Machine Learning for Cardiac MR Image Segmentation

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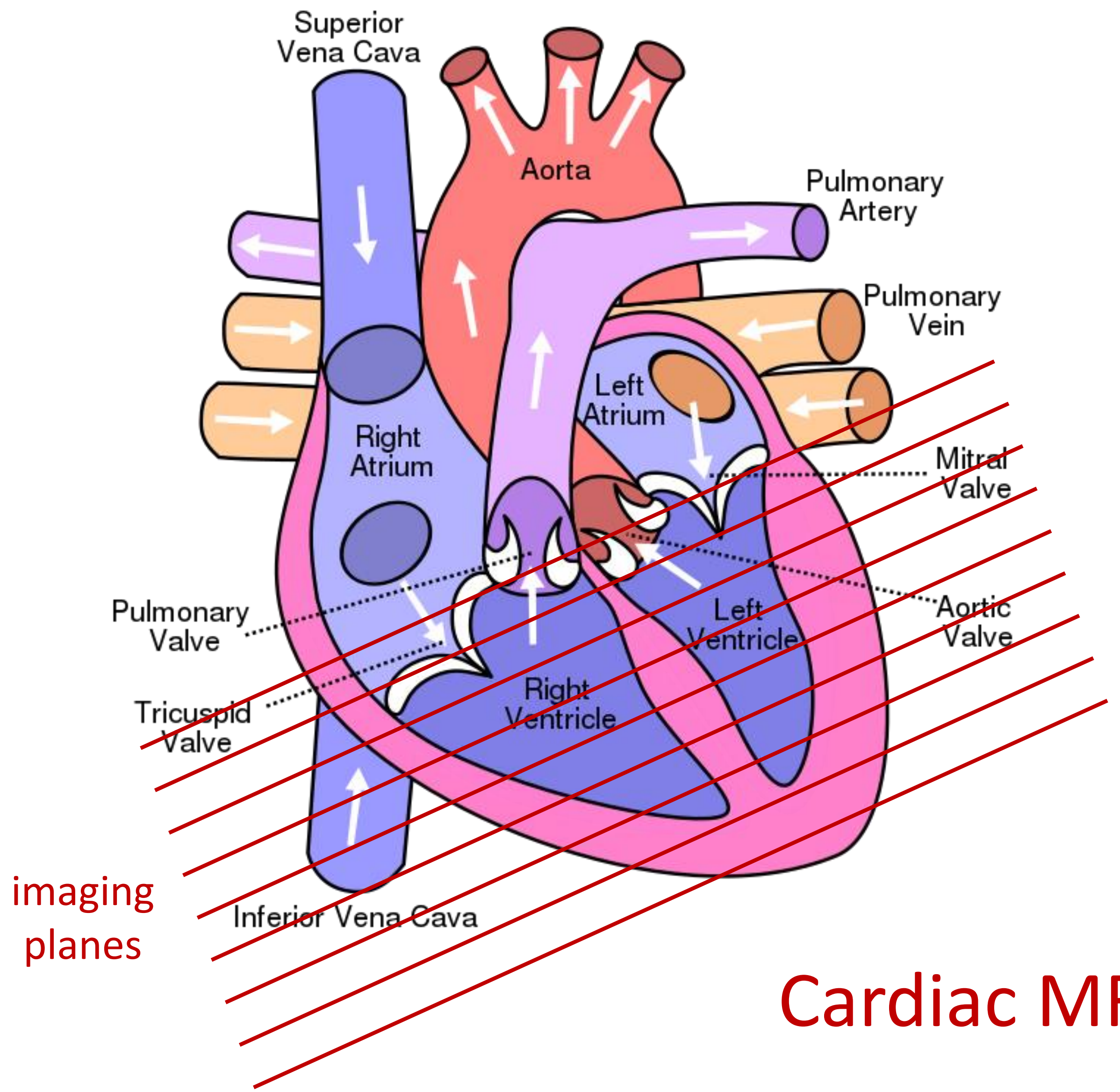
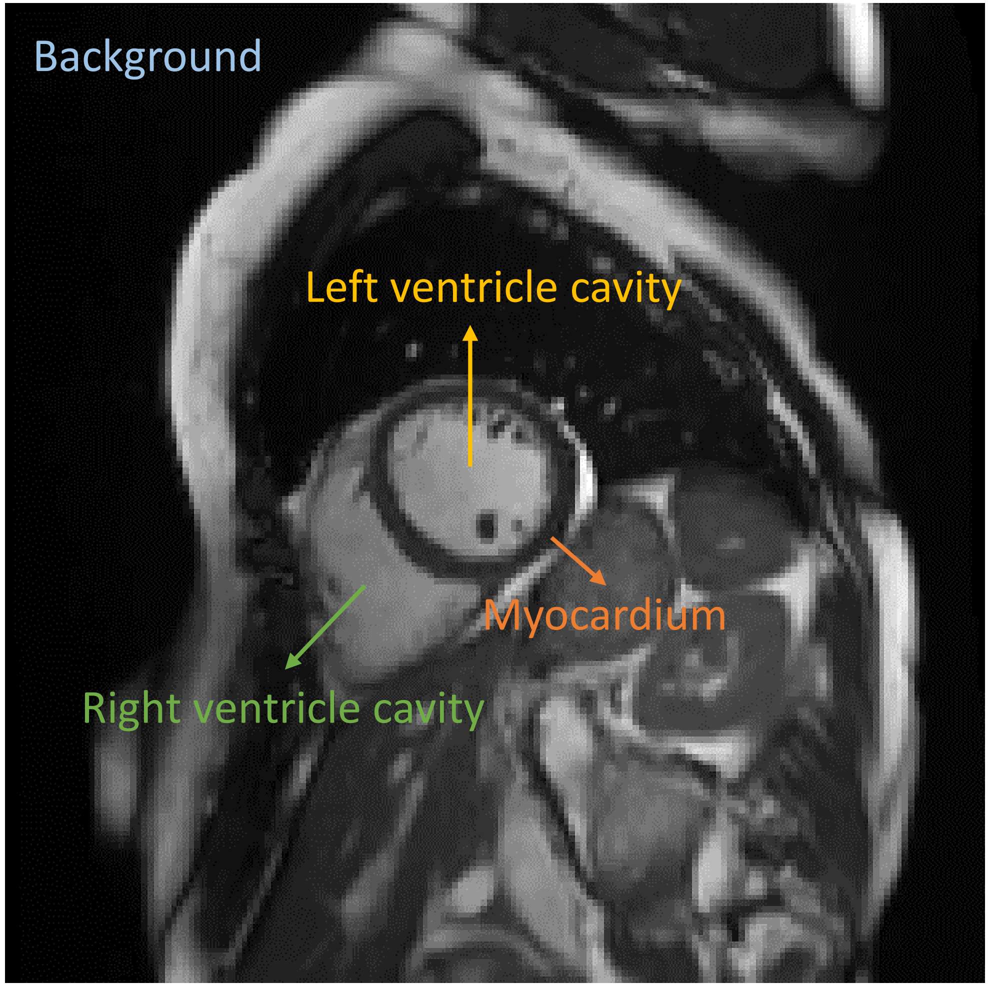




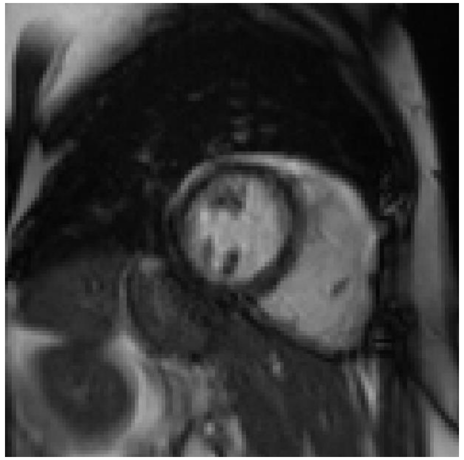
Cardiac MR imaging

Clinical relevance

- Diagnosis of cardiovascular diseases
- Quantitative measures
  - Ventricular volumes across a cardiac cycle
  - Ejection fraction
  - Myocardial mass, myocardial wall thickness

Challenge

- Clinical routine
  - Most medical images are analysed manually (contour drawing)
  - It takes 20 minutes to analyse cardiac MR for a single subject
  - Time consuming and prone to subjective bias
- Can we make the computer understand medical images?
  - Automatically analyse anatomical structures
  - Save time and cost
  - Consistent clinical measures
- My research
  - Medical image segmentation



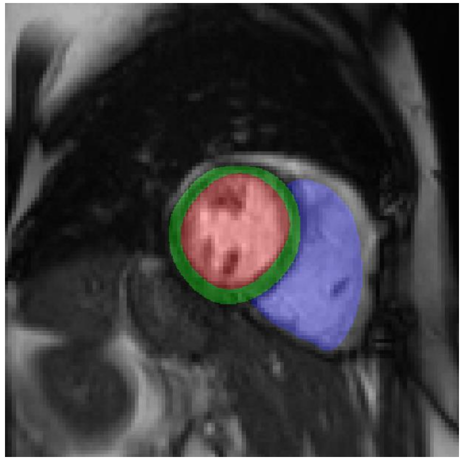


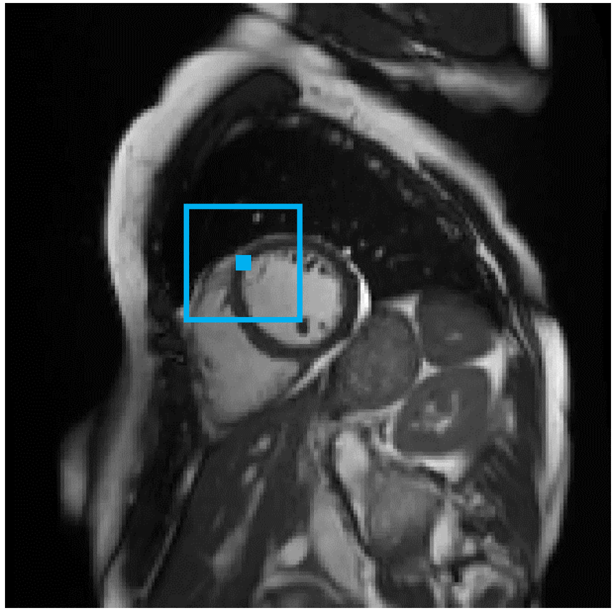
Image segmentation

- Learning a model that maps pixel/patch to label

$$f: x \rightarrow y$$

pixel/patch

label class
0: background
1: left ventricle
2: myocardium
3: right ventricle



Machine learning

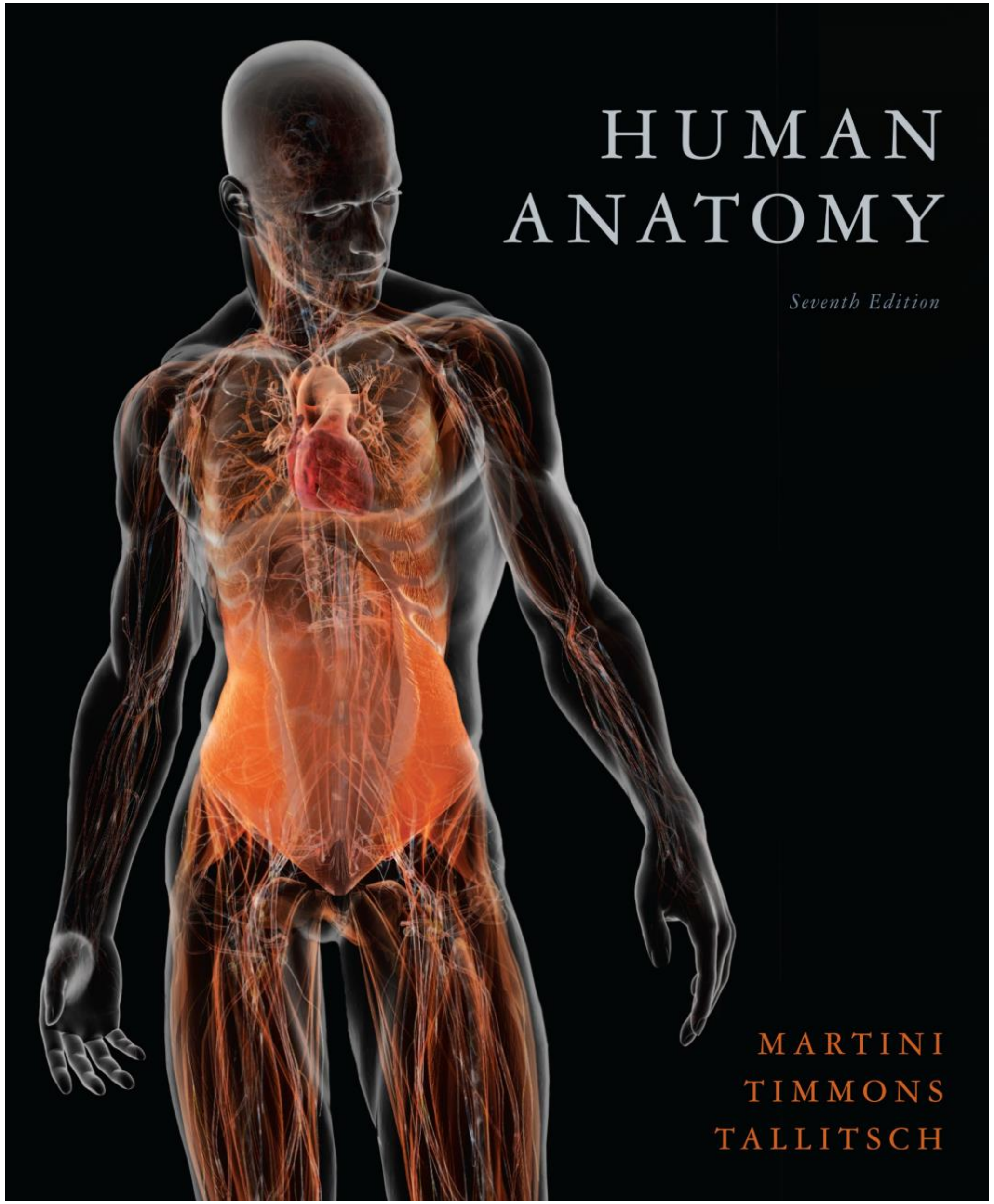
- Segmentation
  - Thresholding
  - Gaussian mixture model
  - Level set
  - ……
  - **Atlas-based segmentation**
  - **Convolutional neural networks**

Atlas-based segmentation

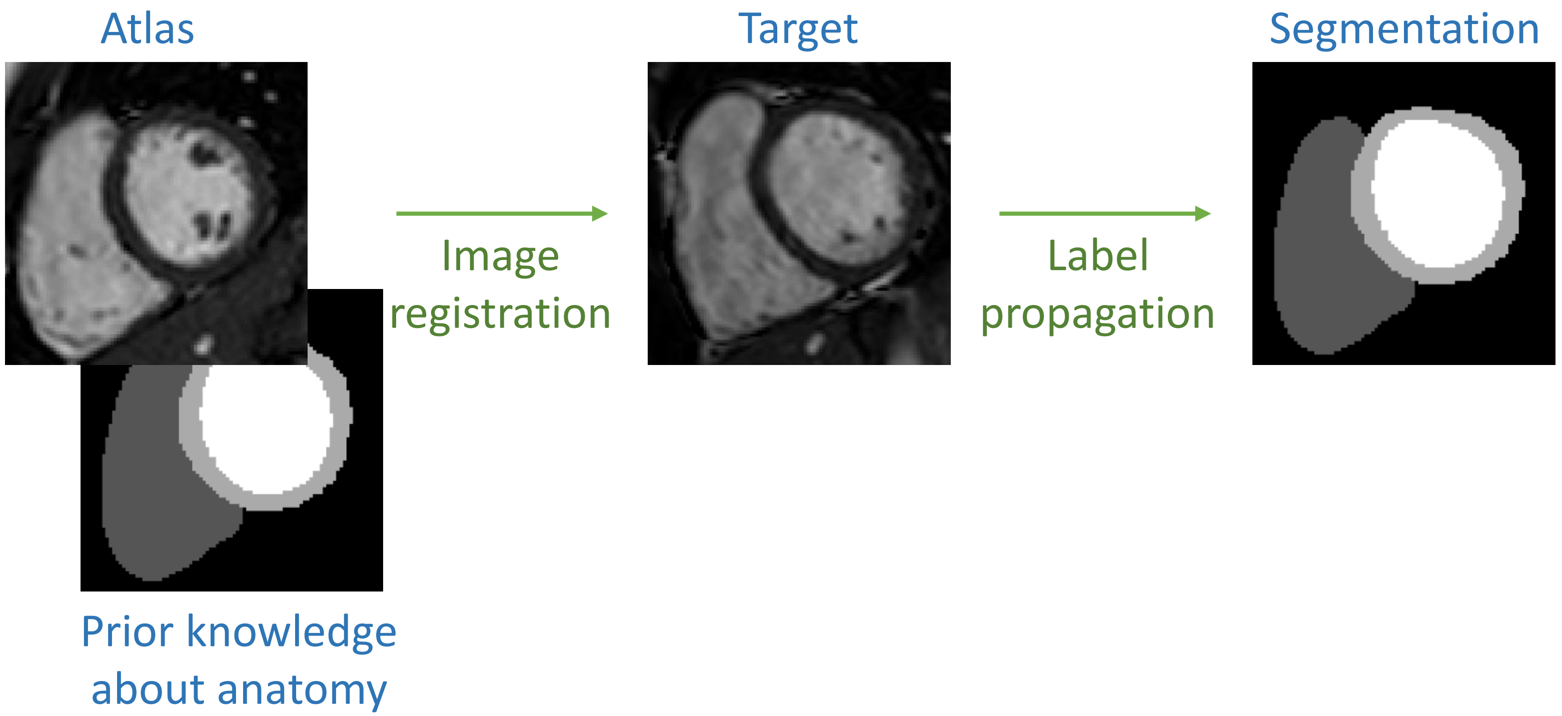
- Template matching

Atlas-based segmentation

- The anatomies of individuals share a lot of similarities (**if** we do not account for pathologies).
- The image of one subject may be transformed to another similar subject via a diffeomorphic deformation.



Atlas-based segmentation



Single-atlas segmentation

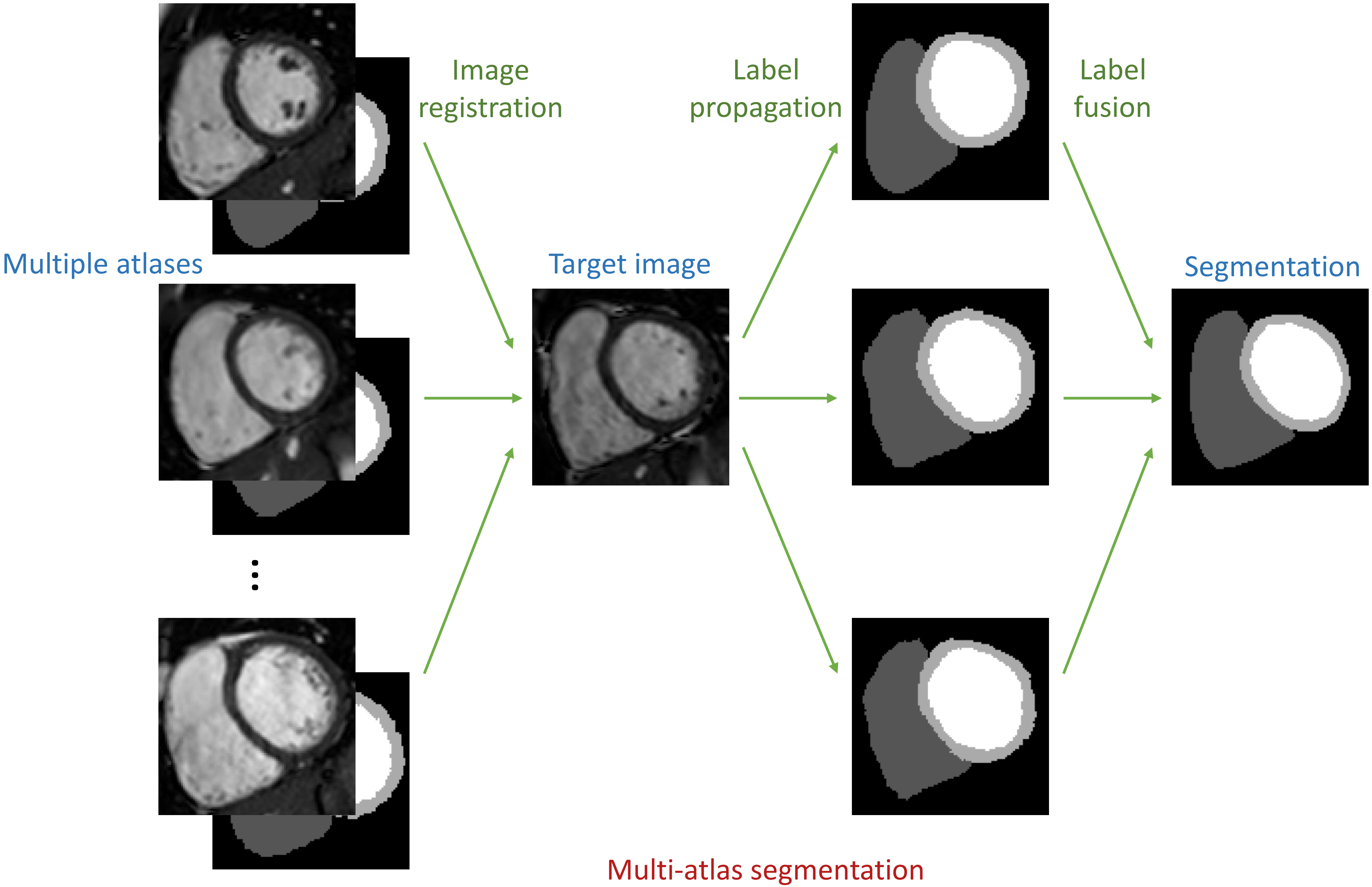
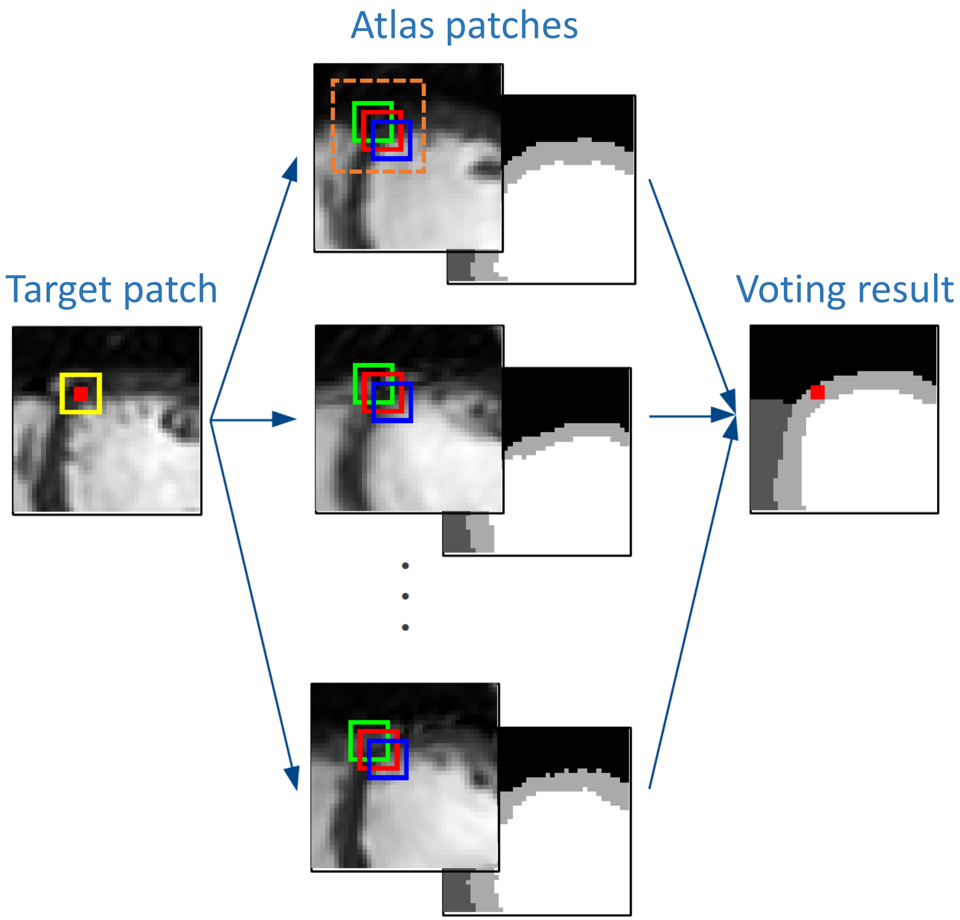


Image registration
Label propagation
Label fusion
Multiple atlases
Target image
Segmentation
Multi-atlas segmentation

Label fusion

- How do we combine propagated label maps from multiple atlases?
- Search for most similar atlas patches and combine by weighted voting



Patch-based label fusion

Label fusion

- Weighted voting

$$\hat{L}(x) = \arg\max_l \underbrace{\sum_n}_{\text{atlases}} \underbrace{\sum_k}_{\substack{\text{patches in} \\ \text{a search window}}} \underbrace{P(I(x)|k, I_n)}_{\text{intensity similarity}} \cdot \underbrace{P(L(x) = l|k, L_n)}_{\text{atlas label}}$$

Bai, IEEE TMI, 2013; Bai MedIA, 2015.

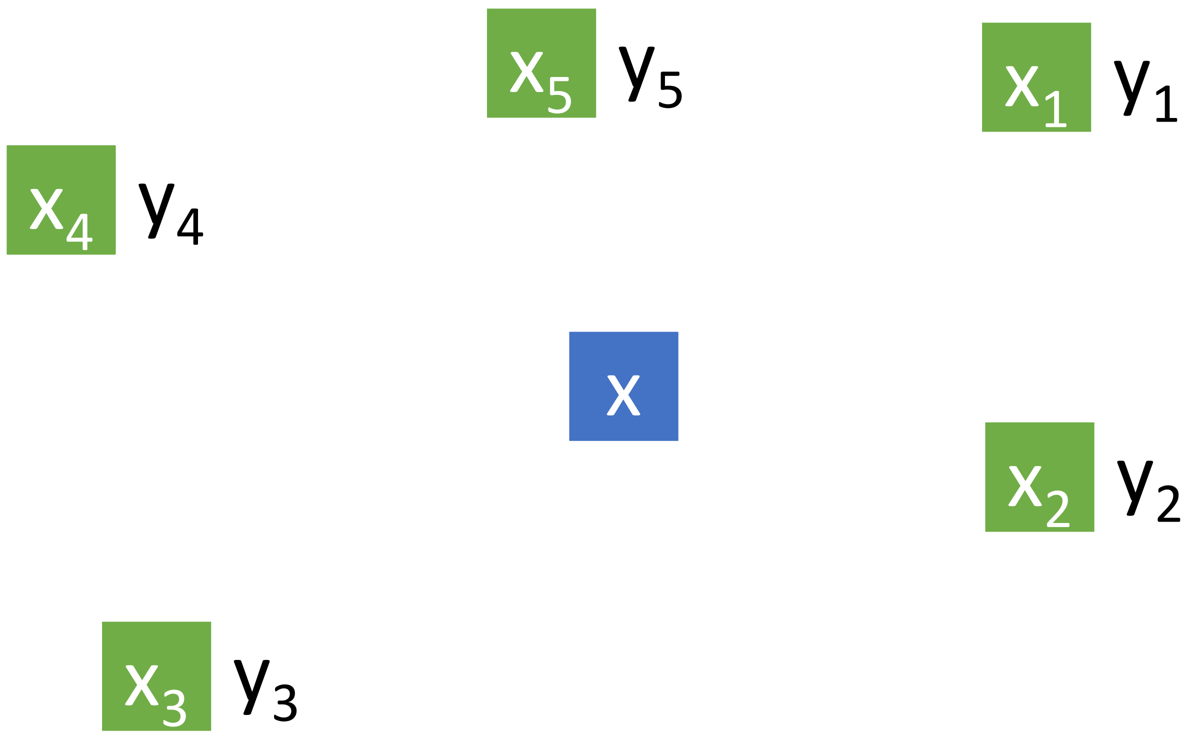
Atlas-based segmentation

- Nearest neighours

$$f: x \rightarrow y$$

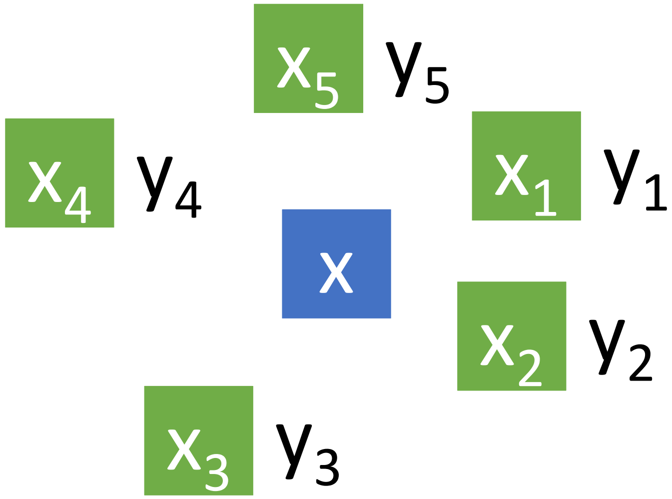
- Look for neighours of x and utilise anatomical knowledge of this neighbourhood.

Image registration



Before image registration

Image registration



After image registration

Atlas-based segmentation

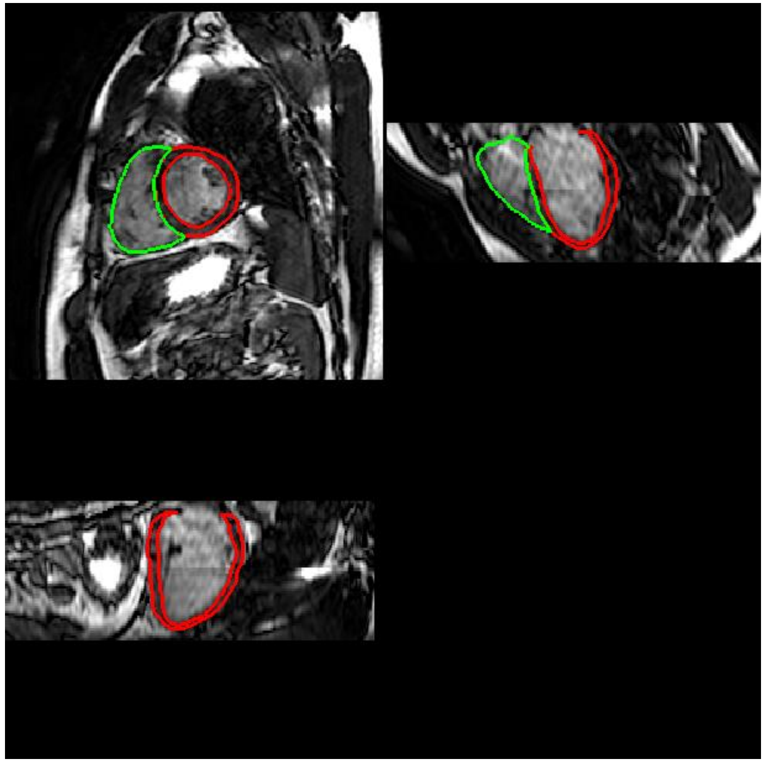
- Nearest neighbours

$$f: x \to y$$

- Utilise prior anatomical knowledge from neighbours of x.
- Pros and cons
  - Interpretability (+)
  - Slow (-)

Atlas-based segmentation

- 1st places in MICCAI segmentation challenges
  - MICCAI 2012 RV Segmentation Challenge
  - MICCAI 2013 SATA Cardiac Data Segmentation Challenge
- UK Digital Heart Project
  - Segmented cardiac MR images for ~2,000 subjects acquired at Hammersmith Hospital London

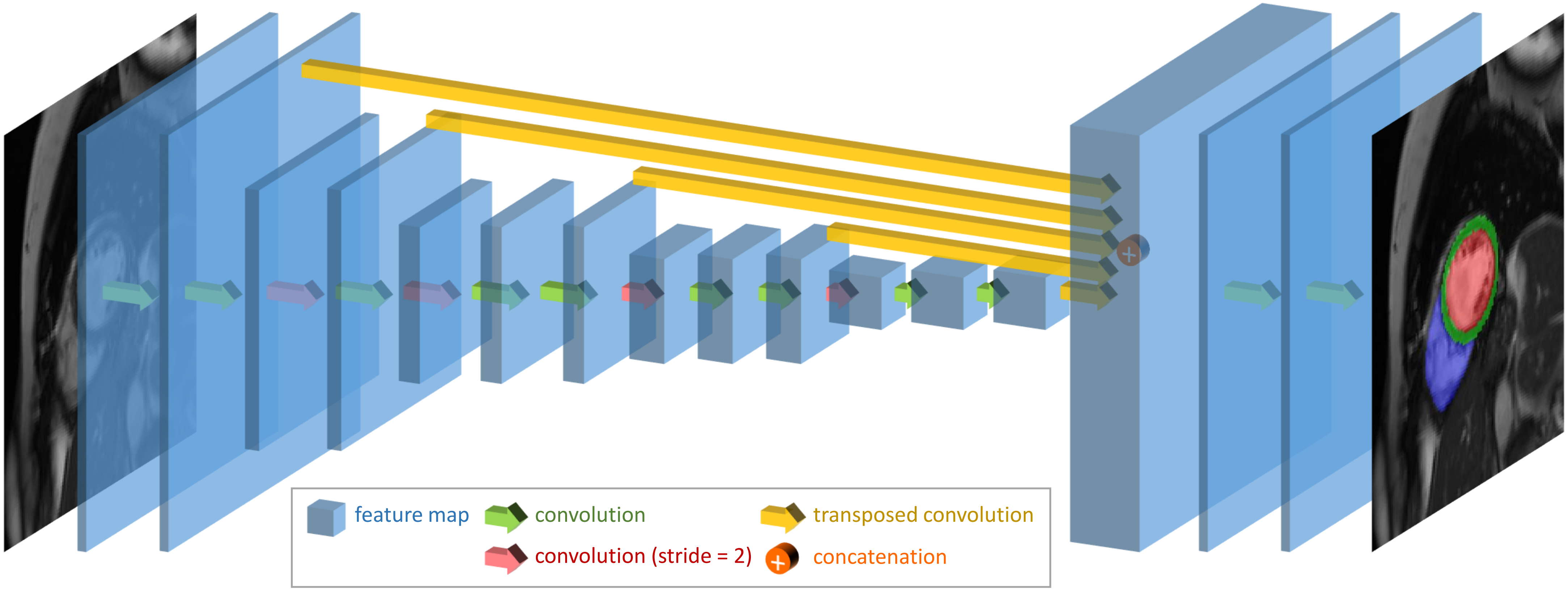


Cardiac image segmentation

Convolutional neural networks

- Encode anatomical knowledge implicitly in a network
- End-to-end learning of image features

Fully convolutional network



$$x^{(1)} = \sigma\left(W^{(1)}x + b^{(1)}\right)$$

feature map · activation function · convolution kernel · image · bias

Fully convolutional network

- Map x to y by a series of convolutions

$$x^{(1)} = \sigma\left(W^{(1)}x + b^{(1)}\right)$$

$$x^{(2)} = \sigma\left(W^{(2)}x^{(1)} + b^{(2)}\right)$$

$$\ldots\ldots$$

$$x^{(n)} = \sigma\left(W^{(n)}x^{(n-1)} + b^{(n)}\right)$$

$$y_i = \frac{\exp(x_i^{(n)})}{\sum_{j=1}^{L} \exp(x_j^{(n)})} \qquad \text{softmax}$$

Optimisation

- Loss function

$$\min_{\theta} L(x, \theta) = -\sum_{i=1}^{L} z_i \log(y_i(x, \theta))$$

$\theta = \{W^{(i)}, b^{(i)}\}$

ground truth

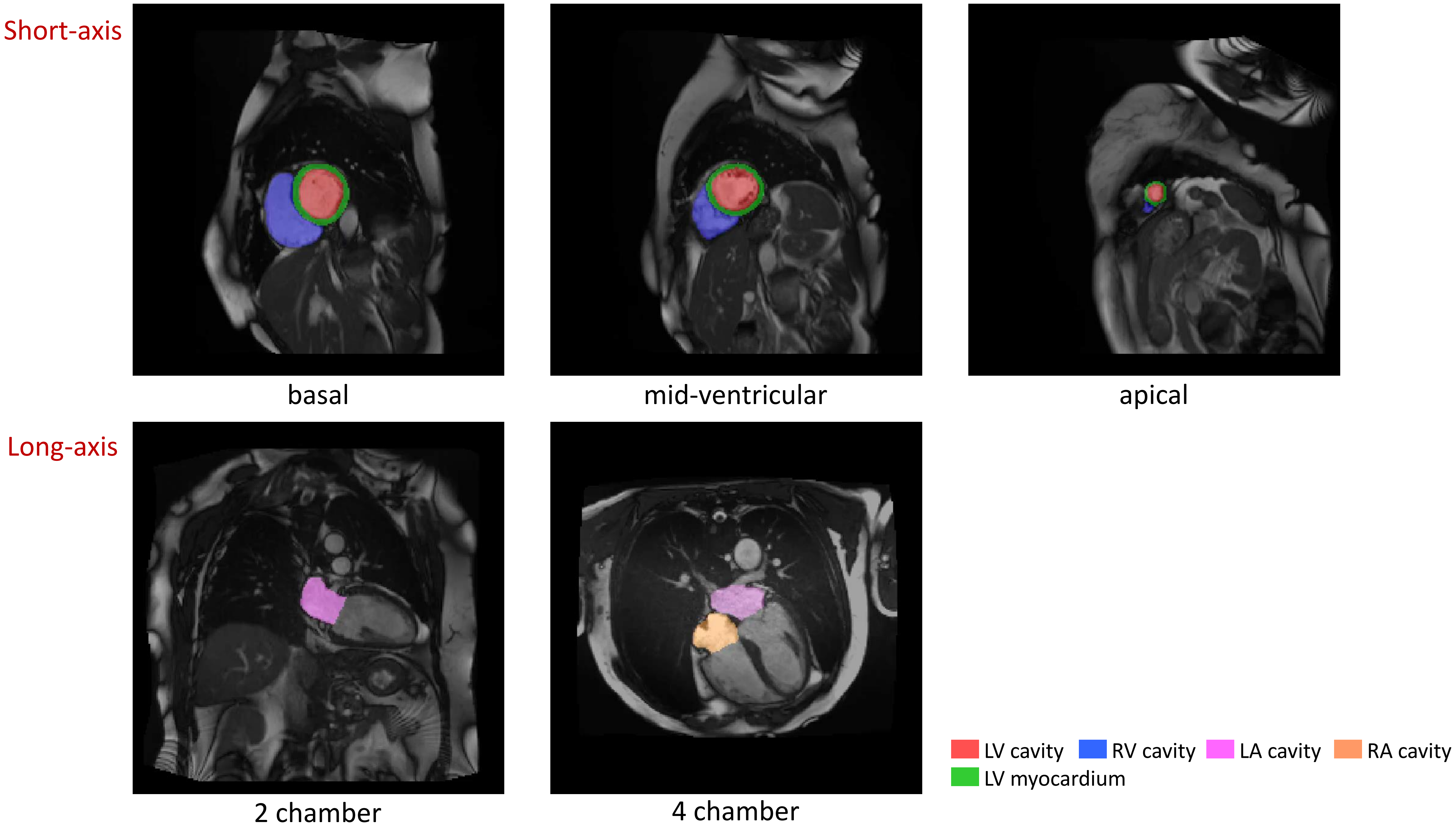
predicted label map

- Stochastic gradient descent (SGD)

$$\theta^{(n)} = \theta^{(n-1)} + \nabla_\theta L(x, \theta^{(n-1)})$$

Dataset

- UK Biobank
  - Manual annotations of 5,000 subjects (QMUL and Oxford)
  - Divide into training(80%)/validation(6.7%)/test(13.3%)
  - Evaluate segmentation accuracy
    - Dice overlap metric between automatic and manual segmentations
    - Clinically relevant measures: ventricular volume and mass



Short-axis
basal
mid-ventricular
apical
Long-axis
2 chamber
4 chamber
LV cavity
RV cavity
LA cavity
RA cavity
LV myocardium

Performance

- Fast
  - 9 seconds to segment 50 time frames across a cardiac cycle
- Accurate

Comparable to human inter-observer variability

	LV cavity	LV myo.	RV cavity	LA (2Ch)	LA (4Ch)	RA (4Ch)
Auto vs Man	0.94 ± 0.04	0.88 ± 0.03	0.90 ± 0.05	0.93 ± 0.05	0.95 ± 0.02	0.96 ± 0.02

Table 1: Dice overlap metrics for 600 test subjects.

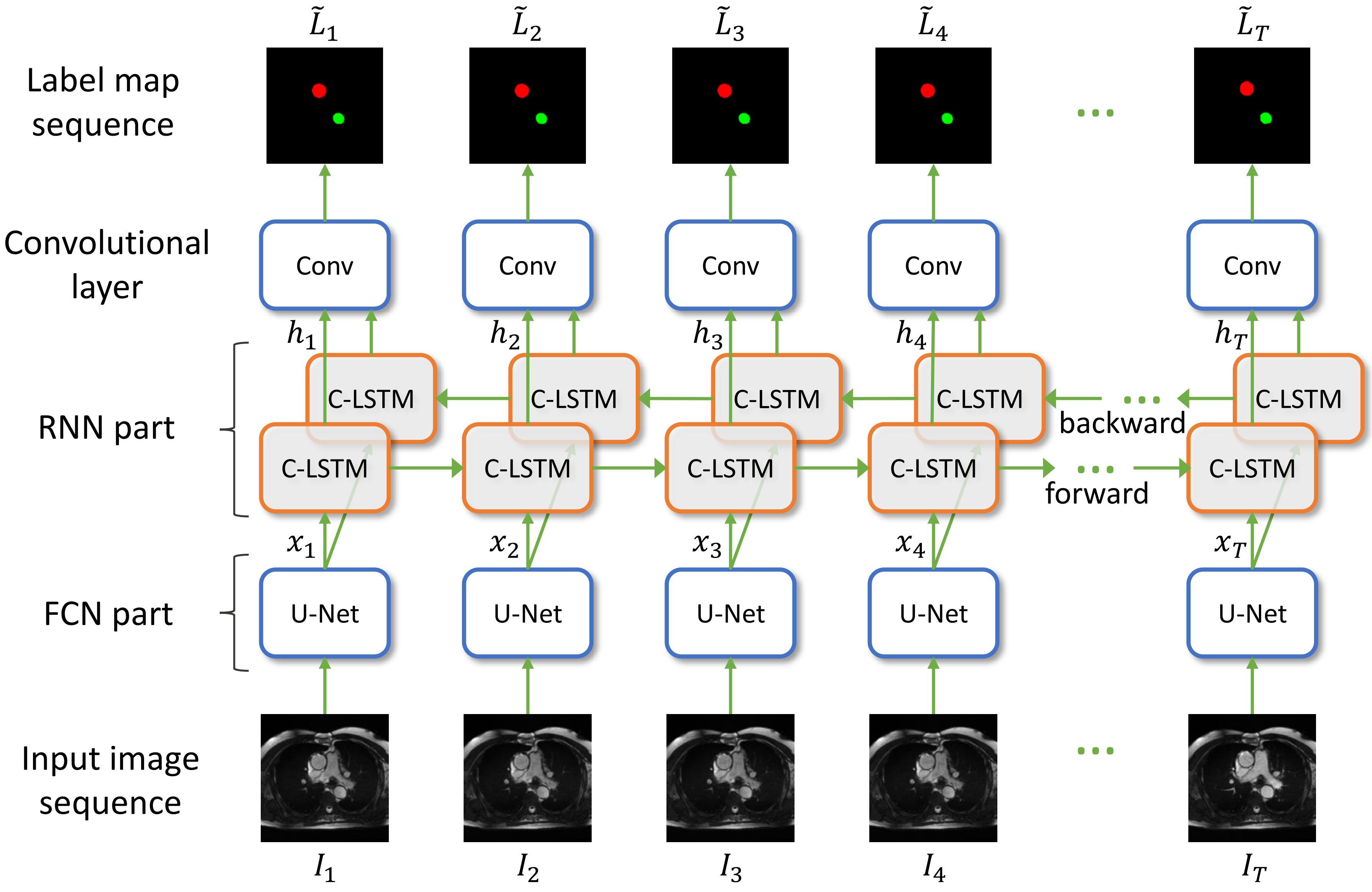
	LVEDV (mL)	LVESV (mL)	LVM (gram)	RVEDV (mL)	RVESV (mL)
Auto vs Man	6.1 ± 5.3	5.3 ± 4.9	6.9 ± 5.5	8.5 ± 7.1	7.2 ± 6.8

Table 2: Difference between automated measurement and manual measurement for ventricular volume and mass.

Bai, MICCAI, 2017; Bai, Arxiv, 2018.

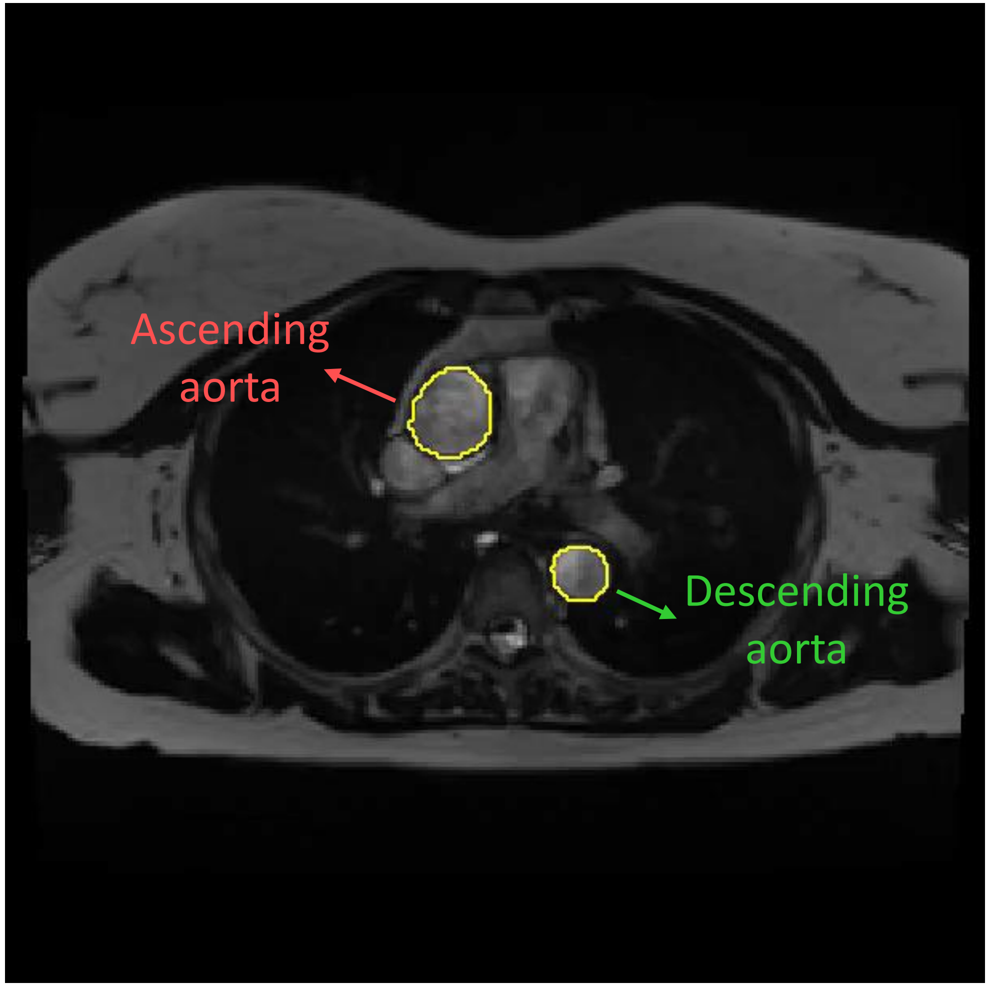
Network architectures

- Deeper
  - Hundreds to thousands of convolutional layers
  - Residual network (He et al. CVPR 2016)
- Denser
  - More connections between layers
  - Dense network (Huang et al. CVPR 2017)
- Wider
  - Higher number of features at each layer
  - Wide Residual Network (Zagoruyko et al. BMVC 2016)
- Better optimisation (Reddi et al. ICLR 2018)
- Uncertainty estimation (Gal. Thesis 2016)



Spatio-temporal network for image sequence segmentation

Noisy image sequence



Segmentation

Fully convolutional network

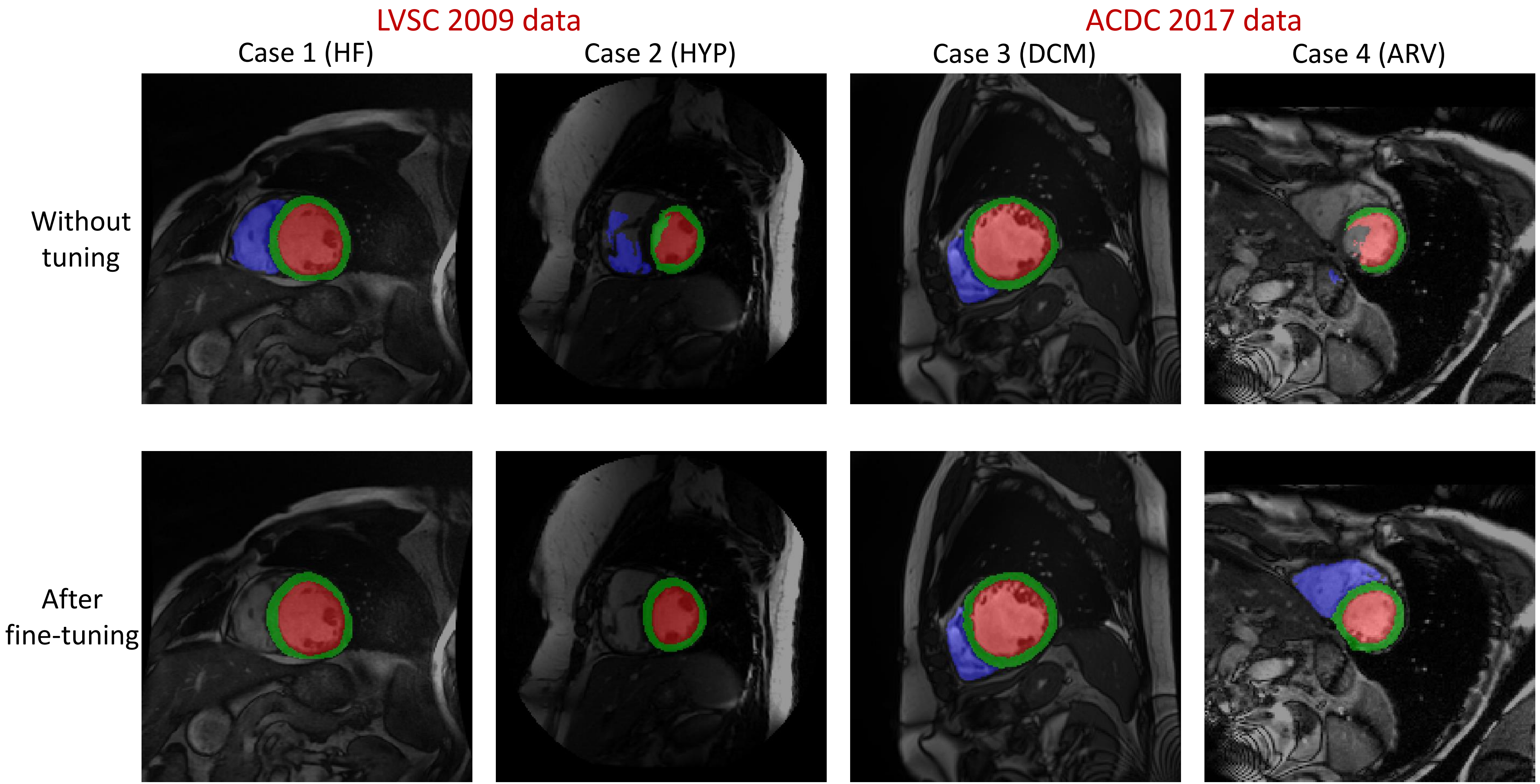
- Pros and cons
  - Fast (+)
  - Interpretability
  - Generalisability

Visualisation of feature maps

Saliency map: $S = \nabla_x L(x, \theta^{(n)})$

Generalisability

- UK Biobank: a relatively homogeneous dataset
  - Standard imaging protocol and MR scanner
- Generalisability
  - Different imaging protocol or MR scanner
- Apply the UK Biobank-trained network to other datasets
  - MICCAI 2009 Left Ventricle Segmentation Challenge (LVSC 2009)
  - MICCAI 2017 Automated Classification and Diagnosis Challenge (ACDC 2017)


LVSC 2009 data
ACDC 2017 data
Case 1 (HF)
Case 2 (HYP)
Case 3 (DCM)
Case 4 (ARV)
Without tuning
After fine-tuning

Generalisability

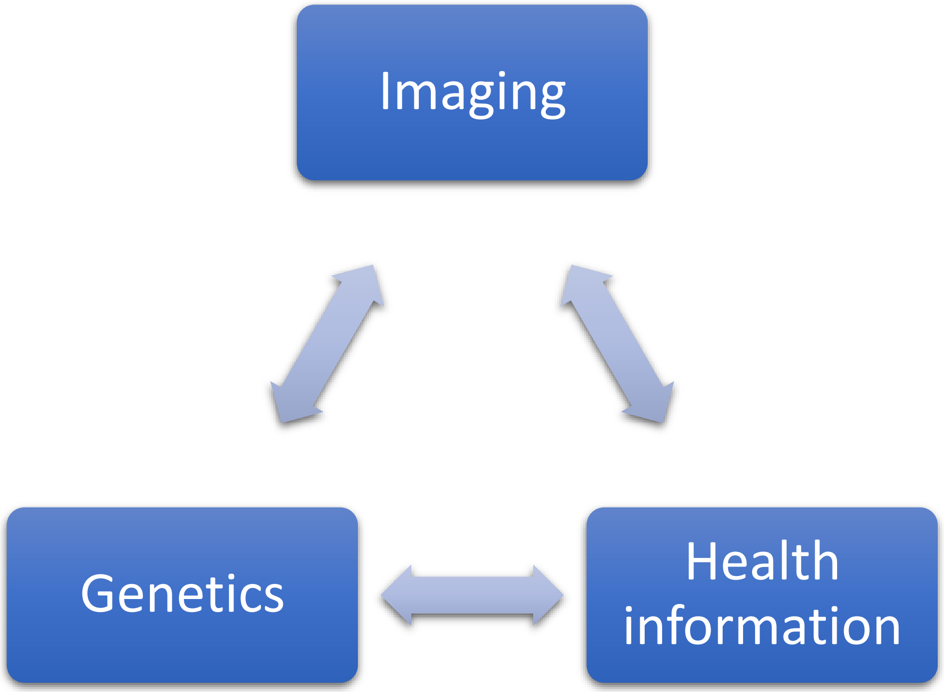
- Domain adaptation
  - Collect training data (annotations) in the new domain
  - If we do not have annotations for the new dataset, can we still make the network adaptable?

Medical image segmentation

- Atlas-based methods
  - Encode anatomical knowledge explicitly
  - Propagate anatomical knowledge using image registration
- Convolution neural networks
  - Encode anatomical knowledge implicitly
  - Learn features from training data

Future research

- Machine learning in medical imaging
  - Accurate in extracting clinical information
  - Interpretability
  - Generalisablity
  - Data collection and annotation
- Not just imaging data
  - UK Biobank (500,000 subjects, 100,000 with imaging data)
  - US Precision Medicine Initiative (1,000,000 subjects)
  - Better understanding between imaging, genetics and health for a large population



Thank you.