Prior-informed Machine Learning for Biomedical Imaging and Perception

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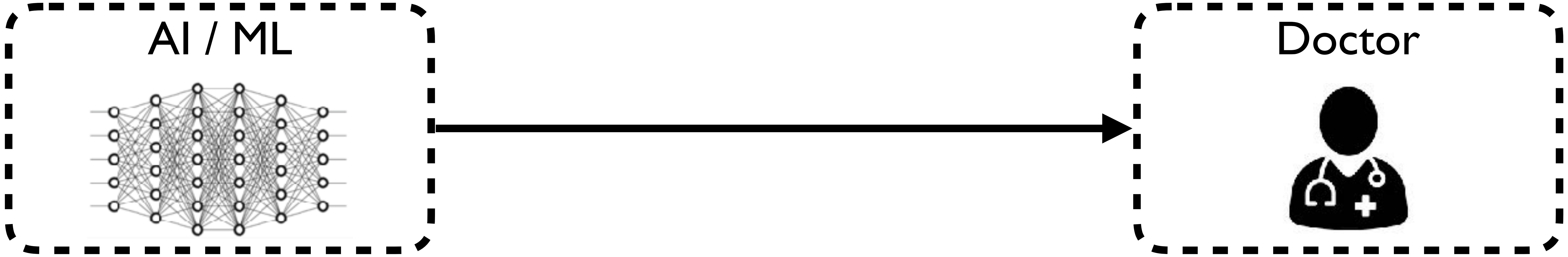
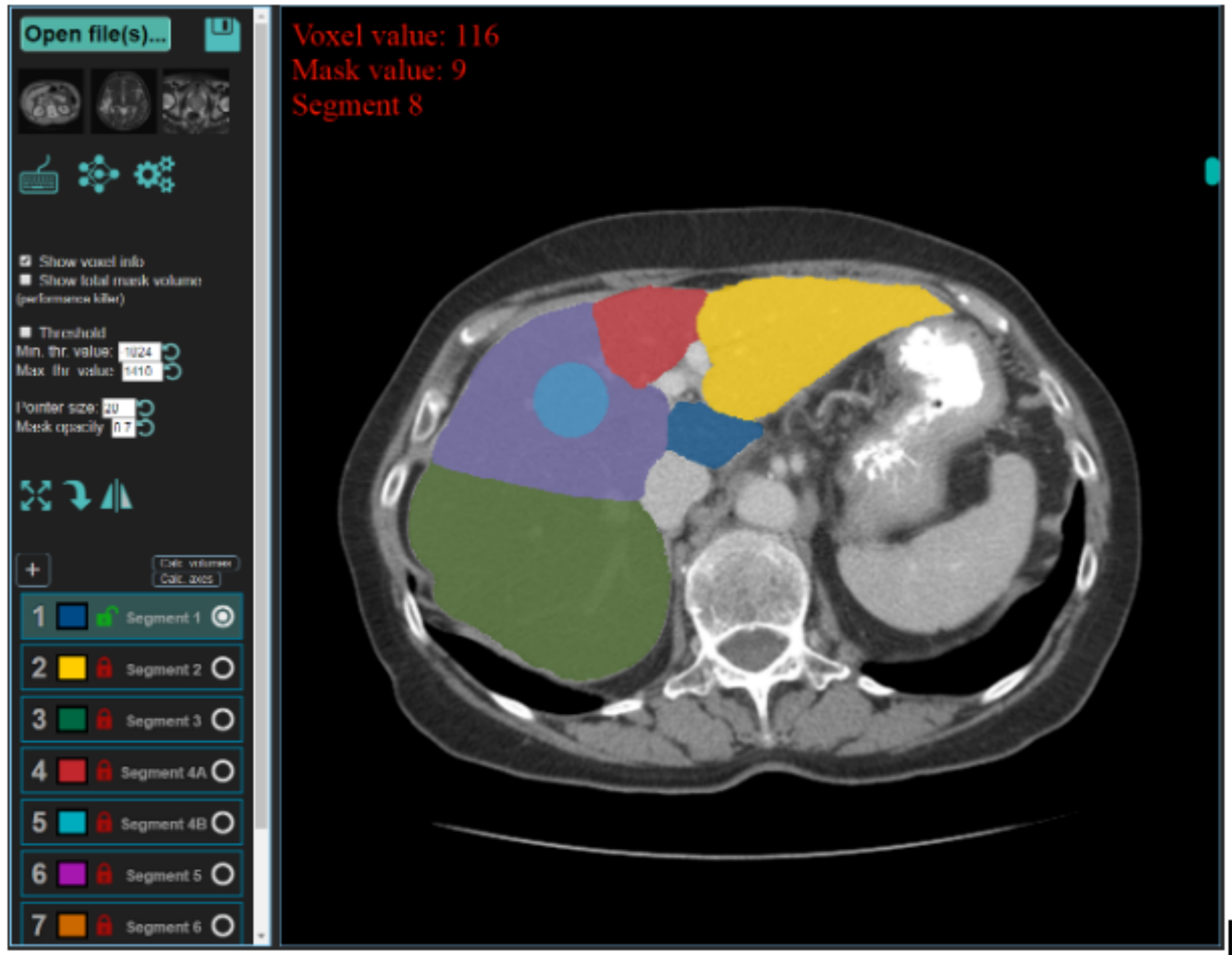
AI in Medicine and Health

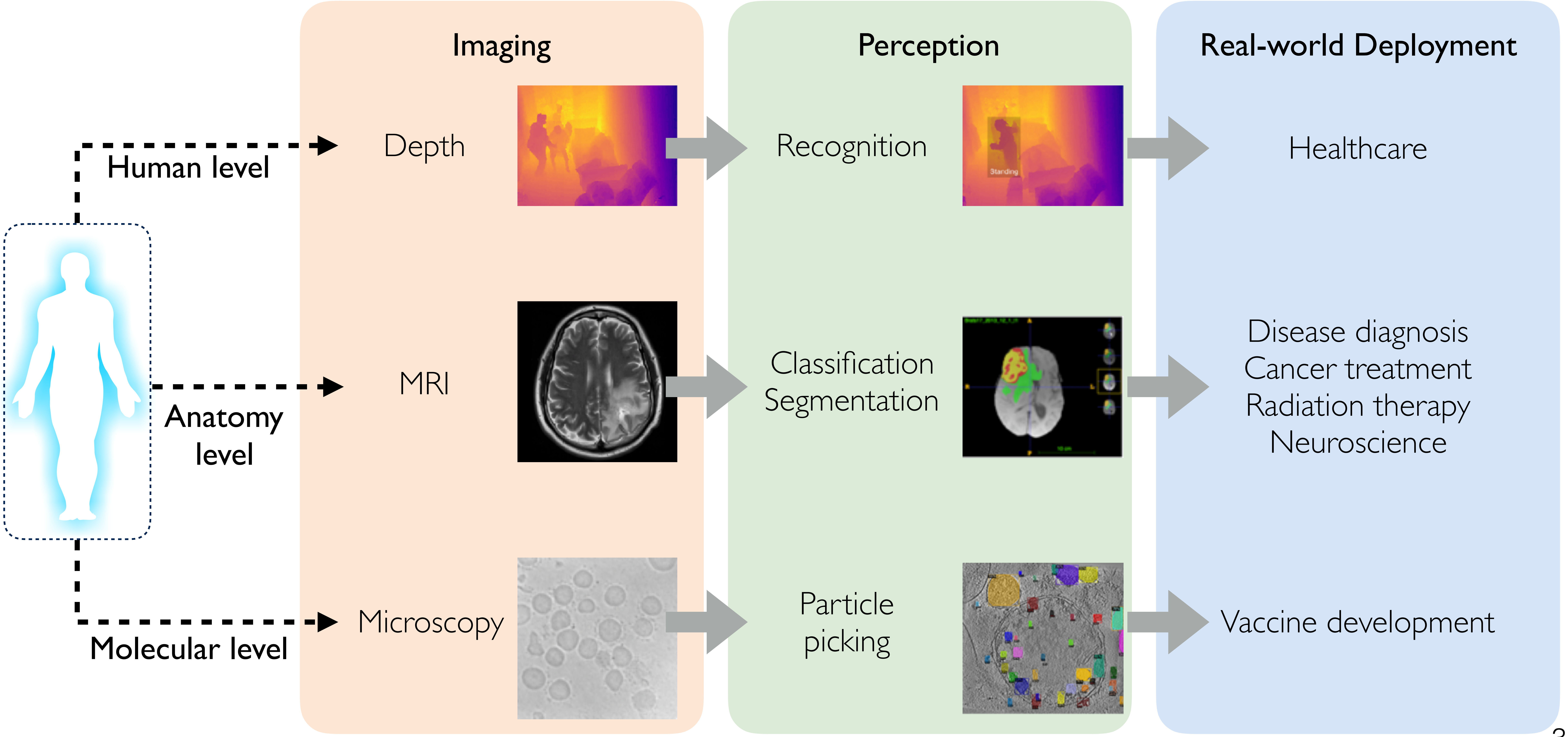


Classification for Diagnostic



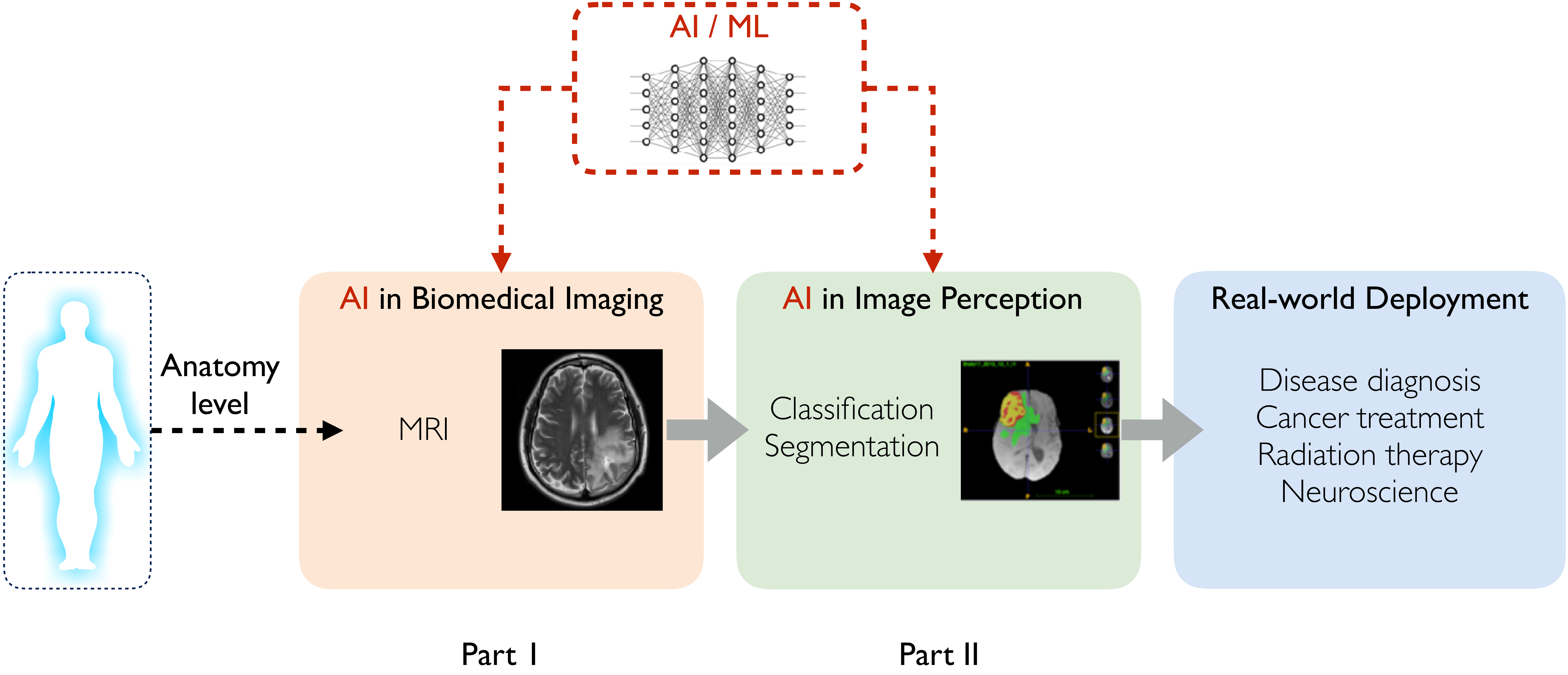
Segmentation for Delineation

Understand human health in different levels

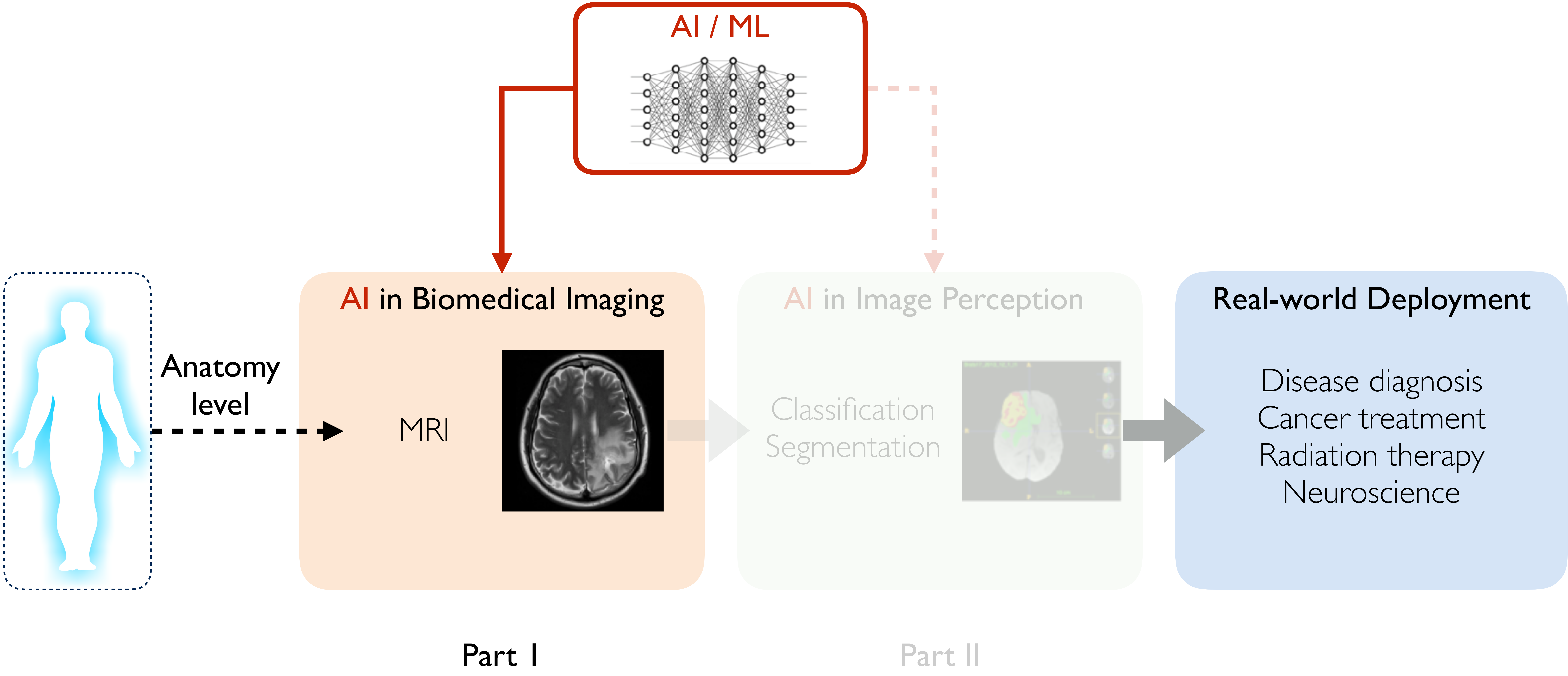


AI helps to understand human health

Today's Roadmap



Part I: AI in Biomedical Imaging



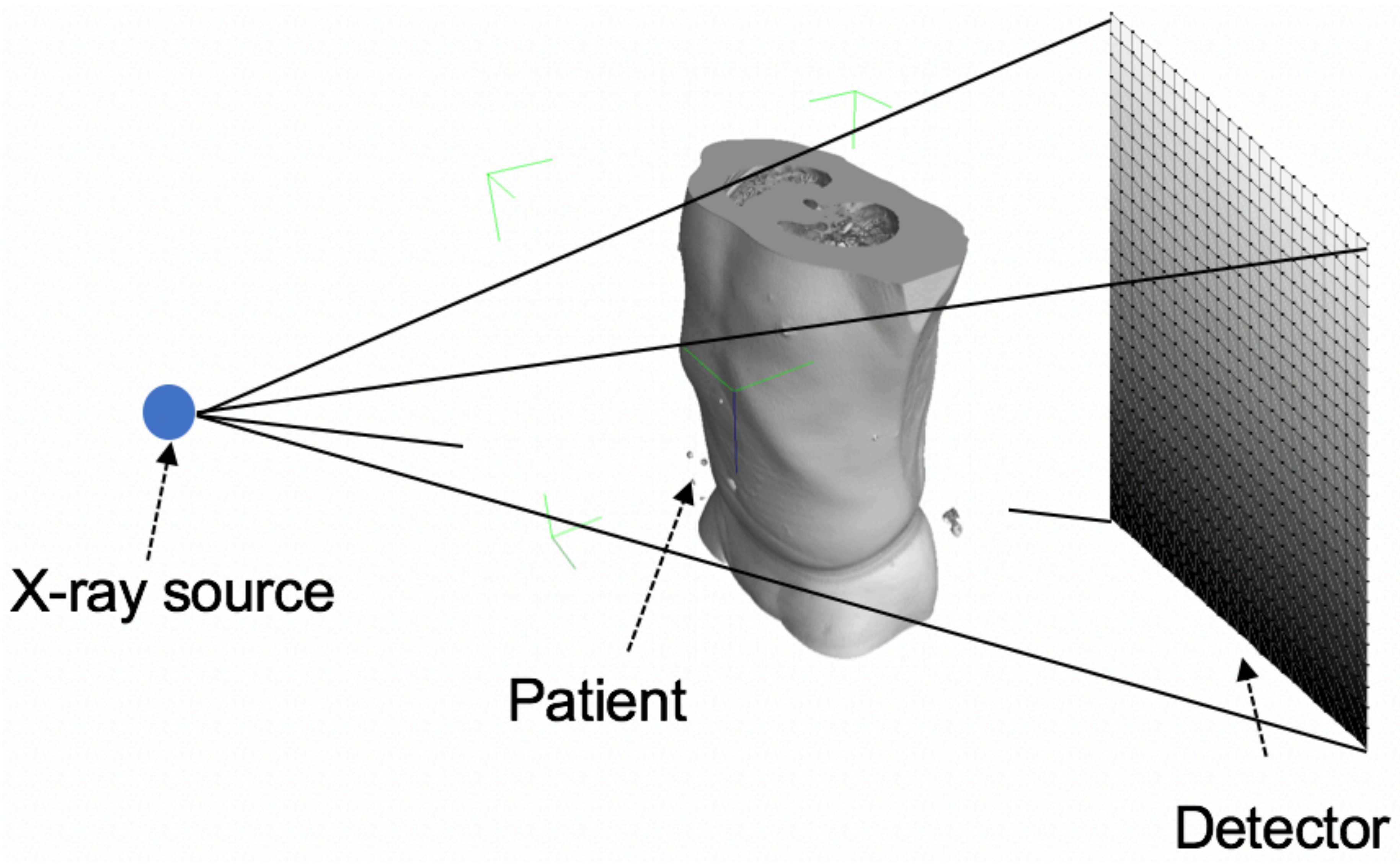
Motivation: why care about sparse-sampling biomedical imaging?

X-ray Computed Tomography (CT) imaging

- Reconstruct volumetric image from projections at different angles

Reduce radiation exposure in CT

- Sample sparse projections



Shen, et al., Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning, Nature BME 2019.

Motivation: why care about sparse-sampling biomedical imaging?

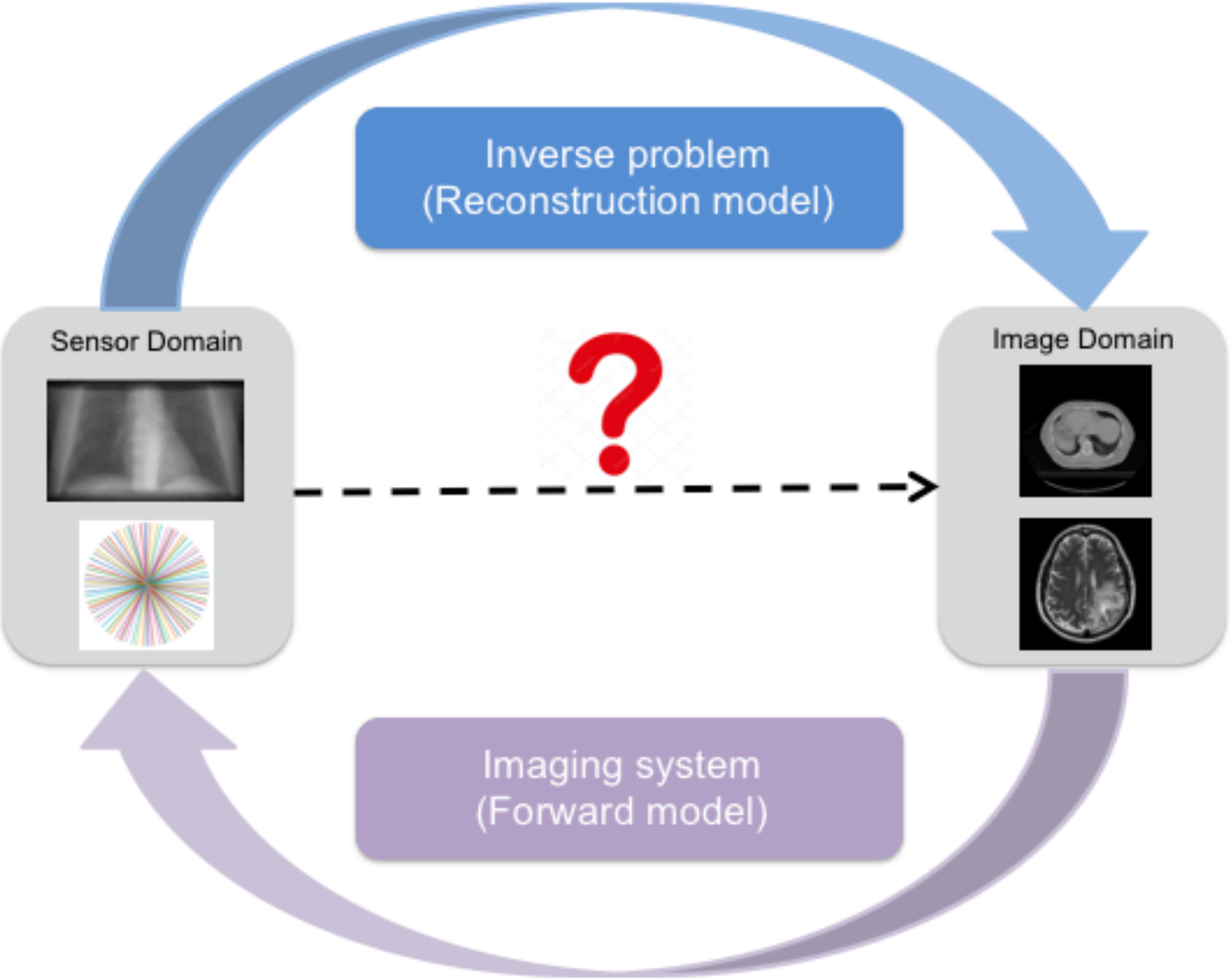
Magnetic Resonance Imaging (MRI)
- Reconstruct volumetric image from measurements in frequency space

Accelerate MRI scanning
- Under-sample frequency space data

Zhu, et al., Image reconstruction by domain-transform manifold learning, Nature 2018.

Problem definition

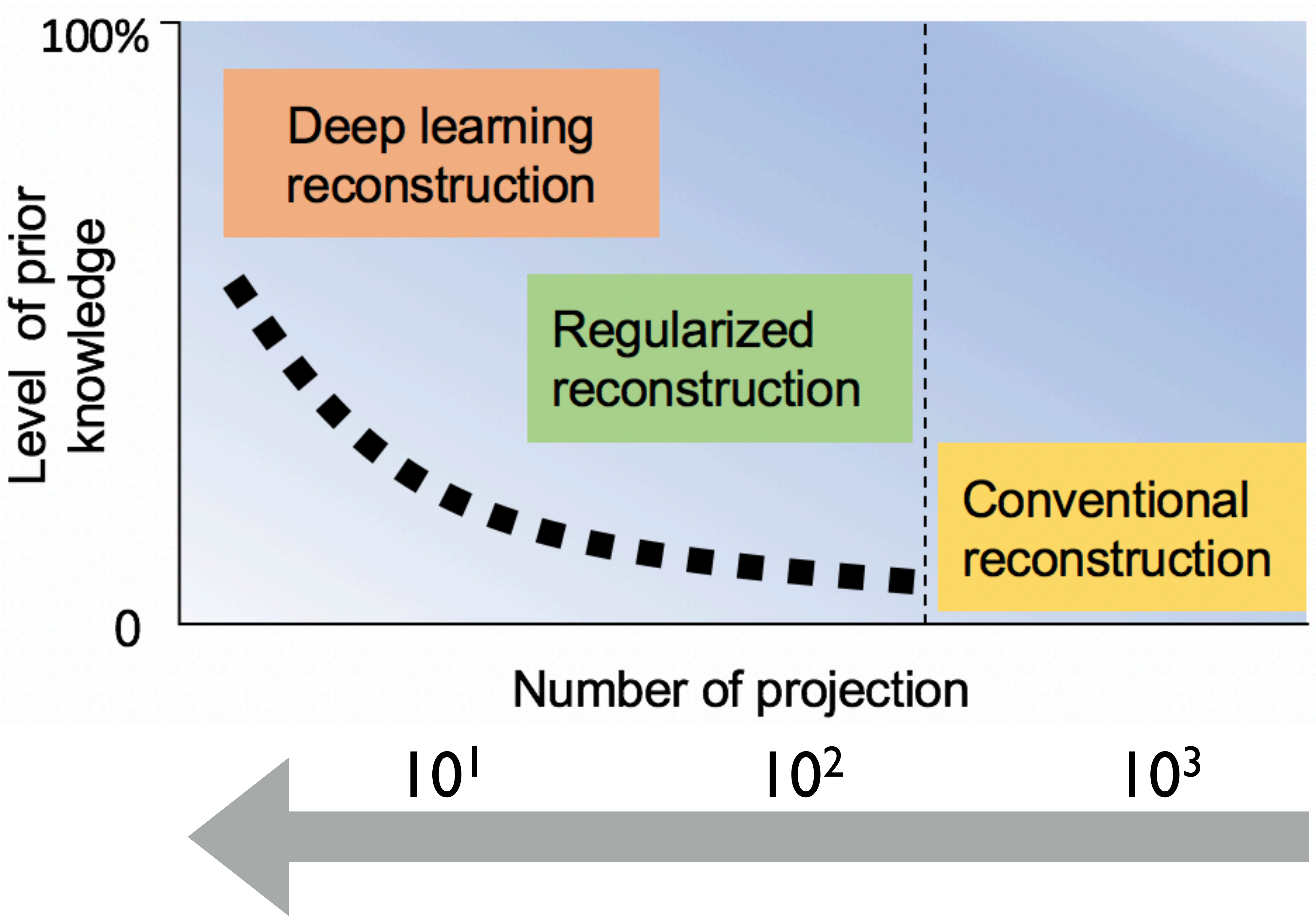
Inverse problem: sparse-sampling image reconstruction



Inverse problem: sparse-sampling image reconstruction

Leverage prior knowledge for solving ill-posed inverse problem

- Conventional reconstruction: require dense sampling ($\sim 10^3$)
- Regularized reconstruction: sparsity in transformed domain ($\sim 10^2$)
- Deep learning reconstruction: learn implicit prior from data-driven ($\sim 10^1$)



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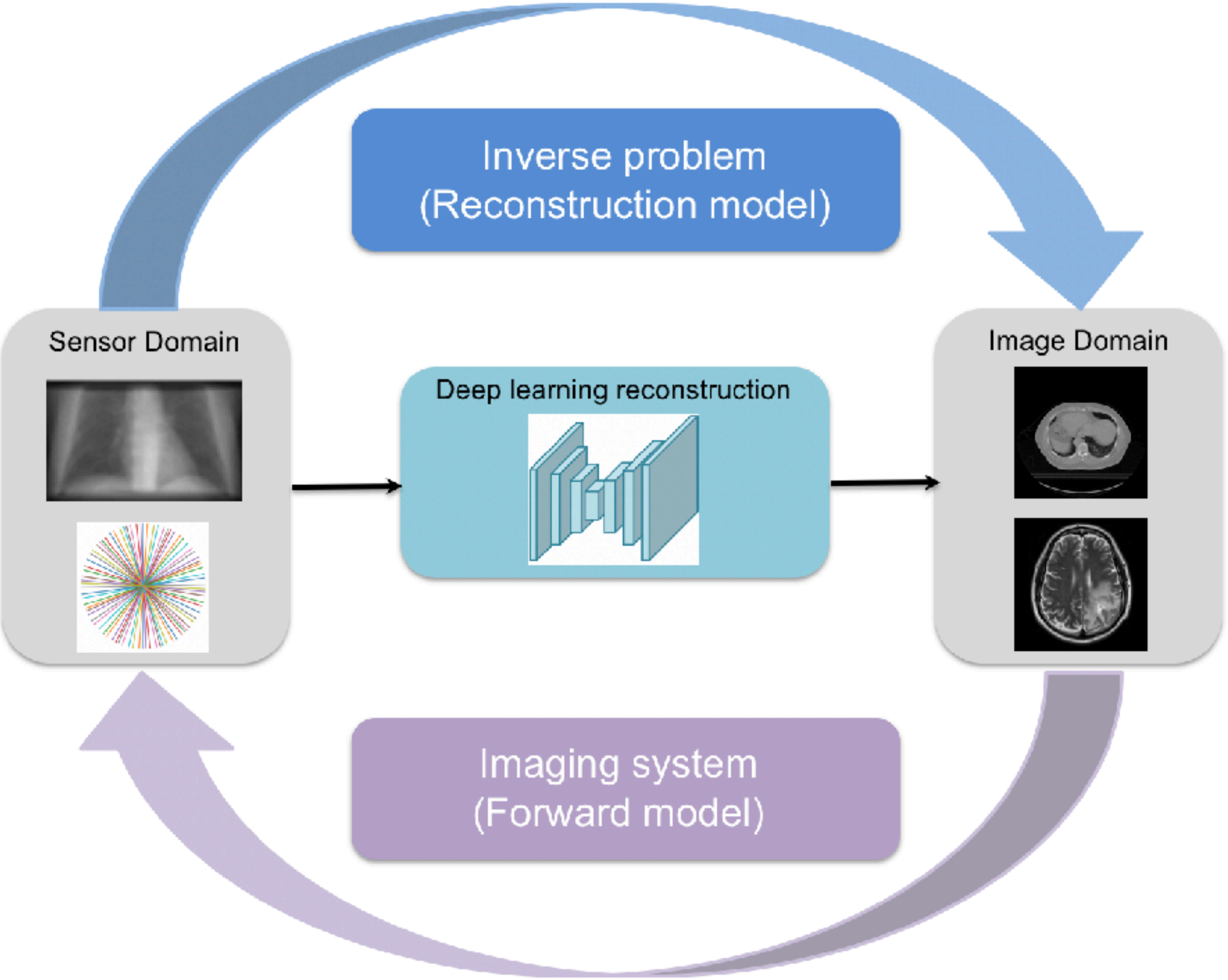
Deep learning-based image reconstruction

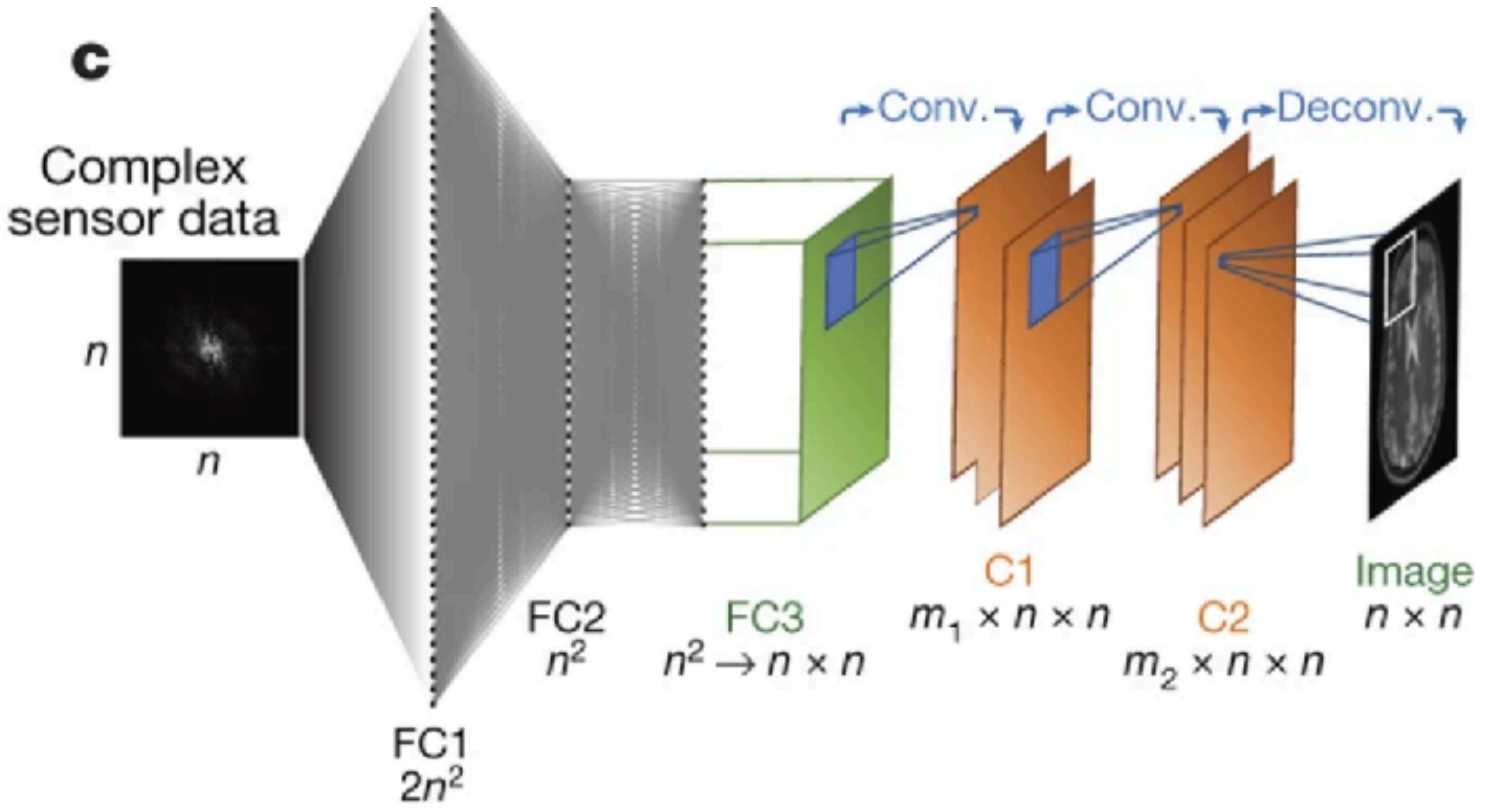
Network learns cross-domain mapping function in a **data-driven** way



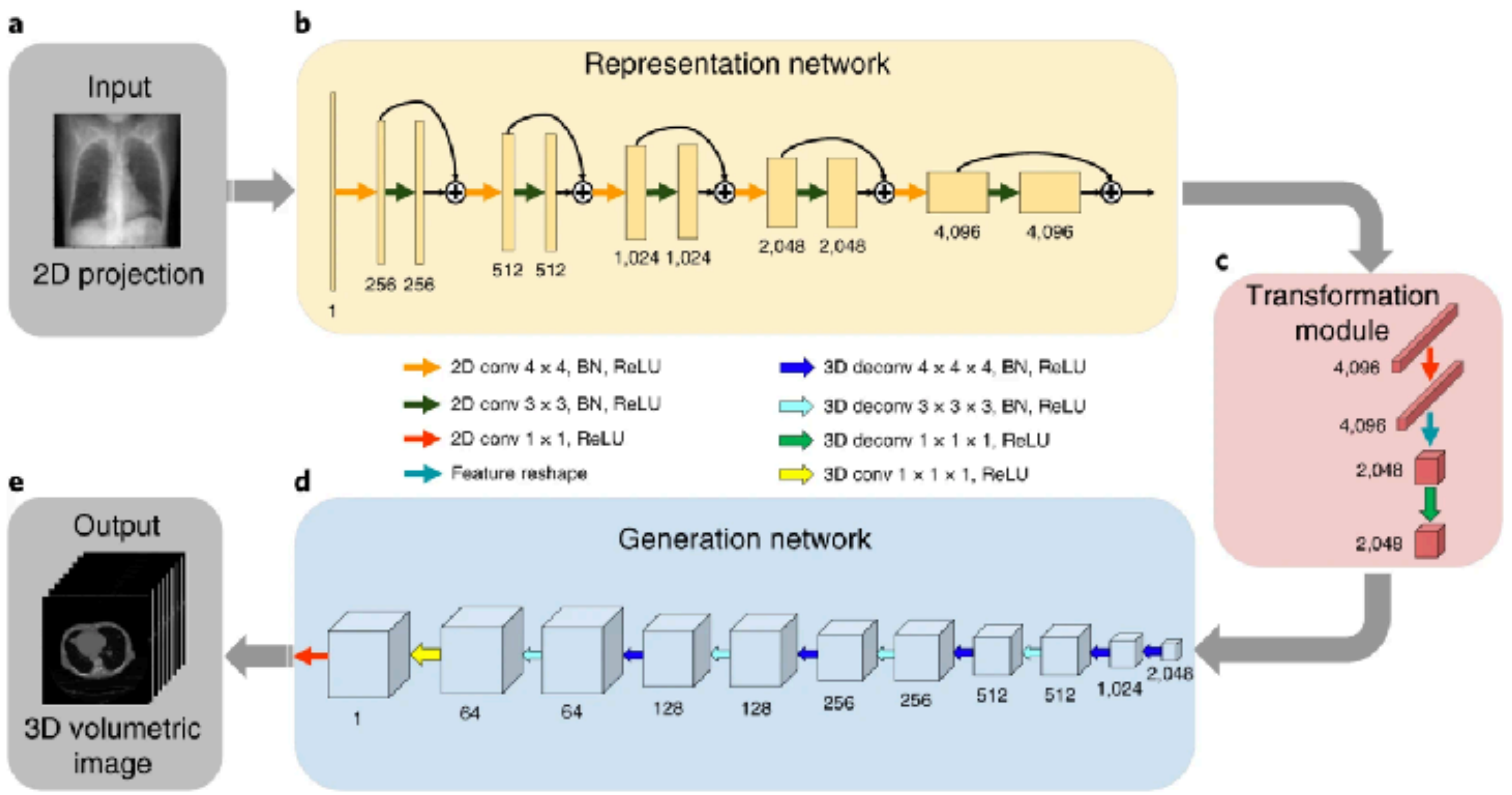
Deep learning-based image reconstruction

Network learns **cross-domain transformation** in a **data-driven** way

Sparse-sampling MRI reconstruction



Sparse-view CT reconstruction



Zhu, et al., Image reconstruction by domain-transform manifold learning, Nature 2018.
Shen, et al., Patient-specific reconstruction of volumetric computed tomography images from a single projection view via deep learning, Nature BME 2019.

Challenges of deep learning-based image reconstruction

On instabilities of deep learning in image reconstruction and the potential costs of AI

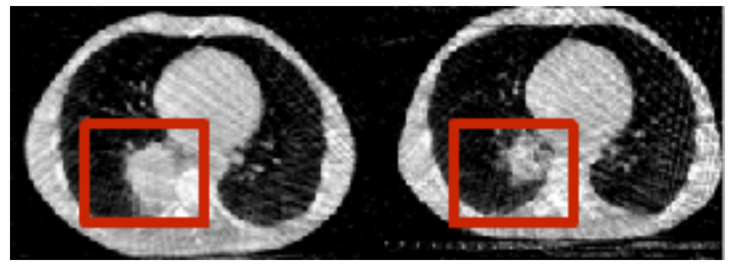
Vegard Antun, Francesco Renna, Clarice Poon, Ben Adcock, and Anders C. Hansen
+ See all authors and affiliations

PNAS December 1, 2020 117 (48) 30088-30095; first published May 11, 2020; https://doi.org/10.1073/pnas.1907377117

Emerging follow-up works:
- Ying, et al., CVPR 2019
- Kasten, et al., MLMIR 2020
- Lei, et al., PMB 2020
- Lu, et al., Nature BME 2021
- Tao, et al., TMI 2021
- Lyu, et al., MedIA 2021
- Zhang, et al., TCI 2021
- Sde-Chen, et al., ICCV 2021
- Eulig, et al., Med Phys 2021
- Zhou, et al., MedIA 2022
- ……

Challenges

Reliability



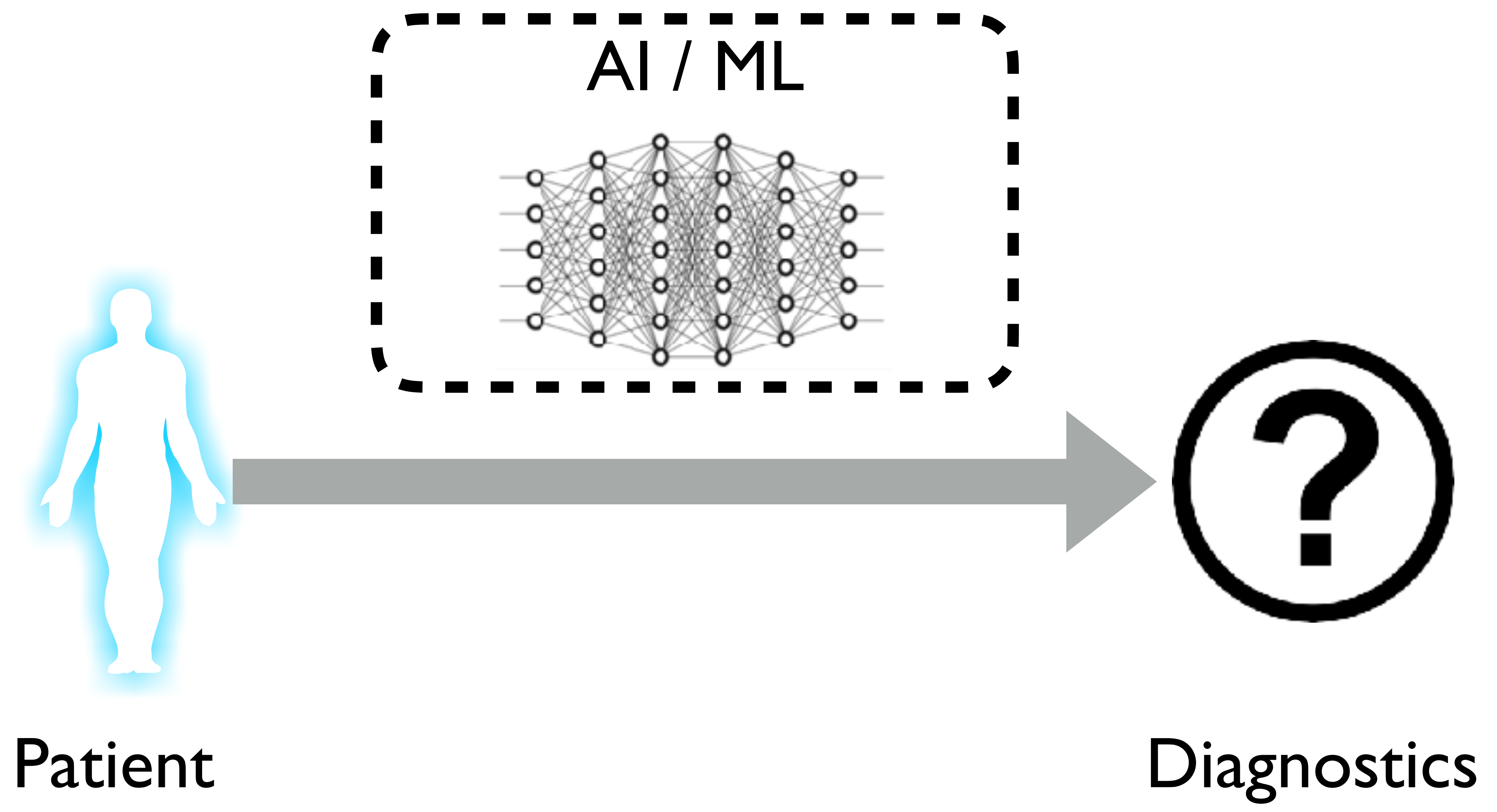
Generalization

Data efficiency

Antun, et al., On instabilities of deep learning in image reconstruction and the potential costs of AI, PNAS 2020.

Challenges of AI in Biomedical Imaging

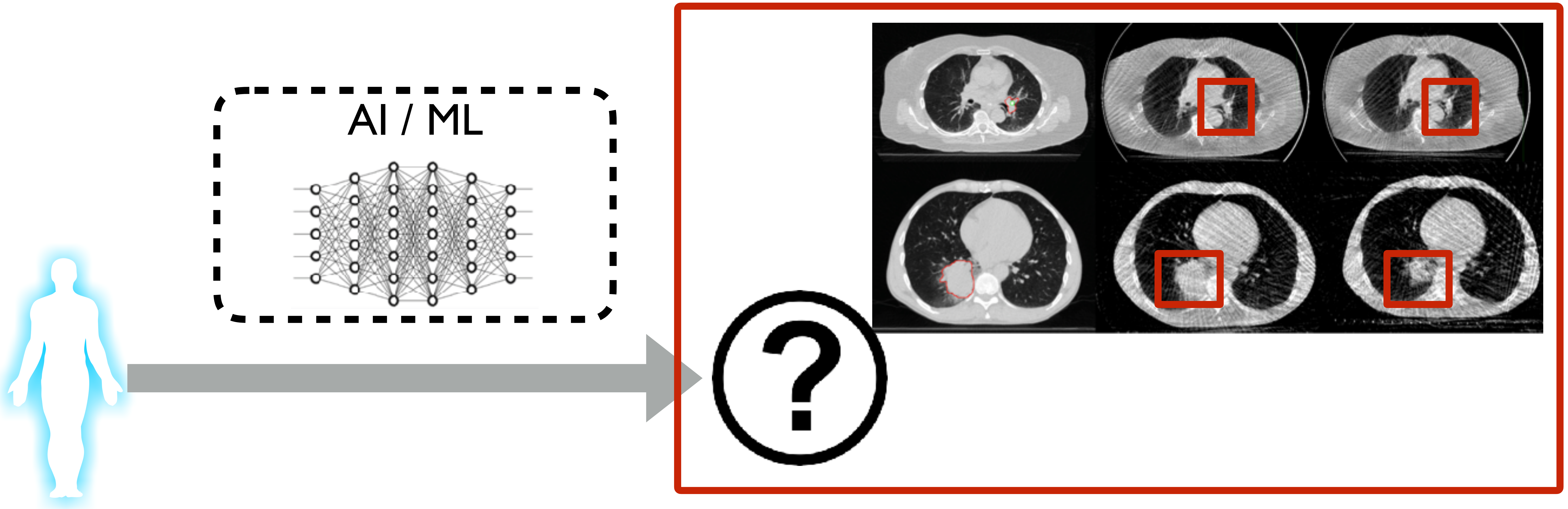
1. Reliability
2. Generalization
3. Data efficiency



Reliability

AI can be insensitive to tumor shrinkage, lesion progression, etc.

Small structural changes such as tumor progression …

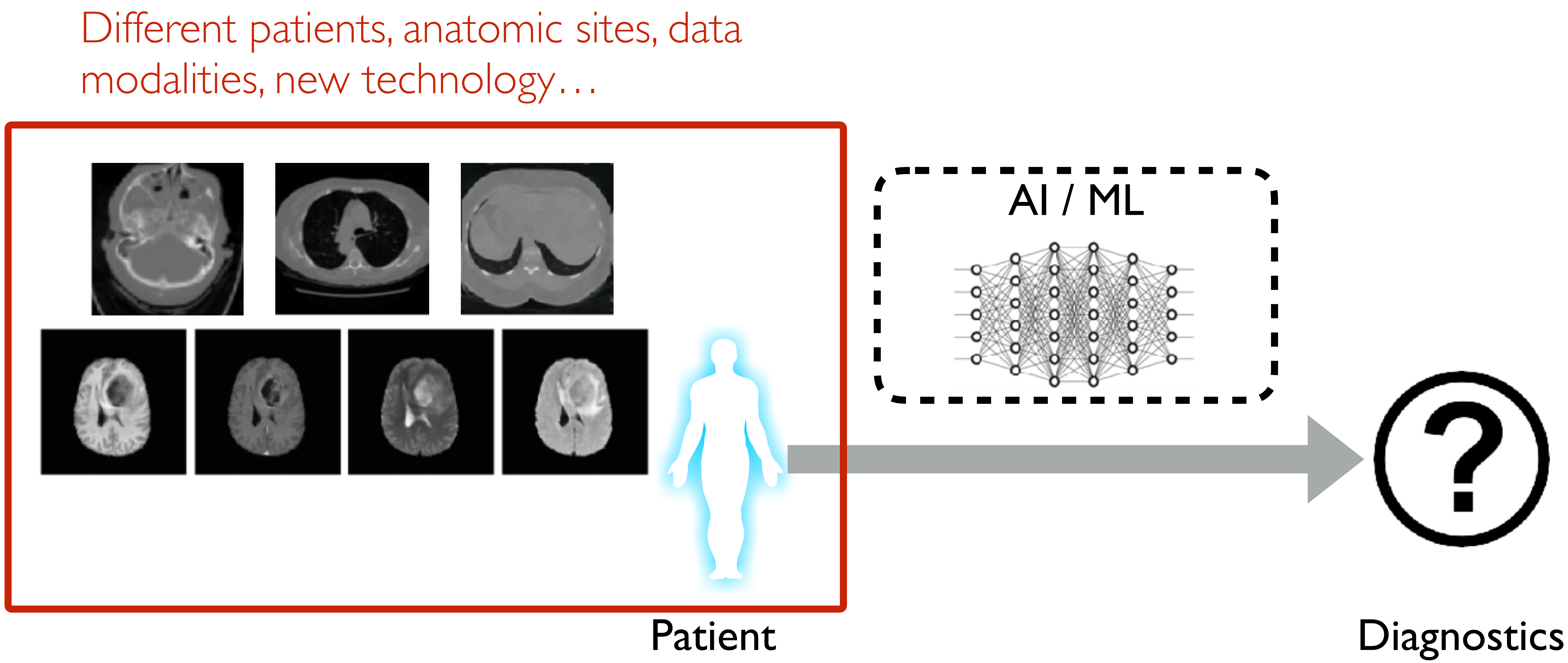


Patient

Diagnostics

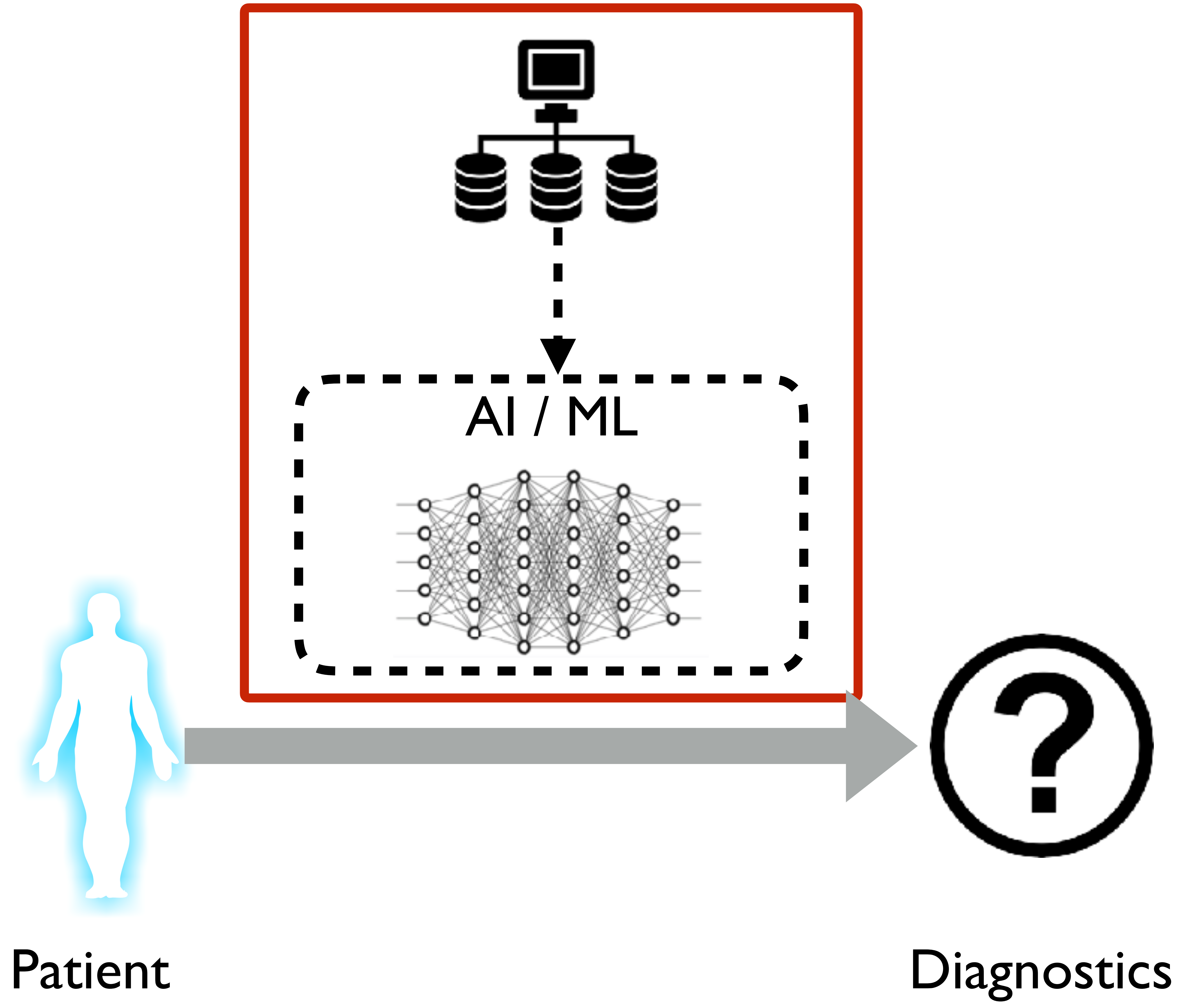
Generalization

AI model is limited when generalized to different input data



Data Efficiency

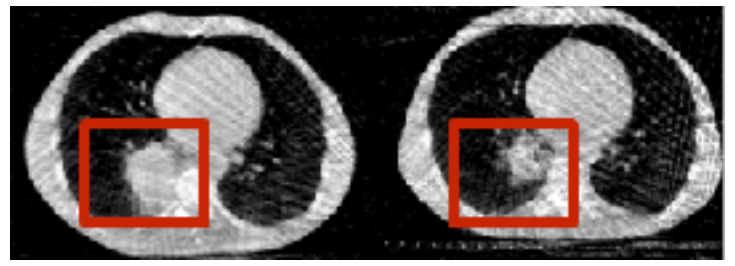
Data collection can be a bottleneck for AI model development



Challenges of AI in Biomedical Imaging

Challenges

Reliability



Generalization

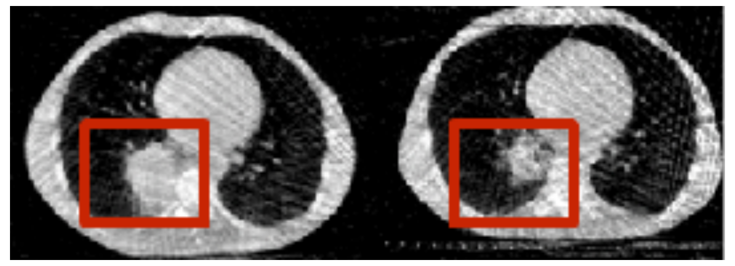
Data efficiency

Can we exploit prior knowledge to design more efficient AI models?

Solution: Exploit Prior Knowledge

Challenges

Reliability



Generalization

Data efficiency

What prior knowledge could be useful?

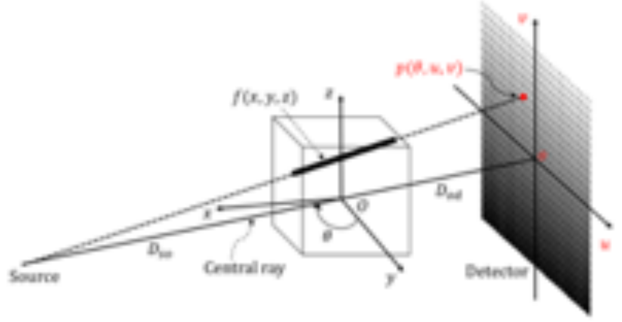
Priors

Personalized prior

Time

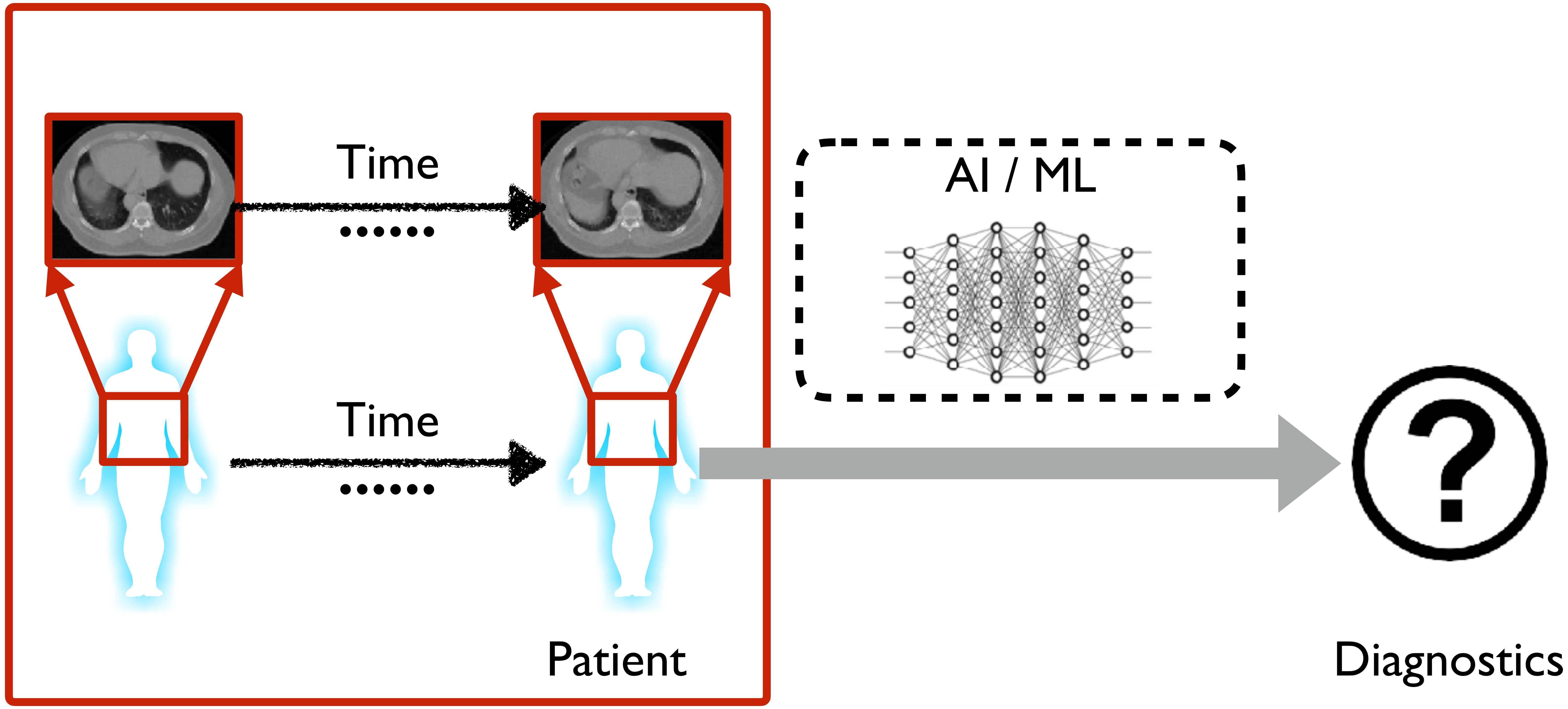
Population prior

Physics prior



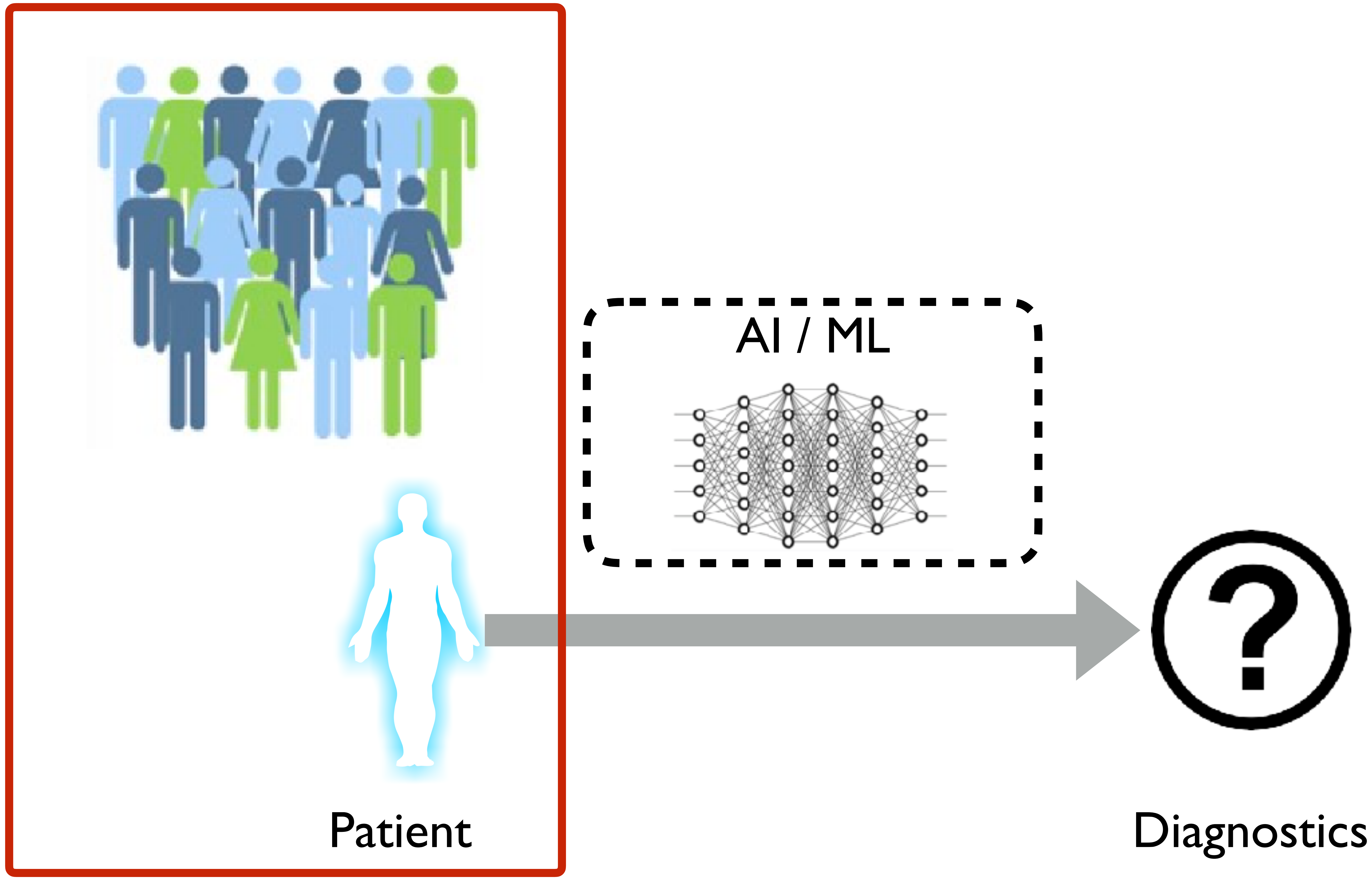
Personalized Prior

Personalized prior: patient-specific information from time series data



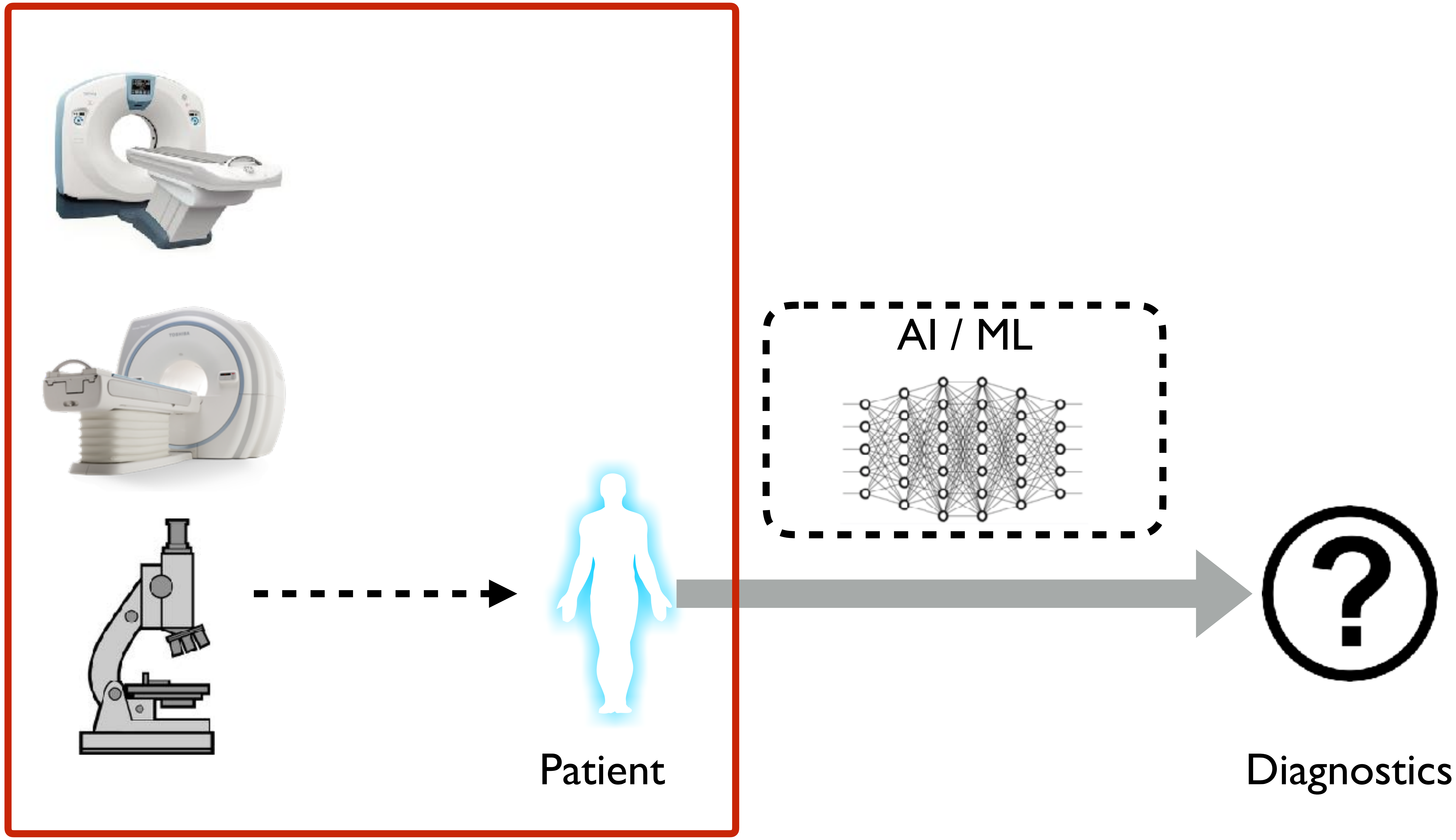
Population Prior

Population prior: data distribution prior knowledge from the patient population

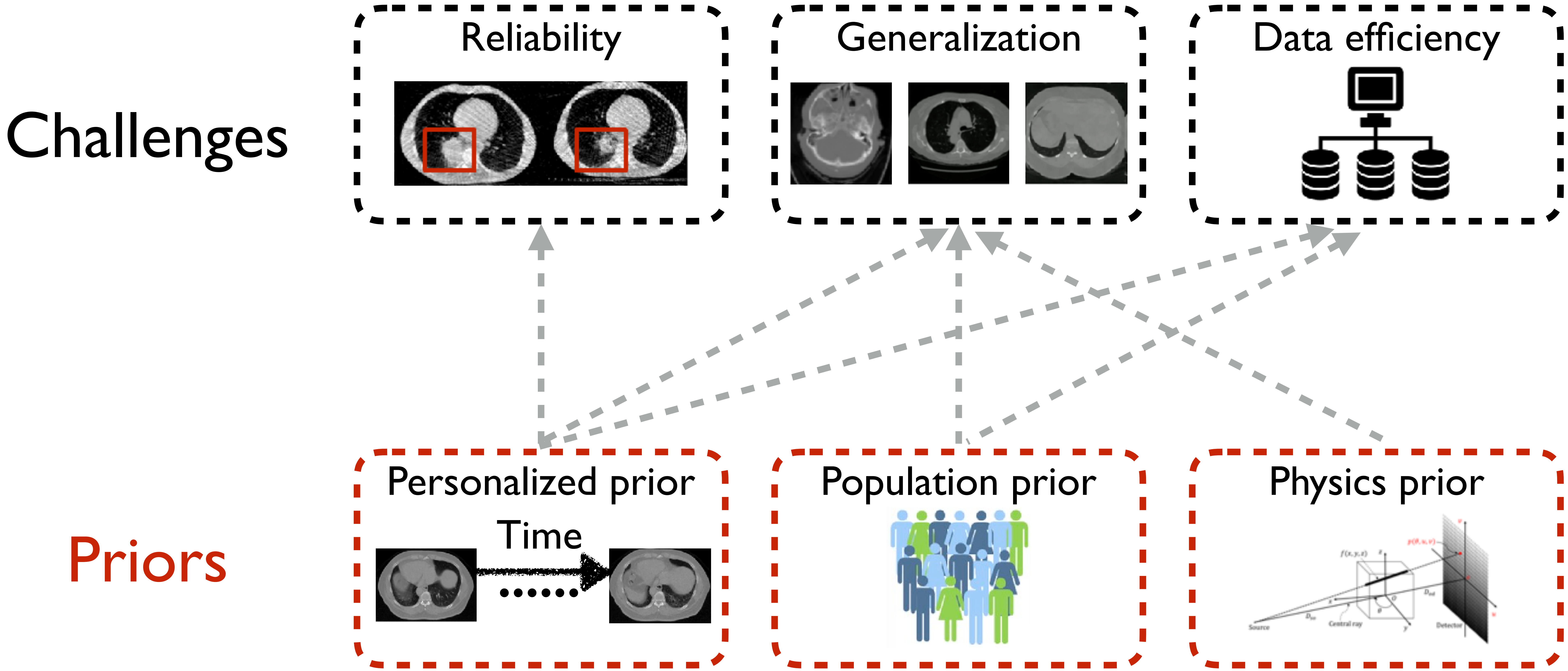


Physics Prior

Physics prior: medical physics knowledge from the imaging system

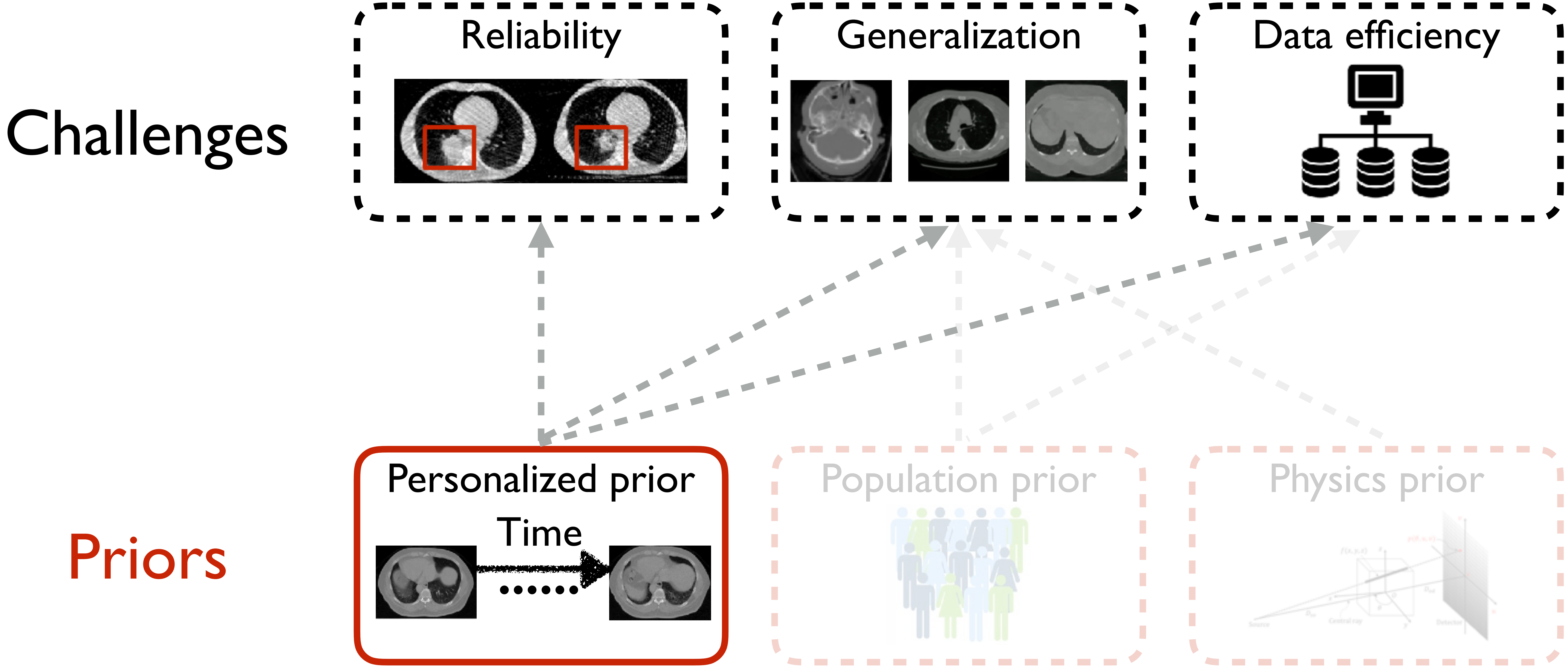


Approach: Prior-informed ML



How can we develop ML models incorporating prior knowledge?

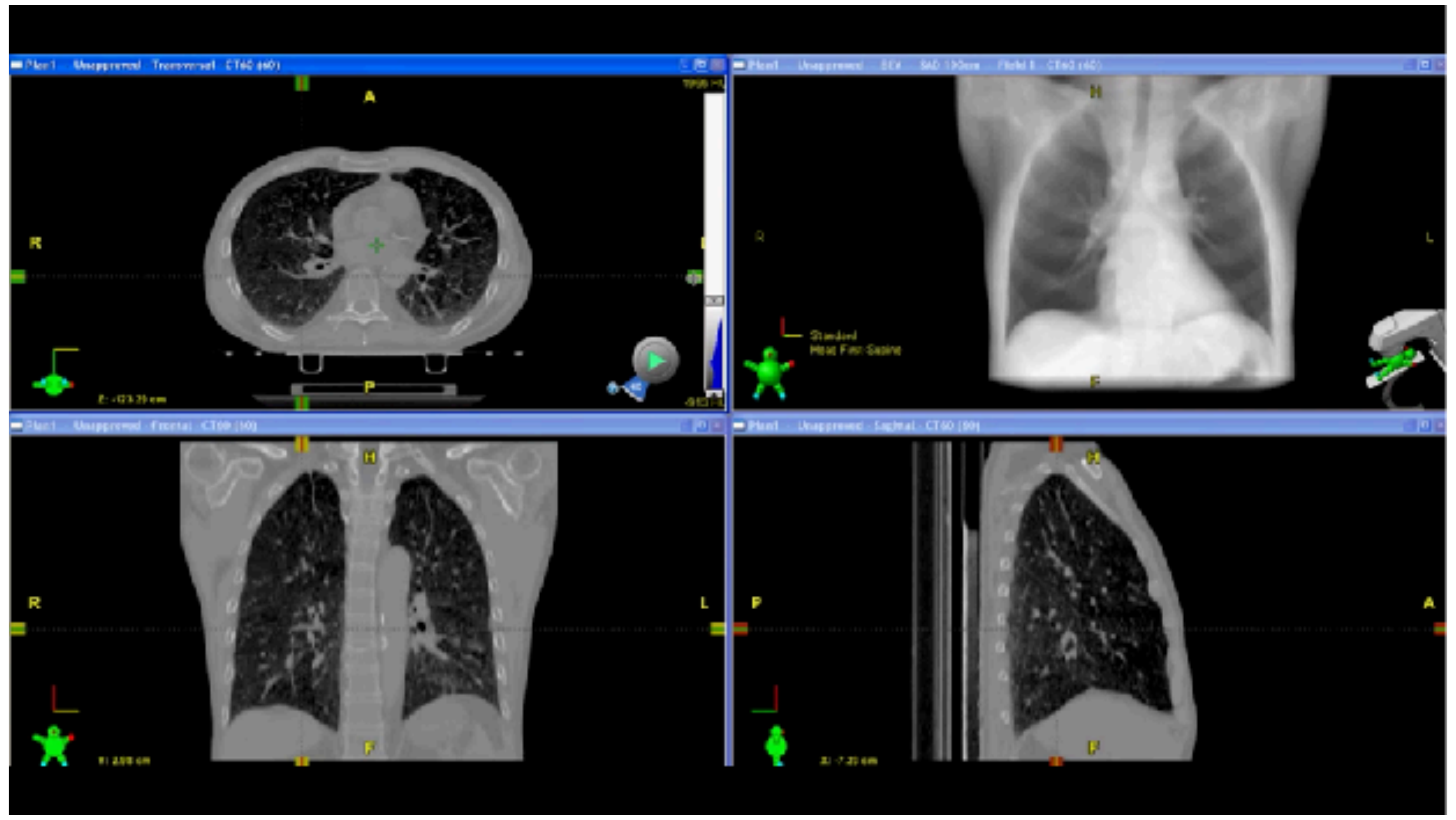
1. Personalized Prior



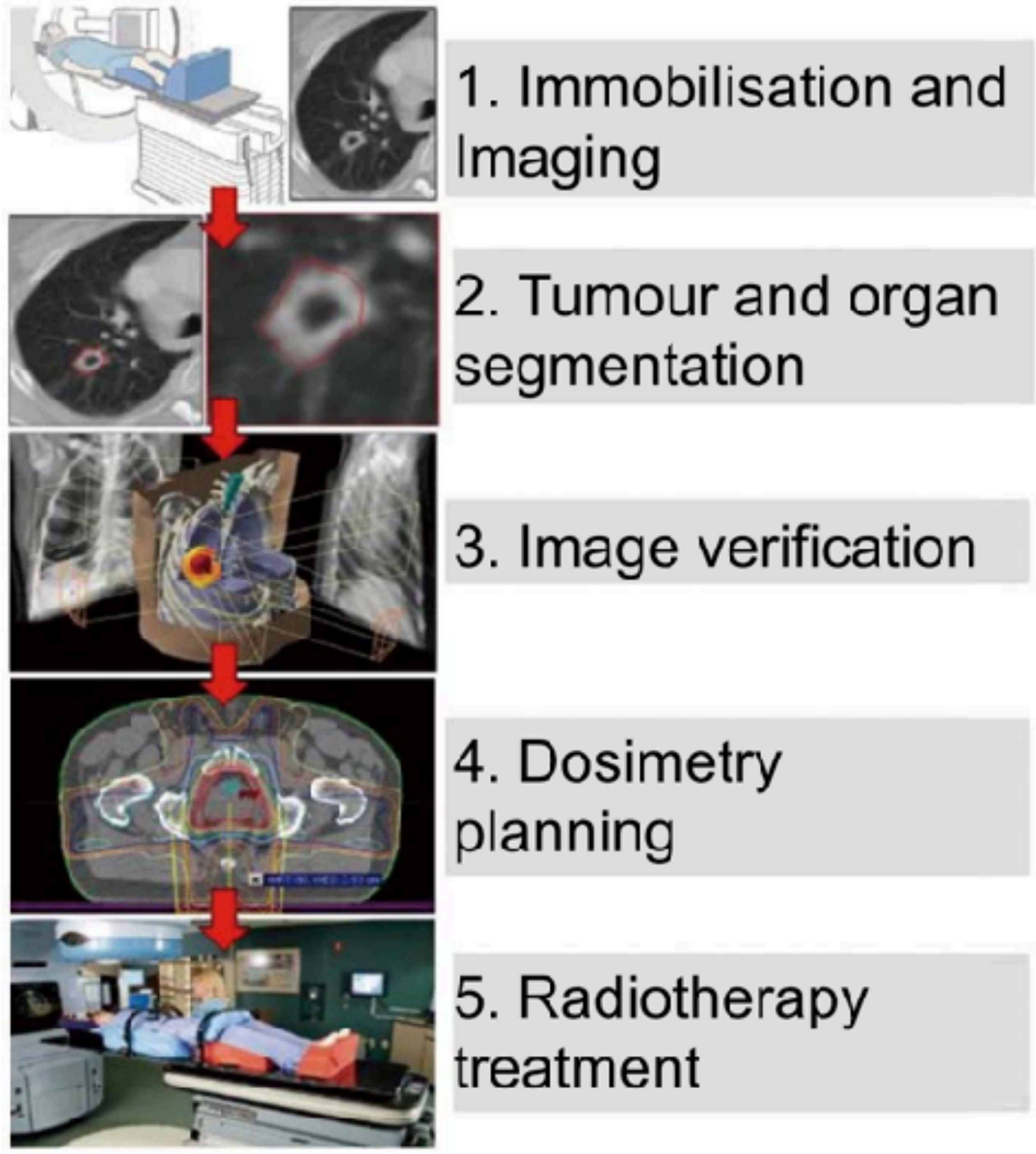
Time series data is common and important in biomedical tasks

Longitudinal data contain **personalized prior knowledge** of patient's anatomy

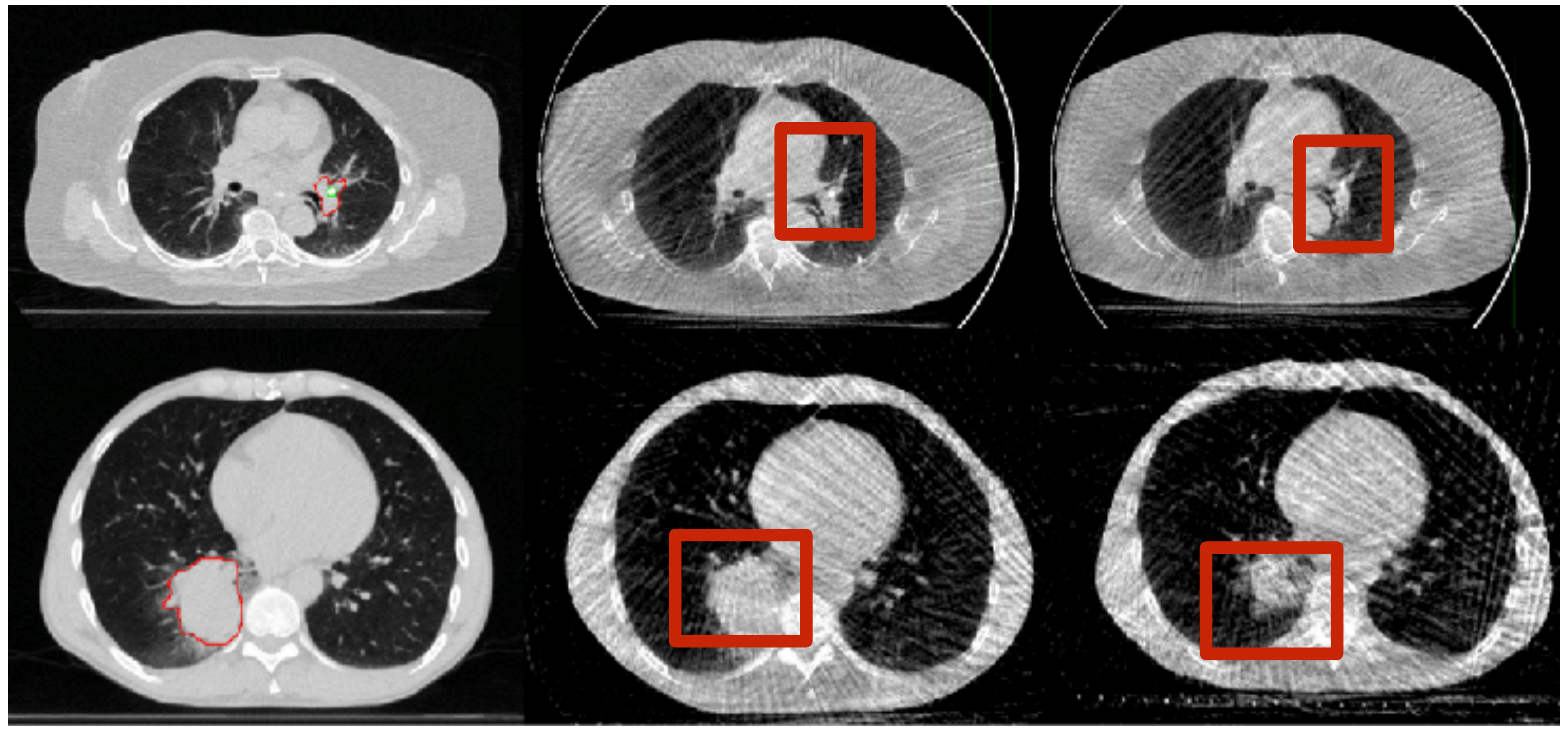
4D CT / 4D MRI characterize motion



Radiation therapy with multiple fractions



Evaluate tumor response to surgery and therapy



Hugo, et al., A longitudinal four-dimensional computed tomography and cone beam computed tomography dataset for image-guided radiation therapy research in lung cancer, Med Phys. 2017
Tino, et al., Additive manufacturing in radiation oncology: a review of clinical practice, emerging trends and research opportunities, IJEM 2020.
Shen, et al., NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction, TNNLS 2022.

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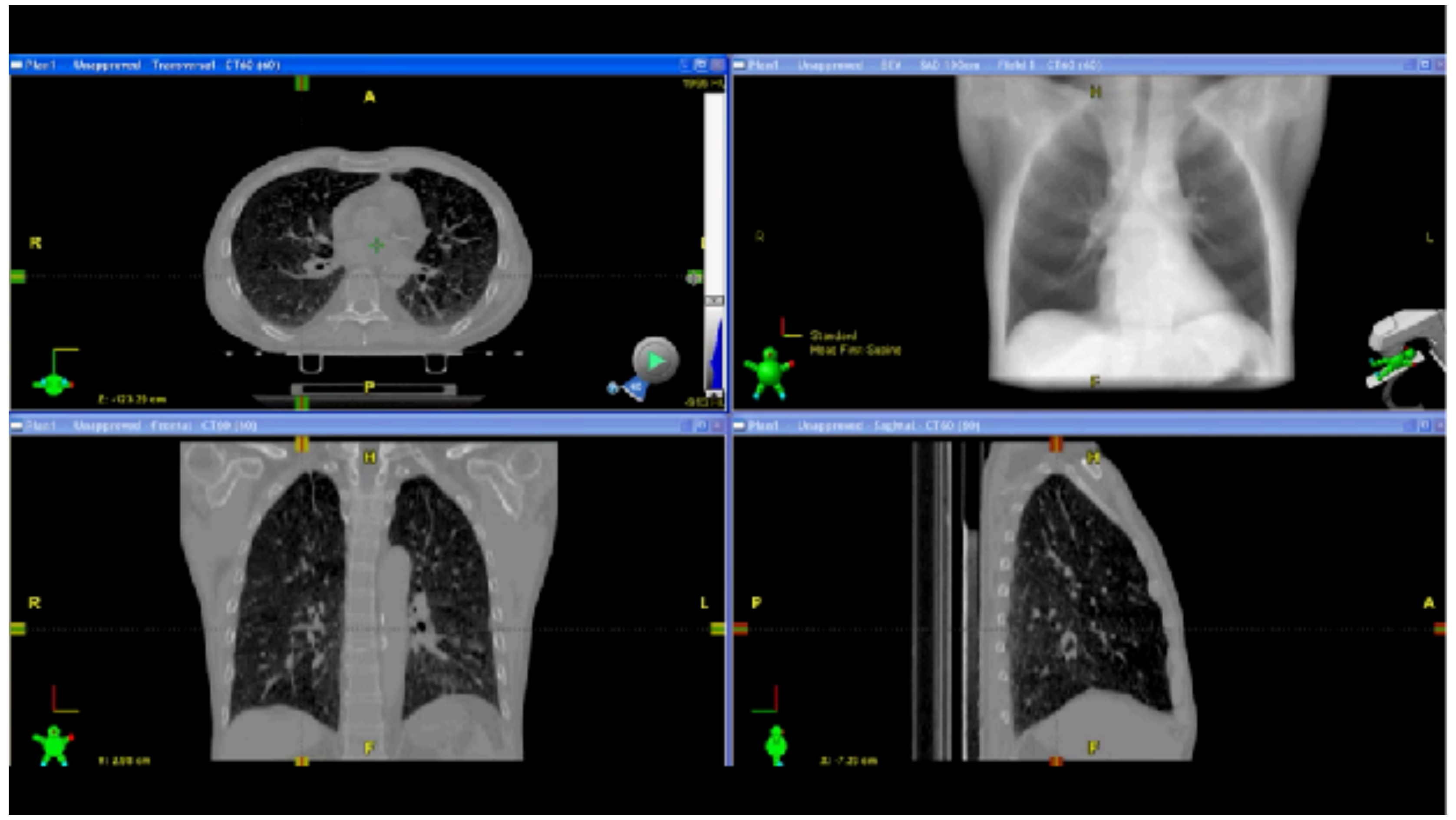
4D CT / 4D MRI
characterize motion



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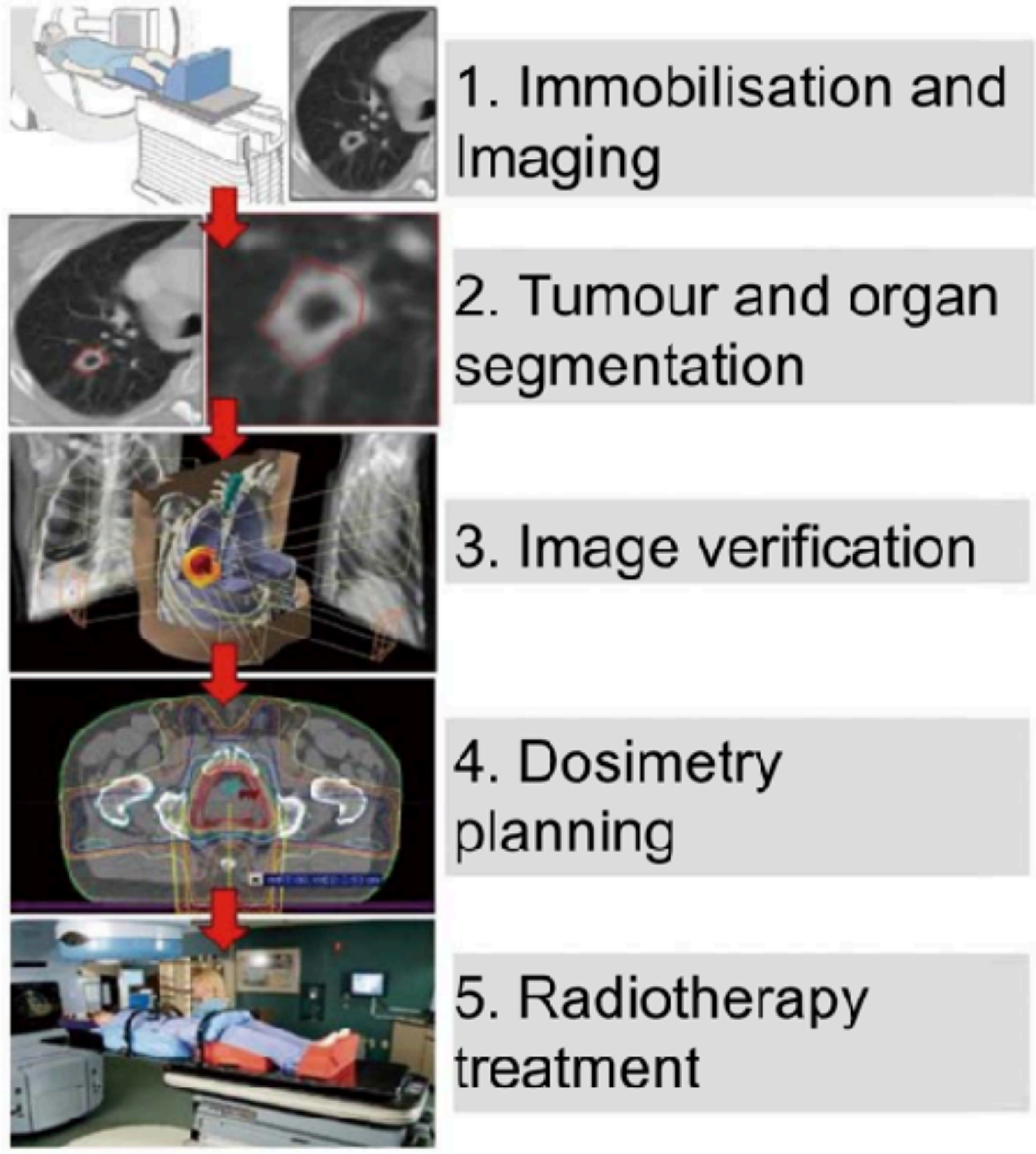

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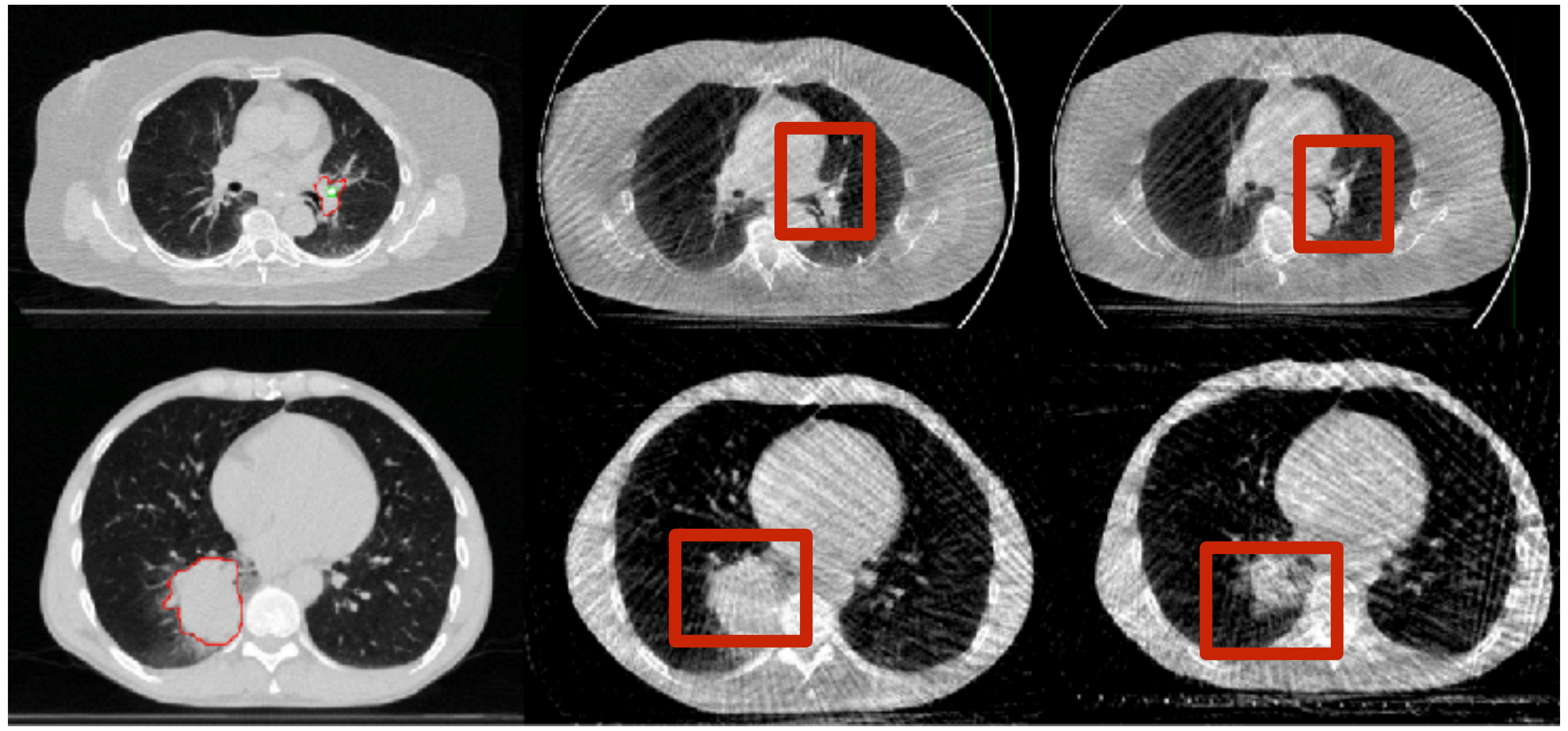

How can we design ML models incorporating personalized prior?

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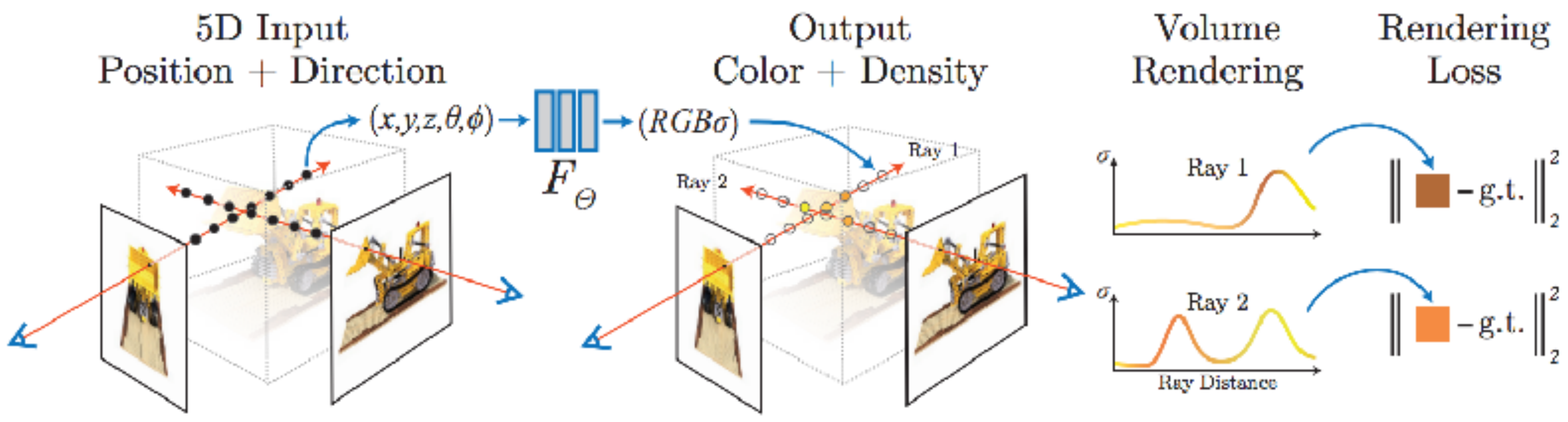
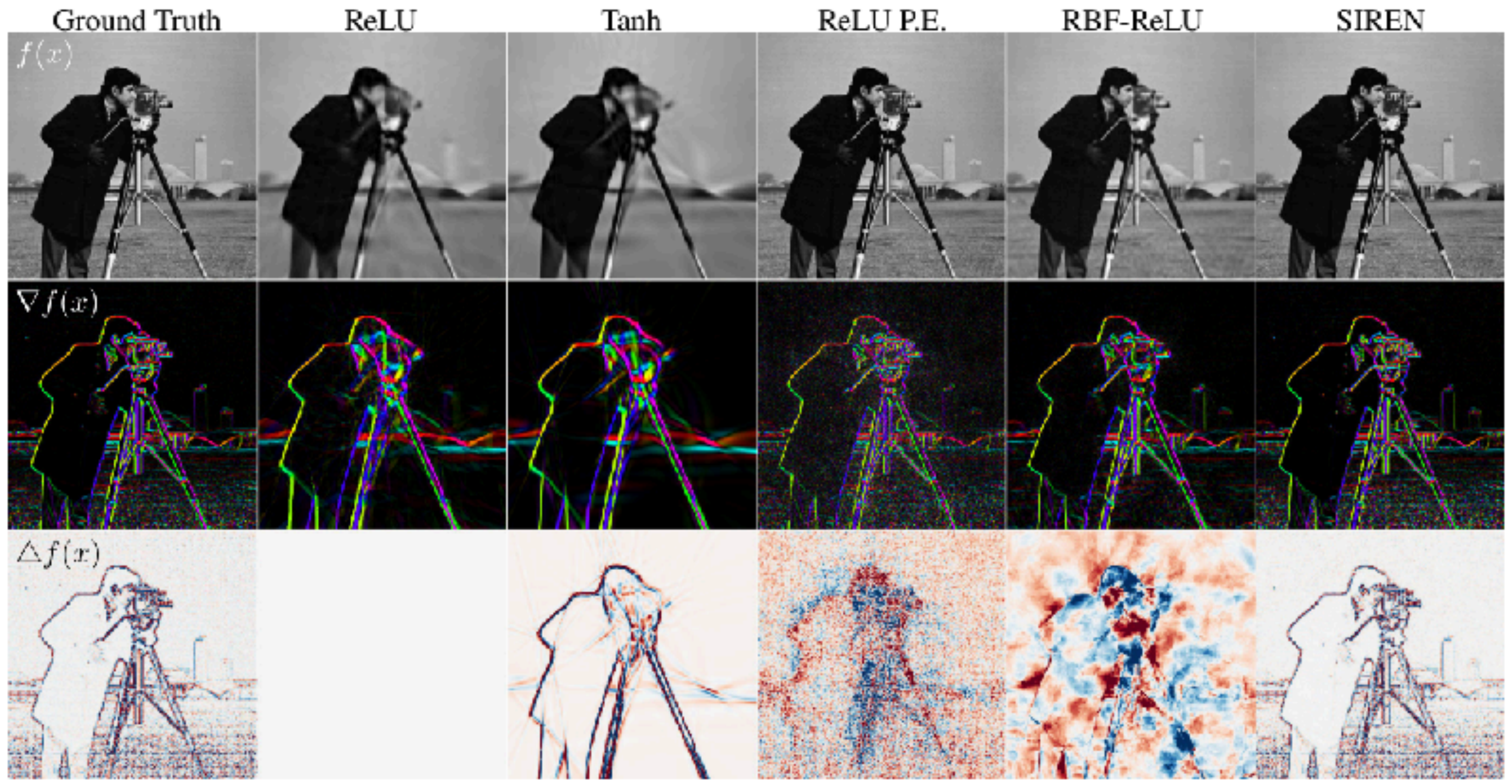
Implicit neural representation learning

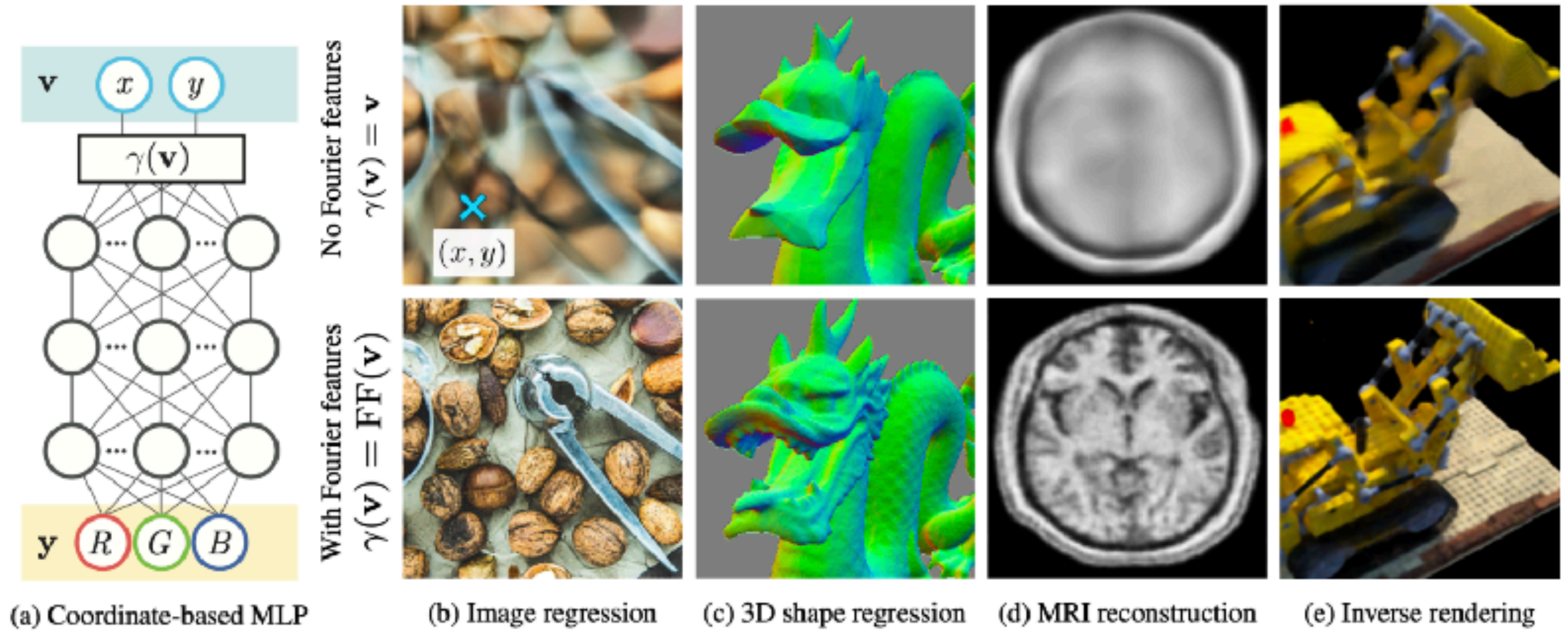
Represent an image as a continuous function parameterized by neural network



NeRF (ECCV 2020)



SIREN (NeurIPS 2020)

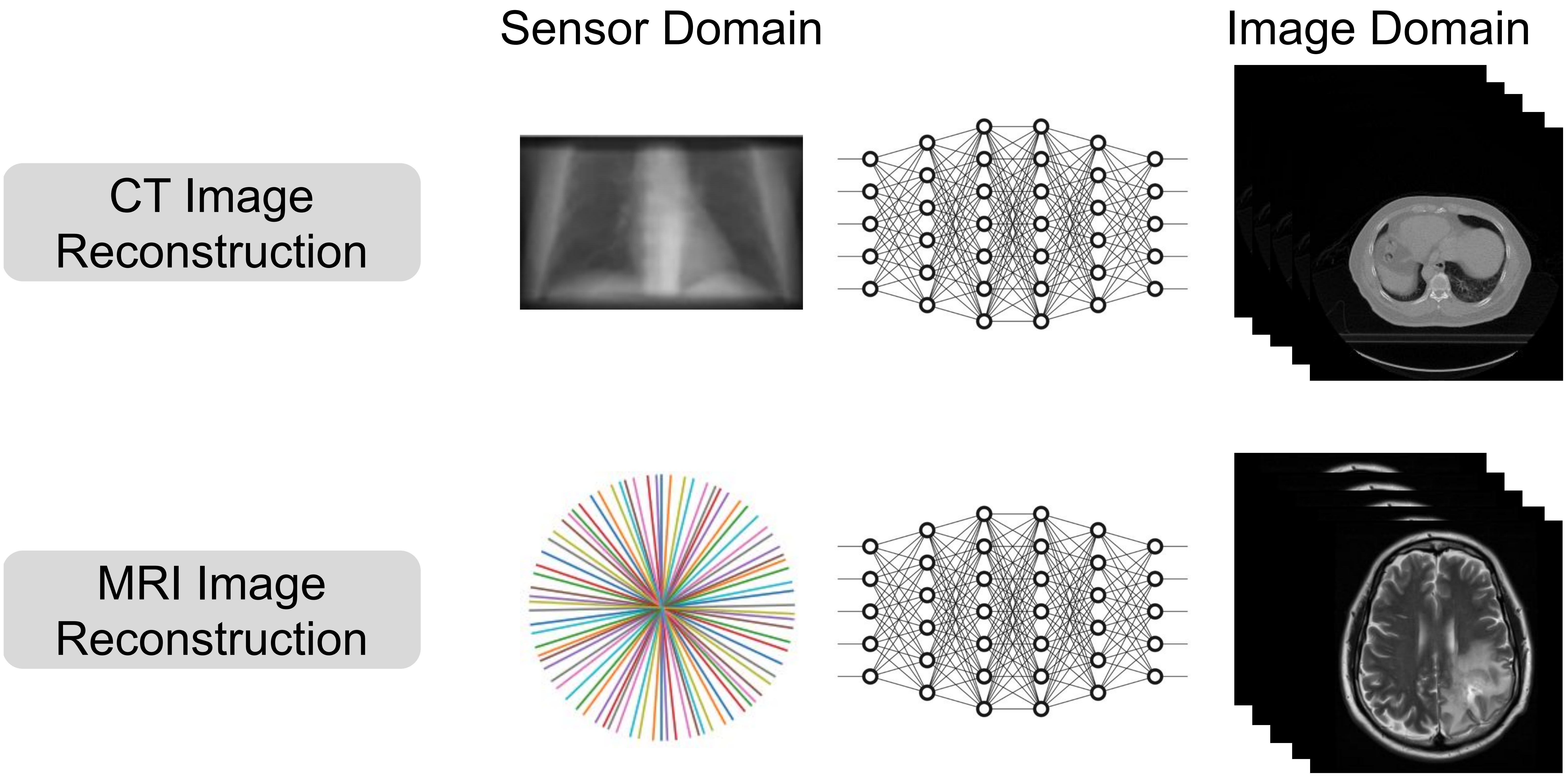


GRFF (NeurIPS 2020)

Mildenhall, et al., NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis, ECCV 2020.
Tancik*, et al., Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains, NeurIPS 2020.
Sitzmann*, et al., Implicit Neural Representations with Periodic Activation Functions, NeurIPS 2020.

Previous approach

Network learns mapping from sensor measurements to the reconstructed image

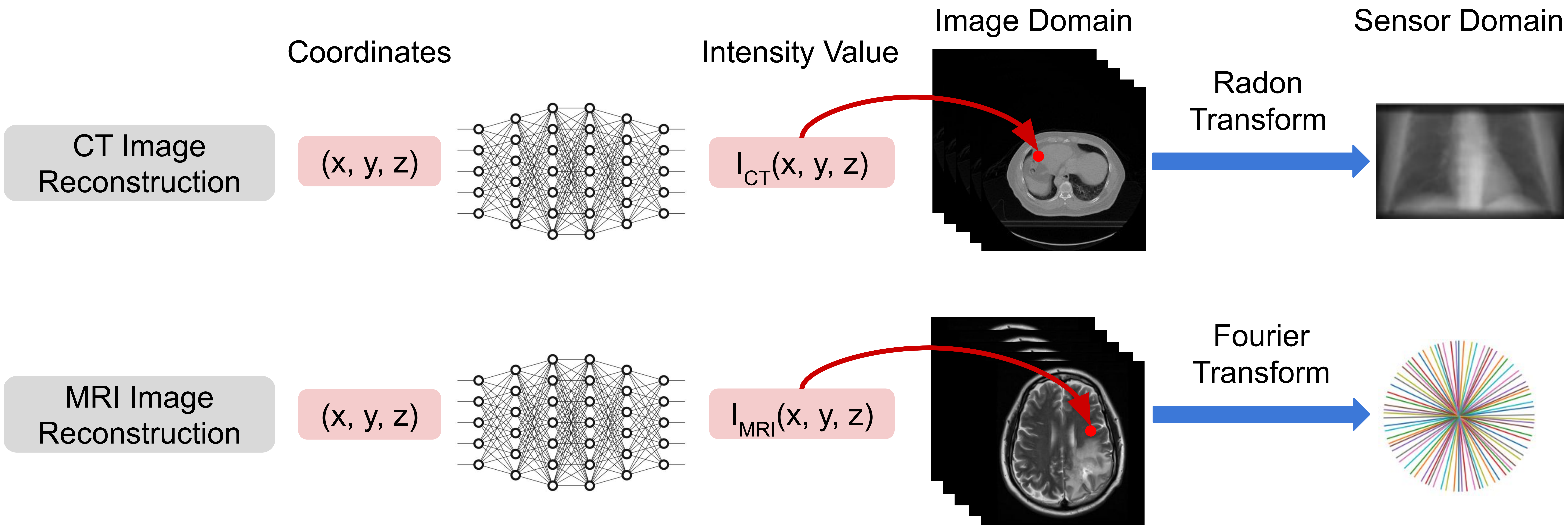


Shen, et al., NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction, TNNLS 2022.

New approach

Implicit neural representation learning for biomedical imaging

- Network learns implicit neural representation of the reconstructed image



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Implicit neural representation learning for biomedical imaging

Reformulate as a continuous function optimization problem

Optimization objective:

- x: image
- y: observed measurements
- A: forward model
- data fidelity + regularizer

$$x^* = \underset{x}{\operatorname{argmin}}\ \mathcal{E}(Ax, y) + \rho(x)$$

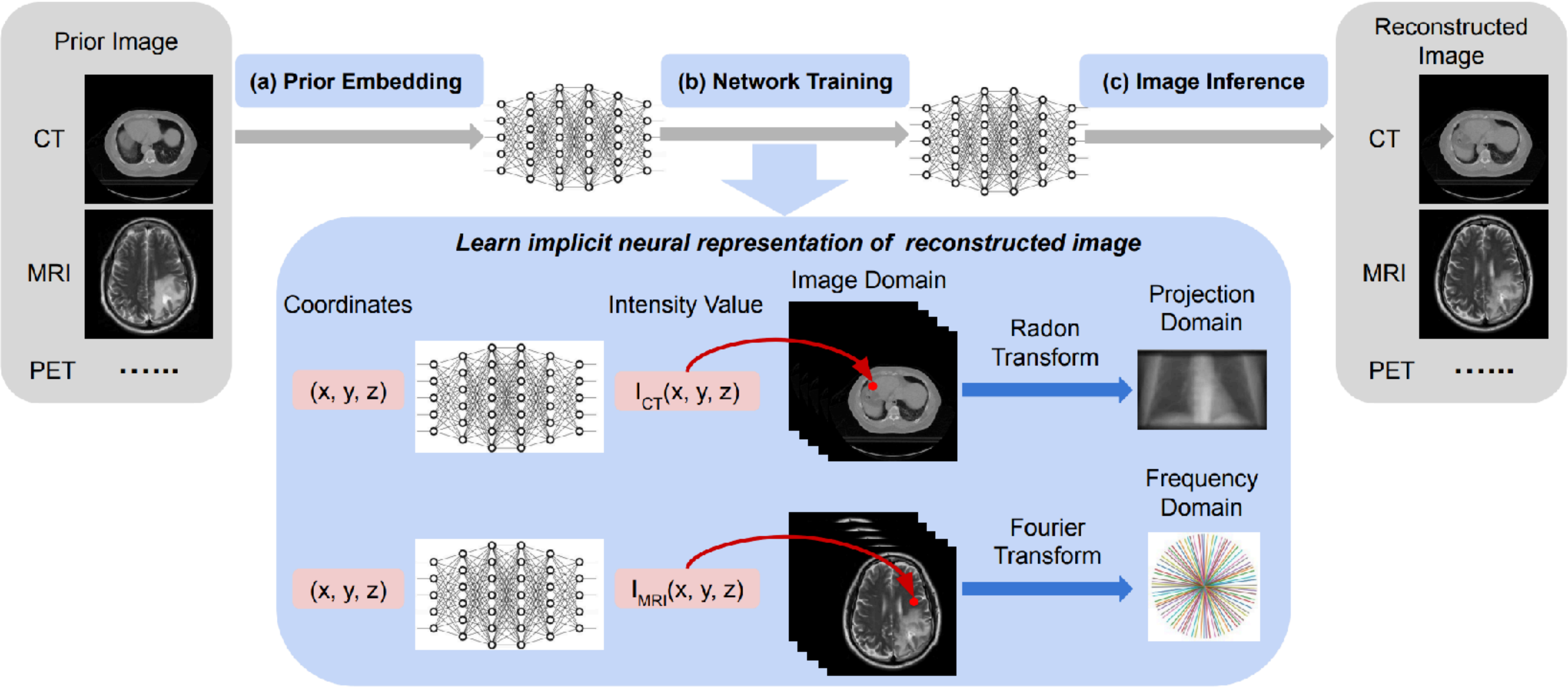
Implicit regularization captured by the network parametrization

How can neural representation learning model incorporate personalized prior?

Shen, et al., NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction, TNNLS 2022.

Our approach

Exploit internal information from **personalized prior** and physics of sparsely sampled measurements to learn the representation of unknown subject



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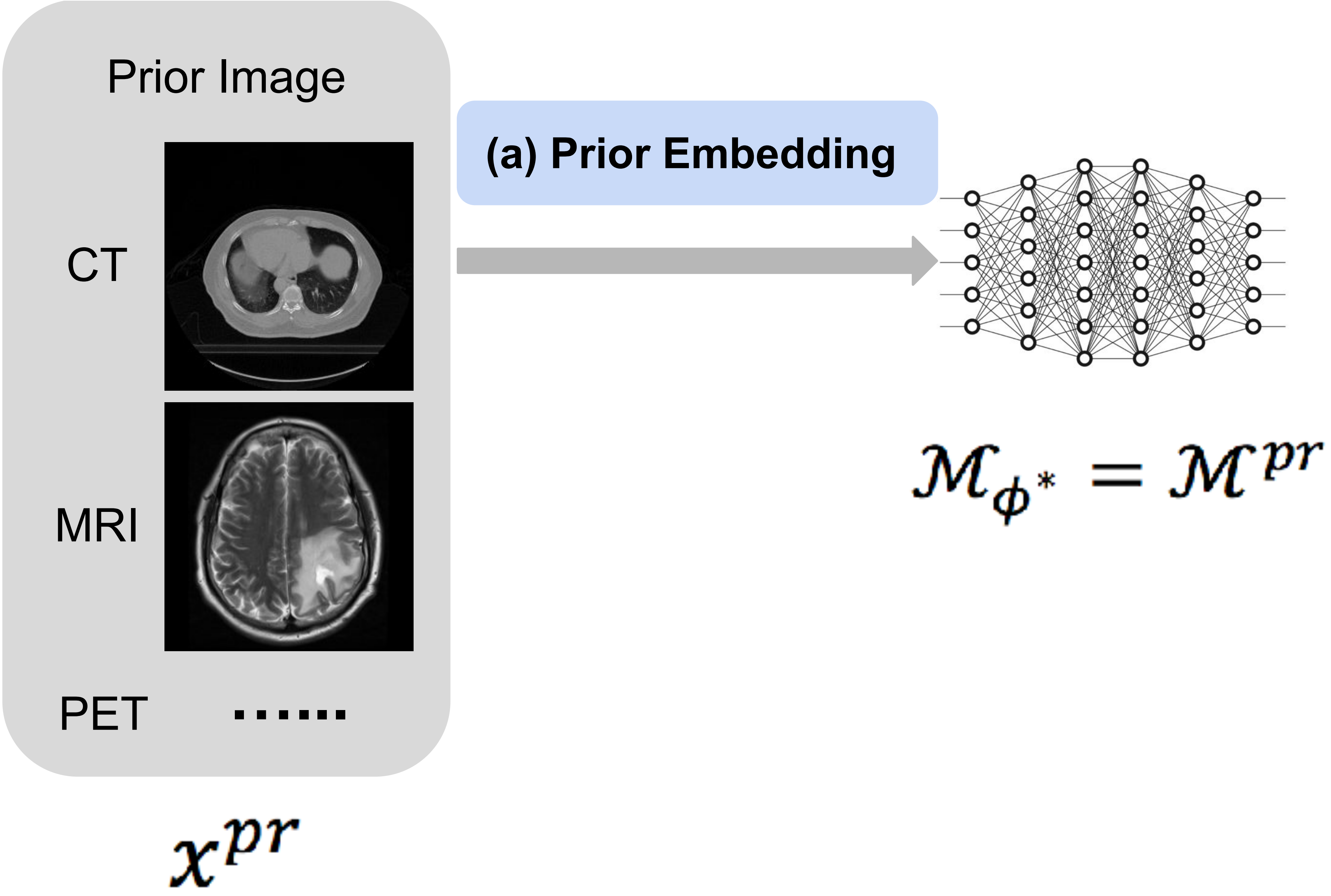
Our approach

1. **Prior embedding:** fit the prior image into the neural network's weights



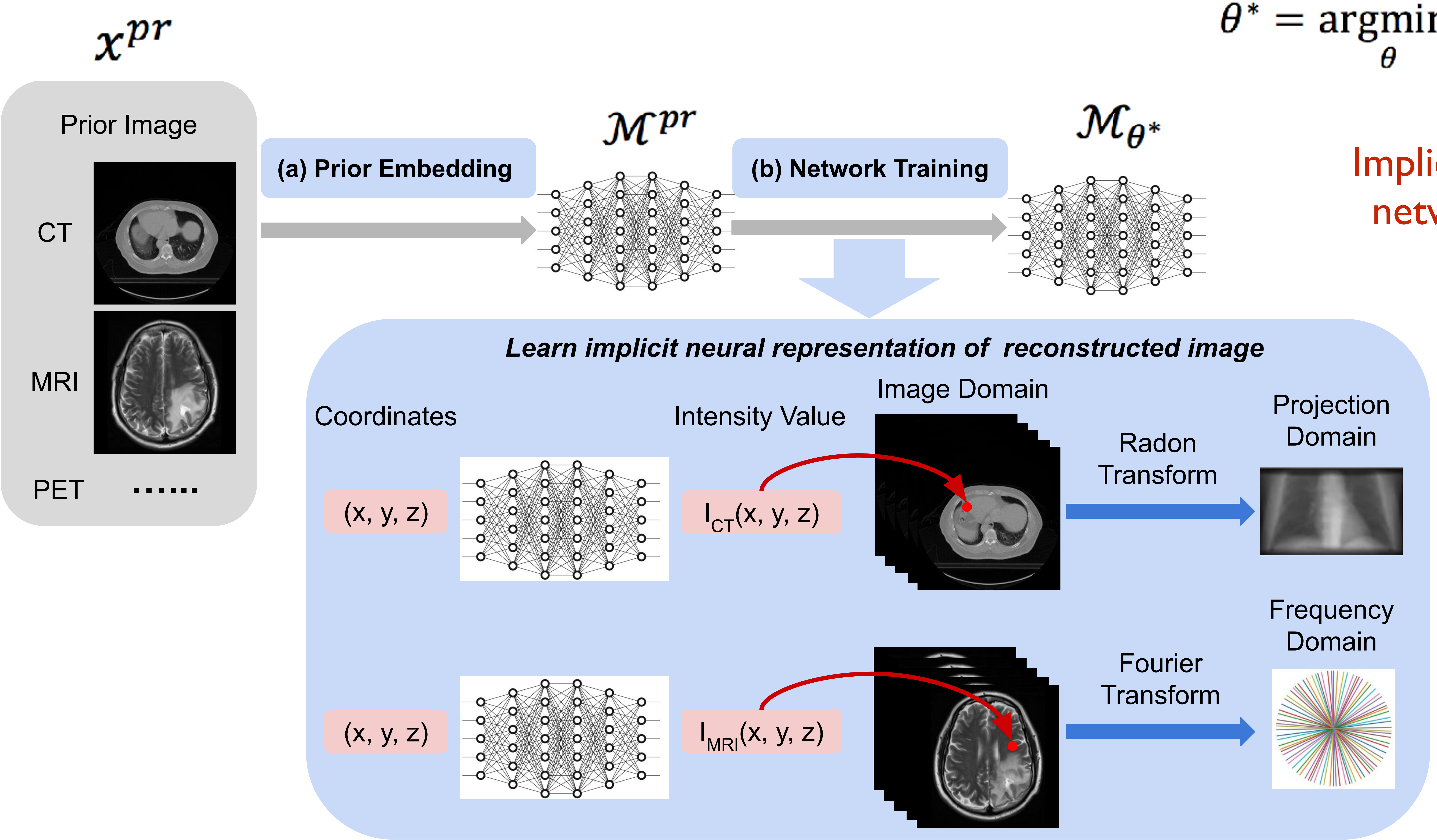
$$\phi^* = \underset{\phi}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^{N} \left\| \mathcal{M}_{\phi}(c_i) - x_i^{pr} \right\|_2^2$$

x: image
i: spatial grid index
c: spatial coordinates
M: network
Φ: network weights

Our approach

2. Network training: fine-tune the network to match the constraints of sparsely sampled measurements

$$\theta^* = \underset{\theta}{\operatorname{argmin}}\ \mathcal{E}(A\boxed{\mathcal{M}_\theta}, y; \boxed{\mathcal{M}^{pr}}), \quad x^* = \mathcal{M}_{\theta^*}$$



Implicit regularization captured by the network parametrization and prior-embedded initialization

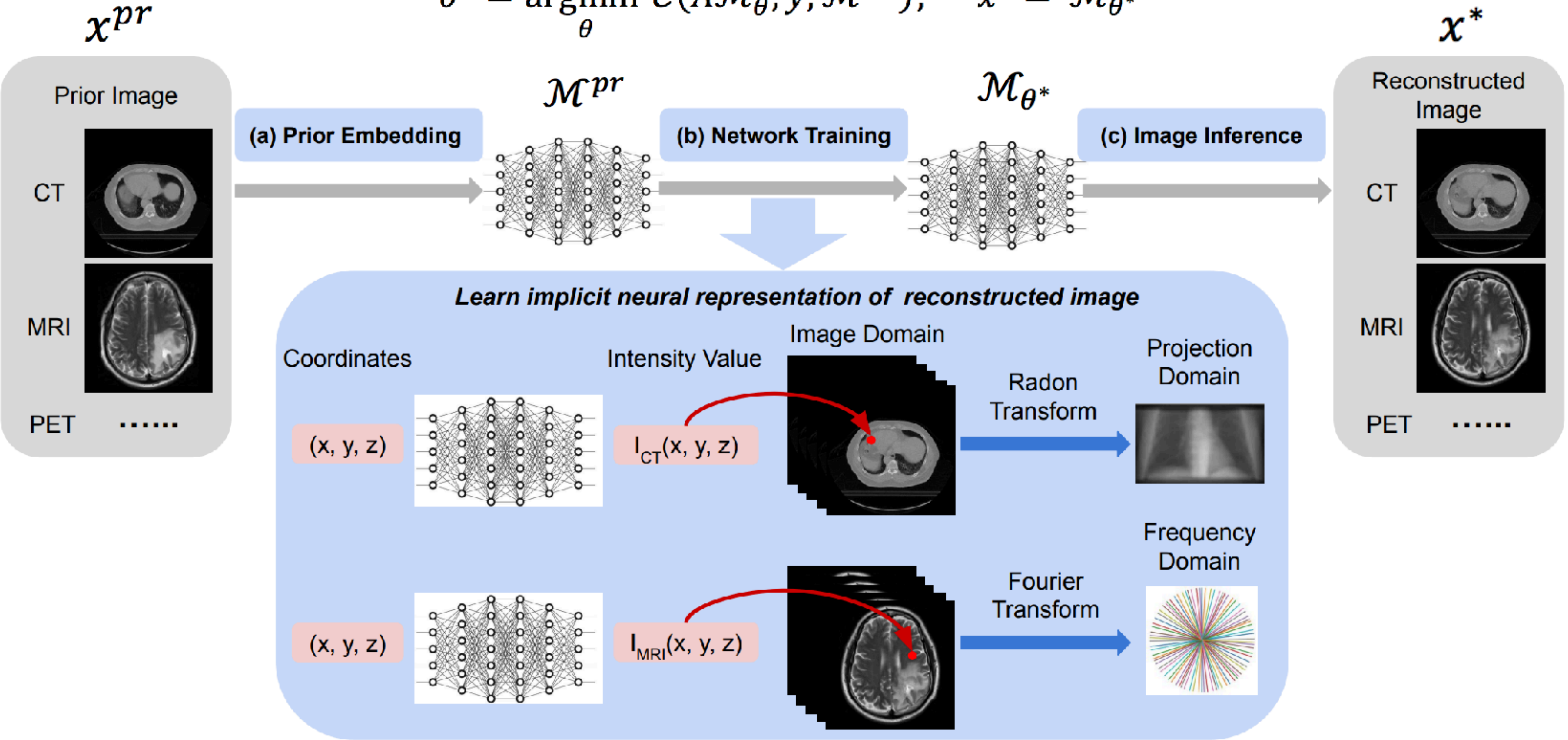
x: image
y: observed measurements
M: network
θ: network weights
A: forward model

Shen, et al., NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction, TNNLS 2022.

Our approach

3. Image inference: infer the trained network across all the spatial coordinates in the image grid

$$\theta^* = \underset{\theta}{\text{argmin}}\ \mathcal{E}(A\mathcal{M}_\theta, y; \mathcal{M}^{pr}), \quad x^* = \mathcal{M}_{\theta^*}$$



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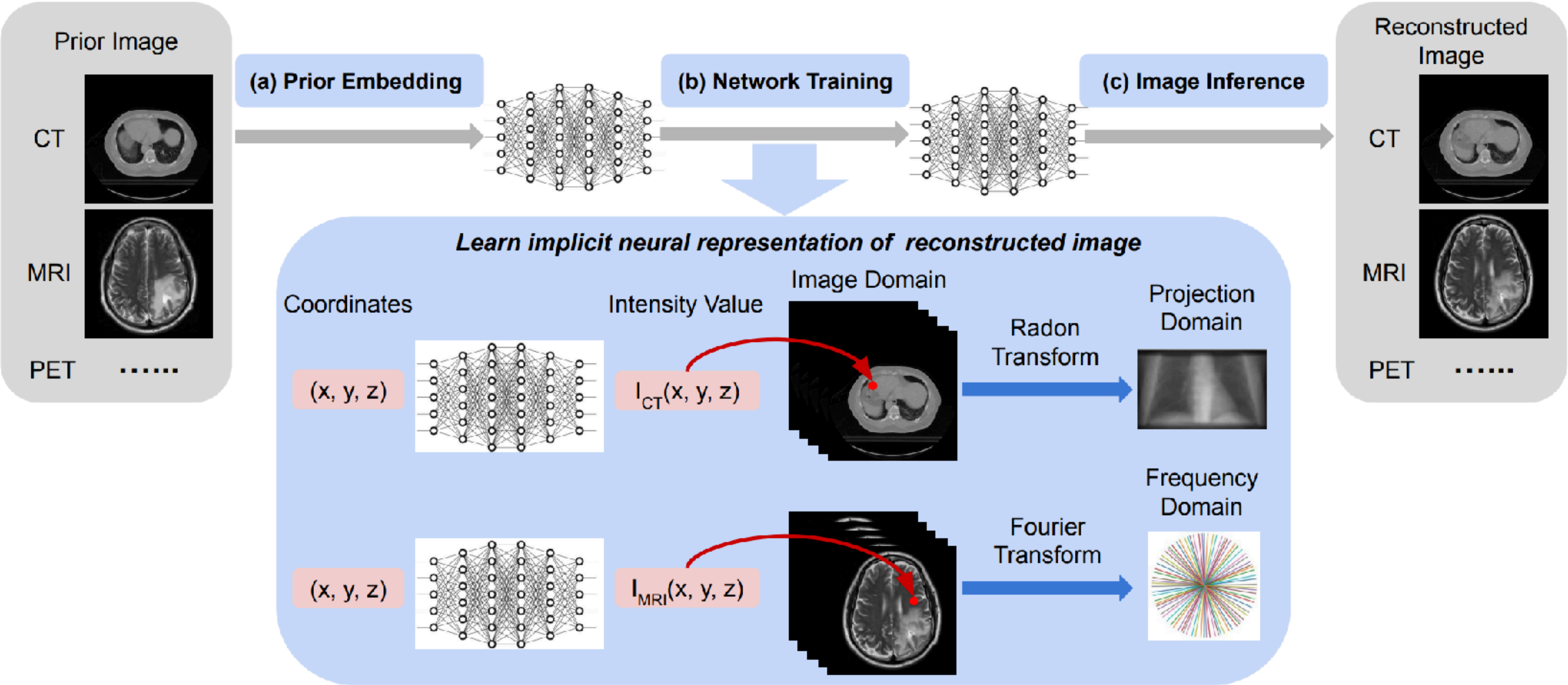
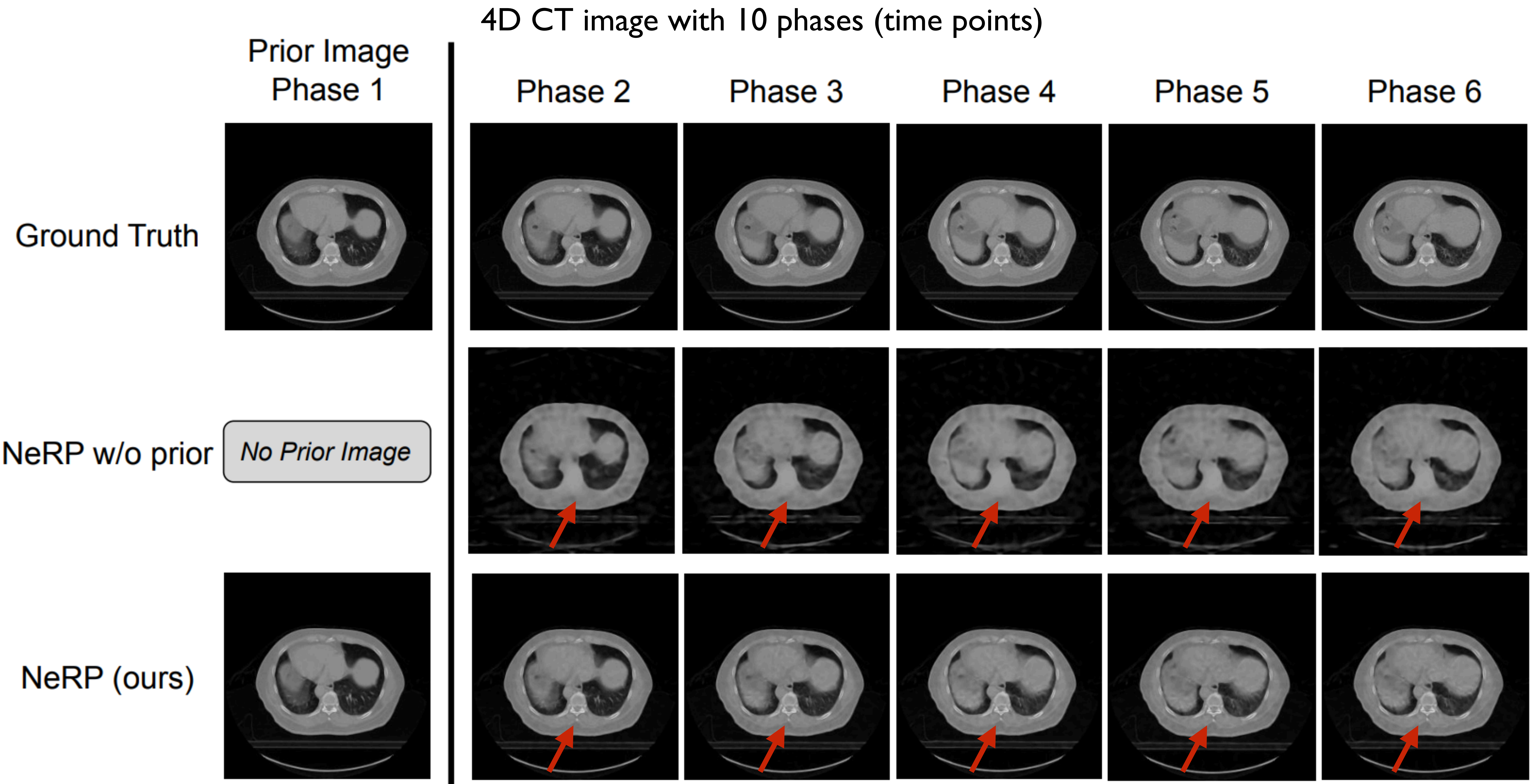
NeRP: Neural Representation learning with Prior embedding

Exploit internal information from **personalized prior** and physics of sparsely sampled measurements to learn the representation of unknown subject



Shen, et al., NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction, TNNLS 2022.

Data-efficiency: no large-scale data from external subjects is required to train model except for a longitudinal prior image and sparsely sampled measurements

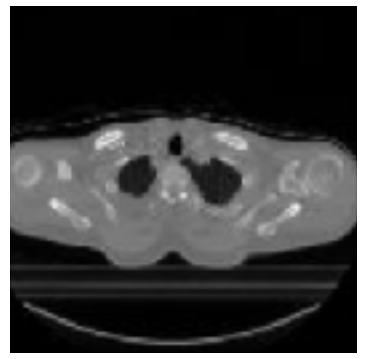


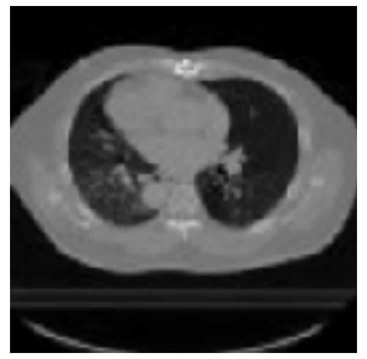
Reliability: robustly capture subtle but significant structural changes required for assessing tumor shrink or progression

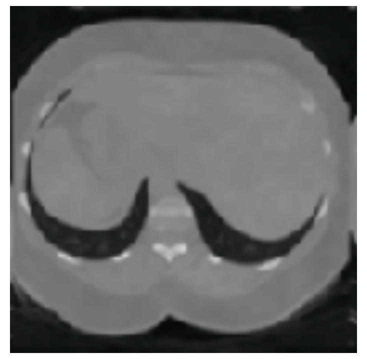
Clinical lung cancer patient case with two longitudinal 3D CT

Generalization: easily generalize to **different anatomic sites**, **imaging modalities**, and **sampling processes**

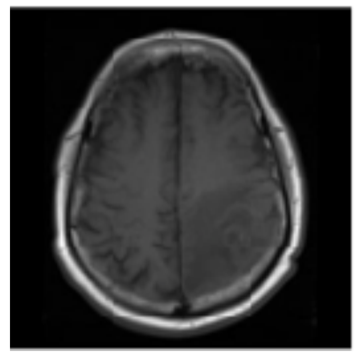
Different anatomic sites

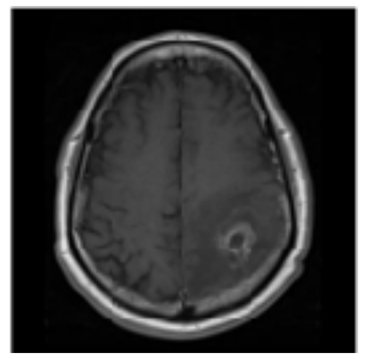

HeadNeck CT

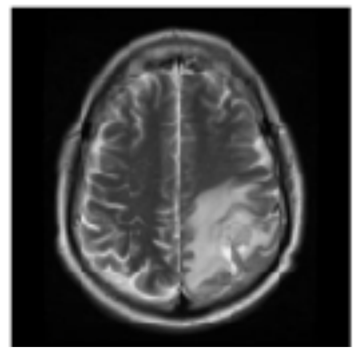

Lung CT

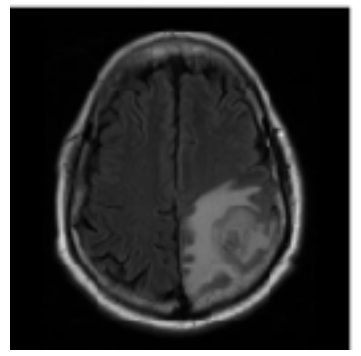

Pancreas CT

Different imaging modalities

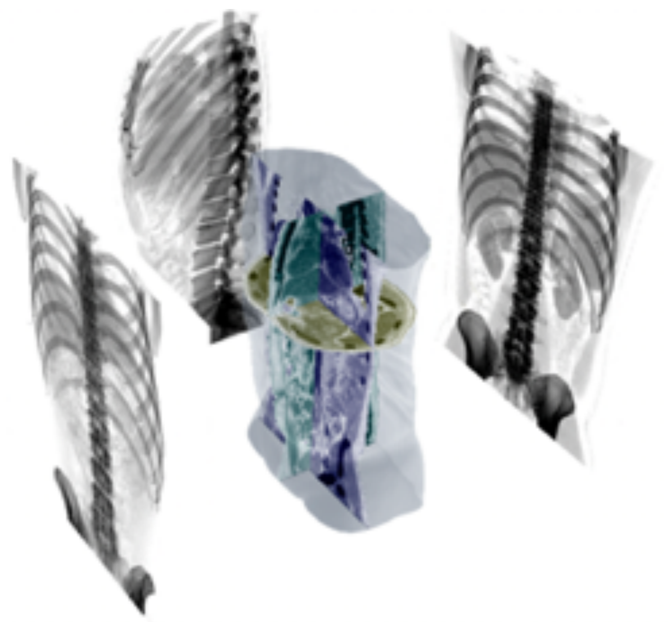

T1 MRI


T1-contrast MRI


T2 MRI


FLAIR MRI

Different sampling processes

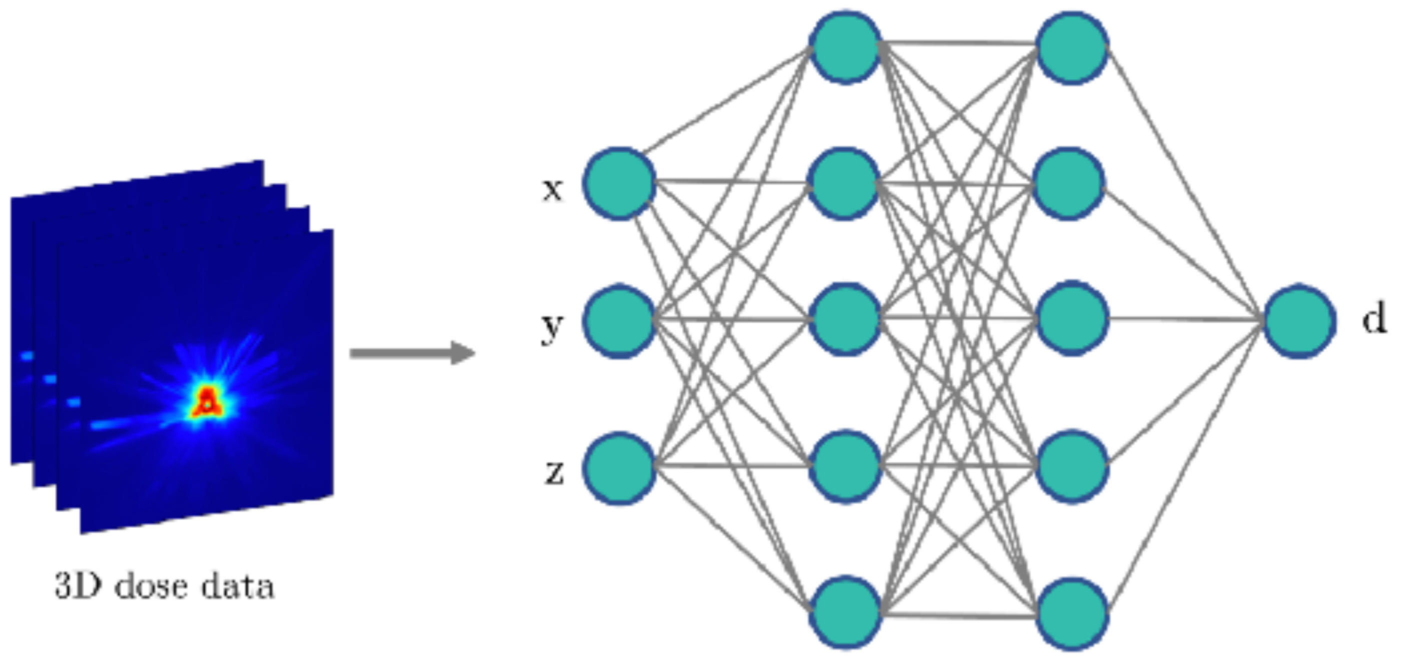

Different projections in CT

Different sampling masks in MRI

Follow-up works …

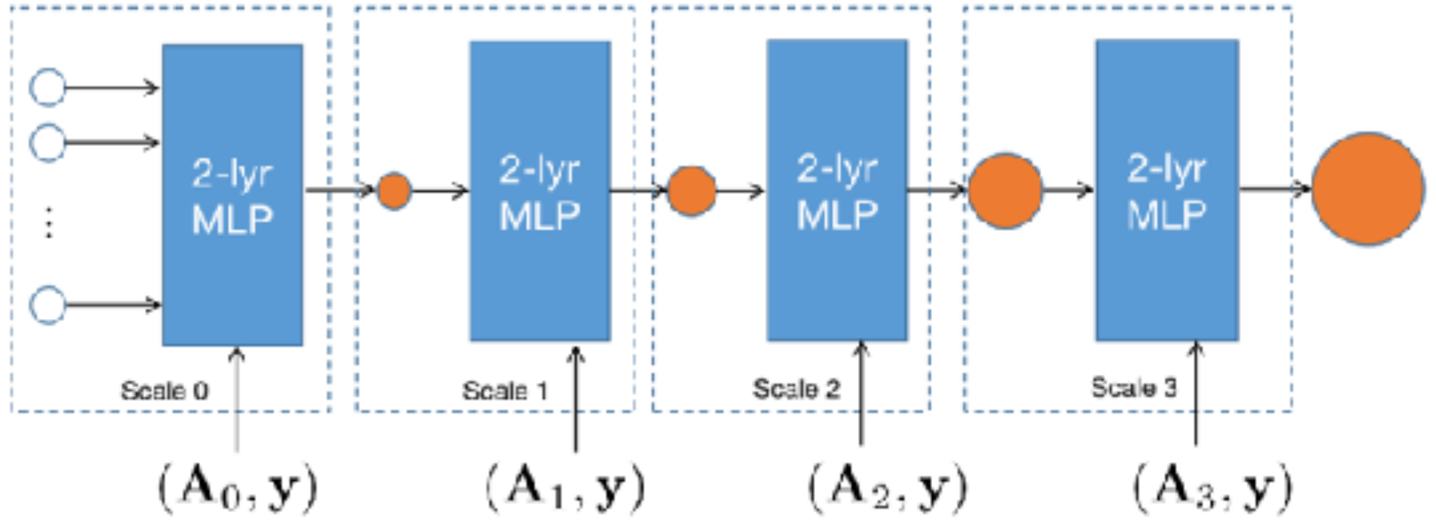
Apply to clinical problem

Radiation therapy dose distribution



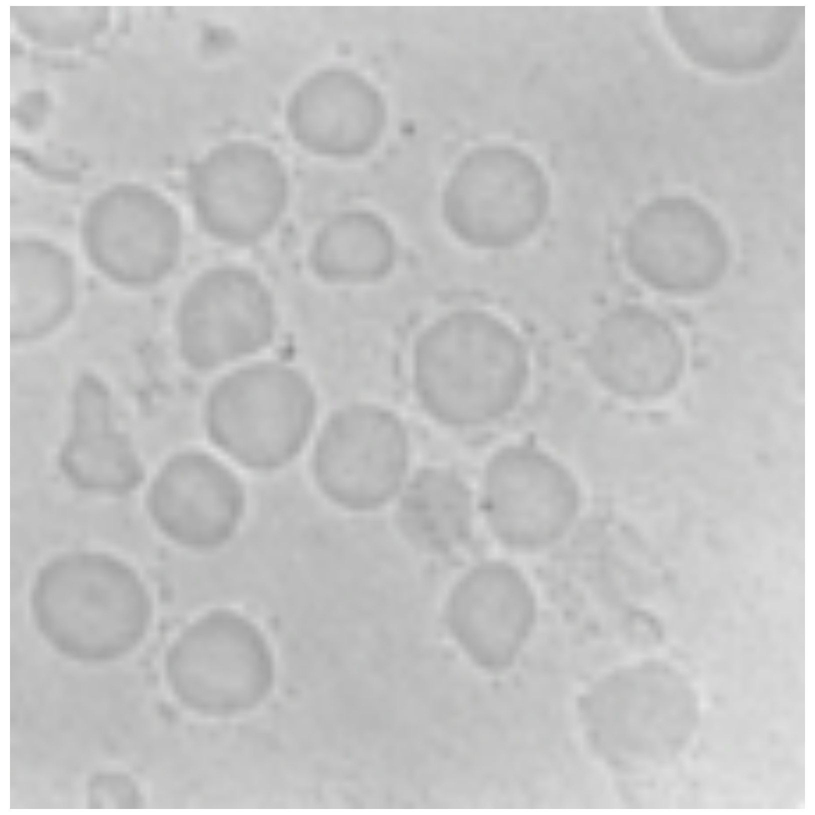
Scale to large-size image

Multi-scale NeRP

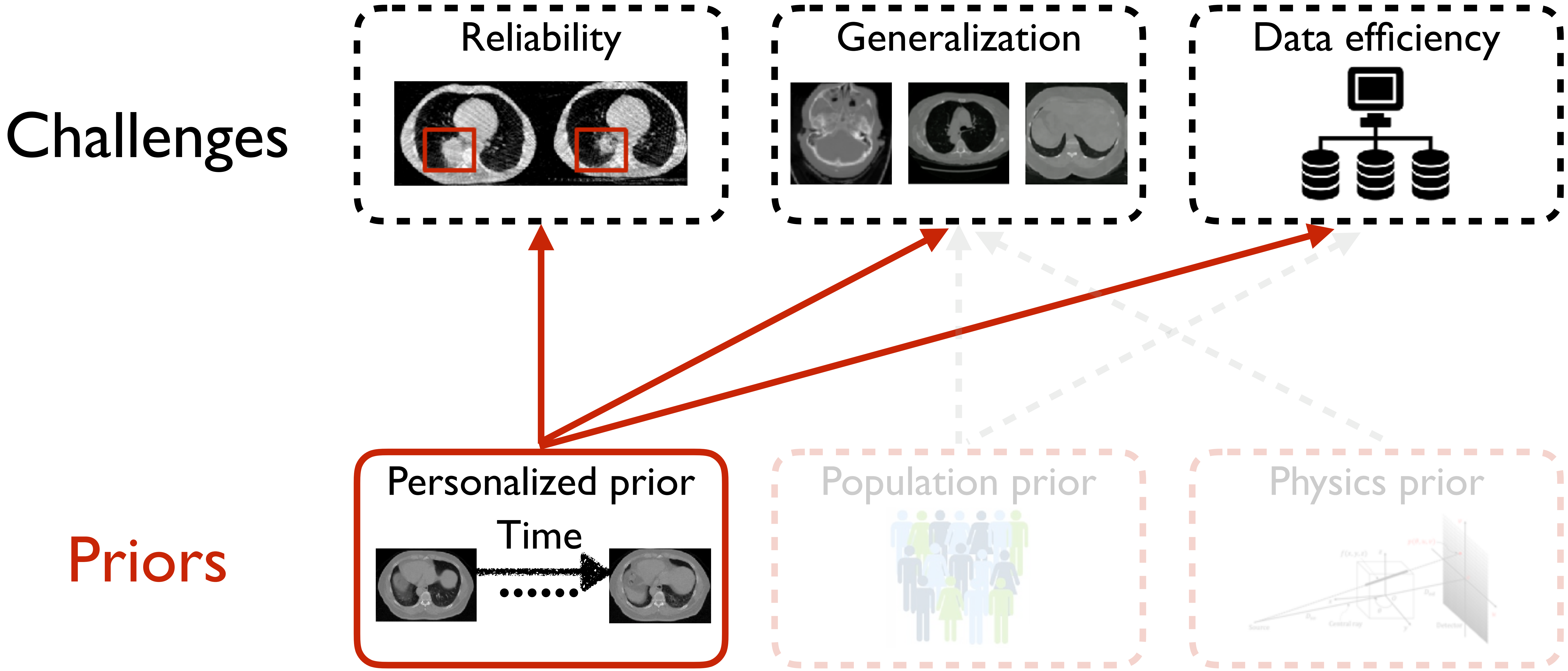


Generalize to new modality

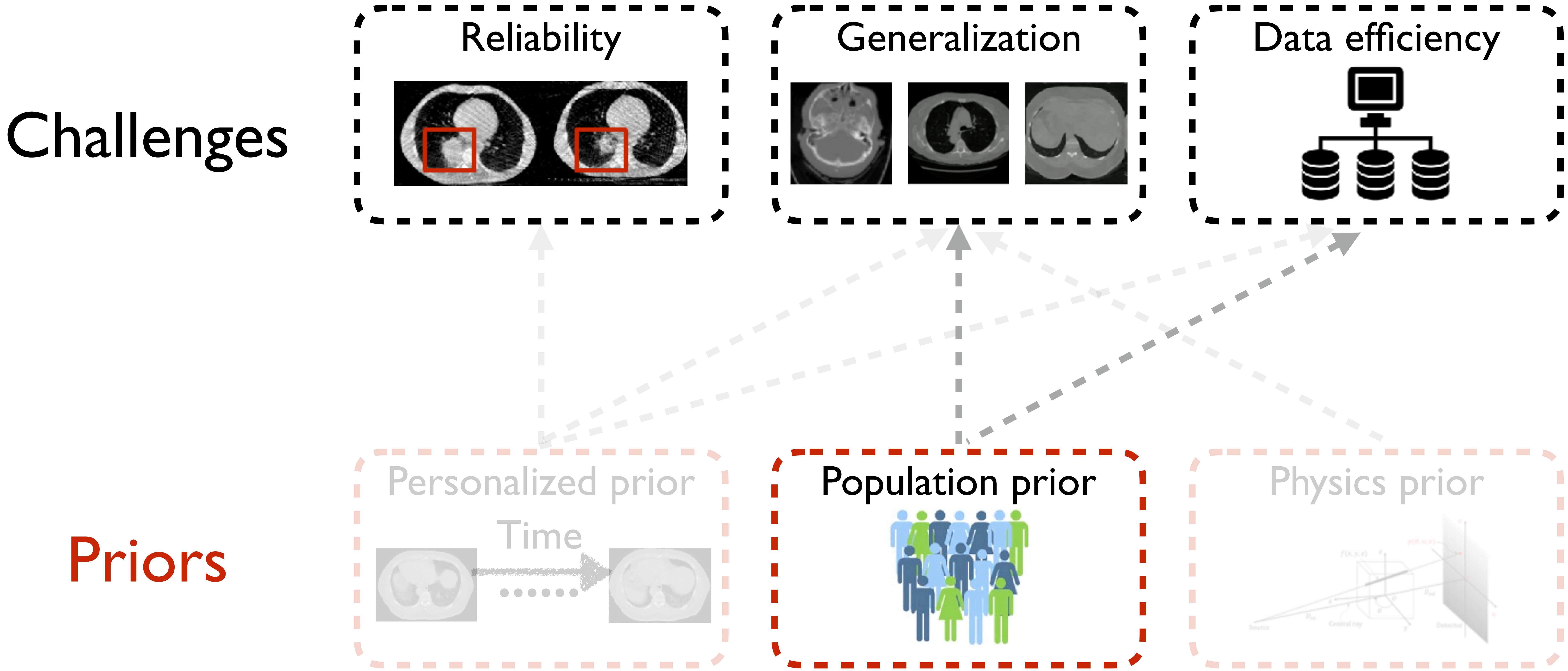
Missing wedge in cryo-EM



Recap: Personalized Prior



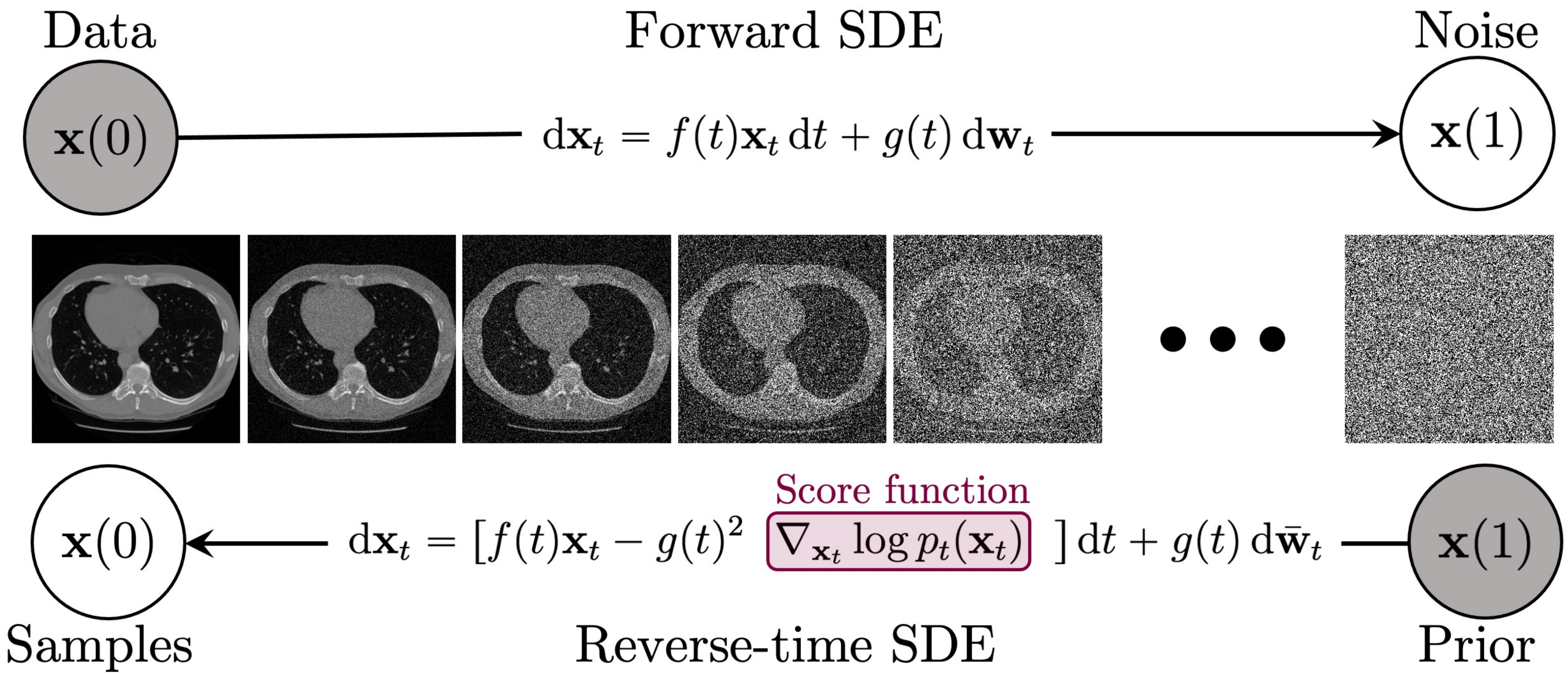
2. Population Prior



Score-based generative model

Train score-based generative model to estimate **prior data distribution (population prior)**

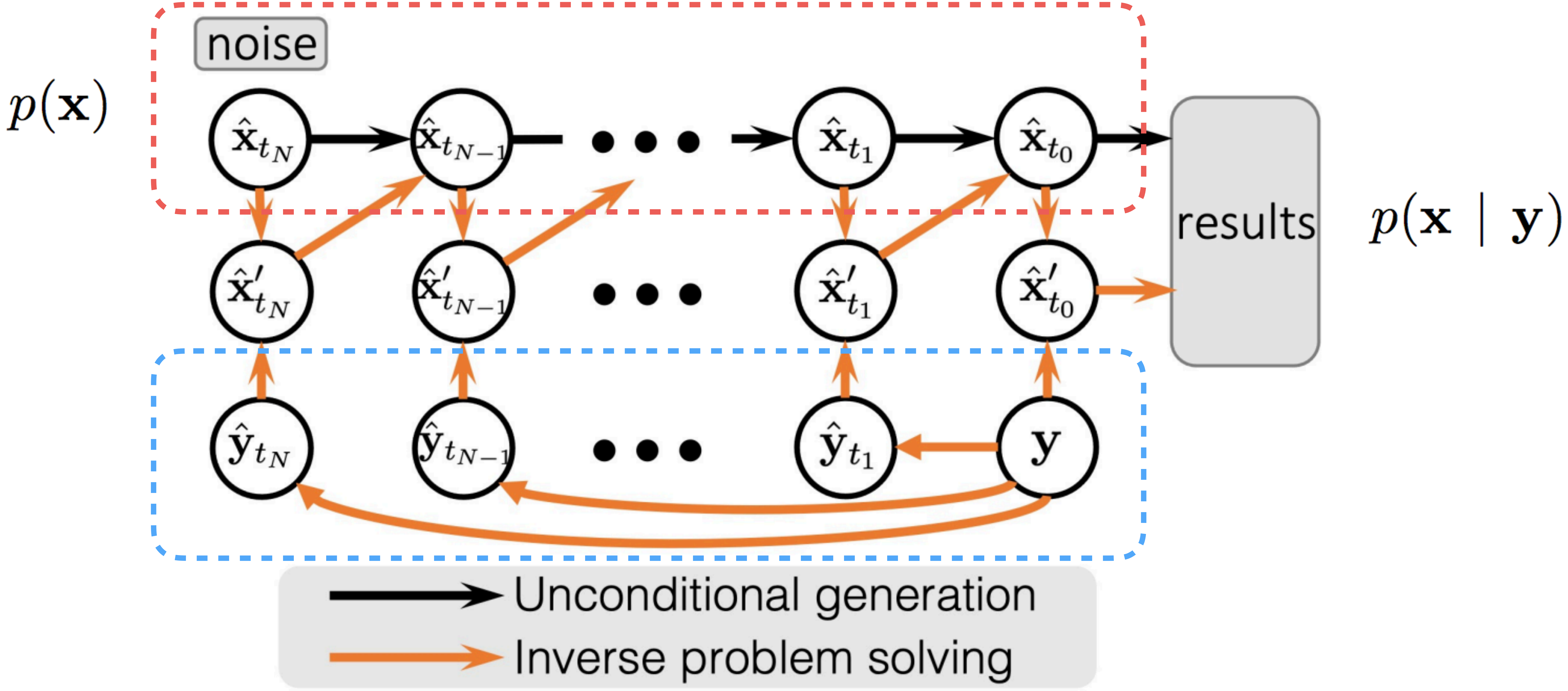
- **Perturbation process:** forward stochastic differential equation
- **Sampling process:** reverse-time stochastic differential equation



Song, et al., Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021.
Song*, Shen*, et al., Solving inverse problems in medical imaging with score-based generative models, ICLR 2022.

Conditional sampling approach for inverse problem solving

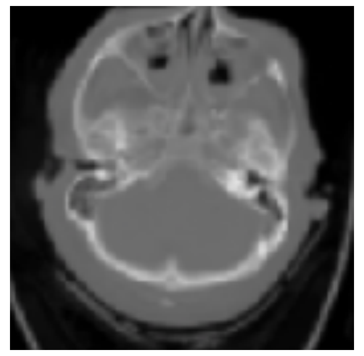
Generate image consistent with population prior and observed measurements

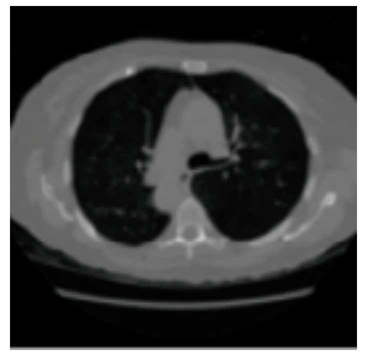


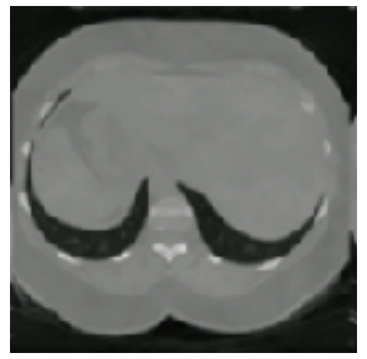
Song*, Shen*, et al., Solving inverse problems in medical imaging with score-based generative models, ICLR 2022.

Generalization: **a single training model** captures population prior of **multi-anatomic sites** and **multi-modal** images

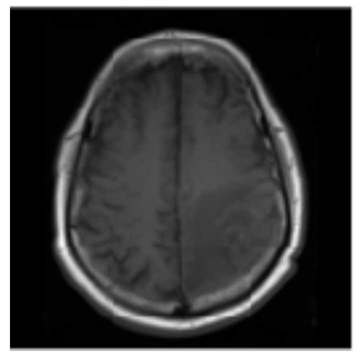
Multiple anatomic sites

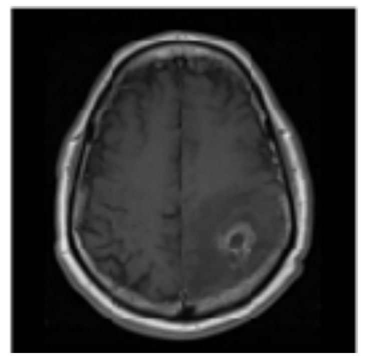

Head CT

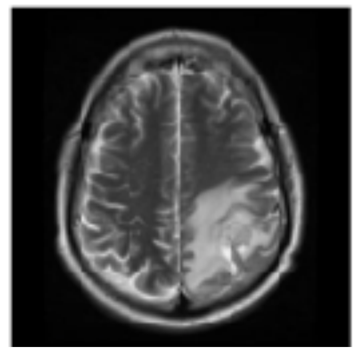

Lung CT

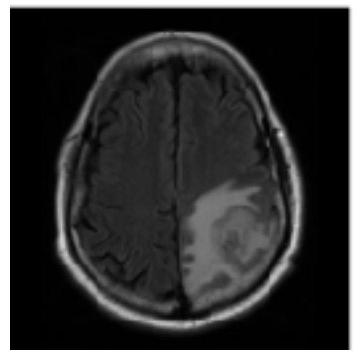

Abdominal CT

Multiple imaging modalities


T1 MRI


T1-contrast MRI


T2 MRI

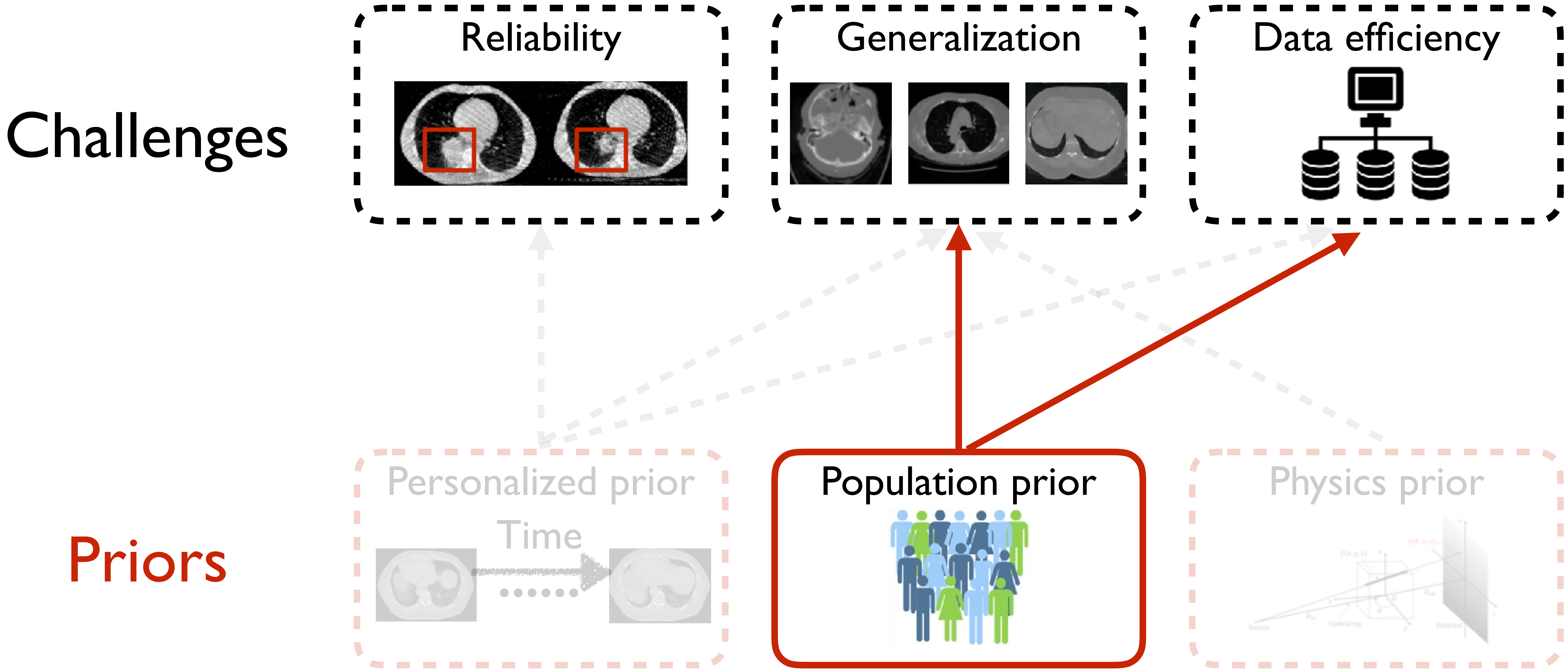

FLAIR MRI

Different sampling processes

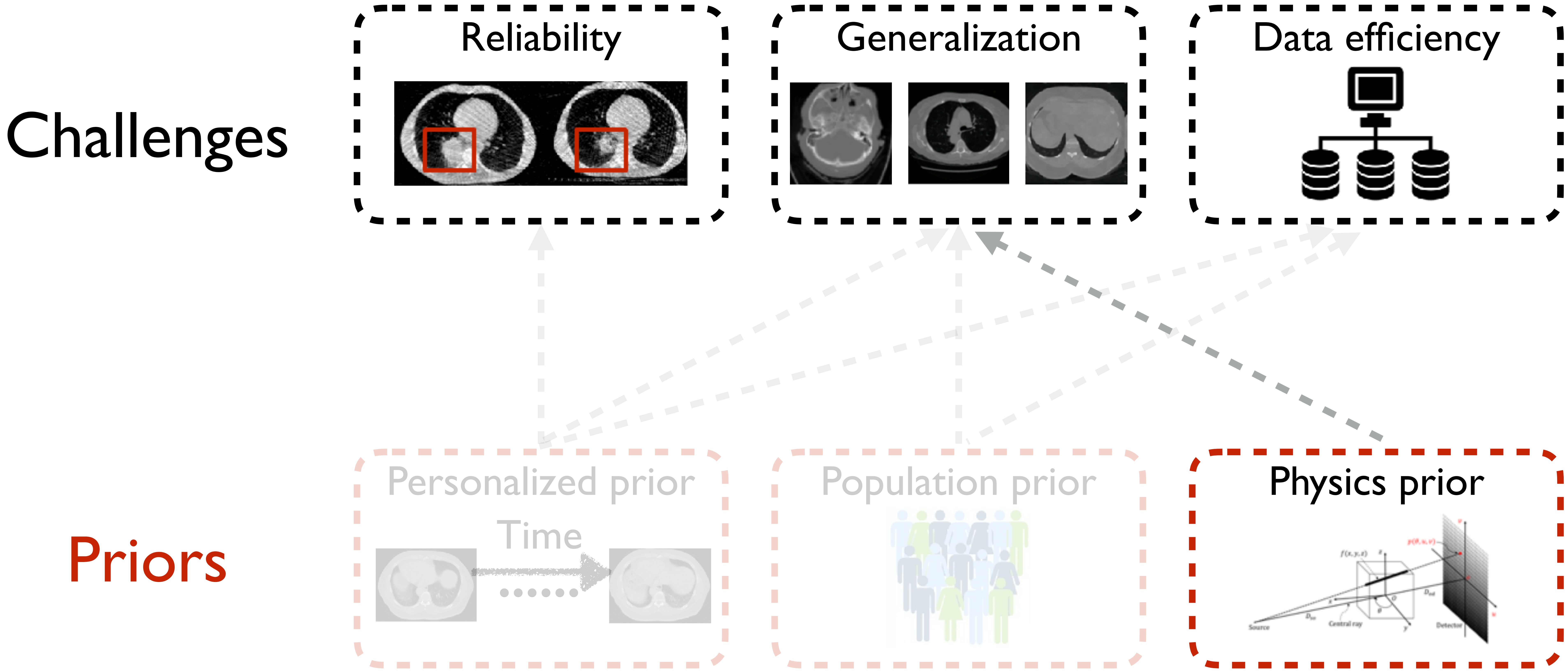

Different projections in CT

Different sampling masks in MRI

Recap: Population prior



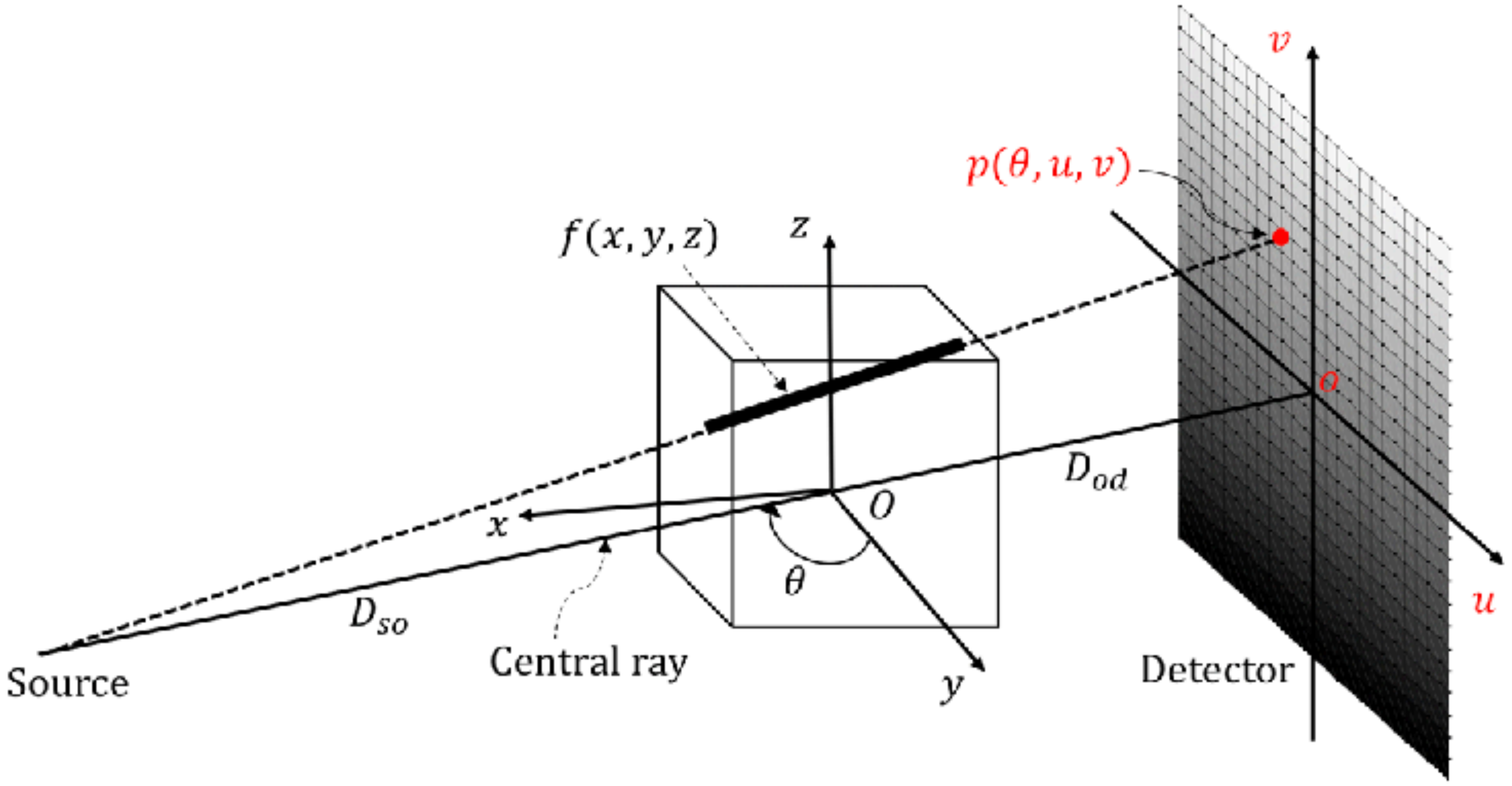
3. Physics Prior

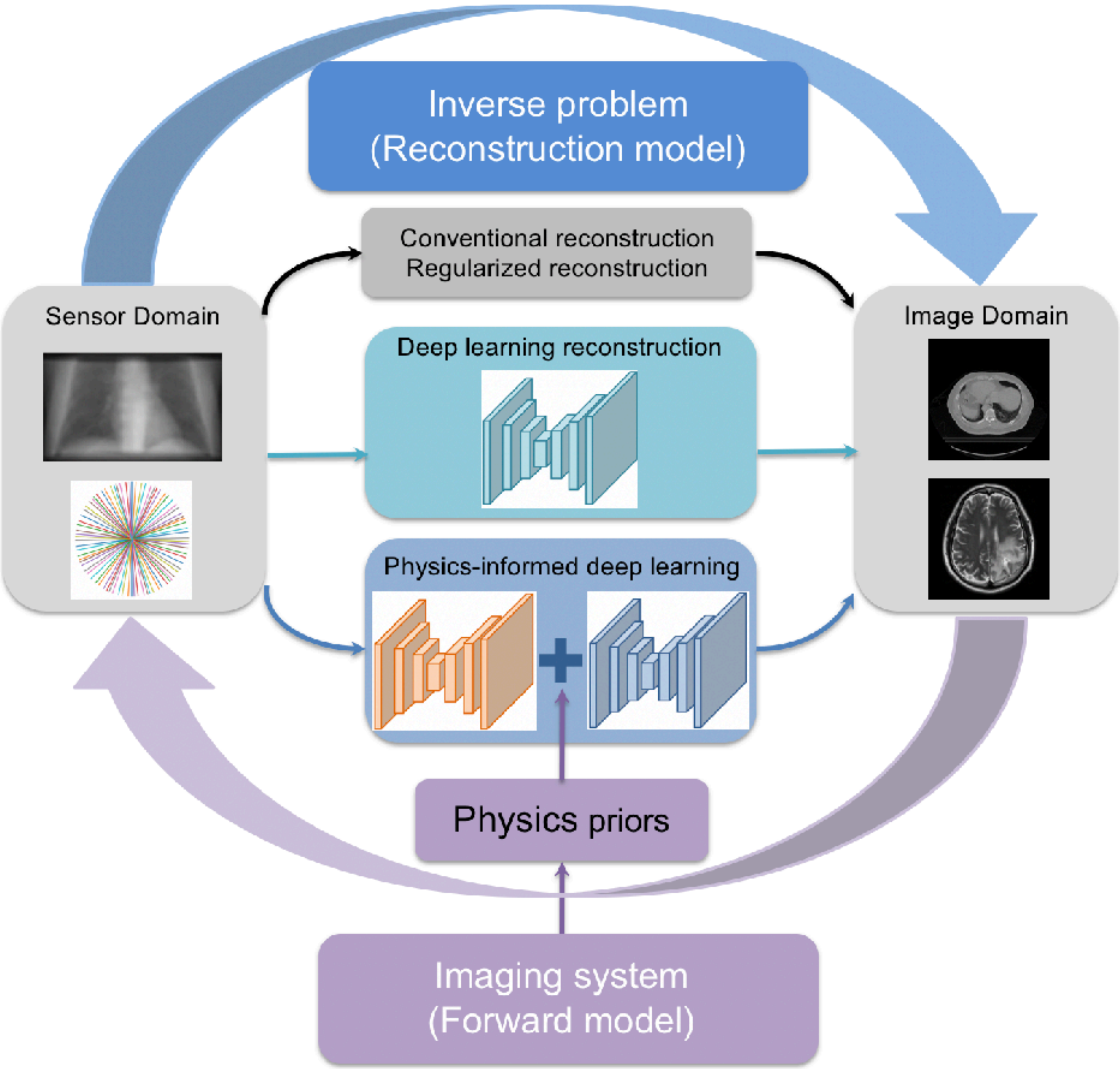


Physics priors from imaging system (forward model)

Physics priors:
- Modality (CT, MRI …)
- Dimension (2D, 3D, 3D+time …)
- Geometry (fan-beam, cone-beam…)
- …

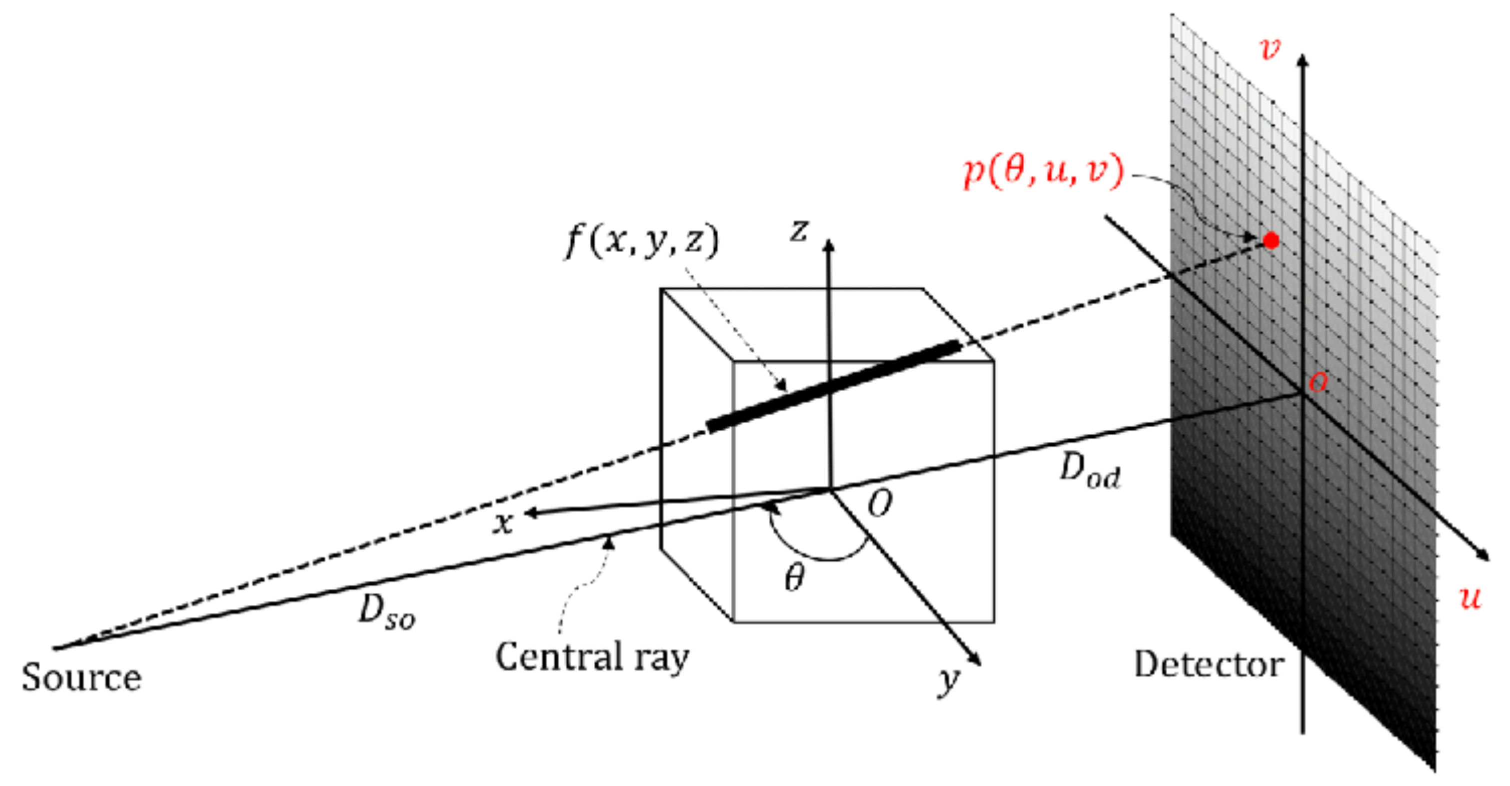
3D cone-beam CT geometry

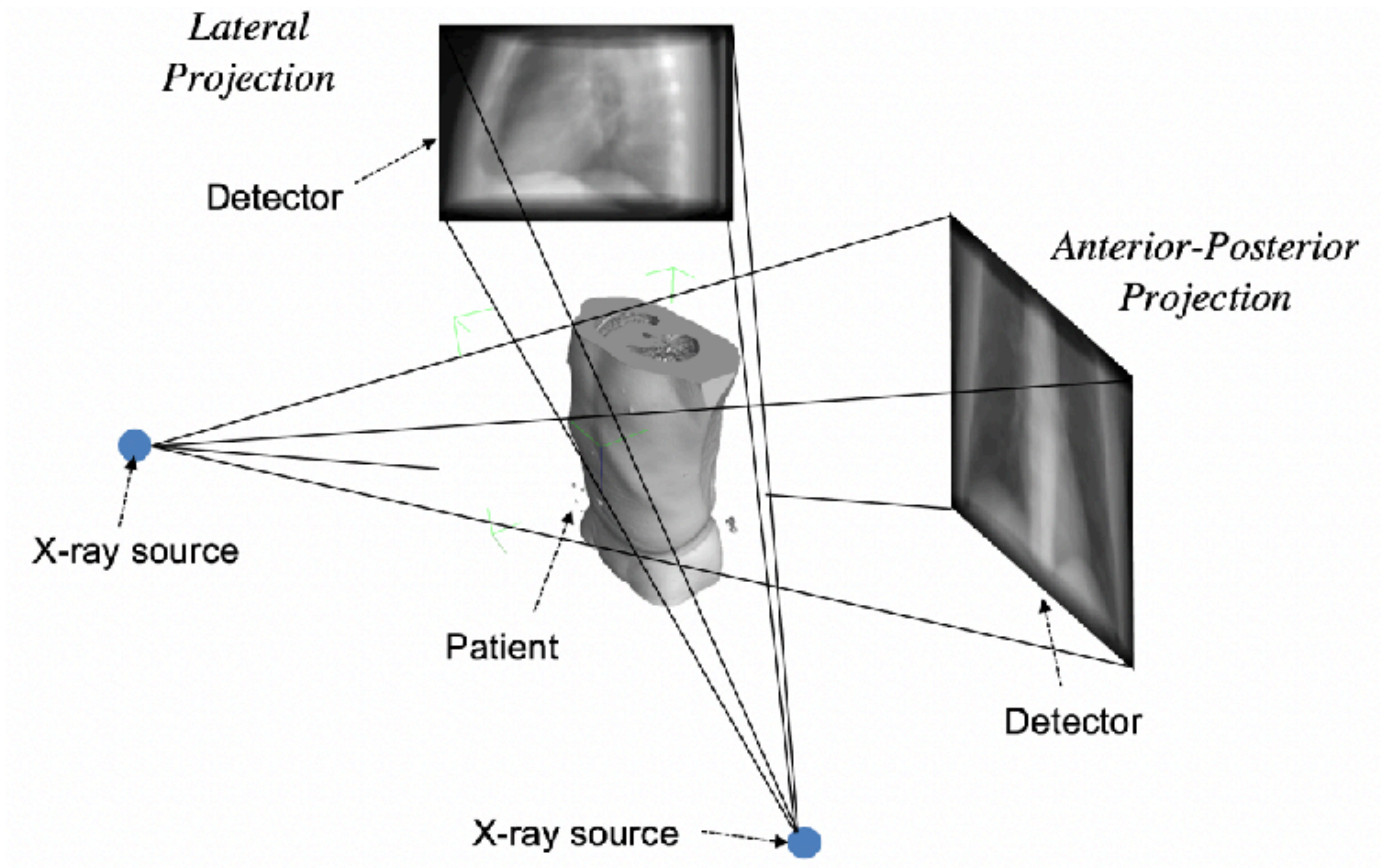


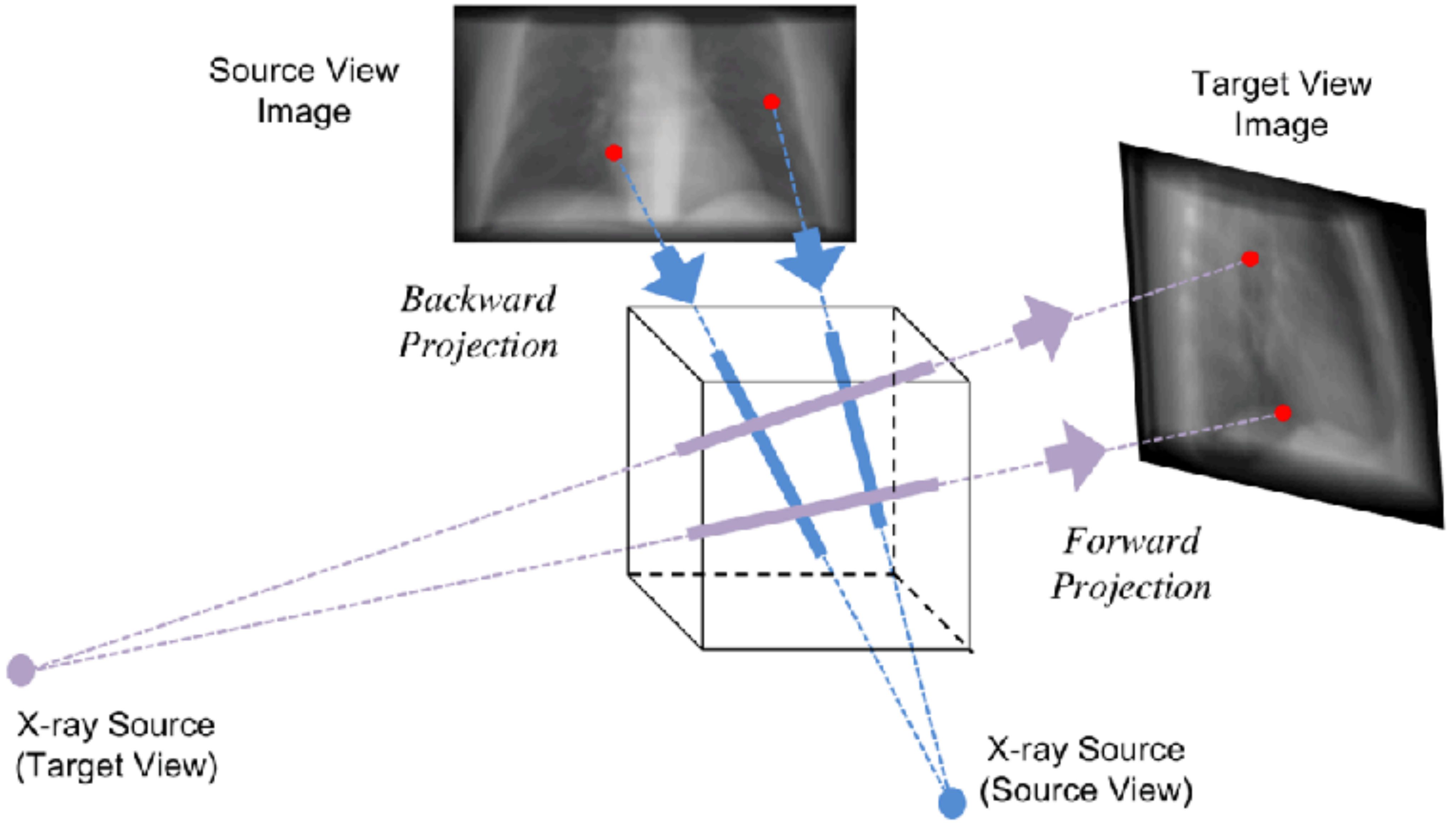


Physics priors from imaging system (forward model)

Physics priors relate and transfer information in different projections



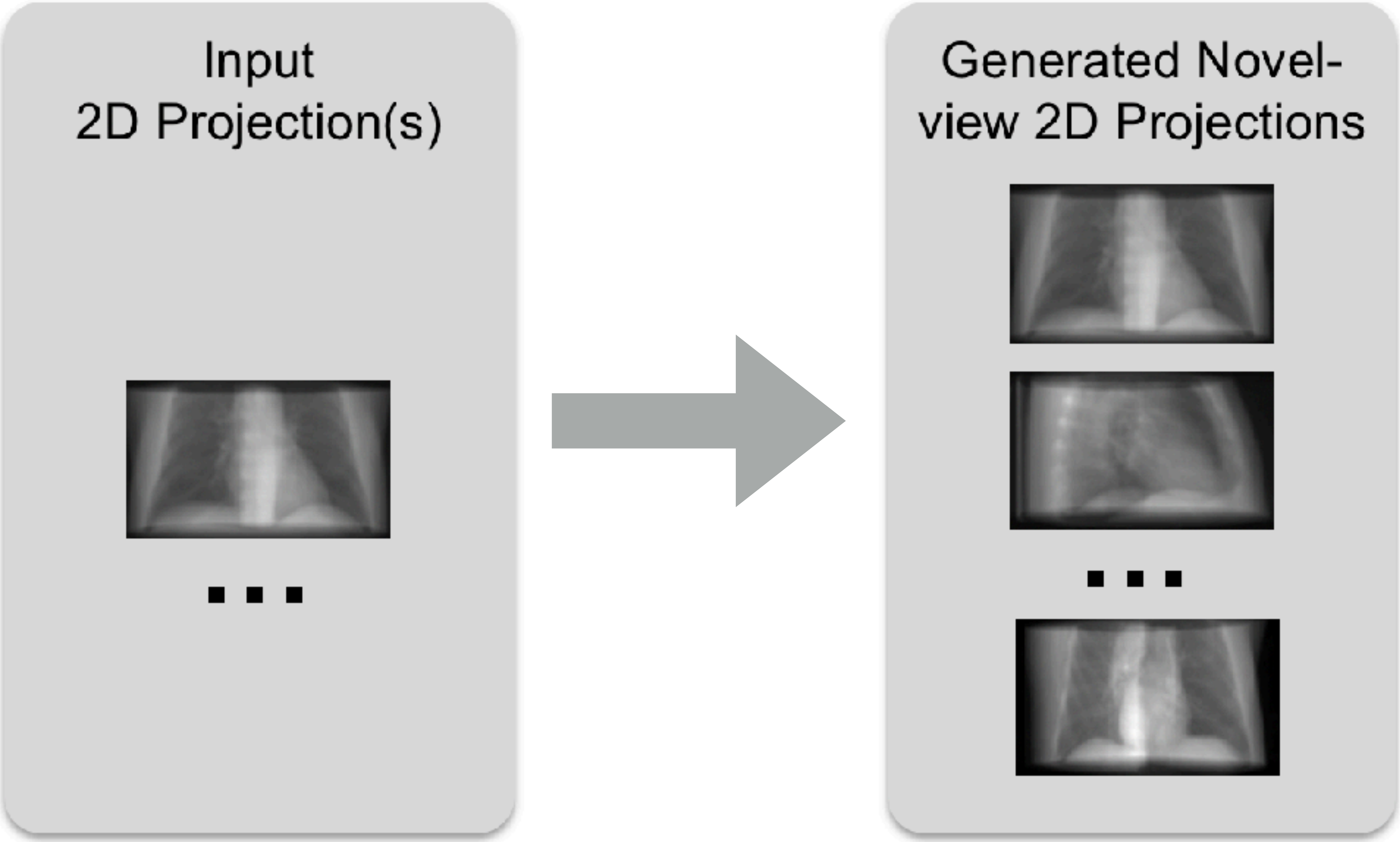




Physics-informed ML

Novel-view projection synthesis

- Synthesize novel-view projections given the source-view image as input

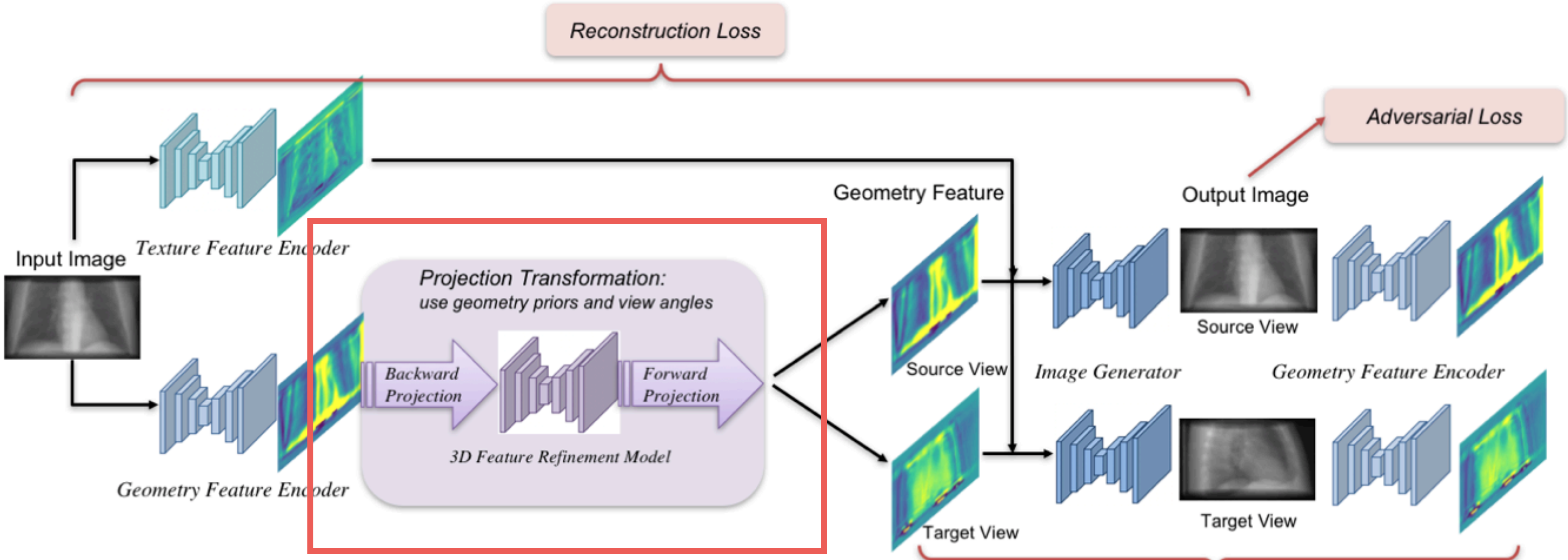


S

Physics-informed ML

DL-GIPS: Deep Learning-based Geometry-Integrated Projection Synthesis

- Physics priors relate and transfer information in different projections



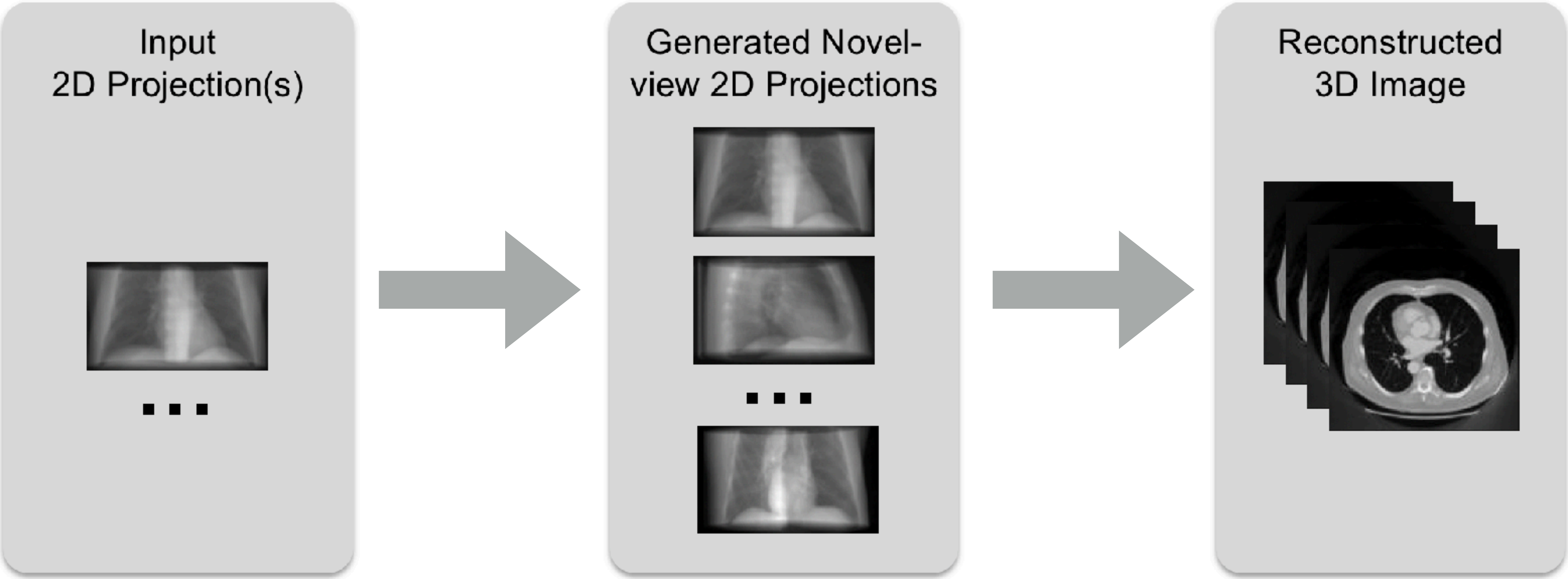
Physics-based cross-domain transformation in feature space

Shen, et al., Novel-view x-ray projection synthesis through geometry-integrated deep learning, MedIA 2021.

Physics-informed ML

Image Reconstruction

- Reconstruct 3D image with dual-domain learning



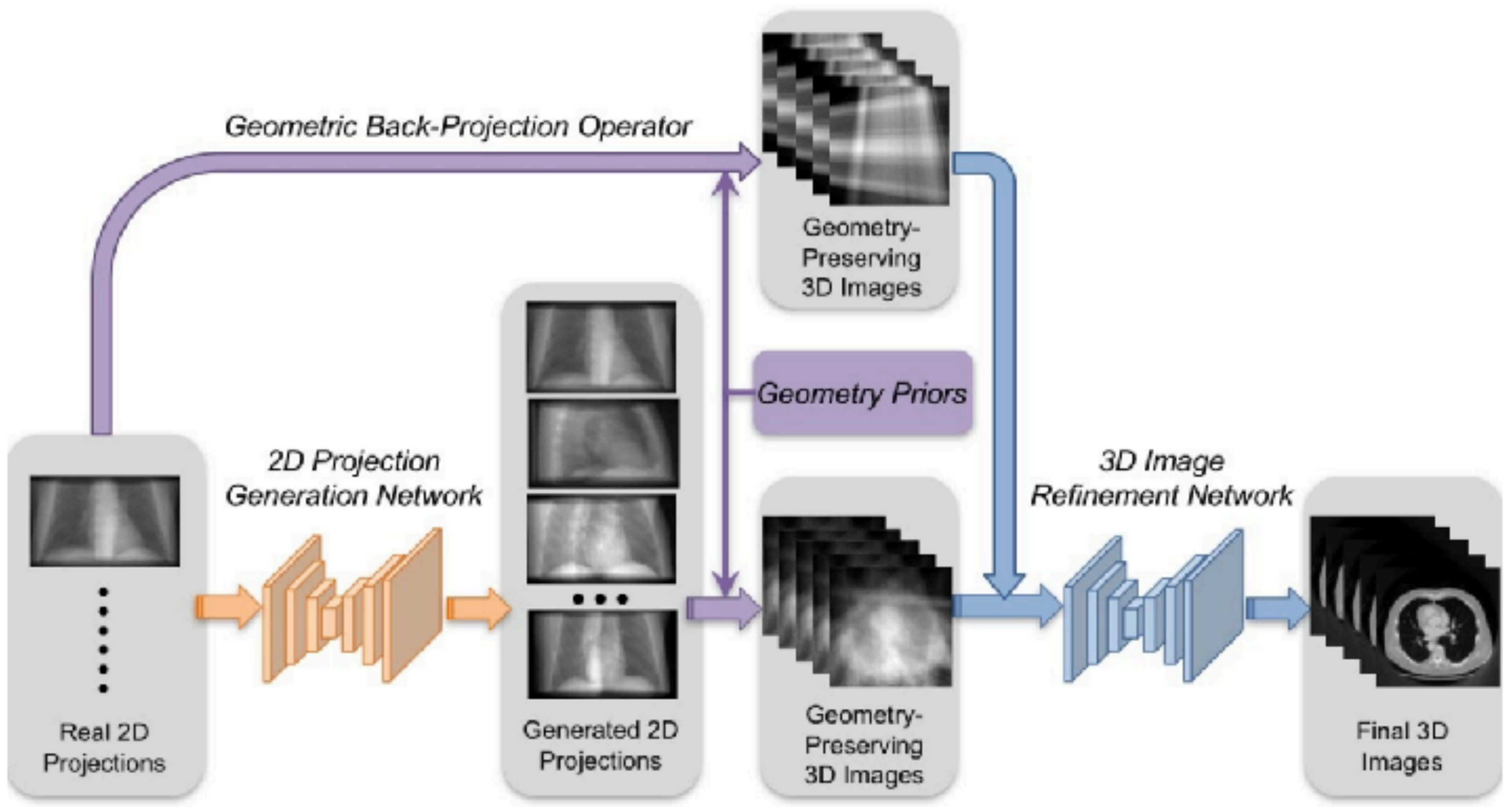
Shen, et al., Novel-view x-ray projection synthesis through geometry-integrated deep learning, MedIA 2021.

Physics-informed ML

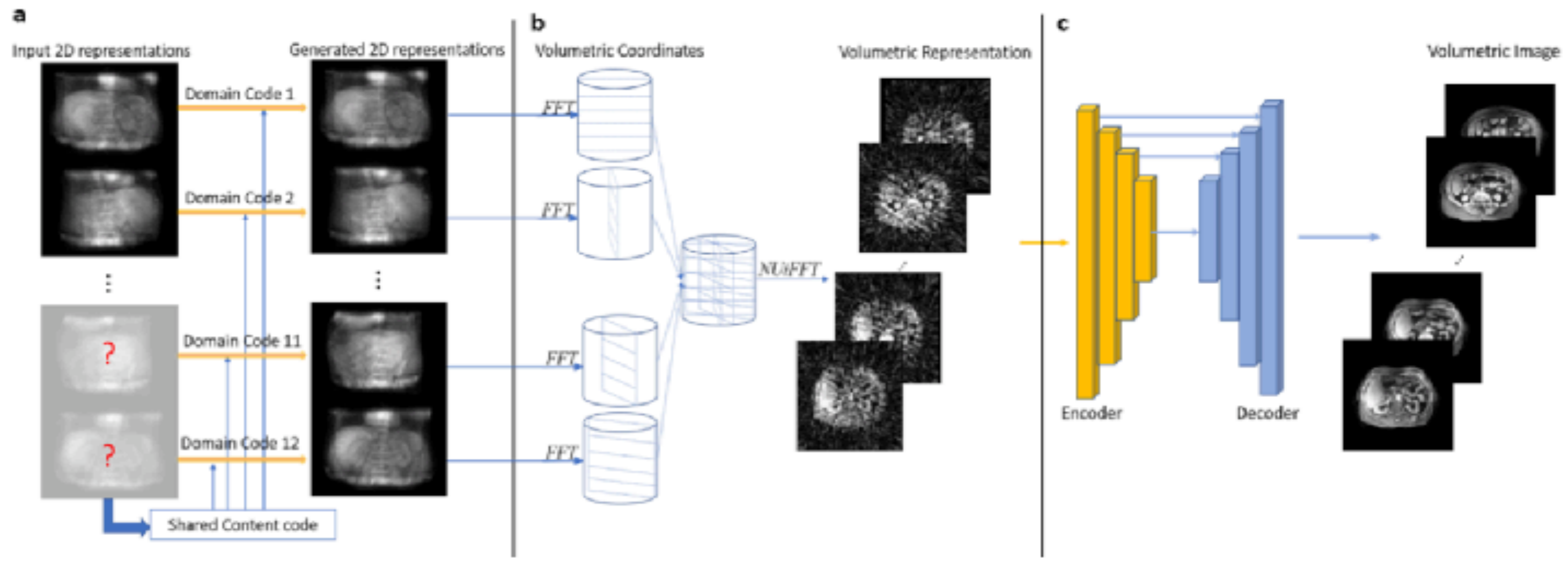
Dual-domain learning:

- Physics priors relate and transfer information in different domains
- Networks learn image synthesis and completion in 2D and 3D domains

Sparse-view CT reconstruction

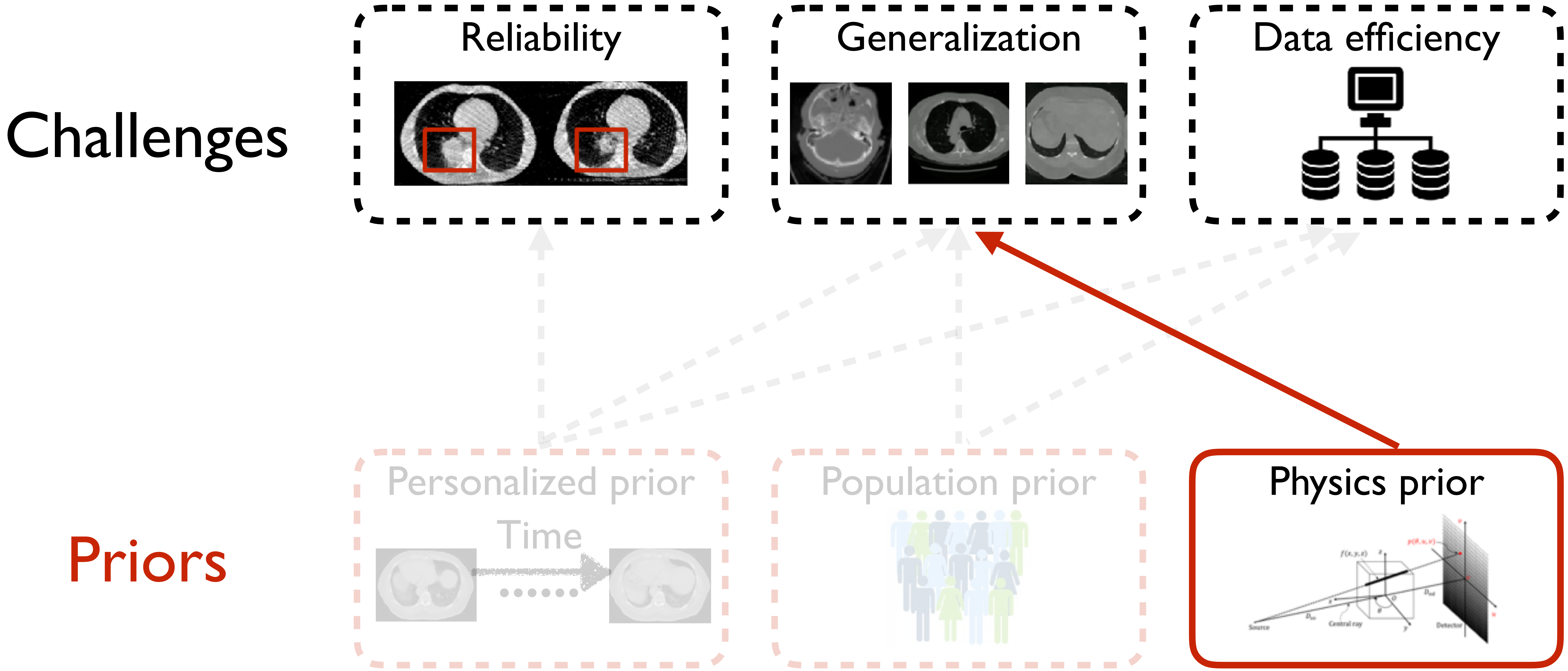


Sparse-sampling MRI reconstruction

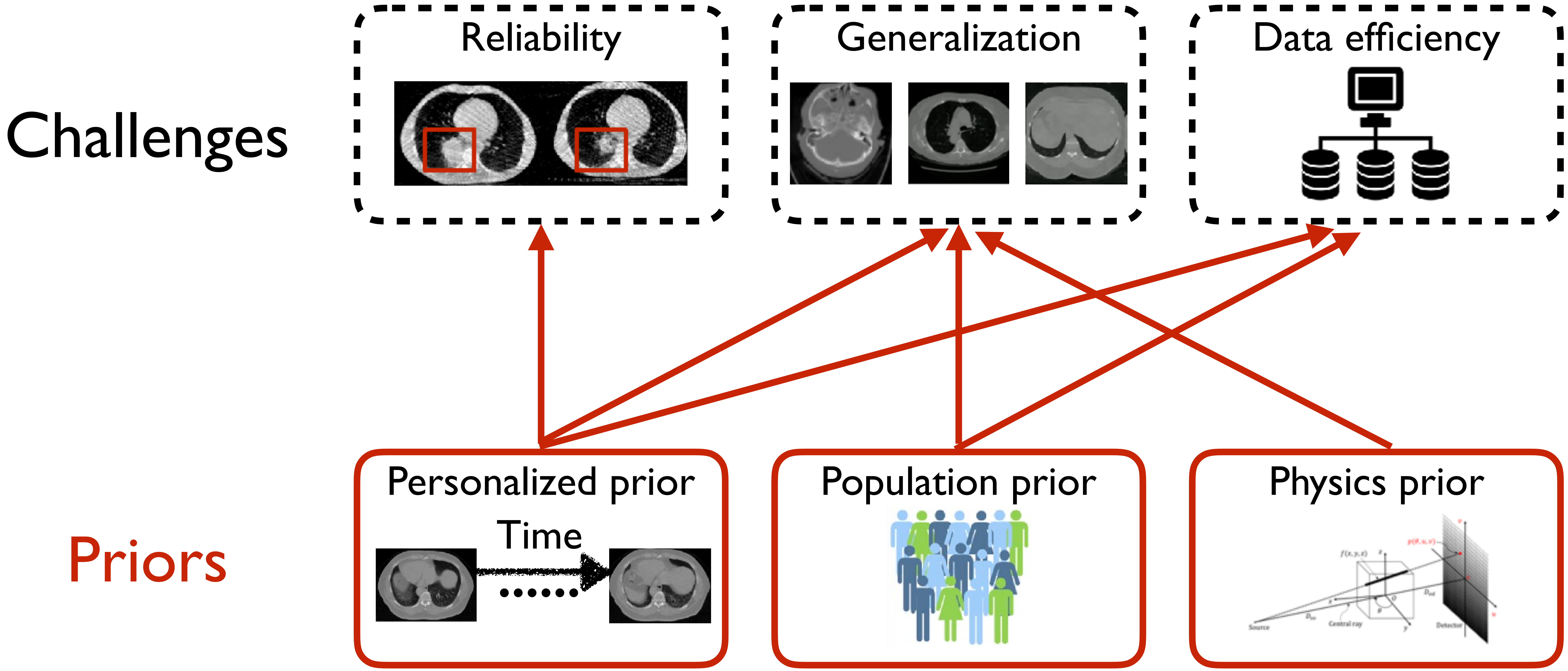


Shen, et al., A geometry-informed deep learning framework for ultra-sparse computed tomography (CT) imaging, CIBM 2022 (revision).
Liu, Shen, et al., Real time volumetric MRI for 3D motion tracking via physics-aware deep learning, Med Phys 2022.

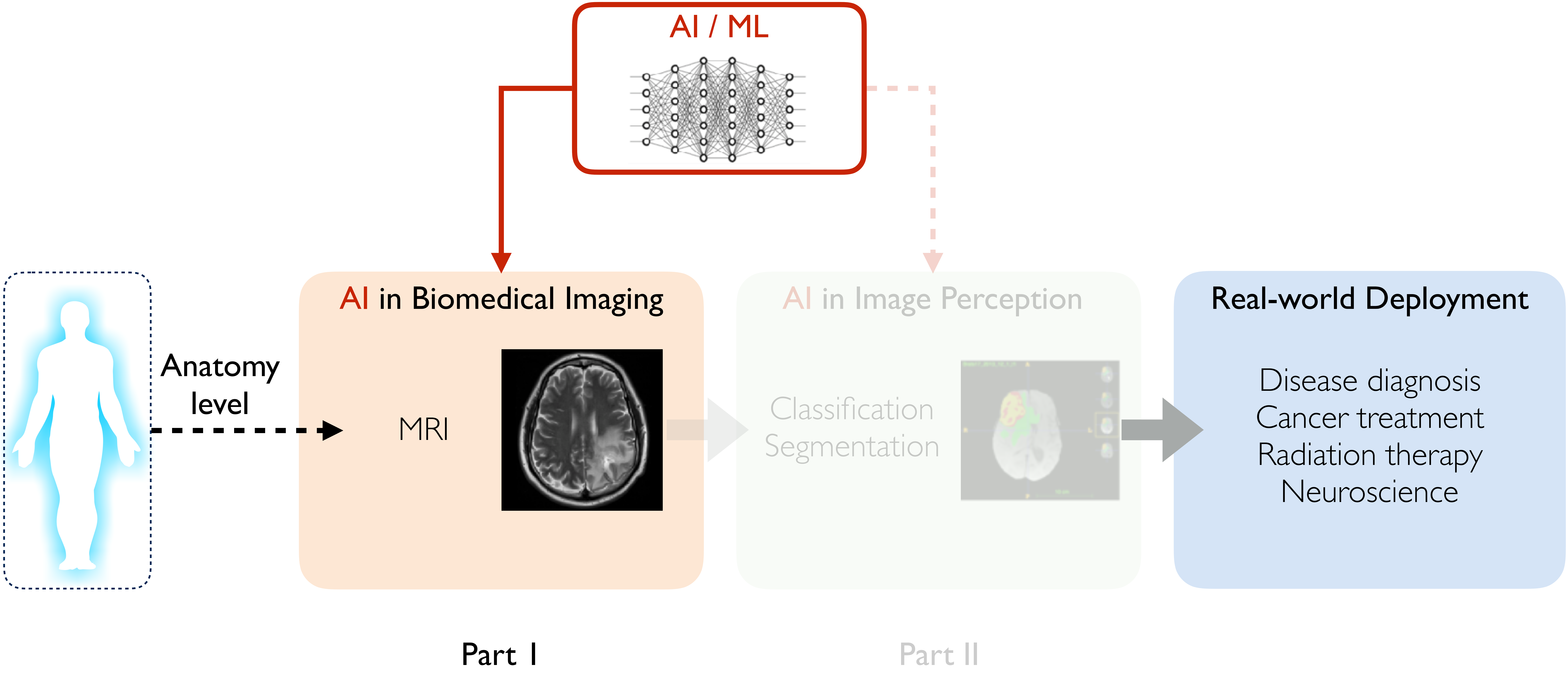
Recap: Physics Prior



Approach: Prior-informed ML



Part I: AI in Biomedical Imaging

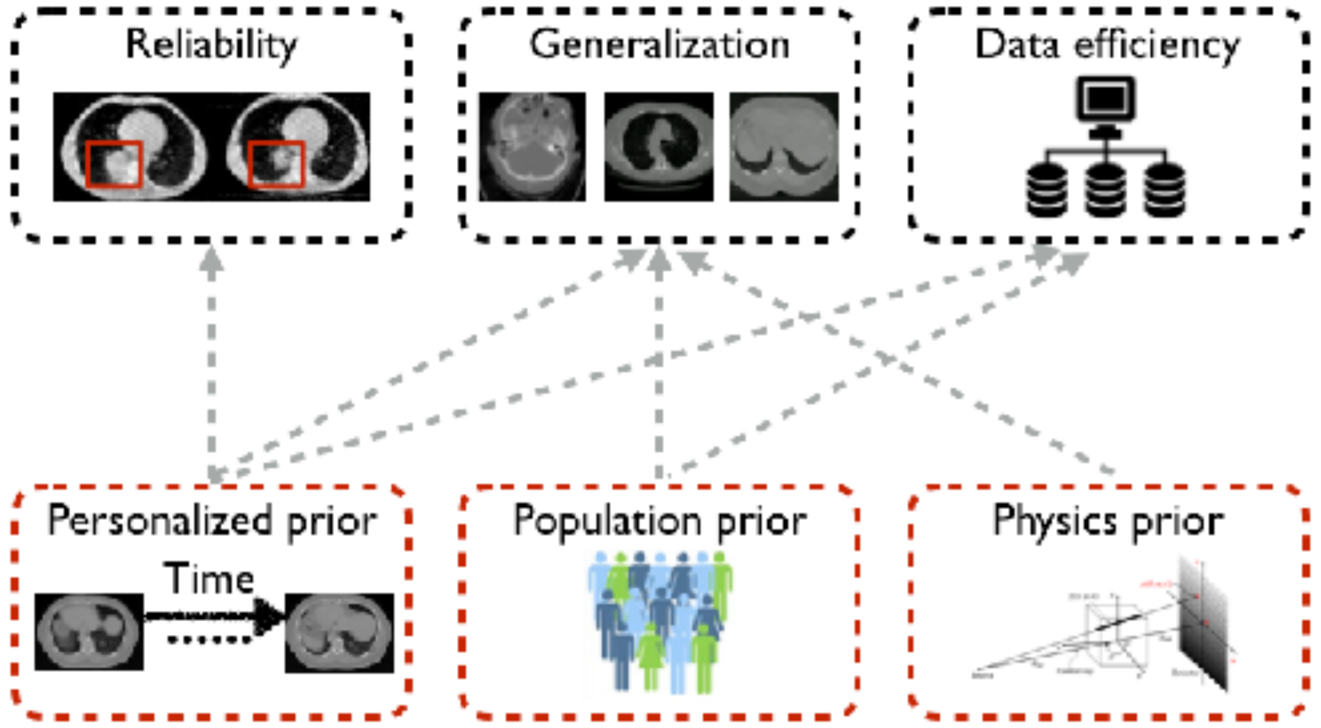


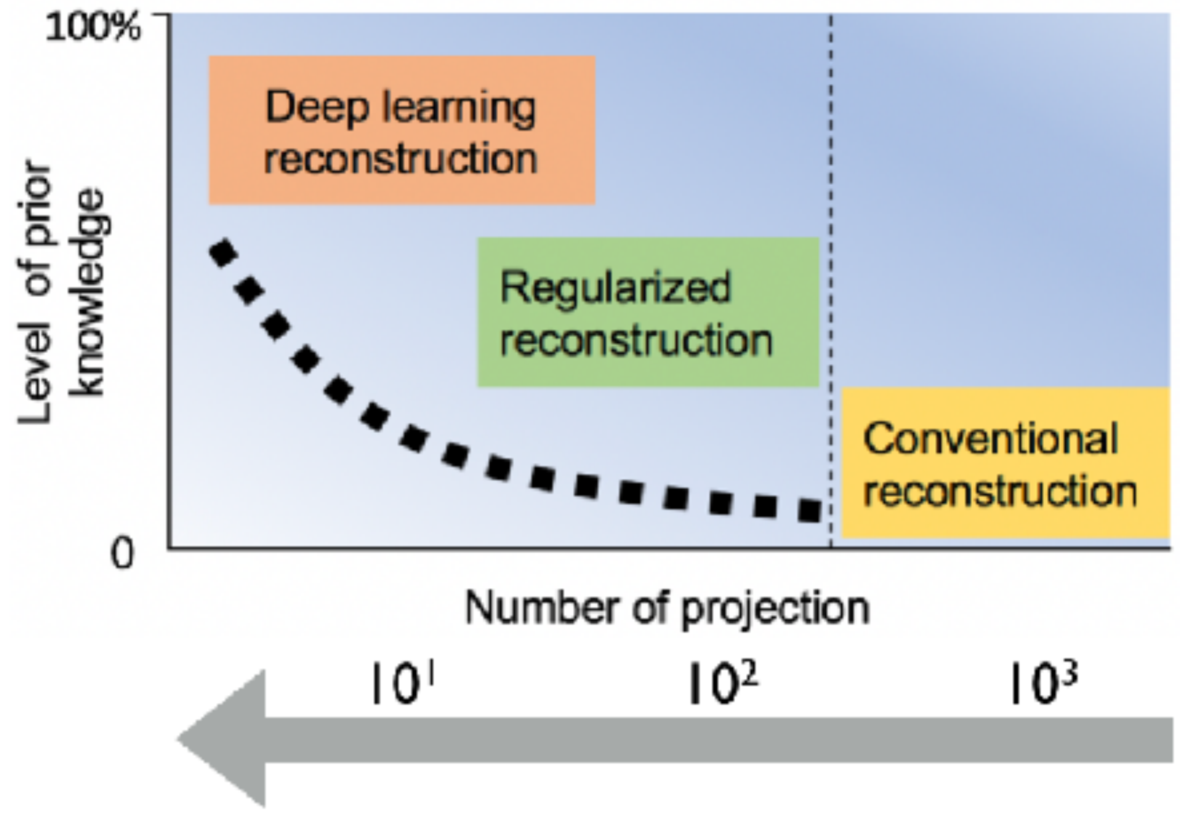
Contribution and Impact

AI / ML: exploit prior knowledge to design novel, reliable and data-efficient ML model

Biomedical imaging: push to a new level of sampling sparsity

Real-world impacts in cancer treatment:
- Reduce patients' radiation in CT scanning
- Real-time MRI guidance for image-guided therapy
- Personalized radiation therapy with adaptive treatment
- 3 patents for technology commercialization





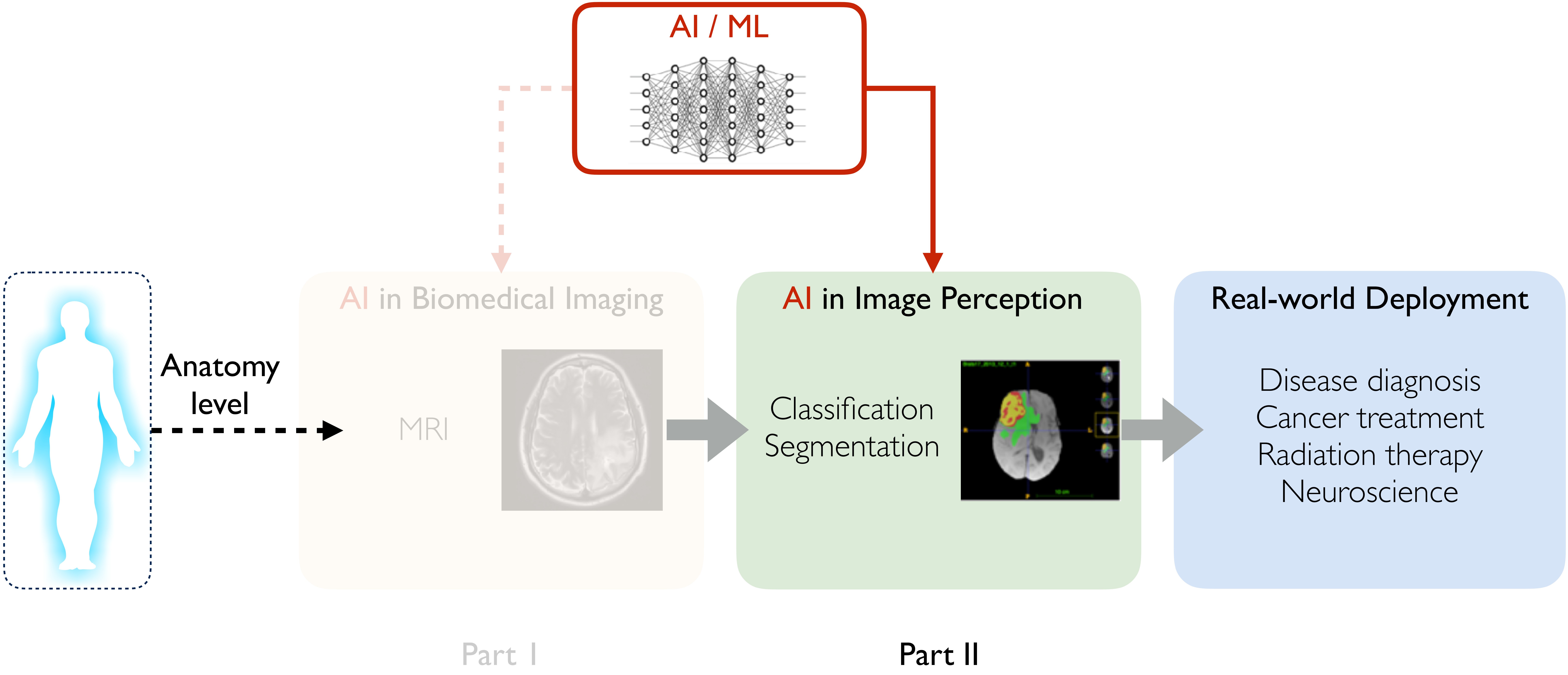
Stanford MEDICINE

Stanford Cancer Institute
A National Cancer Institute Comprehensive Cancer Center

NIH NATIONAL CANCER INSTITUTE

HAI Stanford University Human-Centered Artificial Intelligence

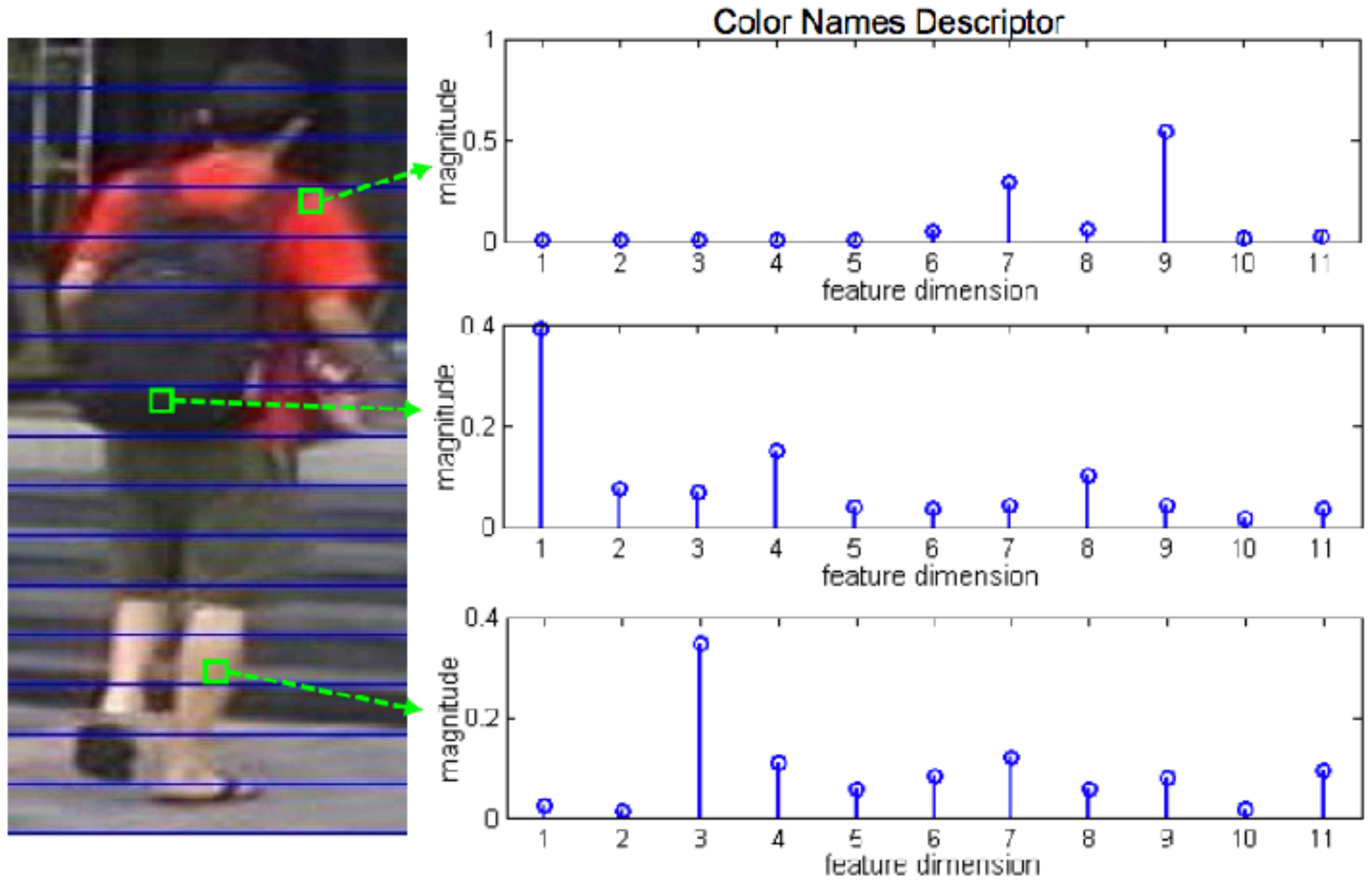
Part II: AI in Image Perception



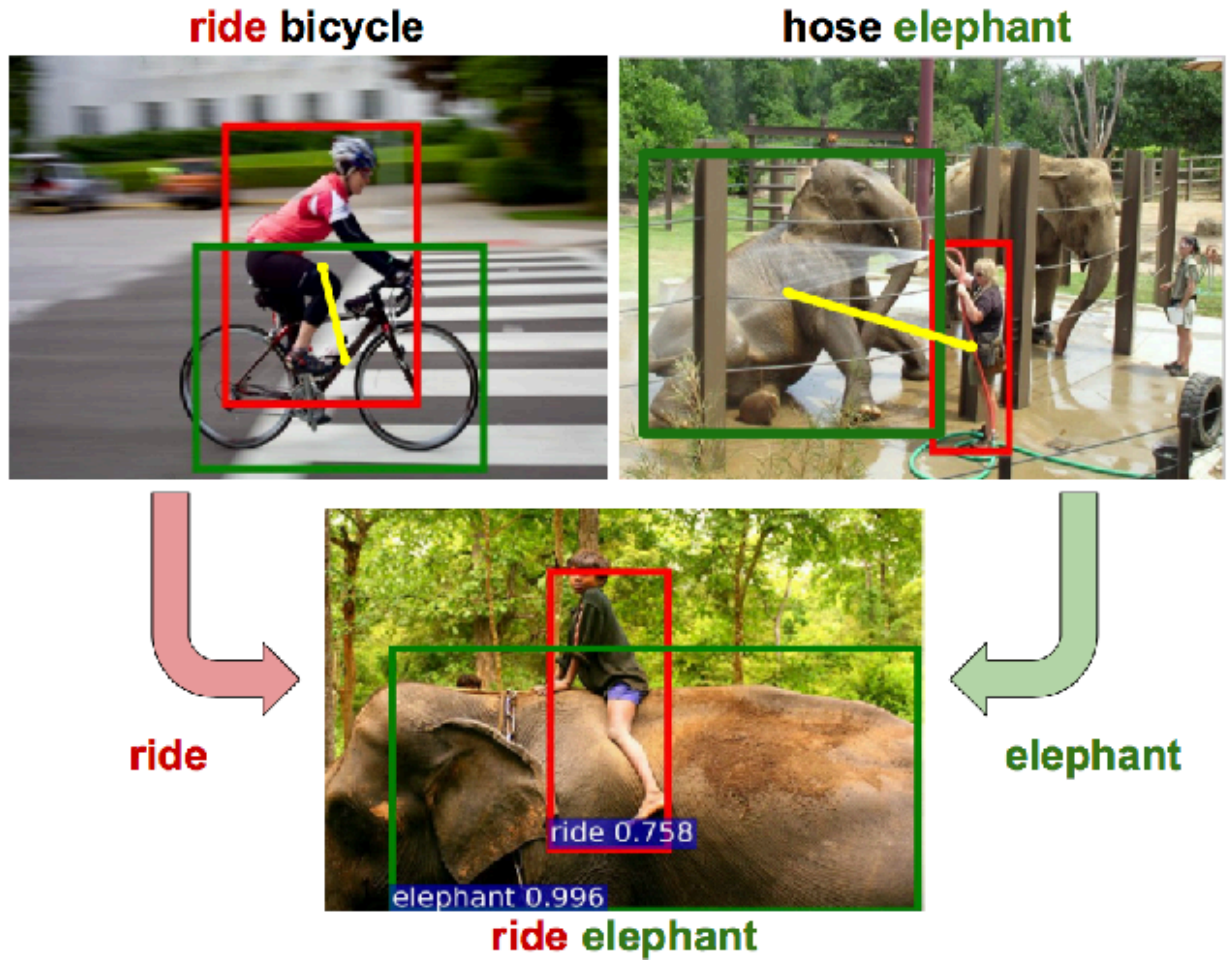
Vision-based perception

Understand human behavior for healthcare applications

Person Re-identification



Human object interaction



Zheng, Shen*, et al., Scalable person re-identification: a benchmark, ICCV 2015.
Shen*, et al., Scaling human-object interaction recognition through zero-shot learning, WACV 2018.

Multi-modal perception

Multi-modal representation learning

Multi-contrast MRI with random missing data

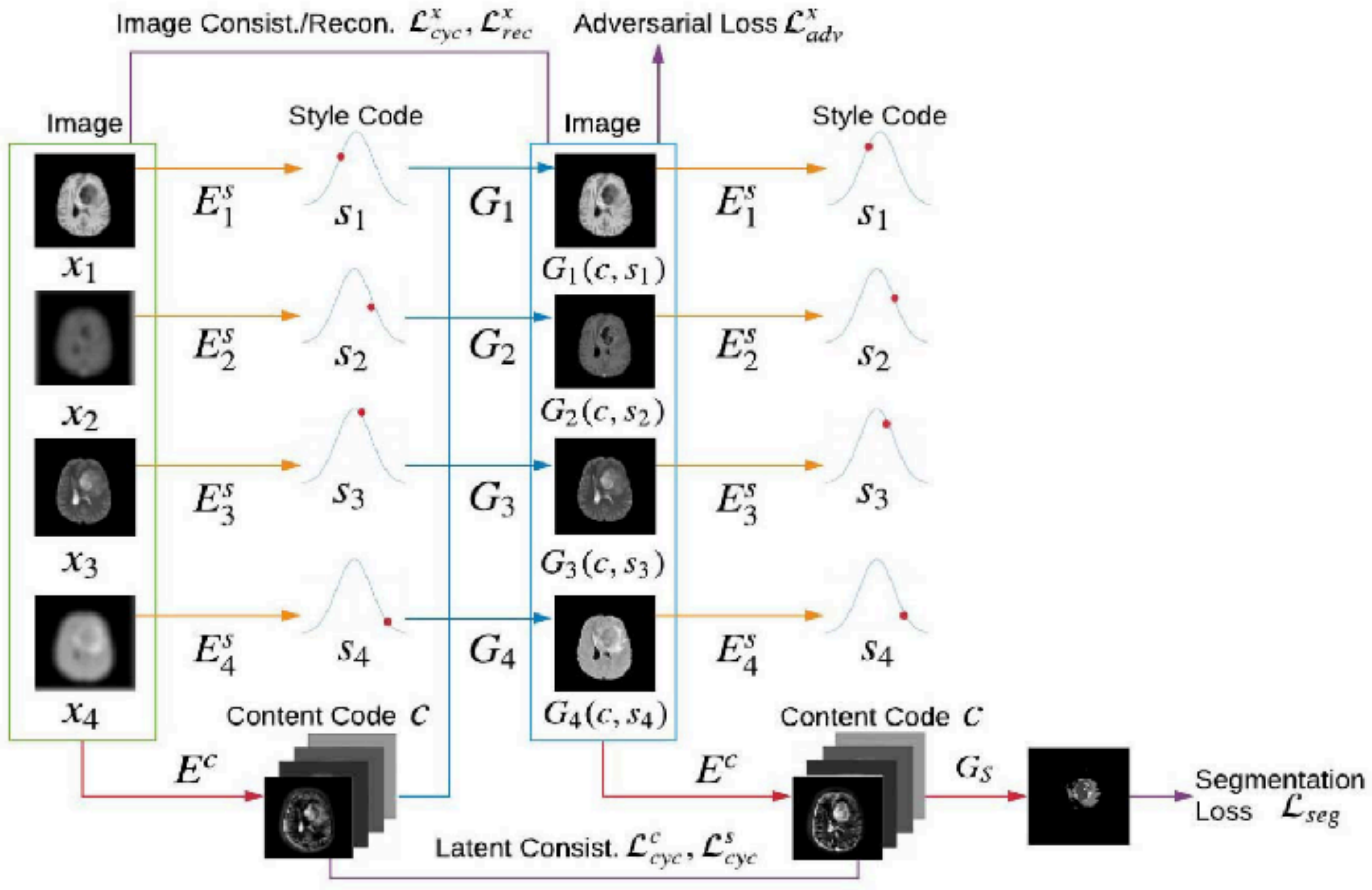
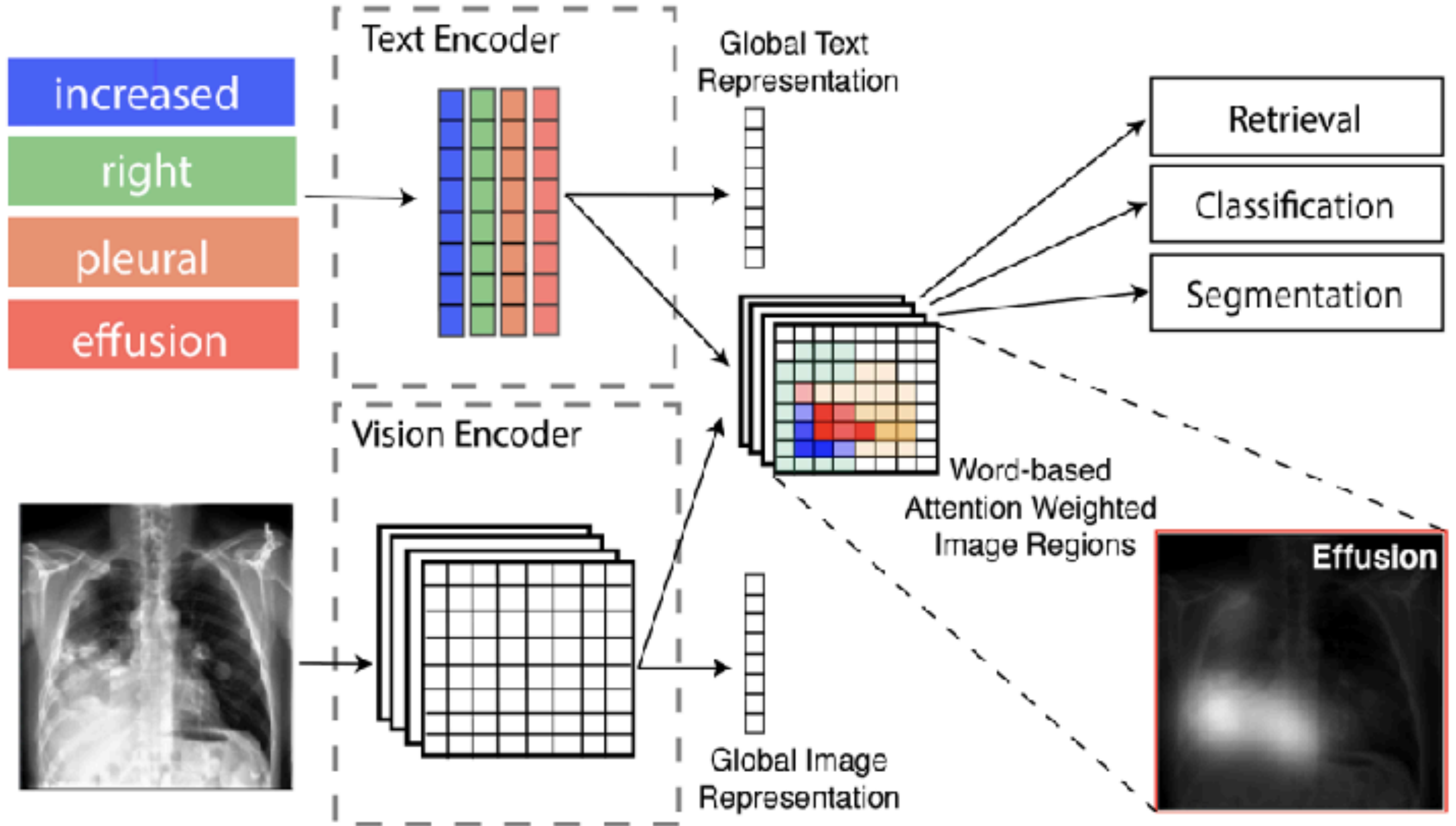


Image + Text



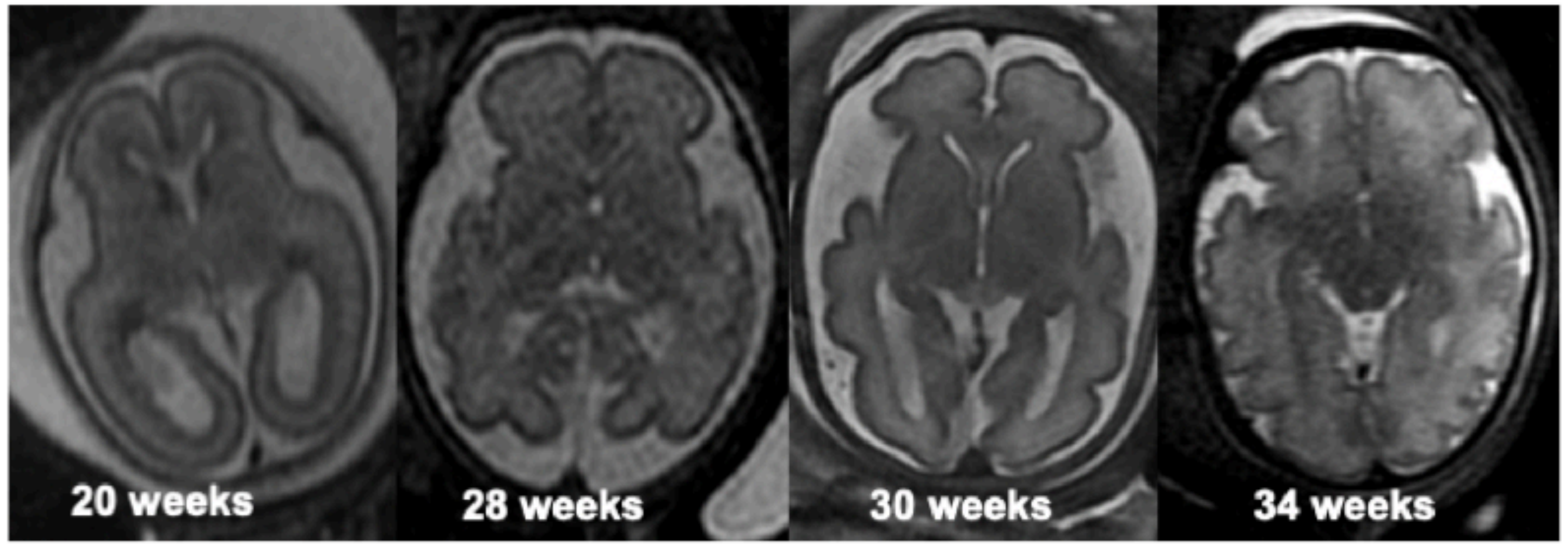
Shen, et al., Multi-domain image completion for random missing input data, TMI 2020.
Huang*, Shen*, et al., GLoRIA: a multimodal global-local representation learning framework for label-efficient medical image recognition, ICCV 2021.

Quantitative perception: fetal brain MRI

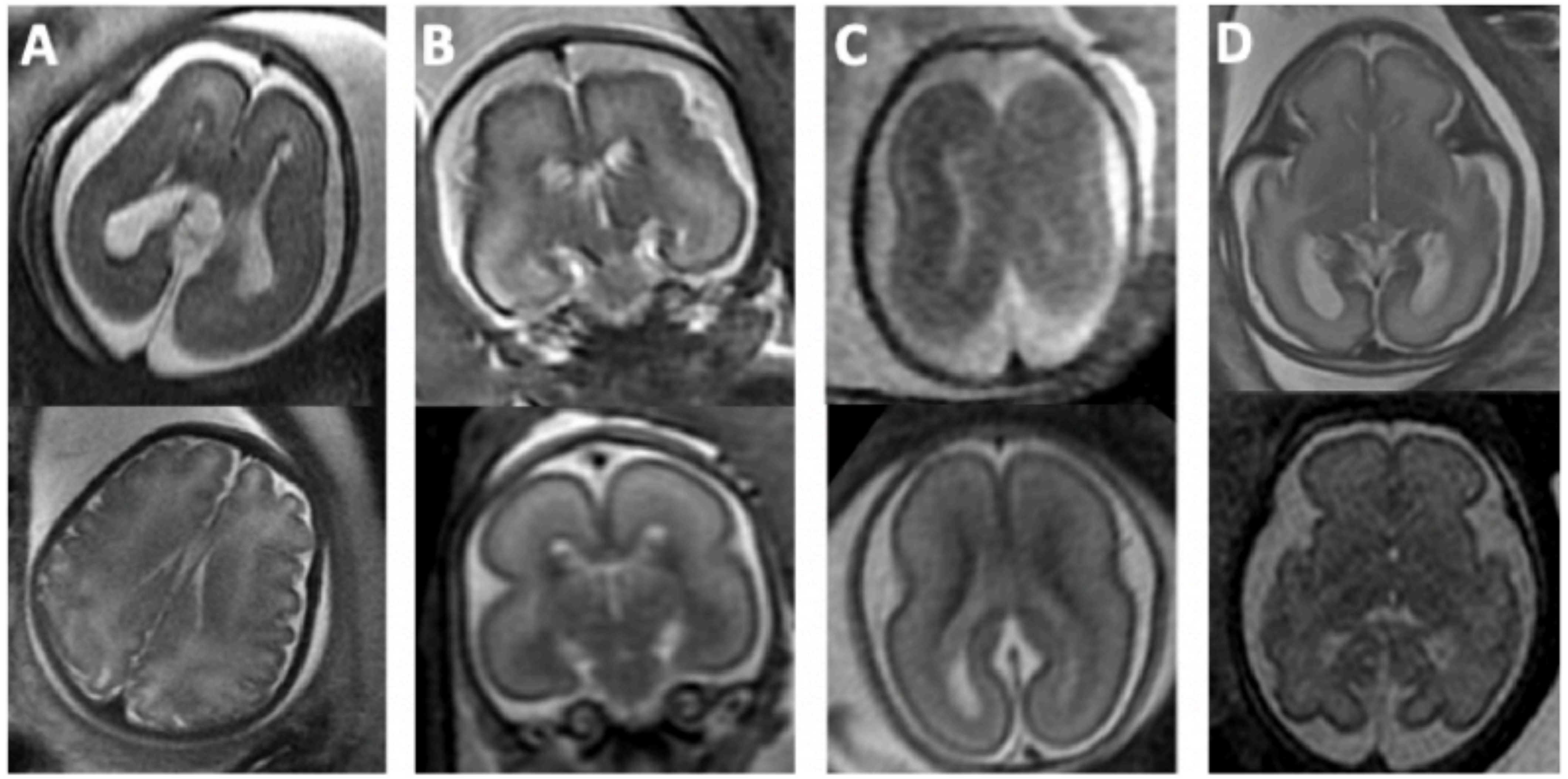
Motivation:

- Deviation from normal features in fetal brain MRI signals potential developmental aberration or congenital anomaly

Normal fetal brain development

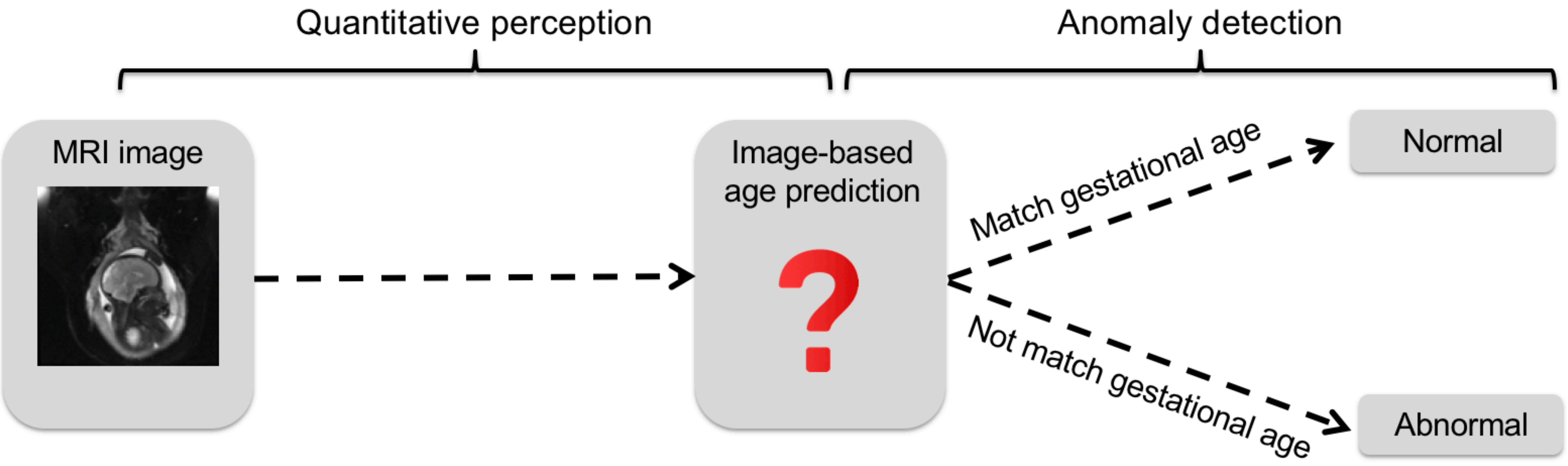


Top: abnormal fetal brain
Bottom: gestational age-matched normal fetus



Gestational age prediction

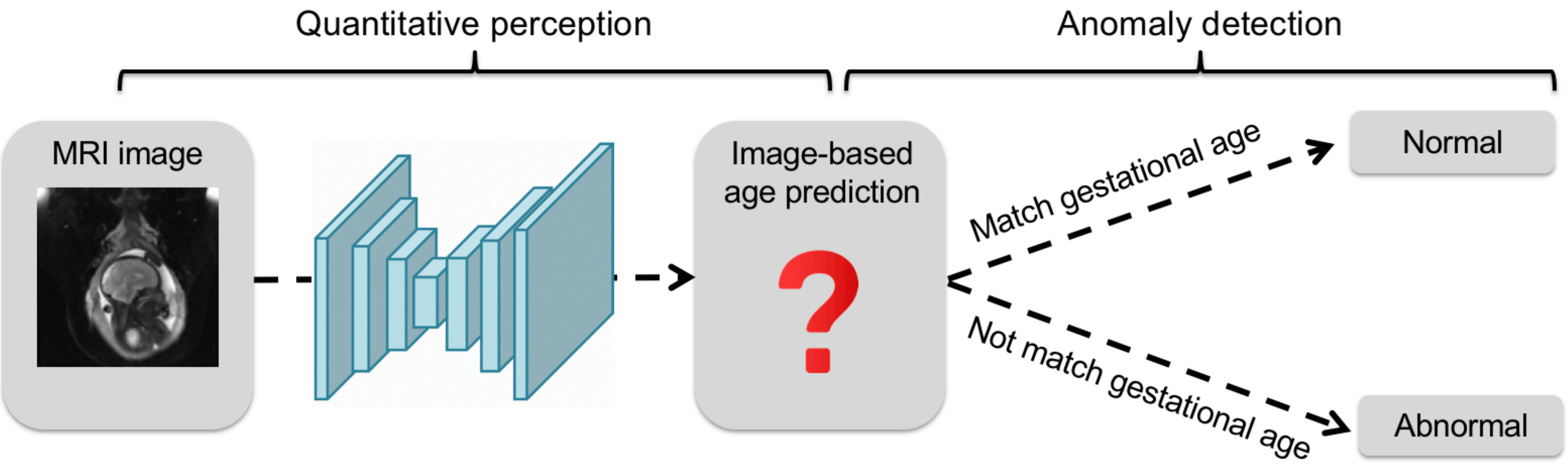
Goal:
- Predict fetal brain age based on features captured from MRI images



Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Quantitative perception

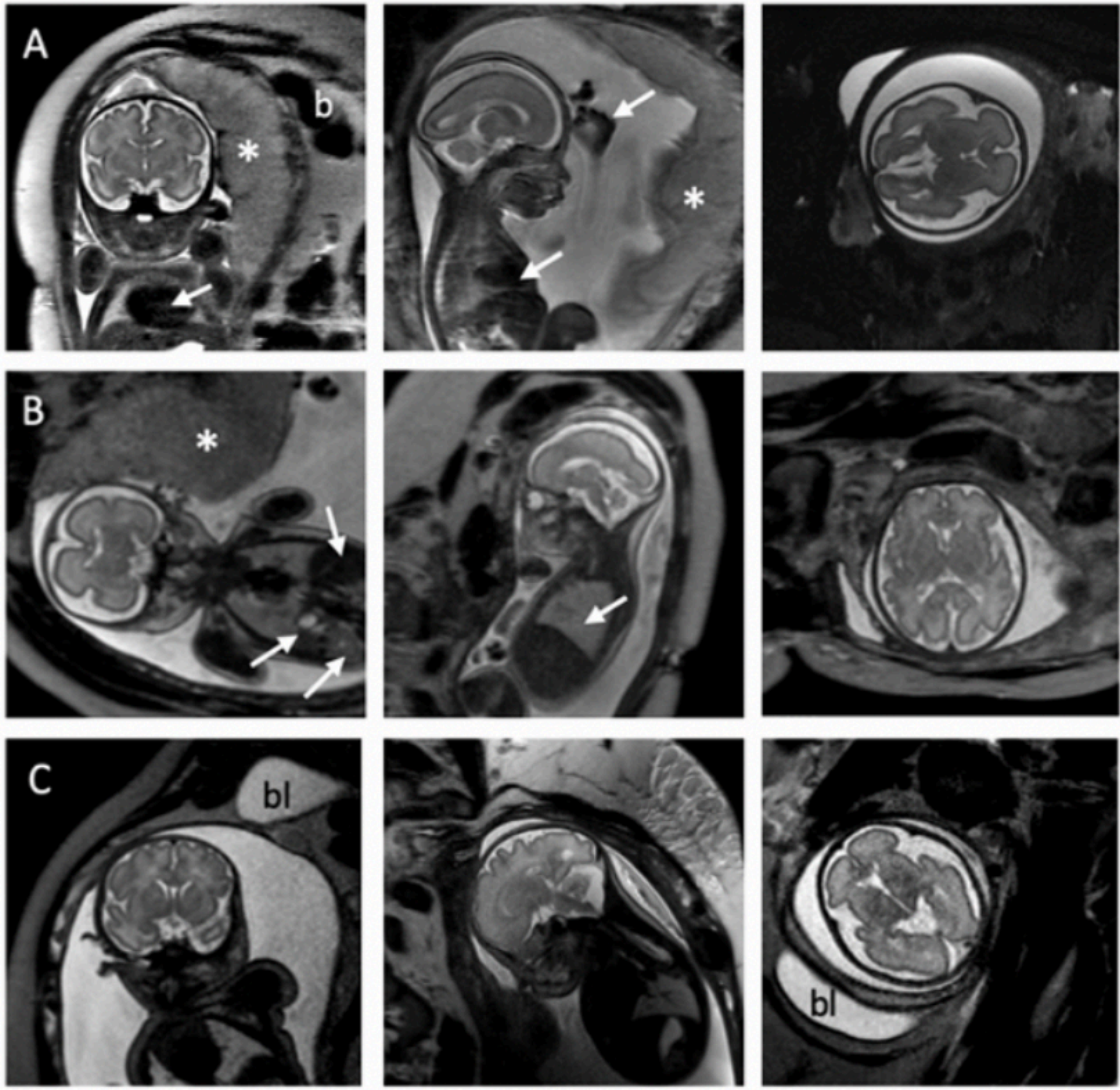
Approach:
- Develop ML models for quantitative perception of fetal brain MRI images



Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Challenges

Variable, unpredictable position and appearance of fetal brain with **random motion** and **background noise**



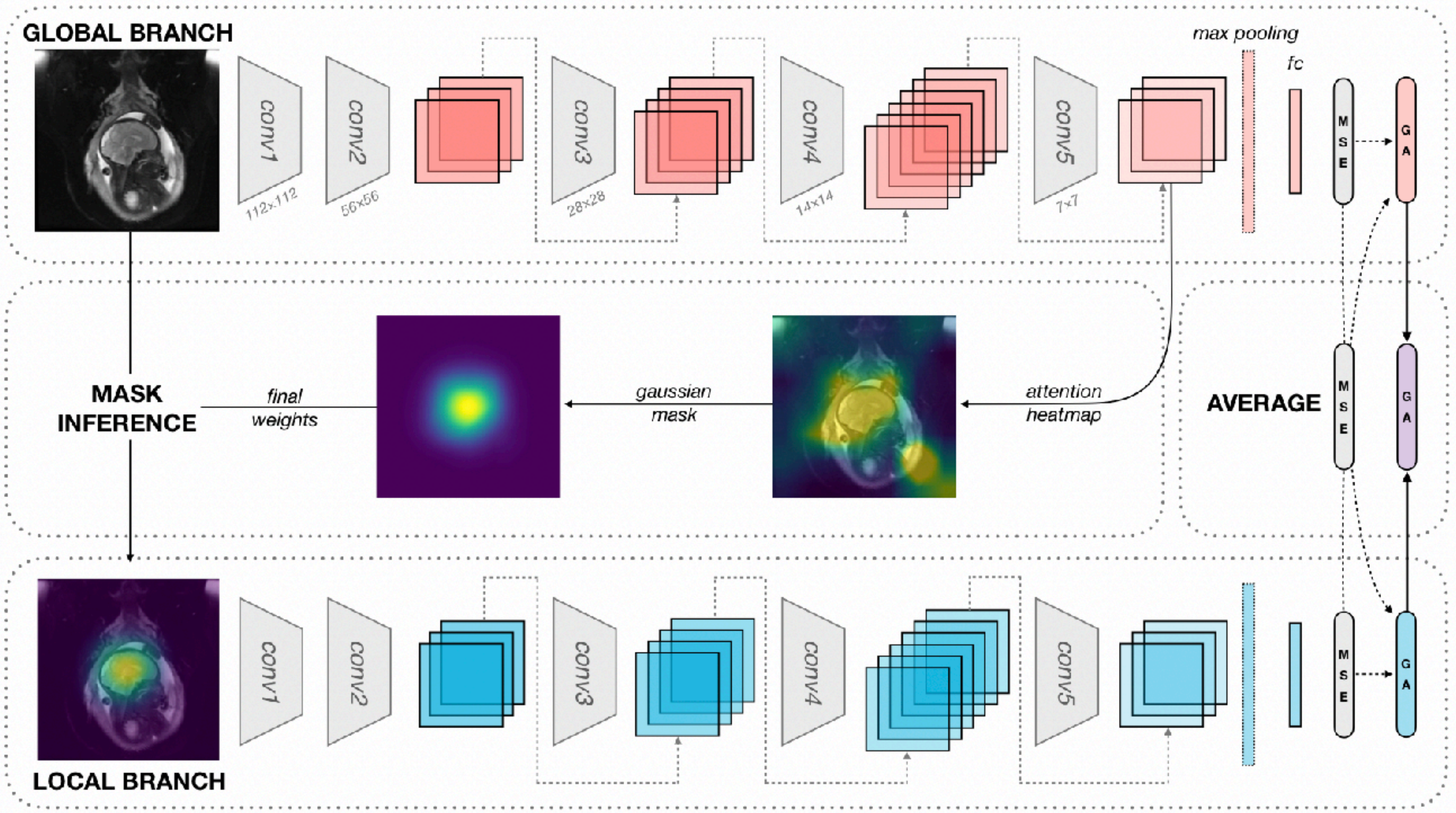
Maternal structures
- bladder (bl), bowel (b), and spine (sp), placenta (*)

Non-neural fetal structures (arrows)
- lung, kidney, heart, liver, gallbladder, and limbs

Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Approach: Self-attention learning

Self-attention learning automatically and adaptively suppresses background noise to localize the fetal brain



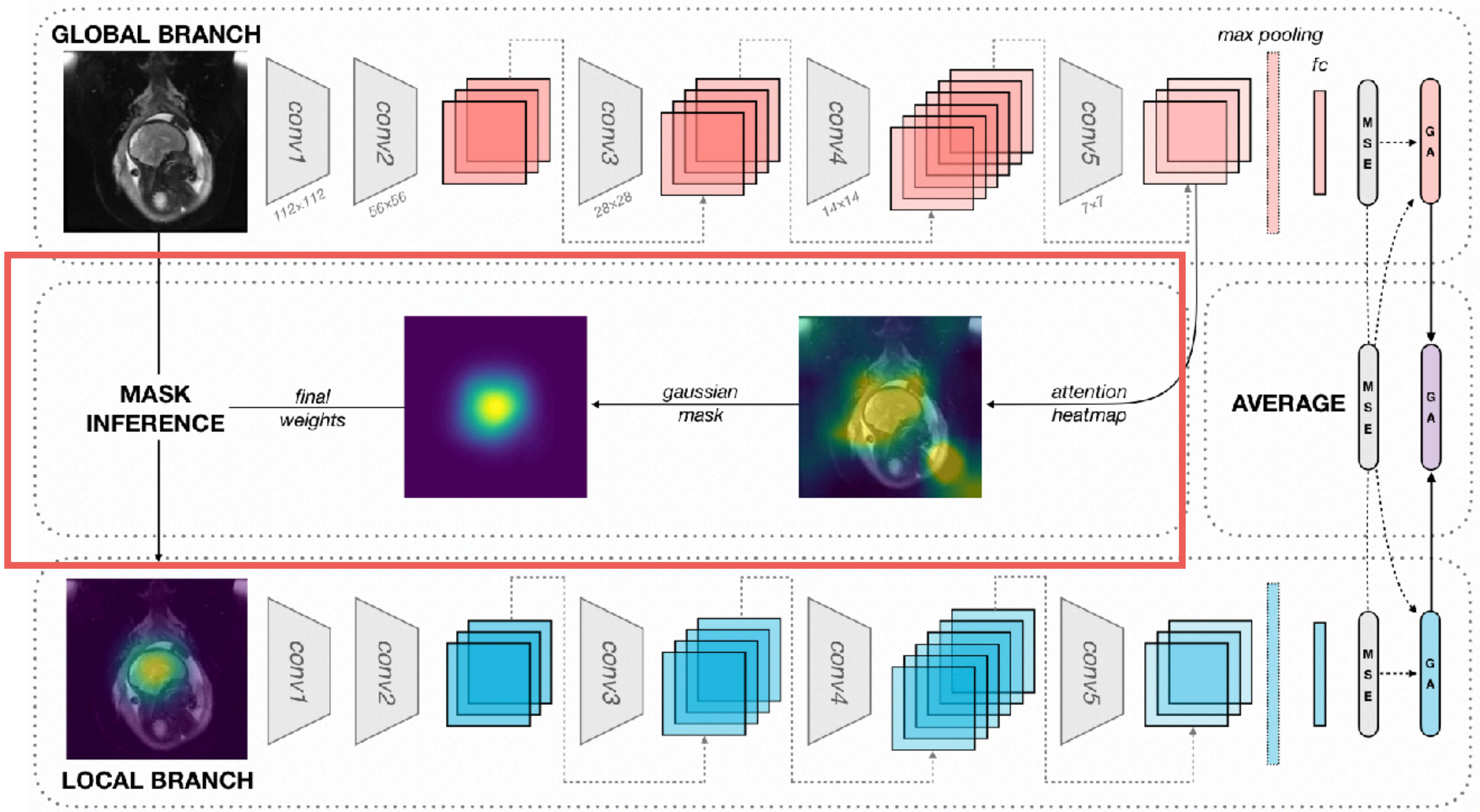
Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Approach: Self-attention learning

Self-attention learning automatically and adaptively suppresses background noise to localize the fetal brain

End-to-end learning framework with differentiable self-attention mechanism

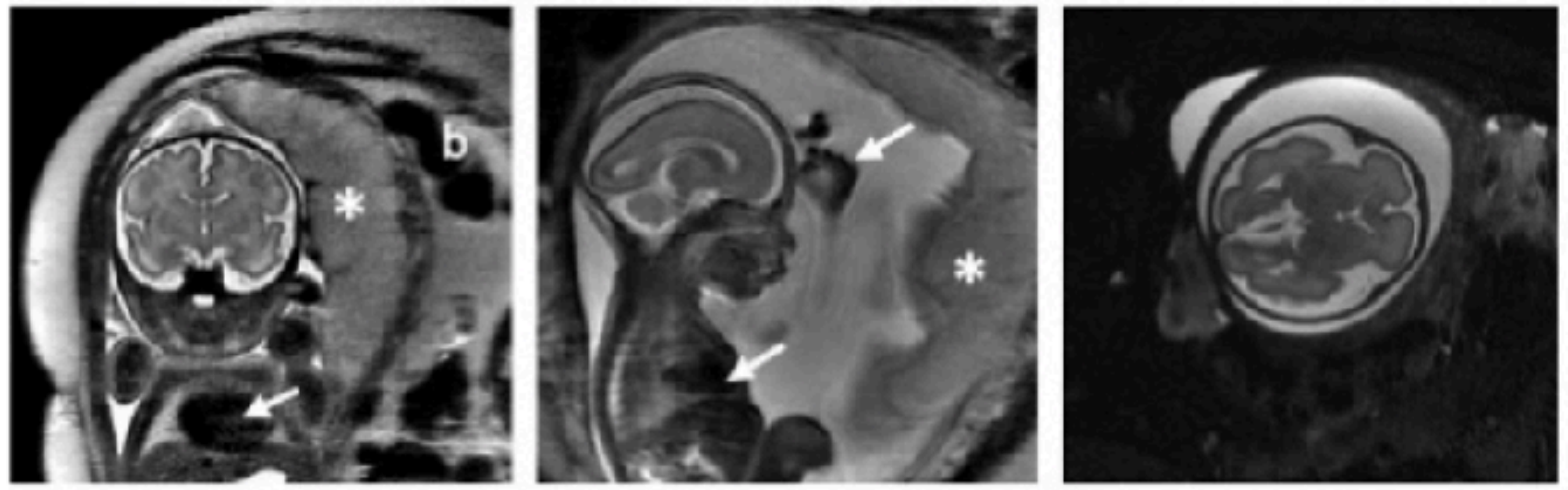
Weak-supervision!



Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Evaluation: Stanford dataset

Collect clinical data from Stanford Children's Hospital with **741 samples**



N=741

	Stanford
No. of subjects	741
Median GA (range), wks	30.6 (19-39)
Field strength	1.5T, 3T
Manufacturer & Scanner	GE Discovery 750W, Optima 450W, Signa HDxt & Excite
Sequence	ssFSE
Repetition time, ms	600-6,000
Echo time, ms	67-420
Flip angle	90°
Field of view, mm	180 x 180 – 440 x 440
In-plane resolution	0.35 x 0.35 – 1.57 x 1.57
Median no. of slices (range)	23 (7-48)
Median slice thickness (range), mm	4 (2-5)

Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Evaluation: Stanford dataset

Collect clinical data from Stanford Children's Hospital with **741 samples**
- Open source the largest public fetal brain MRI dataset
- Deidentified images used in model training and testing are made available at the Stanford Digital Repository (downloading link)


Stanford Digital Repository

Fetal Brain MRI from Stanford Lucile Packard Children's Hospital

PREFERRED CITATION: Shen, L., Zheng, J., Shpanskaya, K., McKenna, E.S., Atluri, M., Guimaraes, C.V., Dahmoush, H., Halabi, S.S. & Yeom, K.W. Fetal Brain MRI from Stanford Lucile Packard Children's Hospital. Stanford Digital Repository. Available at: https://purl.stanford.edu/sf714wg0636 (2021).

COLLECTION: Stanford Research Data

	Stanford
No. of subjects	741
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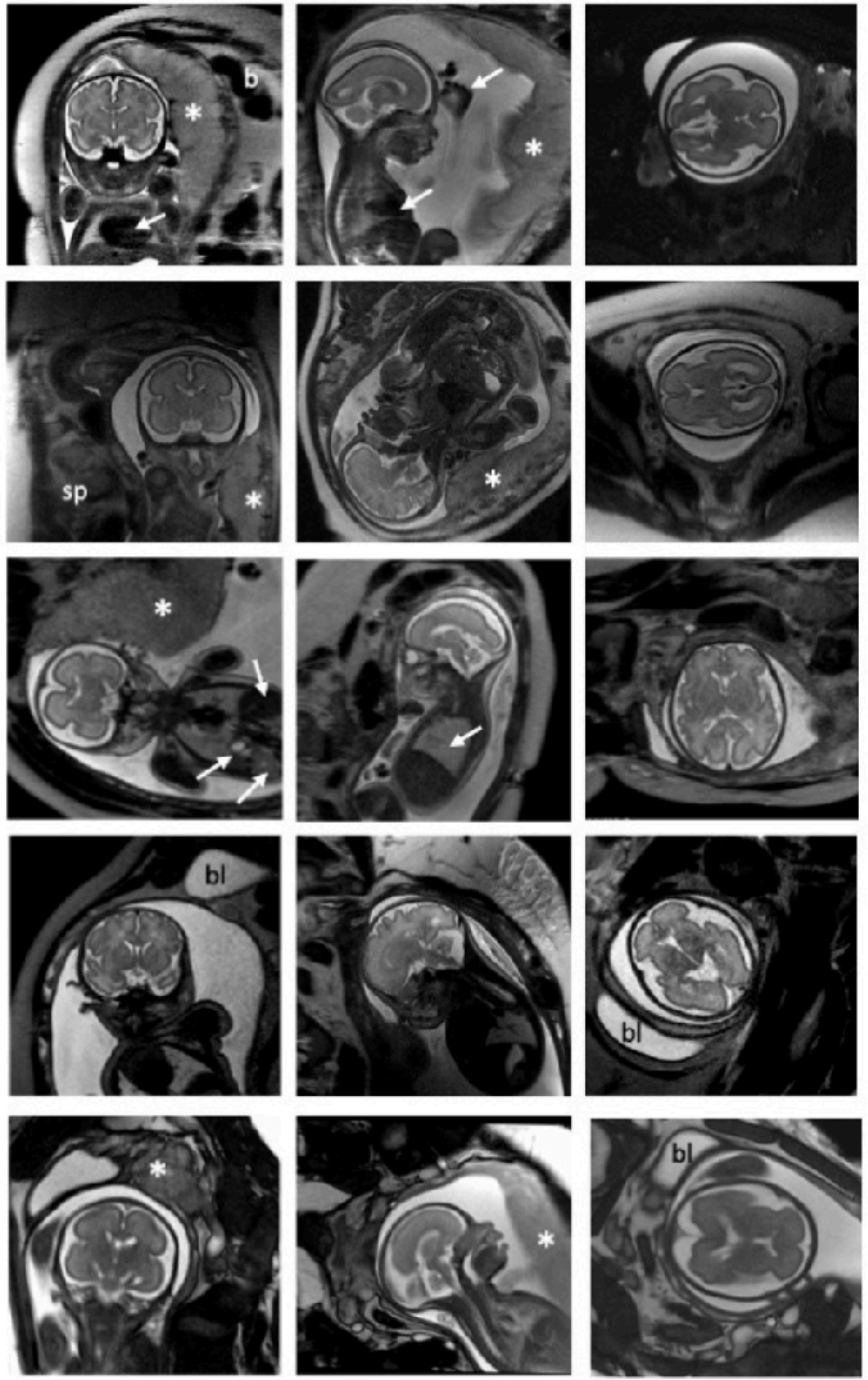
Shen*, et al., Attention-guided deep learning for gestational age prediction using fetal brain MRI, Scientific Reports, 2022.

Evaluation: Multi-center dataset

Model generalizability:

- Collect data from four clinical centers in U.S and an international institute in Turkey



Stanford Children's Health

N=741

Dignity Health. St. Joseph's Hospital and Medical Center

N=25

Children's Hospital LOS ANGELES

N=156

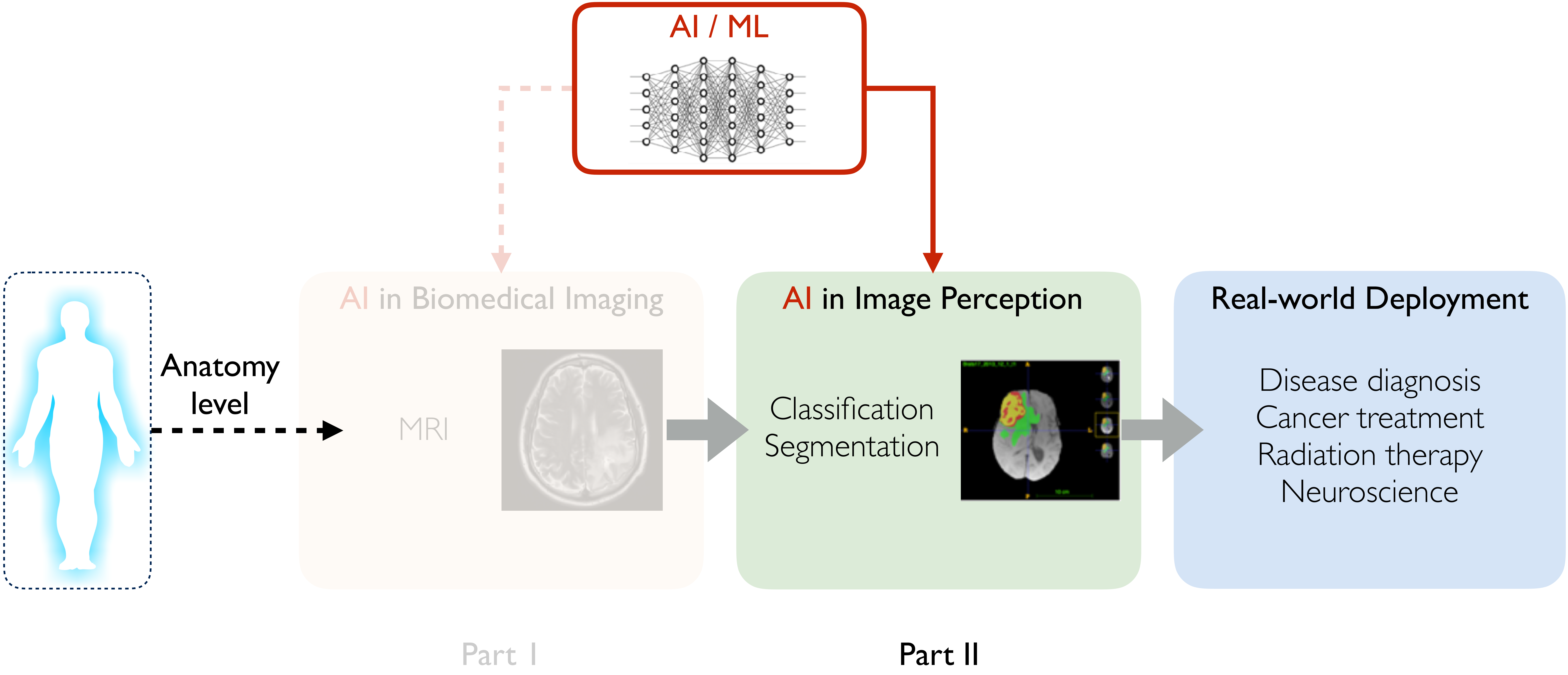
Cincinnati Children's

N=64

T.C. MINISTRY HEALTH
İZMİR PROVİNCİAL HEALTH DİRECTORATE
İZMİR UNİVERSİTY OF HEALTH SCİENCES TEPECİK

N=189

Part II: AI in Image Perception



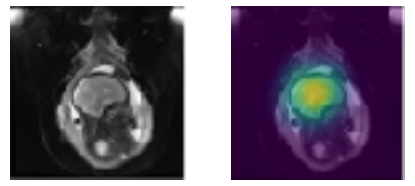
Contribution and Impact

AI / ML: Design novel ML model adaptive to unique characteristics of biomedical data

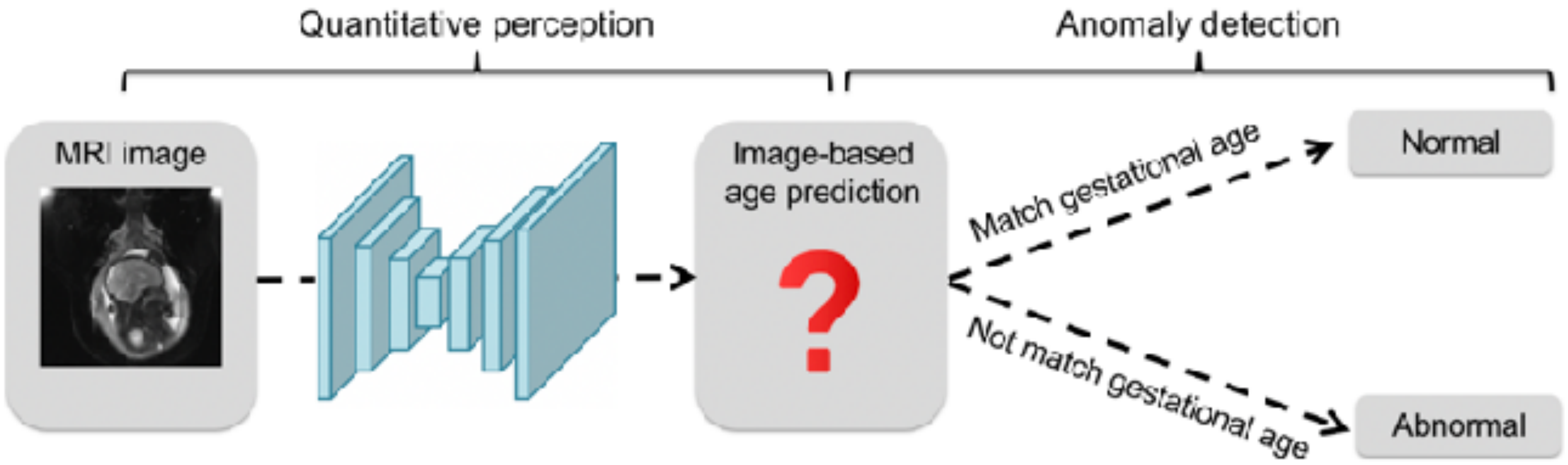
Multi-modality

Medical image analysis: accurate and fast quantitative image perception

Random noise



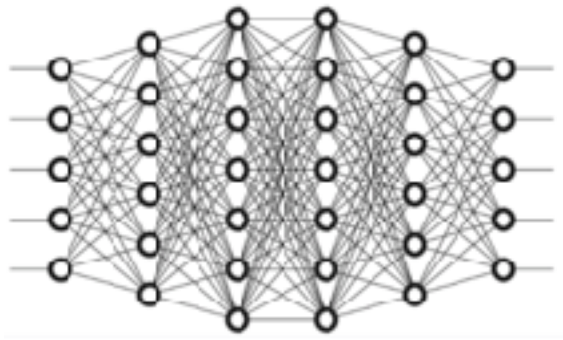
Real-world impacts in clinical disease diagnosis:
- Automatic tools to streamline challenging disease diagnosis and anomaly detection
- Generalizable across multiple medical centers
- Open source the largest public fetal brain MRI dataset

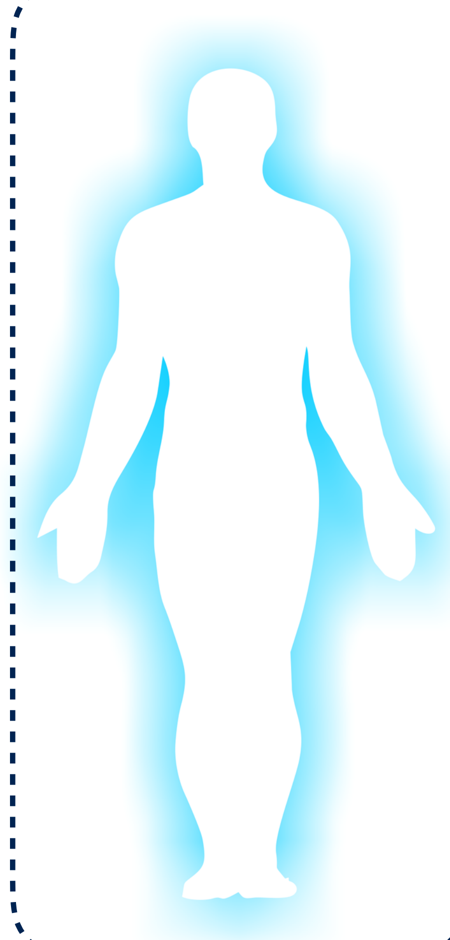


Stanford Children's Health
Dignity Health St. Joseph's Hospital and Medical Center
Cincinnati Children's
NIH Clinical Center
PHIND
T.C. MINISTRY HEALTH İZMİR PROVİNCİAL HEALTH DİRECTORATE İZMİR UNİVERSİTY OF HEALTH SCİENCES TEPECİK
Children's Hospital LOS ANGELES
PHILIPS Healthcare

Today's Roadmap

AI / ML

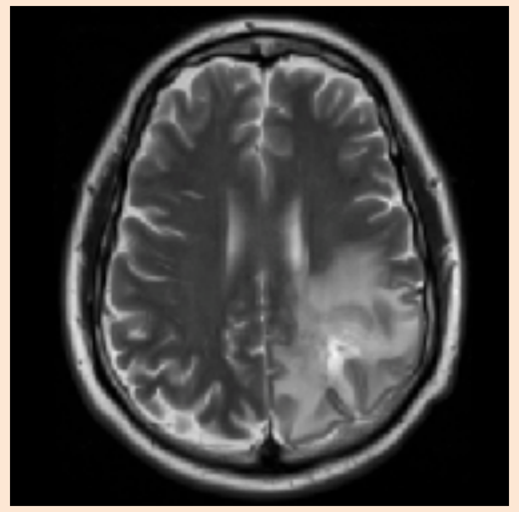




Anatomy level

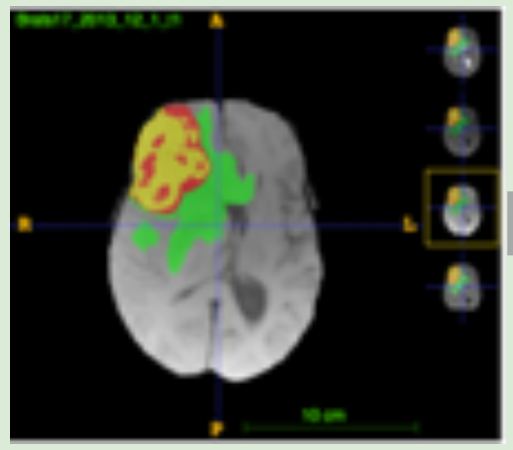
AI in Biomedical Imaging

MRI



AI in Image Perception

Classification
Segmentation



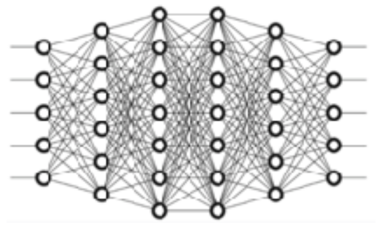
Real-world Deployment

Disease diagnosis
Cancer treatment
Radiation therapy
Neuroscience

Part I

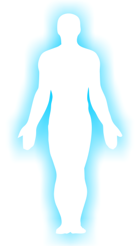
Part II

AI in Health to address real-world challenges



AI / ML

- Reliability
- Generalization
- Data-efficiency

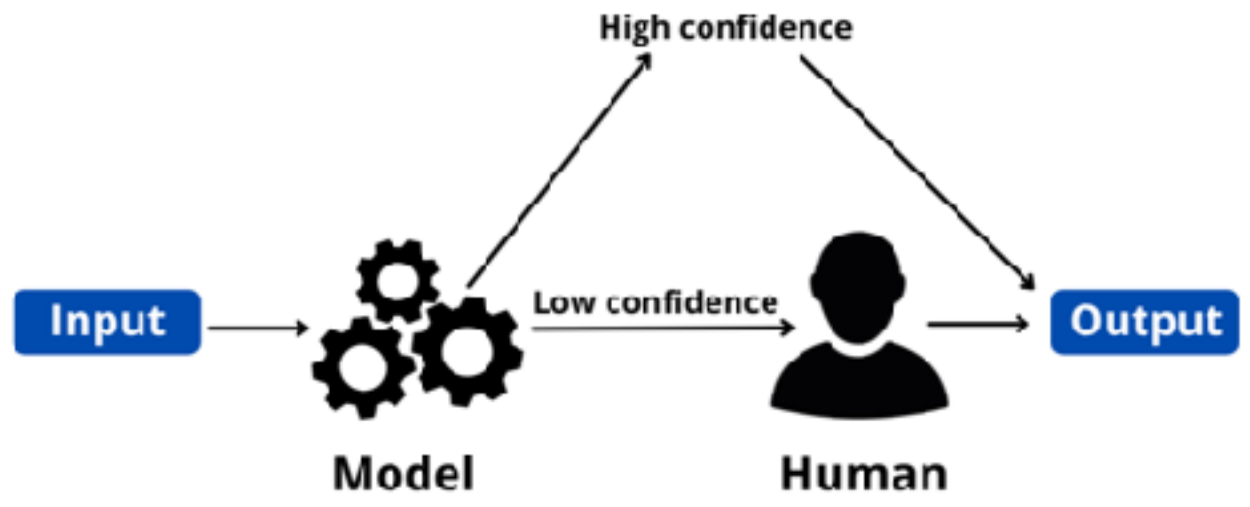


Biomedical

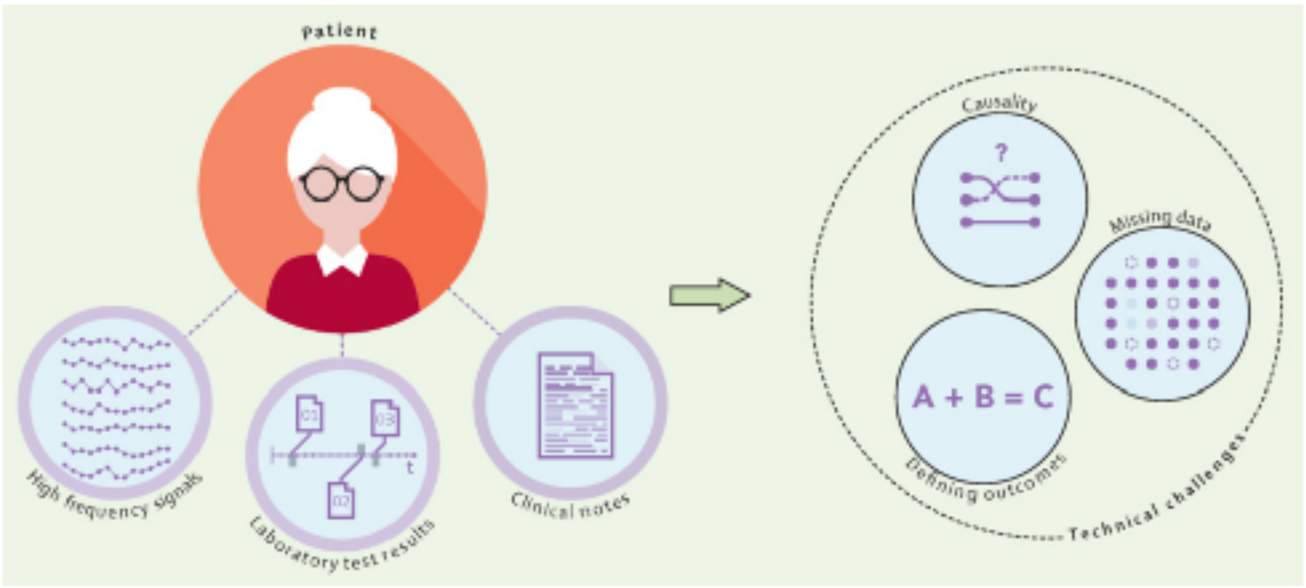
- Computational imaging
- Processing and analysis
- Real-world deployment

Prior-integrated learning for data-efficient ML

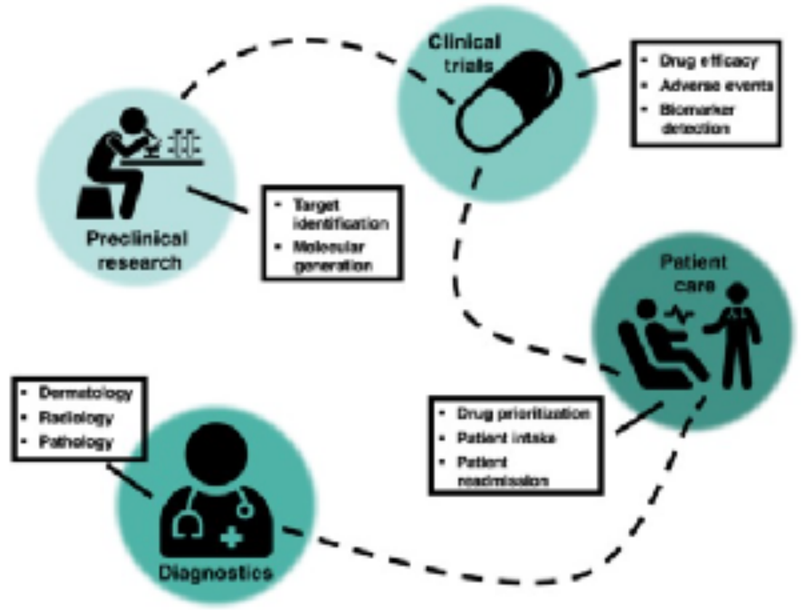
Uncertainty awareness for trustworthy ML



Multi-modal data analysis for decision making



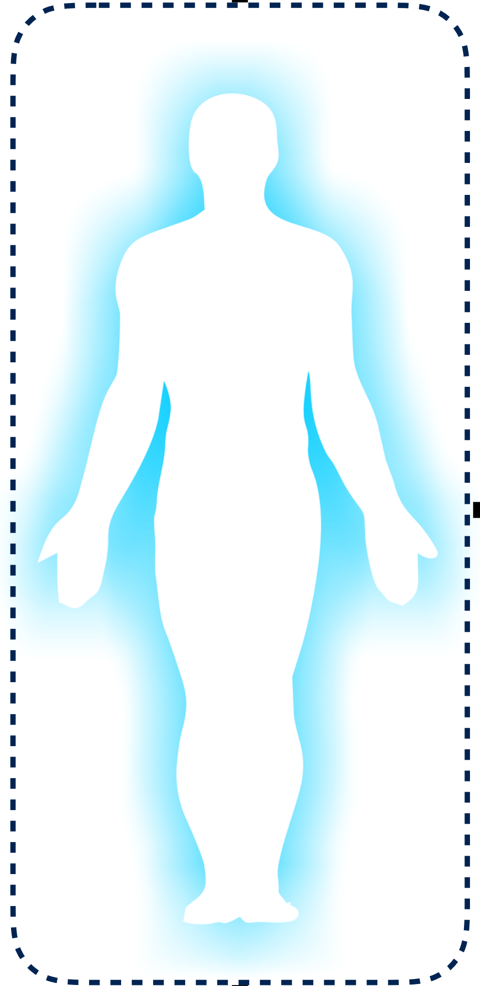
Clinical trial translation for real-world deployment



AI helps to understand human health in different levels

AI for Human

Human level

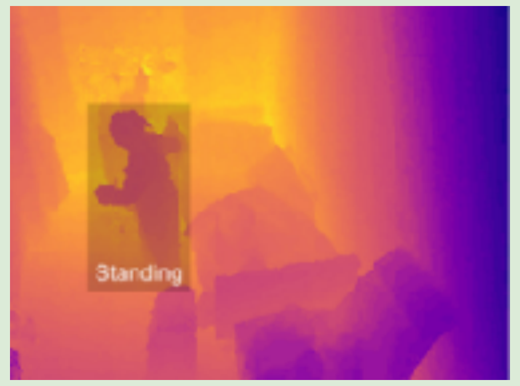
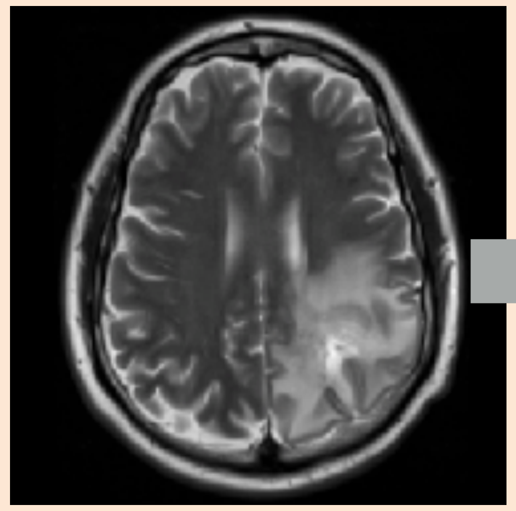
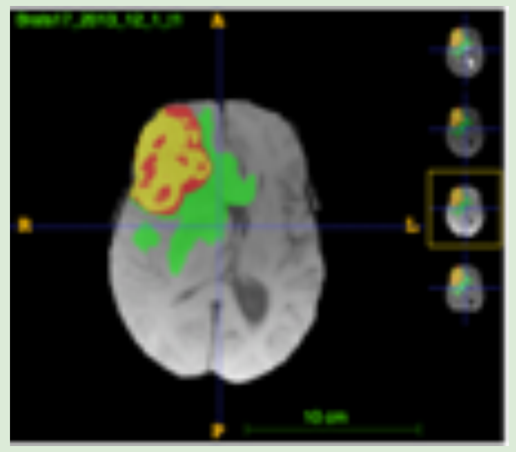
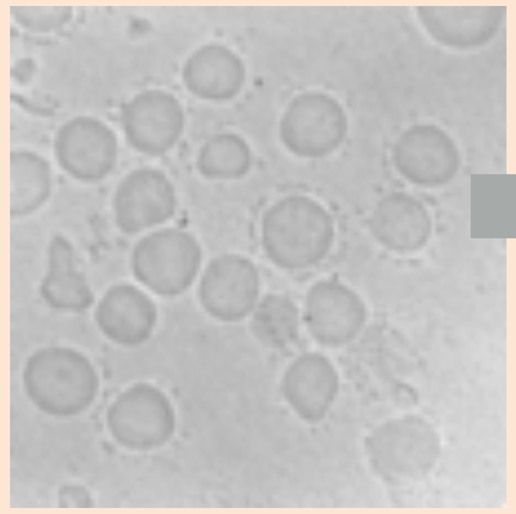
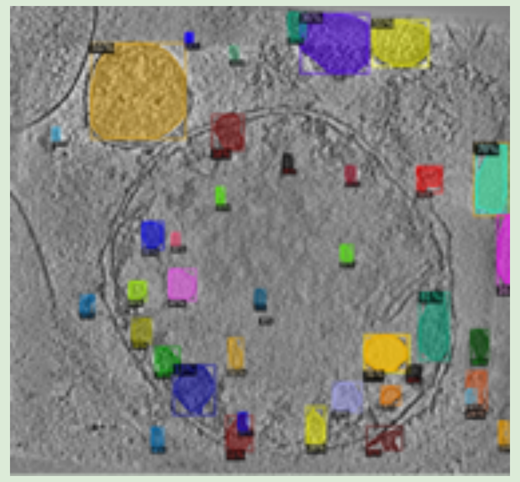


AI for Doctor

Anatomy level

Molecular level

AI for Science

	Imaging		Perception		Real-world Deployment
Depth		Recognition			Healthcare
MRI		Classification Segmentation			Disease diagnosis Cancer treatment Radiation therapy Neuroscience
Microscopy		Particle picking			Vaccine development

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NIH NATIONAL CANCER INSTITUTE
NIH Clinical Center
HAI Stanford University Human-Centered Artificial Intelligence
PHIND
PHILIPS Healthcare
NVIDIA
Stanford Cancer Institute A National Cancer Institute Comprehensive Cancer Center
Stanford Children's Health
T.C. MINISTRY HEALTH İZMİR PROVINCIAL HEALTH DIRECTORATE İZMİR UNIVERSITY OF HEALTH SCIENCES TEPECİK
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Assistant Professor

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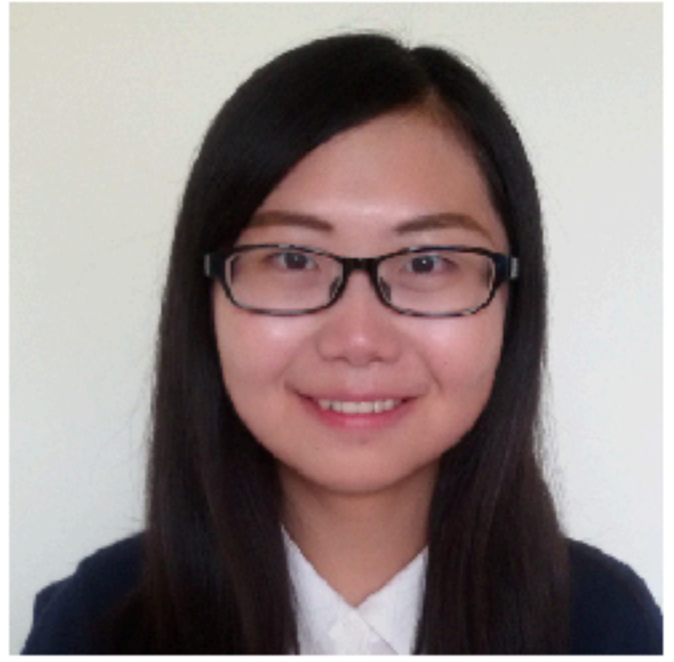
About me Publications Research People Awards



Liyue Shen

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Prospective Students

I am looking for self-motivated students, who are interested in machine learning, computer vision, signal and image processing, medical image analysis, biomedical imaging, and data science. Please feel free to reach out!

- I am looking for Ph.D. students to join my group in Fall 2023. If you are interested, please feel free to send me an email with your CV, and email subject as "[PhD application] ". More application details can be found in the following.
- If you are a UM student interested in doing research with me, please feel free to send me an email with your CV, and email subject as "[Join research lab – UM student] ".
- If you are student from other institutes and interested in collaboration, welcome to drop me an email as well.

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I am looking for Ph.D. students in the areas of signal & image processing (SIP), machine learning (ML), computer vision (CV), especially who is interested in Biomedical AI. Please see the Research page for more