CS 156b Presentation 1

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Beep-Boo-Boo-Bop-Boo-Boo-Bop

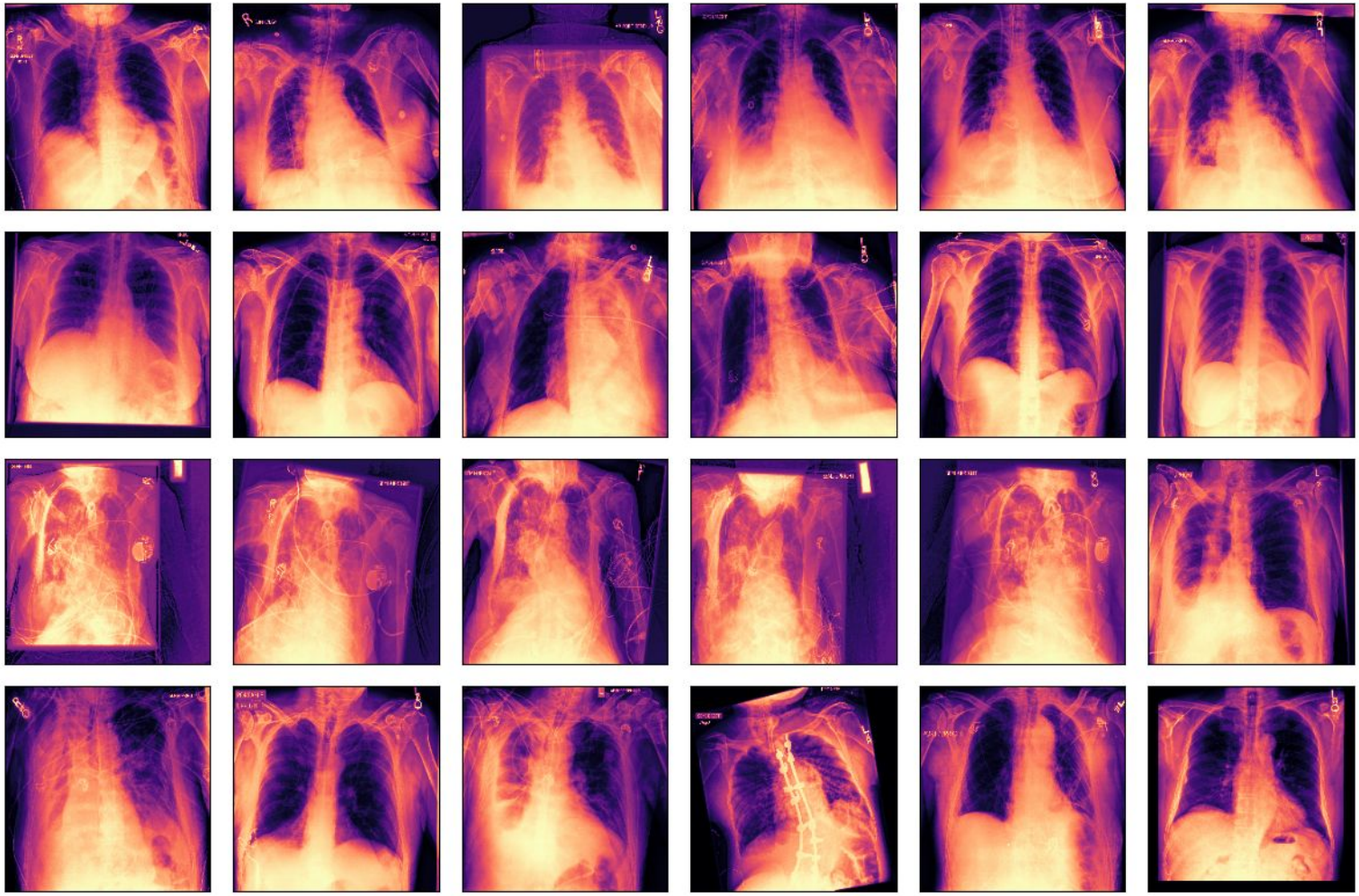


Image Data

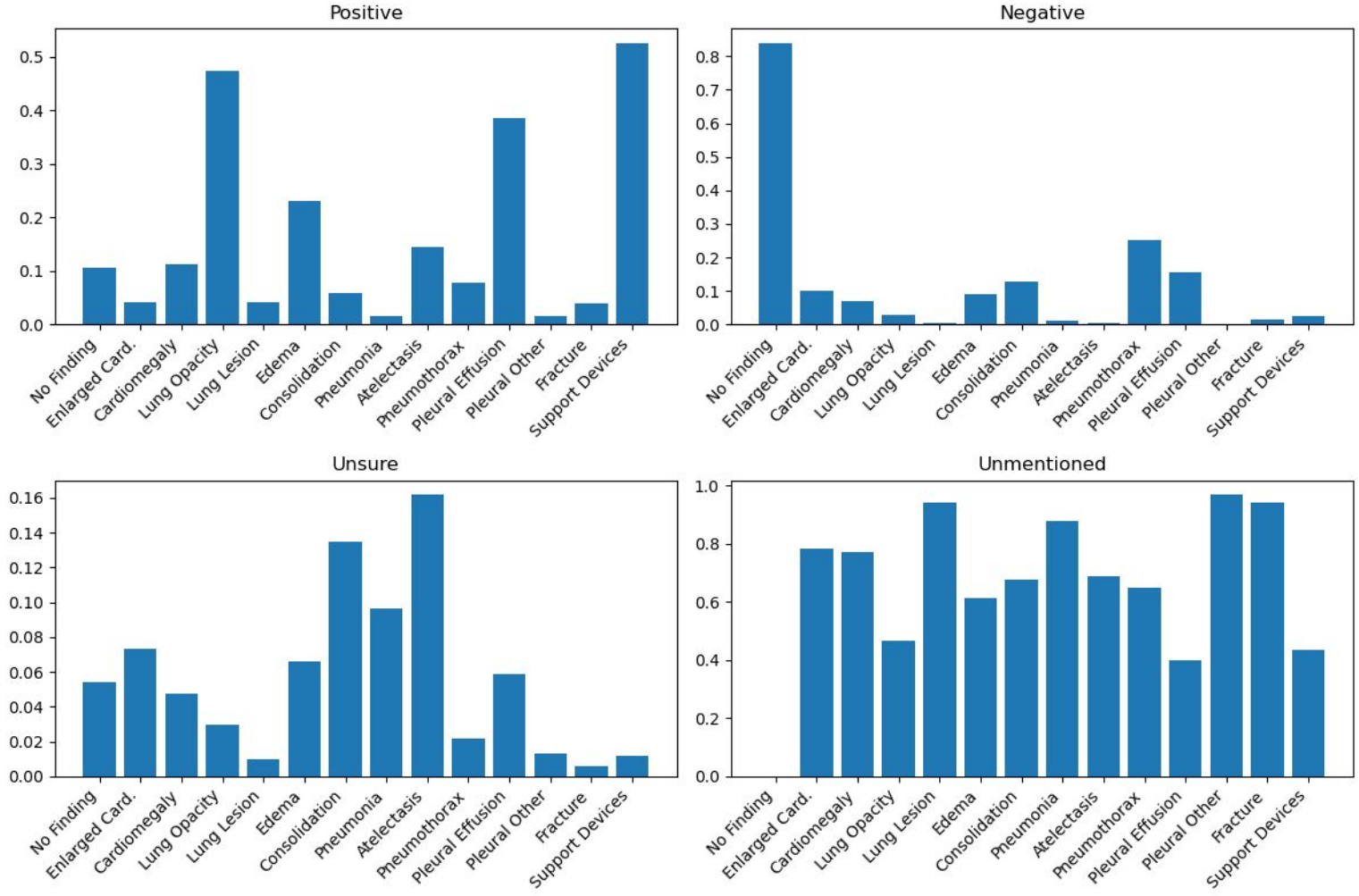
- Significant variation in posture, image type, rotation, borders,...
  - Use standardization based on markers, image augmentation, or combination
  - Mostly frontal
  - Mostly the same size, slight variations
- Bertrand et al.* found that lateral view makes trivial difference if any in classifying on PadChest**
- Wang et al. generated ChestX-ray8 (now 14)***
- Focusing on frontal view for now to get things running

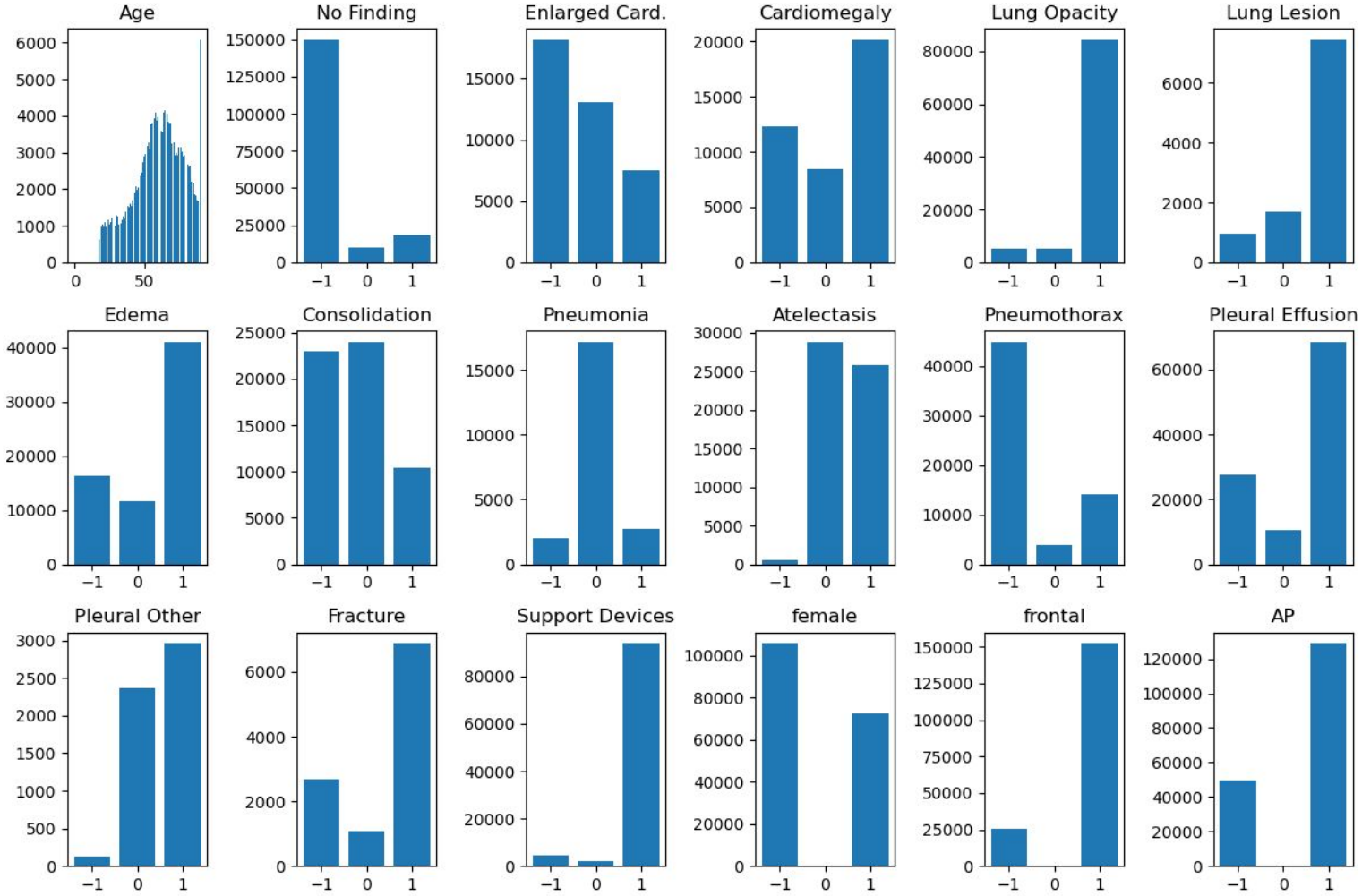
*Bertrand, Hadrien, et al. Do Lateral Views Help Automated Chest X-Ray Predictions? 2019. DOI.org (Datacite), https://doi.org/10.48550/ARXIV.1904.08534.
**Bustos, Aurelia, et al. “PadChest: A Large Chest x-Ray Image Dataset with Multi-Label Annotated Reports.” Medical Image Analysis, vol. 66, Dec. 2020, p. 101797. DOI.org (Crossref), https://doi.org/10.1016/j.media.2020.101797.
***Wang, Xiaosong, et al. “ChestX-Ray8: Hospital-Scale Chest X-Ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases.” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2017, pp. 3462–71. DOI.org (Crossref), https://doi.org/10.1109/CVPR.2017.369.

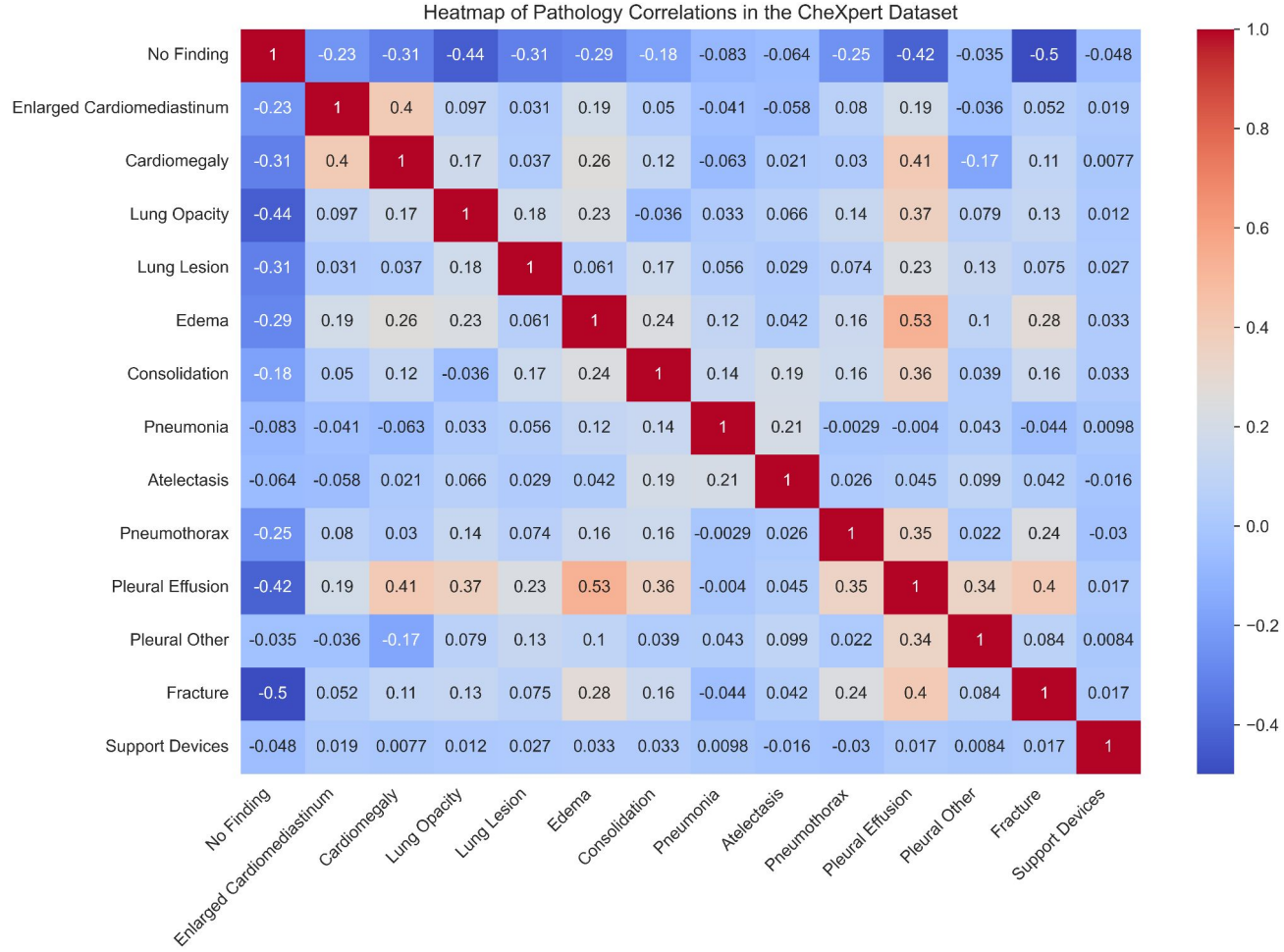
Image Processing

- Downsampling images to reduce computation time
- Maintain detail to make accurate predictions but make computation tractable
- Currently using skimage to get something simple up and running for now
- Resize implements a Gaussian blur, equalizes histogram
- Gielczyk et al.* compared methods found Gaussian blur plus histogram equalization (plus thresholding) to get the best performance on Covid data
- skimage.transform.resize: ~2300x2300 pixels to 200x200 pixels
- Look into machine learning based approach in the future for downsampling that preserves more information (Yasin et al.**)

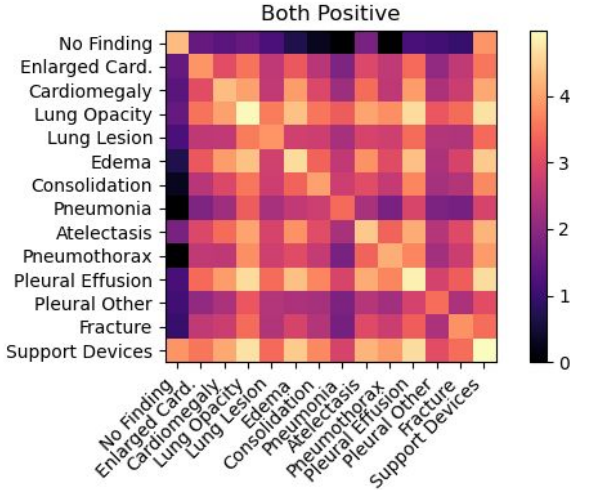
*Giełczyk, Agata, et al. “Pre-Processing Methods in Chest X-Ray Image Classification.” PLOS ONE, edited by Zahid Mehmood, vol. 17, no. 4, Apr. 2022, p. e0265949. DOI.org (Crossref), https://doi.org/10.1371/journal.pone.0265949.
Yasin, Hajar Maseeh, and Adnan Mohsin Abdulazeez. “Image Compression Based on Deep Learning: A Review.” Asian Journal of Research in Computer Science, May 2021, pp. 62–76. DOI.org (Crossref), https://doi.org/10.9734/ajrcos/2021/v8i130193.

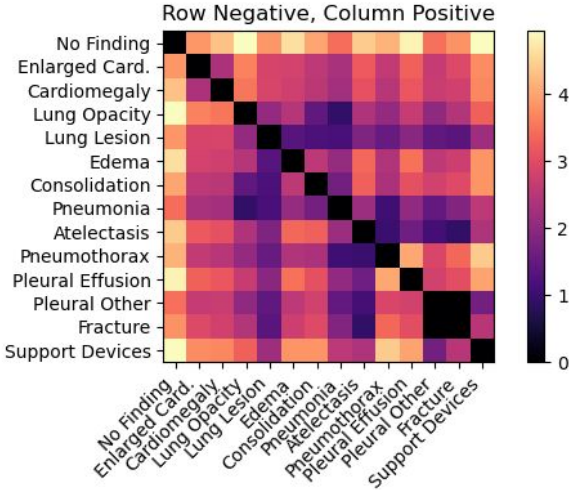

Positive
Negative
Unsure
Unmentioned
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
Consolidation
Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices

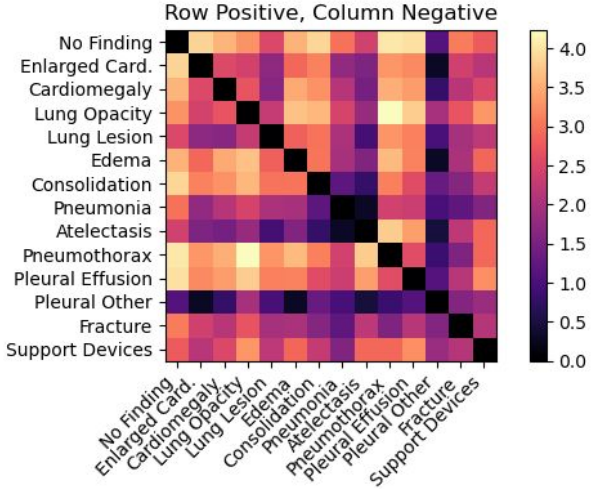

Age
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
Consolidation
Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices
female
frontal
AP

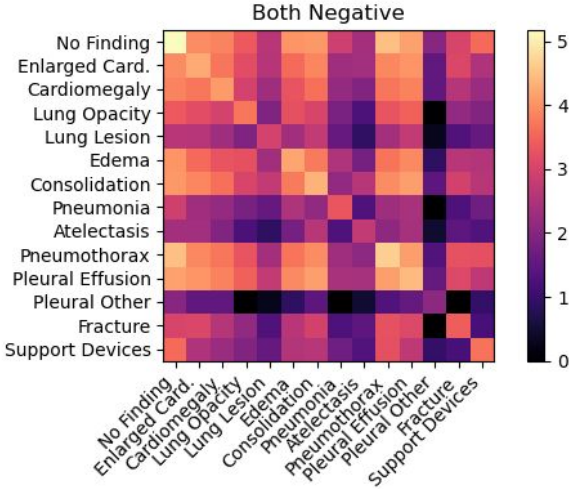


- Highest absolute: edema and pleural effusion (0.53)
- Lowest absolute: cardiomegaly and support devices (0.0077)


Both Positive
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
Consolidation
Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices
0
1
2
3
4


Row Negative, Column Positive
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
Consolidation
Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices
0
1
2
3
4


Row Positive, Column Negative
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
Consolidation
Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Both Negative
No Finding
Enlarged Card.
Cardiomegaly
Lung Opacity
Lung Lesion
Edema
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Pneumonia
Atelectasis
Pneumothorax
Pleural Effusion
Pleural Other
Fracture
Support Devices
0
1
2
3
4
5

Label Data

- Significant variations in frequency
- We have data from all 14 classes, not just the 9 we are using
  - Try using data with and without examples positive for the extra classes
- Lots have support devices, lung opacities, and multiple positives
- Most have some finding
- Most are unmentioned at least half the time
- NaN Filling
  - Fill based on distributions of pathologies
  - Use conditional distributions if enough data
    - Condition on known labels, age, sex, x-ray type
  - Use -½ or similar values for filling NaNs
- Use label frequencies to balance training examples
  - Use image transformations to generate extra examples

Models

- Basic CNN to start
  - Natural for imaging tasks, better for un-regularized data
  - Just use on raw image data and NaN-filled labels
- Take advantage of large pretrained models for transfer learning
- Use drop-in models from torchvision and others with weights from pretraining
  - Lots available, such as resnet, densenet, convnext
  - Vision transformer models
- Combine CNN trained on image data with boosted decision tree or other models on provided and generated features
- Different models for each view (AP/PA, lateral)
- Feature generation
  - Inspect more labeled images
  - Symmetry, average intensity, standard deviations, gradients, break into sections
  - Use filters to separate sections

Division of Labor

- Danny
  - Data processing, also feature generation and alternative models
- Gautam
  - Main model implementation, training, and testing
- Matthew
  - Incorporate additional data sets and investigate alternative models
- Sujai
  - Feature generation, model implementation and testing