Supervised, weakly-supervised and supervised image registration

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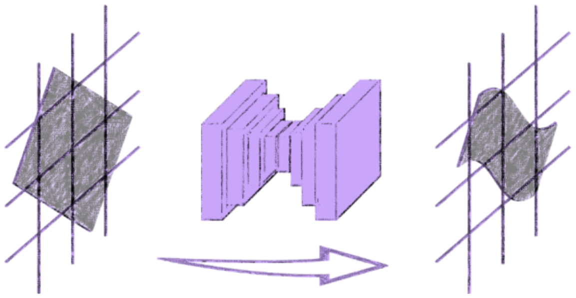

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Content

- An Attempt at Taxonomy
- Supervised Image Registration
- Weakly-supervised Registration
- Conditional Segmentation
- Model-Based Prior and Data-Driven Conditional Segmentation

Haskins, G., Kruger, U., & Yan, P. (2019). Deep Learning in Medical Image Registration: A Survey. *arXiv preprint arXiv:1903.02026.*

Tustison, N. J., Avants, B. B., & Gee, J. C. (2019). Learning image-based spatial transformations via convolutional neural networks: a review. *Magnetic resonance imaging.*

Taxonomy

Supervised Learning

Unsupervised Learning

Deterministic Approach

Generative Approach

Non-end-to-end Methods

End-to-end Methods

Taxonomy

Non-end-to-end Methods

- Learning Transformation Models
- Learning Similarity Measure
- Using Surrogate Ground-Truth (Learning Optimisation)

End-to-end Methods

- Driven by Similarity Measure
- Driven by Anatomical Labels

2017

Supervised Learning

Unsupervised Learning

Deterministic Approach

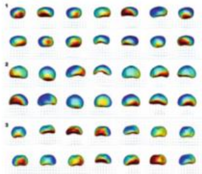
Generative Approach

Learning Registration Components

Learning Transformation Models

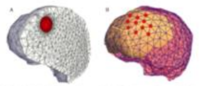
Learning generative models from motion simulations

Hu, Y., Gibson, E., Vercauteren, T., Ahmed, H.U., Emberton, M., Moore, C.M., Noble, J.A. and Barratt, D.C., 2017, September. Intraoperative organ motion models with an ensemble of conditional generative adversarial networks. *In MICCAI 2017*



Approximating finite-element analysis

Tonutti, M., Gras, G. and Yang, G.Z., 2017. A machine learning approach for real-time modelling of tissue deformation in image-guided neurosurgery. *In Artificial intelligence in medicine*



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Learning Registration Components

Learning Similarity Measures

Learning unsupervised features using a two-layer CNN

Wu, G., Kim, M., Wang, Q., Gao, Y., Liao, S. and Shen, D., 2013, September. Unsupervised deep feature learning for deformable registration of MR brain images. *In MICCAI 2013*

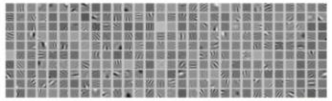
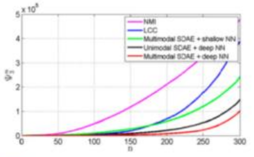


Fig. 3. The learnt bases filters (13 × 13) in the first layer from 60 MR brain images

Learning patch similarity measure from aligned images

Cheng, X., Zhang, L. and Zheng, Y., 2018. Deep similarity learning for multimodal medical images. *In Computer Methods in Biomechanics and Biomedical Engineering*

Simonovsky, M., Gutiérrez-Becker, B., Mateus, D., Navab, N. and Komodakis, N., 2016, October. A deep metric for multimodal registration. *In MICCAI 2016*



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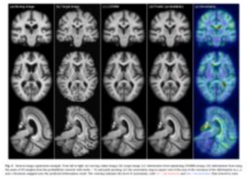
Learning Registration Components

Learning Optimisation

Learning from the Registered Images

Yang, X., Kwitt, R., Styner, M. and Niethammer, M., 2017. Quicksilver: Fast predictive image registration–a deep learning approach. *In NeuroImage*



Learning From the Simulated (spatially-warped) Images

Miao, S., Wang, Z.J. and Liao, R., 2016. A CNN regression approach for real-time 2D/3D registration. *In IEEE transactions on medical imaging*

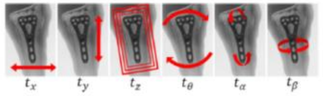


Fig. 1. Effects of the 6 transformation parameters.

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The Roles of Generative Modelling

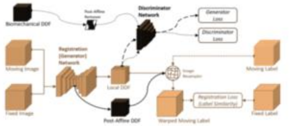
GANs and Autoencoders

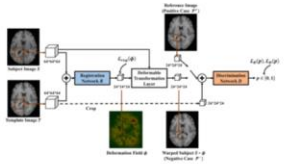
Hu, Y., Gibson, E., Ghavami, N., Bonmati, E., Moore, C.M., Emberton, M., Vercauteren, T., Noble, J.A. and Barratt, D.C., 2018. Adversarial Deformation Regularization for Training Image Registration Neural Networks. *In MICCAI 2018*

Yan, P., Xu, S., Rastinehad, A.R. and Wood, B.J., 2018. Adversarial Image Registration with Application for MR and TRUS Image Fusion. *In MICCAI 2018*

Fan, J., Cao, X., Xue, Z., Yap, P.T. and Shen, D., 2018. Adversarial Similarity Network for Evaluating Image Alignment in Deep Learning Based Registration. *In MICCAI 2018*

Krebs, J., Mansi, T., Mailhé, B., Ayache, N. and Delingette, H., 2018. Unsupervised Probabilistic Deformation Modeling for Robust Diffeomorphic Registration. *In DLMA 2018*





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Using Reinforcement Learning

Q-Learning

$$loss = \Big(\underbrace{r + \gamma \max_{a'} \hat{Q}(s,a')}_{\text{Target}} - \underbrace{Q(s,a)}_{\text{Prediction}}\Big)^2$$

Reward, Decay Rate

Rigid

Liao, R., Miao, S., de Tournemire, P., Grbic, S., Kamen, A., Mansi, T. and Comaniciu, D., 2017, February. An Artificial Agent for Robust Image Registration. *In AAAI 2017*

Non-Rigid via SSM

Krebs, J., Mansi, T., Delingette, H., Zhang, L., Ghesu, F.C., Miao, S., Maier, A.K., Ayache, N., Liao, R. and Kamen, A., 2017, September. Robust non-rigid registration through agent-based action learning. *In MICCAI 2017*

$$Loss = \sum_{k=1}^{M} \sum_{a_{i=1\ldots12} \in A} \|\underbrace{y_i(d_k)}_{\text{Prediction}} - \underbrace{Q(s_k, a_i)}_{\text{Supervised Target}}\|_2$$

Reinforcement Learning for Rigid Registration

The MDP tuple:

- **State:** current transformation, transformed image and the difference
- **Action:** "adjusting" discrete transformation
- **Reward:** difference to ground-truth transformation
- **Learning Algorithm:** Q-agent with supervised registration path

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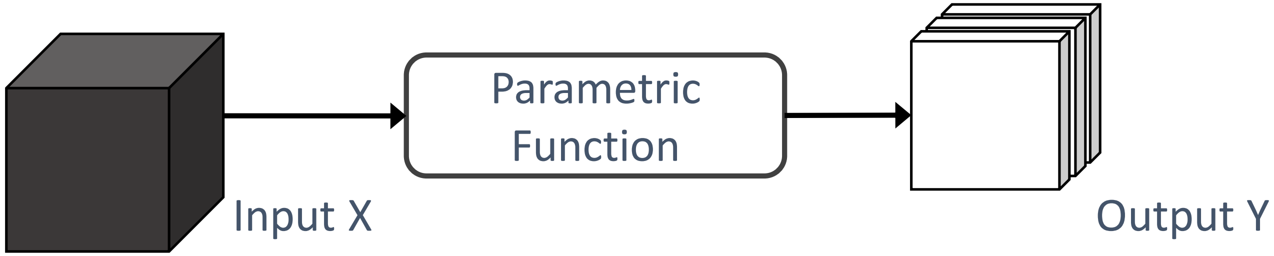
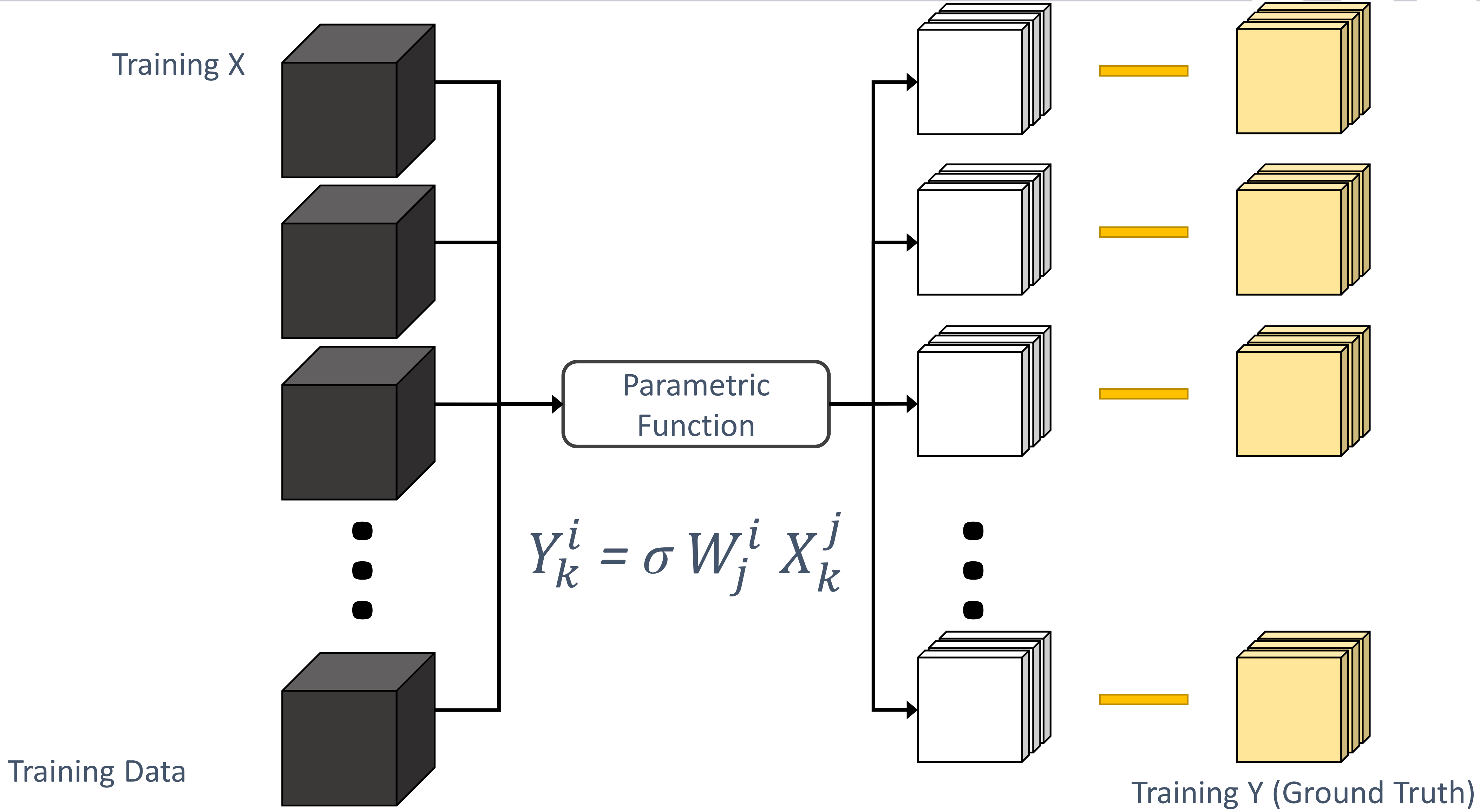
Supervised Learning

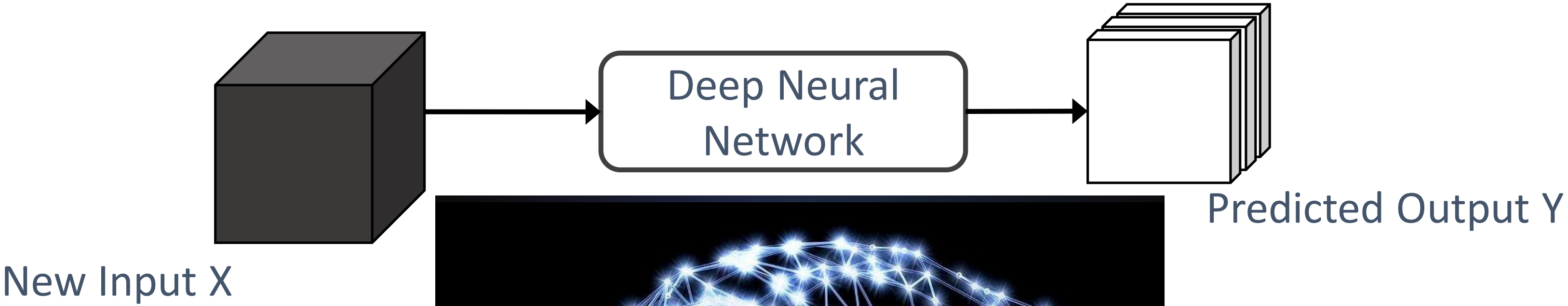


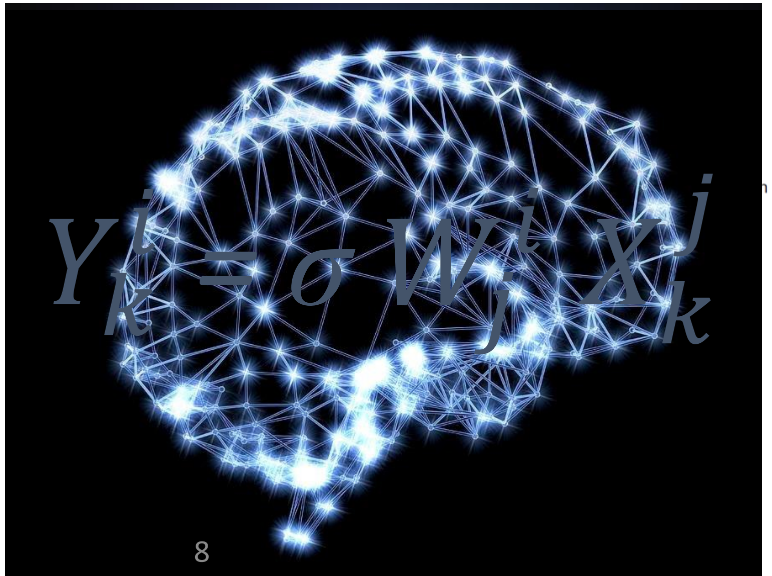
$$Y_k^i = \sigma\, W_j^i\, X_k^j$$

Supervised Learning



Supervised Learning



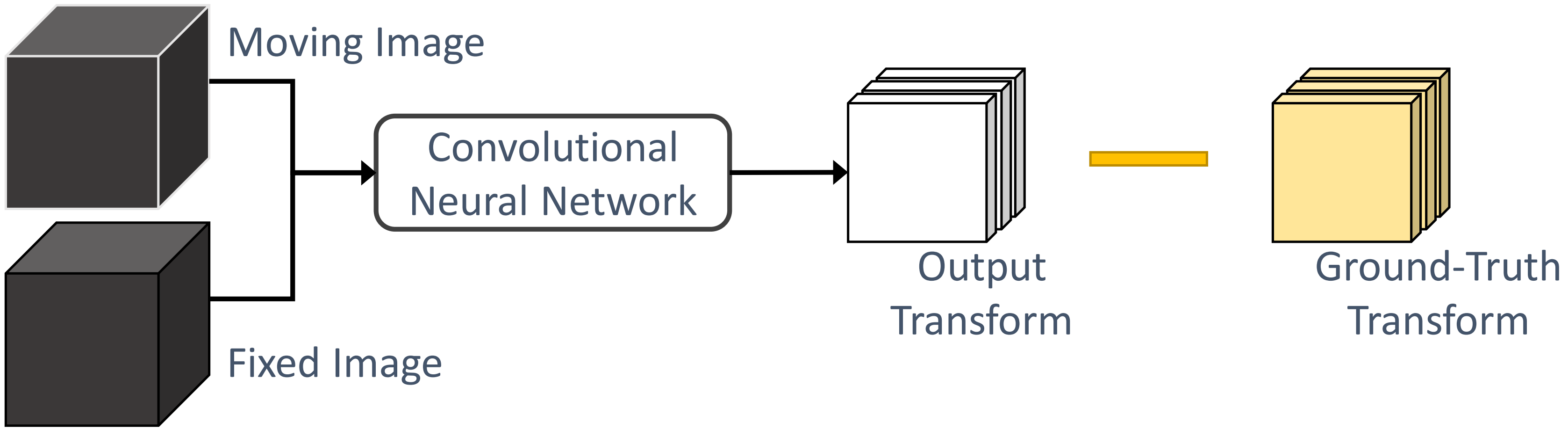


$$Y_k^i = \sigma\left(W_j^i X_k^j\right)$$

Supervised Learning for Image Registration

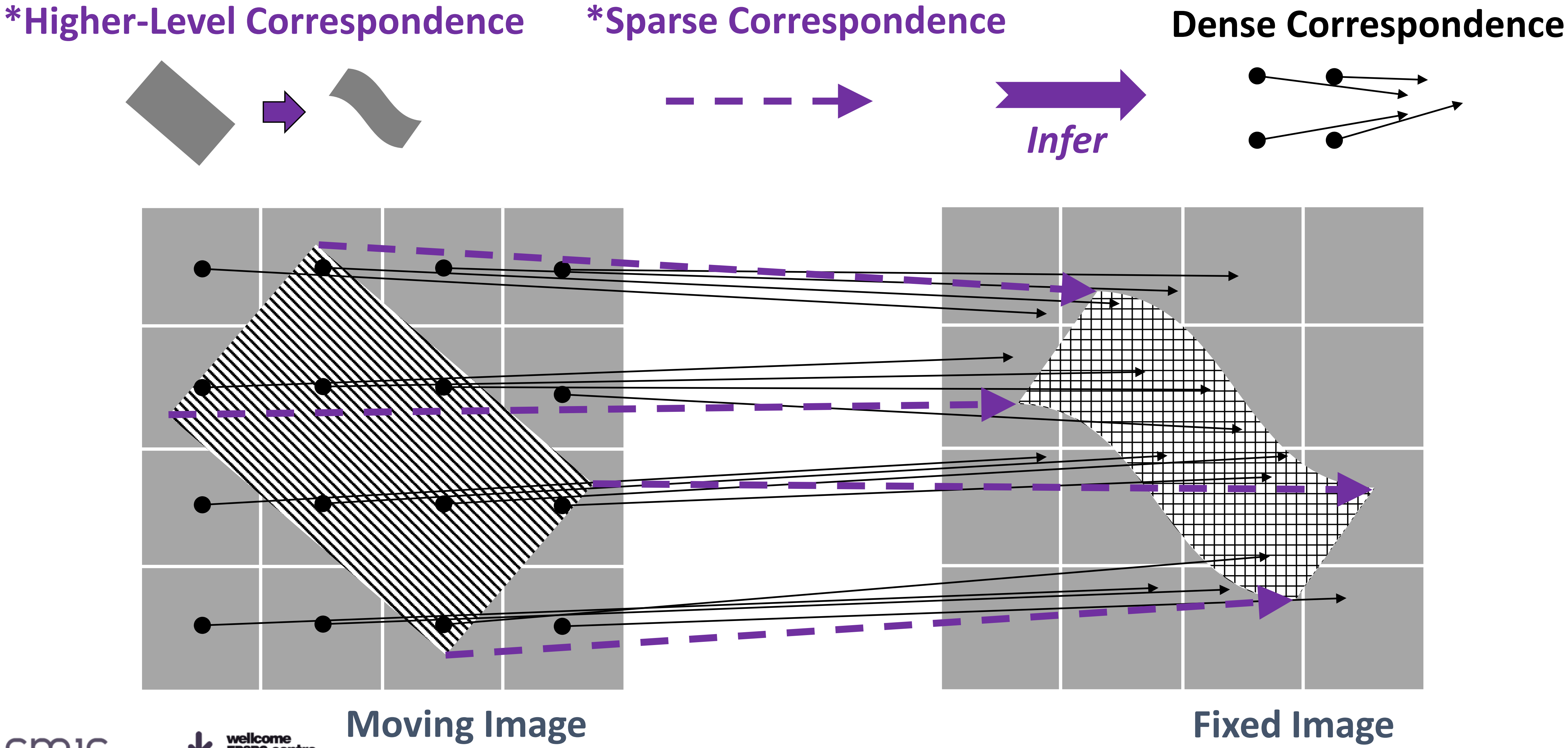
Requiring ground-truth transformation (correspondence)

- Ground-truth
  - Simulations ± domain adaptation
  - Estimates, e.g. pair-wise registration
  - Manual alignment



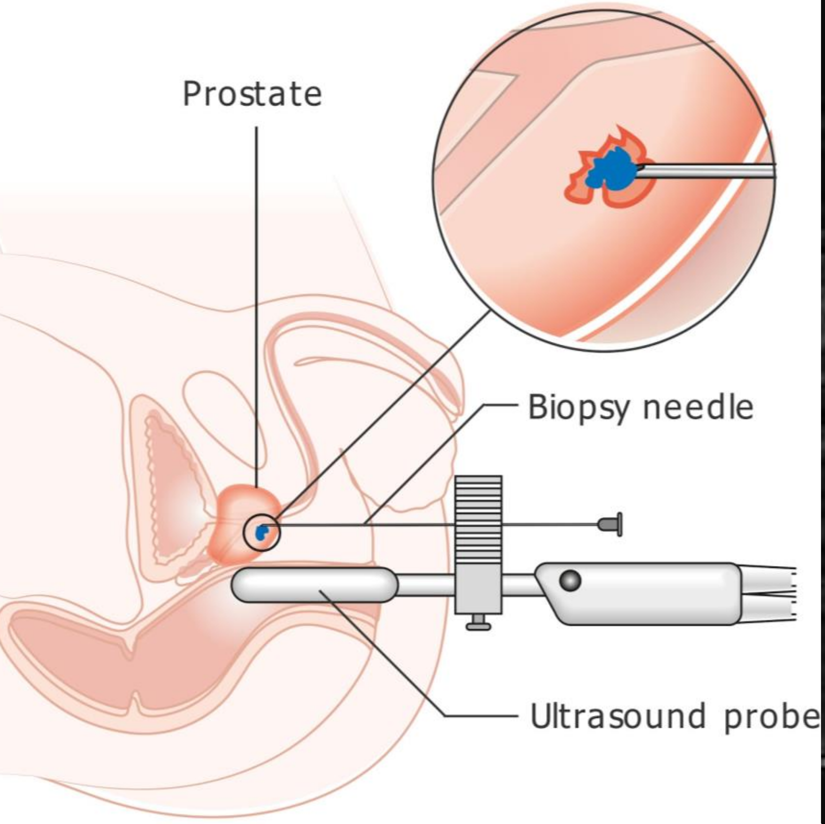
- Loss functions
  - Sum/Mean L1/L2 norm of difference
  - Difference in transformation parameters
  - Explicit regularisation, e.g. gradient of DDF, bending energy
  - Implicit constraints in transformation models
  - Adversarial loss, i.e. divergence between transformations

“Weak Labels” of Correspondence

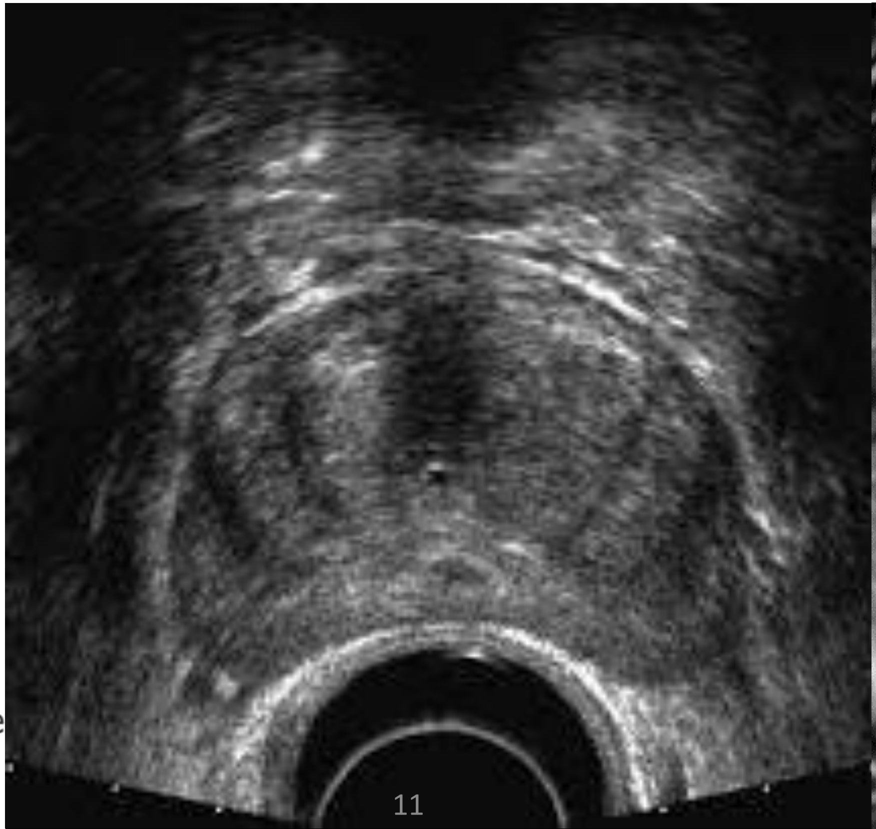


Registration of Prostate MR and Ultrasound Images

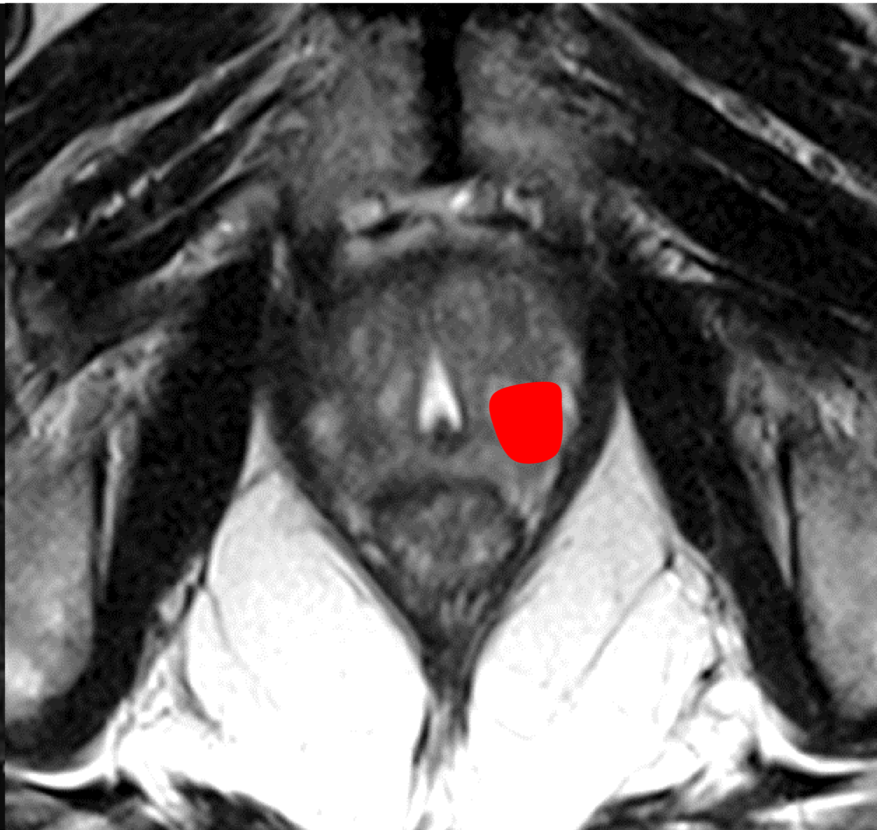
TRUS-guided Procedure



Intra-operative TRUS

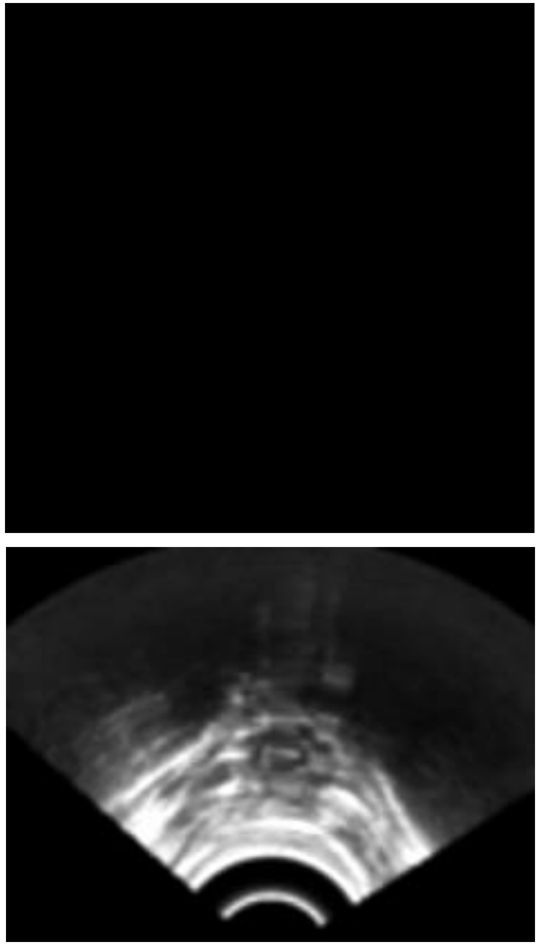


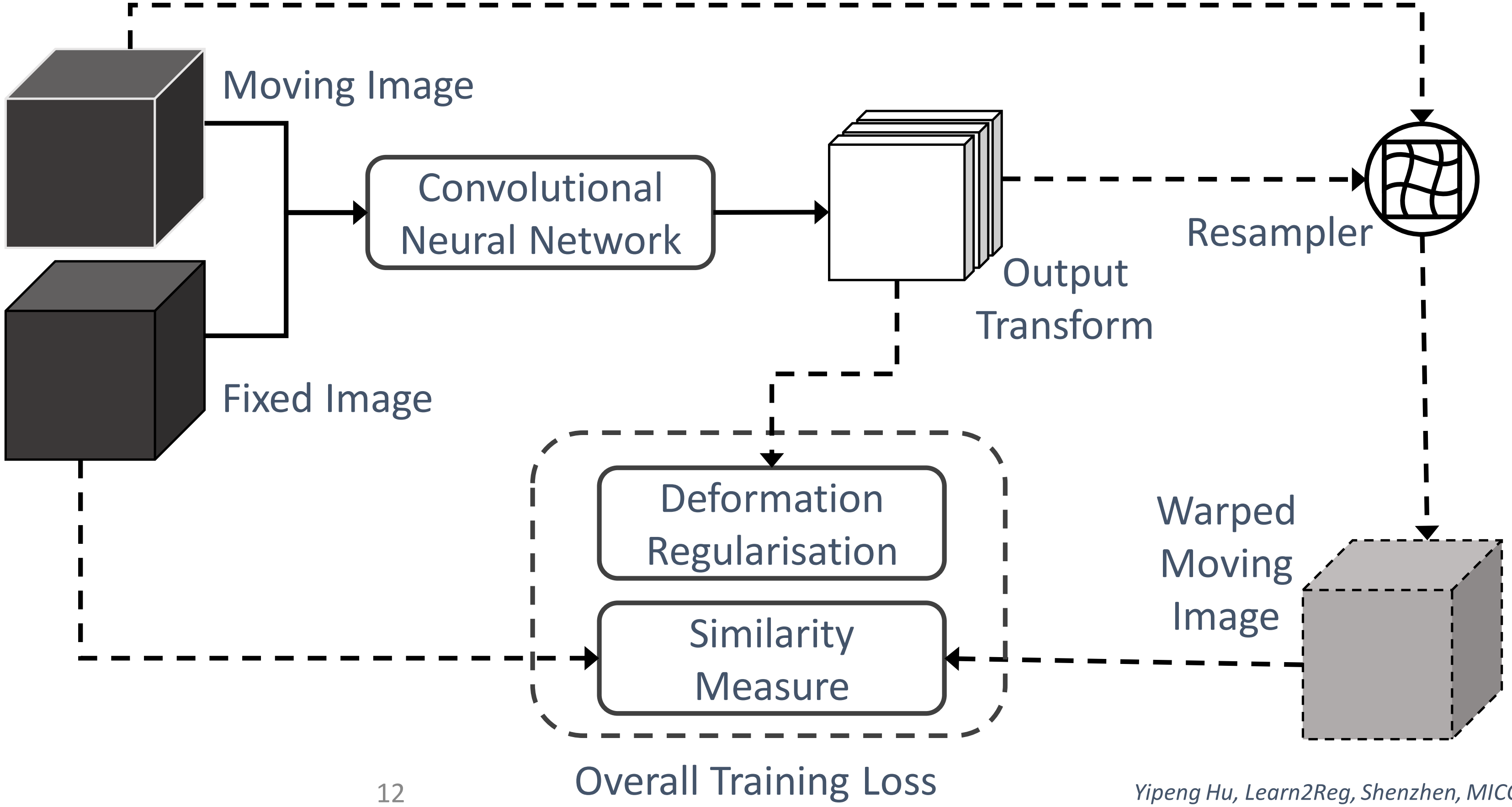
Pre-operative MR



Weakly-Supervised Registration

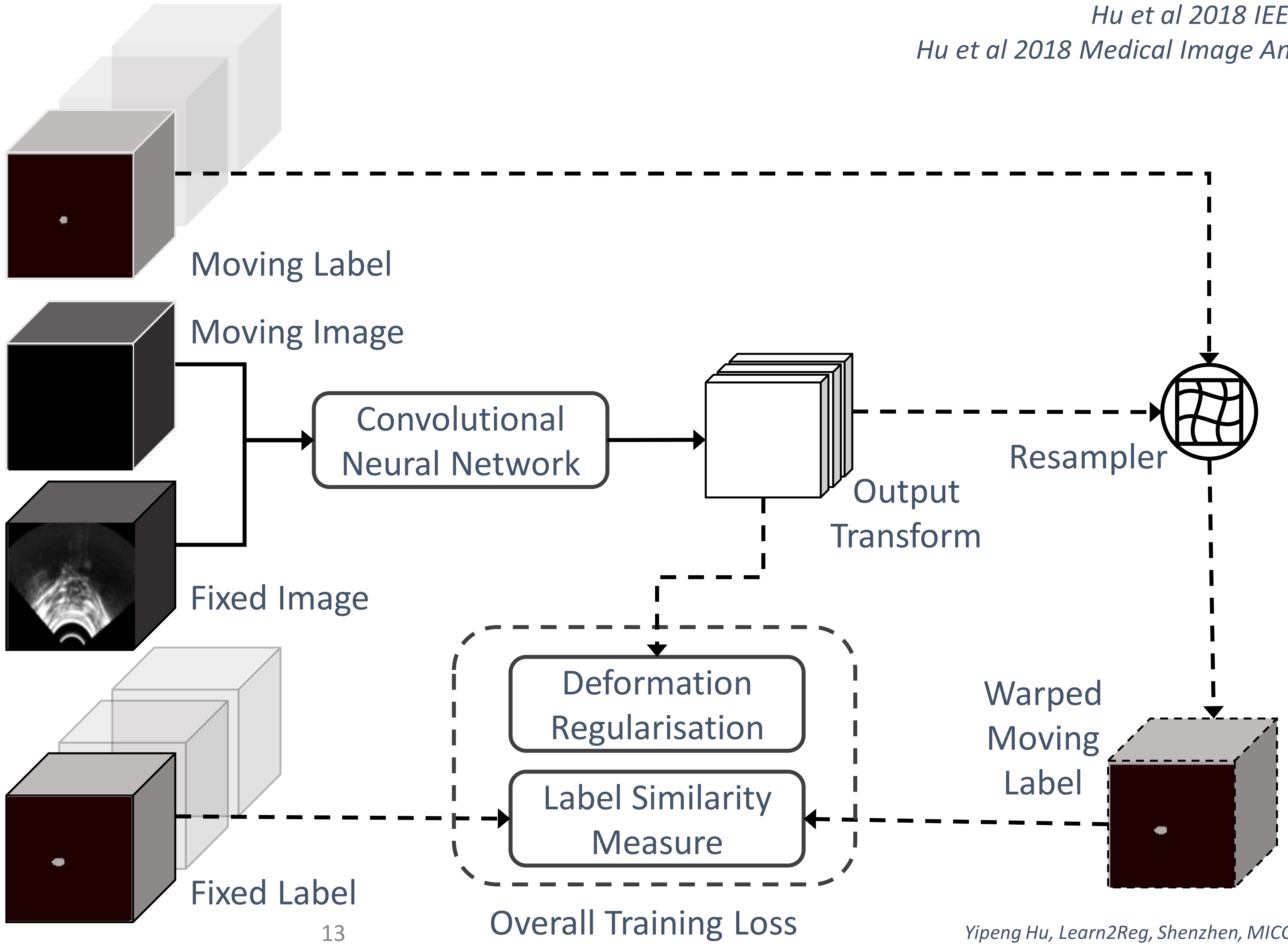
Unsupervised registration driven by similarity measure





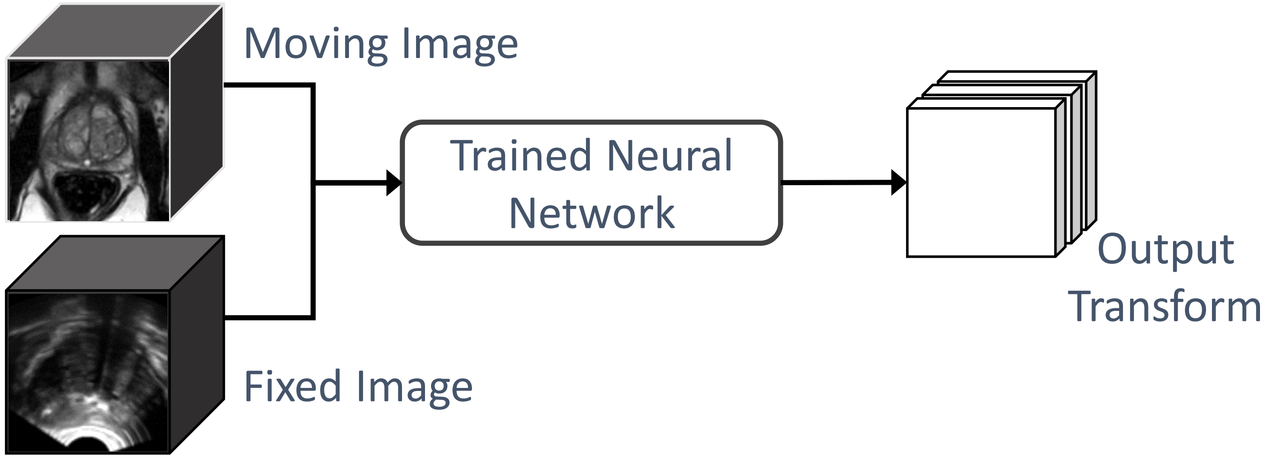
Weakly-Supervised Registration

Hu et al 2018 IEEE-ISBI
Hu et al 2018 Medical Image Analysis



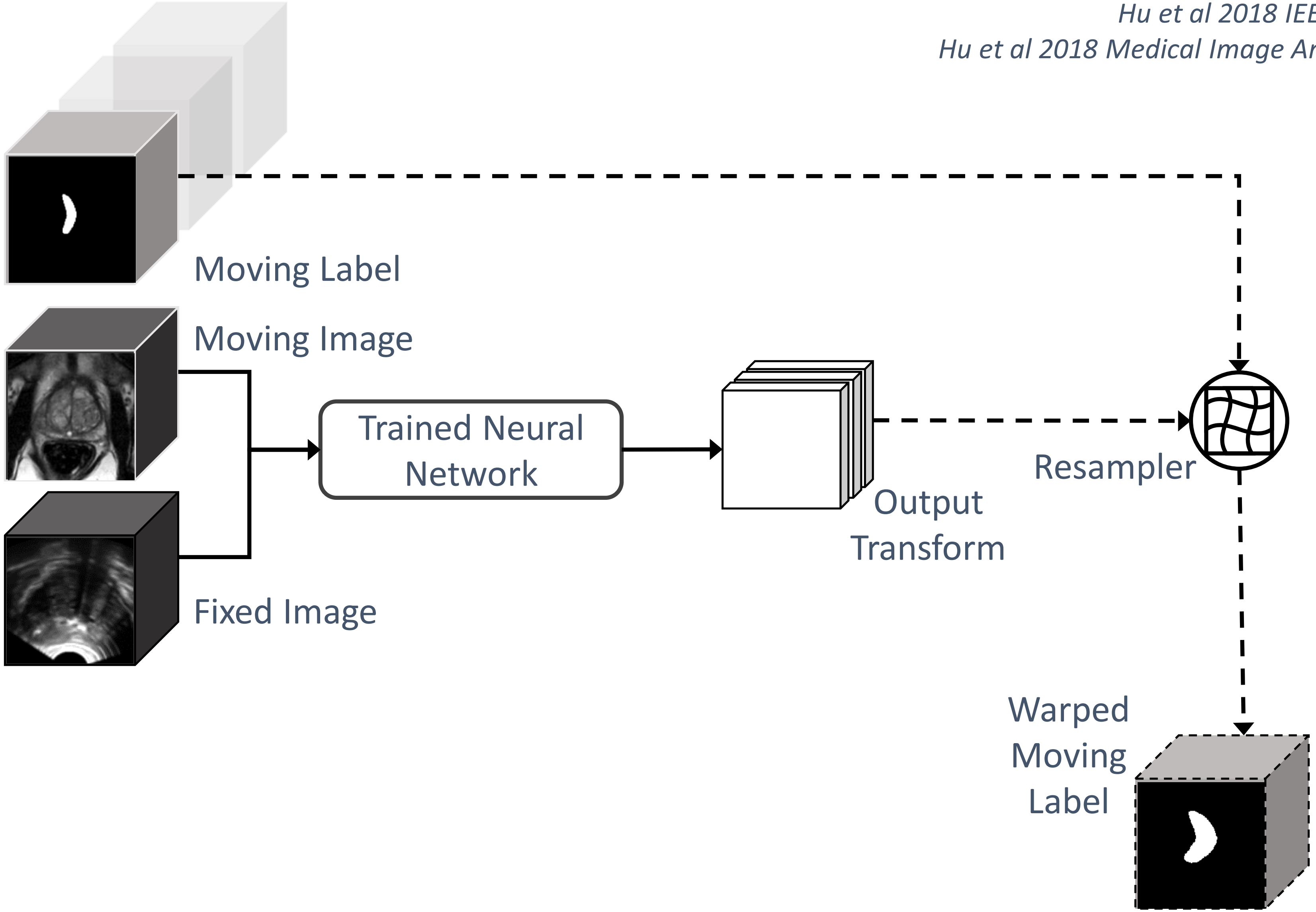
Inference

Hu et al 2018 IEEE-ISBI
Hu et al 2018 Medical Image Analysis



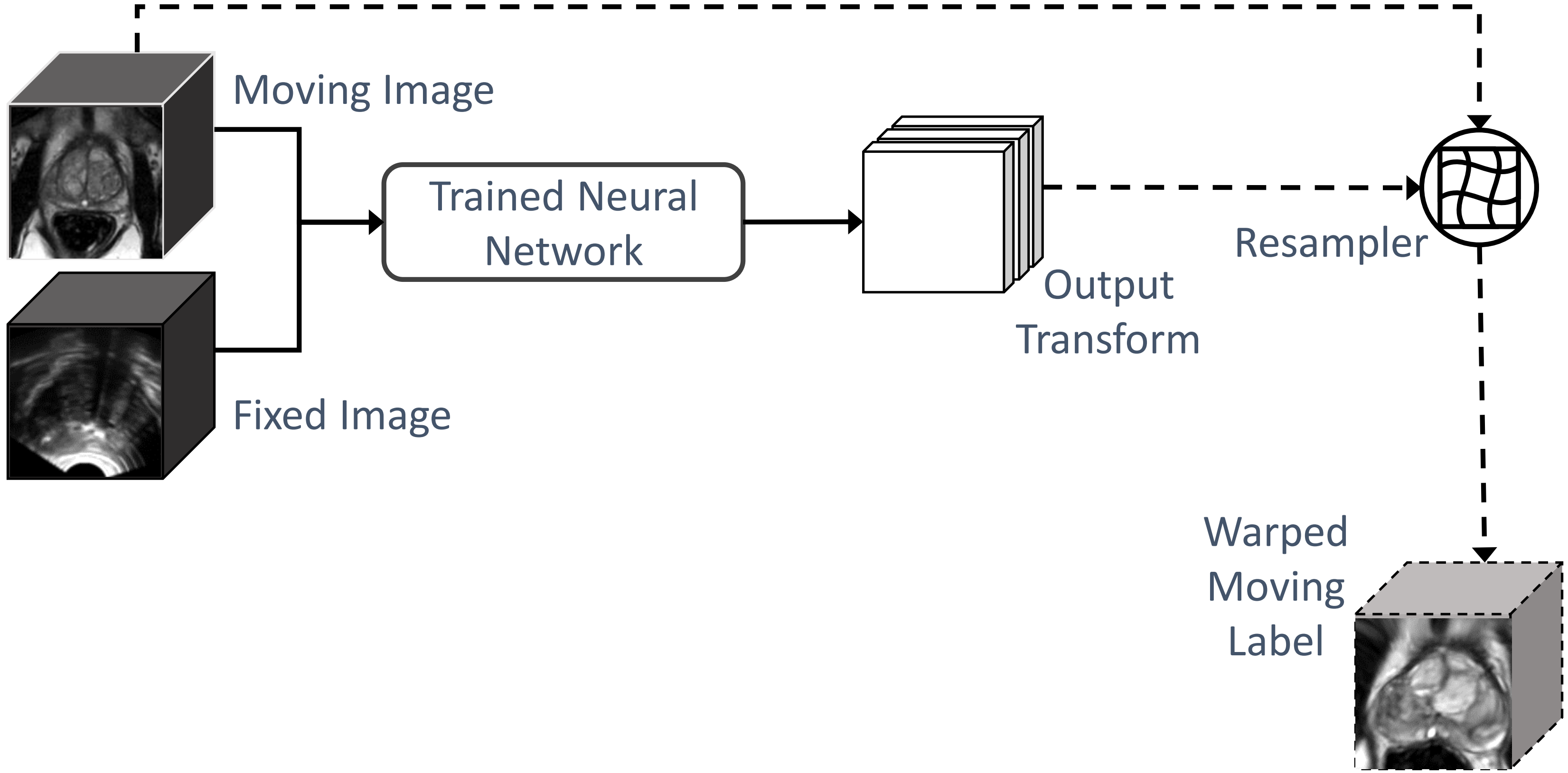
Inference

Hu et al 2018 IEEE-ISBI
Hu et al 2018 Medical Image Analysis



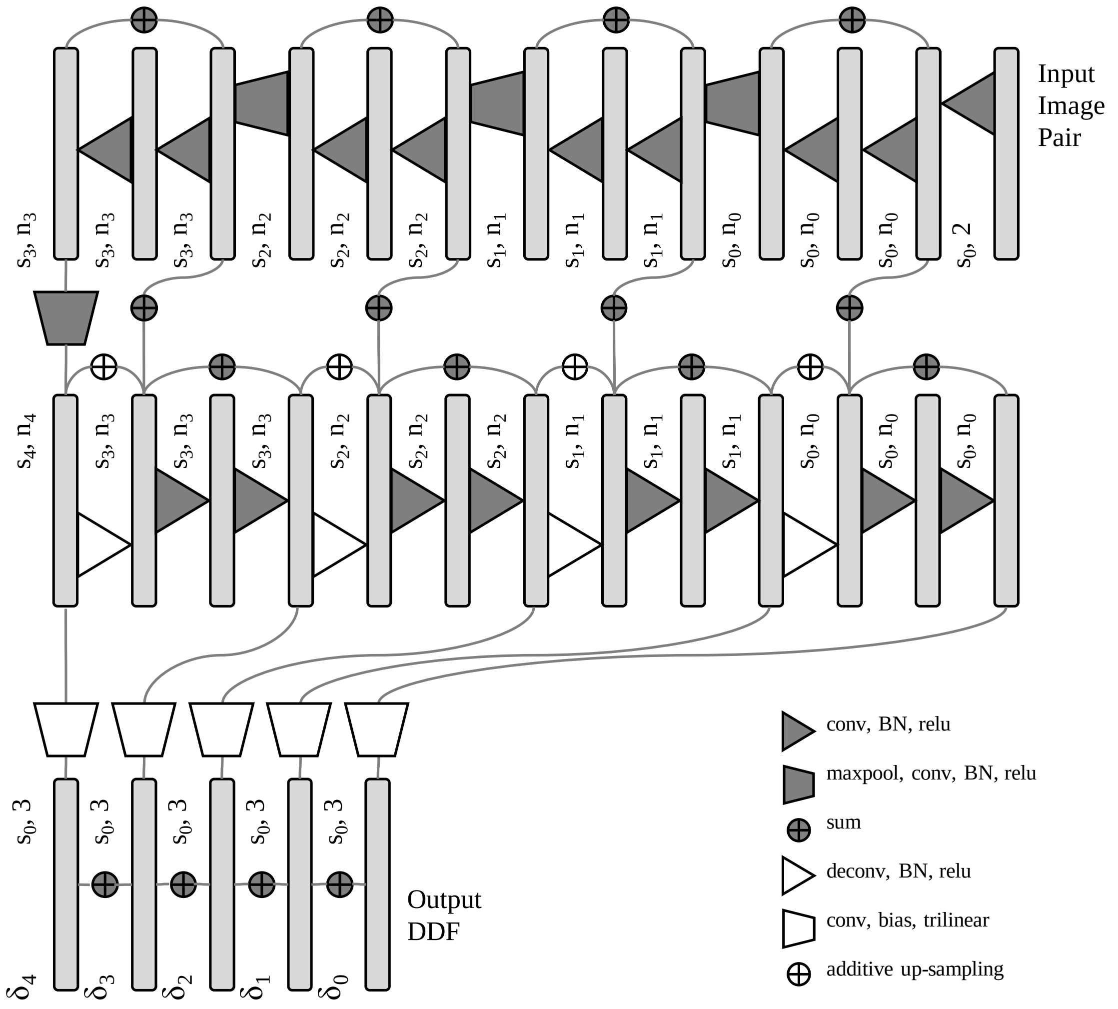
Inference

Hu et al 2018 IEEE-ISBI
Hu et al 2018 Medical Image Analysis



Network Architecture

Hu et al 2018 IEEE-ISBI
Hu et al 2018 Medical Image Analysis

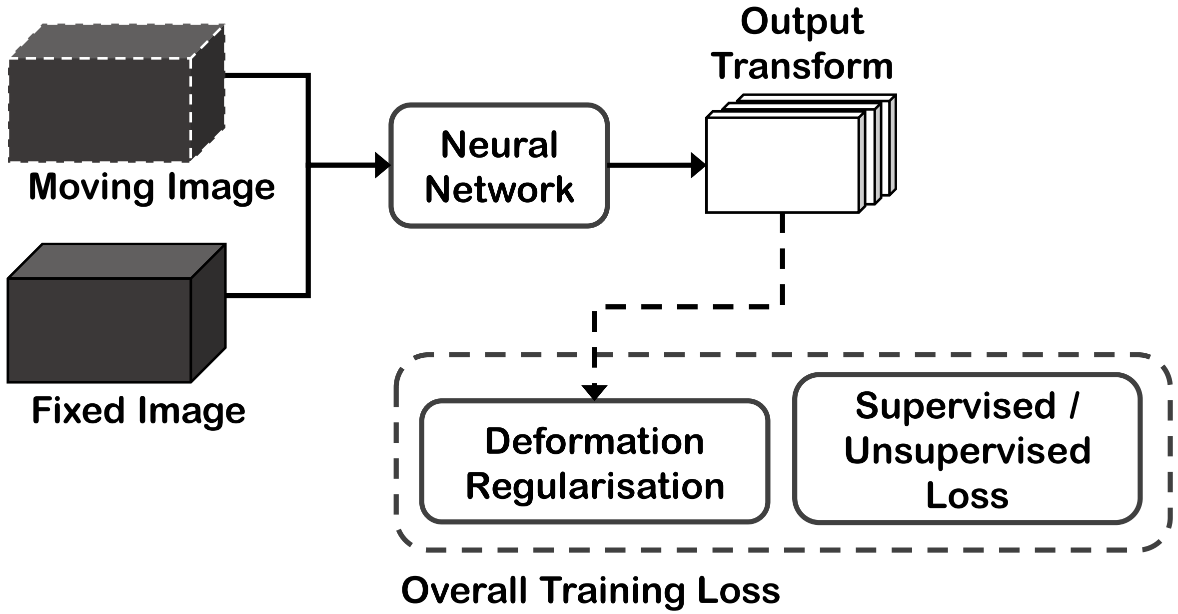


Densely-connected Local-Net

- Additive up-sampling
- Multiple nodes predicting displacement summands at different resolution levels

Results - Regularisation

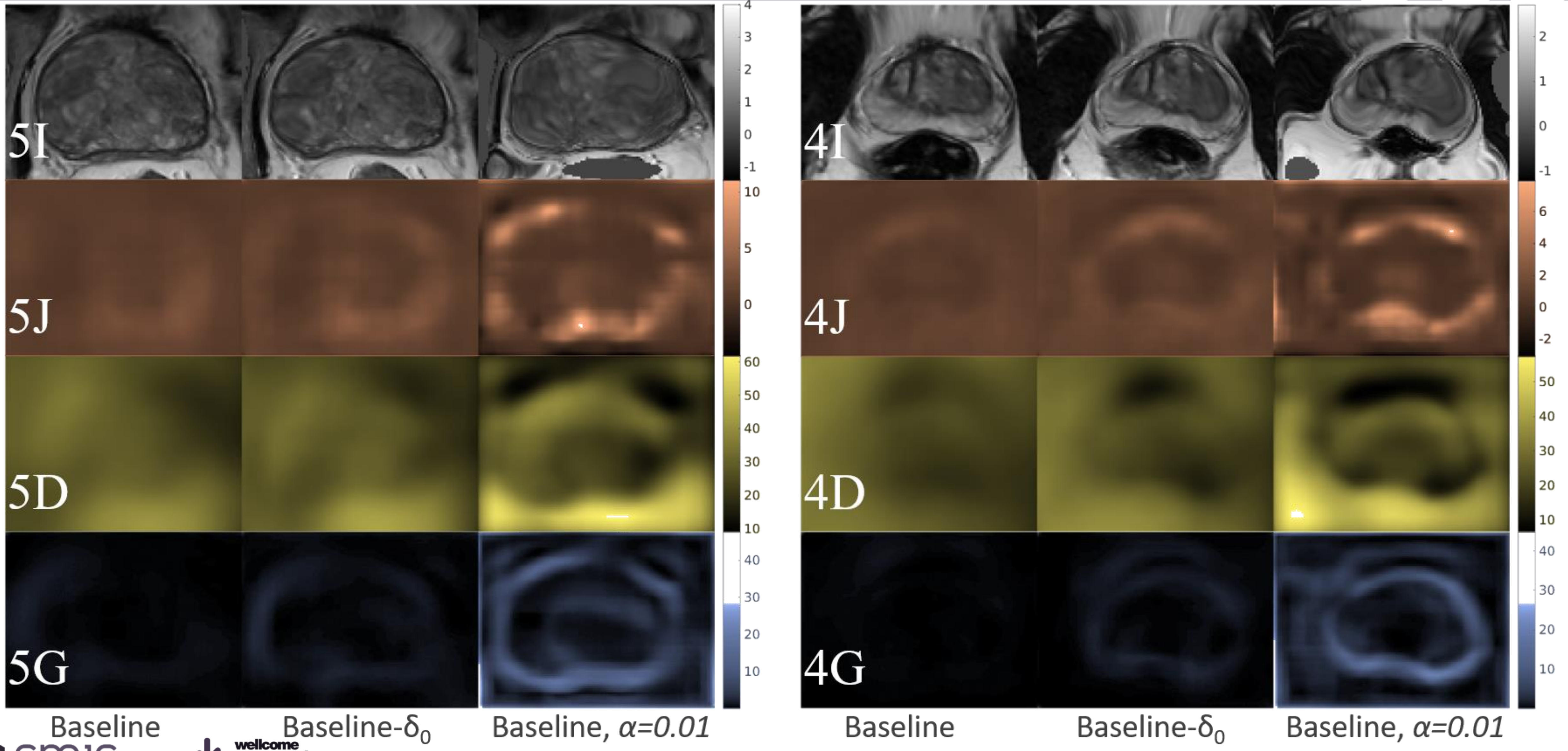
Regularised Registration Network Training



Bending Energy

$$P = \frac{1}{V}\int_0^X\int_0^Y\int_0^Z \Bigg[\left(\frac{\partial^2 \mathbf{T}}{\partial x^2}\right)^2 + \left(\frac{\partial^2 \mathbf{T}}{\partial y^2}\right)^2 + \left(\frac{\partial^2 \mathbf{T}}{\partial z^2}\right)^2 + 2\left(\frac{\partial^2 \mathbf{T}}{\partial xy}\right)^2 + 2\left(\frac{\partial^2 \mathbf{T}}{\partial xz}\right)^2 + 2\left(\frac{\partial^2 \mathbf{T}}{\partial yz}\right)^2 \Bigg] dx\ dy\ dz,$$

Results - Regularisation

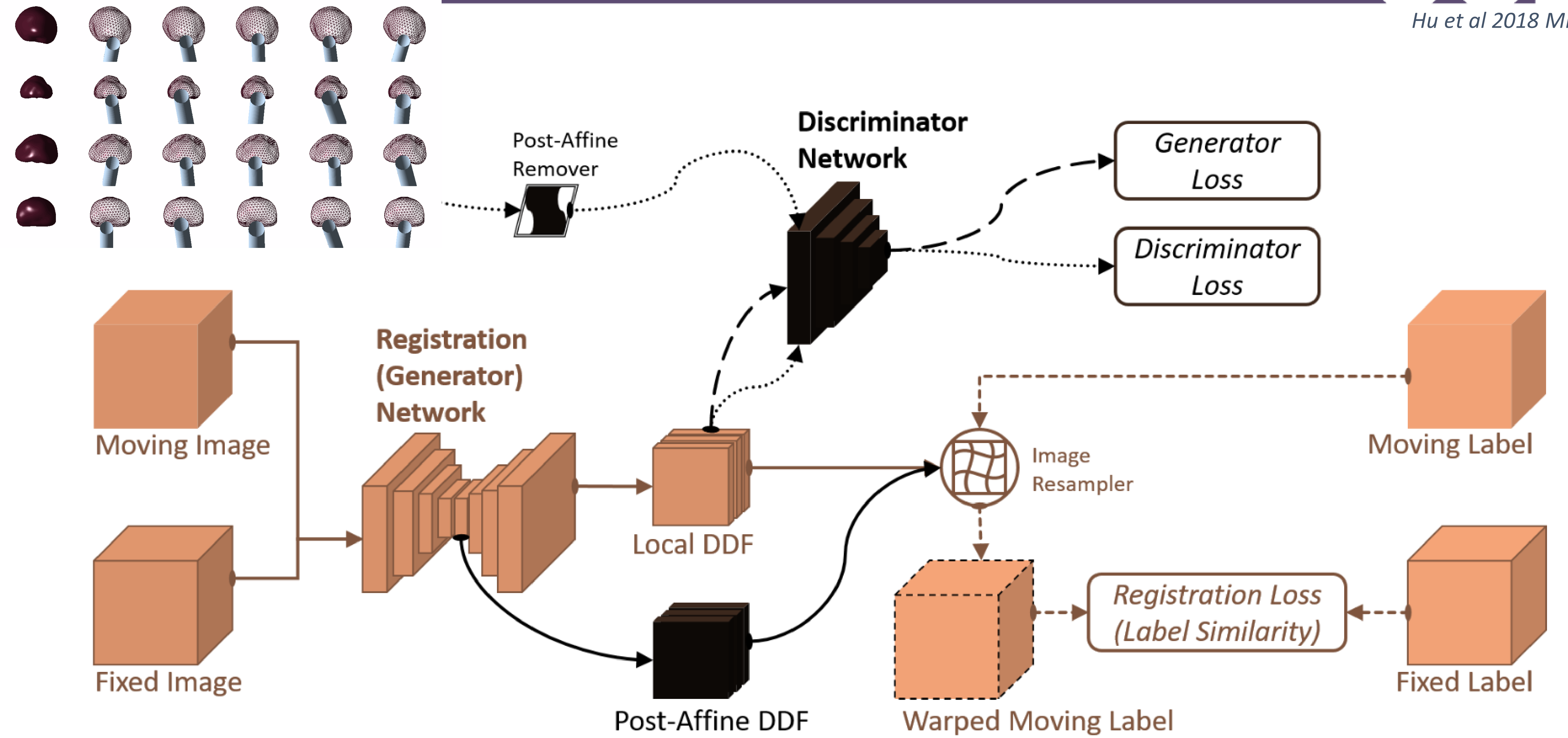


Model-Based Regularisation

Hu et al 2018 MICCAI

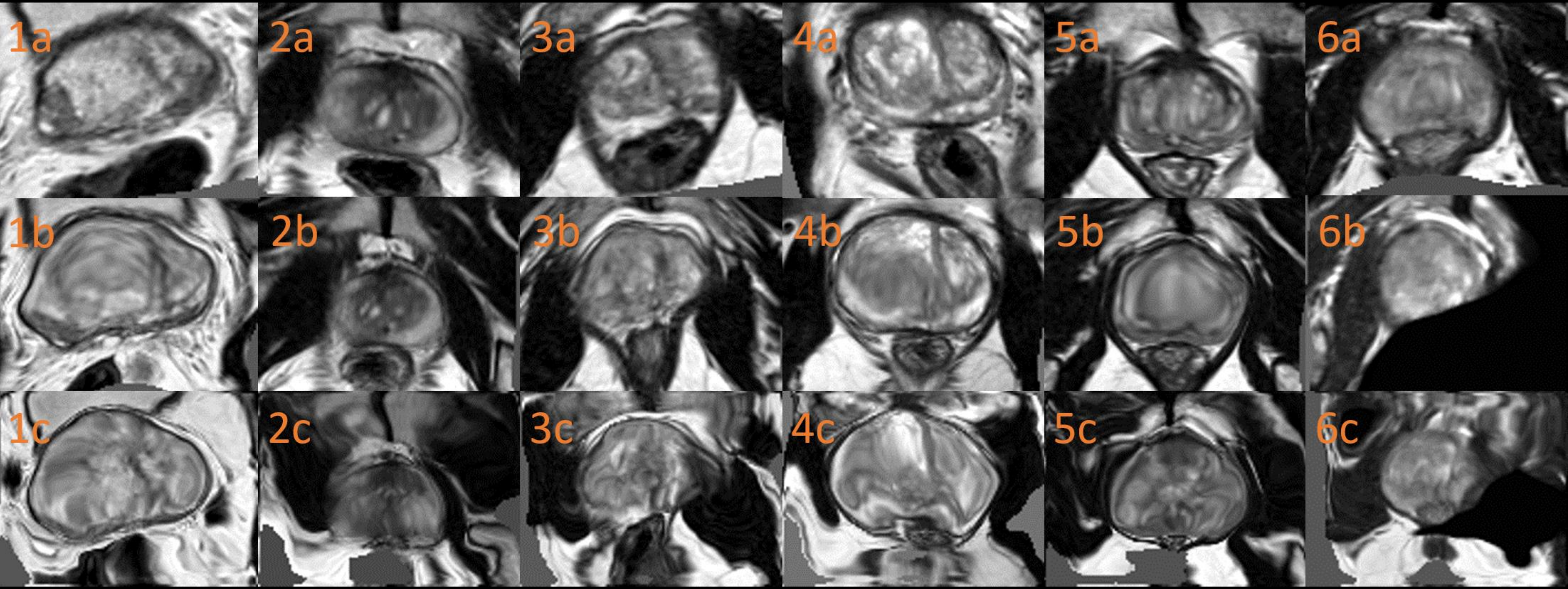
Model-Based Regularisation

Hu et al 2018 MICCAI



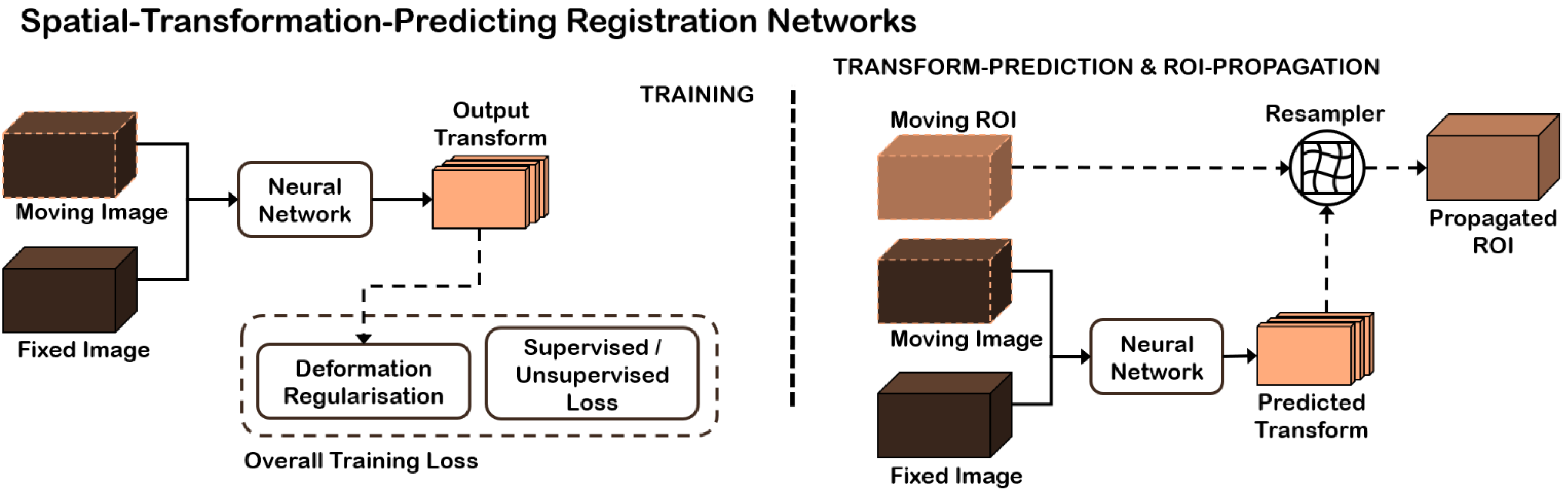
Model-Based Regularisation

Hu et al 2018 MICCAI

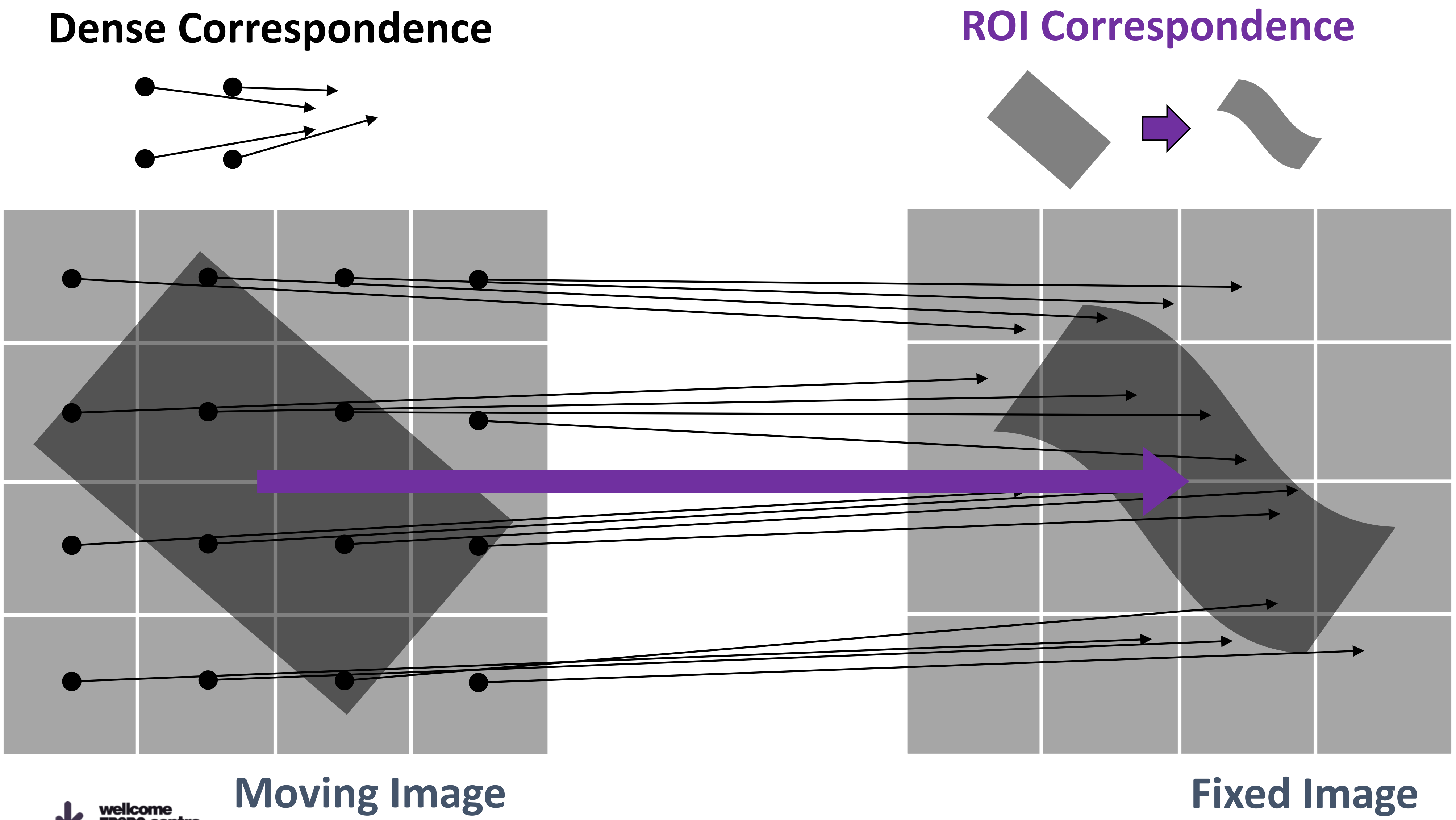


Data-Driven Conditional Segmentation

Hu et al 2019 MICCAI



Data-Driven Conditional Segmentation



Data-Driven Conditional Segmentation

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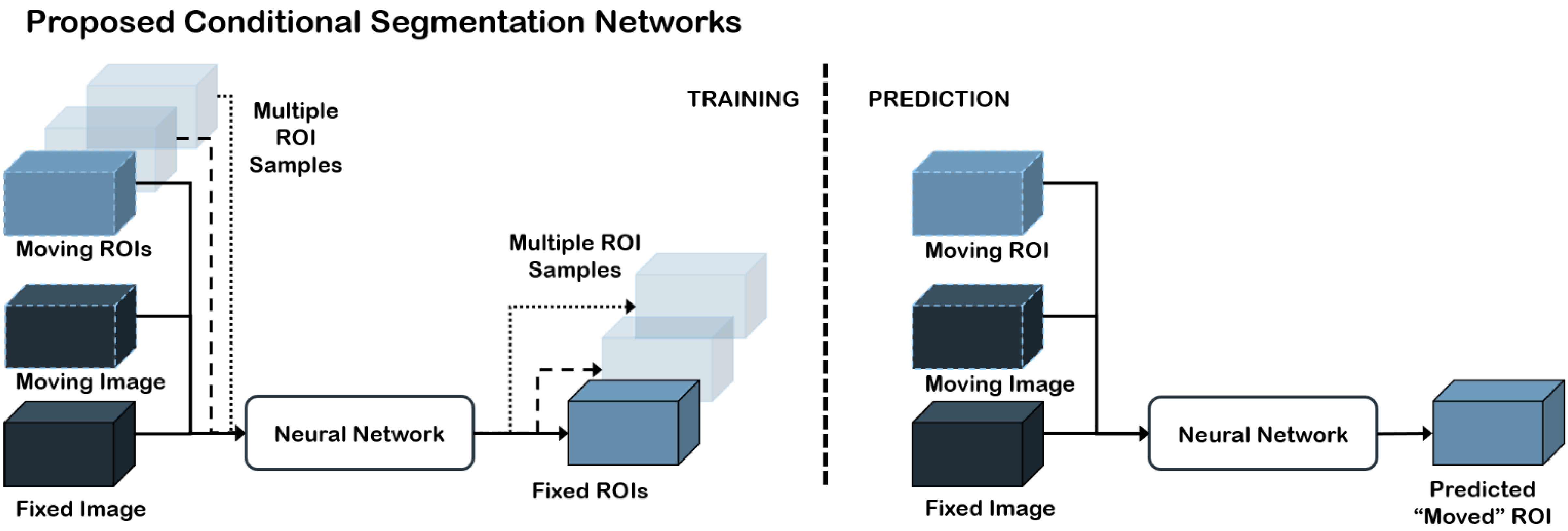

Data-Driven Conditional Segmentation

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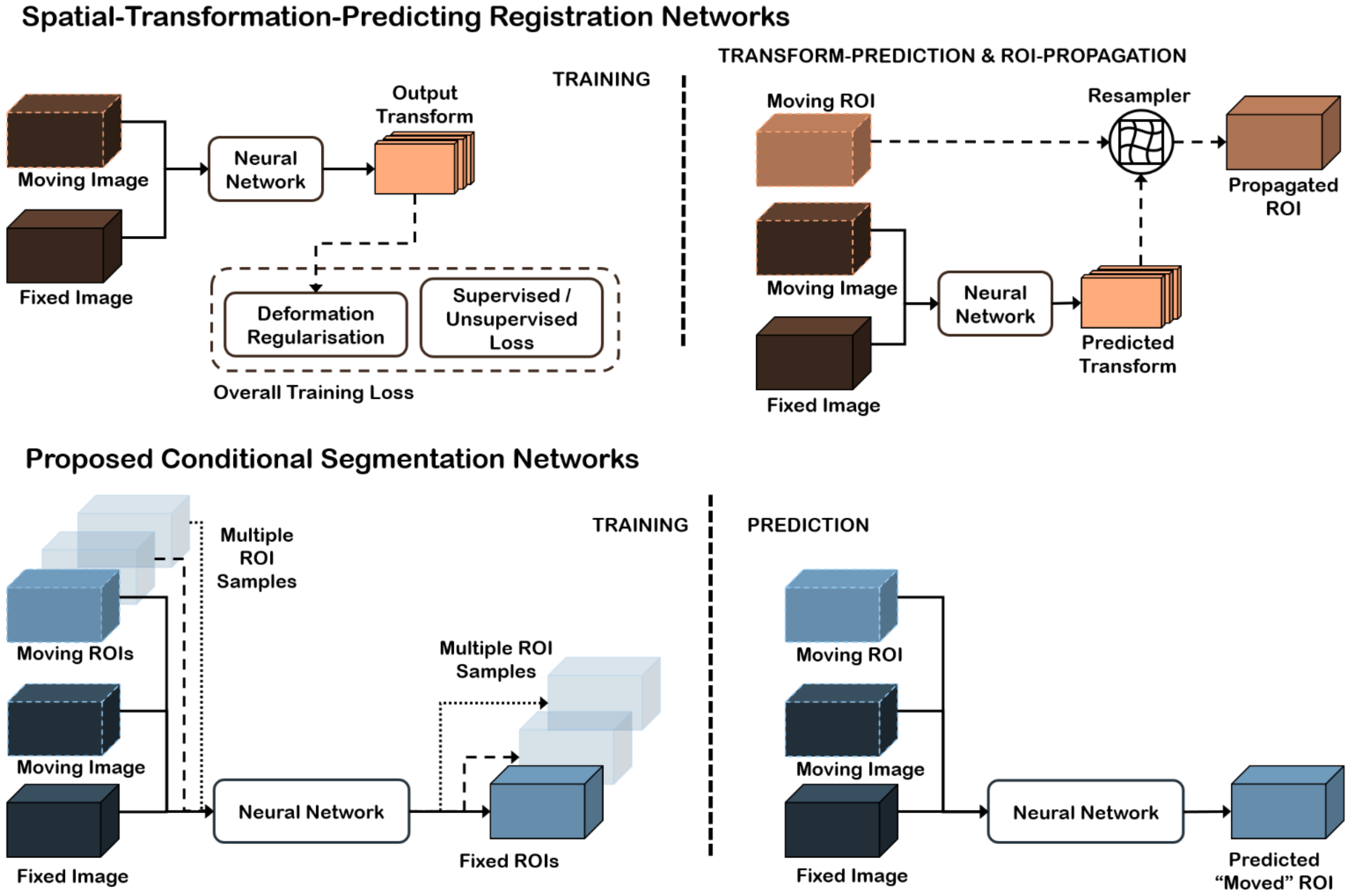
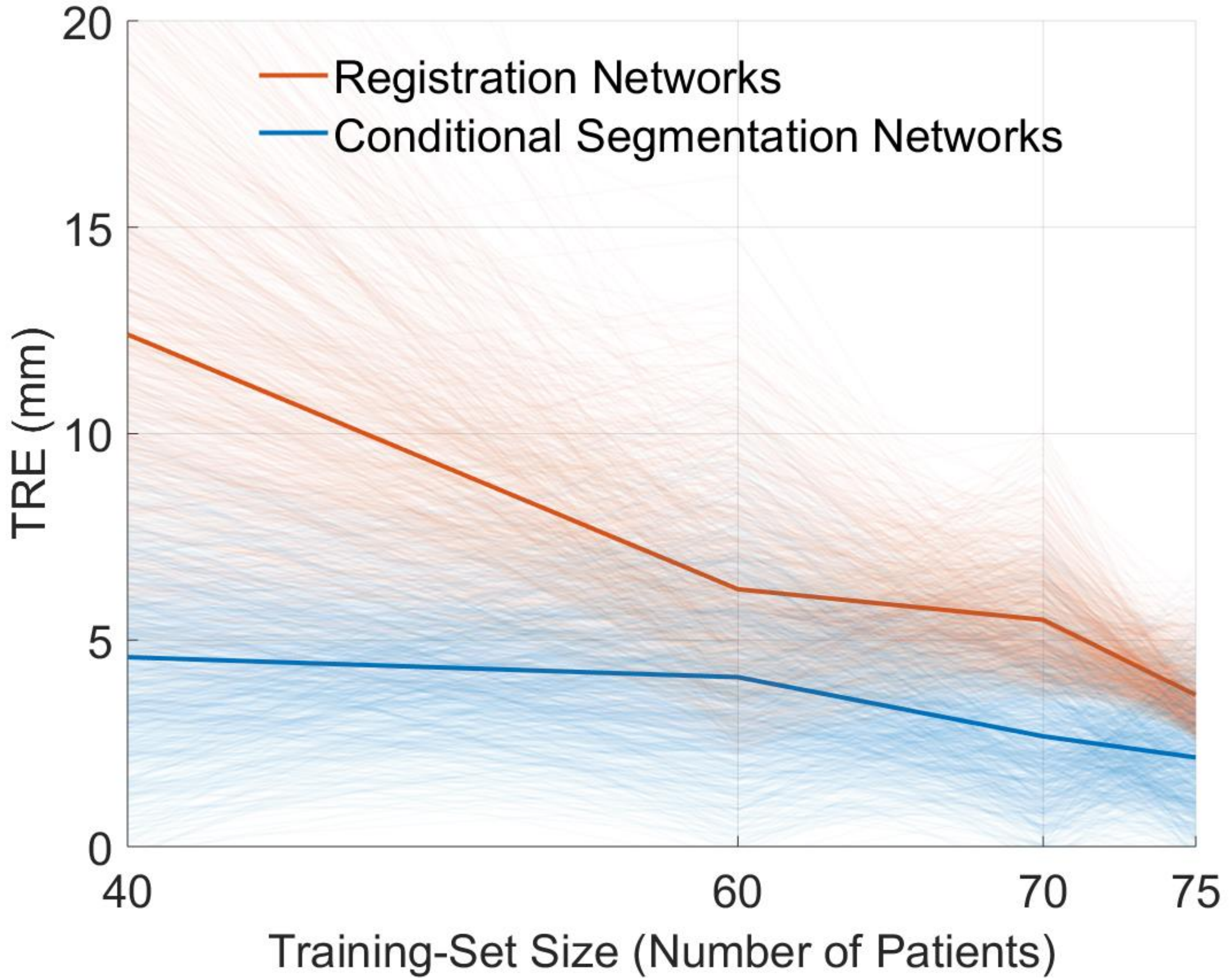


Data-Driven Conditional Segmentation

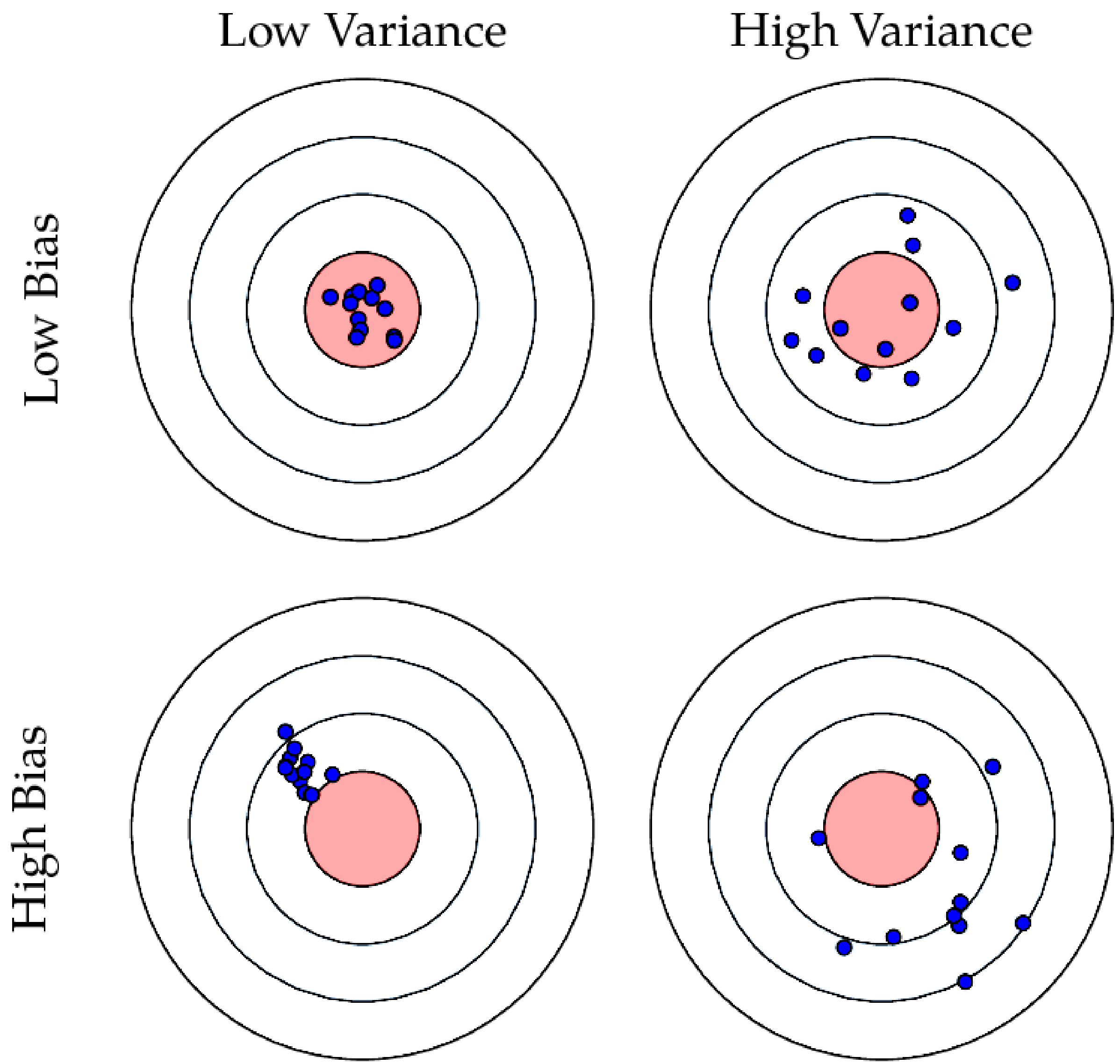
Hu et al 2019 MICCAI



A Bias-Variance Analysis

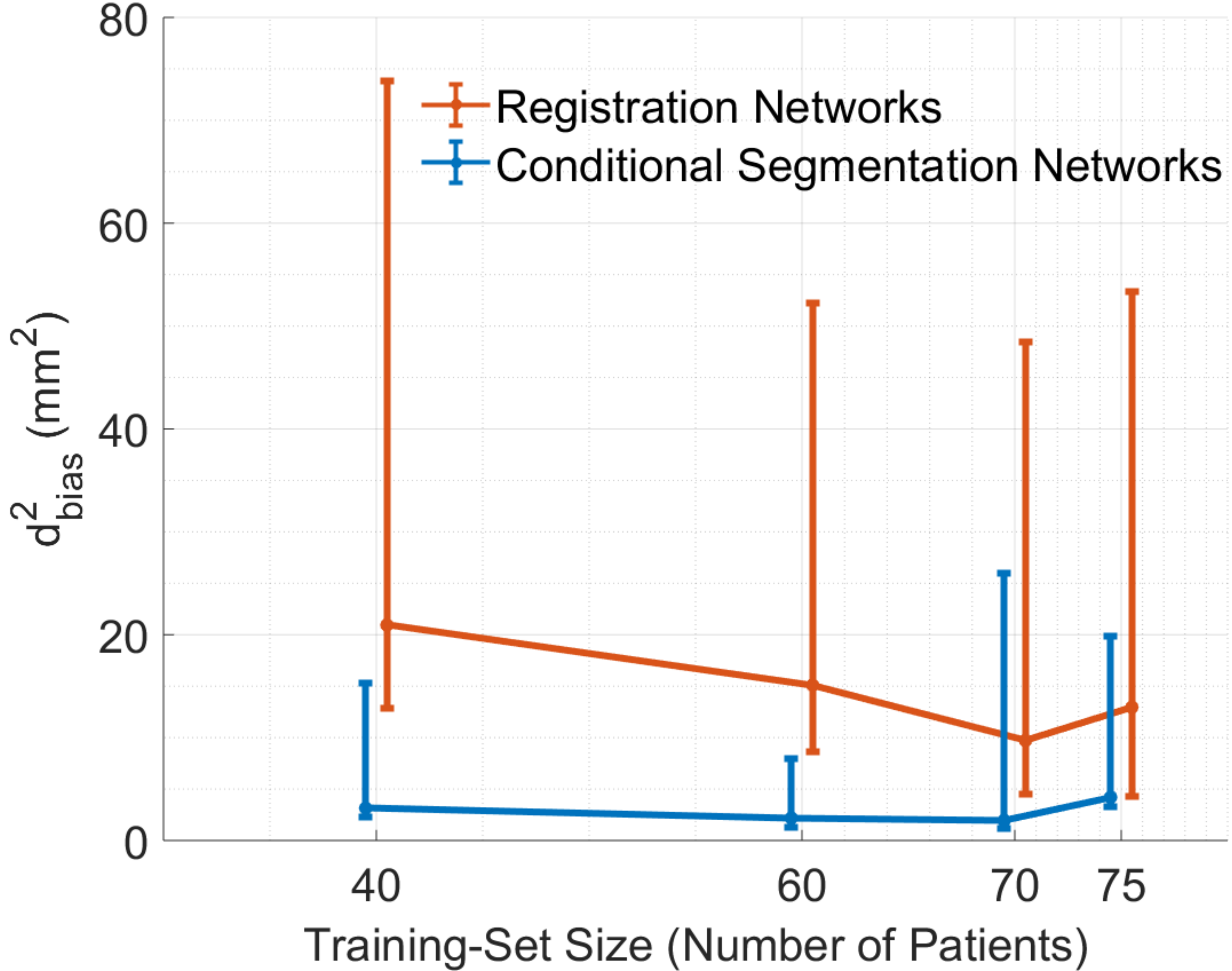
Hu et al 2019 MICCAI

- Error can be decomposed into bias and variance
- Regularisation may introduce bias on TRE
- High bias may limit generalisability, represented by TRE
- Bias may not be reduced by increasing data
- Repeated cross-validation, bootstrap-sampling data sets
- 600 networks trained in total (~36,000 GPU-hours)

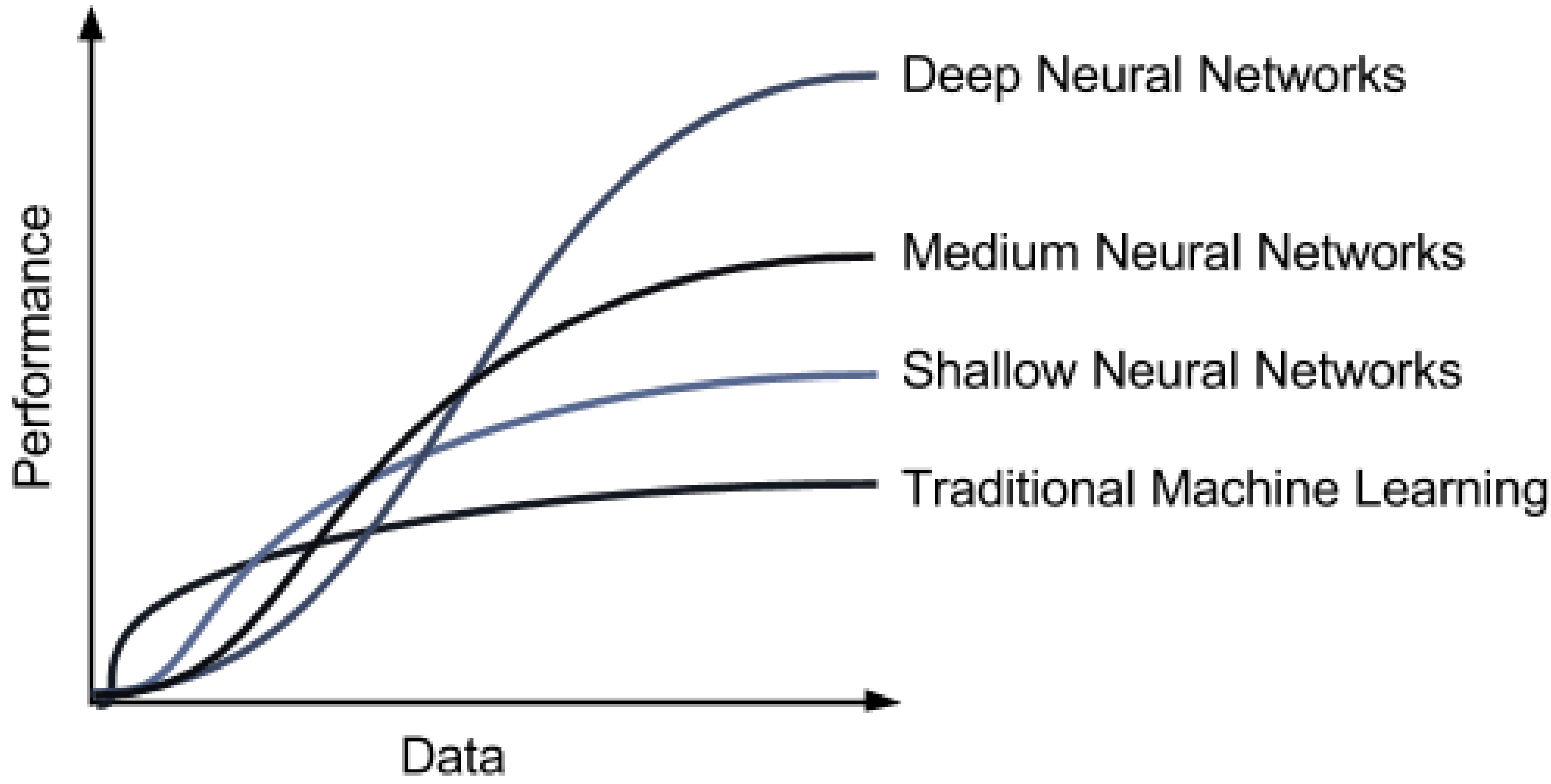


A Bias-Variance Analysis

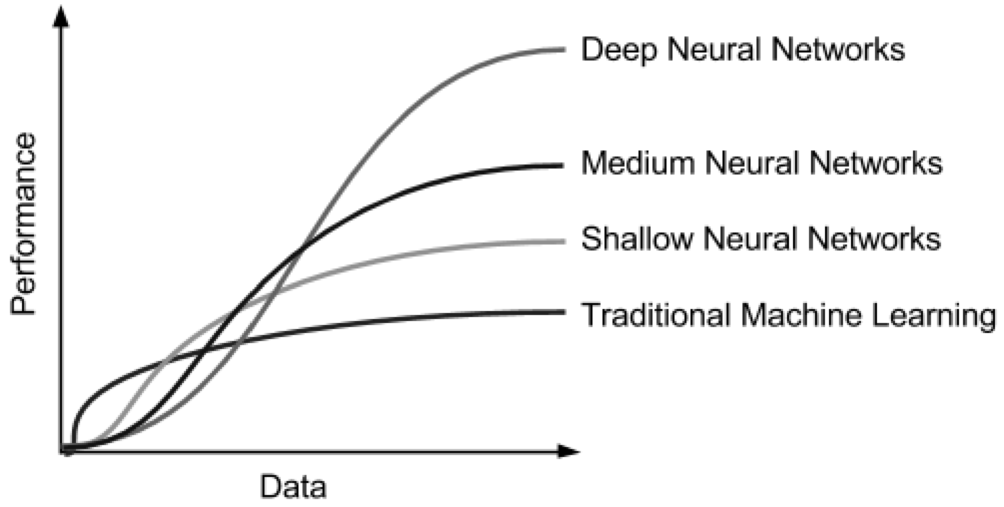
Hu et al 2019 MICCAI



Prior or Data?



Prior or Data?



Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

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Abstract. A neural network model for a mechanism of visual pattern recognition is proposed in this paper. The network is self-organized by "learning without a teacher", and acquires an ability to recognize stimulus patterns based on the geometrical similarity (Gestalt) of their shapes without affected by their positions. This network is given a nickname "neocognitron". After completion of self-organization, the network has a structure similar to the hierarchy model of the visual nervous system proposed by Hubel and Wiesel. The network consists of an input layer (photoreceptor array) followed by a cascade connection of a number of modular structures, each of which is composed of two layers of cells connected in a cascade. The first layer of each module consists of "S-cells", which show characteristics similar to simple cells or lower order hyper-

reveal it only by conventional physiological experiments. So, we take a slightly different approach to this problem. If we could make a neural network model which has the same capability for pattern recognition as a human being, it would give us a powerful clue to the understanding of the neural mechanism in the brain. In this paper, we discuss how to synthesize a neural network model in order to endow it an ability of pattern recognition like a human being.

Several models were proposed with this intention (Rosenblatt, 1962; Kabrisky, 1966; Giebel, 1971; Fukushima, 1975). The response of most of these models, however, was severely affected by the shift in position and/or by the distortion in shape of the input patterns. Hence, their ability for pattern recognition was not so high.

A general reinforcement learning algorithm that masters chess, shogi and Go through self-play

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[*]These authors contributed equally to this work.

Abstract

The game of chess is the longest-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. By contrast, the AlphaGo Zero program recently achieved superhuman performance in the game of Go by reinforcement learning from self-play. In this paper, we generalize this approach into a single AlphaZero algorithm that can achieve superhuman performance in many challenging games. Starting from random play and given no domain knowledge except the game rules, AlphaZero convincingly defeated a world champion program in the games of chess and shogi (Japanese chess) as well as Go.

Acknowledgement

Code: github.com/learn2reg/tutorials2019

Page: learn2reg.github.io

Thank you!

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