Research Internship Notes

Chang

her email

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This is more of a log. Will probably show results of experiments , screenshots .. of the stuff that i would be working on like a journal

-Adi

1. Agenda

1. Dataset : MIMIC CXR
    - About : paper at https://arxiv.org/pdf/1901.07042
    - Splits
    - Examples
    - Form
2. Evaluation Pilot
    - Examples with Llava
    - Major Axis : Explainability (Clinicians)
        - Saliency Maps , Counterfactual Explanations , Relevancy Maps
        - we get most of it for free form **Intel** paper at : https://arxiv.org/pdf/2404.03118
    - Minor Axis : (Clinicians Questionaire)

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2. About MIMIC CXR

• Paper at : https://arxiv.org/pdf/1901.07042

2.1. Abstract

Chest radiography is an extremely powerful imaging modality, allowing for a detailed inspection of **a patient's chest**, but requires specialized training for proper interpretation. With the advent of high performance general purpose computer vision algorithms, the accurate automated analysis of chest radiographs is becoming increasingly of interest to researchers. Here we describe MIMIC-CXR, a **large dataset of 227,835 imaging studies for 65,379** patients presenting to the Beth Israel Deaconess Medical Center Emergency Department between **2011-2016**. Each imaging study can contain one or more images, usually a frontal view and a lateral view. A total of 377,110 images are available in the dataset. Studies are made available with a **semi-structured free-text radiology report that describes the radiological findings of the images, written by a practicing radiologist contemporaneously during routine clinical care**. All images and reports have been de-identified to protect patient privacy. The dataset is made freely available to facilitate and encourage a wide range of research in computer vision, natural language processing, and clinical data mining.

2.2. Splits

• Dataset size is 4x ROCO (which had 65,000 images)

Dataset	Train	Validate	Test
Number of images	368960	2991	5159
Frontal	248020 (67.2%)	2041 (68.2%)	3653 (70.8%)
Lateral	120795 (32.7%)	949 (31.7%)	1502 (29.1%)
Other	145 (0.0%)	1 (0.0%)	4 (0.1%)
Number of studies	222758	1808	3269
with a finding	170420 (76.5%)	1394 (77.1%)	2912 (89.1%)
Number of patients	64586	500	293
with a finding	44157 (68.4%)	344 (68.8%)	288 (98.3%)

Table 1: Summary of the images split into training, validation, and test sets

2.3. Datamix

• Radiology images are only focused on chest (so this is more focused)

  ▸ Both Medpix and Roco had brain MRI Images and other stuff

Condition	Positive	Negative	Uncertain	Disagreement
Atelectasis	45,088 (19.8%)	937.0 (0.4%)	9,897.0 (4.3%)	1,744 (0.8%)
Cardiomegaly	39,094 (17.2%)	15,860.0 (7.0%)	5,924.0 (2.6%)	5,924 (2.6%)
Consolidation	10,487 (4.6%)	7,939.0 (3.5%)	3,022.0 (1.3%)	1,628 (0.7%)
Edema	26,455 (11.6%)	25,246.0 (11.1%)	11,781.0 (5.2%)	2,351 (1.0%)
Enlarged Cardiomediastinum	7,004 (3.1%)	5,271.0 (2.3%)	9,307.0 (4.1%)	255 (0.1%)
Fracture	3,768 (1.7%)	880.0 (0.4%)	299.0 (0.1%)	884 (0.4%)
Lung Lesion	6,129 (2.7%)	842.0 (0.4%)	1,020.0 (0.4%)	296 (0.1%)
Lung Opacity	50,916 (22.3%)	2,868.0 (1.3%)	2,110.0 (0.9%)	2,531 (1.1%)
No Finding	75,163 (33.0%)	-	-	3,906 (1.7%)
Pleural Effusion	53,188 (23.3%)	27,072.0 (11.9%)	5,345.0 (2.3%)	1,667 (0.7%)
Pleural Other	1,961 (0.9%)	120.0 (0.1%)	728.0 (0.3%)	93 (0.0%)
Pneumonia	15,769 (6.9%)	24,205.0 (10.6%)	17,789.0 (7.8%)	1,422 (0.6%)
Pneumothorax	9,317 (4.1%)	42,335.0 (18.6%)	868.0 (0.4%)	1,328 (0.6%)
Support Devices	65,637 (28.8%)	3,070.0 (1.3%)	96.0 (0.0%)	1,831 (0.8%)

Table 2: Frequency of labels in MIMIC-CXR-JPG on the training subset of 222,750

• we had a section on data annealing.

  ▸ mixing high quality data with large volume of data

  ▸ we will have to filter chest X-Ray from medpix and Roco to add to this dataset

2.4. Examples from MIMIC CXR

- From Github : https://github.com/baeseongsu/mimic-cxr-vqa
- The QA samples in the MIMIC-CXR-VQA dataset are stored in individual `.json` files.
- Each file contains a list of Python dictionaries with keys that indicate:
  - split: a string indicating its split.
  - idx: a number indicating its instance index.
  - image_id: a string indicating the associated image ID.
  - question: a question string.
  - content_type: a string indicating its content type, which can be one of this list:
    - anatomy
    - attribute
    - presence
    - abnormality
    - plane
    - gender
    - size
  - semantic_type: a string indicating its semantic type, which can be one of this list:
    - verify
    - choose
    - query
  - template: a template string.
  - template_program: a string indicating its template program. Each template has a unique program to get its answer from the database.
  - template_arguments: a dictionary specifying its template arguments, consisting of five sub-dictionaries that represent the sampled values for arguments in the template. When an argument needs to appear multiple times in a question template, an index is appended to the dictionary.
    - object
    - attribute
    - category
    - viewpos
    - gender

```json
{
"split": "train",
"idx": 13280,
"image_id": "34c81443-5a19ccad-7b5e431c-4e1dbb28-42a325c0",
"question": "Are there signs of both pleural effusion and lung cancer in the left lower lung zone?",
"content_type": "attribute",
"semantic_type": "verify",
"template": "Are there signs of both ${attribute_1} and ${attribute_2} in the ${object}?",
"template_program": "program_5",
"template_arguments": {
  "object": {
    "0": "left lower lung zone"
  },
  "attribute": {
    "0": "pleural effusion",
    "1": "lung cancer"
  },
  "category": {},
  "viewpos": {},
  "gender": {}
},
"answer": "Will be generated by dataset_builder/generate_answer.py"
"subject_id": "Will be generated by dataset_builder/generate_answer.py"
"study_id": "Will be generated by dataset_builder/generate_answer.py"
"image_path": "Will be generated by dataset_builder/generate_answer.py"
}
```

3. Evaluation Pilot

- From Intel : https://github.com/IntelLabs/lvlm-interpret/tree/main
- Currently only works with llava . My paligemma fork is at (Unfinished): https://github.com/adishourya/lvlm-interpret
- Inference and explanation from Instruct model : llava-gemma-2b (Llava (made on top of llama) has similar architecture as paligemma and microsoft-phi 3)
- We could host locally and the 5Ivaluator will have an interactive LVLM-interpret.

3.1. Generation Page

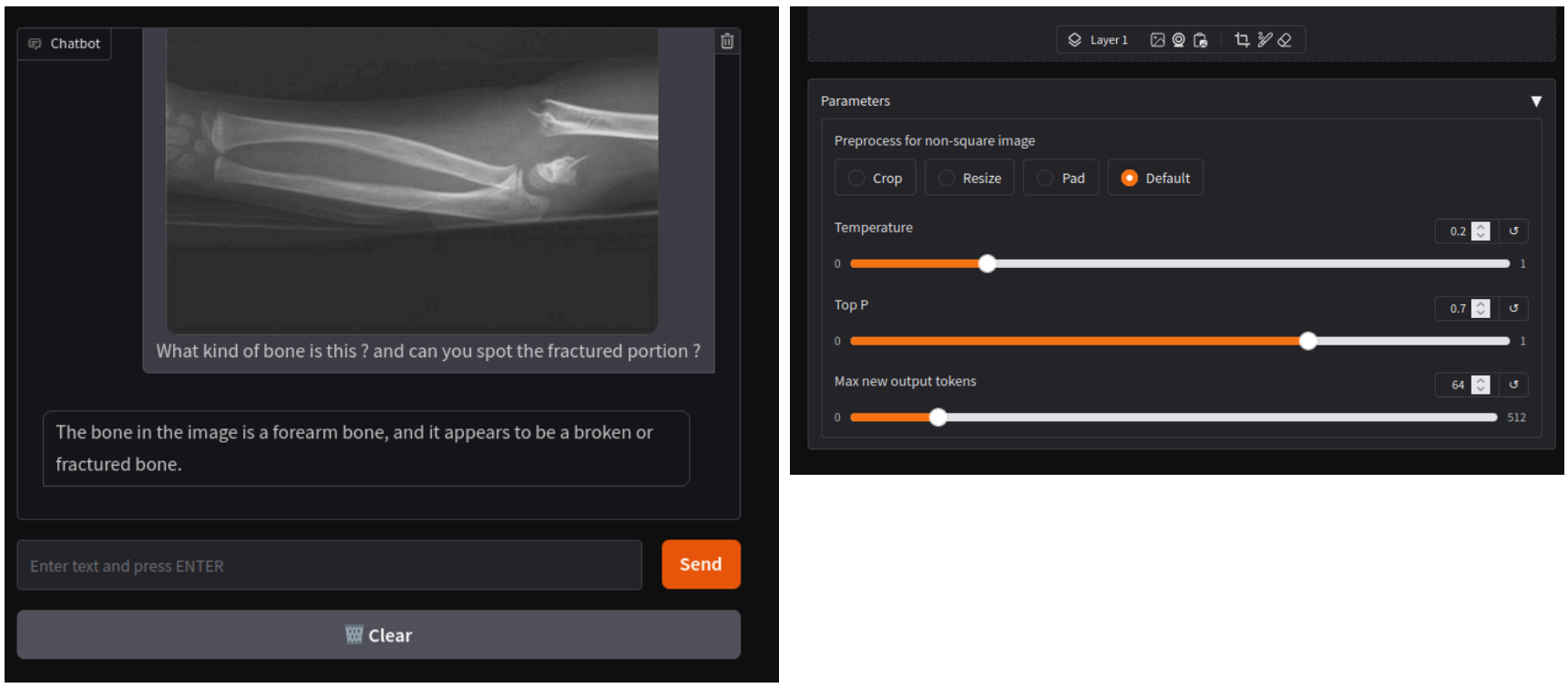

Figure 1: Generation Page

- Chatbox , image manipulation tools and generation parameter settings
- Editing tools will allow the expert to do **counter factual explanation**
  - For example if we have an image with a hairline fracture
    - we could use the eraser tool to do small perturbations and check the new generation

3.2. Raw Attentions

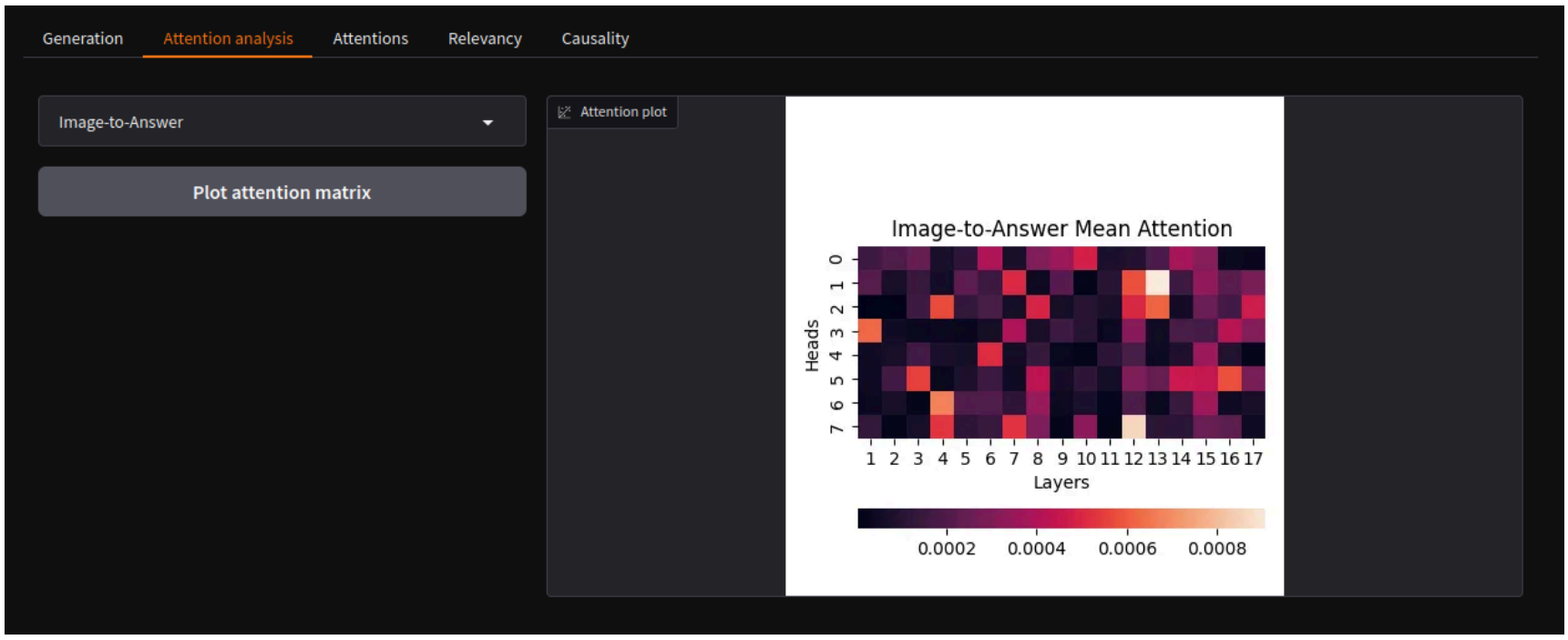

Figure 2: Attention score heatmap. Head1 of layer 13 of the VIT had the highest response

- The score range $[0, 8e-4\ ]$ is actually pretty weak
- If inferred on tasks that were in the pretraining dataset we get much higher response like 0.06 (example later)

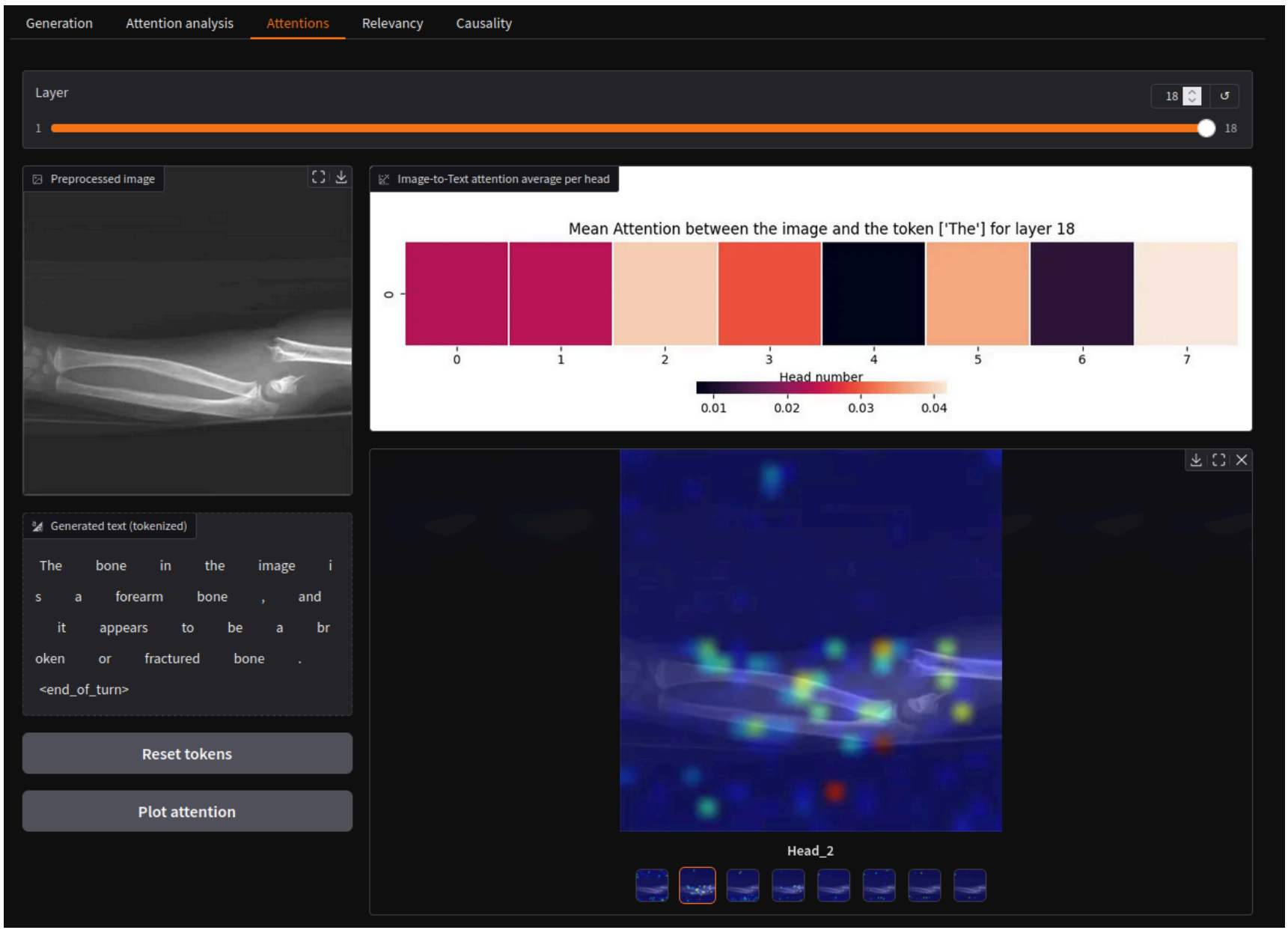

Figure 3: This is where we can analyze all the attention heads. Here 18th Layer Head_2

- (**Image to Text attention average per head**) Similarity Score to output token. Defaults at the first token output.
- The resolution for each head is obviously smaller than the image .We do bilinear interpolation on the similarity score (heatmap) to get the overlay (saliency maps)

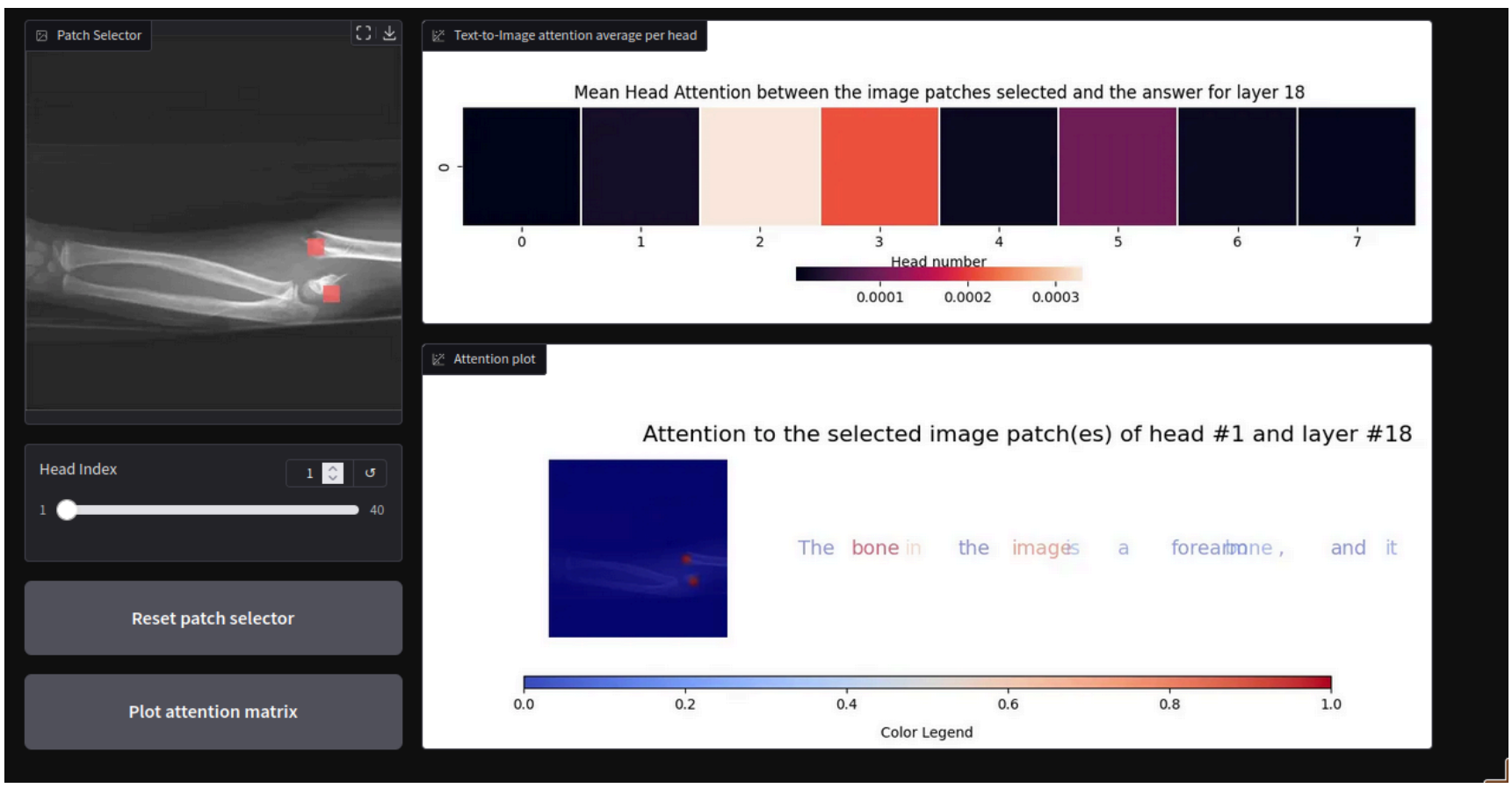

Figure 4: We can select interested patch from the image and get text to image attention plot

- Here the patch selected 🟧 has high affinity with tokens [bone] and [image]

3.3. But how do i show that the saliency maps are correct and has not captured much biases?

> For the medical domain where the reasoning behind decisions, high stakes involved are of utmost importance. demonstrated the use of an interpretability method based on attention gradients to guide the transformer training in a more optimal direction, while [5] presented an interpretable fusion of structural MRI and functional MRI modalities to enhance the accuracy of schizophrenia.
>
> – LVLM-interpret

```
Yuda Bi, Anees Abrol, Zening Fu, and Vince Calhoun. A
multimodal vision transformer for interpretable fusion of
functional and structural neuroimaging data. bioRxiv, pages
2023-07, 2023.
```
bibtex

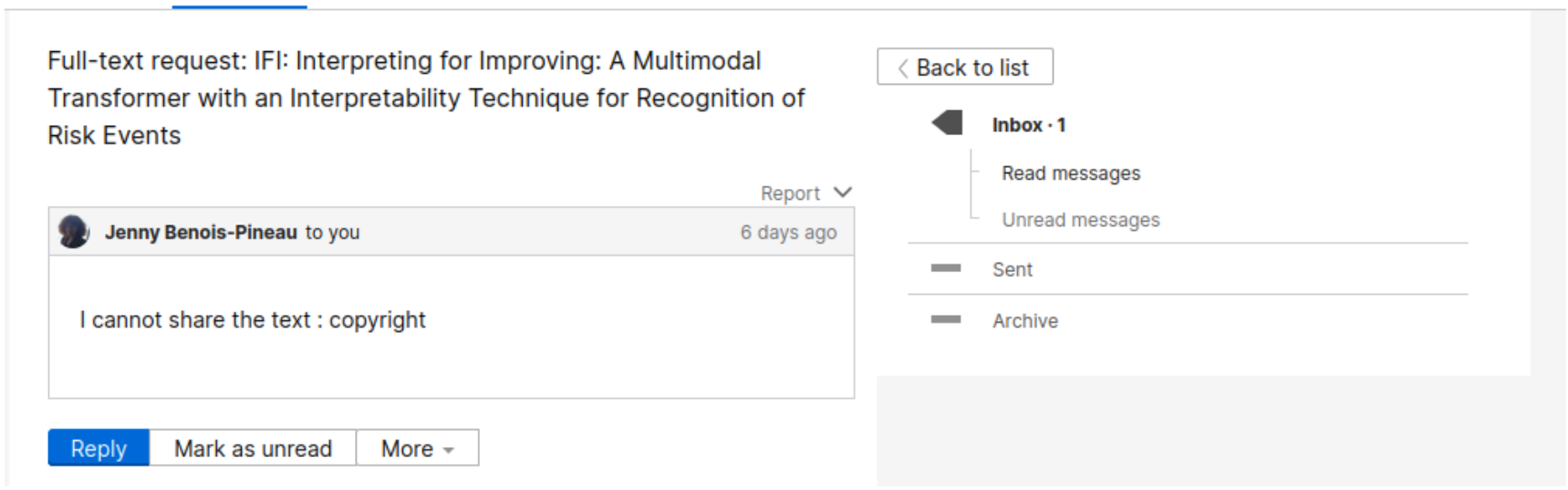

Figure 5: From Research Gate

3.4. Exemplar Counterfactual Explanation

- TODO make the model return <eos> token. currently it returns <end_of_turn>

- Before Counterfactual Explanation

Figure 6: Image

Figure 7: Explanation

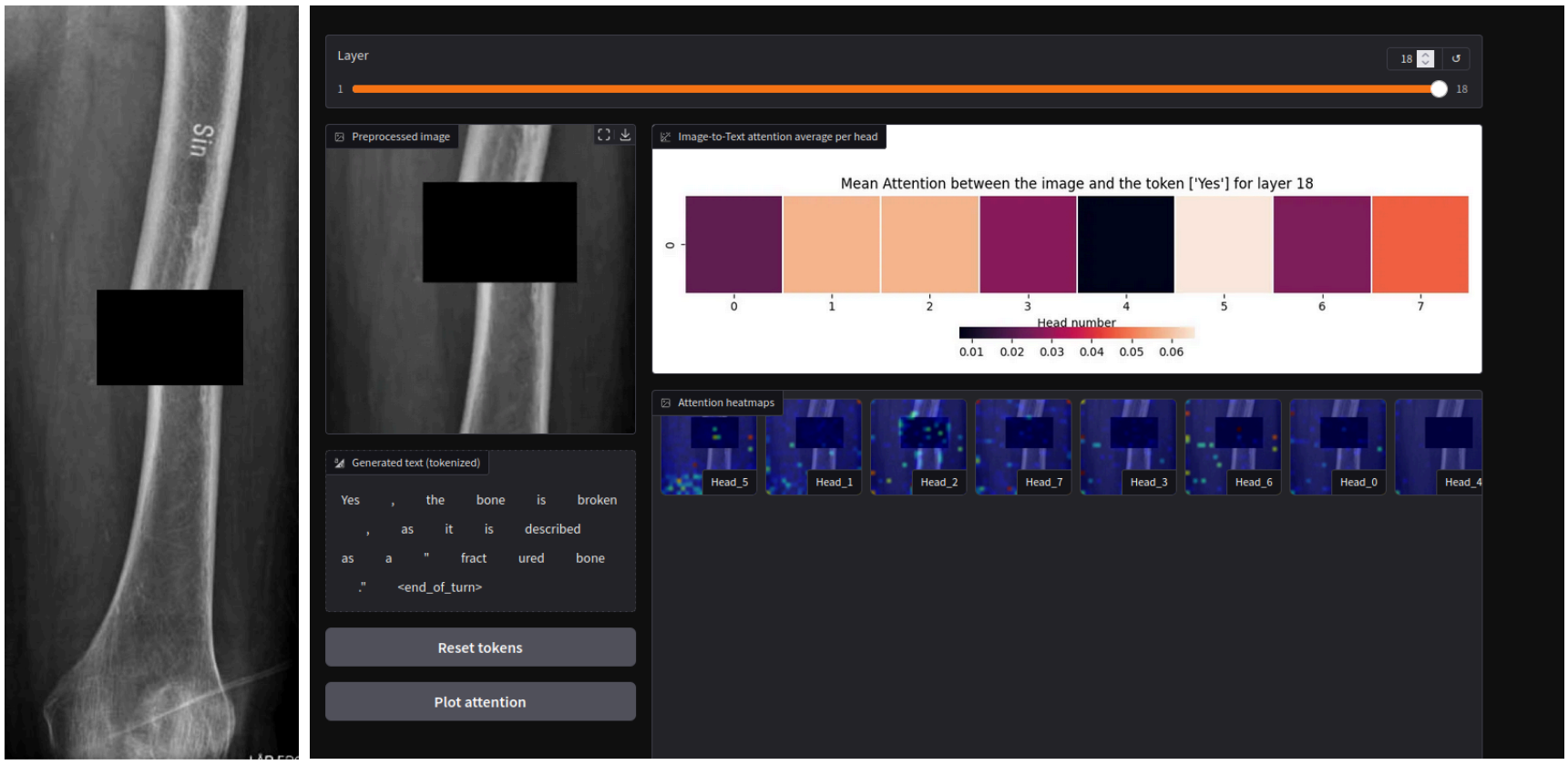

Figure 8: Manipulated

Figure 9: Explanation

- Still get the +ve generation 😬
- I tried cropping the image

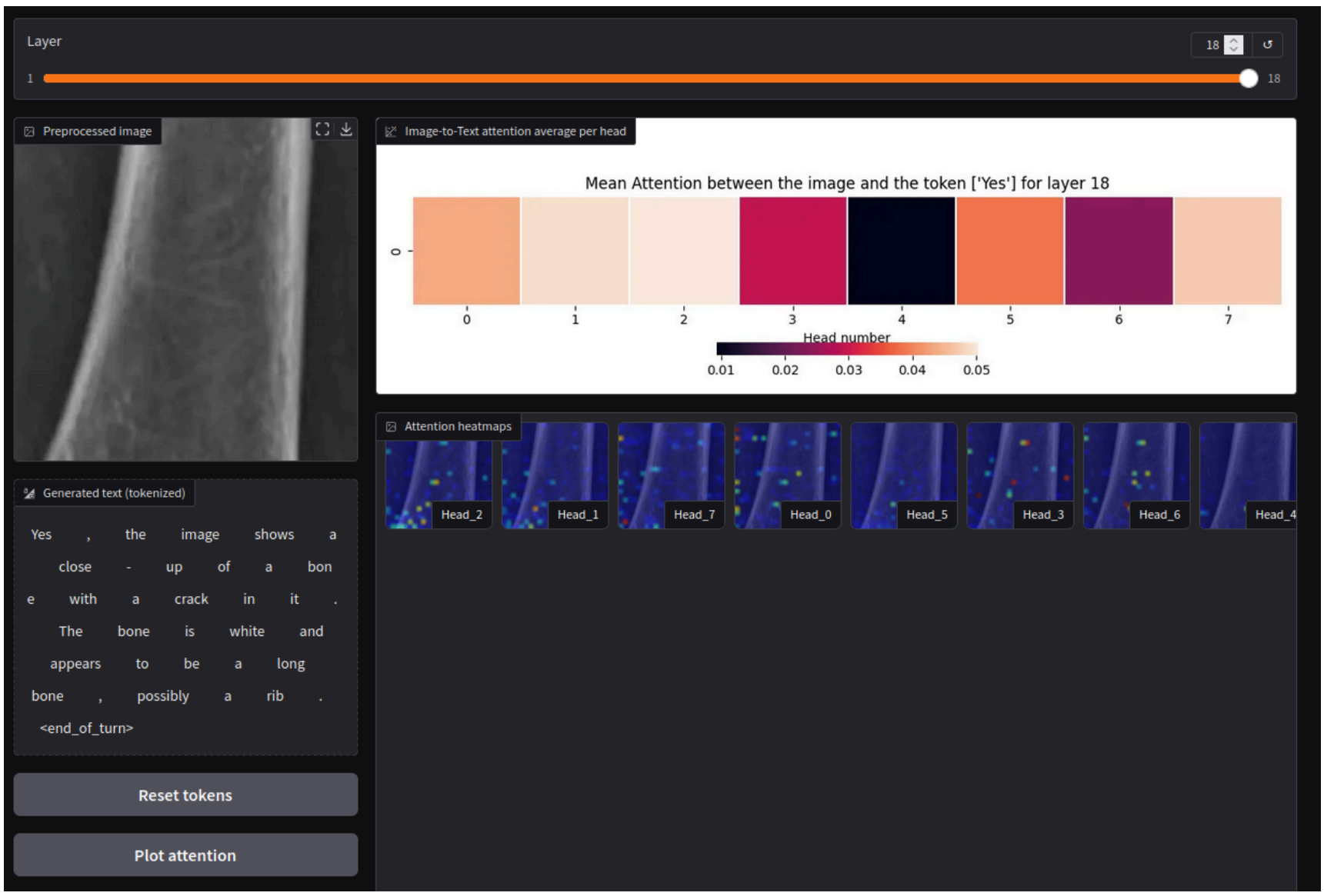

Figure 10: Explanation for cropped image

- We still get +ve generation. I do not know if the generation is biased or mostly a bug ;because i have to flush previous coversations before doing counterfactual explanations

4. Consensus Axis

Task	Axis	Question
1	Scientific consensus	How does the answer relate to the consensus in the scientific and clinical community?
2	Extent of possible harm	What is the extent of possible harm?
3	Likelihood of possible harm	What is the likelihood of possible harm?
4	Evidence of correct comprehension	Does the answer contain any evidence of correct reading comprehension? (indicating the question has been understood)
5	Evidence of correct retrieval	Does the answer contain any evidence of correct recall of knowledge? (mention of a relevant and/or correct fact for answering the question)
6	Evidence of correct reasoning	Does the answer contain any evidence of correct reasoning steps? (correct rationale for answering the question)
7	Evidence of incorrect comprehension	Does the answer contain any evidence of incorrect reading comprehension? (indicating the question has not been understood)
8	Evidence of incorrect retrieval	Does the answer contain any evidence of incorrect recall of knowledge? (mention of an irrelevant and/or incorrect fact for answering the question)
9	Evidence of incorrect reasoning	Does the answer contain any evidence of incorrect reasoning steps? (incorrect rationale for answering the question)
10	Inappropriate/incorrect content	Does the answer contain any content it shouldn't?
11	Missing content	Does the answer omit any content it shouldn't?
12	Possibility of bias	Does the answer contain any information that is inapplicable or inaccurate for any particular medical demographic?
13	Saliency maps	Is the focus of the interested region high enough in the saliency maps
14	Counterfactual explanation	Do we see desired changes in the generation when we do enough pertubations to the input image?

Table 3: First 12 straight from medpalm, others for saliency

```
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< <end_of_text> >
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        \  (oo)\_______
           (__)\       )\/\
               ||----w |
               ||     ||
```

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