Variational Autoencoders for Brain Tumor Prograssion

Sptember , 1st

Outlines

- Why Autoencoders (Variational Autoencoders)?
- Autoencoders
  - Network model
  - Objective function
  - Applications
- Variational Autoencoders
  - Network model
  - Objective function
- Why VAE is a candidade model for our work?

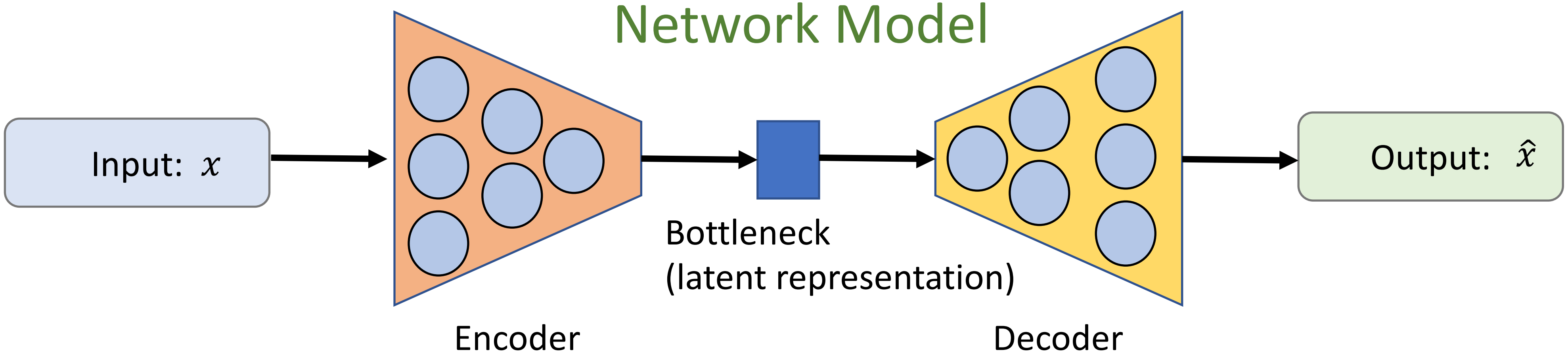
Why Autoencoders (Variational Autoencoders)?

- In many real world data (Image, audio, text) the underline factors which represents the data can be much simpler.
- Machine Learning (ML) algorithms transform (non-linear) high dimensional data into a smaller representation.
- One of the techniques are Autoencoders (Variational Autoencoders).
- Why?
  - Discover useful representations
    - Not just for current task but unknown tasks (future tasks)
  - Ignores irrelevant information or redudant information

Autoencoders -> learn the underlying manifold

- Takes higher dimensional data and runs it into a neural network.
- It does that with 2 components
  - Encoder -> higher dimension to lower representation
  - Decoder -> reconstruct lower representation back to input
  - Bottleneck -> specify the dimension of compression (number of variables)

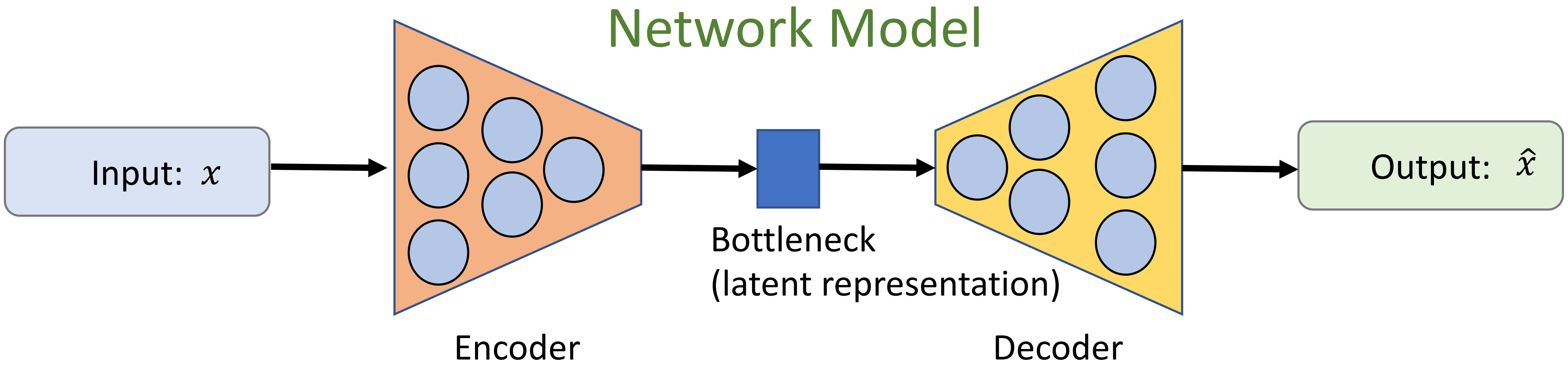
Network Model



Objective Function

$$loss = reconstruction(\hat{x}, x)$$

Remarks on Autoencoders

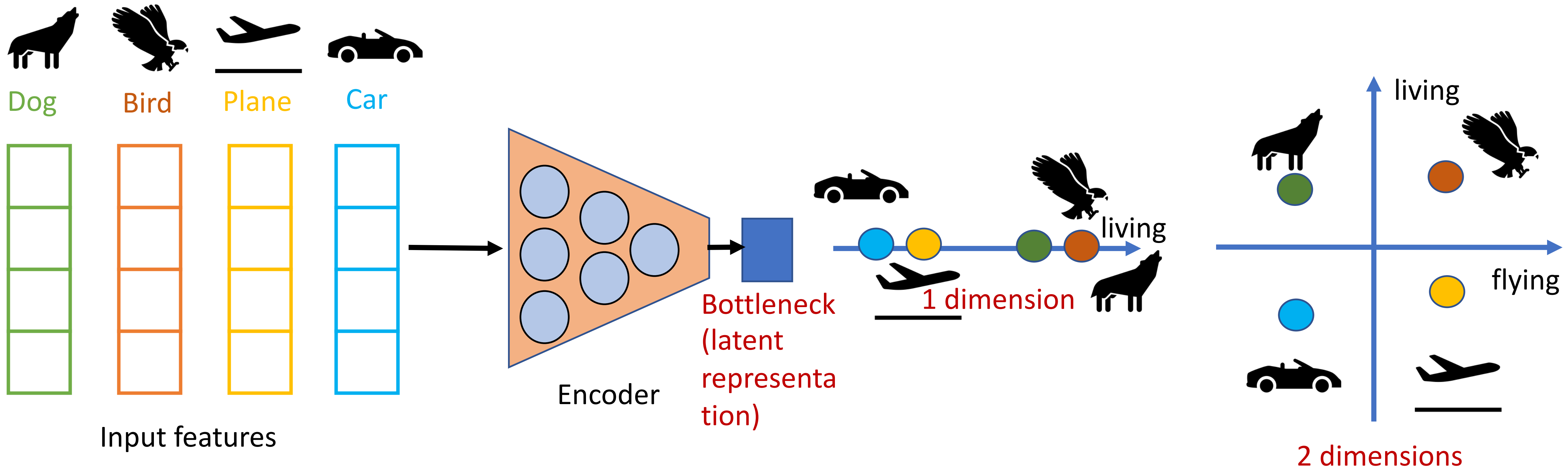


- How does feature learning or dimension reduction happen if the result is the same as the input?

- The transformation from input -> latent representation -> output allow us learn relevant properties of the dataset.

Remarks on Autoencoders

- When compressing the data we want to keep the main structure that well describe the data.



Applications of Autoencoders

- Image segmentation
  - Instead of reconstruction the input, we target the label (mask).

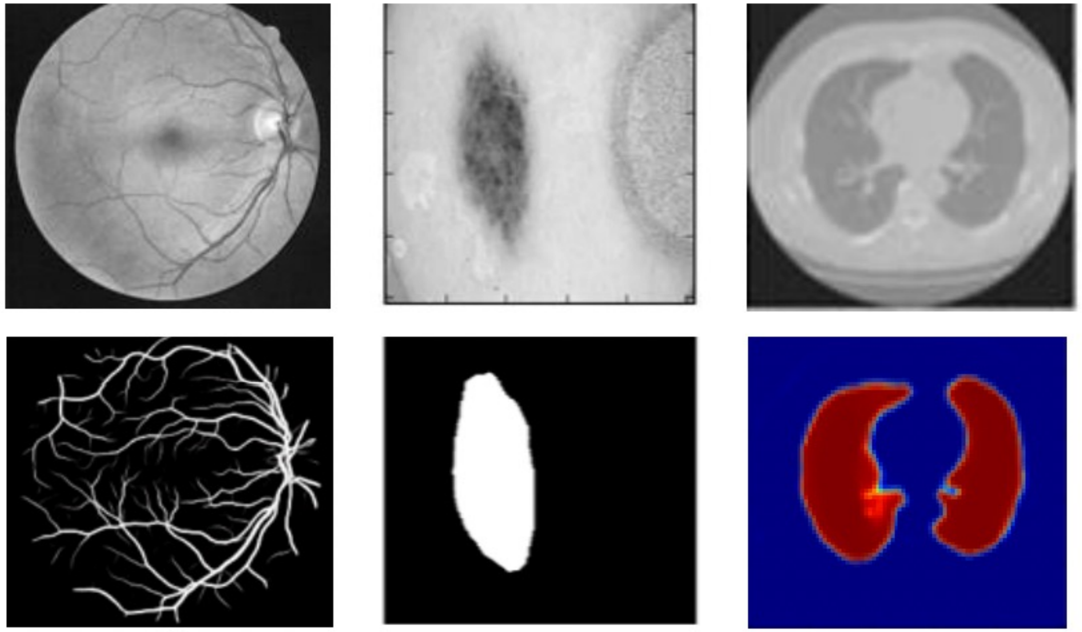


Fig. 1. Medical image segmentation: retina blood vessel segmentation in the left, skin cancer lesion segmentation, and lung segmentation in the right.

Alom et al.

Applications of Autoencoders - Denoising Image/image inpainting

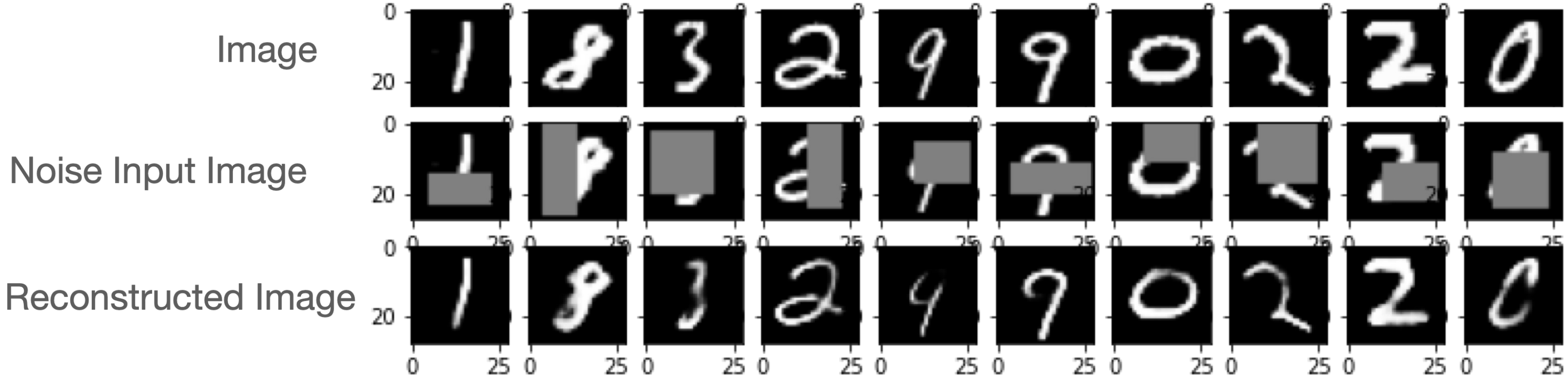
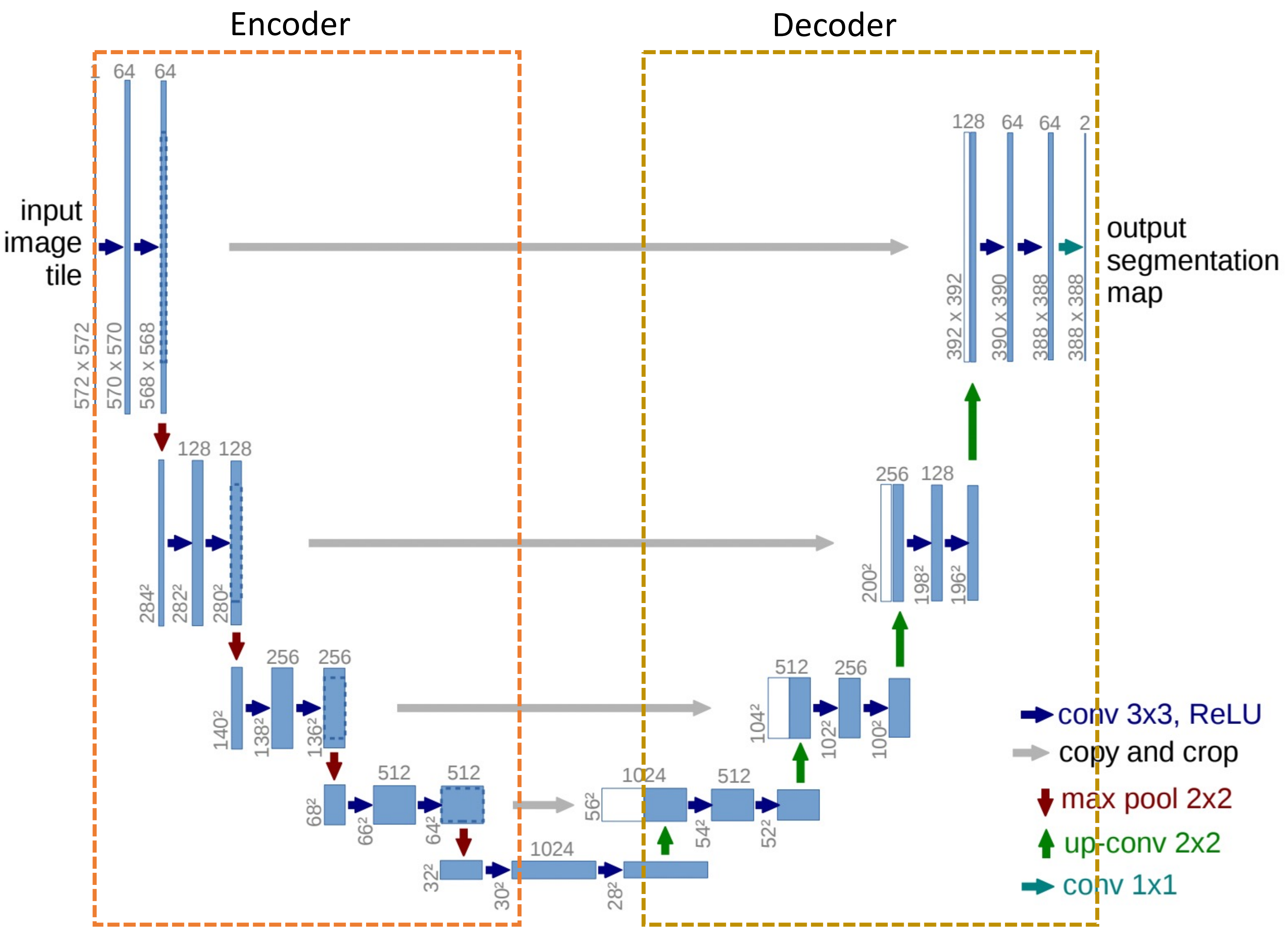


Image Denoising

Image Impainting - [Yu et al.]

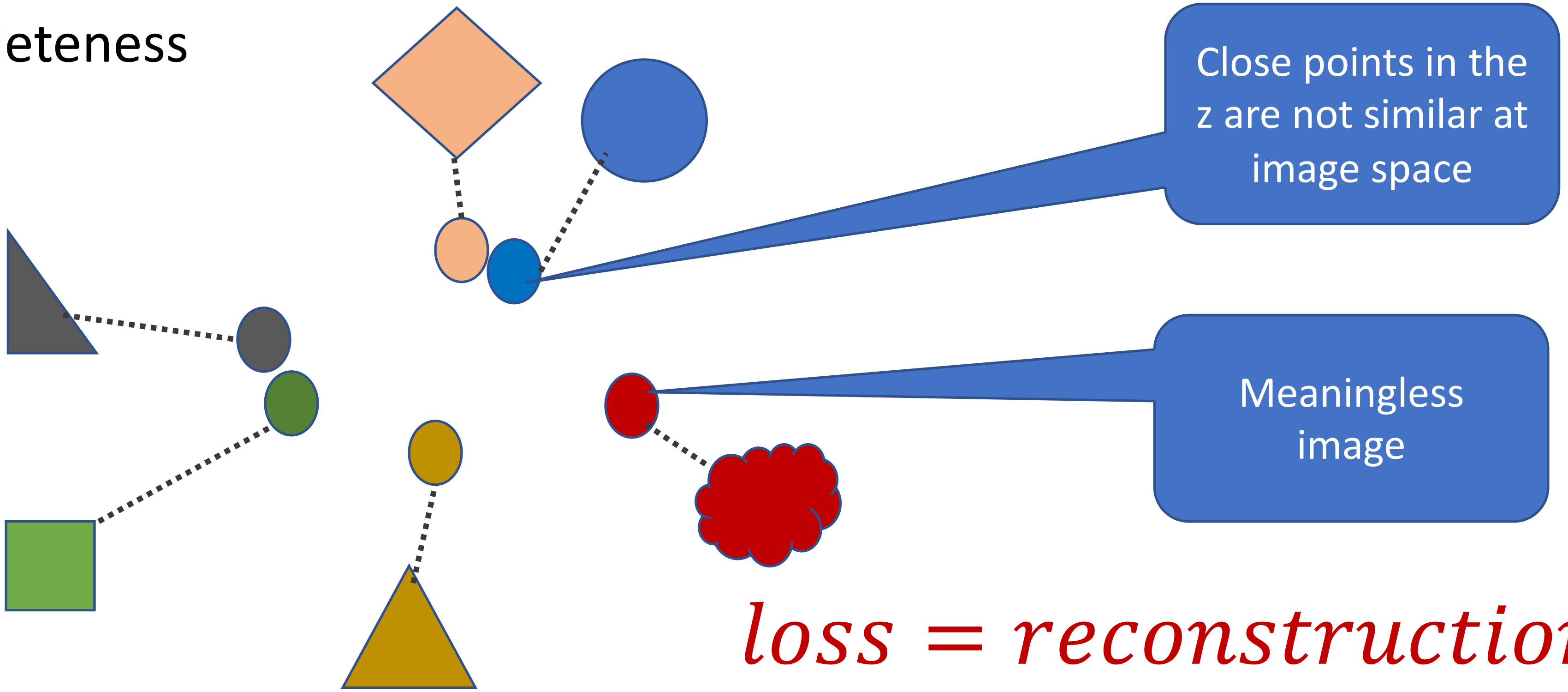
- During training, we encourage the model to learn a clean image
- For the model to be able to reconstruct clean image has to learn higher level semantics of the data.

U-net architecture [Image Segmentation]



Limitations of Autoencoders

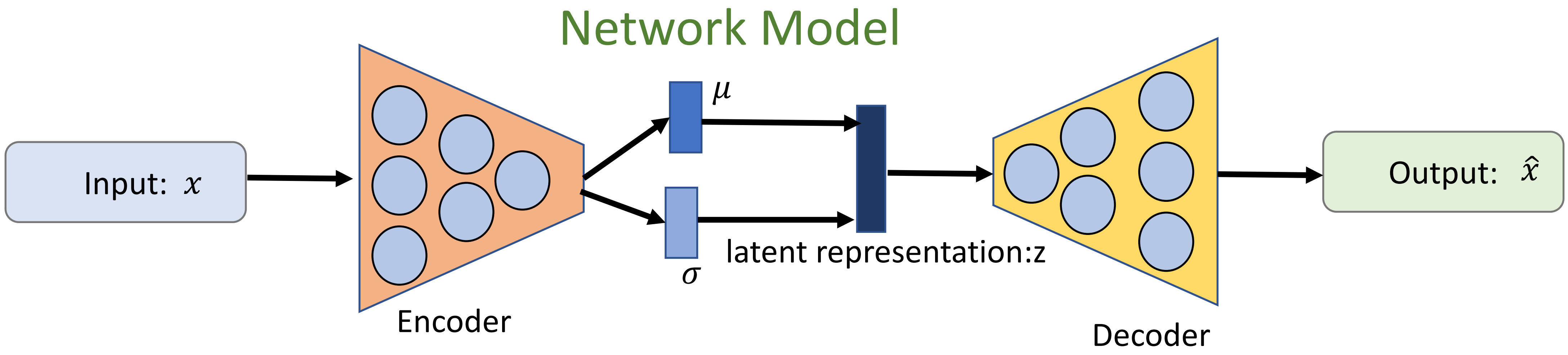
- The latent representation is not well structured (no regularization on latent representation).
- The loss function is not optimized to enforce a regular latent space.
- It lacks two main properties for generation.
  - Continuity (smooth interpolation)
  - Completeness



$$loss = reconstruction(\hat{x}, x)$$

Variational Autoencoders

- Modern version of Autoencoders
- We map an input to a distribution instead of a vector space as in AE.



$$Loss = reconstruction(\hat{x}, x) - KL_D(posterior[N(\mu, \sigma) \mid prior(0, I))$$

- Reconstruction -> Pixel difference between input and output (MSE)
- KL divergence -> Regularize the latent representation (to have desired structure) for generation

Why VAE is a candidade model for our work?

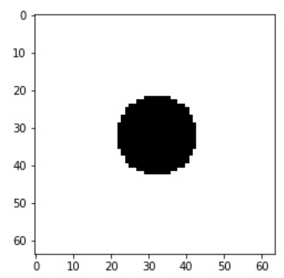
- Learn a powerful feature representation (manifold learning)
- For instance in our case:
  - For the model to be able to do a smooth interpolation, it has to learn the object localization, size and shape variability.
  - Fill the missing parts
  - Generative capability
- Easily we can transfer the knowledge learned to a new domain.

What can be Learned

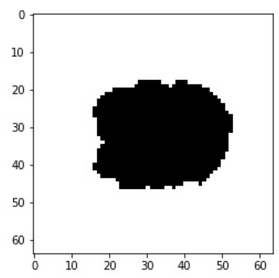
- The relationship between the hidden manifold and the clinical parameters.
- How the tumour develop in certain:
  - Ages,
  - Gender,
  - Location

Front Propagation (Dataset)

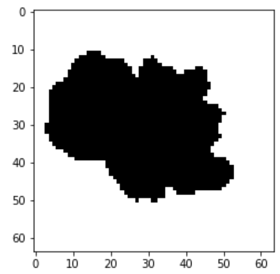
- Intially, we are working with toy dataset



1st Time Stamp



2nd Time Stamp

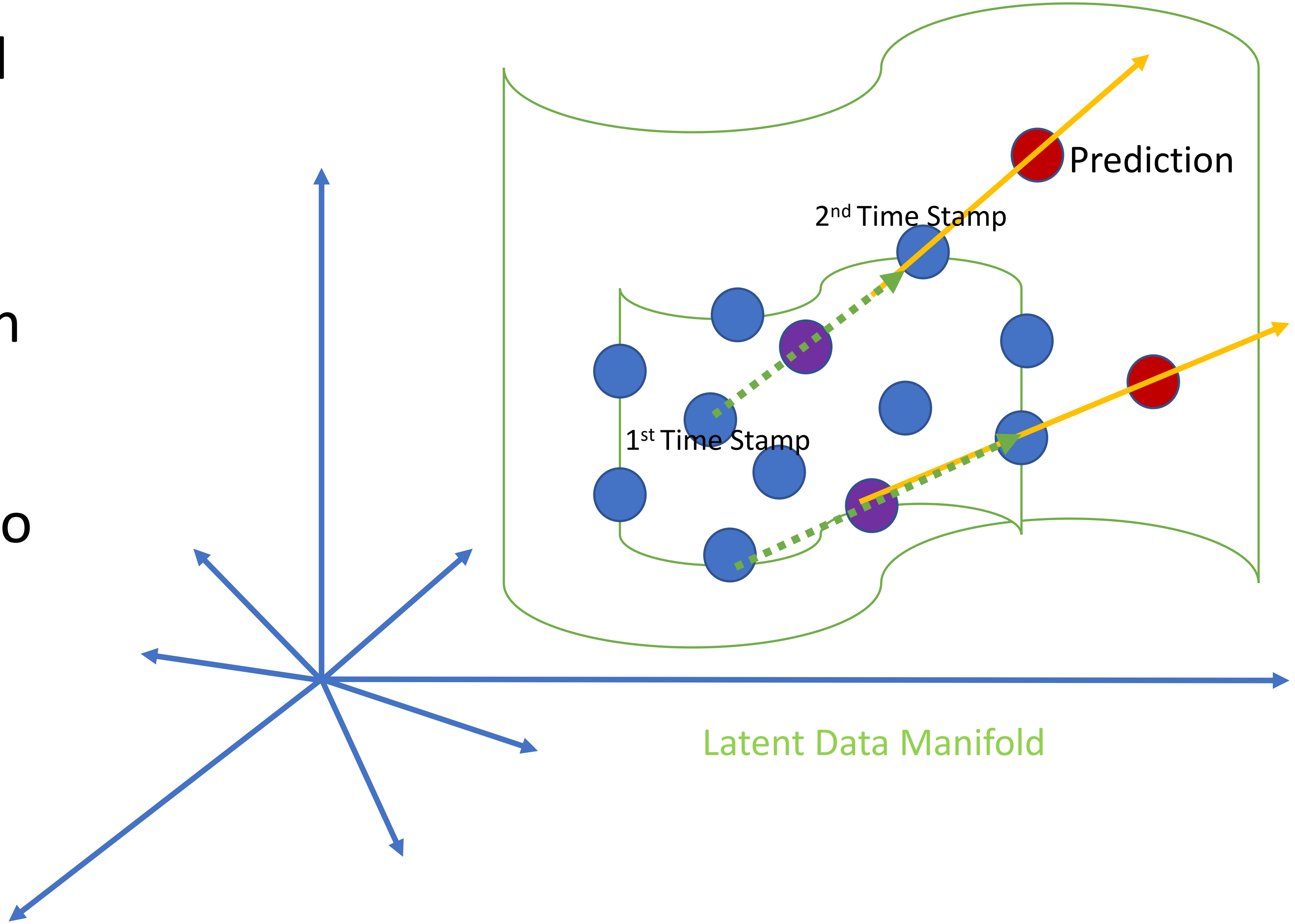


3rd Time Stamp

- Objective
  - Predict the progression of the front at specific time stamp knowing the first and second time stamp

The Model is based on VAE

- The objective is to control the latent space representations.
- We aim to have a latent manifold that allow smoth linear interpolation and extrapolation.
- Linear Interpolation of two blues points generates a purple one.
- Linear Extrapolation generates a red point



Results on Toy Dataset - Reconstruction

- Goal: Reconstruct the initial input data
- This is just a sanity check to evaluate if the model learned the structure (geometry) of the data.

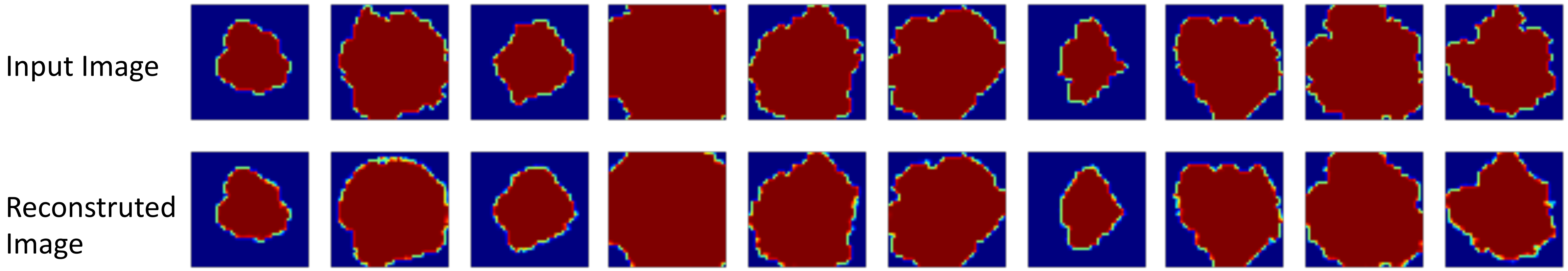
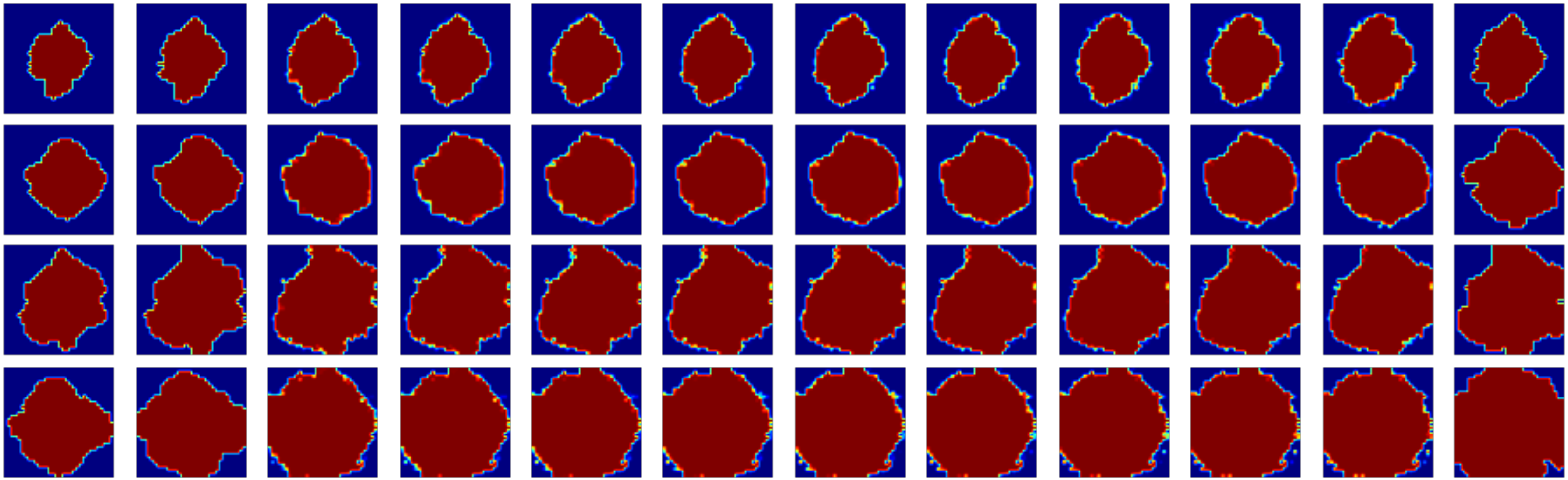


Image Extrapolation [main objective]

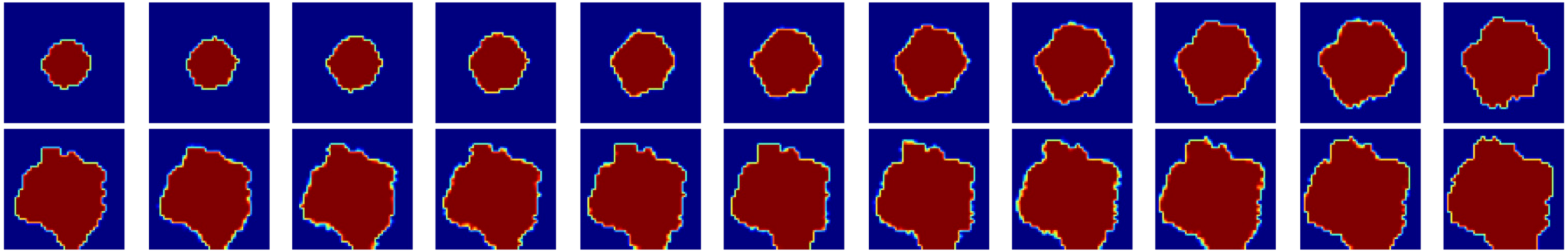
- Linear Extrapolation
- Img1*alpha + img2(1-alpha)

For smaller displacement between (img1,img2) it looks fine [1st row]. However, for large one does not give good results



Intial front 0 Intial front1 Extrapolation Intial front 2

Image Interpolation [sanity check]



Intial front

Propagation

Final front

Future work

- Work with actual brain tumor image [The dataset sample is in pdf file]