AI Research in Tuberculosis @ BRICS

Deep Learning: GANs for Medical Image Synthesis

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Agenda

- Learning from Small Data;
- Data Augmentation;
- Learning Transformations from Data;
- Challenges:
  - Null data problem;
  - Representation flaws.
- How to Evaluate and Compare GAN Models.

> Learning from Small Data

For Tuberculosis Screening Using Chest X-Ray Images

- Convolutional networks are well-suited for handling high-dimensional topological data;
- However, such AI (computer vision) methods were developed considering big data conditions:
  - Not the case for medical data…
- Gathering data is not straightforward:
  - Can involve human suffering or discomfort;
  - Data can be expensive to collect;
  - Privacy issues;
  - Lack or expensive experts for annotating data;
  - Small number of positive cases.
- Lack of data becomes the major performance bottleneck for fully benefitting of the currently best performing computer vision methods;

Is there any workaround?

> Data Augmentation

- Create artificial data;

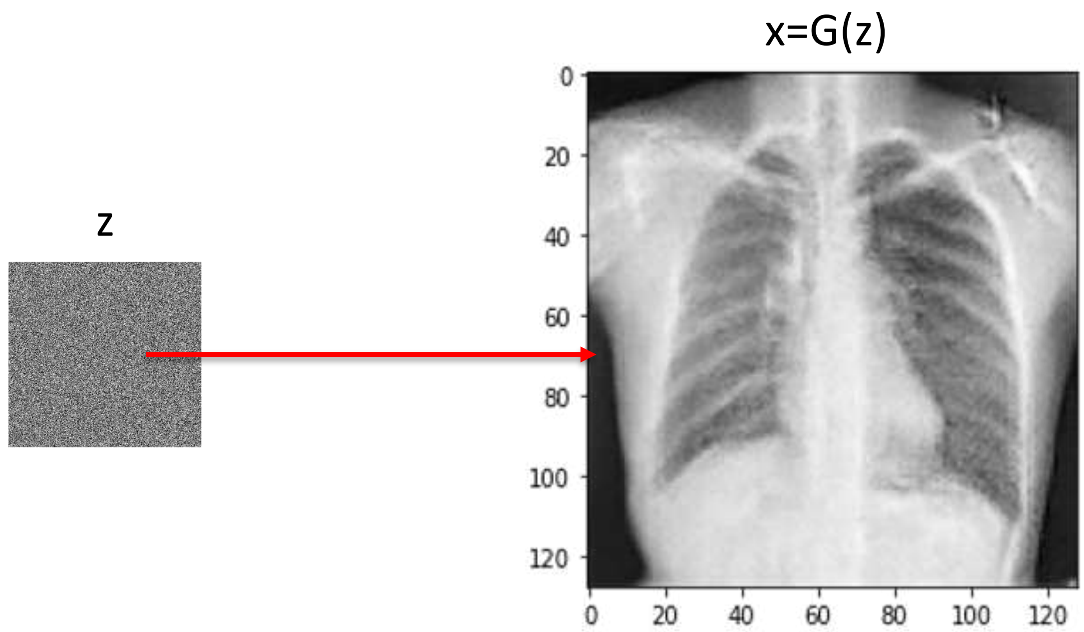
But HOW?

- "Ultimate goal" of classification:
  - Data transformations that do not result in class variations;
- If we know transformations where the label is not changed, we can apply use them to augment data:
  - Weak supervision: do not provide labels, but variations;
- In computer vision (domain knowledge):
  - Rotation, translation, scaling, squeezing (vertical compression/horizontal elongation or the reverse), horizontal shearing;
- However:
  - Not every transformation is easy to implement computationally;
  - Hard-coded transformations may require knowledge that we lack.
- I.e.: how to map variations in pathologies as a function?

Learning Data Transformations

For Data Augmentation

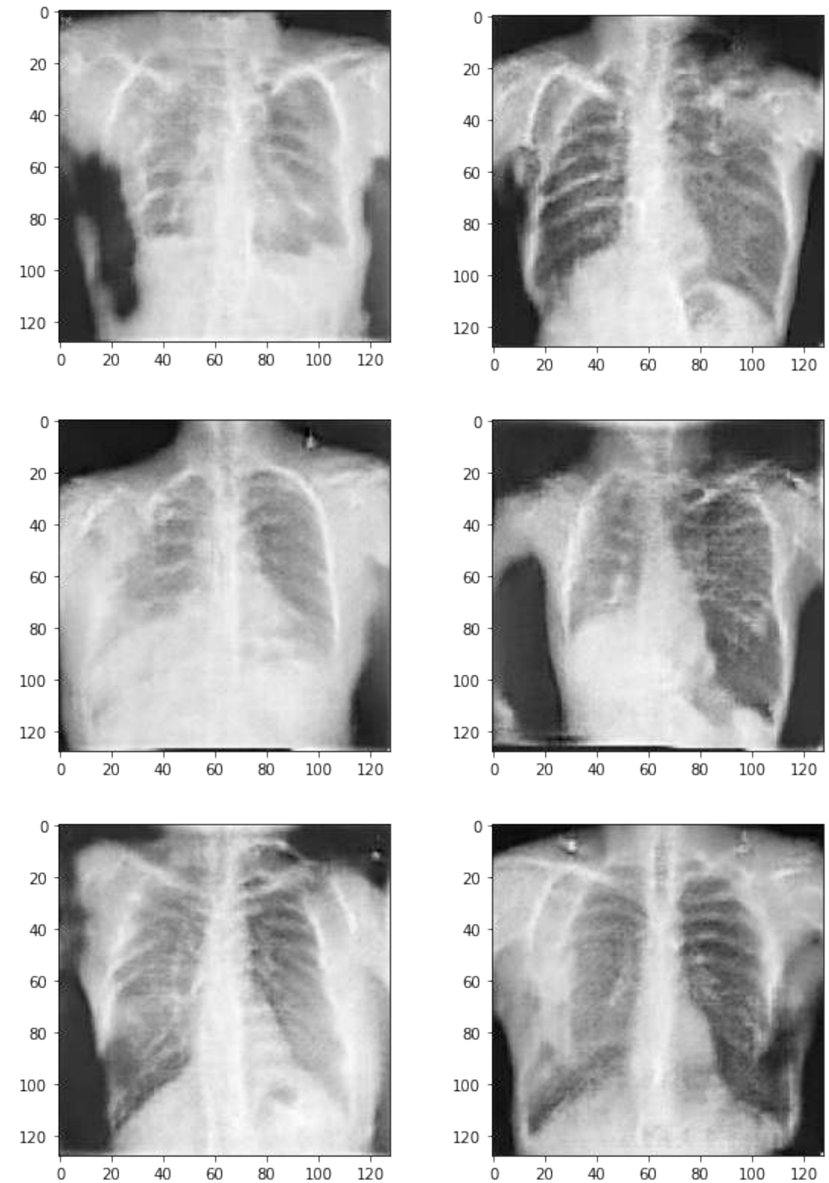
- Decoder-based generative networks (e.g. GANs) provide a way to capture the data structure:
  - Many use cases for medical image synthesis for data augmentation;
- Unconditional synthesis: transform arbitrary structure (“noise”) into the data structure;



> Learning Data Transformations

Challenges: Null Data

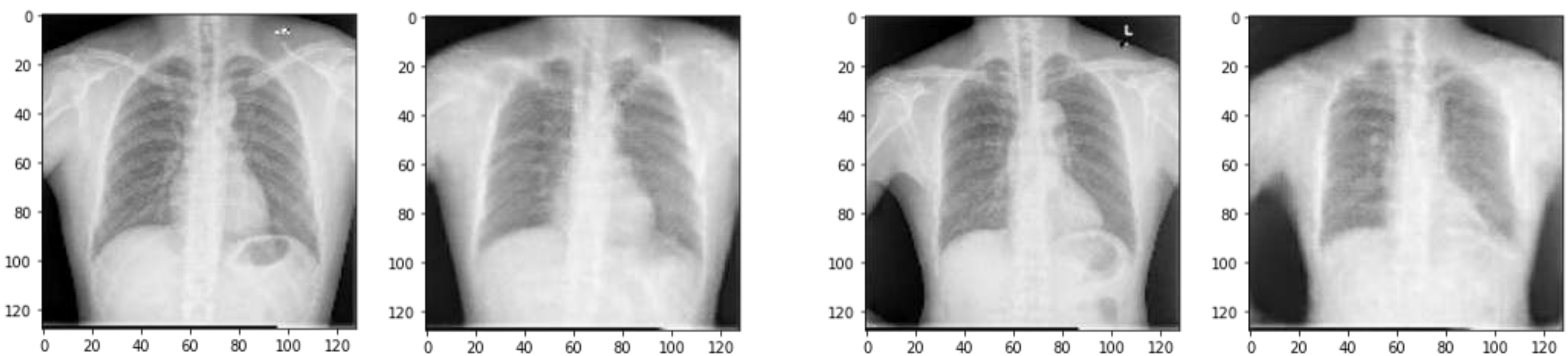
- Unconditional synthesis for data augmentation is an ill-posed problem:
    - We only **implicitly** aim **to approximate** the data density;
    - Sampling is performed fully relying that we managed to capture such structure;
    - Going beyond, we are relying on that knowing that we have a poorly sampled distribution;
- We can end up sampling null data (out-of-distribution samples);



Learning Data Transformations

Challenges: Representation Flaws

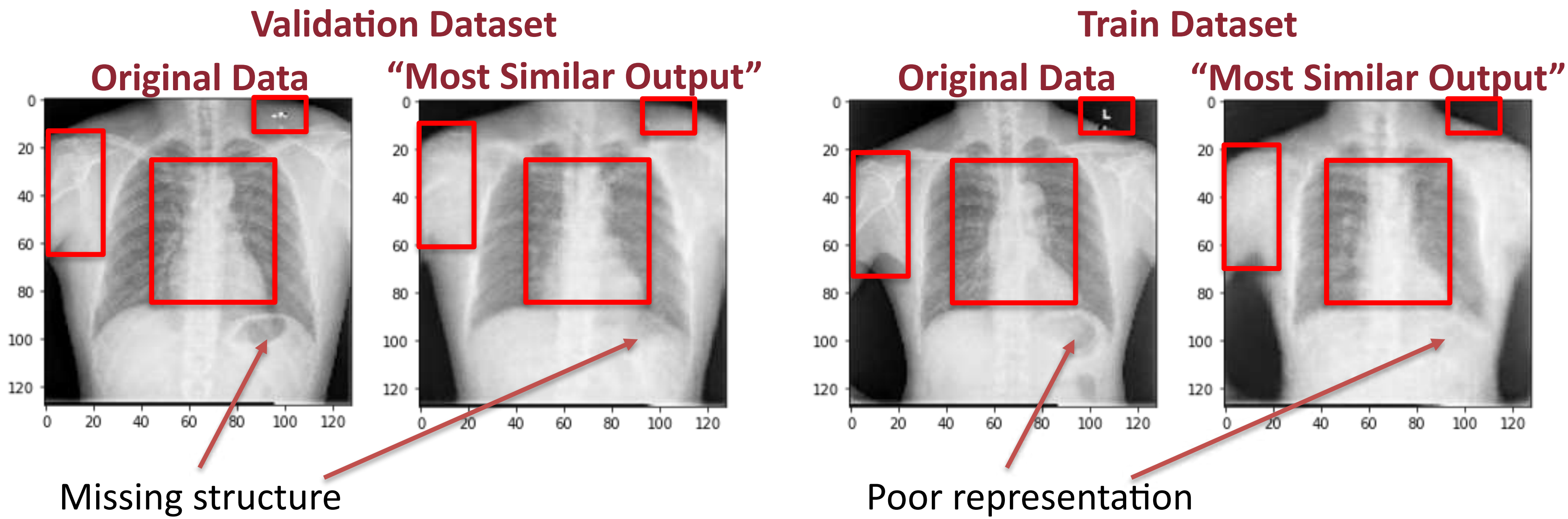
- **Finite model** from a family that most likely **does not include** the **data generating process;**
- Optimization further limits model effective representation capacity;
- In other words, most likely to lose some structures present on data:
- Actually, this is a known limitation of GANs:
    - “Missing modes” problem;
- For instance, compare:



- Is there something strange?

› How to Evaluate Models and Compare

- Annealed importance sampling sheds some light to these challenges:
  - Provide a way for mitigation of null data sampling;
  - Allow to diagnose possible representation flaws;

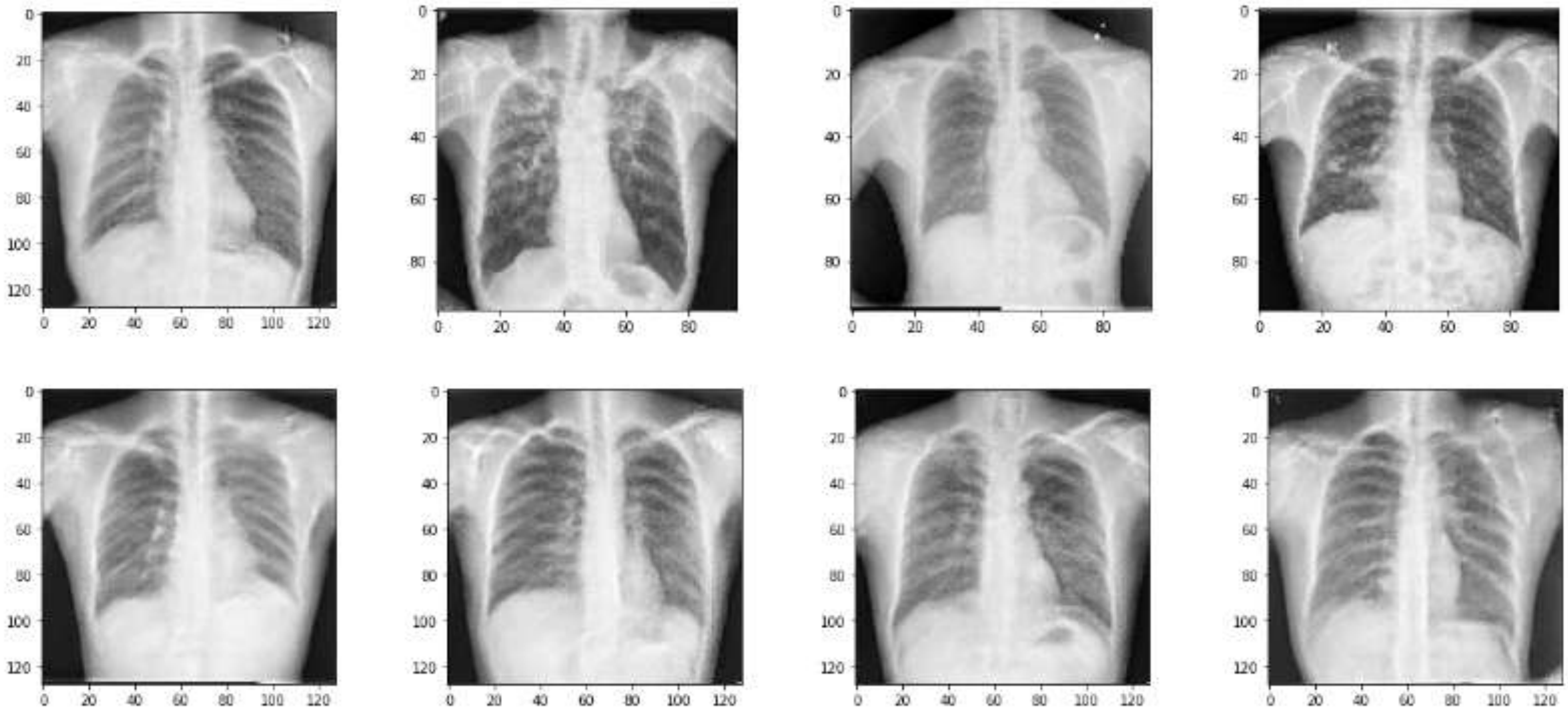


- Allow comparing models (and evaluating overfitting);
- If the generator is a well suited model:
  - Provide insights of which structure are more or less common for a given pathology.

› Learning Data Transformations

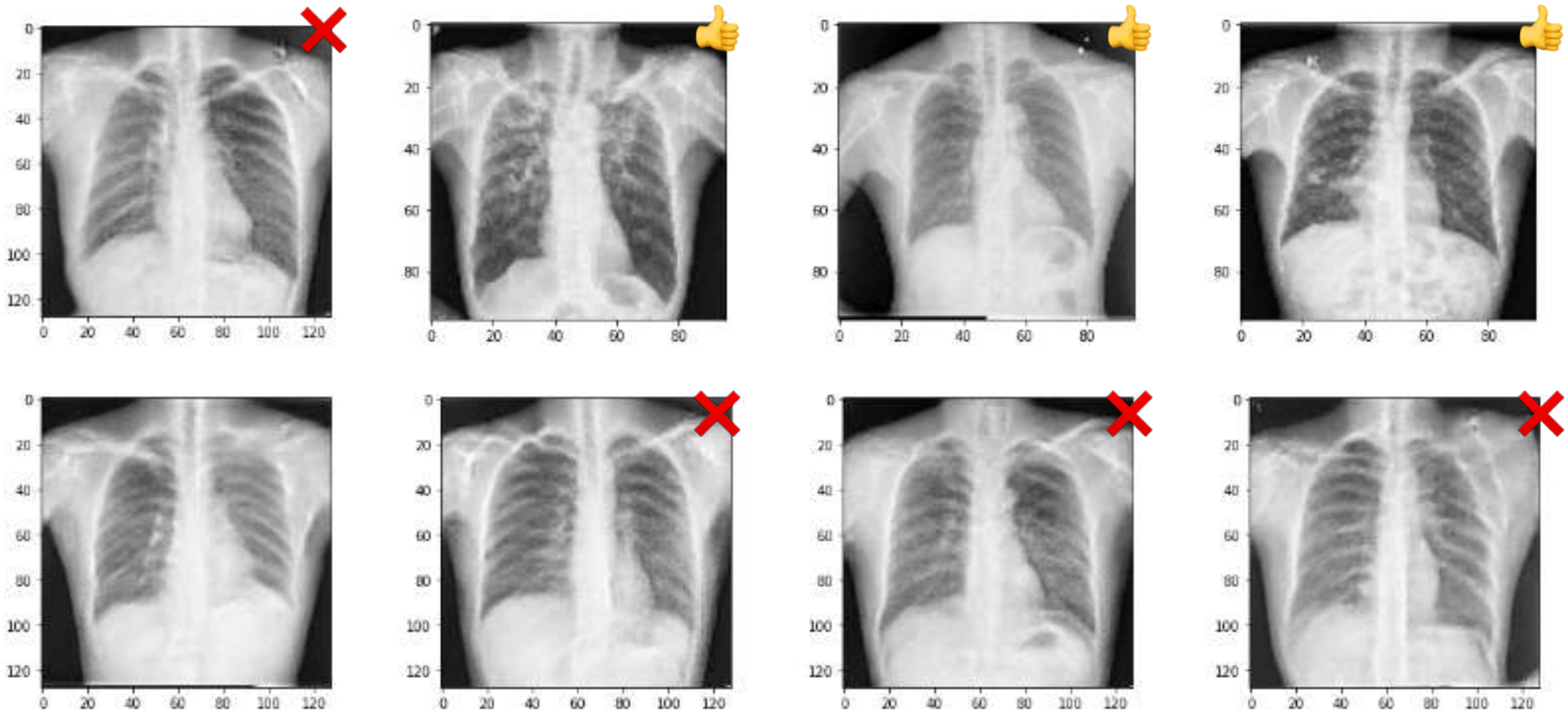
For Data Augmentation

Real or Deep Fake?



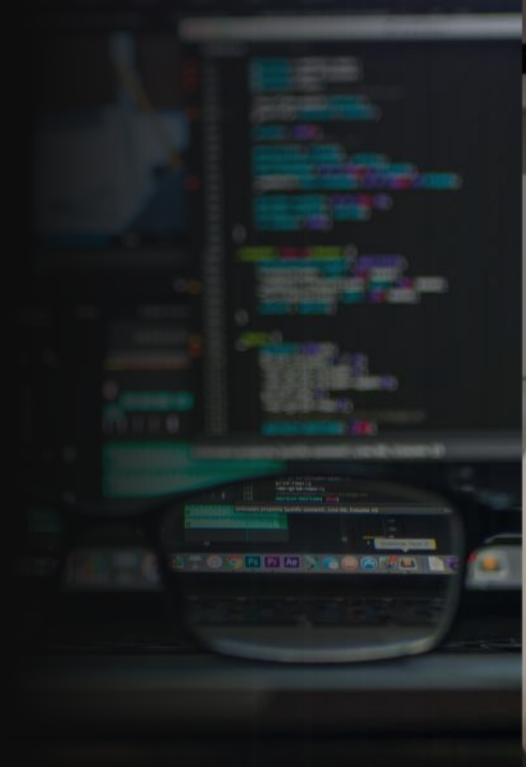
Thumbs up for real data!

Real or Deep Fake?



A huge thank you to Guilherme Goldman, which worked hard for tuning the GANs and provided the images for this presentation

Back-up

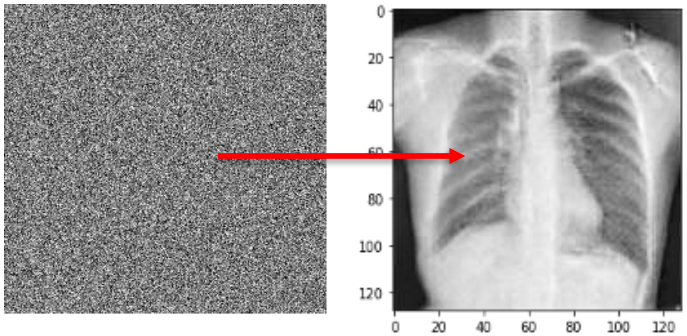


> Learning Data Transformations

For Data Augmentation

- Decoder-based generative networks (e.g. GANs) provide a way to capture the data structure:
  - Many use cases for medical image synthesis for data augmentation;
- Main synthesis schemes:
  - Unconditional synthesis (**currently using**): transform arbitrary structure (“noise”) into data structure;
  - Conditional synthesis (more useful, but demanding): transform arbitrary structure into the data structure under some conditions
    - i.e. consider variations only on the lungs, or use segmentation information;

Unconditional Synthesis



Conditional Synthesis