Online Learning for Multi-Label Medical Images

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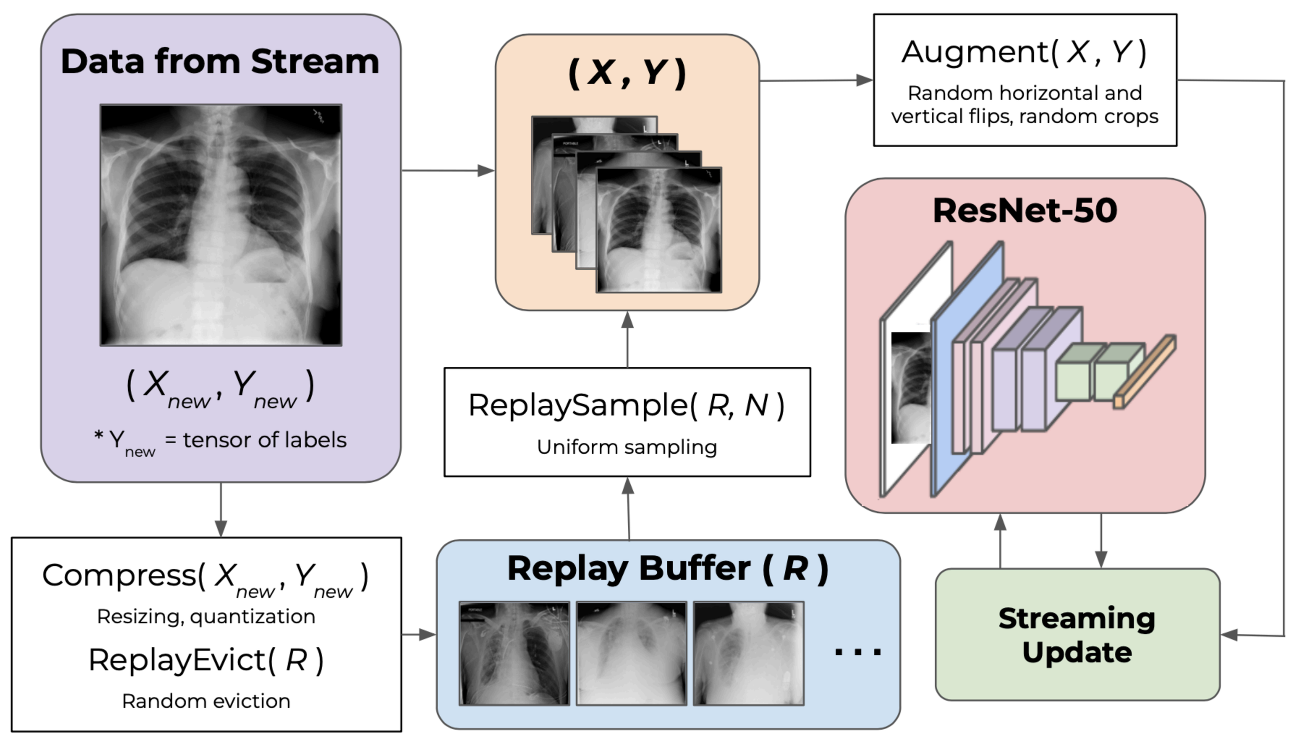
Background & Motivation

What is Online Learning?

- **Online Learning** is a machine learning method in which the full dataset is never available to the model at once and the data becomes available in a sequential order
- It is useful when…
  - It is computationally impractical to train over the entire dataset
  - An algorithm must adapt dynamically to new patterns
  - Data generated as a function of time
- We must address **Catastrophic Forgetting,** when an online model 'forgets' how to classify previous data as it is exposed to new data.

The CSSL Algorithm

- In the **CSSL** Algorithm, a unique data example from the *data stream* is compressed then sent to the *replay buffer*. If the replay buffer if full, an example is deleted
- The sample is added to the *collection of replay samples* along with a random sample from the replay buffer of size *N*
- The collection is then *augmented* and the streaming update changes the learner parameters of the initiated model



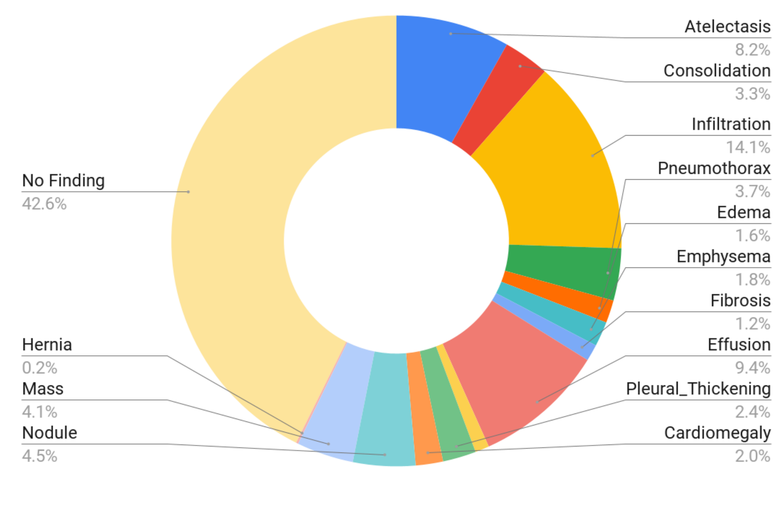
The Reality of Medical Data

- Medical Image sets are typically **small**, take a long time to accumulate, and require an expert to annotate.
- Inconsistent between sources
- **High Fidelity** is especially important in this setting
- If we can predict an image's label before it reaches the expert, it will **speed up** the labeling process. The model will learn from mistakes waste of the doctors' time
- Offline training wastes computation and does not **dynamically** learn well in contrast to Online training.

Methodology & Contribution

NIH Chest X-Ray Dataset

- Collection of **112,000+** x-ray images
- Over **60,000** 'No Finding' examples and **50,000** images with at least 2 labels
- X-Rays are only 1 channel so the **ResNet50** model must be changed
- Used to explore the effects of vastly **unbalanced** data

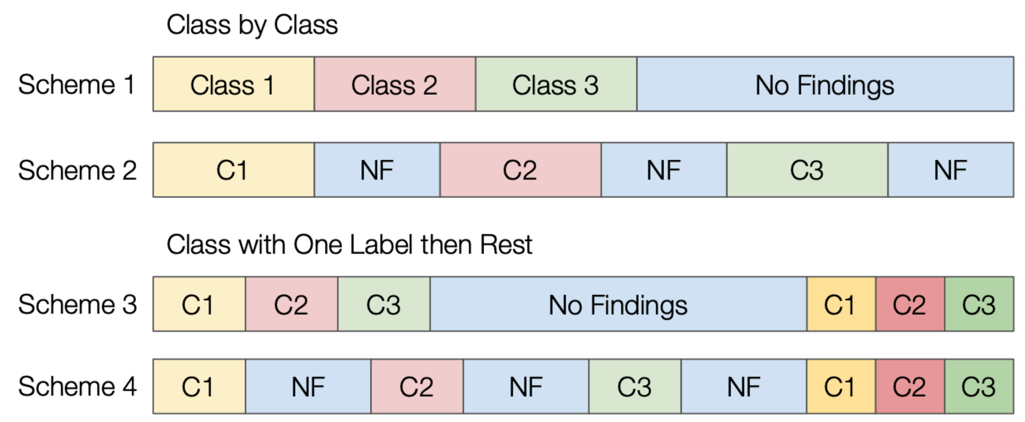


Changes to CSSL

- To apply CSSL to medical data, we must use traditional medical image data augmentation (horizontal and vertical flips, random crops, rotation)
- Consider how to pass "classes" when they are not mutually exclusive
  - How do we treat 'No Finding' examples
- How to handle learning rates given that there are no clear classes

Index Schemes

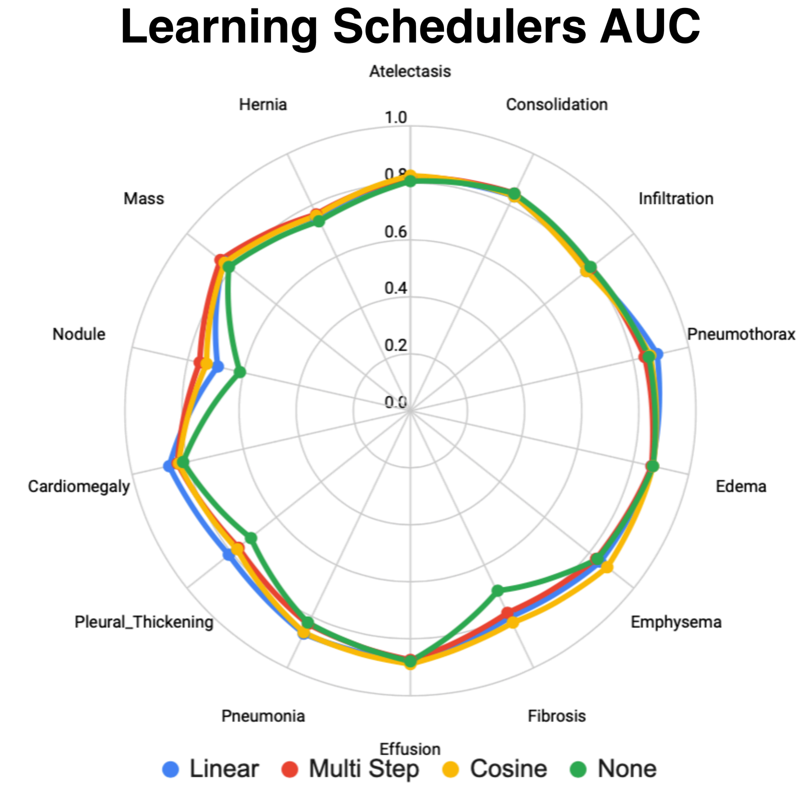
- In the case of **Multi-label Classification**, classes are not mutually exclusive so training is less intuitive
- Index schemes are used to fed the model "classes" at a time
- Schemes 1 and 2: Classes of pathologies as passed together as a group without revisiting previous data
- Schemes 3 and 4: Each class with only one label is passed first then multi-labels are passed in
- Schemes 2 and 4: Distribute the 'No Finding' examples



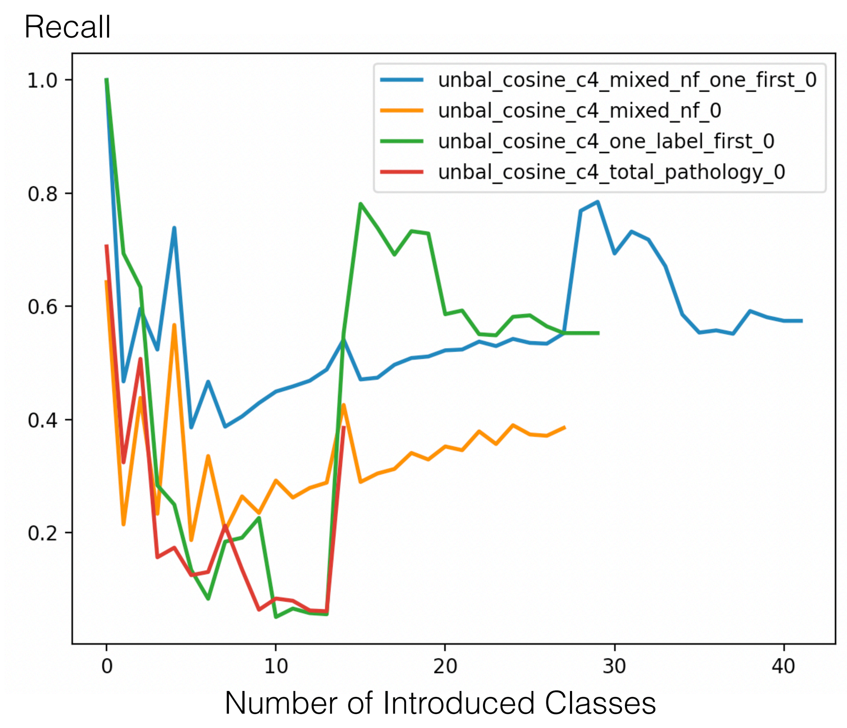
Results & Conclusions

Baselines

- Implement baselines with different learning schedulers
- Does not consider 'No Findings' as a pathology
- Area under **ROC** curve: measure across all possible thresholds with parameters (True Positive Rate, False Positive Rate)
- Baselines were more refined however the CSSL model is still in preliminary testing.

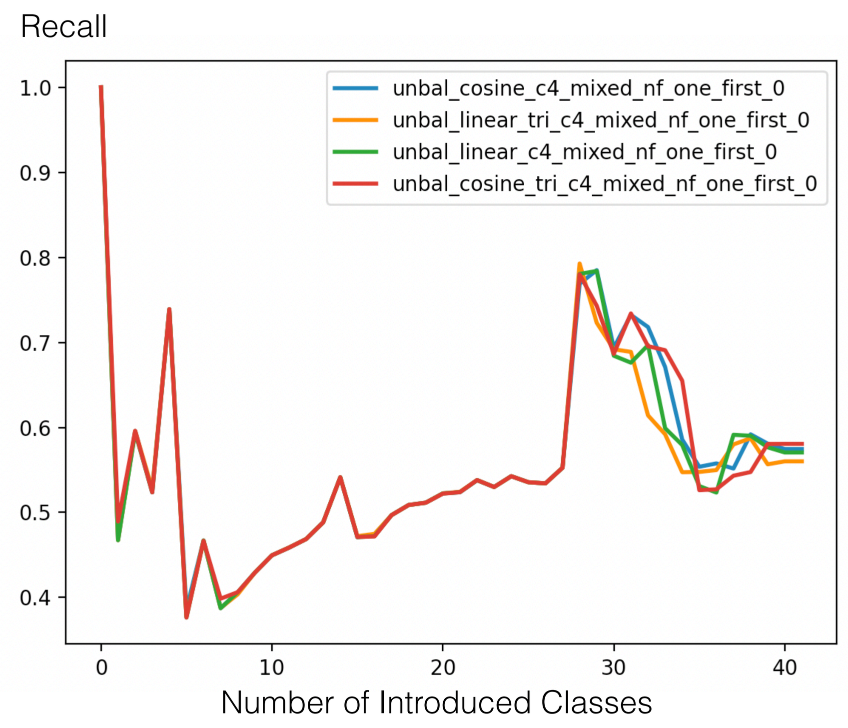


Index

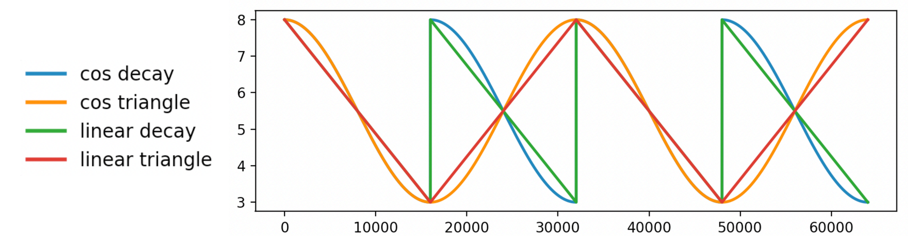


- After being exposed 'No Finding' classes, there is a **sharp spike** in recall
- By separating the 'No Finding' class, recall increases steadily

Learning Rate Schedulers



- Example of learning rates below



Future Work

Challenges and Limitations

- Open sourced data is hard to come by and inconsistent
- Since CNNs are blackbox methods and bugs are difficult to catch you must start simple and build up
- Only for one channel X-rays
- Online learning was worse performance than offline learning

New Directions

- Medical images as typically unbalance: how does this effects online learning scenarios
- Exploit the algorithms dynamic nature for multi-task learning
- Random index scheme with un-random replay eject
- Segmentation Tasks
- Incorporate more metadata for multi-nodal learning

Acknowledgements

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The QR code includes relevant sources and links