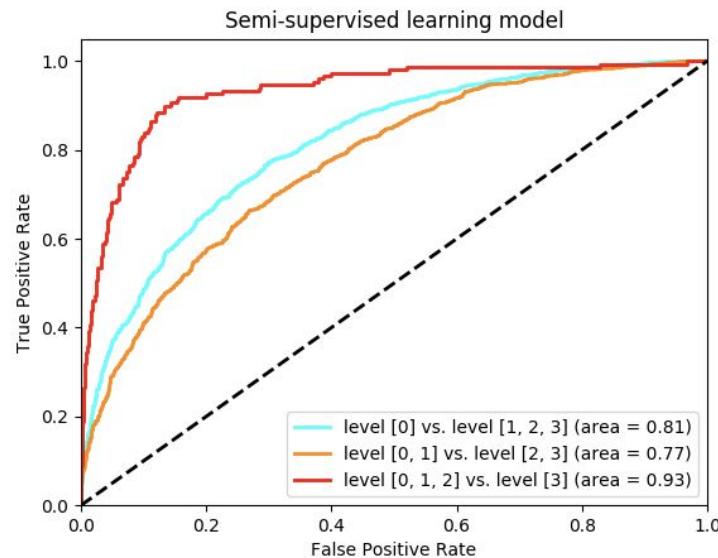
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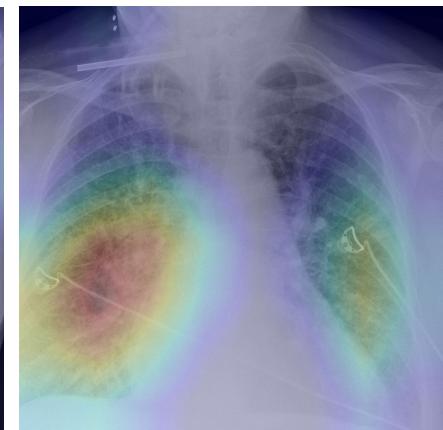
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Semi-supervised learning trained with regex labels and evaluated on consensus labels



1: Vascular congestion

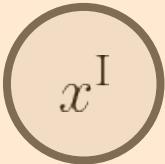


3: Alveolar edema

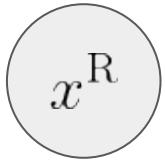
Outline



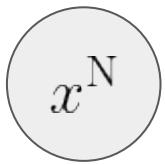
Images



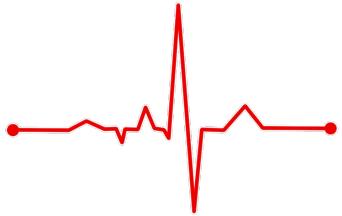
Text



Numerical signals



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Latent feature representation



Diagnosis
Disease stage

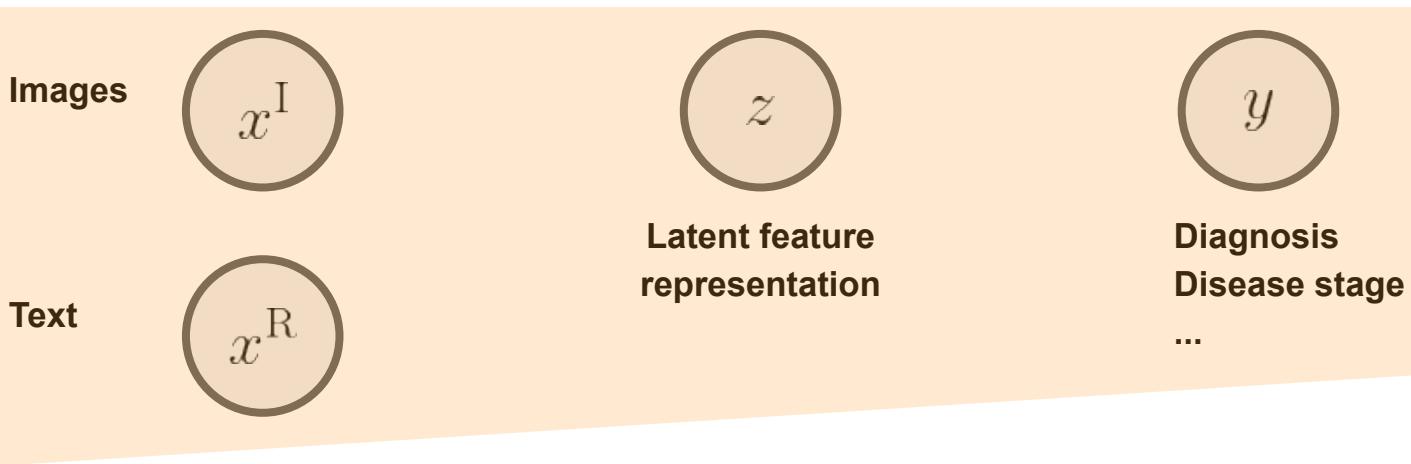
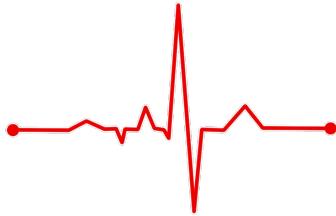
...

y

Outline - Joint Image-text Modeling [Chauhan*, Liao* et al., 2020]



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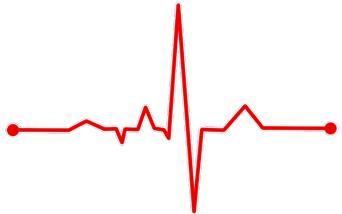


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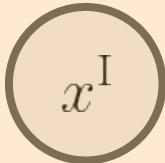
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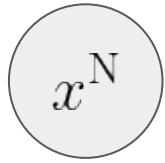
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Text



Numerical signals



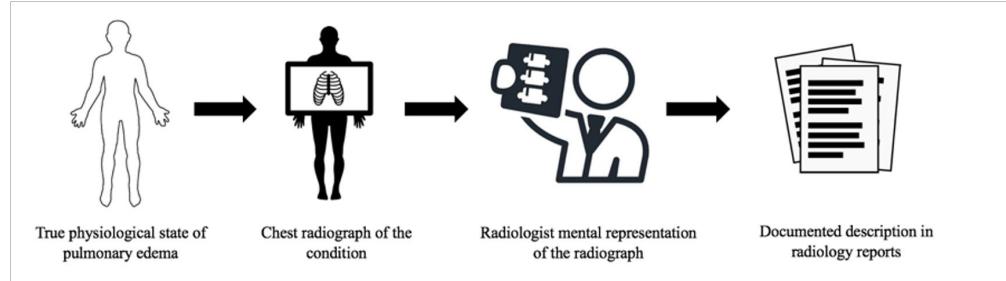
...

z

Latent feature representation

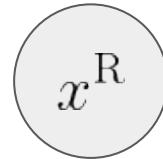
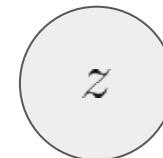
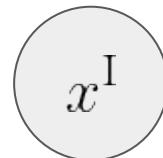
y

Diagnosis
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Prior work in image-text modeling

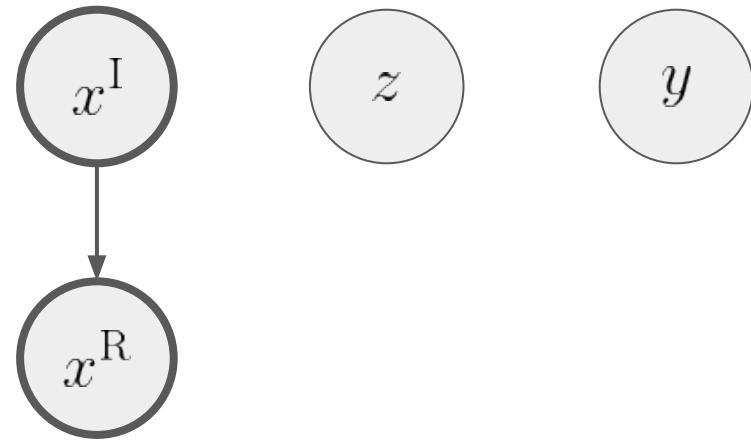
- Image captioning
 - The model generates text from an image
- Visual question answering
 - Training based on both images and text
 - Inference performed on an image-text pair
- Joint representation learning
 - Training based on both images and text
 - Inference performed on an image



[Anderson et al. 2018, Antol et al. 2015, Lu et al. 2016, Jing et al. 2017, Plummer et al. 2017, Vasudevan et al. 2017, Xu et al. 2015]

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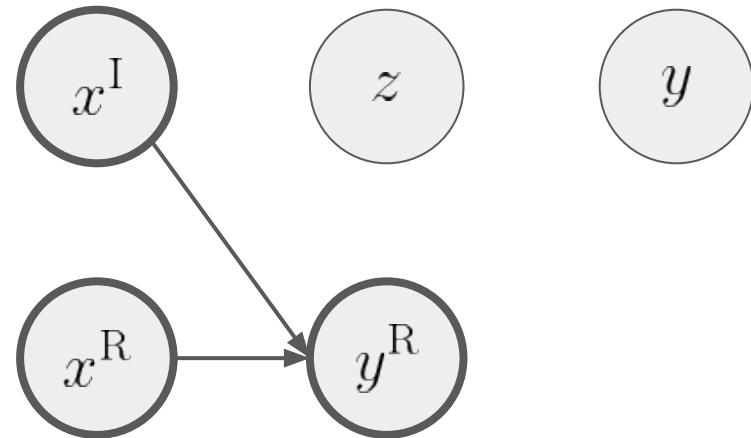
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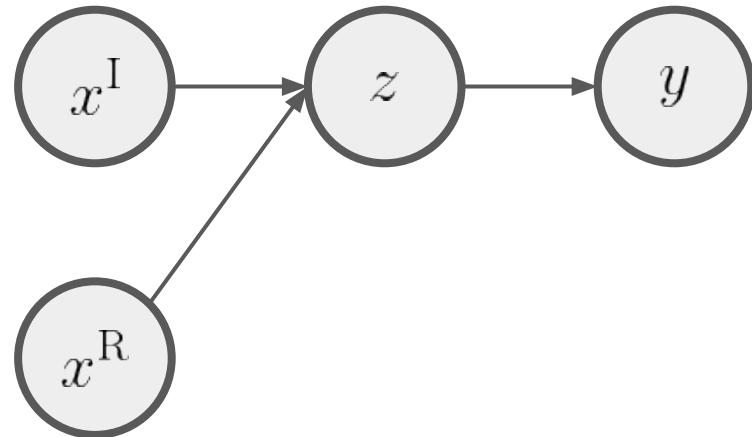
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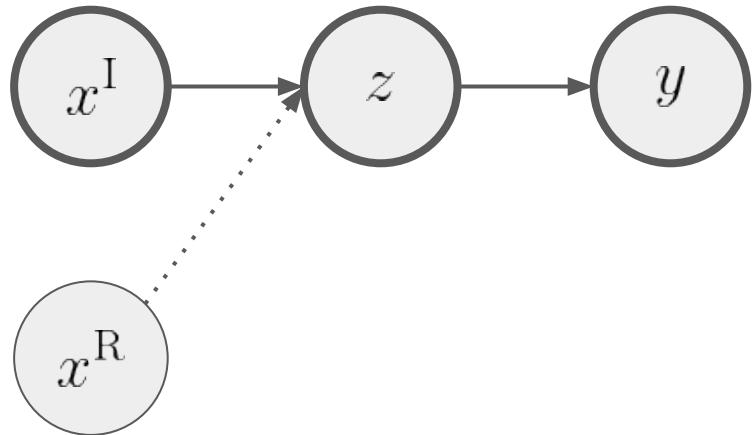
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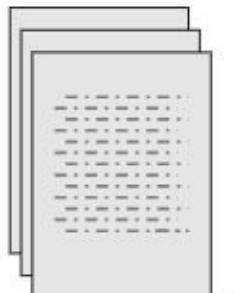
[Anderson et al. 2018, Antol et al. 2015, Lu et al. 2016, Jing et al. 2017, Plummer et al. 2017, Vasudevan et al. 2017, Xu et al. 2015]

Training: joint image-text representation learning model



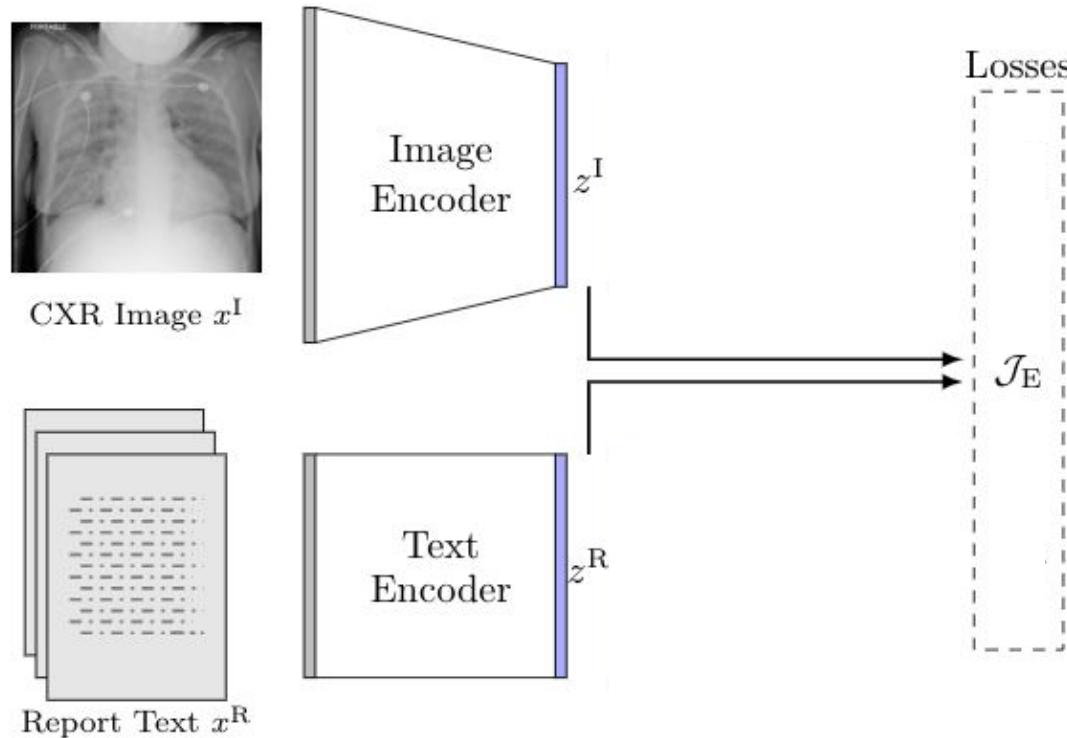
CXR Image x^I

y

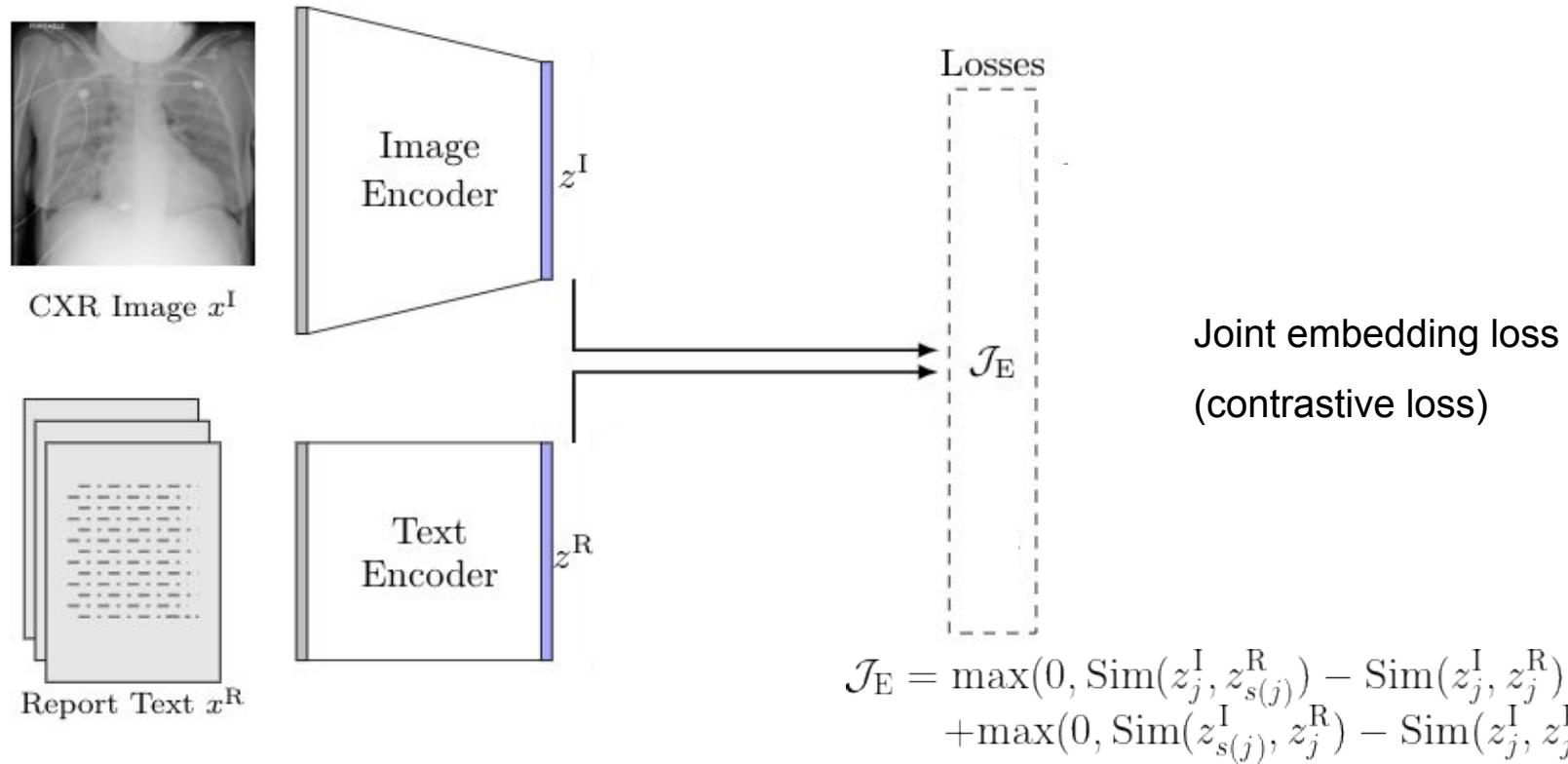


Report Text x^R

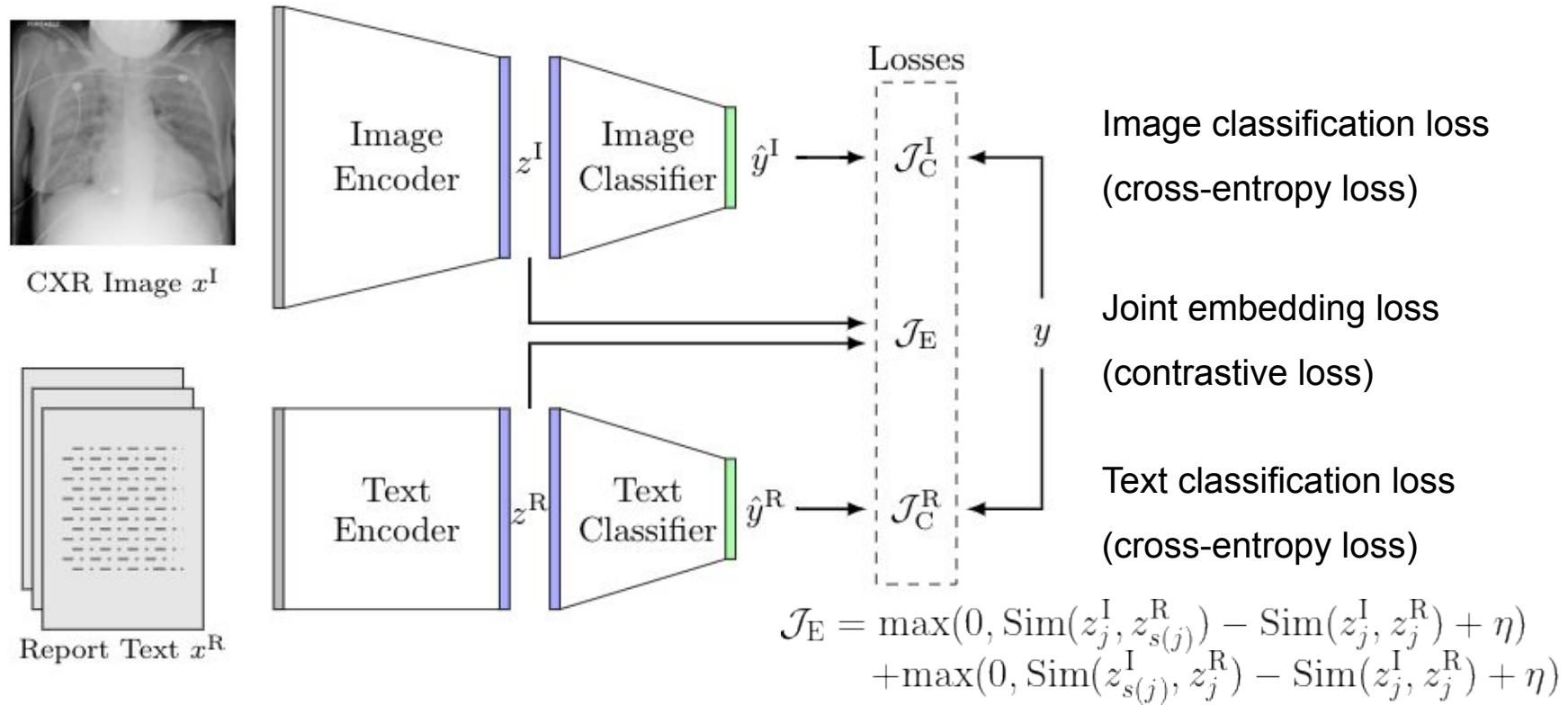
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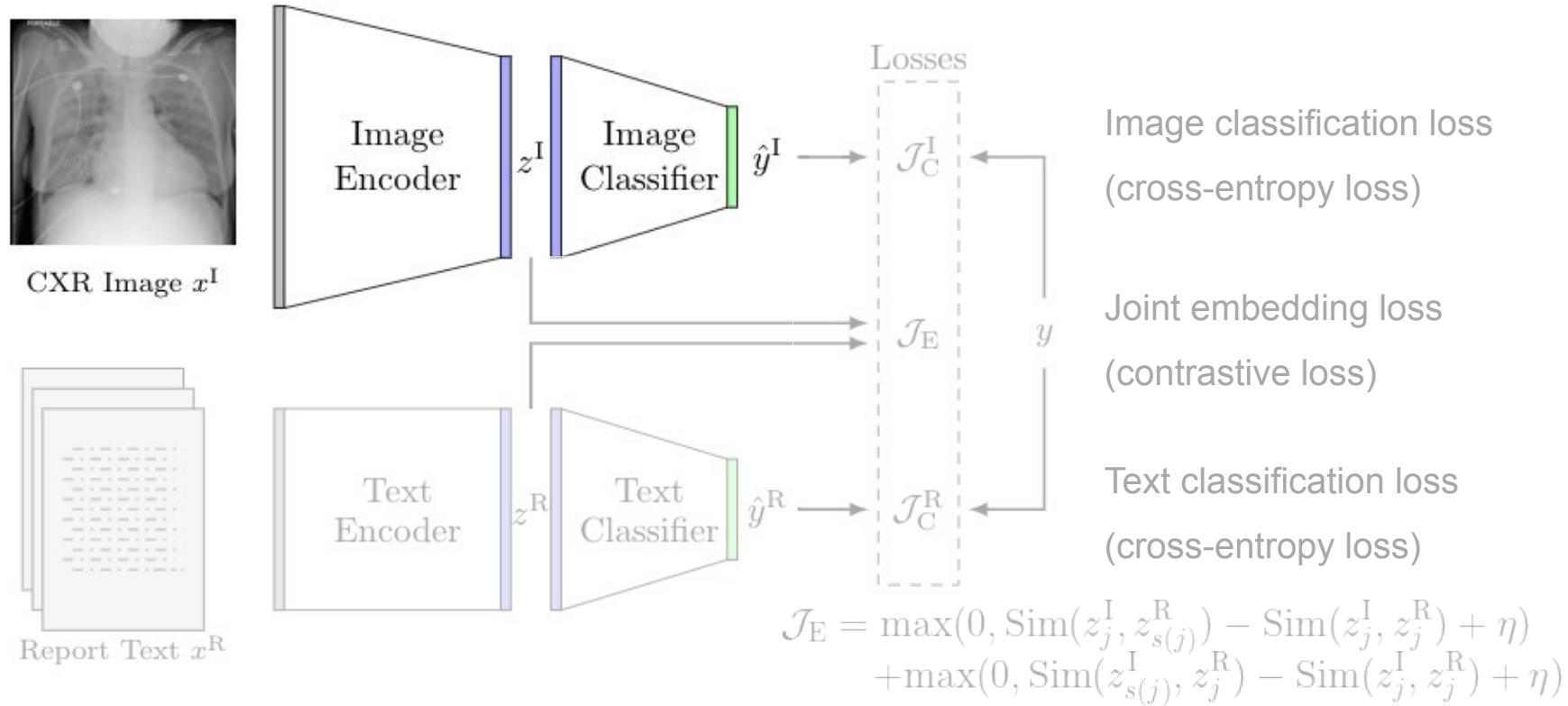
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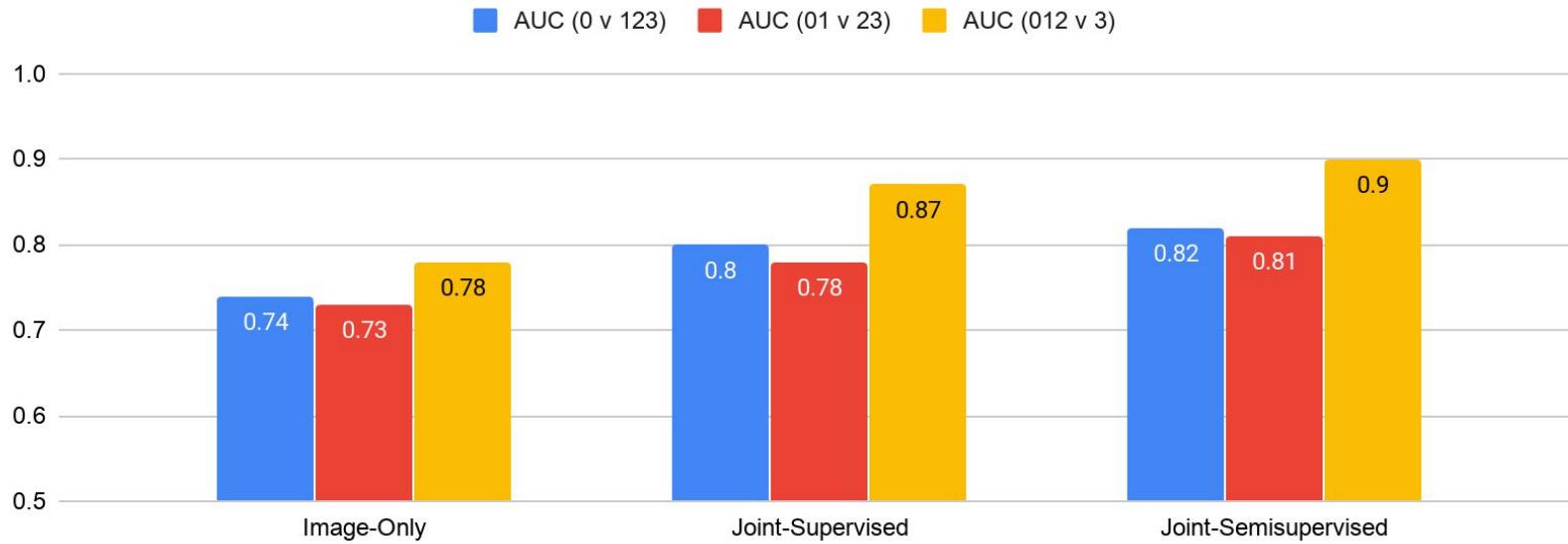
Training: joint image-text representation learning model



Inference: image classification



Results: Leveraging free-text radiology reports improves the image model performance



Results: Image model *interpretation* with free text

Level 1



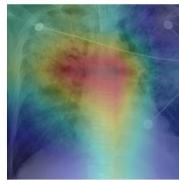
[CLS] frontal and lateral radiographs of the chest demonstrates slight decrease in size of the severely enlarged cardiac silhouette . persistent small bilateral pleural effusion s . probable small hiatal hernia . there is persistent mild pulmonary vascular congestion . clear lungs . no pneumothorax . decrease in severe enlargement of the cardiac silhouette likely due to decrease in pericardial effusion with persistent small effusion s and pulmonary vascular congestion . no pneumonia [SEP]

Level 2



[CLS] surgical clips are again present in the right axilla . the cardiac , mediastinal and hilar contours appear unchanged . upward tenting of the medial right hemidiaphragm is very similar . there is a persistent small - to - moderate pleural effusion on the right side and a small number on the left . fissures are mildly thickened . subpleural thickening at the right lung apex appears stable . there is a new mild interstitial abnormality including Kerley B lines and peribronchial cuffing suggesting mild - to - moderate interstitial pulmonary edema . however , there is no definite new focal opacity . bony structures are unremarkable . findings most consistent with pulmonary edema . [SEP]

Level 3

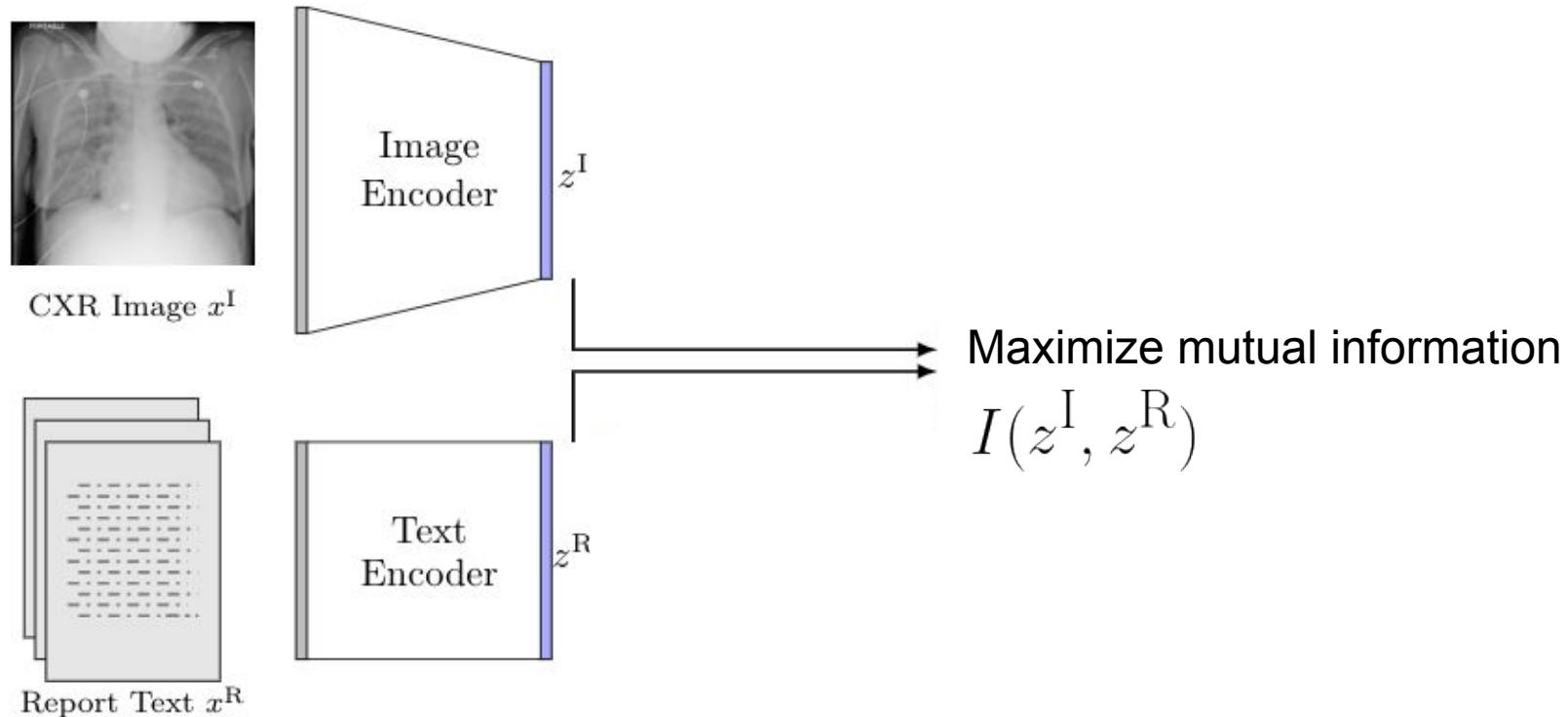


[CLS] a tracheostomy and left - side decubitus are stable in position . widespread alveolar opacities have increased from are less significant in extent compared to . this likely reflects a combination of increasing edema and persistent multifocal infection . no pleural effusion or pneumothorax is identified . the cardio mediastinal and hilar contours are within normal limits . widespread alveolar opacities are increased from the most recent prior exam consistent with increasing edema in the setting of persistent multifocal infection . [SEP]

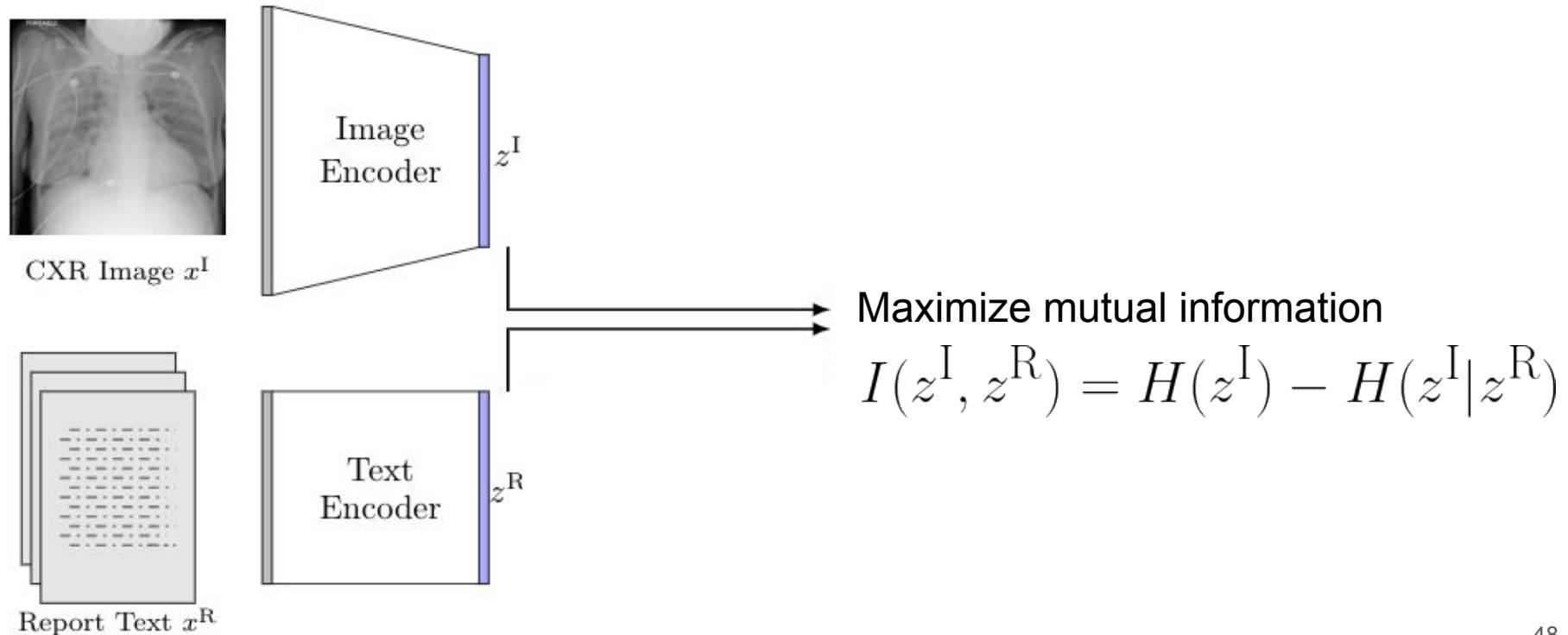
Outline

1. Motivating Clinical Problem
2. Image-based Model for Pulmonary Edema Assessment [Liao et al., 2019,
Horng*, Liao* et al., 2021]
3. Joint Image-text Modeling [Chauhan*, Liao* et al., 2020]
4. **Mutual Information for Representation Learning [Liao et al., 2021]**
5. Conclusions

Mutual information (MI) quantifies statistical dependencies between two random variables



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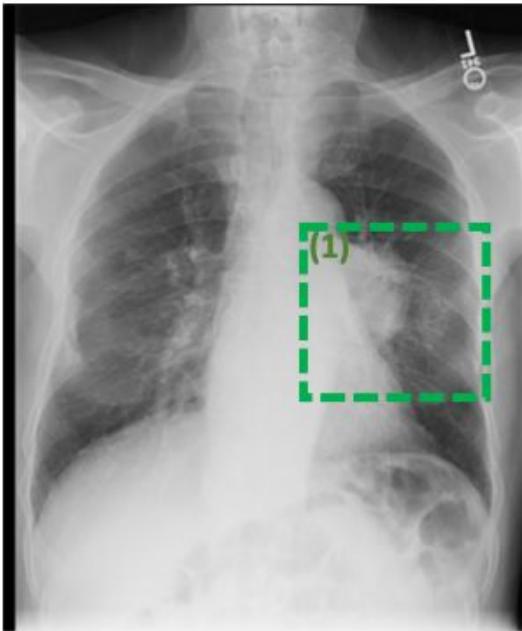


Leveraging local correspondences: each sentence in the report describes the findings in a particular region of the image



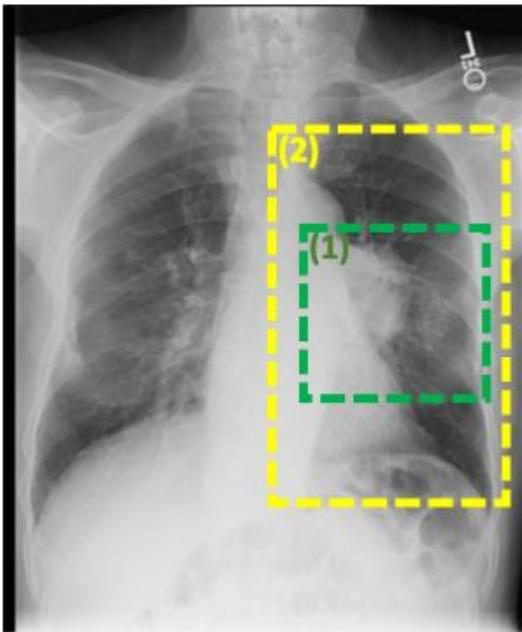
- (1) A mass is present in the superior segment of the left lower lobe and therefore malignancy must be considered.
- (2) Elsewhere, the left lung appears clear.
- (3) There is no pleural effusion.
- (4) Calcified pleural plaque is present in the right mid zone.
- (5) The right lung appears clear.

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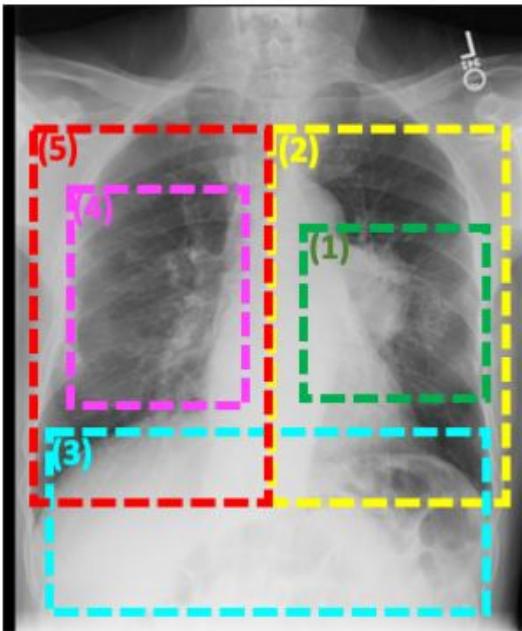
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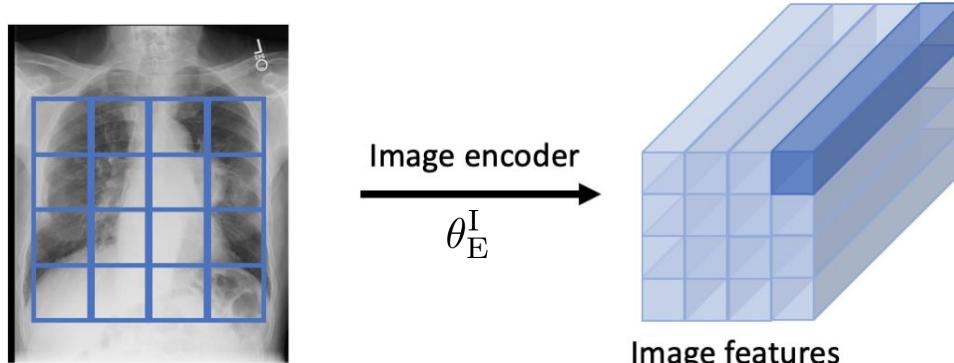
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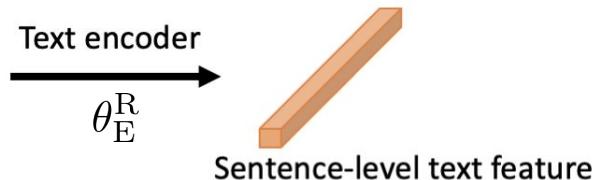


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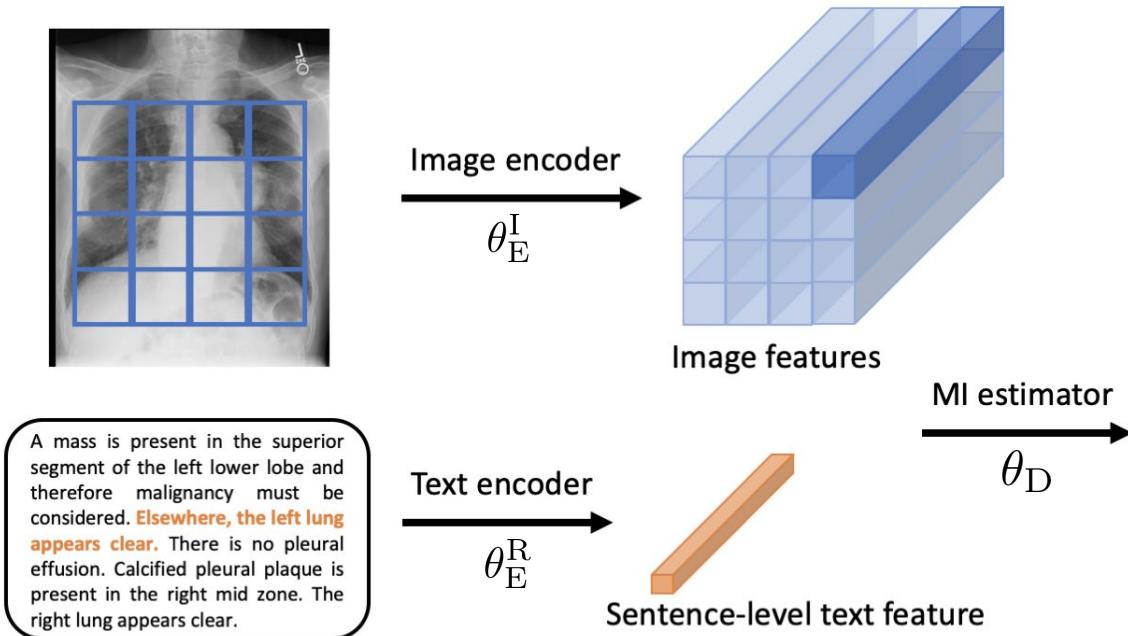
Maximize local mutual information



A mass is present in the superior segment of the left lower lobe and therefore malignancy must be considered. **Elsewhere, the left lung appears clear.** There is no pleural effusion. Calcified pleural plaque is present in the right mid zone. The right lung appears clear.

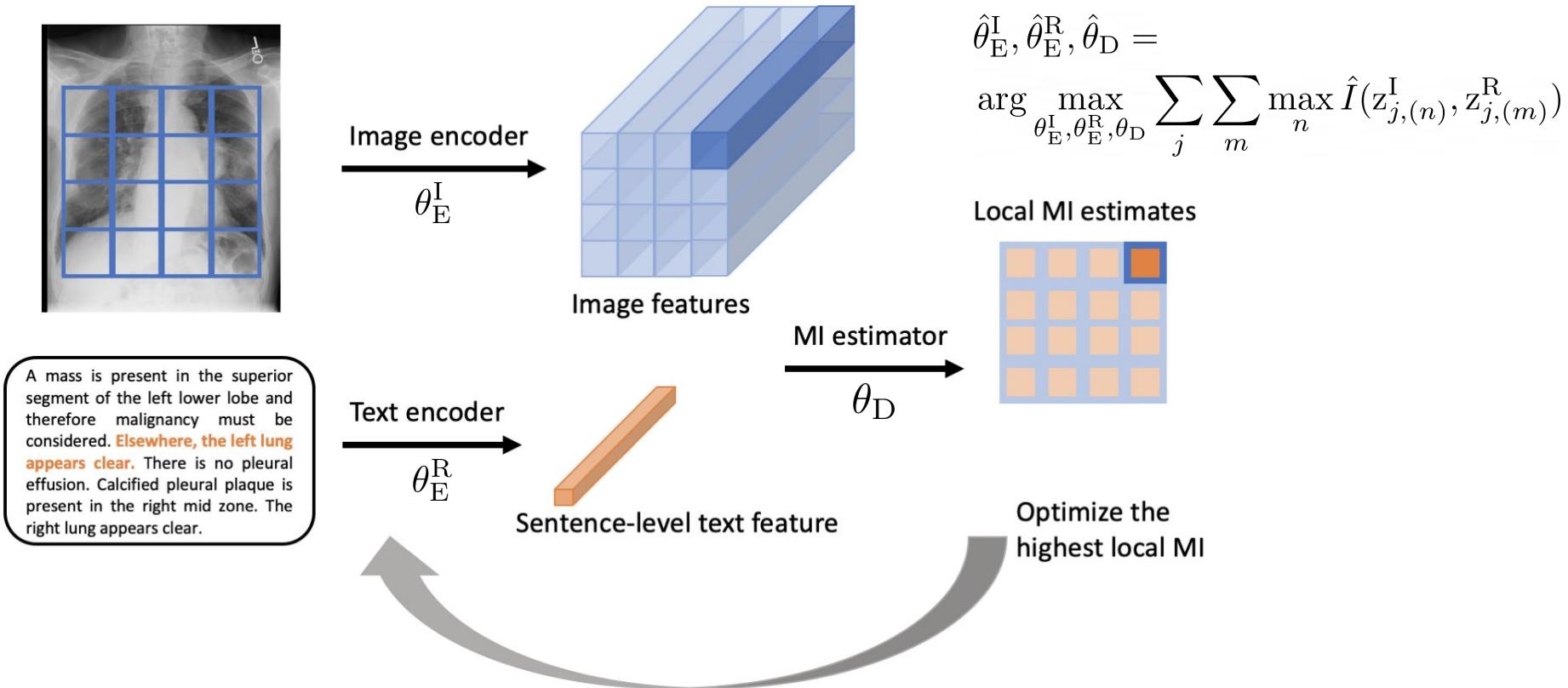


Maximize local mutual information

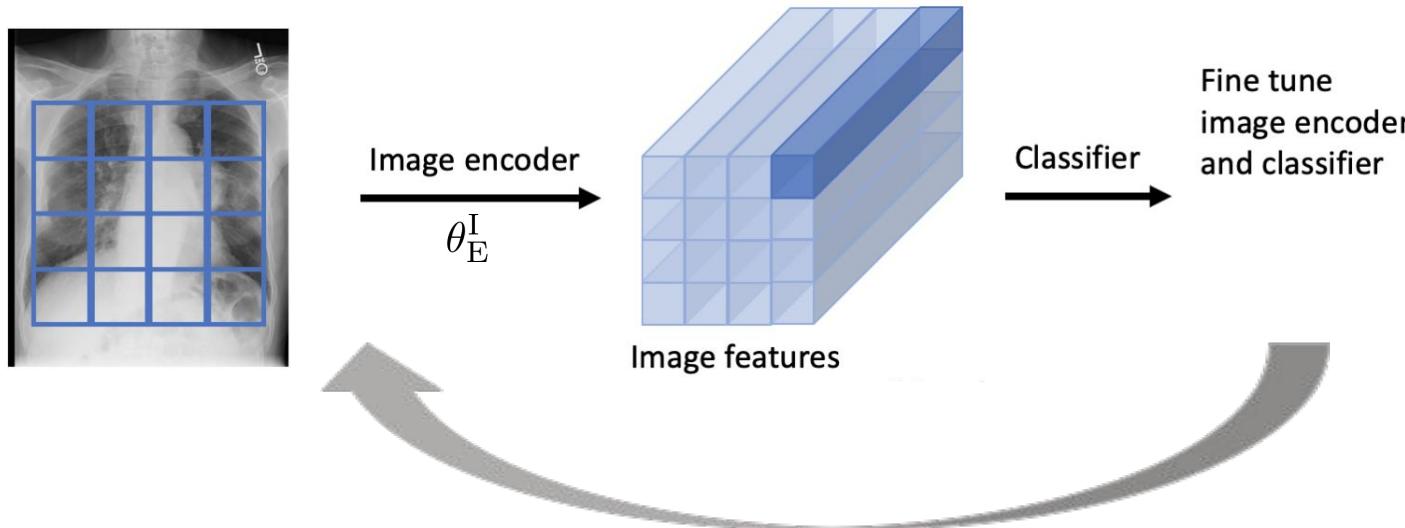


- **Mutual Information Neural Estimation (MINE):**
Donsker-Varadhan (DV) representation for the KL divergence as the lower bound
- **Contrastive Predictive Coding (CPC/infoNCE):**
Approximating the lower bound of the likelihood ratio

Maximize local mutual information



Fine tune for downstream image classification



Results: local MI to learn joint image-text representation leads to the best performance of downstream image classification

Method	<i>Re-train Encoder?</i>	Level 0 vs 1,2,3		Level 0,1 vs 2,3		Level 0,1,2 vs 3	
		CPC	MINE	CPC	MINE	CPC	MINE
image-only	N/A	0.80		0.71		0.90	
global-mi	frozen	0.81	0.83	0.77	0.78	0.93	0.89
global-mi	tuned	0.81	0.82	0.79	0.81	0.93	0.93
local-mi	frozen	0.77	0.76	0.72	0.76	0.75	0.86
local-mi	tuned	0.87	0.83	0.83	0.85	0.97	0.93

Method	<i>Re-train Encoder?</i>	Atelectasis		Cardiomegaly		Consolidation	
		CPC	MINE	CPC	MINE	CPC	MINE
image-only	N/A	0.76		0.71		0.78	
global-mi	frozen	0.65	0.63	0.79	0.79	0.67	0.65
global-mi	tuned	0.74	0.77	0.81	0.81	0.81	0.82
local-mi	frozen	0.74	0.61	0.73	0.77	0.65	0.65
local-mi	tuned	0.73	0.86	0.82	0.84	0.83	0.83
—	—	Edema		Lung Opacity		Pleural Effusion	
		CPC	MINE	CPC	MINE	CPC	MINE
image-only	N/A	0.89		0.86		0.69	
global-mi	frozen	0.81	0.81	0.69	0.68	0.74	0.74
global-mi	tuned	0.87	0.88	0.83	0.84	0.90	0.90
local-mi	frozen	0.78	0.80	0.66	0.69	0.69	0.72
local-mi	tuned	0.89	0.89	0.82	0.88	0.92	0.92
—	—	Pneumonia		Pneumothorax		Support Devices	
		CPC	MINE	CPC	MINE	CPC	MINE
image-only	N/A	0.75		0.65		0.72	
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global-mi	tuned	0.75	0.76	0.75	0.77	0.77	0.79
local-mi	frozen	0.61	0.66	0.70	0.67	0.72	0.74
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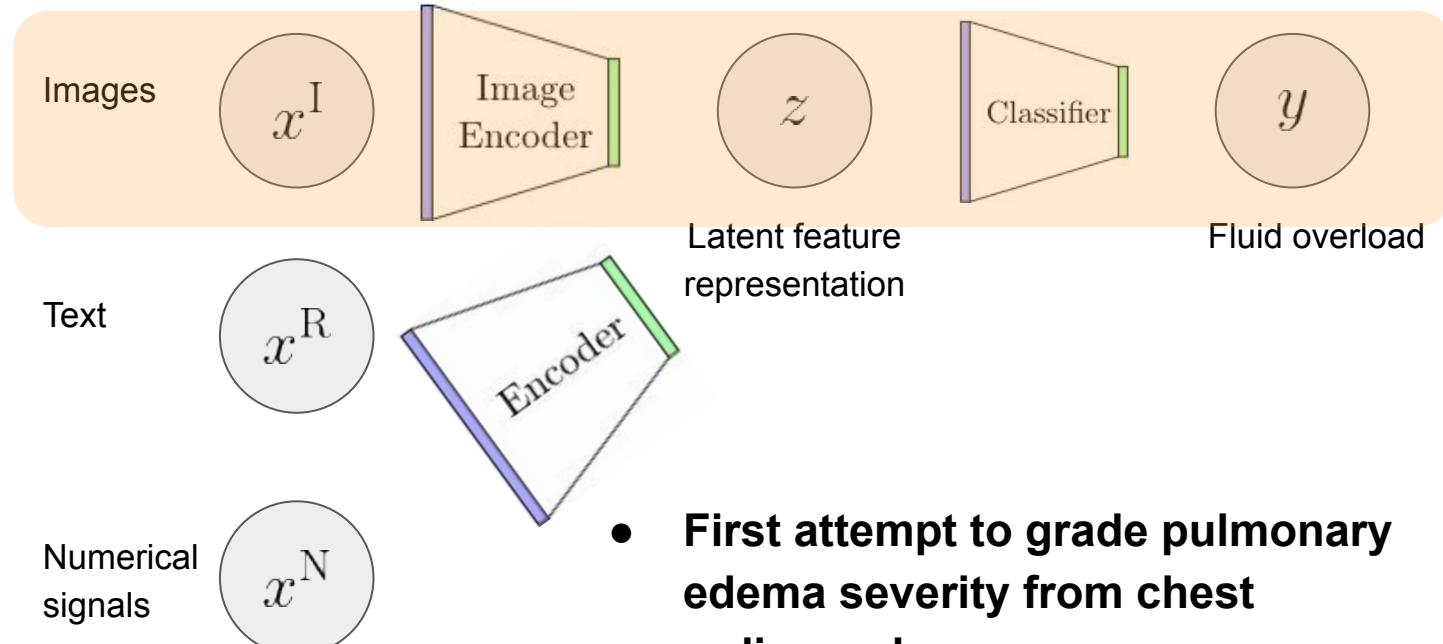
Advantages of local MI

- Better fit to image-text structure
- Better optimization landscape
- Better representation fit to downstream tasks

Conclusions



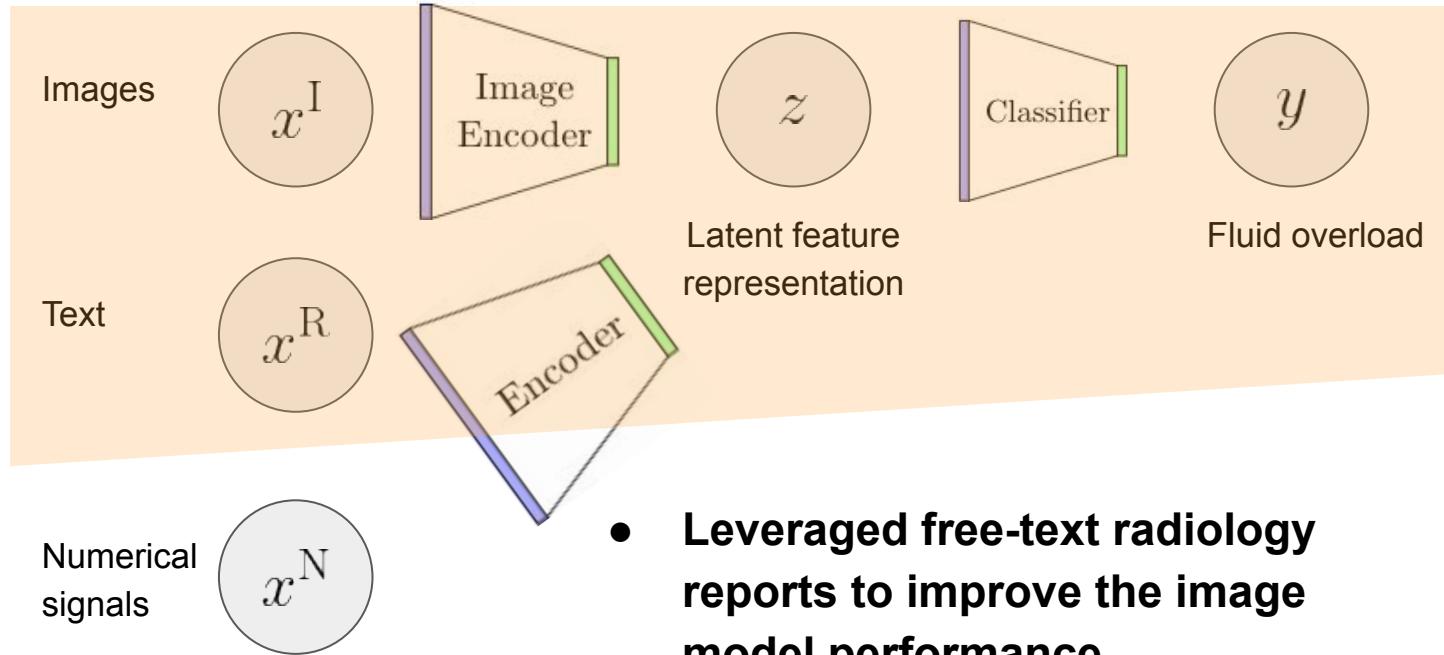
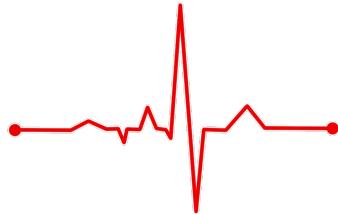
FINAL REPORT
EXAMINATION: CHEST (PORTABLE AP)
INDICATION: ____ year old man with respiratory failure, ARDS // Volume overload?
TECHNIQUE: Single frontal view of the chest
COMPARISON: ____
IMPRESSION:
Moderate left pleural effusion decreased. Large right pleural effusion is probably unchanged. Tracheostomy tube is in unchanged position. Extensive bilateral alveolar opacities have improved, consistent with improve severe pulmonary edema. Cardiac size is obscured by the pleural parenchymal abnormalities



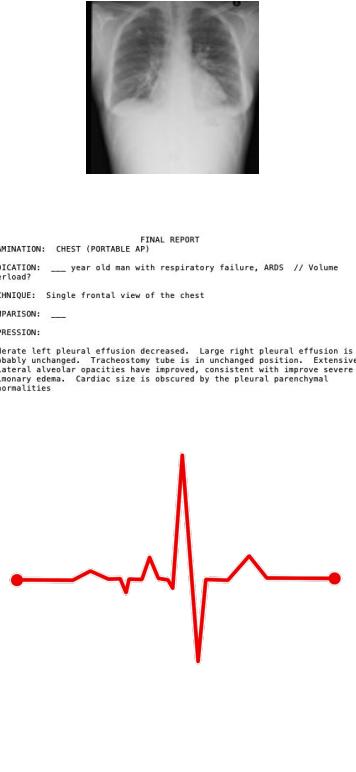
Conclusions



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Conclusions



[Liao et al., 2020, Liao et al., 2021]

- **Developed a novel multimodal representation learning approach**

Conclusions



Images

$$x^I$$

Text

$$x^R$$

Numerical signals

$$x^N$$

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...

$$z$$

Latent feature representation

$$y$$

Underlying physiological process

- **What's next?**

- Improve clinical data inference
- Impute missing clinical data
-

Multimodal Representation Learning for Medical Image Analysis

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