Deep Learning Techniques for EHR Analysis

Presented by: Chandresh Kumar Maurya
CSE, IIT Indore

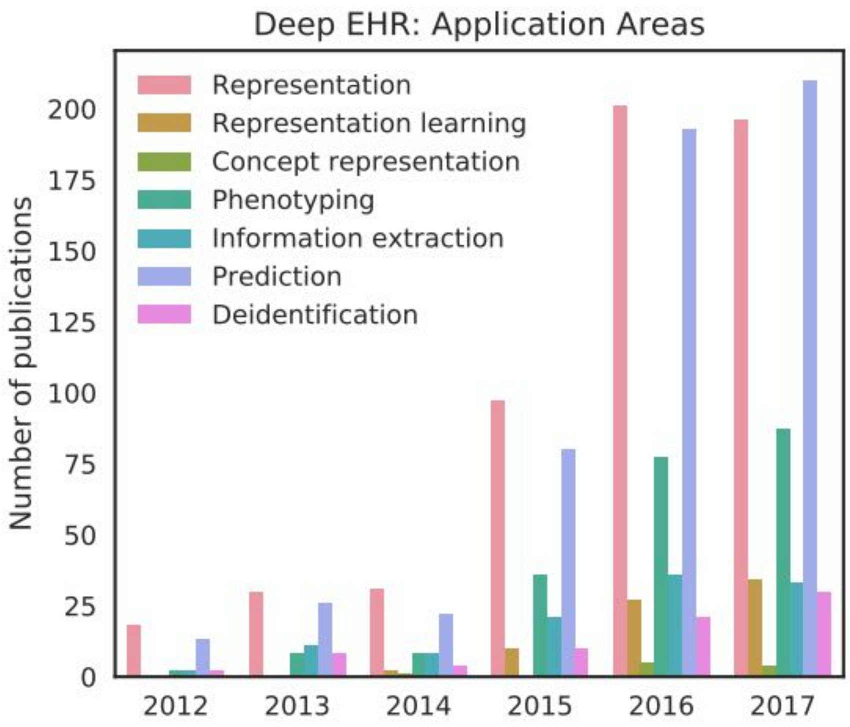
Outline of the Talk

1. Introduction
2. Motivation
3. The problem
4. Solution Approach
5. Results
6. Discussion
7. Future direction

Introduction

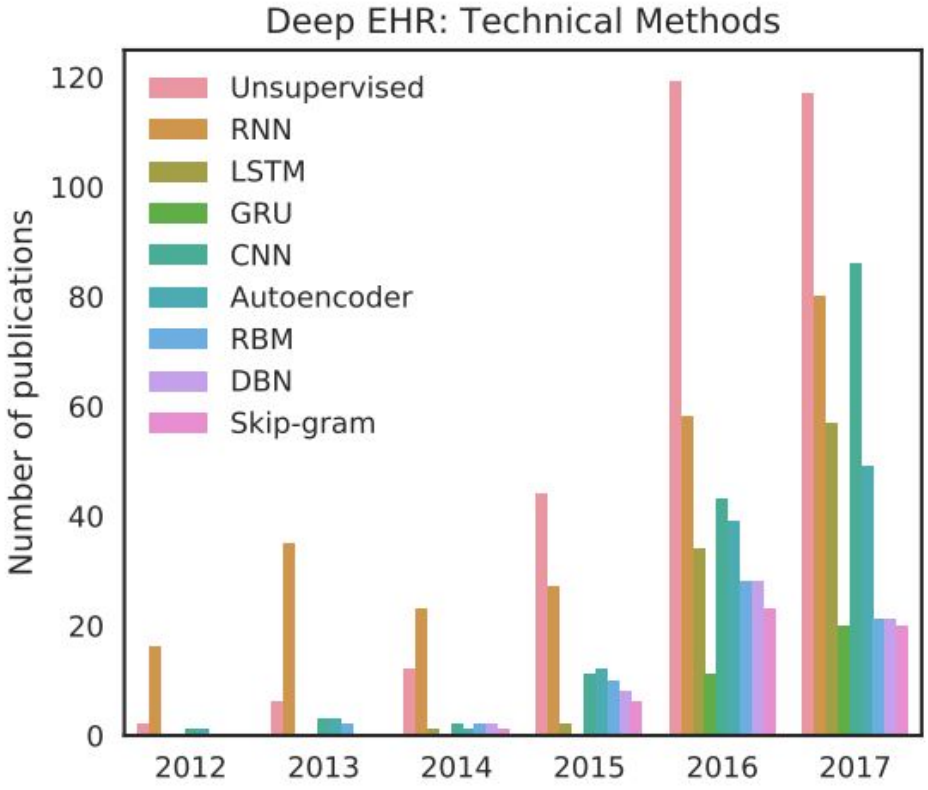
- Maintaining digital record of patient's history is crucial for diagnosing the problem.
- Traditional way: carry hard copies of reports and prescription such as x-rays, CT scan and related reports
- The Problem: losing reports, forgetting to carry it is quite common.
- The Solution: Past years have seen rapid growth in the volume of the digital health record also called Electronic Health Record (EHR).
- Previously, it was used mostly for administrative tasks such as billing, insurance etc.
- However, researchers have now realized that EHR has more potential than just billing etc.

Tasks on EHR data



Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2017). Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. *IEEE journal of biomedical and health informatics*, *22*(5), 1589-1604.

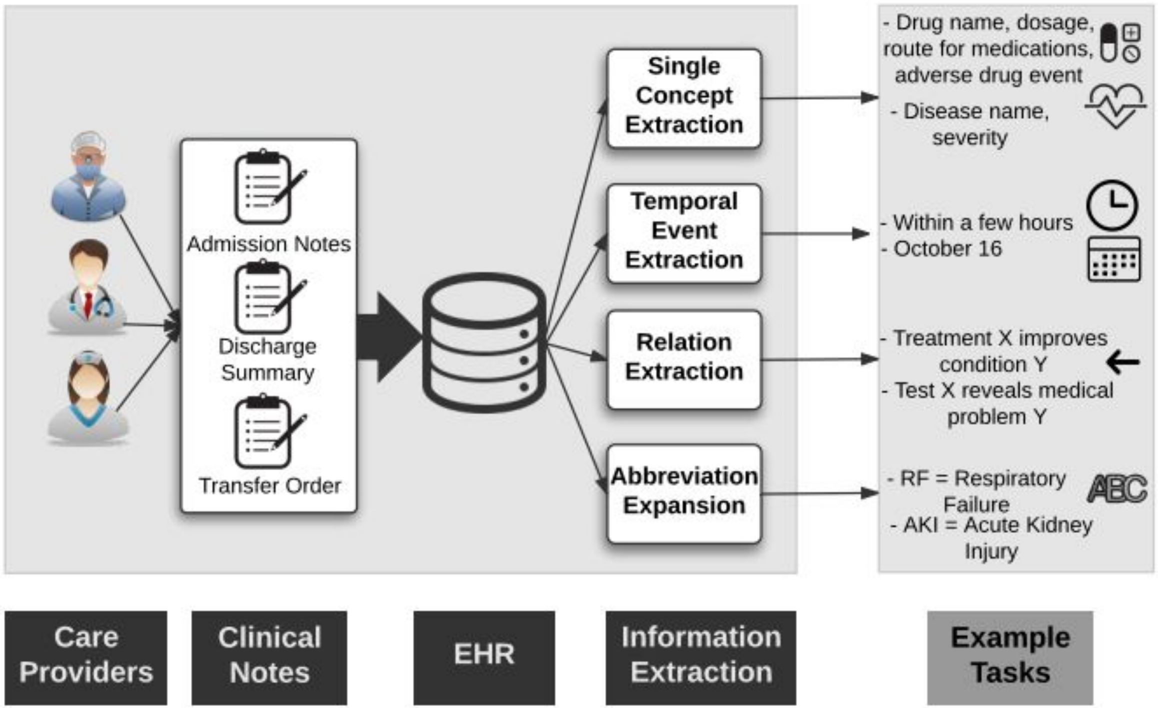
Tasks on EHR data



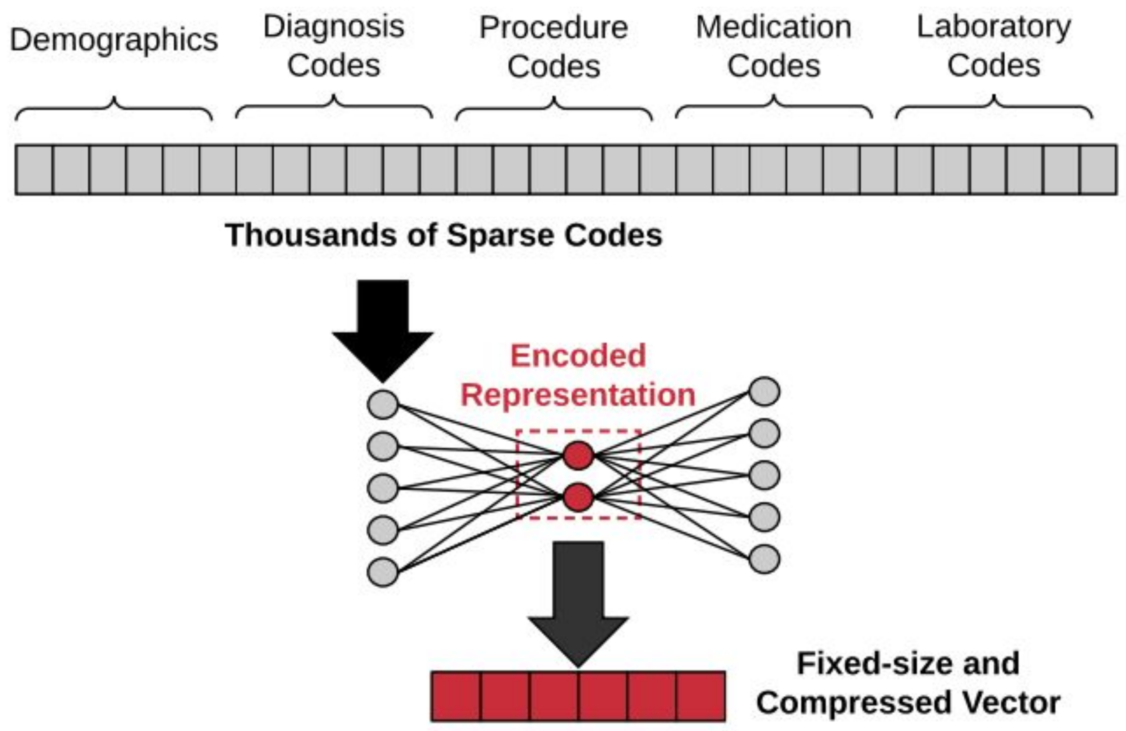
Tasks on EHR data

Task	Subtasks	Input Data	Models
Information Extraction	(1) Single Concept Extraction (2) Temporal Event Extraction (3) Relation Extraction (4) Abbreviation Expansion	Clinical Notes	LSTM, Bi-LSTM, GRU, CNN RNN + Word Embedding AE Custom Word Embedding
Representation Learning	(1) Concept Representation (2) Patient Representation	Medical Codes	RBM, Skip-gram, AE, LSTM RBM, Skip-gram, GRU, CNN, AE
Outcome Prediction	(1) Static Prediction (2) Temporal Prediction	Mixed	AE, LSTM, RBM, DBN LSTM
Phenotyping	(1) New Phenotype Discovery (2) Improving Existing Definitions	Mixed	AE, LSTM, RBM, DBN LSTM
De-identification	Clinical text de-identification	Clinical Notes	Bi-LSTM, RNN + Word Embedding

Clinical Information Extraction



Representation learning

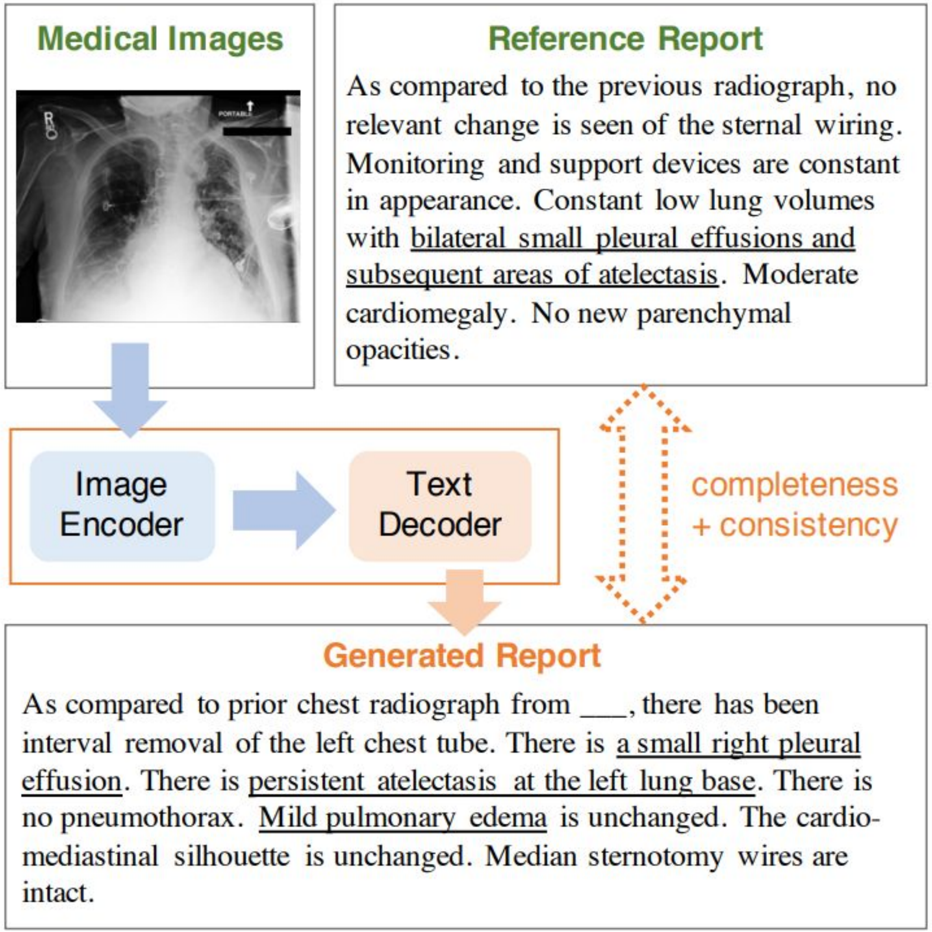


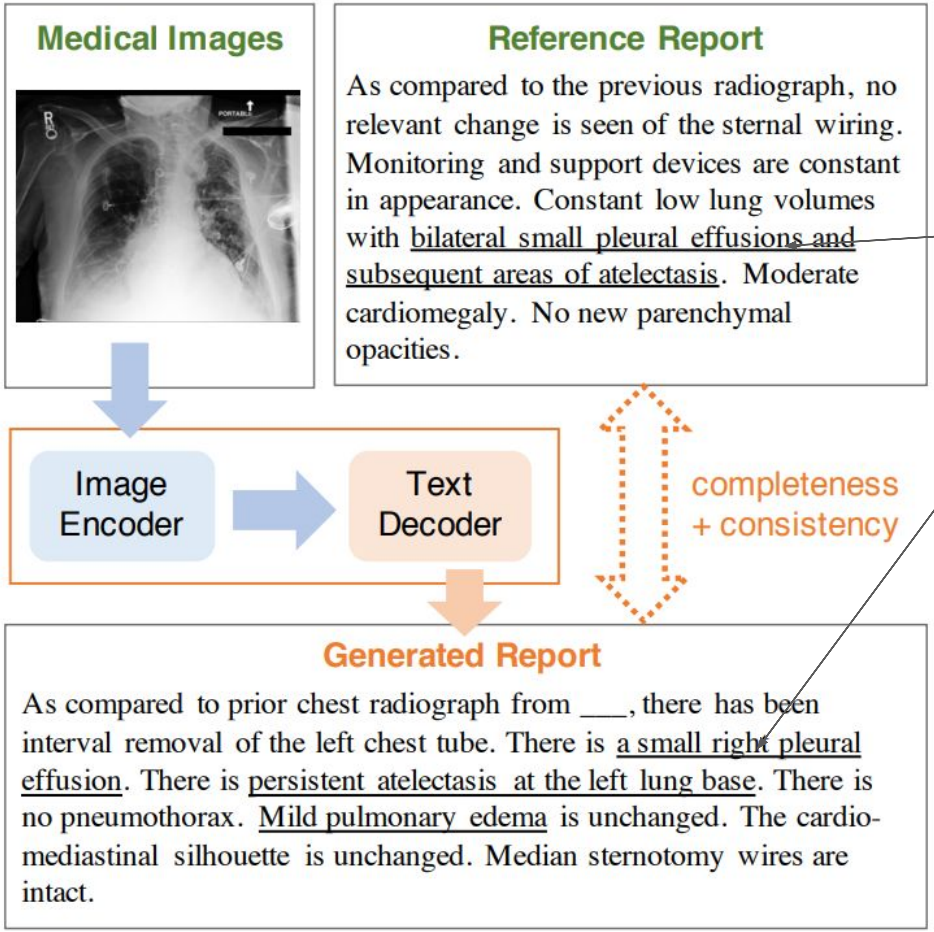
Patient Outcome Prediction

Outcome Type	Outcome	Model
Static	Heart Failure	MLP [18]
	Hypertension	CNN [41]
	Infections	RBM [42]
	Osteoporosis	DBN [43]
	Suicide risk stratification	RBM [23]
Temporal	Cardiovascular, Pulmonary	CNN [44]
	Diabetes, Mental Health	LSTM [20]
	Re-admission	TCNN [19]
	Heart Failure	GRU [21], [38]
	Renal	RNN [47]
	Postoperative Outcomes	LSTM [46]
	Multi-outcome (78 ICD codes)	AE [14]
	Multi-outcome (128 ICD codes)	LSTM [45]

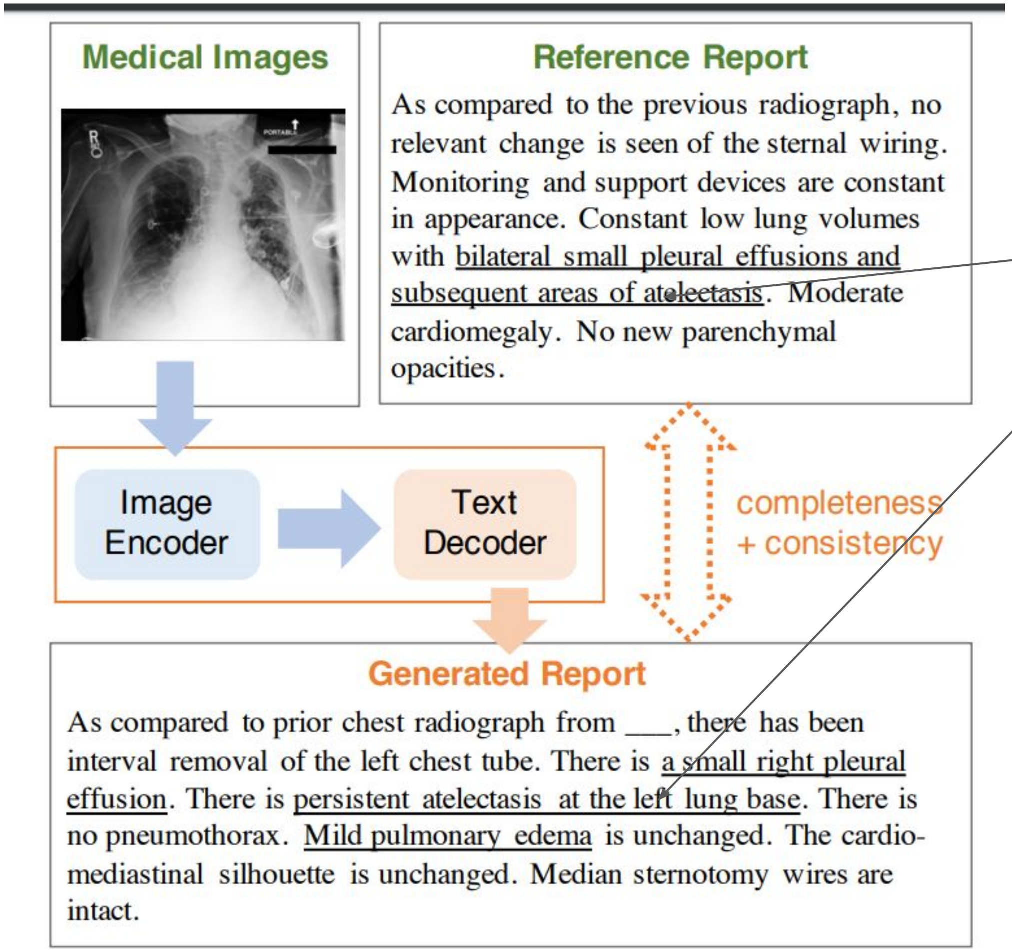
Radiology Report Generation [2]

- Radiology report generation is automatic generation of report through the use of machine learning techniques.
- This offers potential to accelerate the report generation process which is time-consuming, repetitive, and error-prone.
- Current techniques suffer from incomplete and inconsistent report generation problem.

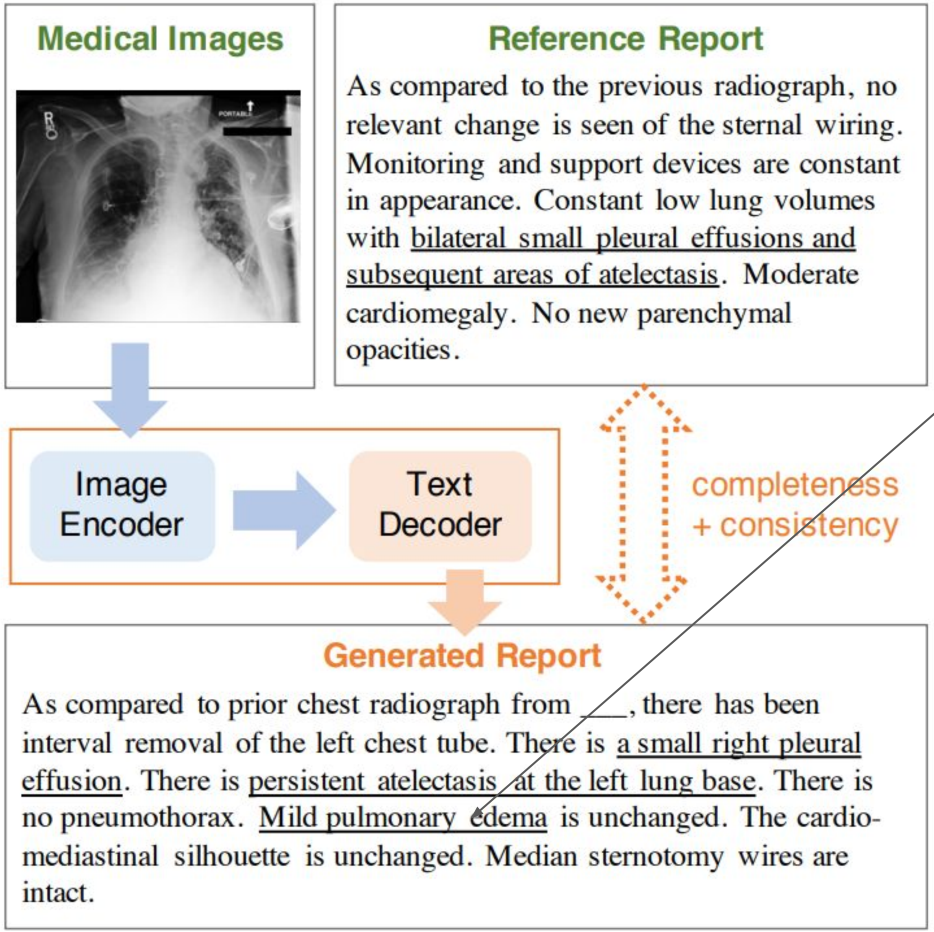

Medical Images
Reference Report
As compared to the previous radiograph, no relevant change is seen of the sternal wiring. Monitoring and support devices are constant in appearance. Constant low lung volumes with bilateral small pleural effusions and subsequent areas of atelectasis. Moderate cardiomegaly. No new parenchymal opacities.
Image Encoder
Text Decoder
completeness
+ consistency
Generated Report
As compared to prior chest radiograph from ___, there has been interval removal of the left chest tube. There is a small right pleural effusion. There is persistent atelectasis at the left lung base. There is no pneumothorax. Mild pulmonary edema is unchanged. The cardio-mediastinal silhouette is unchanged. Median sternotomy wires are intact.



It is incomplete since it neglects a critical observation of right pleural effusion for bilateral pleural effusions



It is also inconsistent since atelectasis is seen in left lung base along with right pleural effusion.



it includes pulmonary edema which is not present in the image.

Highlights of the Paper

- The author present two new metrics for image-to-text radiology report generation, which focus on evaluating the factual completeness and consistency of generated reports, and a weak supervision-based approach for training a radiology-domain NLI model that realizes the metrics.
- They present a new radiology report generation model that directly optimizes the two new metrics with RL, and show its improved performance against existing models on two publicly available datasets.

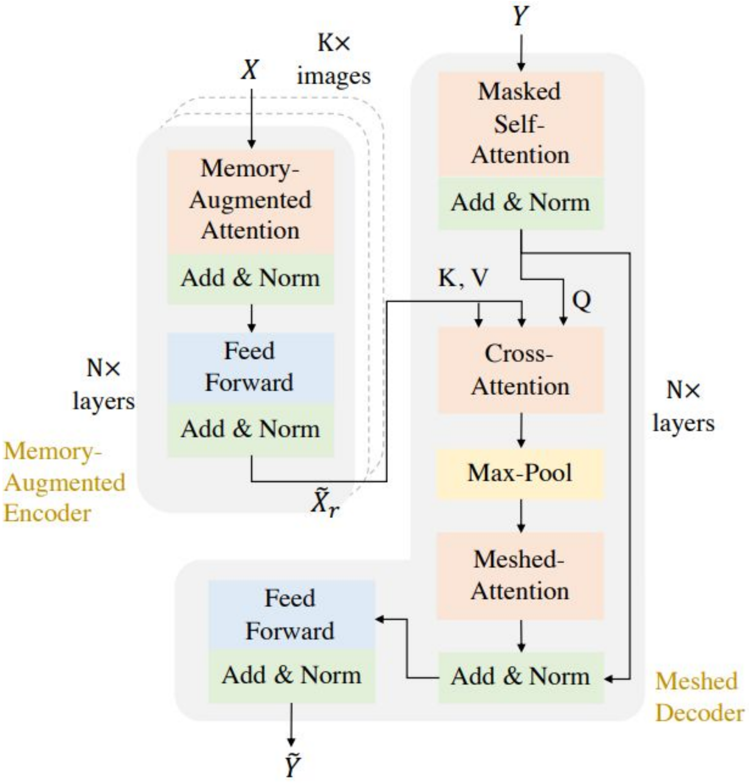
Image-to-Text Radiology Report Generation with Meshed-Memory Transformer

- Given K individual images x1...K of a patient, our task involves generating a sequence of words to form a textual report yˆ, which describes the clinical observations in the images.

Image-to-Text Radiology Report Generation with Meshed-Memory Transformer

- Given K individual images x1...K of a patient, the task involves generating a sequence of words to form a textual report yˆ, which describes the clinical observations in the images.
- This task has close resemblance to the image captioning task, with the difference that the input involves multiple images and the generated sequences are usually longer in the task.
-

Image-to-Text Radiology Report Generation with Meshed-Memory Transformer



Meshed Memory Transformer

- Given an image x, image regions are first extracted with a CNN as X = CNN(x).
- X is then encoded with a memory-augmented attention process $M_{mem}(X)$ as

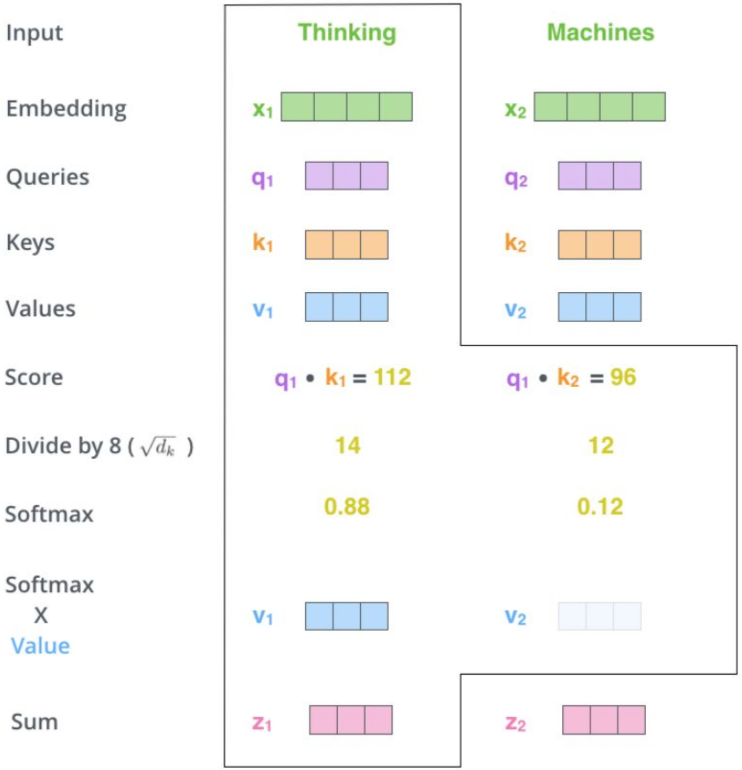
$$\mathcal{M}_{\text{mem}}(\boldsymbol{X}) = \text{Att}(\text{W}_{\text{q}}\boldsymbol{X}, \boldsymbol{K}, \boldsymbol{V})$$

$$\text{Att}(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}) = \text{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^{\text{T}}}{\sqrt{\text{d}}}\right)\boldsymbol{V}$$

$$\boldsymbol{K} = [W_k\boldsymbol{X}; \boldsymbol{M}_k]$$
$$\boldsymbol{V} = [W_v\boldsymbol{X}; \boldsymbol{M}_v]$$

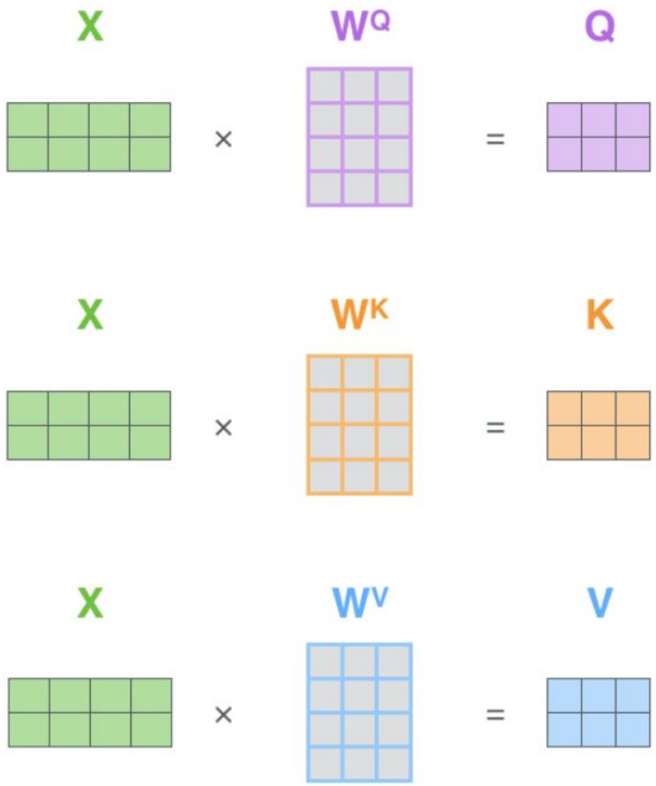
where Wq, Wk, Wv are weights, Mk,Mv are memory matrices, d is a scaling factor, and [∗; ∗] is concatenation operation.

Attention in Transformer

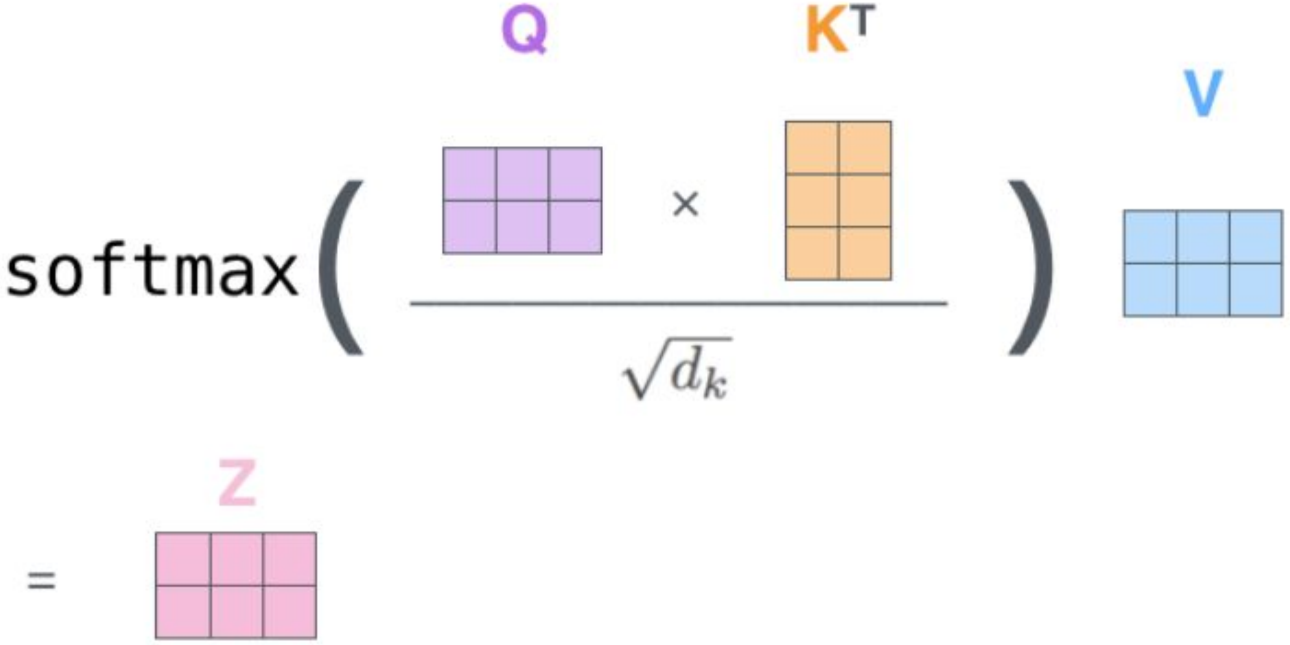


Source: http://jalammar.github.io/illustrated-transformer/

Attention in Transformer- Matrix way

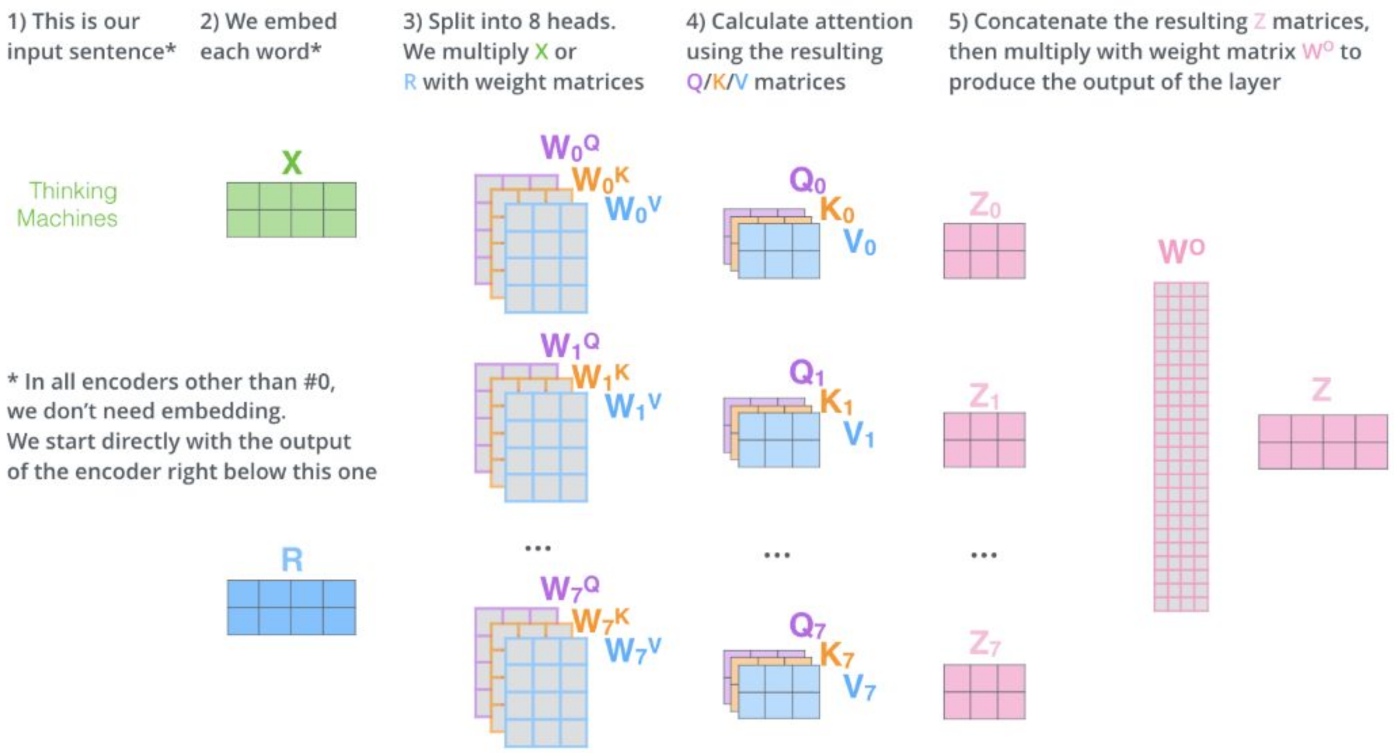


Attention in Transformer- Matrix way

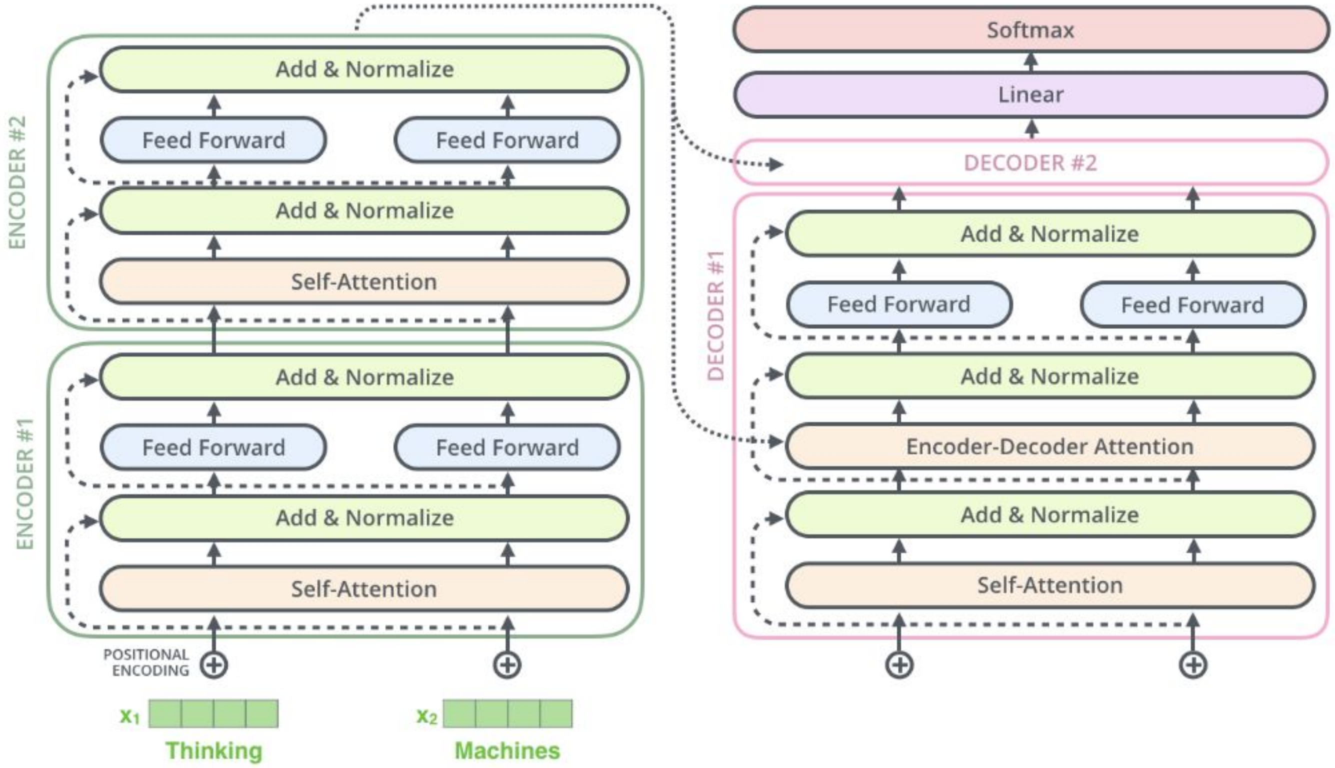


The self-attention calculation in matrix form

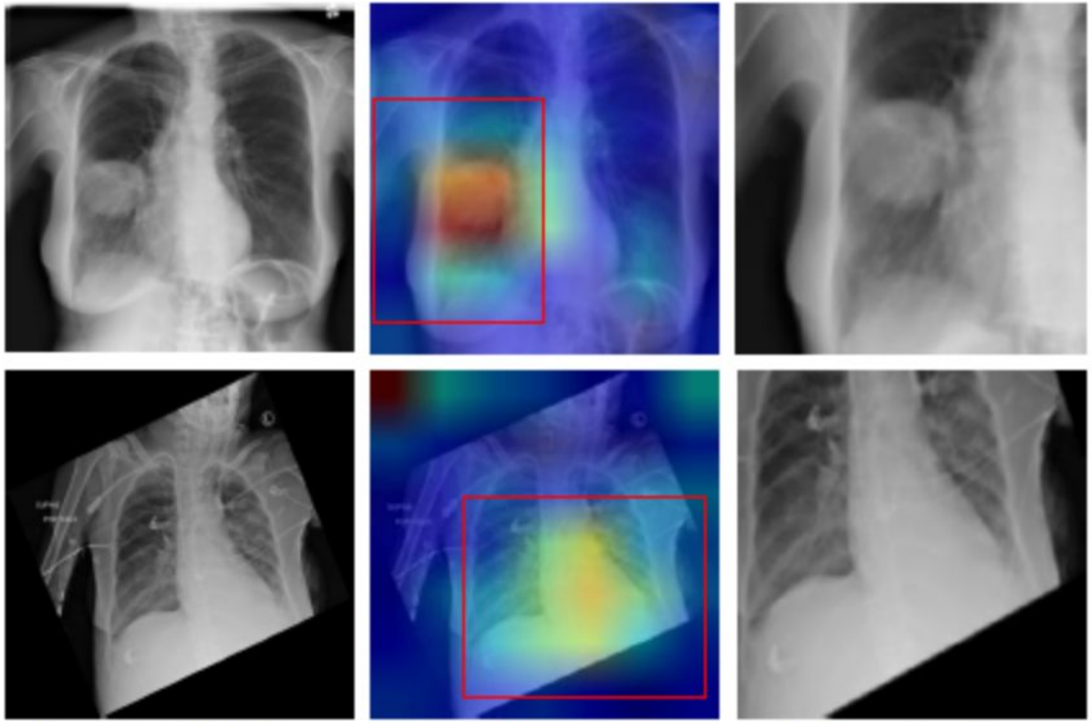
Attention in Transformer- Matrix way



The Transformer



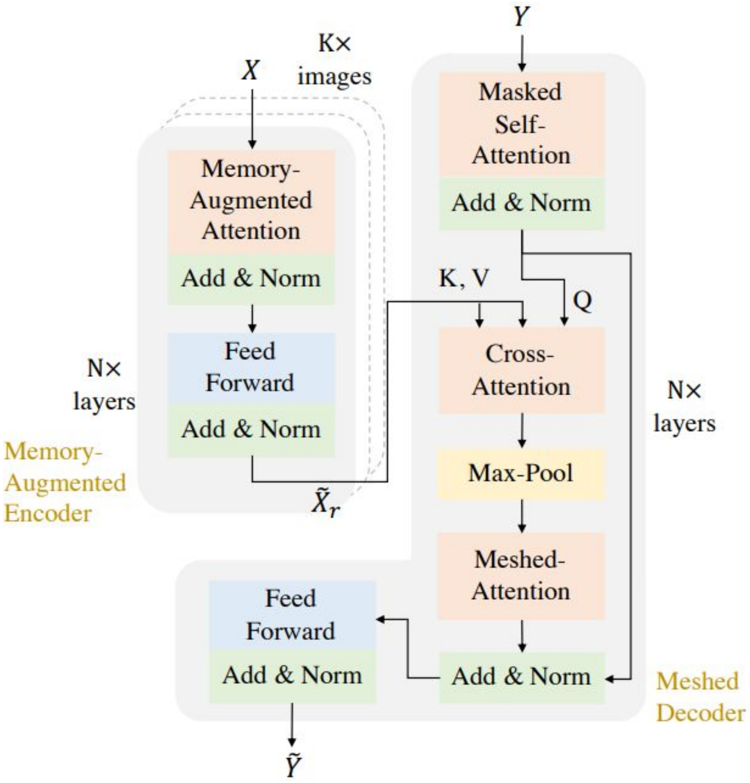
Why Attention?



(a) original global image (b) heatmap (c) cropped local image

Source: see ref [3]

Back to Meshed-Memory Transformer



$$\mathcal{M}_{\mathrm{mesh}}(\tilde{\boldsymbol{X}}_{\boldsymbol{N},\boldsymbol{K}}, \ddot{\boldsymbol{Y}}) = \sum_{n} \boldsymbol{\alpha}_n \odot \mathcal{C}(\tilde{\boldsymbol{X}}_{n,\boldsymbol{K}}, \ddot{\boldsymbol{Y}})$$

$$\mathcal{C}(\tilde{\boldsymbol{X}}_{n,\boldsymbol{K}}, \ddot{\boldsymbol{Y}}) = \max_{\boldsymbol{K}}(\mathrm{Att}(\mathrm{W_q}\ddot{\boldsymbol{Y}}, \mathrm{W_k}\tilde{\boldsymbol{X}}_{\mathrm{n},\boldsymbol{K}}, \mathrm{W_v}\tilde{\boldsymbol{X}}_{\mathrm{n},\boldsymbol{K}}))$$

$$\boldsymbol{\alpha}_n = \sigma\left(W_n[\boldsymbol{Y}; \mathcal{C}(\tilde{\boldsymbol{X}}_{n,\boldsymbol{K}}, \ddot{\boldsymbol{Y}})] + b_n\right)$$

Where ◯ is element-wise multiplication, $\max_K$ is maxpooling over K images, σ is sigmoid function, Wn is a weight, and bn is a bias. The weighted summation in Mmesh(X˜ N,K,Y¨) exploits both low-level and high-level information from the N stacked encoder.

Optimization with Factual Completeness and Consistency

Exact Entity Match Score : designed to measure factual completeness. A named entity recognizer is applied against yˆ and the corresponding reference report y. Given entities Egen and Eref recognized from ygen and yref respectively, precision (pr) and recall (rc) of entity match are calculated as

$$\mathrm{pr}_{\mathrm{ENT}} = \frac{\sum_{e \in E_{\mathrm{gen}}} \delta(e, E_{\mathrm{ref}})}{|E_{\mathrm{gen}}|}$$

$$\mathrm{rc}_{\mathrm{ENT}} = \frac{\sum_{e \in E_{\mathrm{ref}}} \delta(e, E_{\mathrm{gen}})}{|E_{\mathrm{ref}}|}$$

$$\delta(e, E) = \begin{cases} 1, & \text{for } e \in E \\ 0, & \text{otherwise} \end{cases}$$

The harmonic mean of precision and recall is taken as $\mathrm{fact}_{\mathrm{ENT}}$

Contd...

fact$_{\text{ENTNLI}}$ Entailing Entity Match Score: an F-score style metric that expand factENT with NLI to evaluate factual consistency. δ is expanded to

$$\phi(e, E) = \begin{cases} 1, & \text{for } e \in E \wedge \mathrm{NLI_e}(\boldsymbol{P}, h) \neq \text{contradiction} \\ 1, & \text{for } \mathrm{NLI_e}(\boldsymbol{P}, h) = \text{entailment} \\ 0, & \text{otherwise} \end{cases}$$

$$\mathrm{NLI_e}(\boldsymbol{P}, h) = \mathrm{NLI_s}(p, h) \text{ where } \underset{p \in \boldsymbol{P}}{\arg\max}\, sim(h, p)$$

The Loss function

A loss L is minimized as the negative expectation of the reward r and its gradient is estimated with a single Monte Carlo sample as

$$\nabla_\theta \mathcal{L}(\theta) = -\nabla_\theta \log P_\theta(y|x_{1\ldots K})\,(r(\hat{y}_{sp}) - r(\hat{y}_{gd}))$$

where yˆsp is a sampled text and yˆgd is a greedy decoded text. They combine a factual metric loss with a language model loss and an NLG loss as

$$\mathcal{L} = \lambda_1 \mathcal{L}_{\mathrm{NLL}} + \lambda_2 \mathcal{L}_{\mathrm{NLG}} + \lambda_3 \mathcal{L}_{\mathrm{FACT}}$$

Results

Dataset: MIMIC-CXR dataset

	Images	Reference	NLL + BERTScore	NLL + BERTScore + $\text{fact}_{\text{ENTNLI}}$
Example 1		As compared to the previous radiograph, no relevant change is seen of the sternal wiring. Monitoring and support devices are constant in appearance. Constant low lung volumes with bilateral small pleural effusions and subsequent areas of atelectasis. Moderate cardiomegaly. No new parenchymal opacities.	As compared to prior chest radiograph from __, there has been interval removal of the left chest tube. There is a small right pleural effusion. There is persistent atelectasis at the left lung base. There is no pneumothorax. Mild pulmonary edema is unchanged. The cardiomediastinal silhouette is unchanged. Median sternotomy wires are intact.	The cardiomediastinal and hilar contours are stable. The lung volumes are lower compared to the prior chest radiograph. Small bilateral pleural effusions are present. There is bibasilar atelectasis. Mild pulmonary edema is unchanged. There is no pneumothorax.
	Images	Reference	NLL + BERTScore + fact_{ENT}	NLL + BERTScore + fact_{ENT}
Example 2		PA and lateral views of the chest are obtained. There is mild atelectasis at the left lung base. The previously seen endotracheal tube and nasogastric tube are no longer present on this study. There is no evidence of pneumonia, pleural effusion or pulmonary edema. The cardiomediastinal silhouette is unremarkable.	Heart size is normal. The mediastinal and hilar contours are normal. The lungs are clear without focal consolidation. No pleural effusion or pneumothorax is seen. There are no acute skeletal findings.	Heart size is normal. The mediastinal and hilar contours are normal. The lung volumes are low. There is minimal atelectasis at the left lung base. Lungs are otherwise clear without focal consolidation. No pleural effusion or pneumothorax is seen.
	Images	Reference	NLL + BERTScore + fact_{ENT}	NLL + BERTScore + $\text{fact}_{\text{ENTNLI}}$
Example 3		There is moderate pulmonary edema, but no pleural effusion or pneumothorax. Heart size is top-normal, stable. Mediastinal contours are within normal limits. Osseous structures are intact.	Heart size remains mildly enlarged. The mediastinal and hilar contours are unchanged. There is mild pulmonary edema. Minimal atelectasis is noted in the lung bases. No focal consolidation, pleural effusion or pneumothorax is seen. Median sternotomy wires are intact.	The cardiomediastinal and hilar contours are normal. The heart is mildly enlarged. The patient is status post median sternotomy. The lung volumes are lower compared to the prior chest radiograph. Mild pulmonary edema is noted. There is no focal consolidation. No pleural effusion or pneumothorax is seen. Median sternotomy wires and mediastinal clips are noted.

References

- Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2017). Deep EHR: a survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE journal of biomedical and health informatics, 22(5), 1589-1604.

- Miura, Y., Zhang, Y., Langlotz, C. P., & Jurafsky, D. (2020). Improving Factual Completeness and Consistency of Image-to-Text Radiology Report Generation. *arXiv preprint arXiv:2010.10042*.

- Guan, Qingji, et al. "Diagnose like a radiologist: Attention guided convolutional neural network for thorax disease classification." *arXiv preprint arXiv:1801.09927* (2018).