# Predicting Radiotherapy Replanning for Head and Neck Cancer

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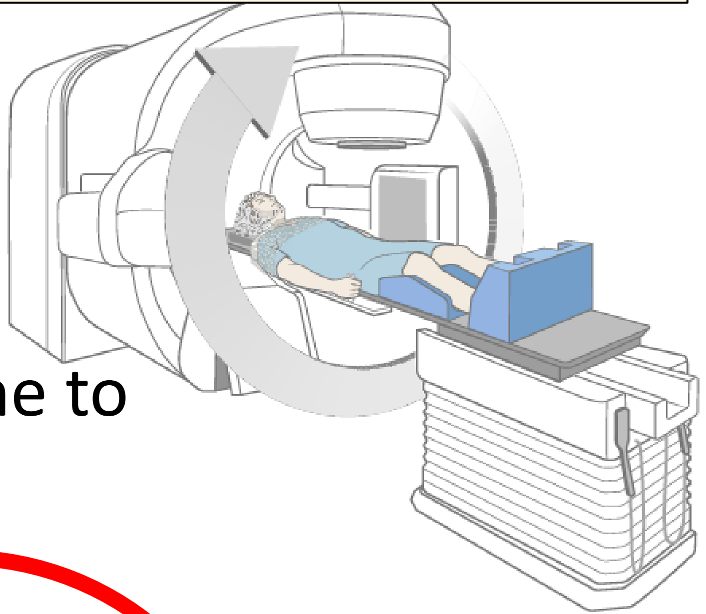
NSERC CRSNG

# Radiotherapy & Anatomy Changes

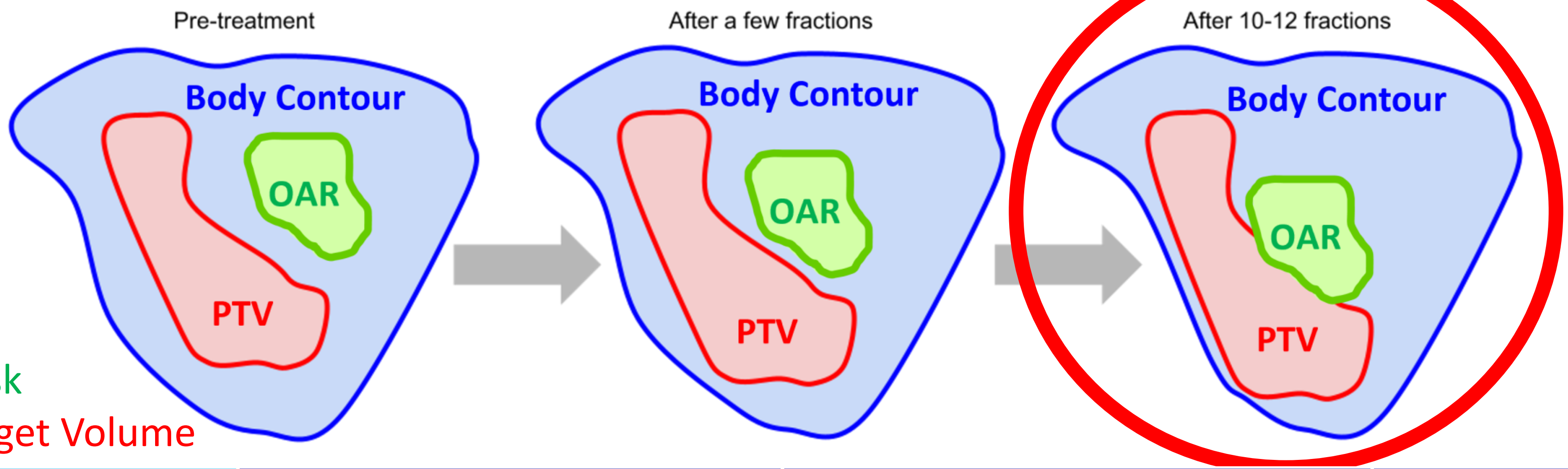
Image-Guided Radiotherapy (IGRT)



- **Inter- and intra-fractional changes** during radiotherapy (bladder filling, patient positioning…)

- In particular, **head and neck cancer** patients are prone to **anatomical changes** over the course of radiotherapy

  → Not anatomically rigid → Weight loss




**Replan Patient**

OAR = Organ At Risk
PTV = Planning Target Volume

# The current problem with replanning

Radiotherapy replanning is resource-intense and decisions are often made at the last minute

Workflow disruption and resource burden to the planning team.

- Can affect other patient's timelines
- Continued use of suboptimal plans

**Overall Aim:** to predict which patients will need replanning ahead of time.

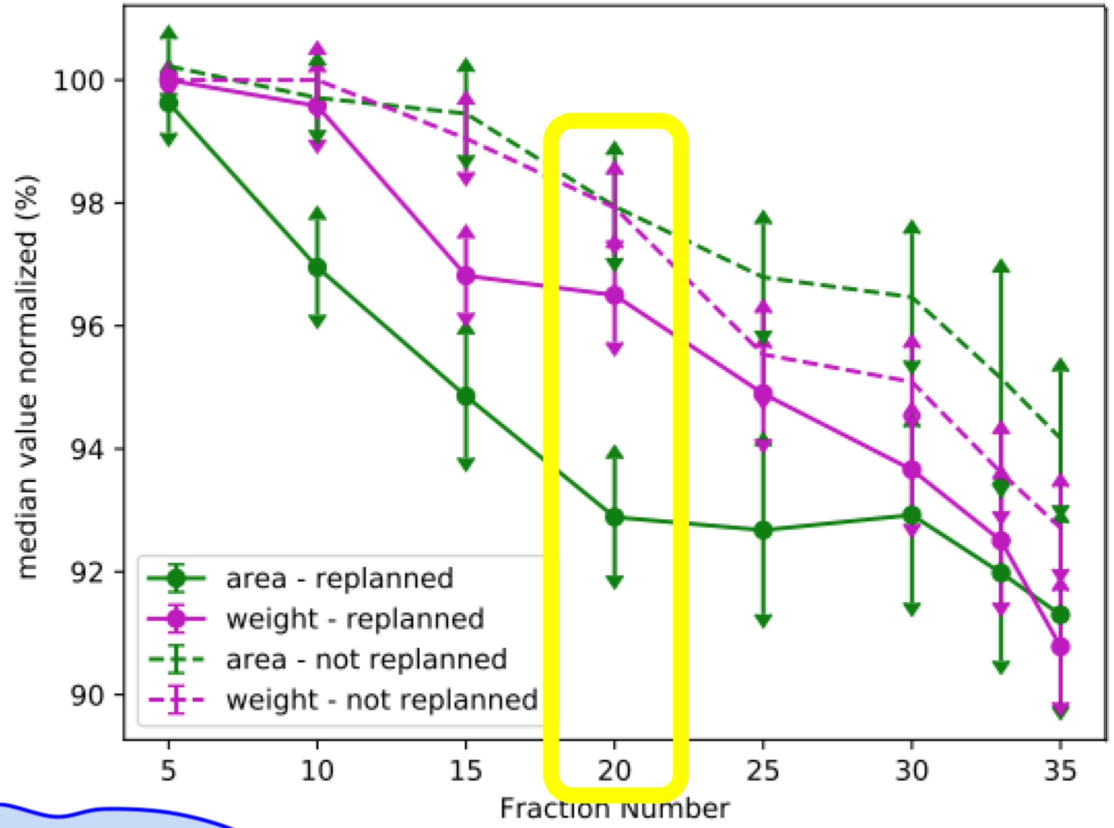
# Weight-related metrics and replanning decisions

- **Weight** loss

  - Insufficient for replanning decisions

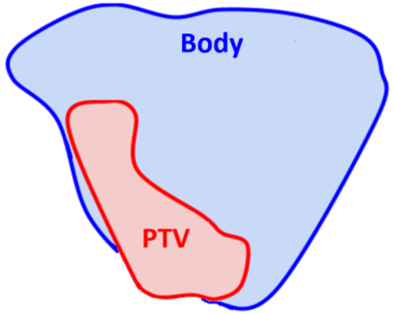
- **Cross sectional neck area** from daily CBCTs


  - Most sensitive around 20 fractions




- **Indicator used in clinic:**

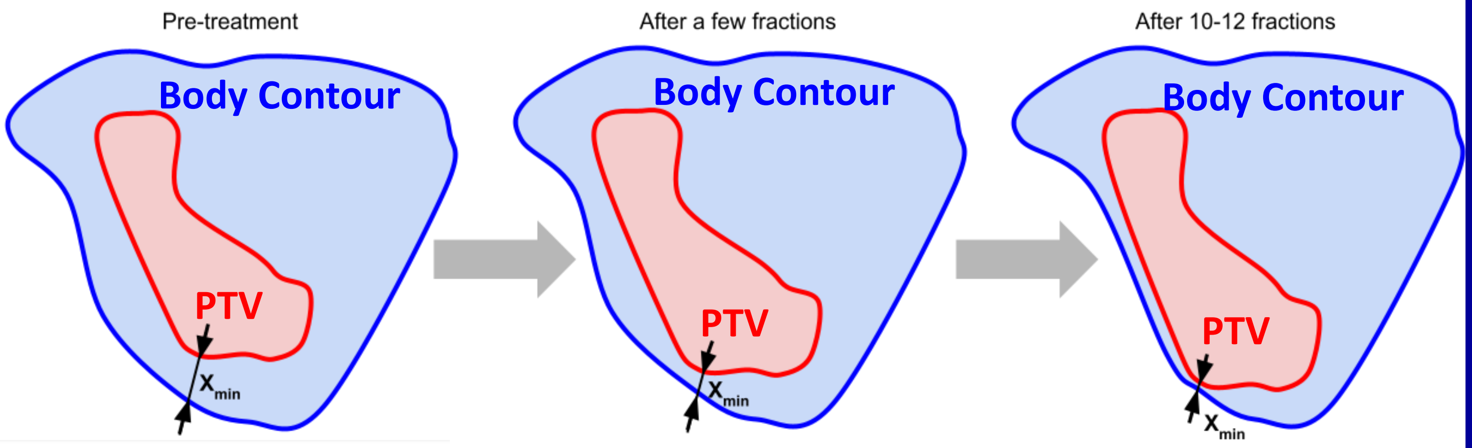
  → target volume (PTV) exits neck

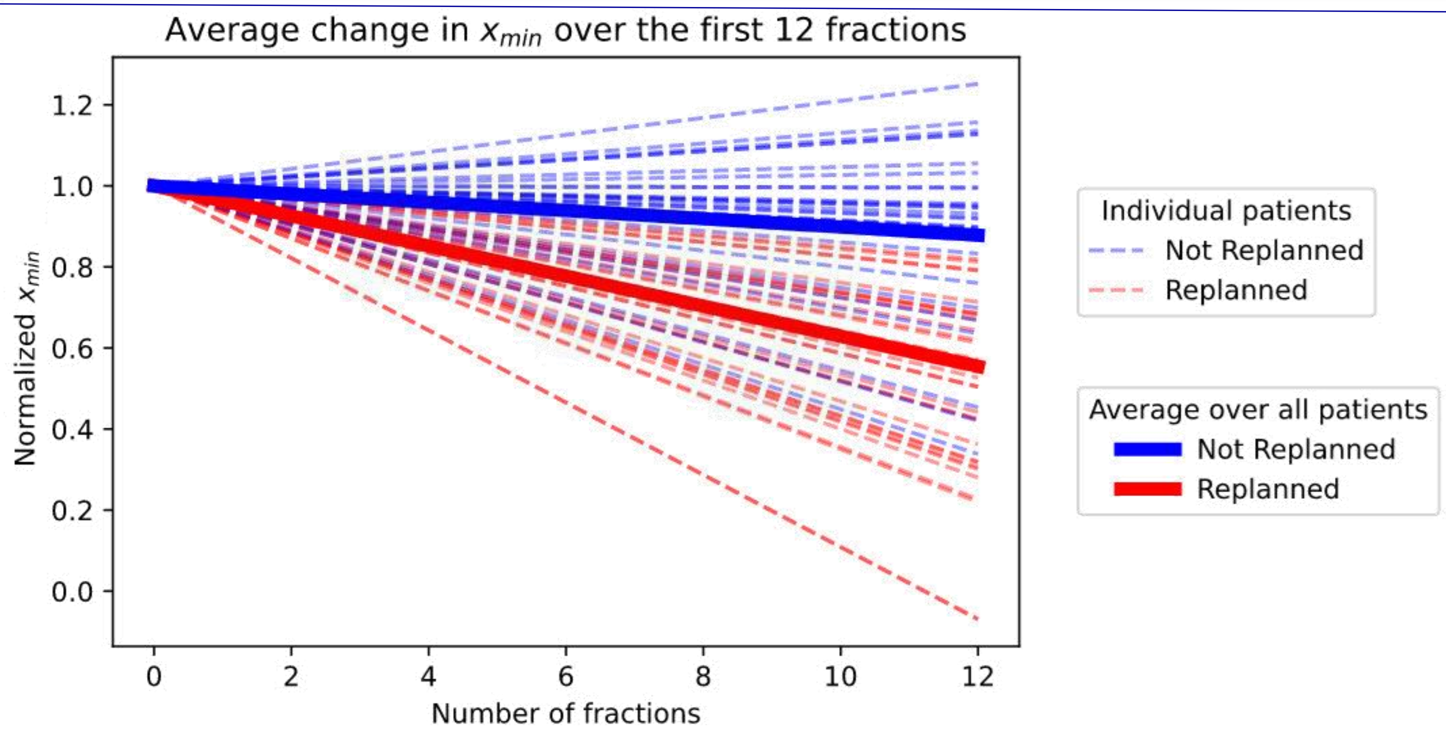



**Metric to describe this?**

# New Metric: $x_{min}$

$x_{min}$: minimum distance between the PTV and skin

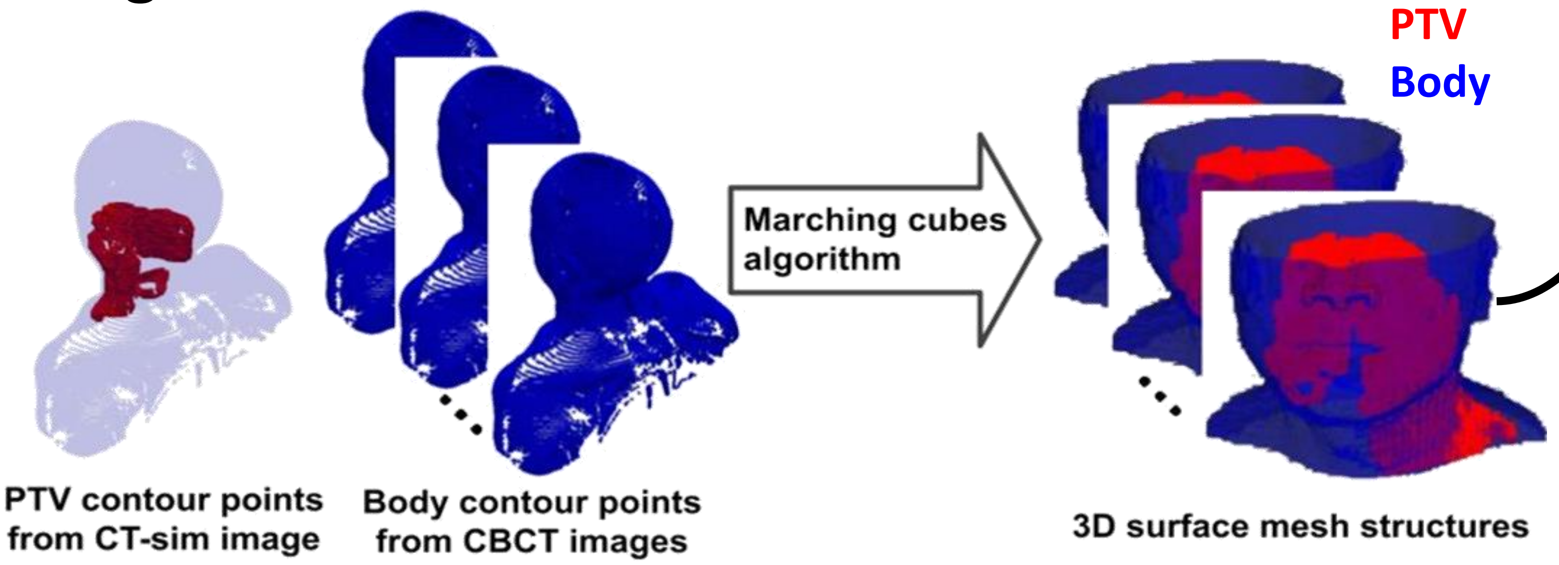



In particular, the ***rate of change of $x_{min}$*** may be predictive of the need to replan

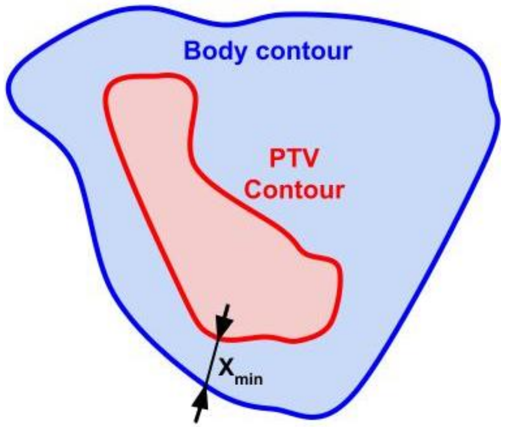
# 3D Metrics

- Algorithms to extract 3D features




**Extract 3D features**

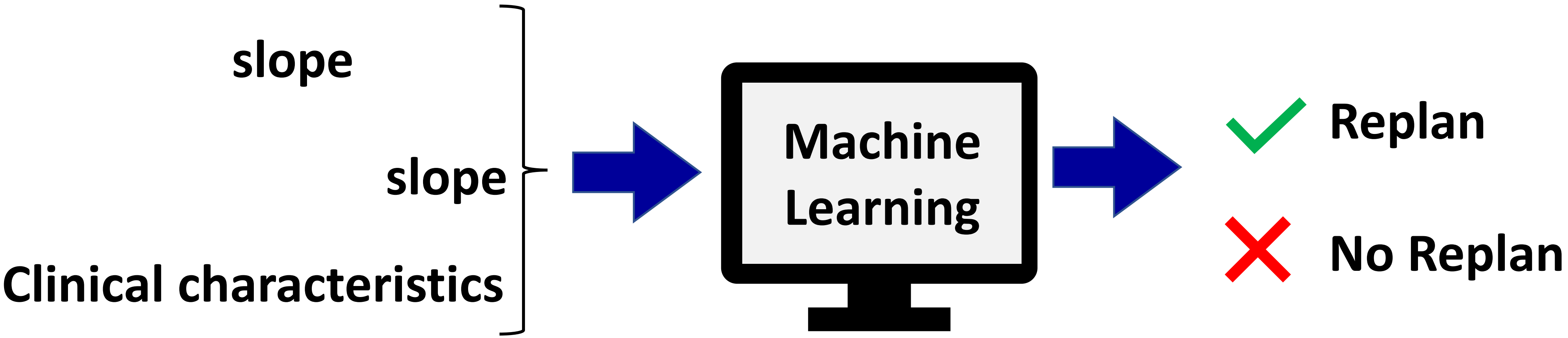
- PTV and Body Volumes
- True (3D) $x_{min}$
- …




- **Rate of change of $x_{min}$ and PTV-Body volume ratio** were statistically significant predictors of replanning as of the **10th treatment fraction**

Work by James Manalad & Srishti Ahlawat

# 3D Metrics & Machine Learning

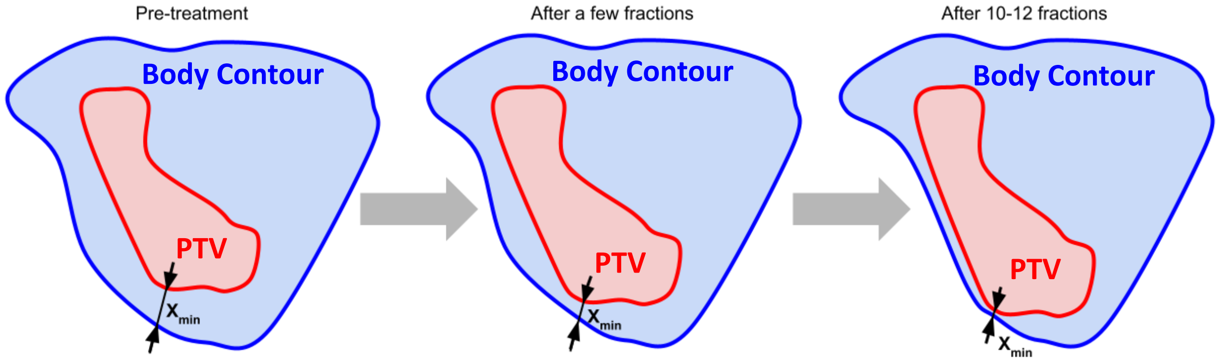


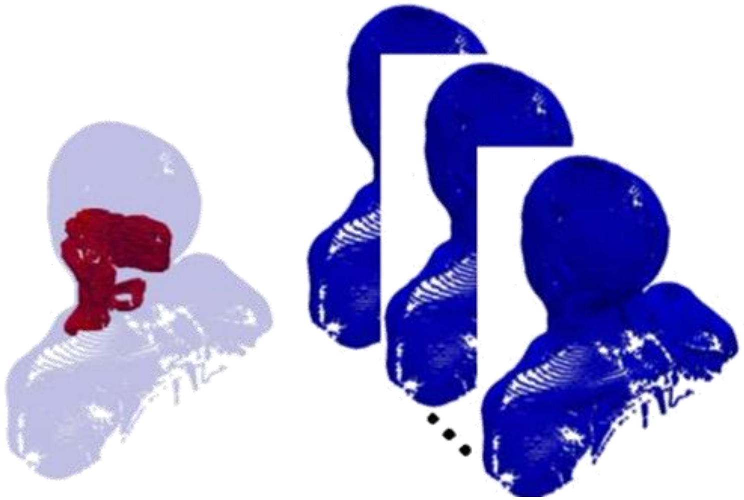

**Limitation:** only 59 patients

**Solution**: Working on automatic extraction pipeline using Eclipse Scripting API.

# Summary of work so far

- Identified $x_{min}$ (minimum distance between PTV and skin)
- Algorithm to extract 3D anatomical metrics predictive of replanning.
- Started looking into machine learning algorithms to predict replanning.

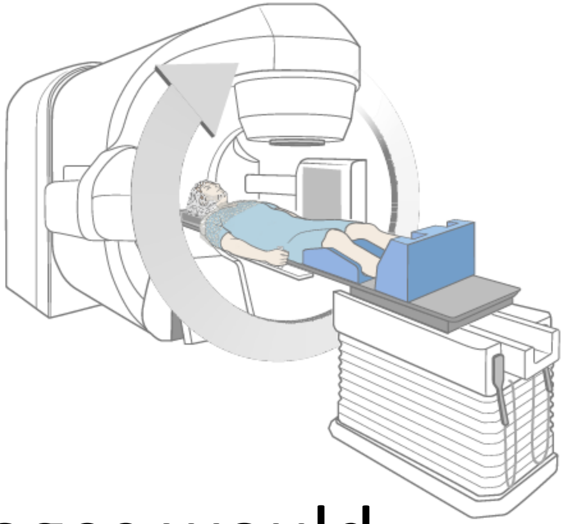


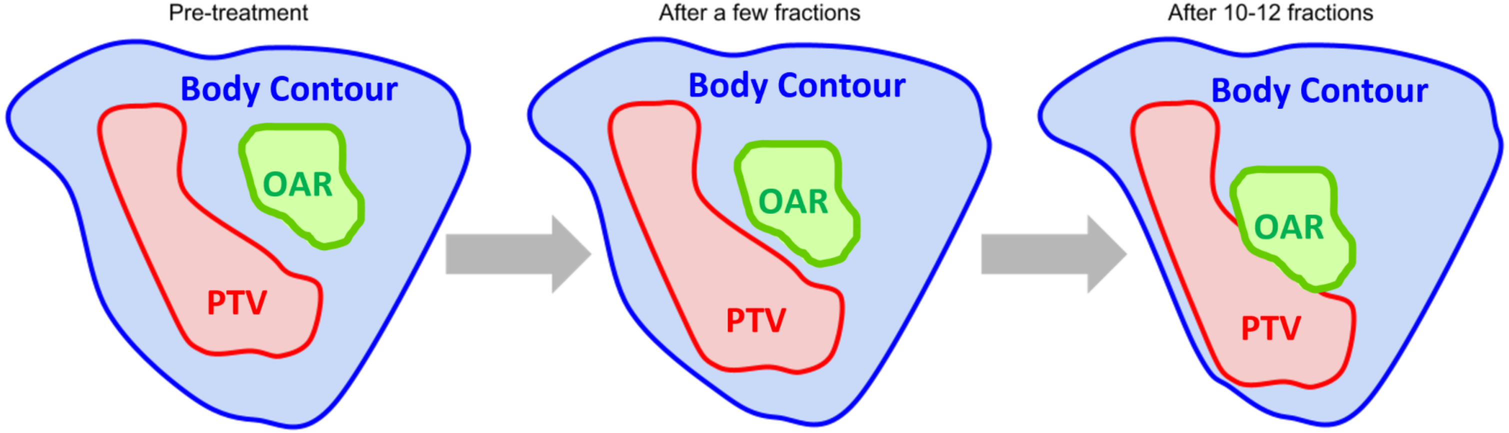
# Looking towards the future

**What now?**

Ultimate decision to replan will likely still be made based on CBCT images.



**What if…** we could predict what those CBCT images would look like in advance?



# Predicting future images

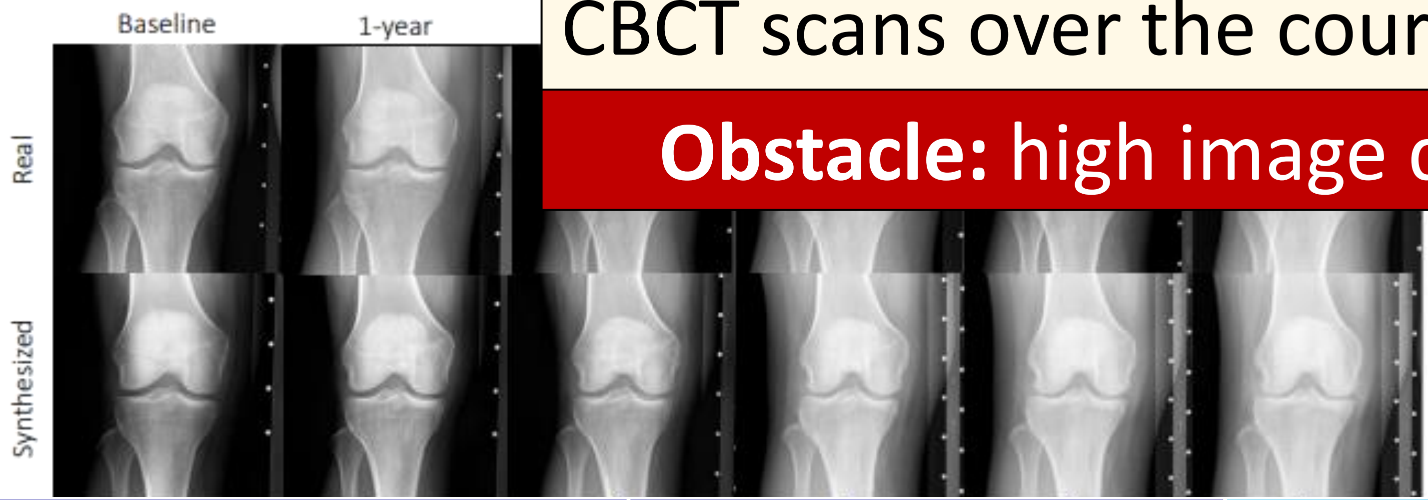
nature machine intelligence

Article | Published: 16 November 2022

**Image prediction of disease progression for osteoarthritis by style-based manifold extrapolation**

Tianyu Han, Jakob Nikolas Kather, Fede… Schulze-Hagen, Marc Terwoelbeck, Peter I… Volkmar Schulz, Sven Nebelung & Dani…

*Nature Machine Intelligence* **4**, 1029–1039…



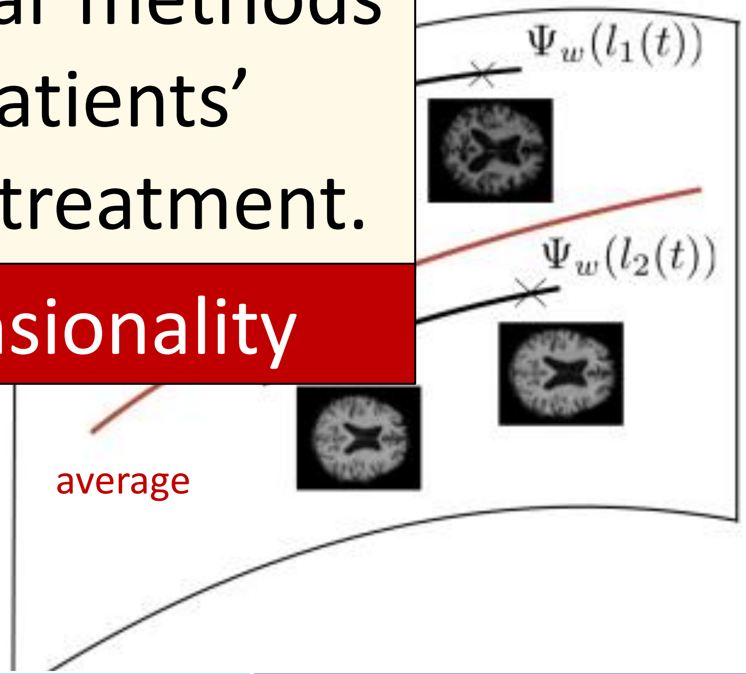

Riemannian Geometry Learning for Disease Progression Modelling

Maxime Louis, Raphaël Couronné, Igor Koval, Benjamin Charlier & Stanley Durrleman

Conference paper | First Online: 22 May 2019

**4543** Accesses | **11** Citations

Part of the Lecture Notes in Computer Science book series (LNIP,volume 11492)

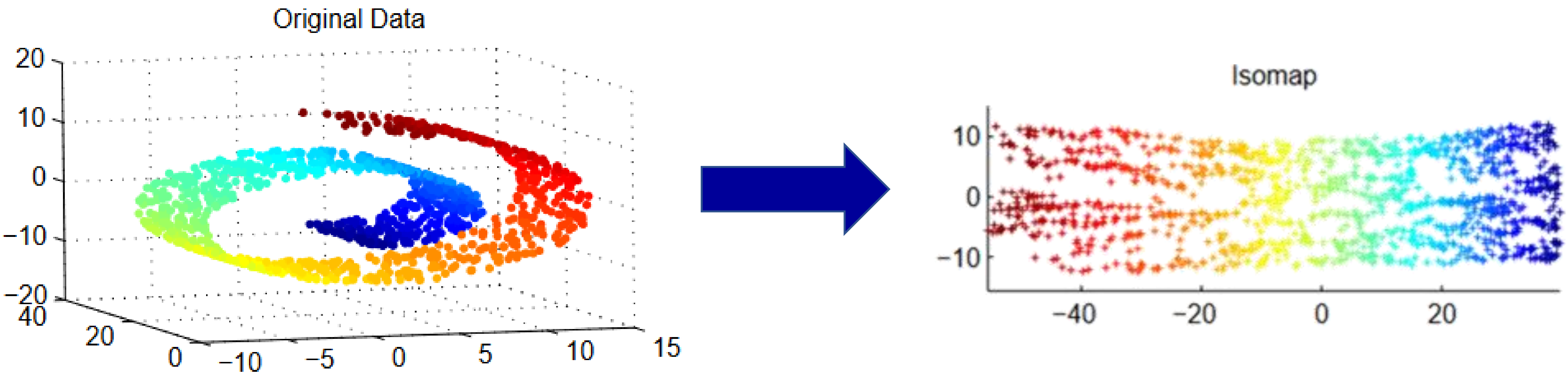



**Our future goal:** to apply similar methods to predict the progression of patients' CBCT scans over the course of treatment.

**Obstacle:** high image dimensionality

# Manifolds for reducing dimensionality

- High dimensional data is difficult to work with, but can have overlapping/redundant features
- **Manifolds**: the data set lies along a low-dimensional manifold embedded in a high-dimensional space.




$\mathbb{R}^3$ $\mathbb{R}^2$

# Manifolds for reducing dimensionality

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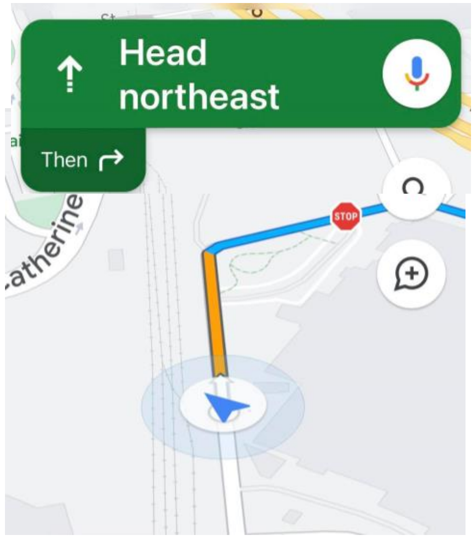
$\mathbb{R}^3$

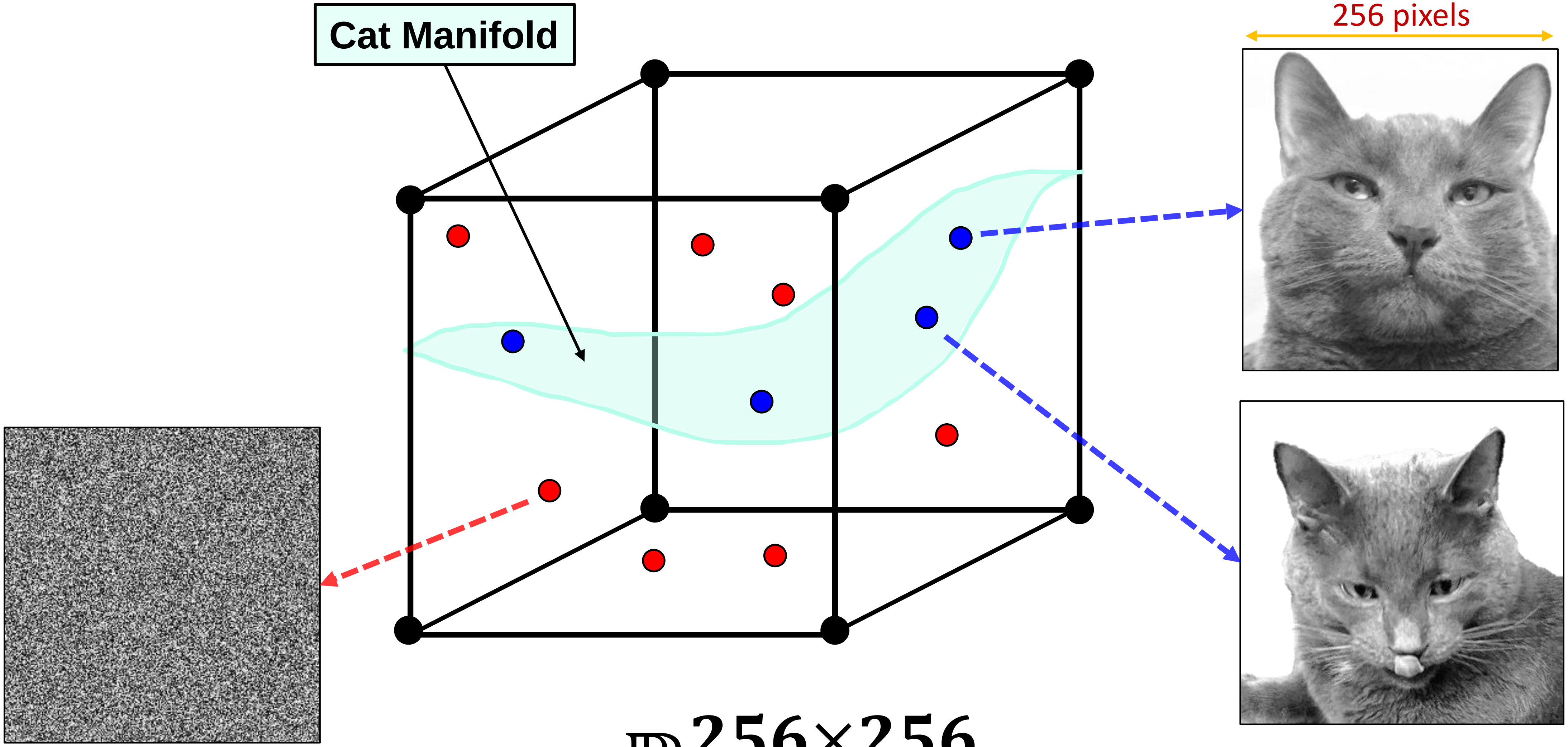
$\mathbb{R}^2$




$\mathbb{R}^1$

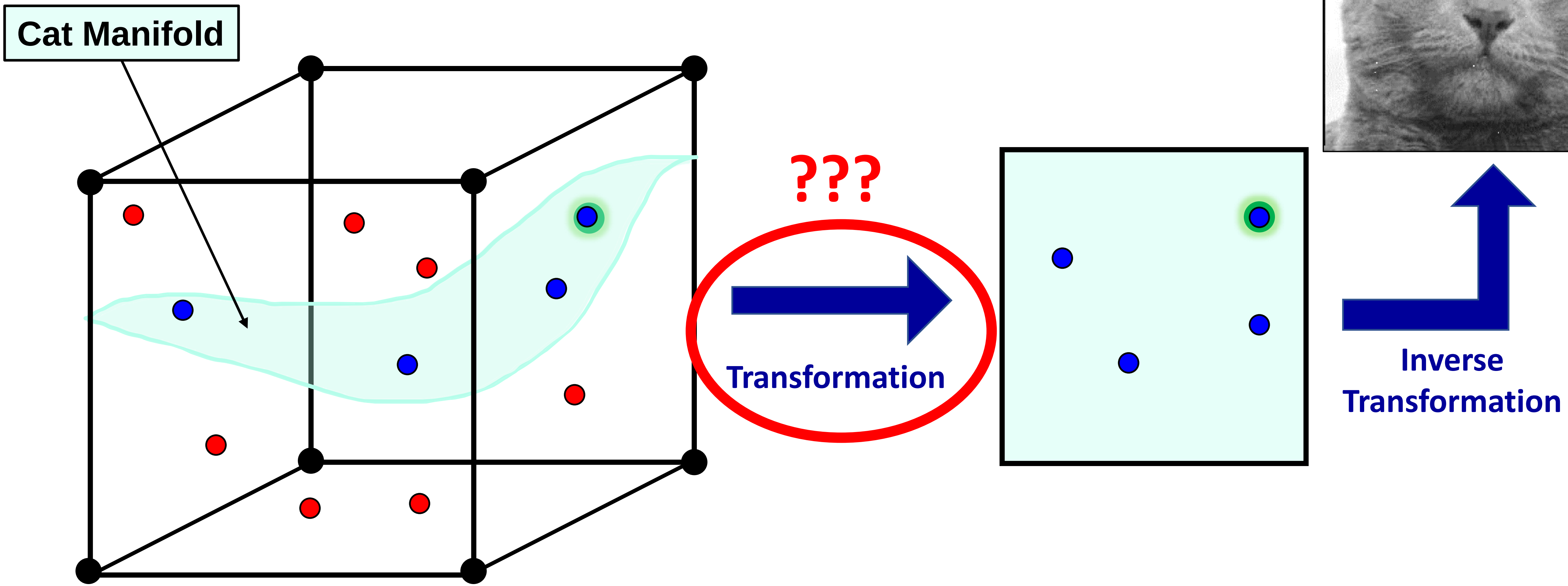
# Image Manifolds

$$pixels = [0.1, 0.55, 1,\ 0.4, \dots, 0.98]$$



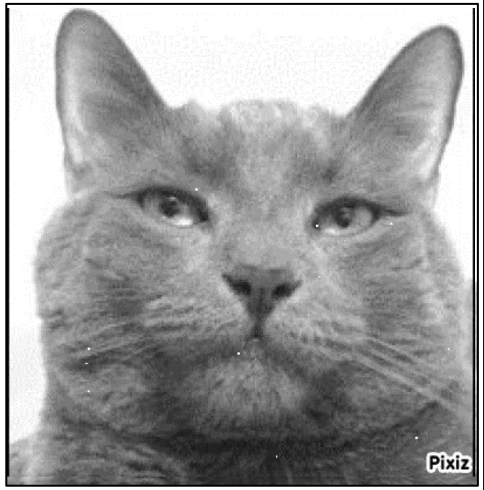

$$\mathbb{R}^{256\times256}$$

# Image Manifolds

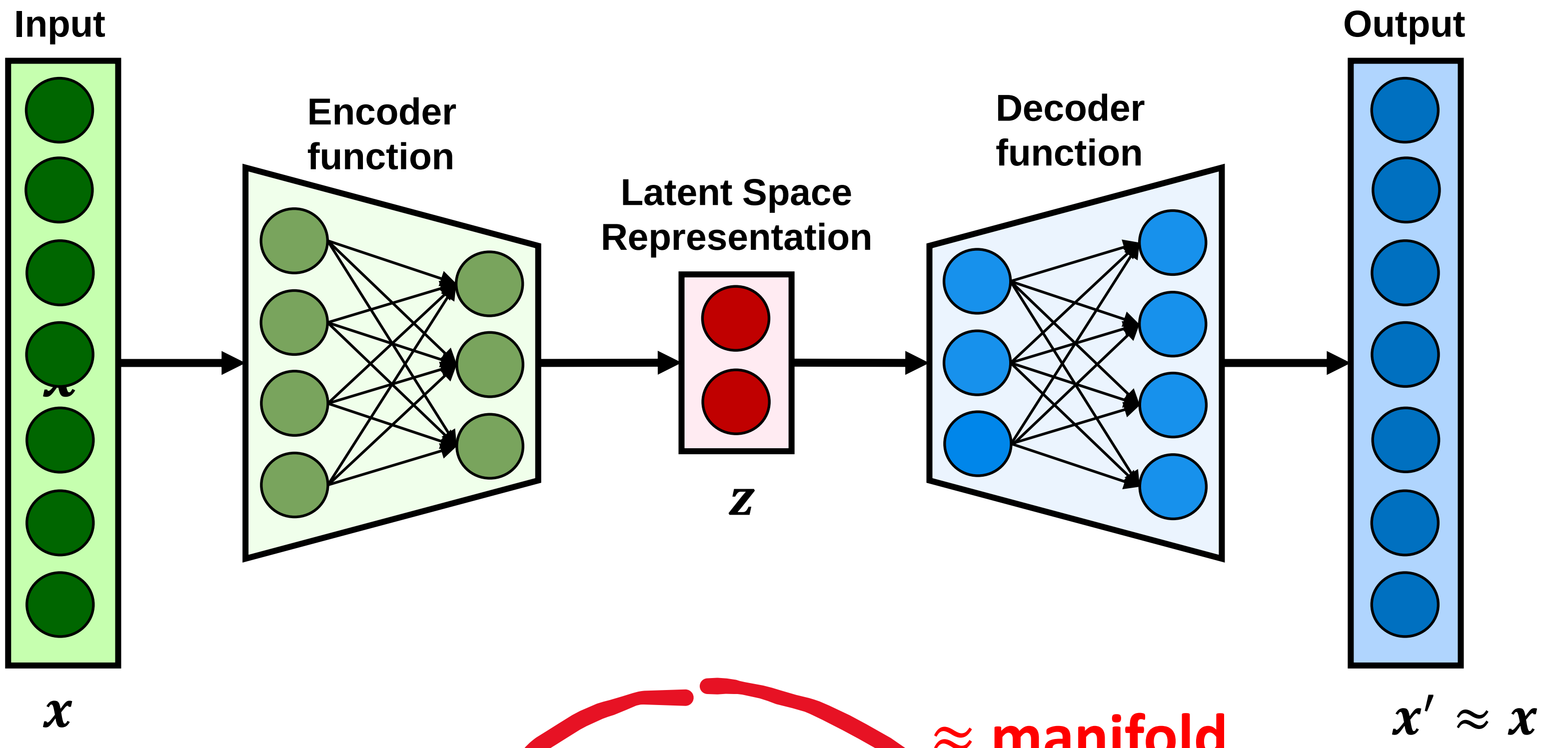


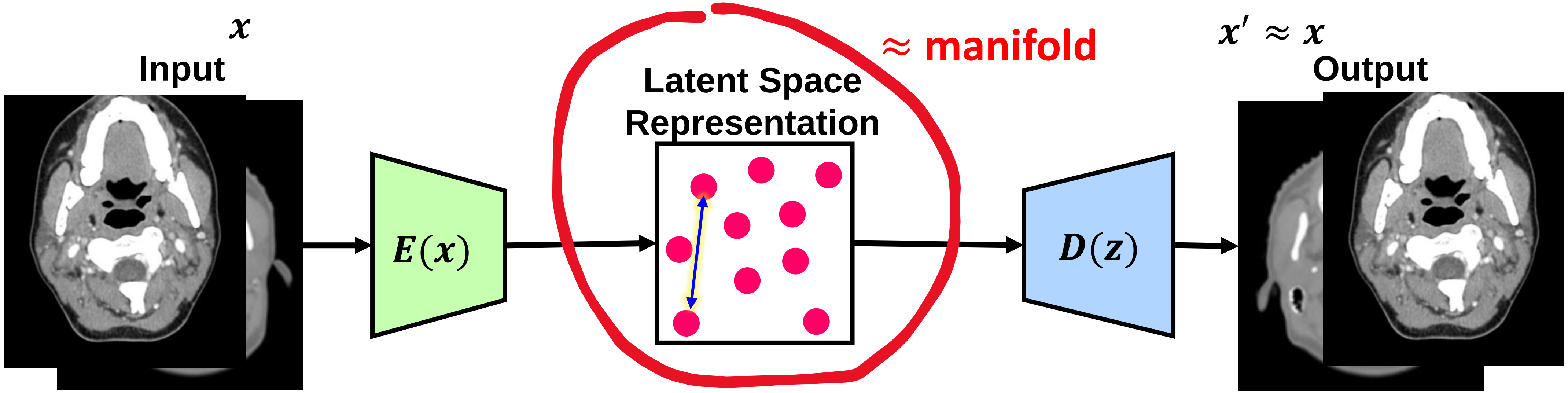

$\mathbb{R}^{256\times256}$

$\mathbb{R}^{smaller}$

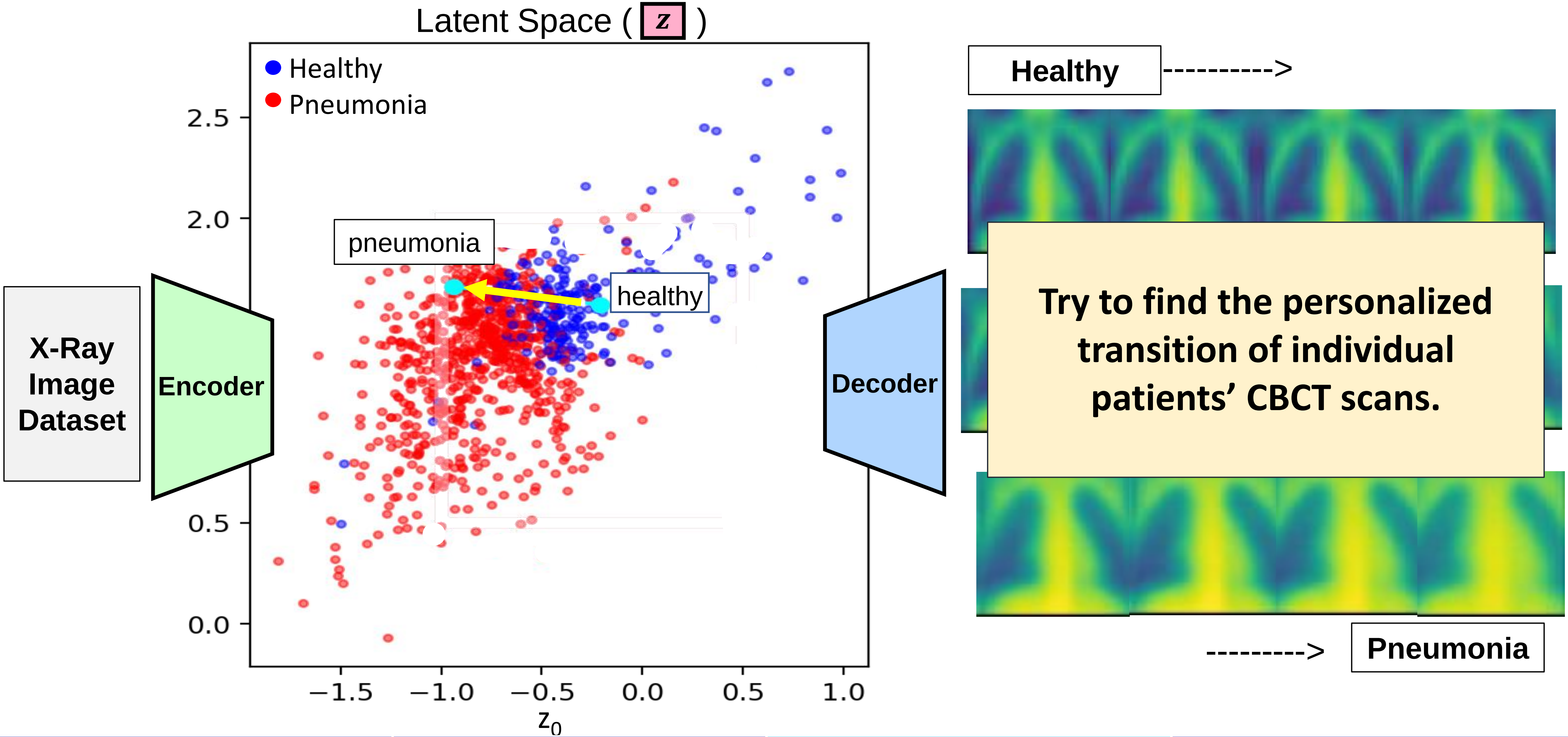


# Autoencoders to learn manifolds



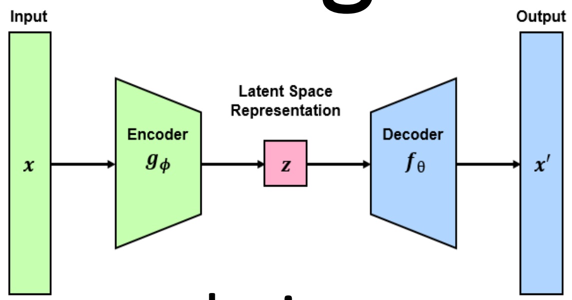



# My past project: Autoencoders on X-Ray images



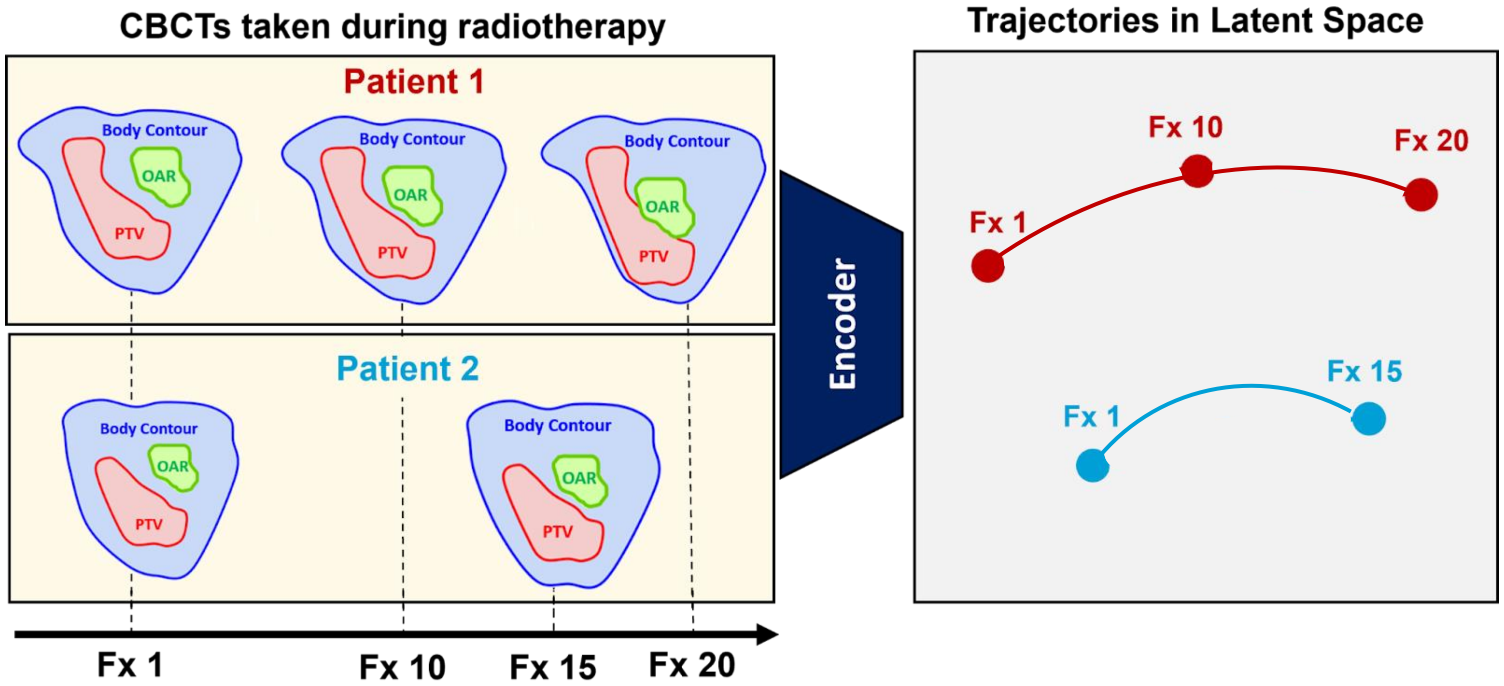

**Try to find the personalized transition of individual patients' CBCT scans.**

# Application to Head and Neck Replanning




**Proposed Methodology:**

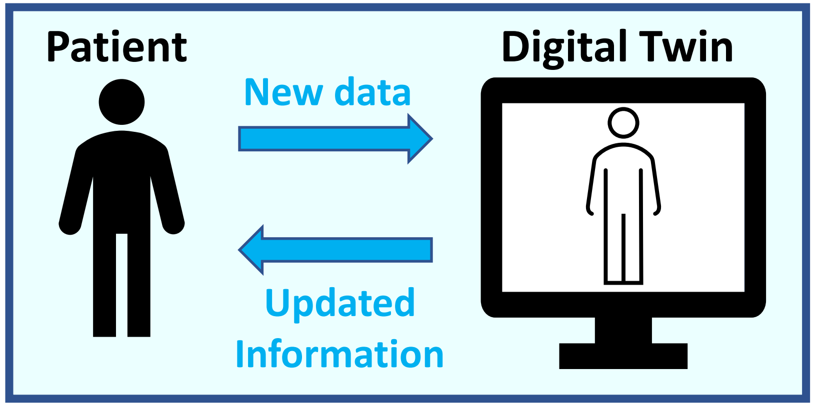
1. Train an autoencoder on CBCT images
2. Encode past patients' CBCTs into latent space & map their trajectory over treatment

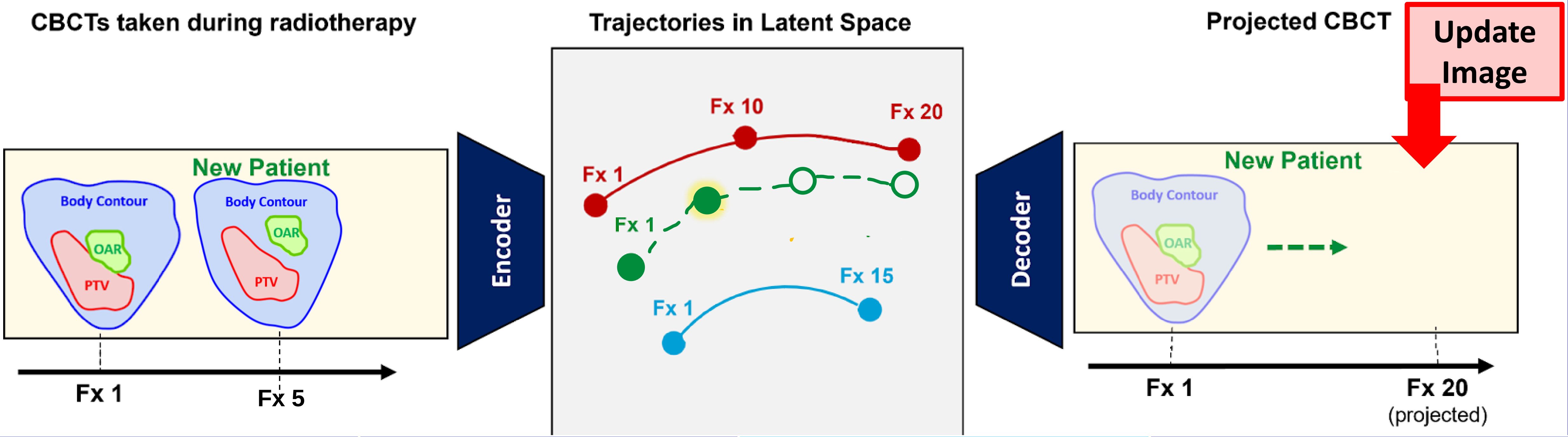


# Application to Head and Neck Replanning

**Proposed Methodology:**

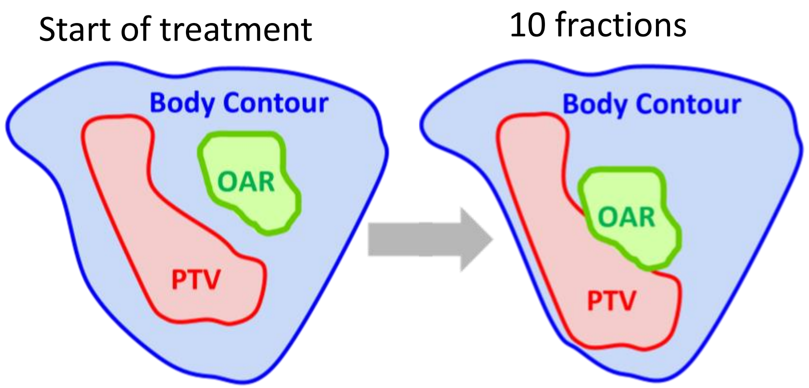
3. Predict trajectories of new patients
4. Dynamically update trajectory with new data



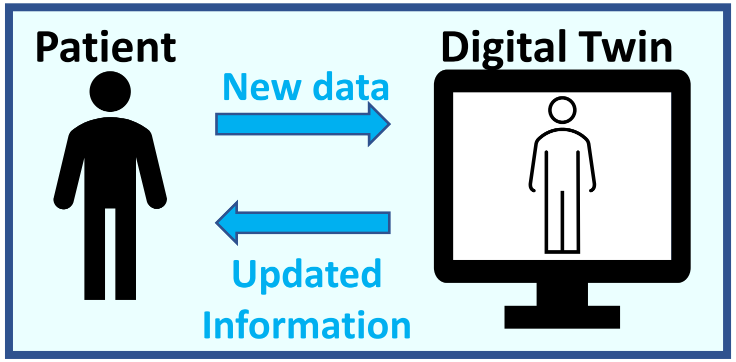
# Potential Outcomes & Conclusions

- Ability to make replanning decisions ahead of time
  - More easily manage resources and time
  - Lessen burden on planning team




- Possibly start re-planning process ahead of time?

**Exciting future ahead!!**



# Merci! Thank you!

- Dr. John Kildea
- Head and Neck Project Team
  - Srishti Ahlawat
  - Aixa Andrade
  - Luc Galarneau
  - Julia Khriguian
  - James Manalad
- NICE ROKs Team


https://kildealab.com/

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McGill UNIVERSITY

Réseau de cancérologie Rossy

Rossy Cancer Network