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Assessing the Accuracy of NRR with and without Ground Truth

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… including

Generalised Overlap Measures

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Overview

- Background and motivation
- Assessment methods
  - overlap-based
  - model-based
- Experiments
  - validation
  - comparison of methods
- Conclusions

Non-rigid Registration (NRR)

- Alignment of image sets
  - dense correspondence
  - alignment of anatomical structures
- Alignment established by
  - image warping
  - comparison with other image(s)
  - maximising similarity
- Competing NRR algorithms produce different results

Motivation for Assessment

- Different methods for NRR
  - representation of warp (including regularisation)
  - similarity measure
  - optimisation
  - pair-wise vs group-wise
- Limitations of current methods of assessment
  - ground-truth deformations
  - binary overlap measures

Two New Approaches

- Generalised overlap
  - multiple labels
  - label interpolation
  - multiple images
- Model-based
  - NRR $\Rightarrow$ combined appearance model
  - good registration $\Rightarrow$ good model

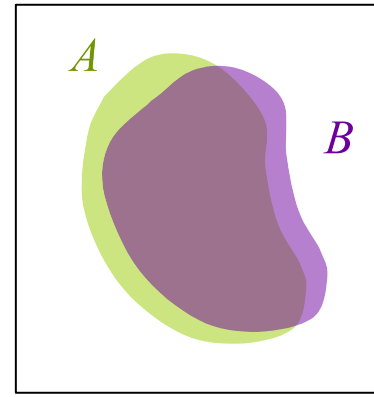
Generalised Overlap

Overlap Measures

- Existing overlap measures
  - assume binary labels
  - evaluate one label at a time
  - cannot easily be applied to groupwise registration
- In practice
  - labels may be interpolated (pv) or fuzzy
  - there may be lots of labels
  - there may be lots of images
- Generalise existing overlap measures

Binary Overlap Measures

- Consider label regions A and B
- Tanimoto/Jacaard overlap



$$O_P = \frac{N(A \quad B)}{N(A \quad B)} = \frac{\text{Number of voxels in } A \text{ AND } B}{\text{Number of voxels in } A \text{ OR } B}$$

- Dice overlap

$$O_Q = \frac{2N(A \quad B)}{N(A) + N(B)} = \frac{\text{Number of voxels in } A \text{ AND } B}{\text{Mean number of voxels in } A \text{ and } B}$$

Alternate Form

- Binary value at each voxel A_i and B_i

```
00000000000000000000
00000000000111110000
00000000011111100000
00000011111111000000
00011111111110000000
00001111111111000000

00000111111111100000
00000111111111000000
00000111111110000000
00000011111100000000
00000000000000000000
```

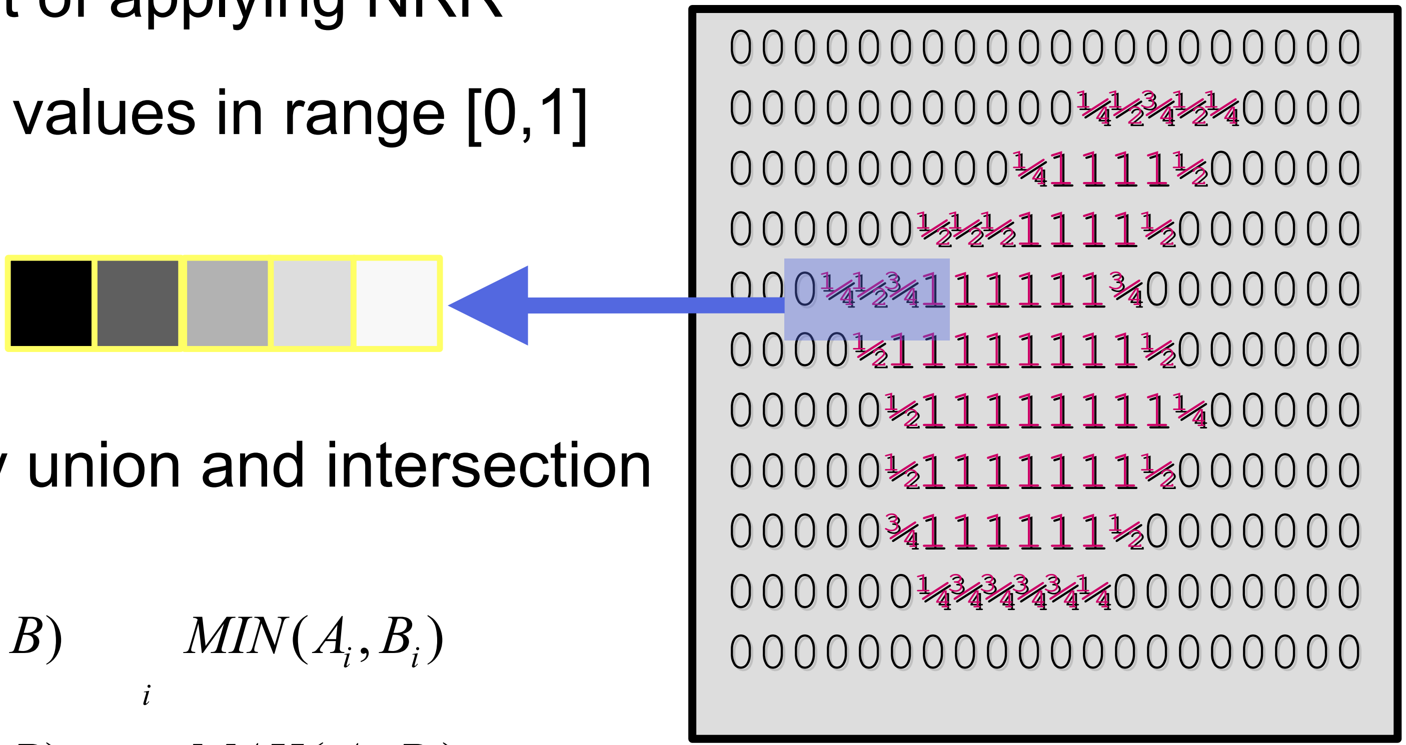
Region A

$$N(A = B) \qquad {}_{i} \; MIN(A_i, B_i)$$

$$N(A = B) \qquad {}_{i} \; MAX(A_i, B_i)$$

Interpolated Label Images

- Result of applying NRR
- Label values in range [0,1]



- Fuzzy union and intersection

$$N(A= B) \quad {}_{i} \quad MIN(A_i, B_i)$$

$$N(A= B) \quad {}_{i} \quad MAX(A_i, B_i)$$

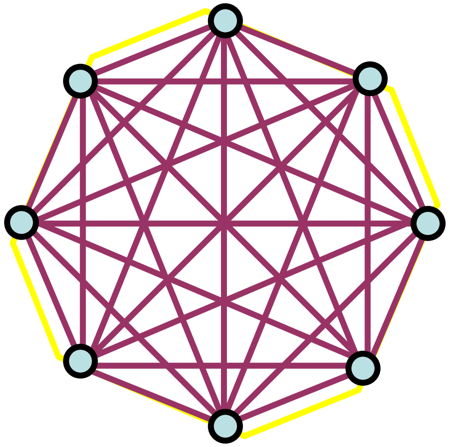
Generalised Overlap

- Fractional overlap

$$O_F = \frac{\underset{voxels,i}{} MIN(A_i, B_i)}{\underset{voxels,i}{} MAX(A_i, B_i)}$$

- Accumulated over labels and image pairs

$$O_{PMF} = \frac{\underset{pairs,k}{} \; \underset{labels,l}{} \alpha_l \; \underset{voxels,i}{} MIN(A_{kli}, B_{kli})}{\underset{pairs,k}{} \; \underset{labels,l}{} \alpha_l \; \underset{voxels,i}{} MAX(A_{kli}, B_{kli})}$$



Label Weighting

- Implicit volume weighting

$$\alpha = 1$$

- Equal weighting

$$\alpha = \frac{1}{V_l}$$

- Inverse volume weighting

$$\alpha = \frac{1}{\left(V_l\right)^2}$$

- Label complexity

$$\alpha = \underset{label\,voxels}{\quad} \left| \quad (\text{Intensity}) \right|$$

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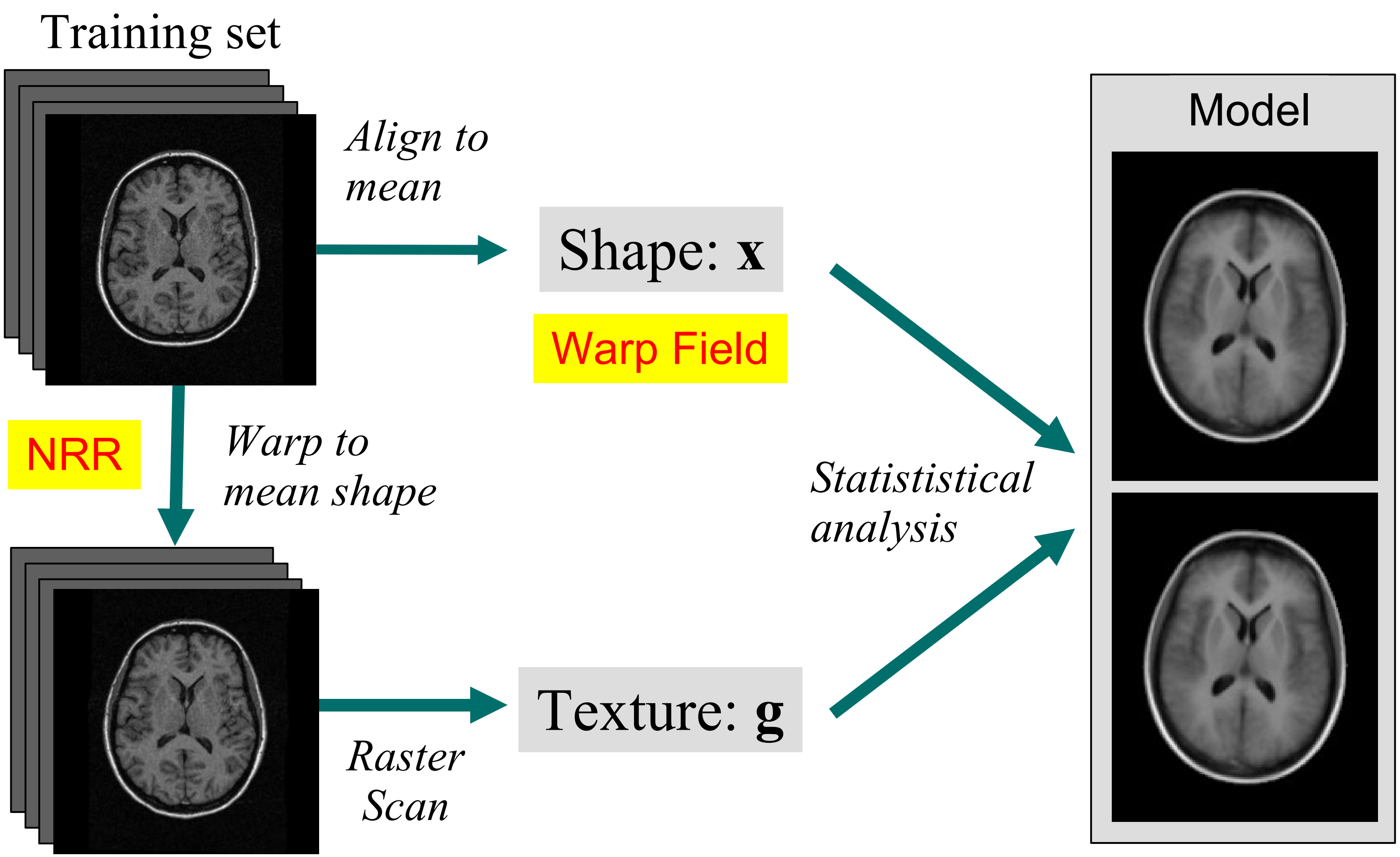
Model-Based Assessment

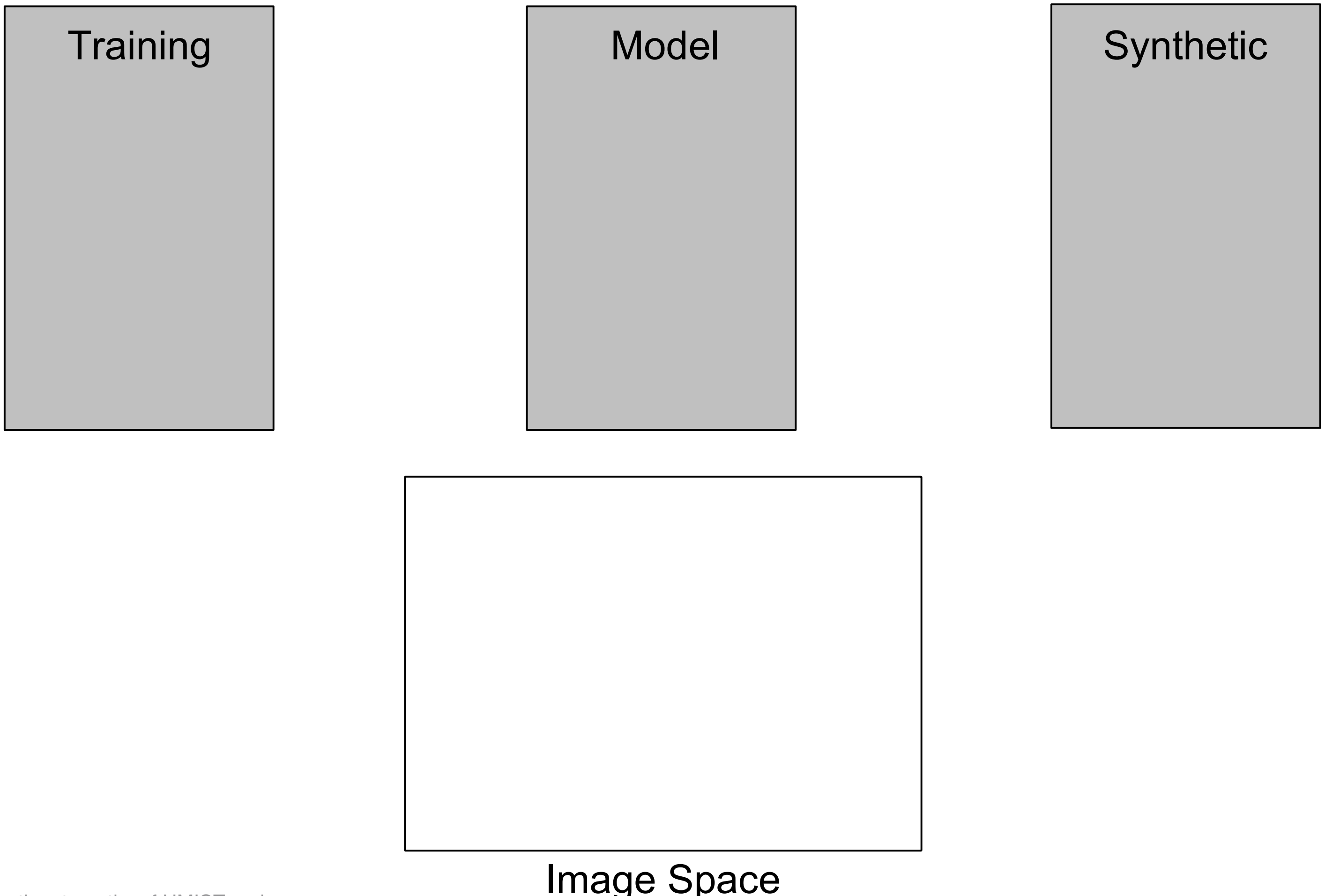
Model-based Framework

- Registered image set $\Rightarrow$ statistical appearance model
- Good registration $\Rightarrow$ good model
  - generalises well to new examples
  - specific to class of images
- Registration quality $\Leftrightarrow$ Model quality
  - problem transformed to defining model quality
  - ground-truth-free assessment of NRR

Building an Appearance Model



Training and Synthetic Images



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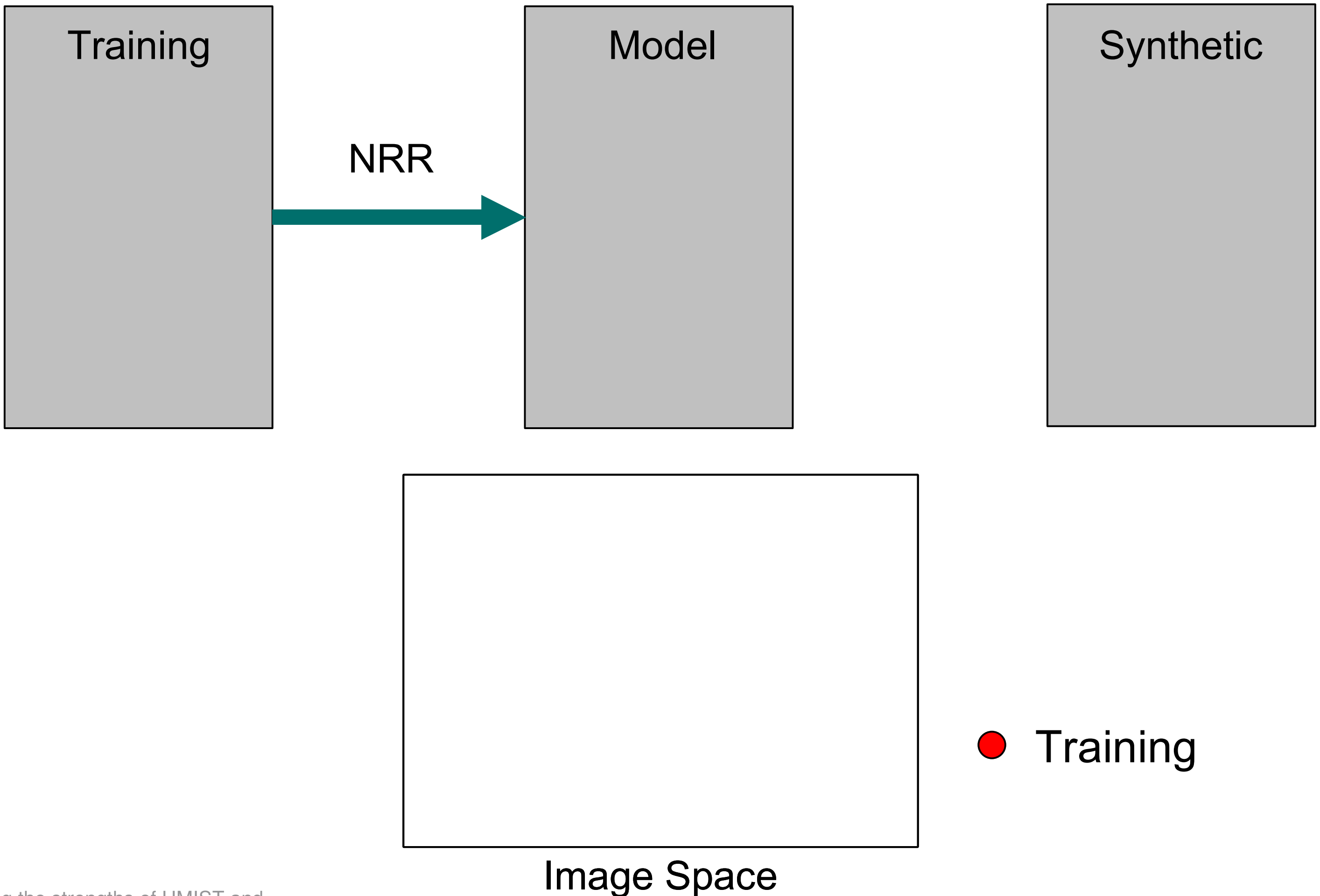

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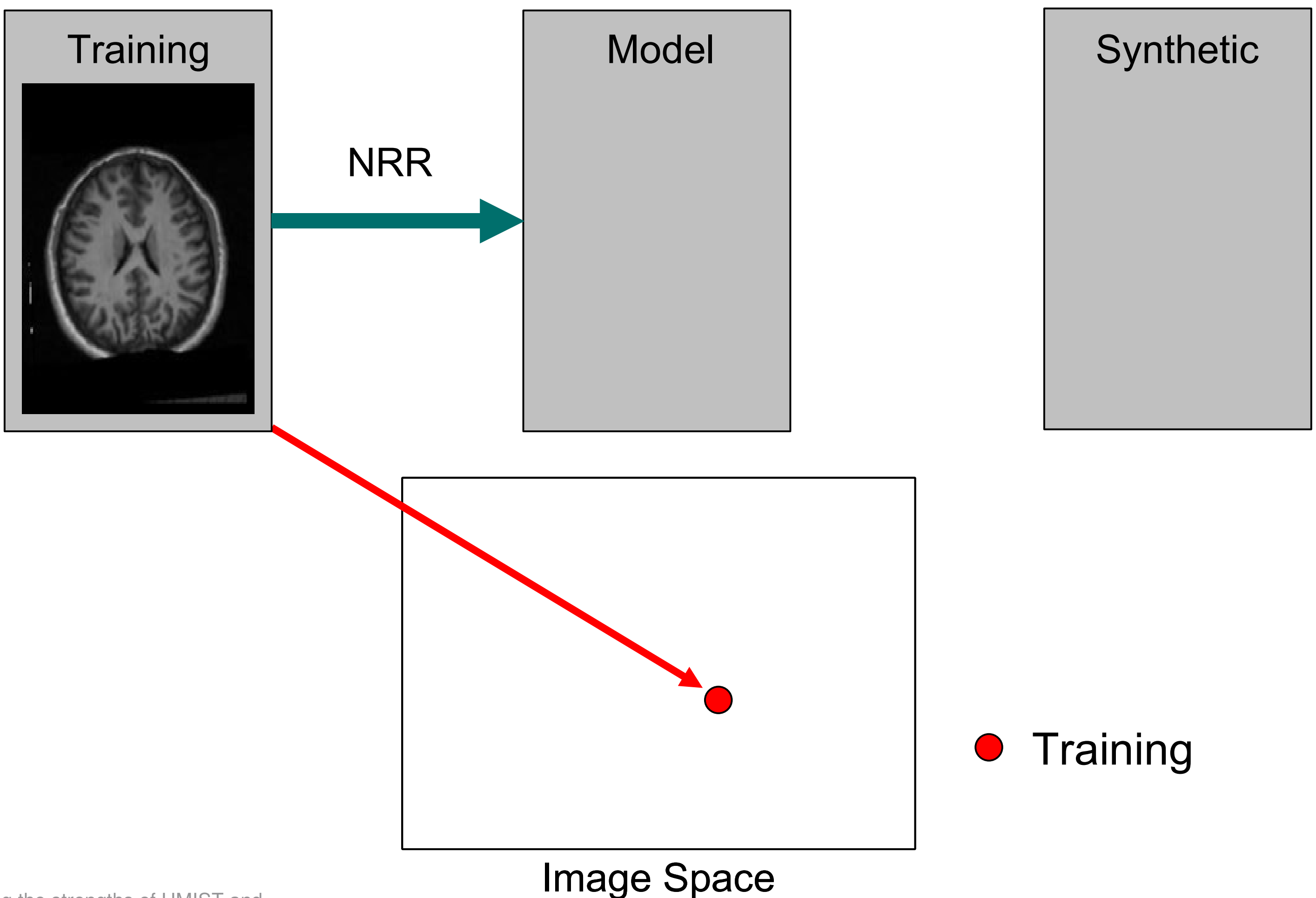

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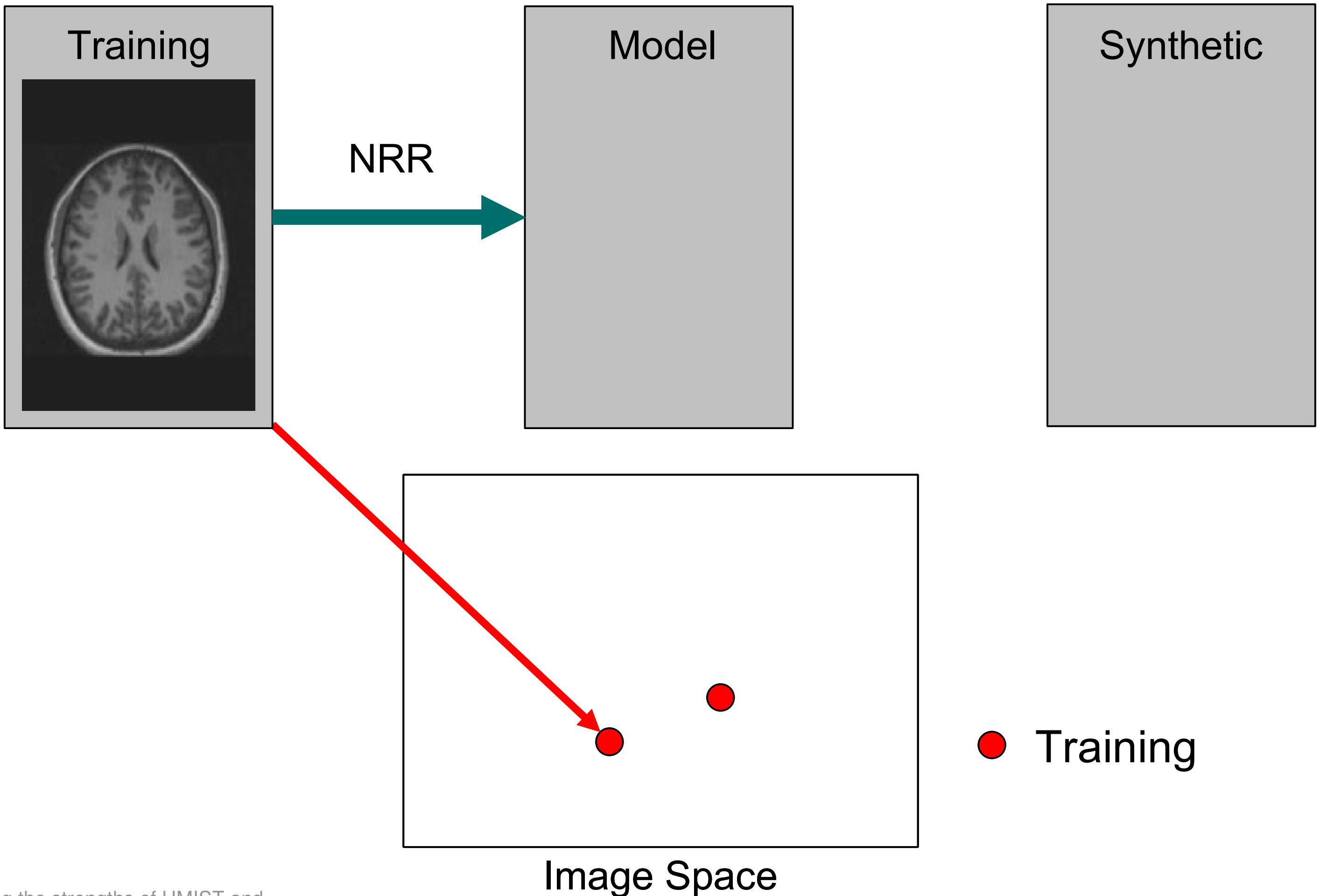

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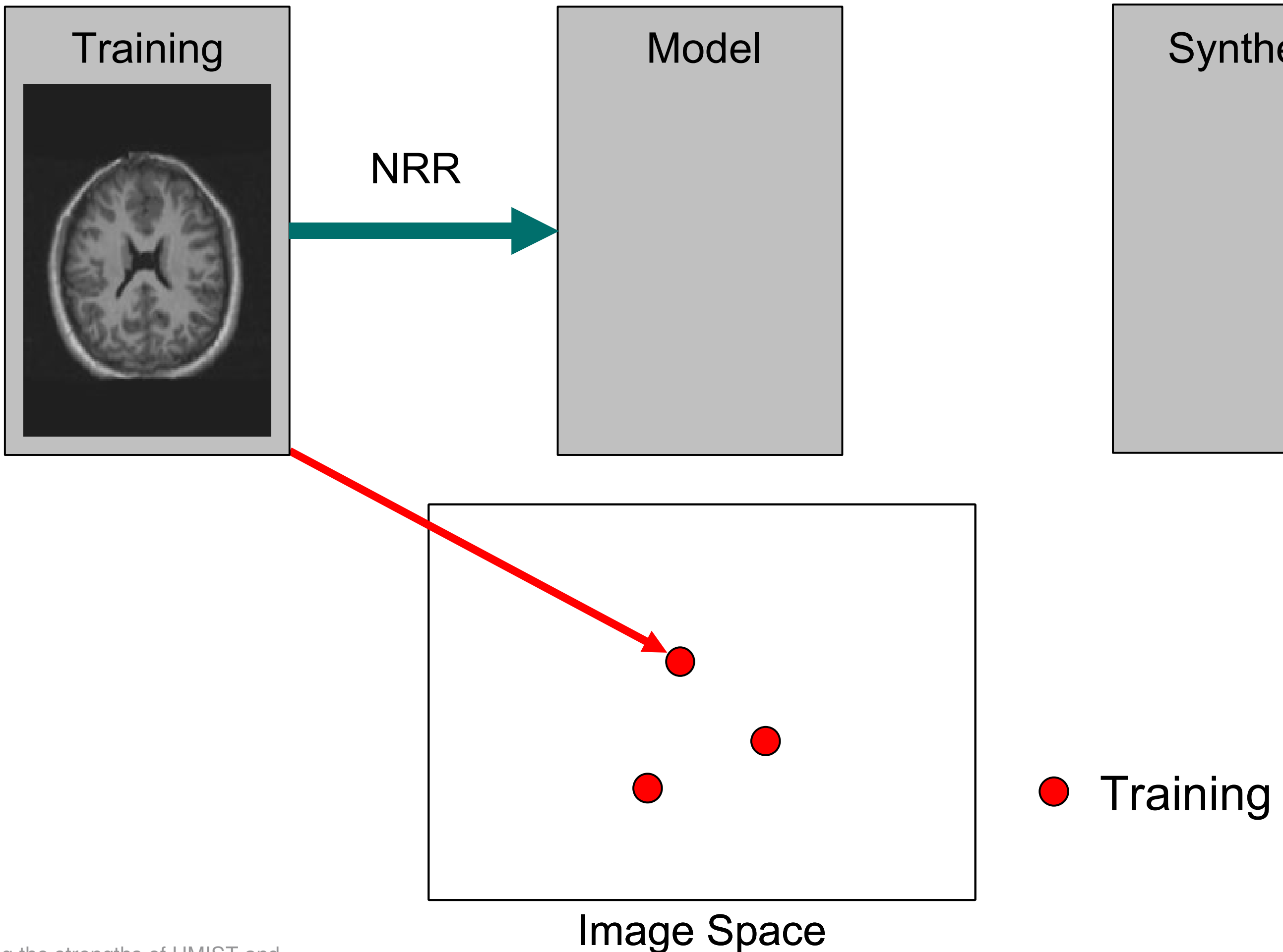

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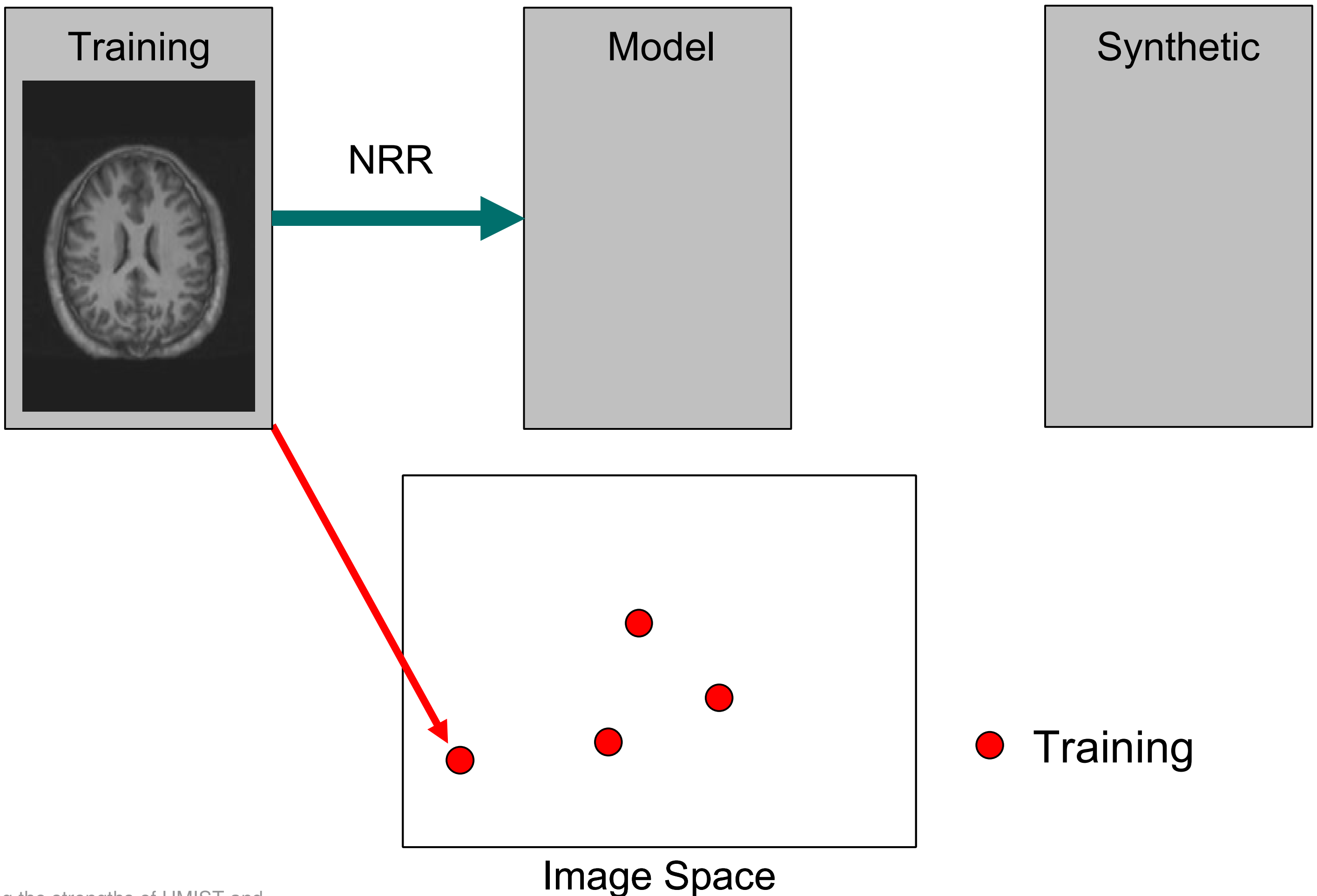

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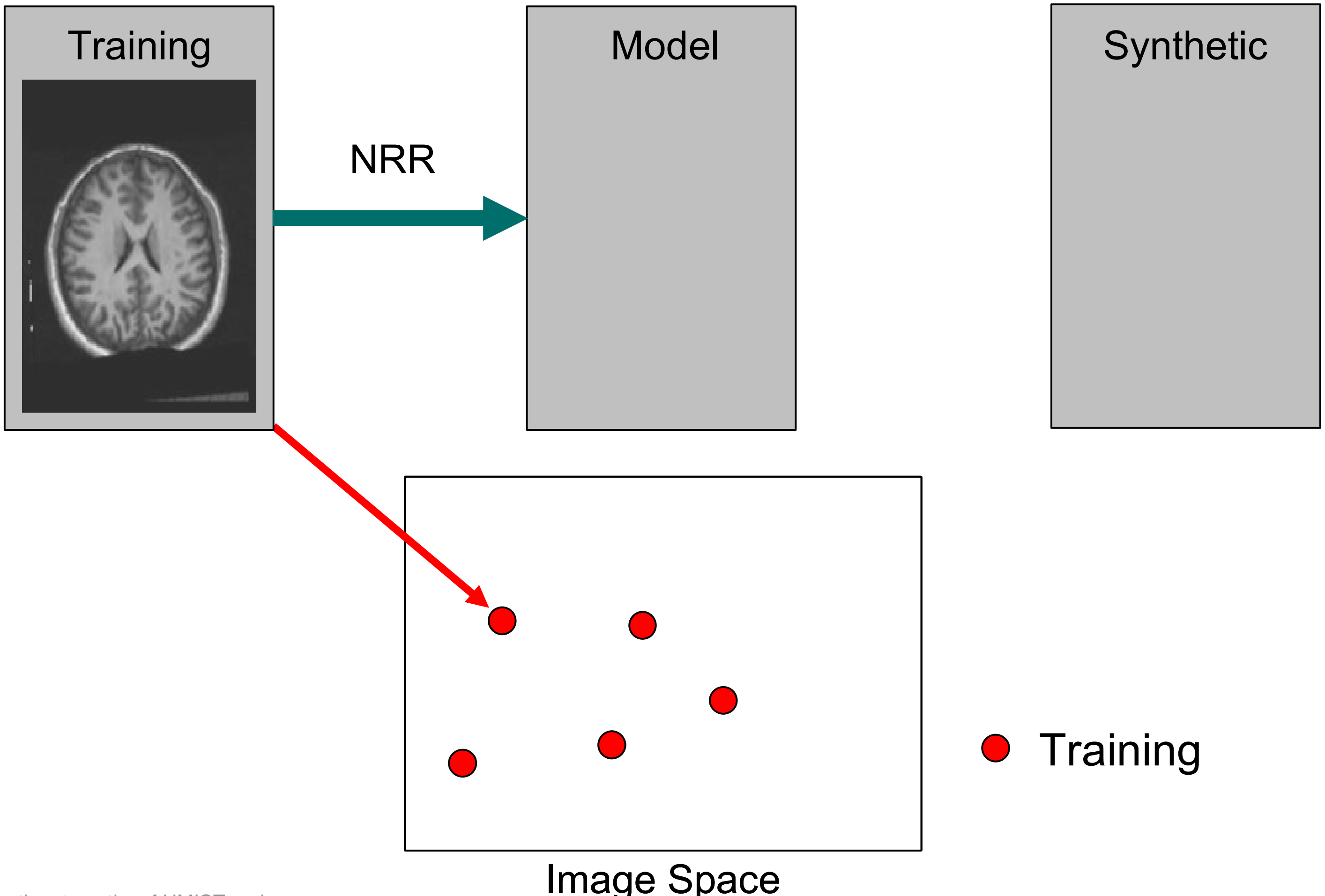

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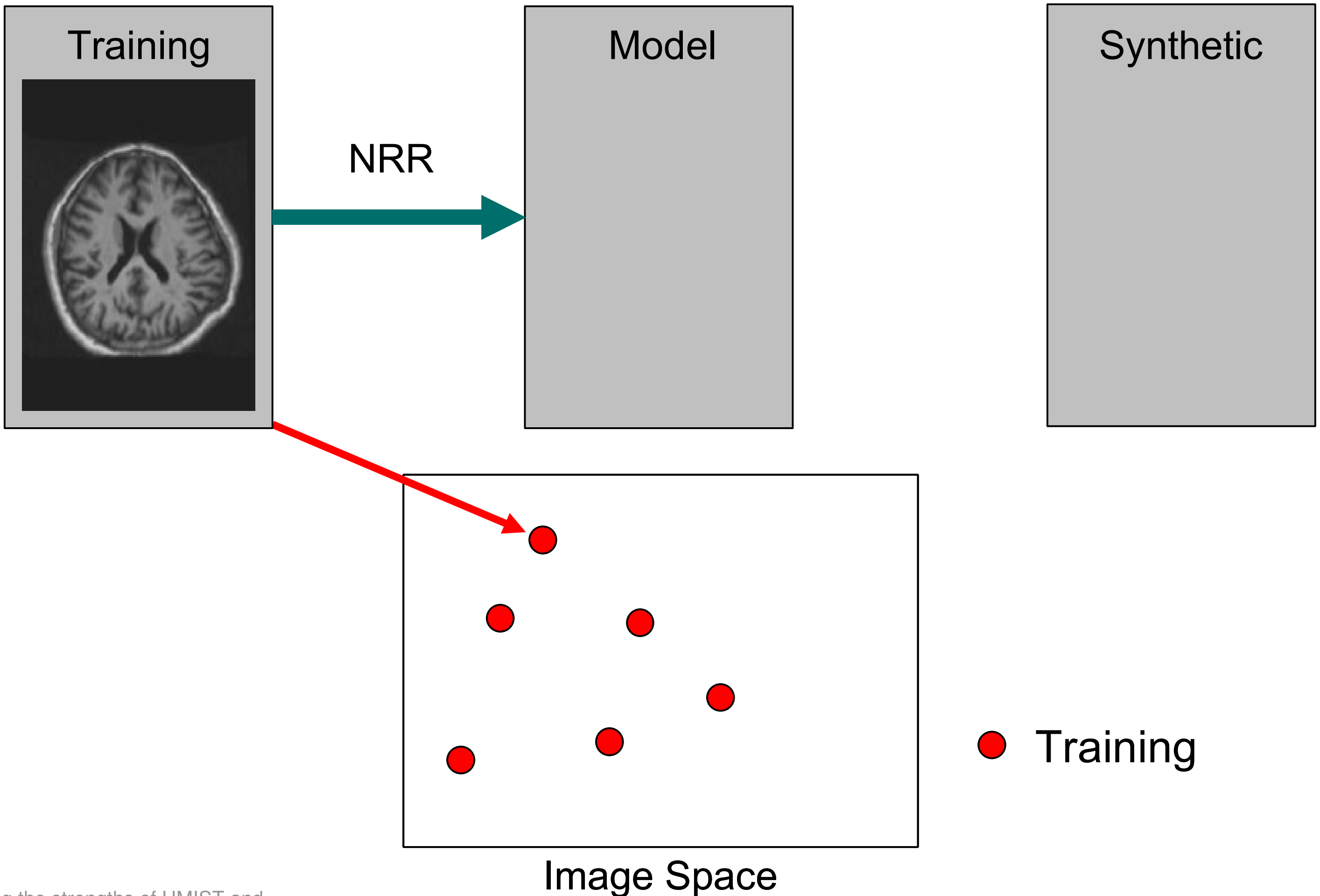


Training and Synthetic Images

Training

Model

Synthetic

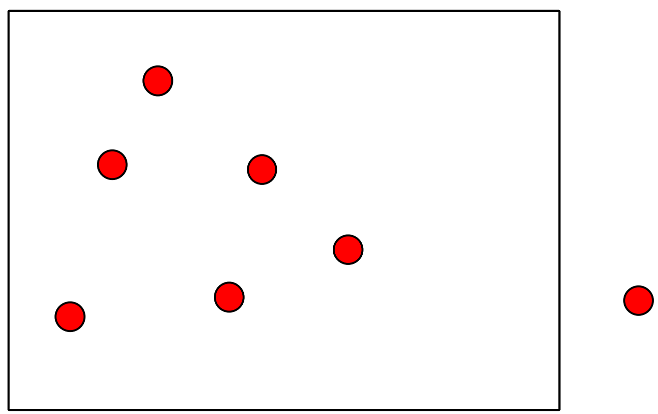
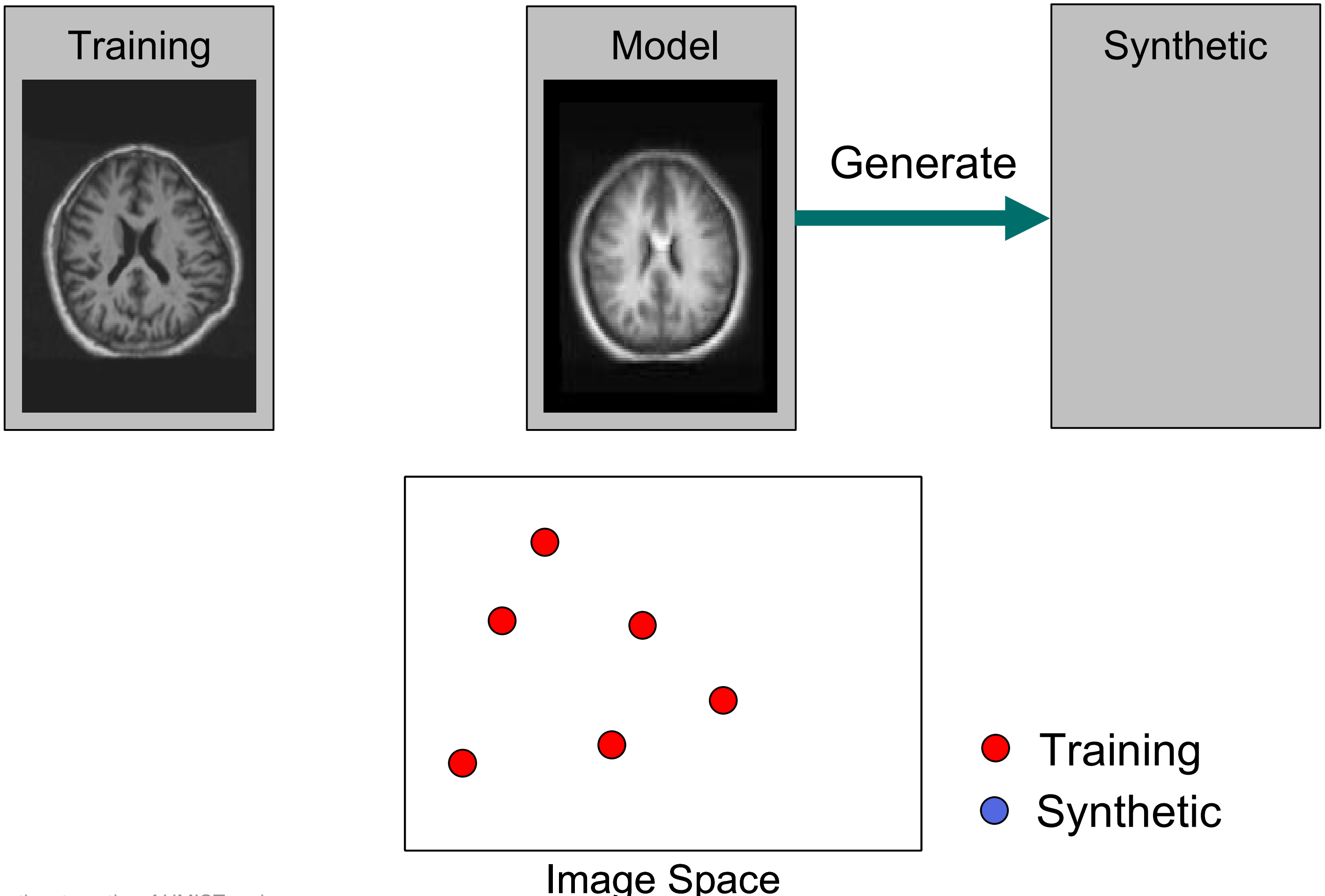


Image Space

Training and Synthetic Images



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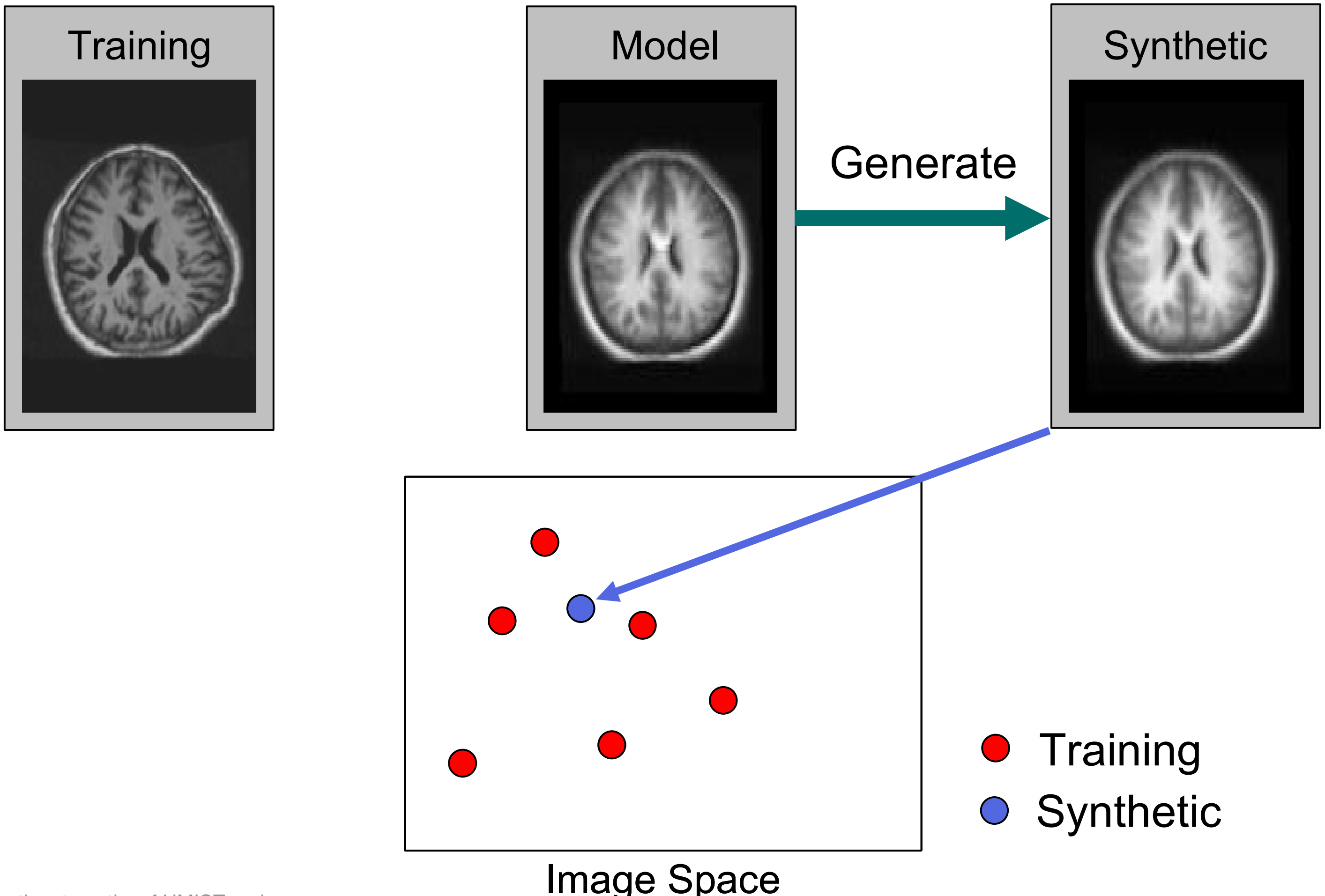

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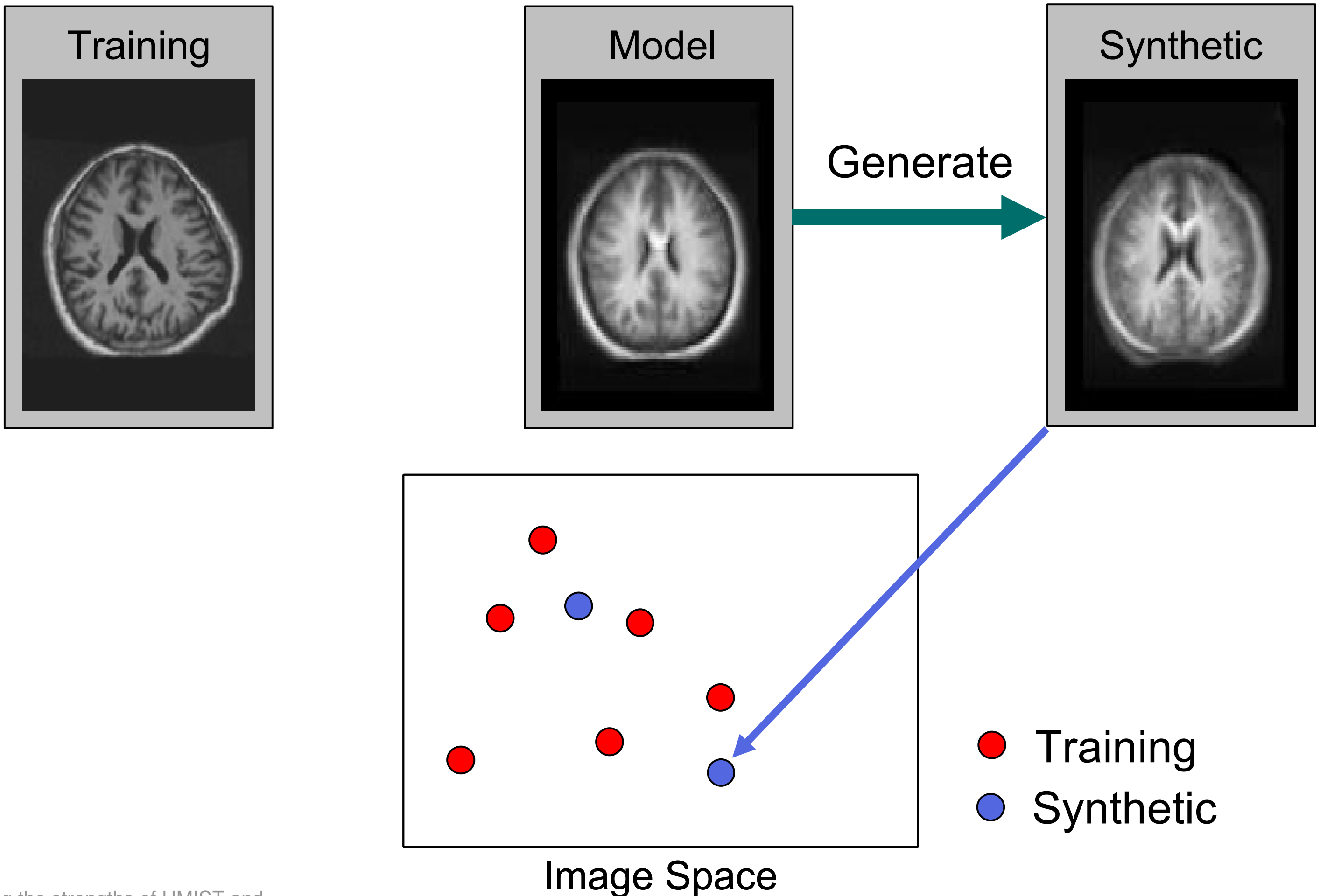
Training and Synthetic Images



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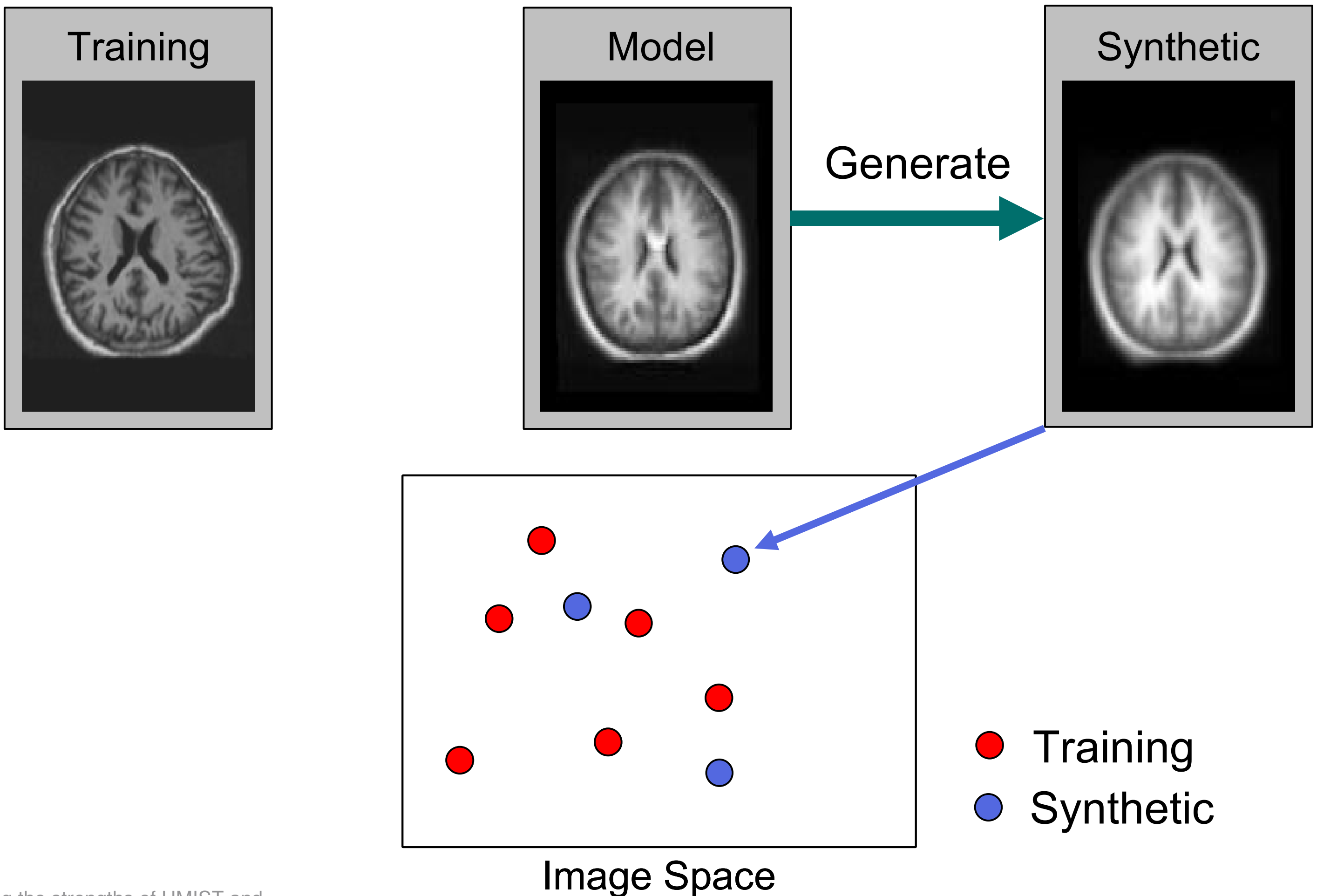

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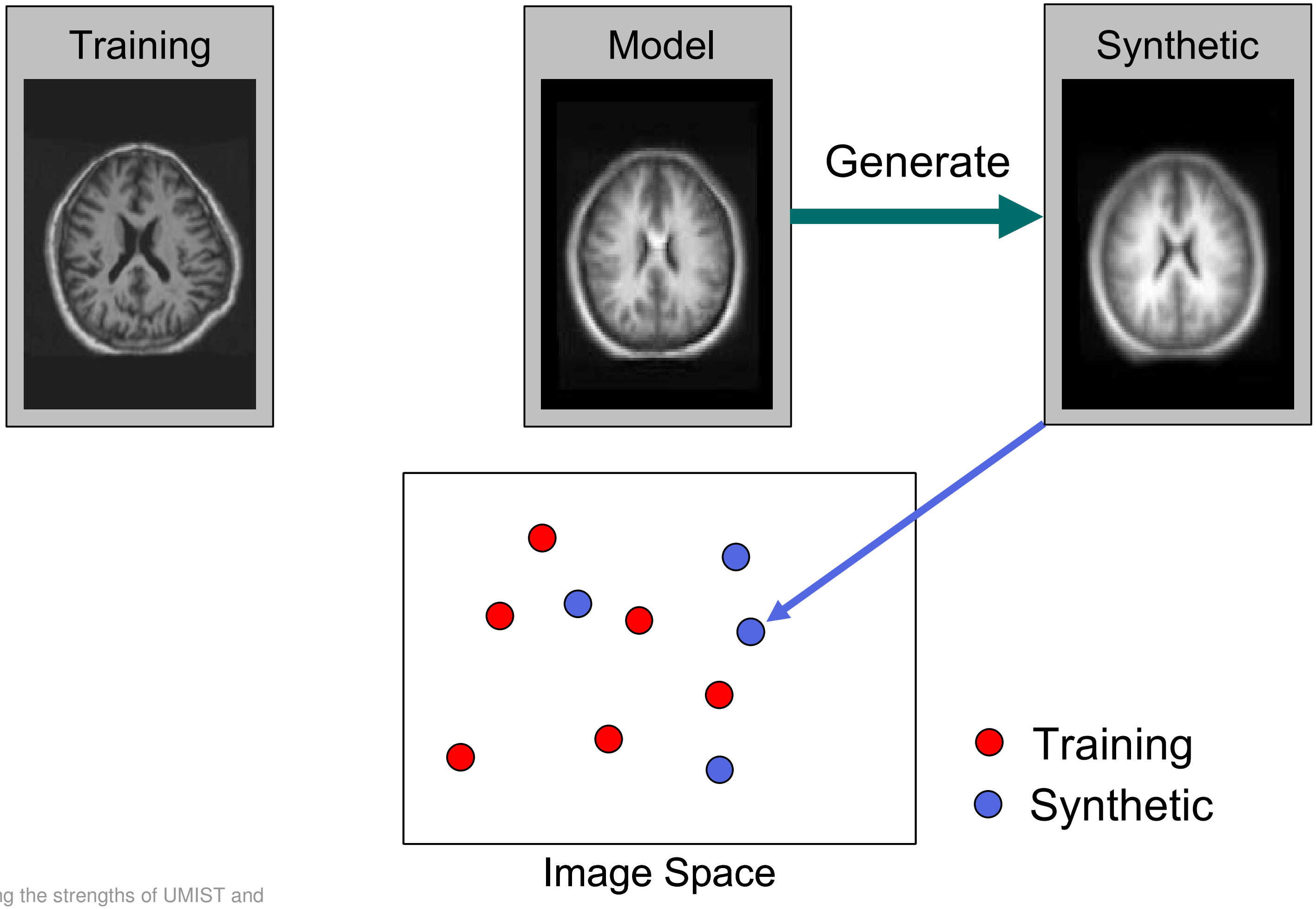
Training and Synthetic Images



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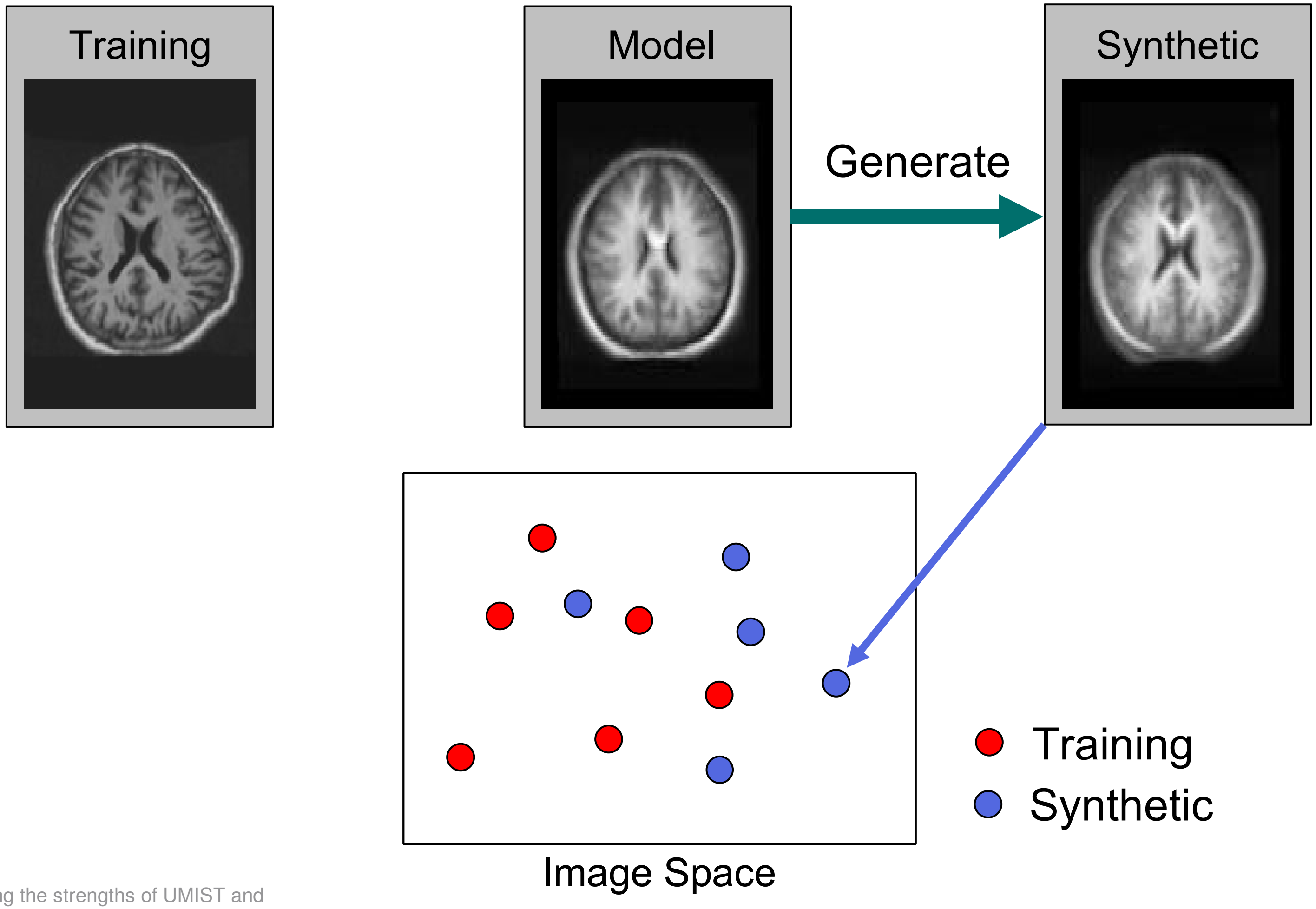
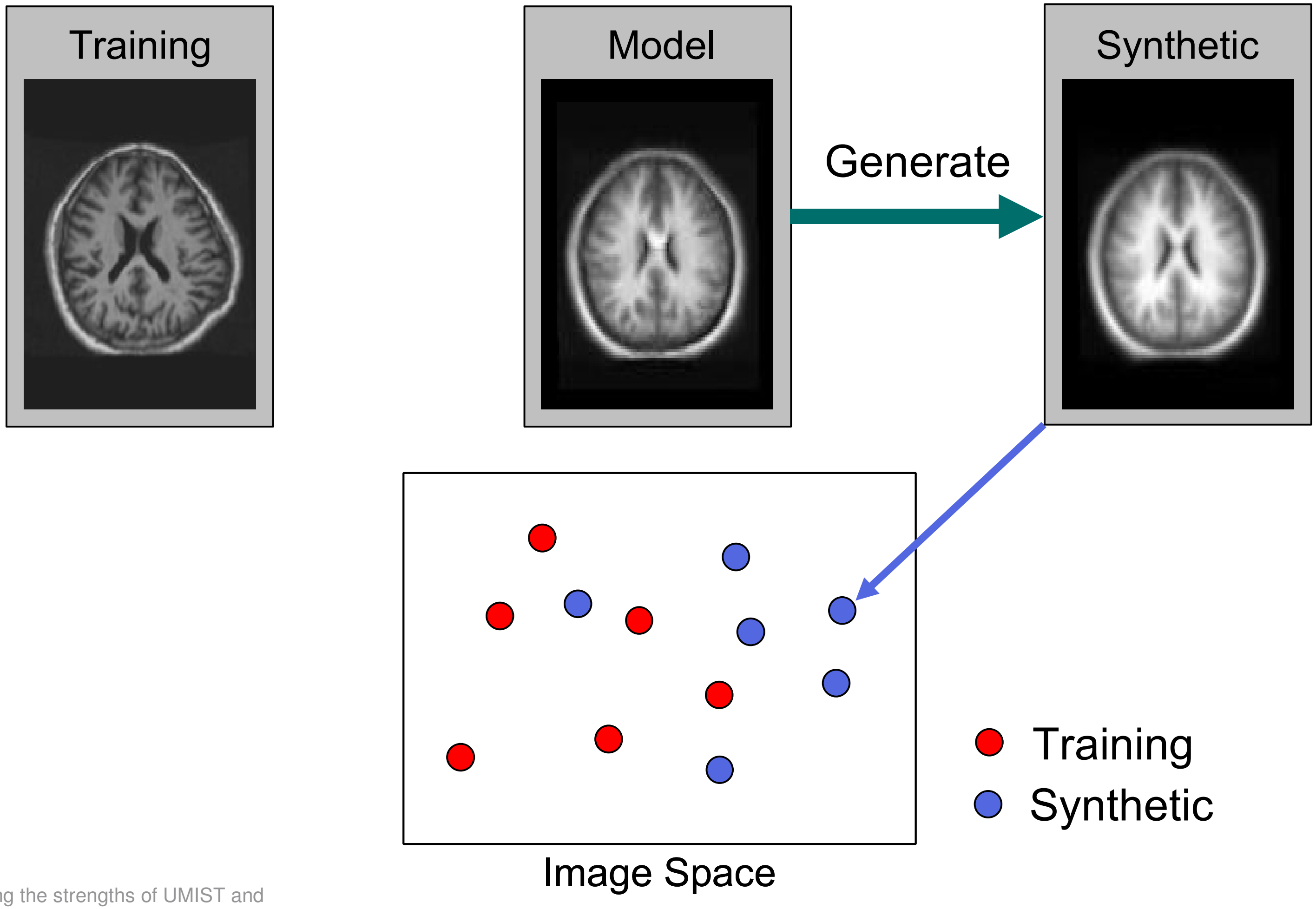
Training and Synthetic Images



Training and Synthetic Images



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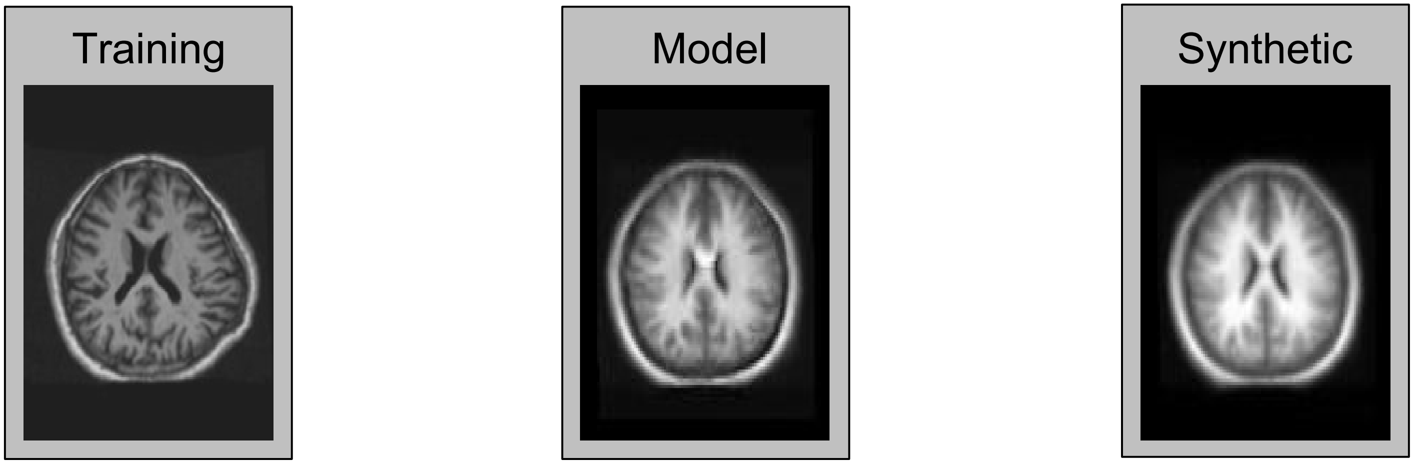


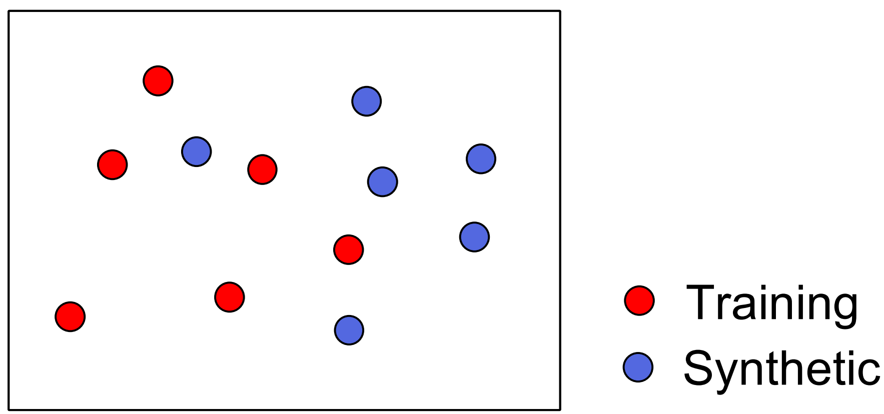
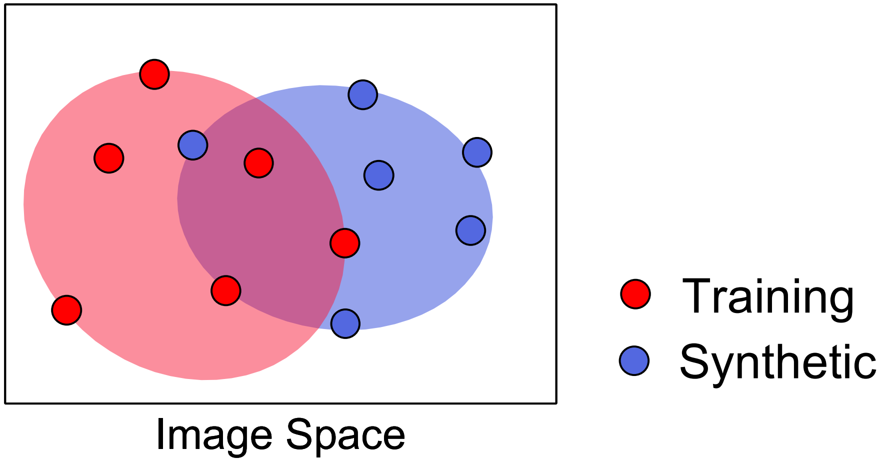
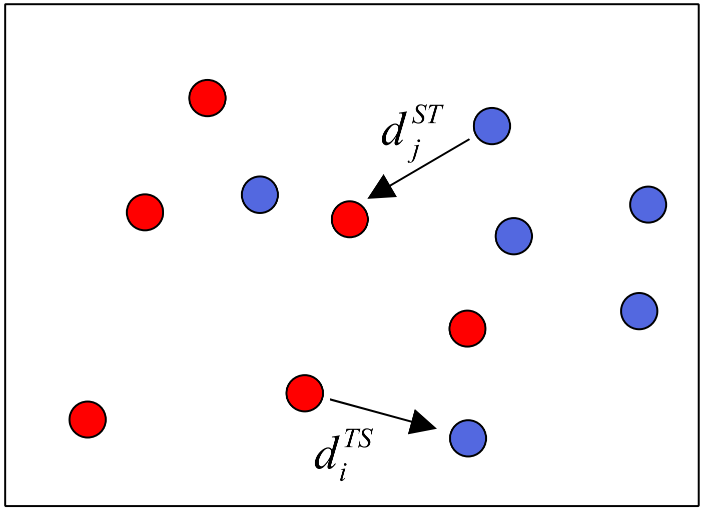


Image Space

Training and Synthetic Images



Model Quality



Training

Synthetic

Given measure d of image distance

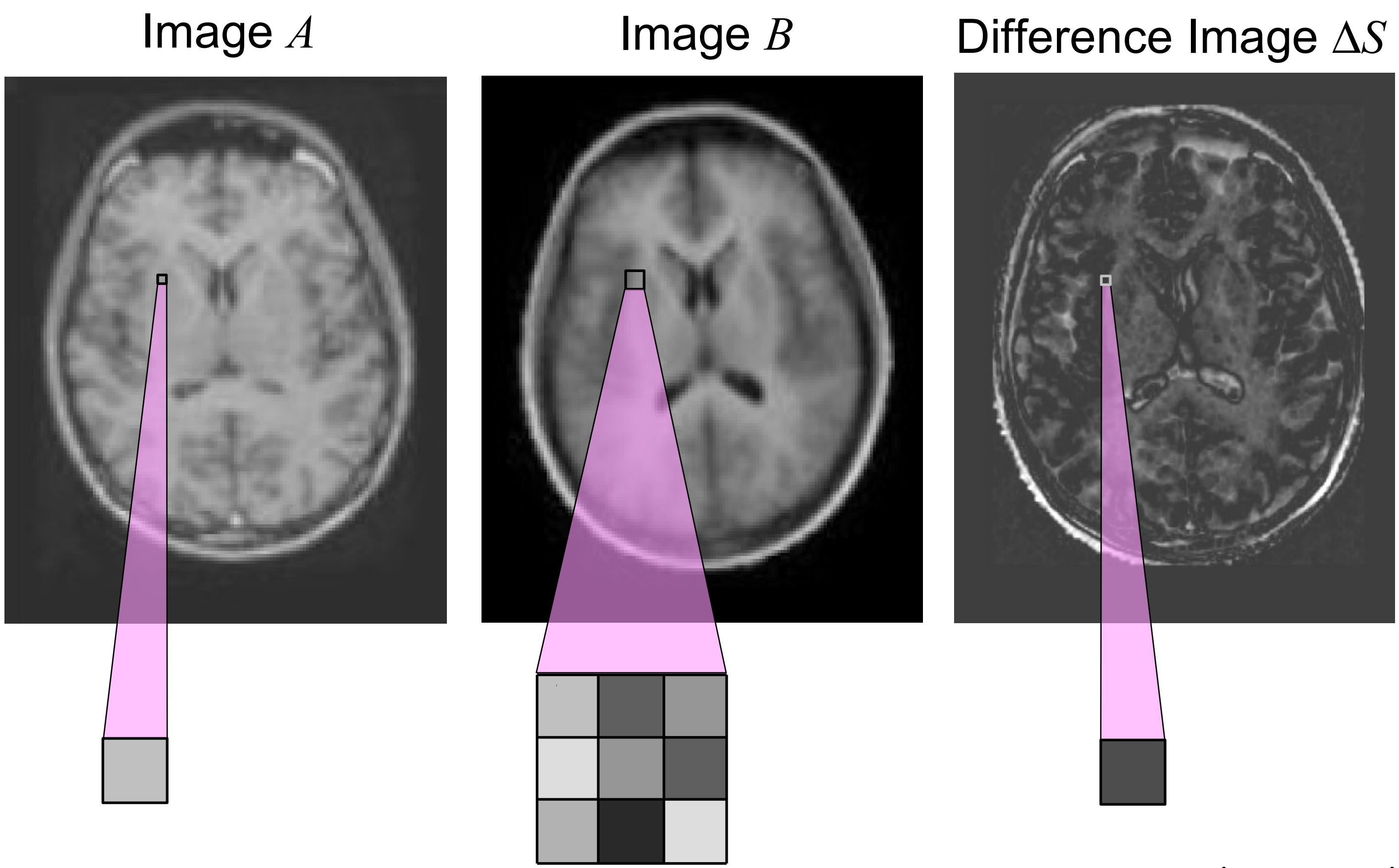
$$Specificity = \sum_{j=1}^{m} \left| d_j^{ST} \right| \Big/ m$$ Mean distance to nearest training image

$$Generalisation = \sum_{i=1}^{n} \left| d_i^{TS} \right| \Big/ n$$ Mean distance to nearest model image

Measuring Inter-Image Distance

- Euclidean
  - simple and cheap
  - sensitive to small misalignments
- Shuffle distance
  - neighbourhood-based pixel differences
  - less sensitive to misalignment

Shuffle Distance



$$A_i \qquad B_{ij} \qquad \Delta S_i = \mathrm{Min}_j \left| A_i - B_{ij} \right|$$

Varying Shuffle Radius

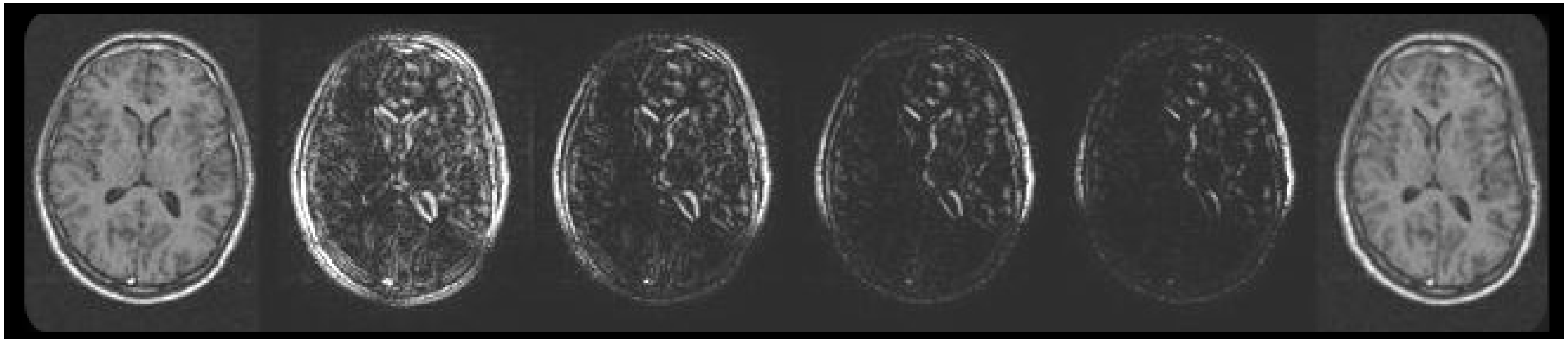


Image A r = 1 r = 1.5 r = 2.1 r = 3.7 Image B

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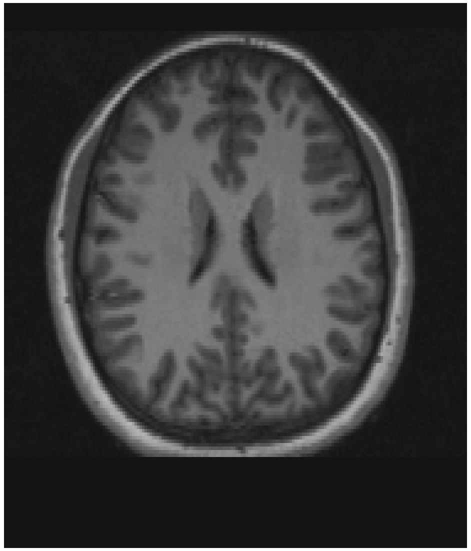
Experimental Evaluation

Experimental Design

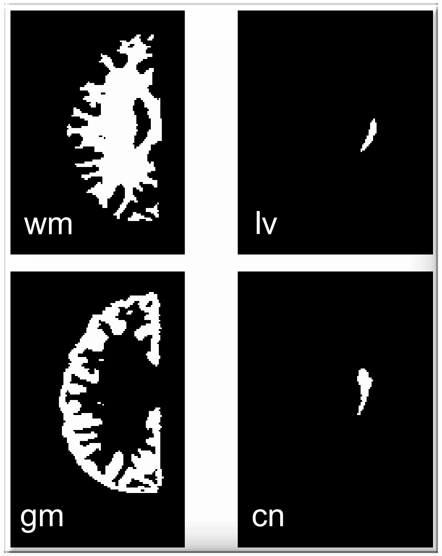
- MGH dataset (37 brains)
- Selected 2D slice
- Initial ‘correct’ NRR
- Progressive perturbation of registration
  - 10 random instantiations for each perturbation magnitude
- Comparison of the two different measures
  - overlap
  - model-based

Brain Data

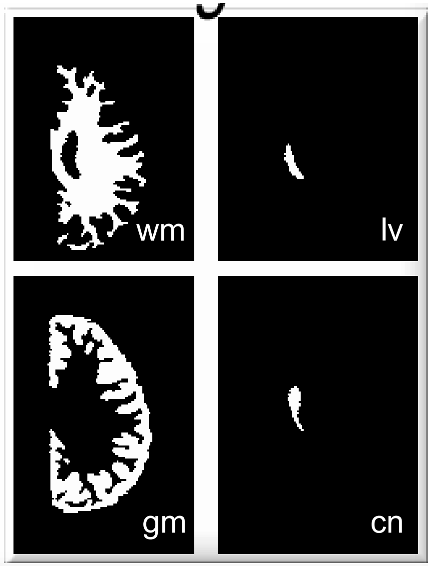
- Eight labels per image
  - L/R white/grey matter
  - L/R lateral ventricle
  - L/R caudate nucleus



Image



LH Labels



RH Labels

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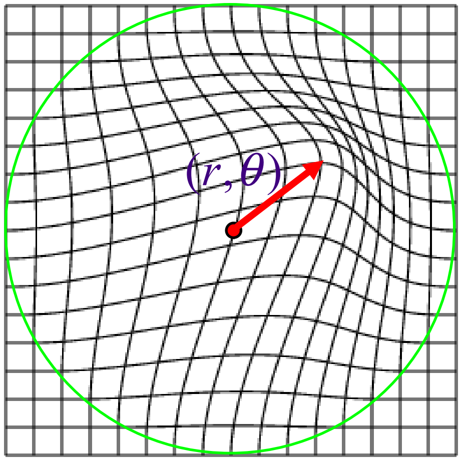
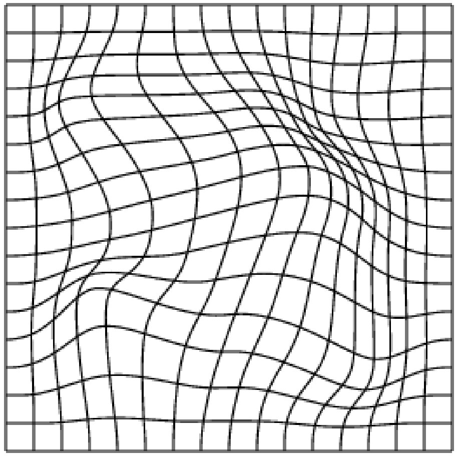
Perturbation Framework

- Alignment degraded by applying warps to data
- Clamped-plate splines (CPS) with 25 knot-points
- Random displacement (r, θ) drawn from distribution

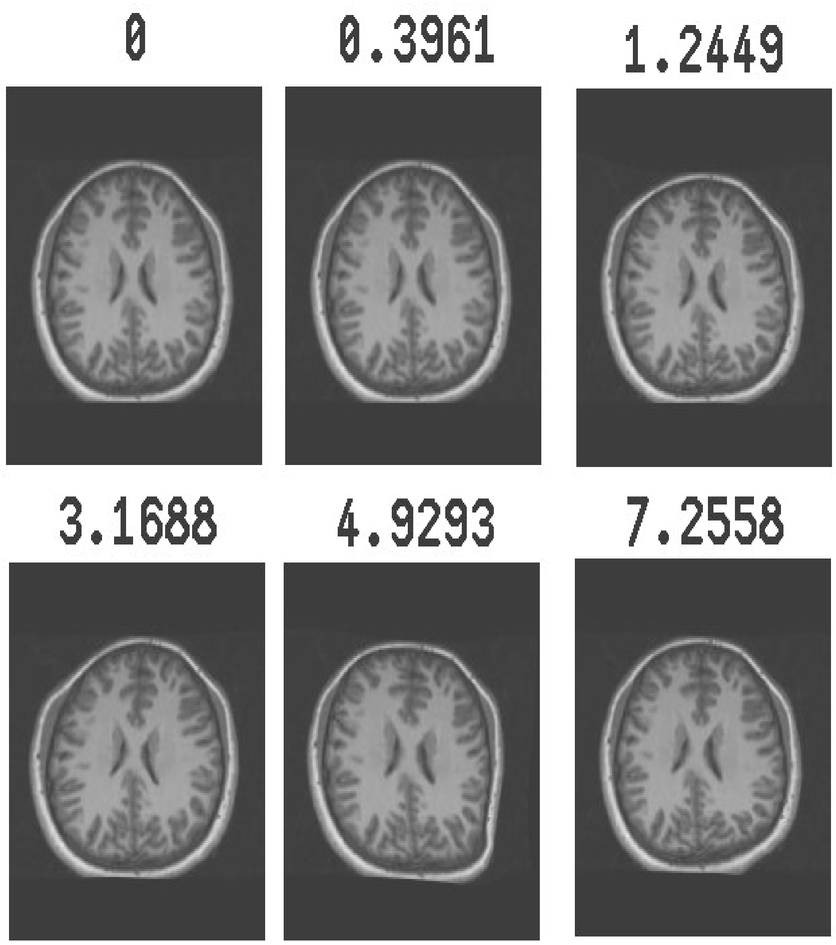


CPS with 1 knot point



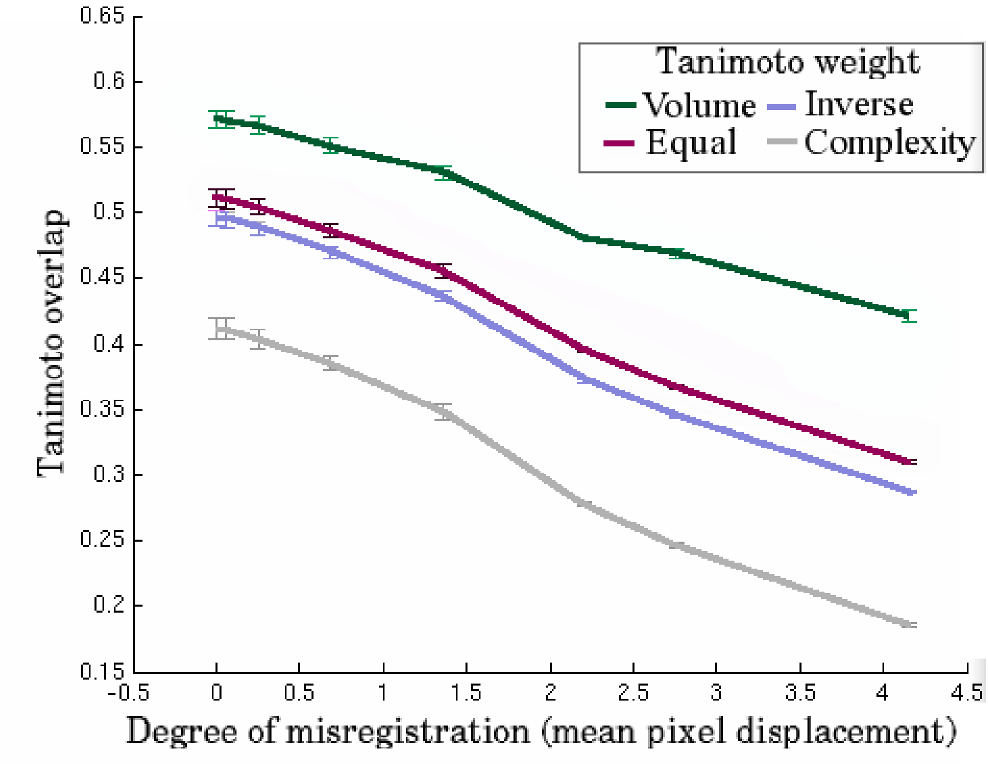
Multiple knot points

Examples of Perturbed Images



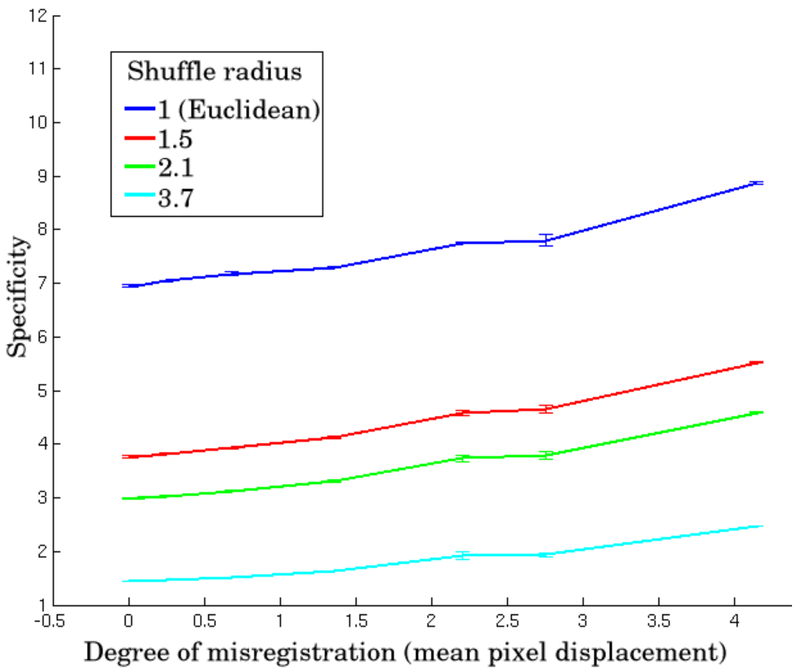
Results – Overlap

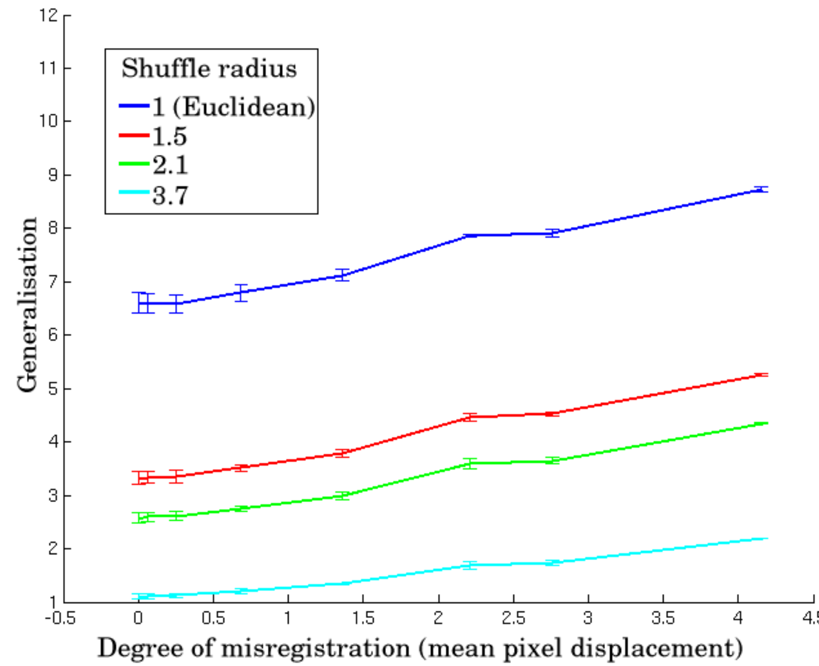
- Overlap decreases monotonically with misregistration



Results – Model-Based

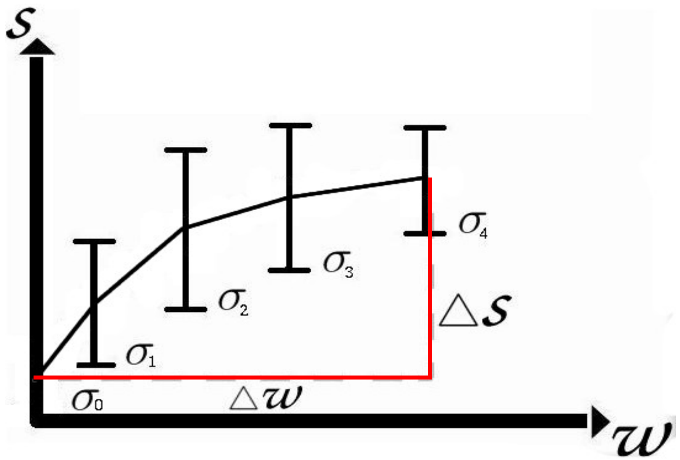
- Measures increase monotonically with misregistration





Results – Comparison

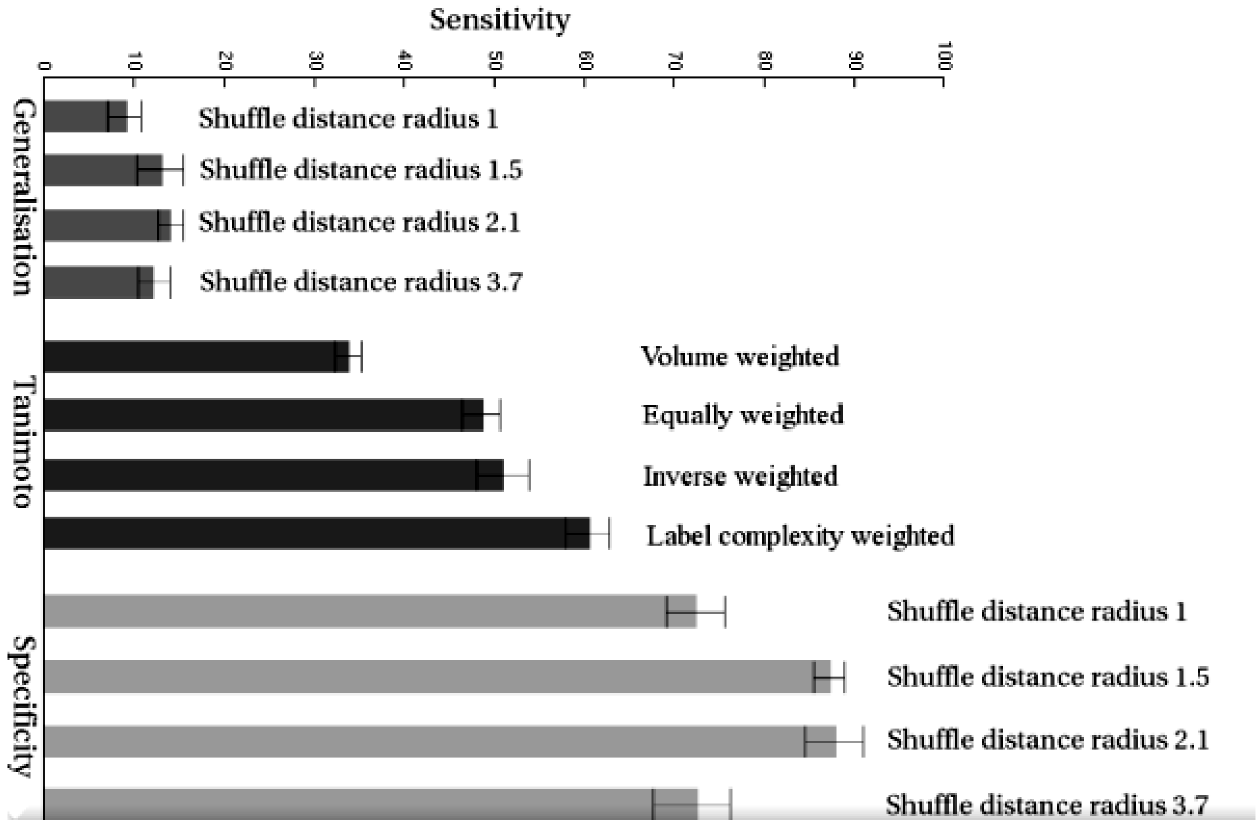
- All three measures give similar results
  - overlap-based assessment requires ground truth (labels)
  - model-based approach does not need ground truth
- Compare sensitivity of methods
  - ability to detect small changes in registration



$$Sensitivity = \frac{\Delta S}{\Delta w} \Big/ \bar{\sigma}$$

Results – Sensitivities

- Specificity most sensitive method



Further Tests – Noise

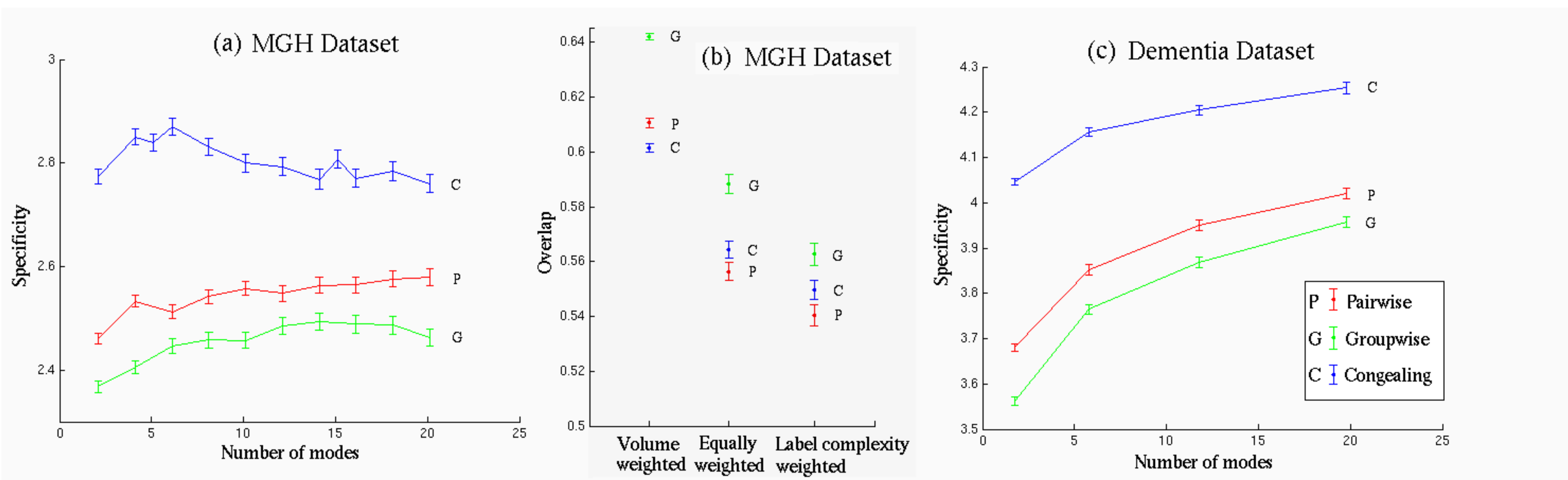
- Measure of robustness to noise is sought
- Previous experiments were repeated with noise applied
- Each image had up to 10% white noise added
- Changes in Generalisation and Sensitivity detectable
- Curves remain monotonic

Practical Application – NRR Benchmark

- 3 registration algorithm compared
  - Pairwise registration
  - Groupwise registration
  - Congealing
- 2 brain datasets used
  - MGH dataset
  - Dementia dataset
- 3 assessment methods
  - Model-based: Generalisation and Specificity
  - Overlap-based

Practical Application - Results

- Results are consistent
- Groupwise outperforms pairwise, which outperforms congealing



Extension to 3-D

- The method was implemented and tested in 3-D
- Shuffle neighbourhood to be considered can be a:
  - box
  - cube
  - plane-based comparison (slice-by-slice)
  - or sphere
- Validation experiments too laborious to replicate
- Instead, 4-5 NRR algorithms will be compared
- Ongoing work using annotated IBIM data
- Results to be compared against label overlap

Conclusions

- Both approaches sensitive to subtle misregistration
- Overlap and model-based approaches ‘equivalent’
- Overlap provides ‘gold standard’
- Specificity is a good surrogate
  - monotonically related
  - no need for ground truth
  - more sensitive
  - only applies to groups (but any NRR method)