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A Generic Method for Evaluating Appearance Models and Assessing the Accuracy of NRR

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Overview

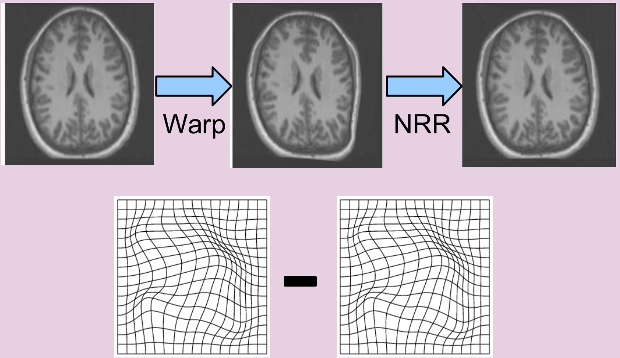
- Motivation
- Assessment methods
  - overlap-based
  - model-based
- Experiments
  - validation
  - comparison of methods
  - practical application
- Conclusions

Motivation

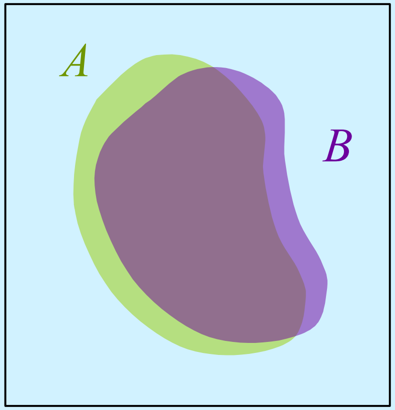
- Competing approaches to NRR
  - representation of warp (including regularisation)
  - similarity measure
  - optimisation
  - pair-wise vs group-wise
- Different results for same images
- Need for objective method of comparison
- QA in real applications (how well has it worked?)

Existing Methods of Assessment

- Artificial warps
  - recovering known warps
  - may not be representative
  - algorithm testing but not QA



- Overlap measures
  - ground truth tissue labels
  - overlap after registration
  - subjective
  - too expensive for routine QA



- Need for new approach

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Model-Based Assessment

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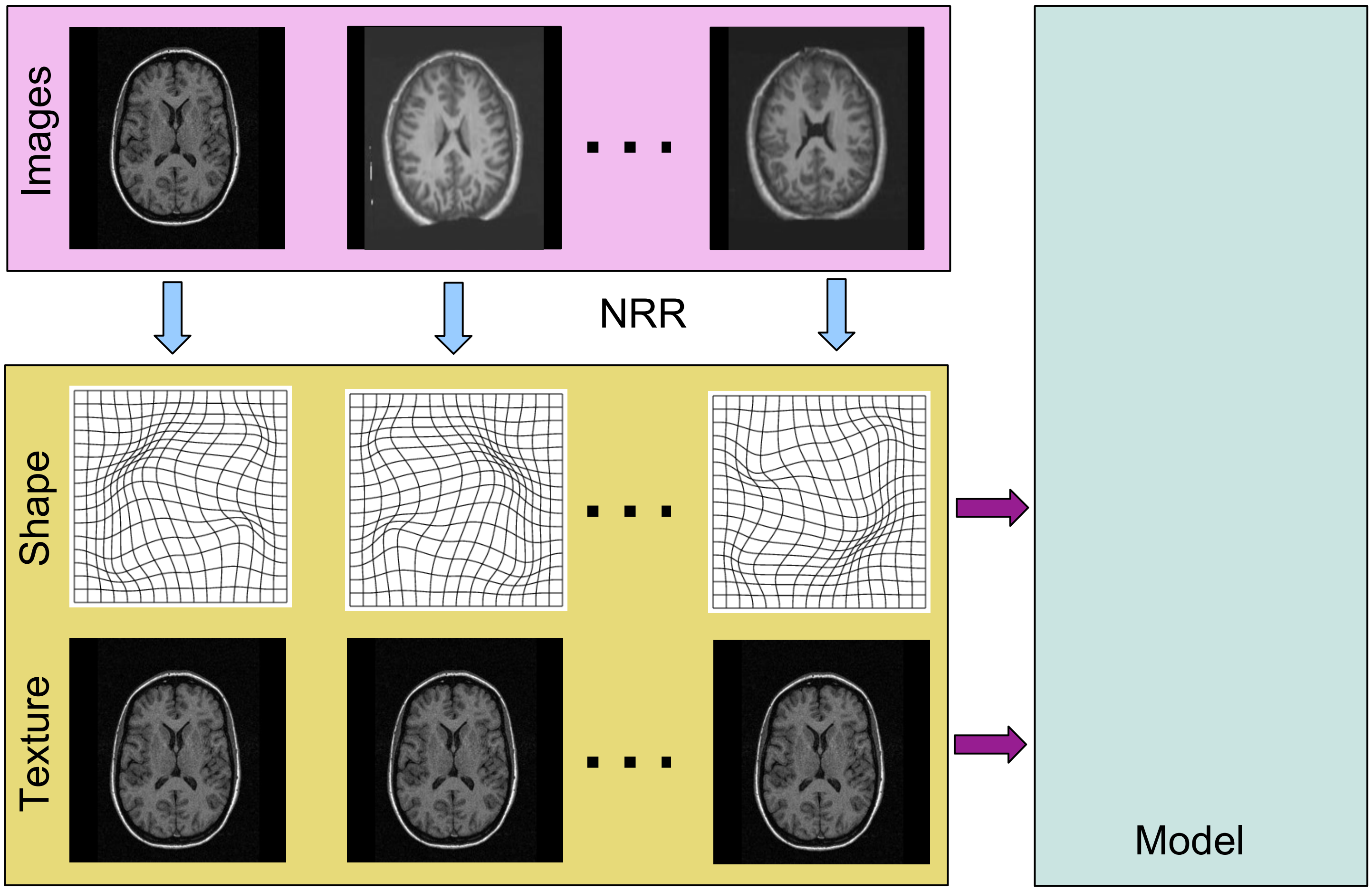
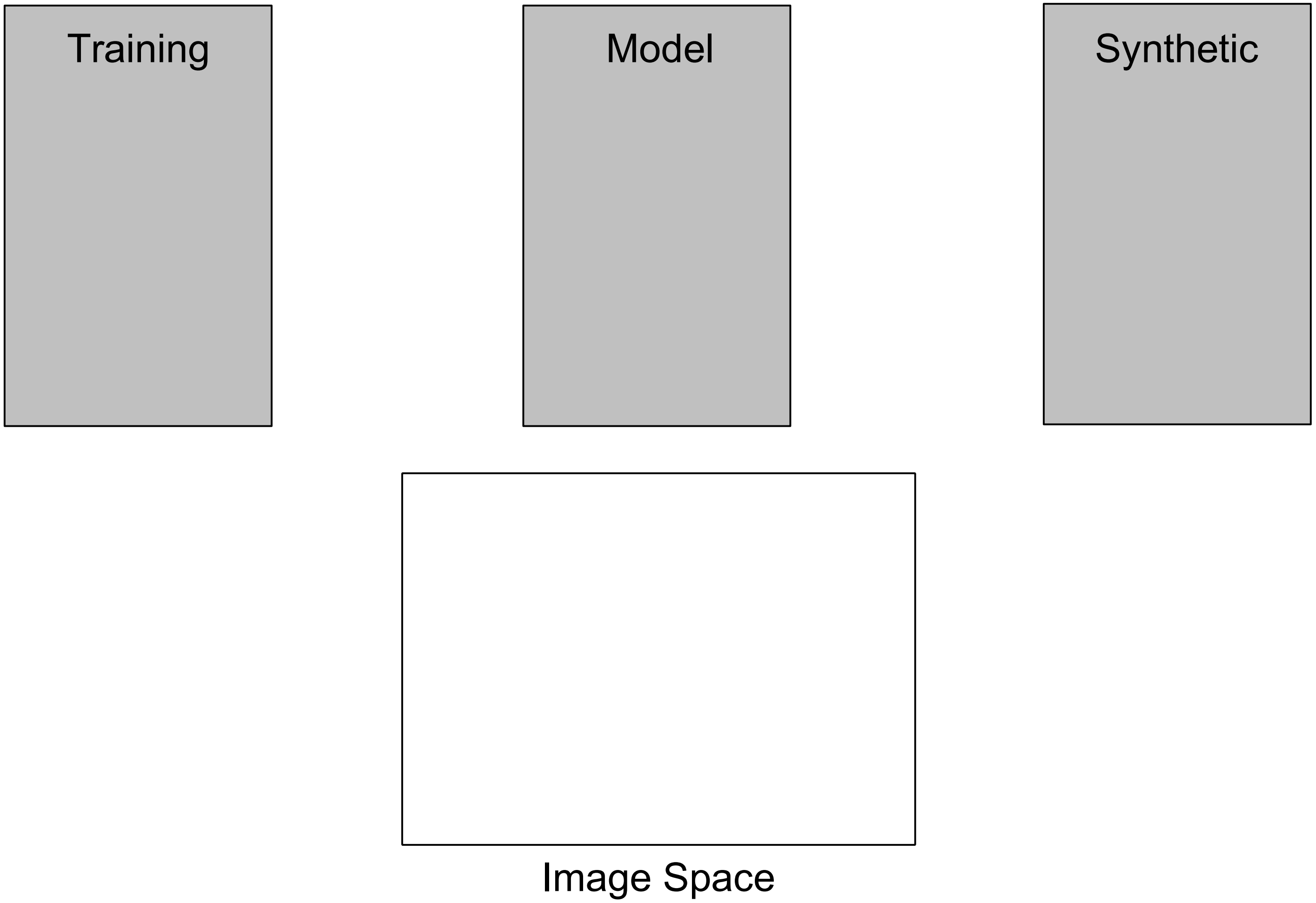
Model-based Framework

- Registered image set ⇒ statistical appearance model
- Good registration ⇒ good model
  - generalises well to new examples
  - specific to class of images
- Registration quality ⇔ 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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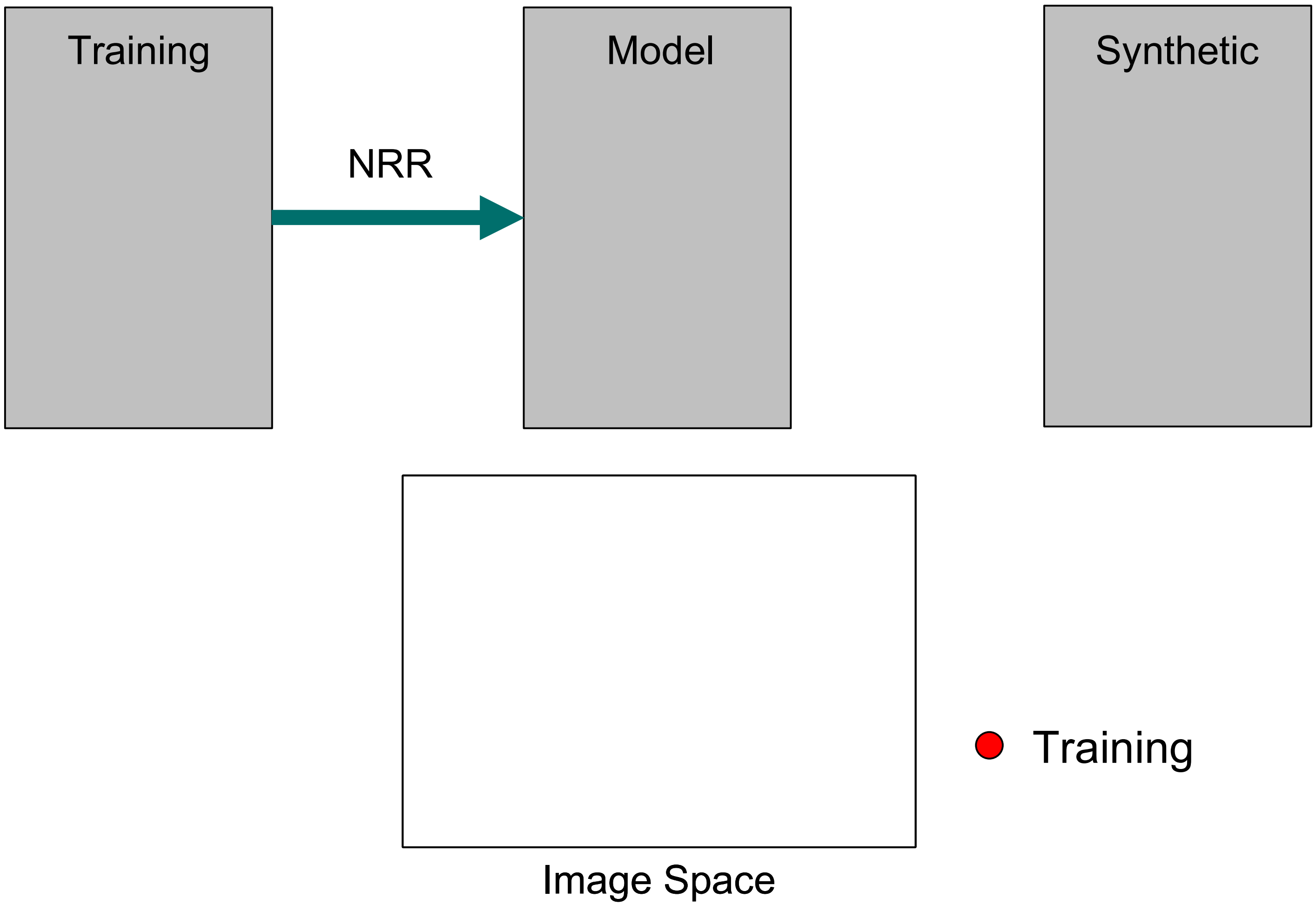

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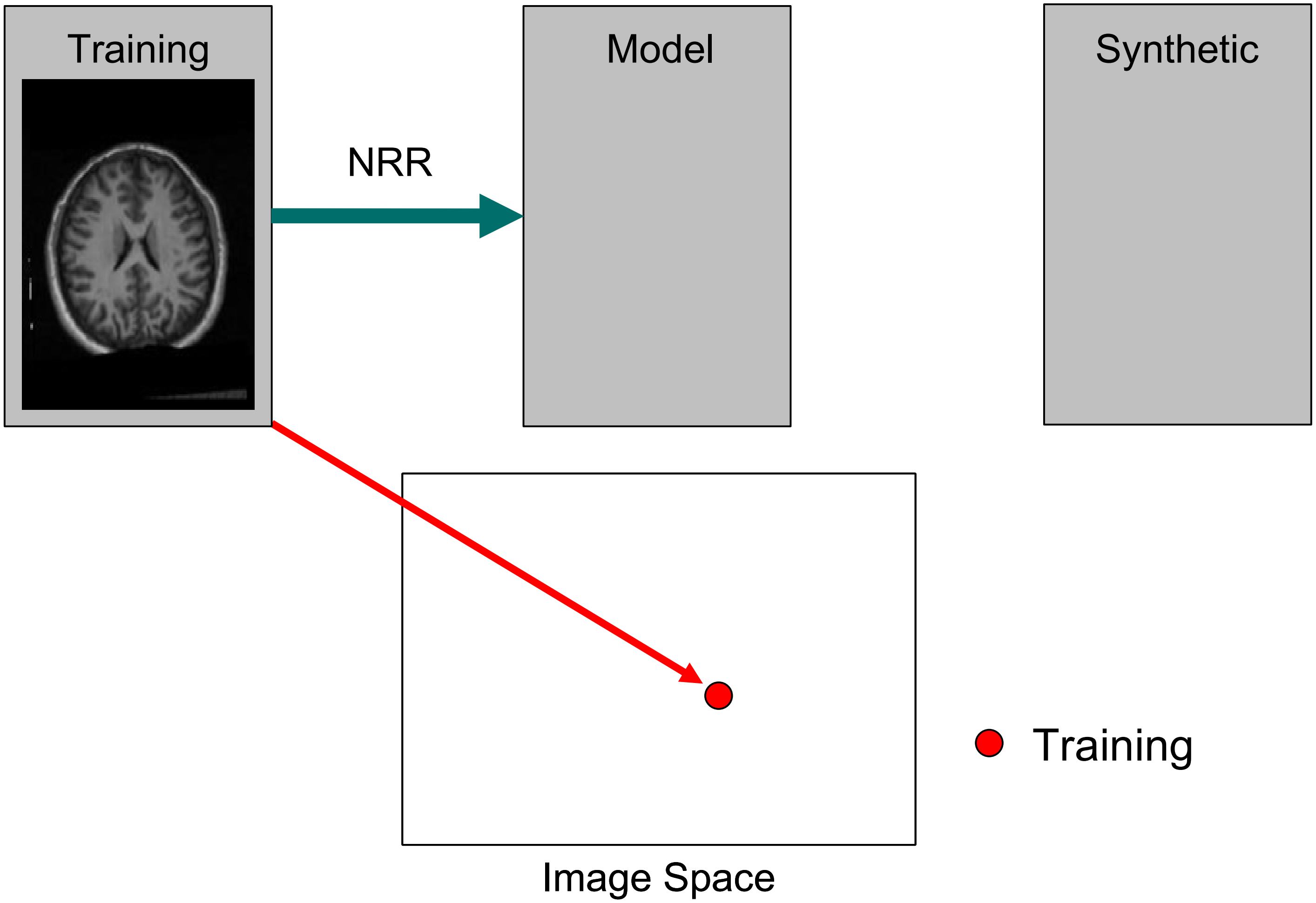

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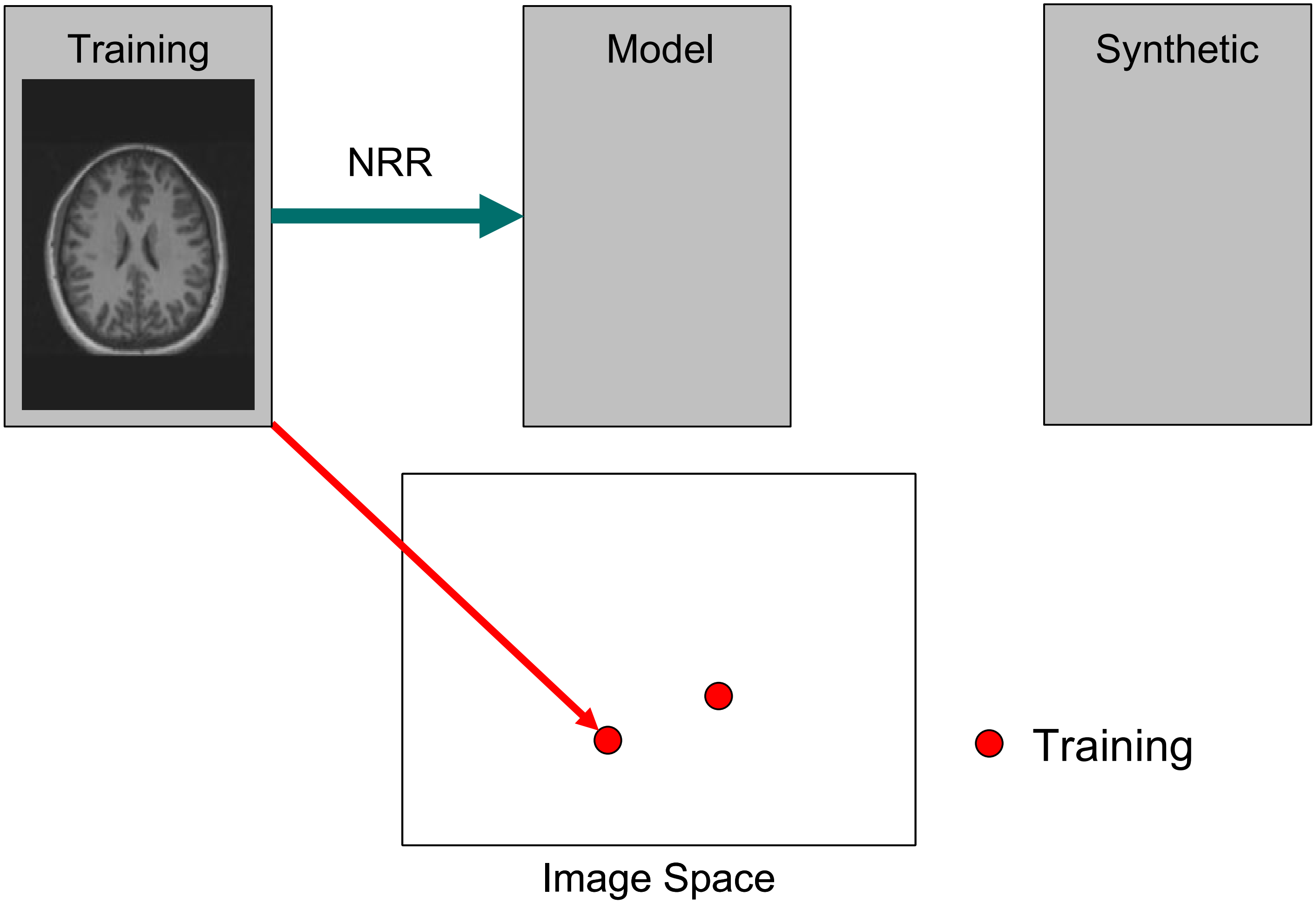

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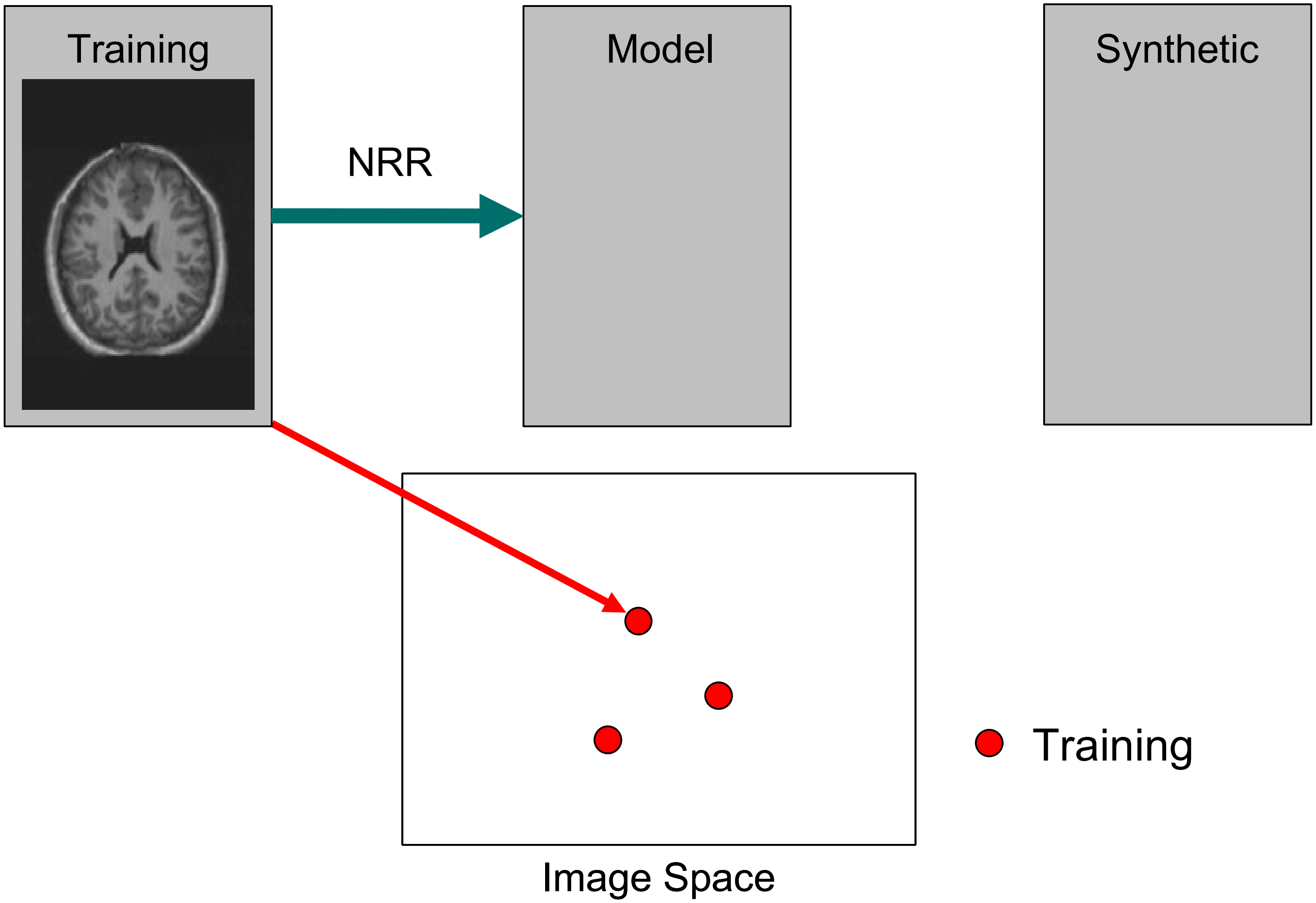

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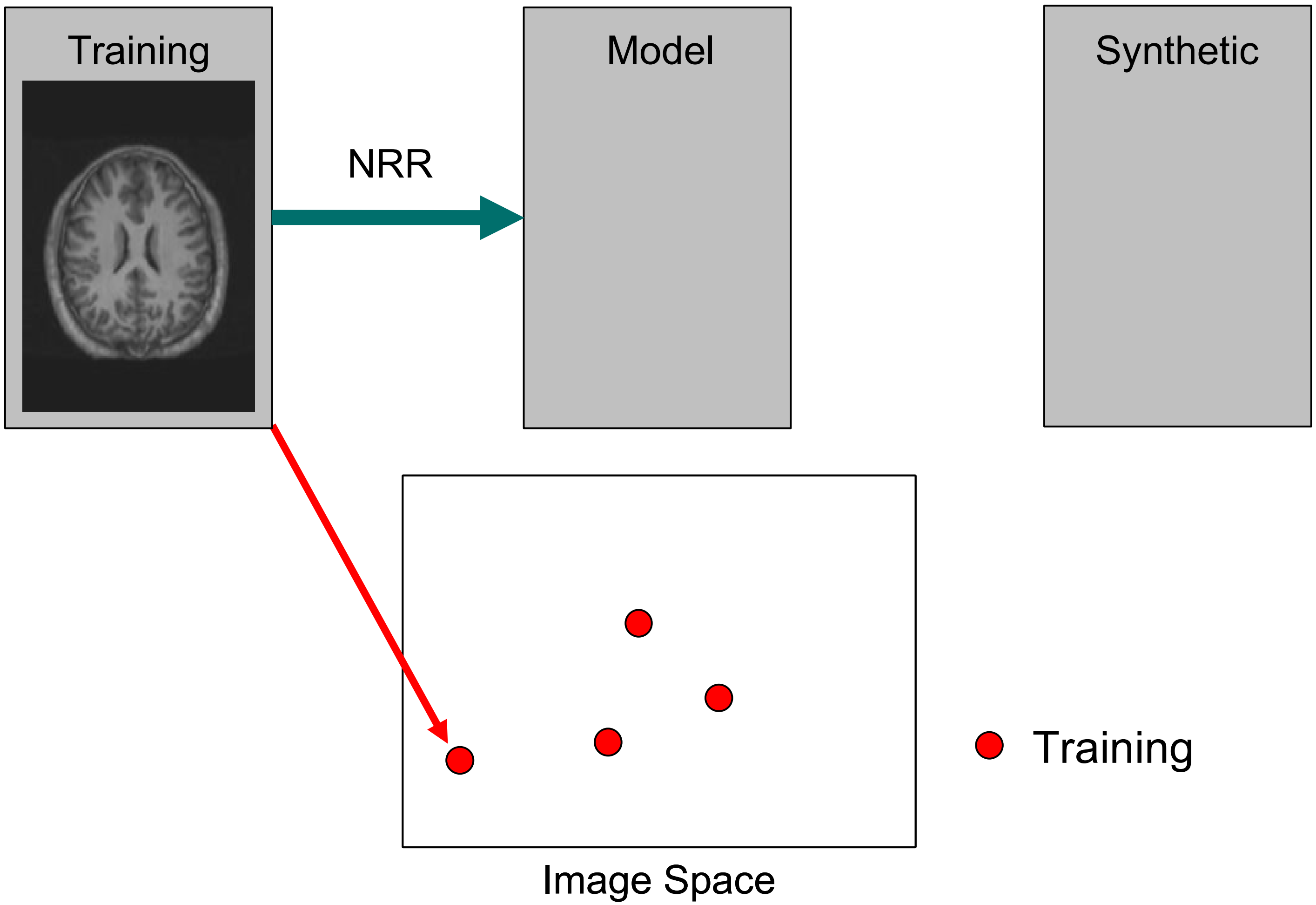

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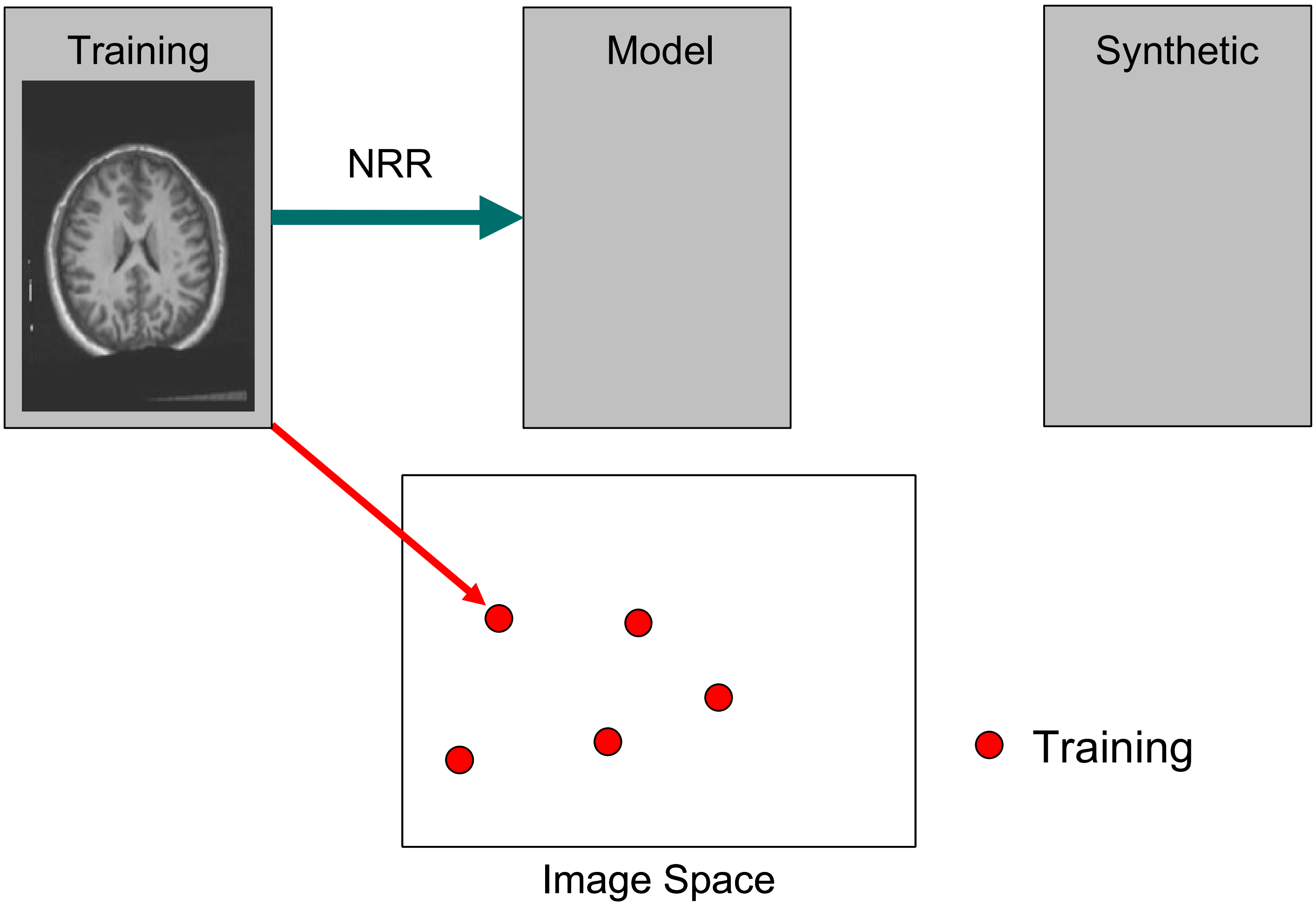
Training and Synthetic Images



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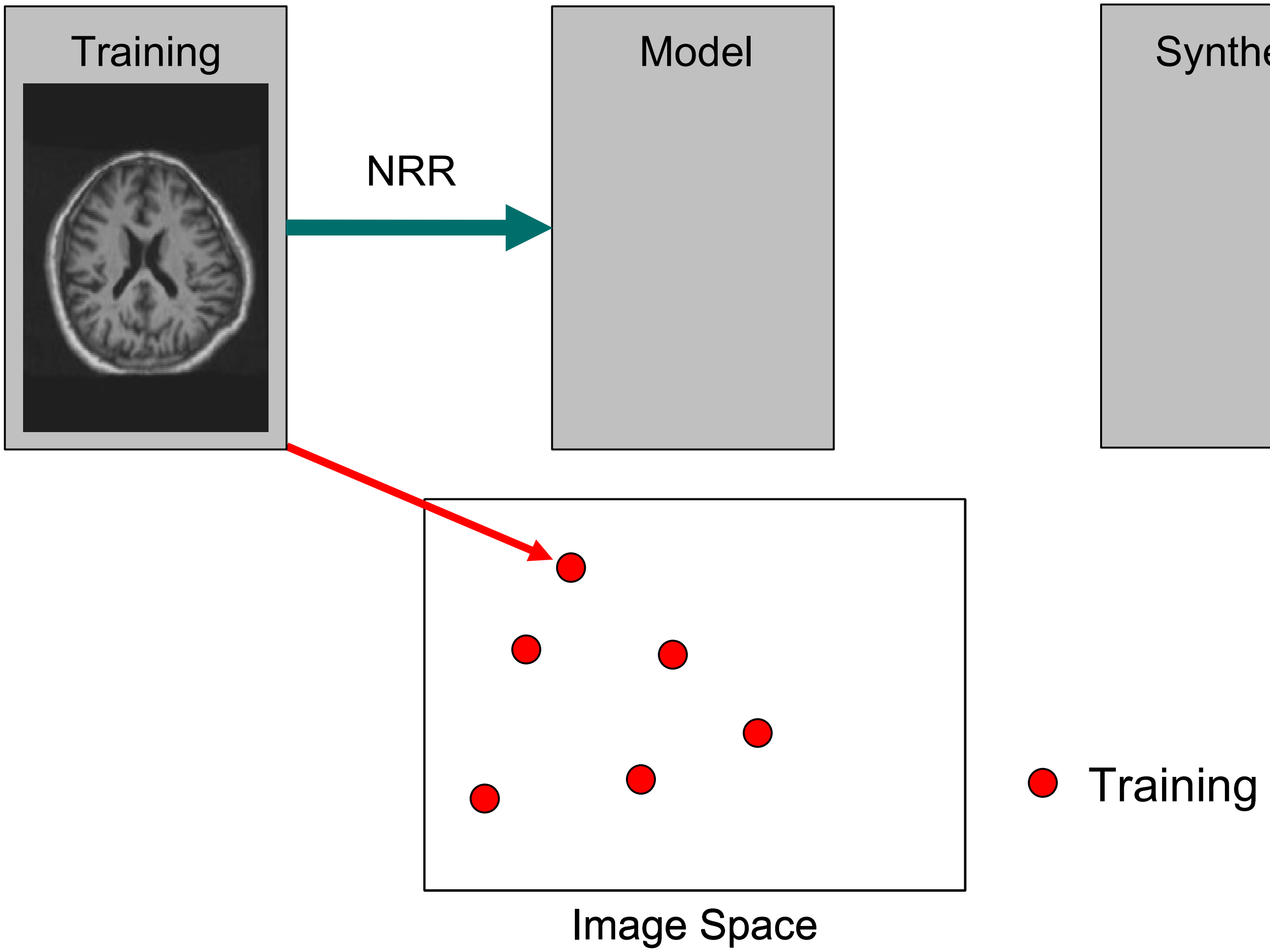

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Training and Synthetic Images

Training

Model

Synthetic

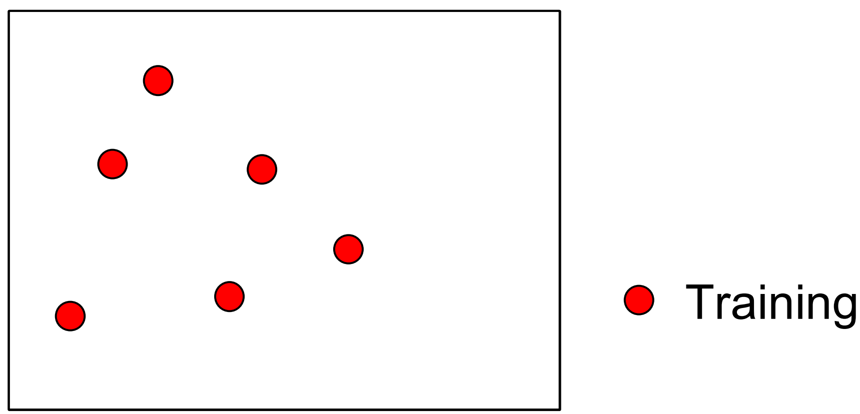
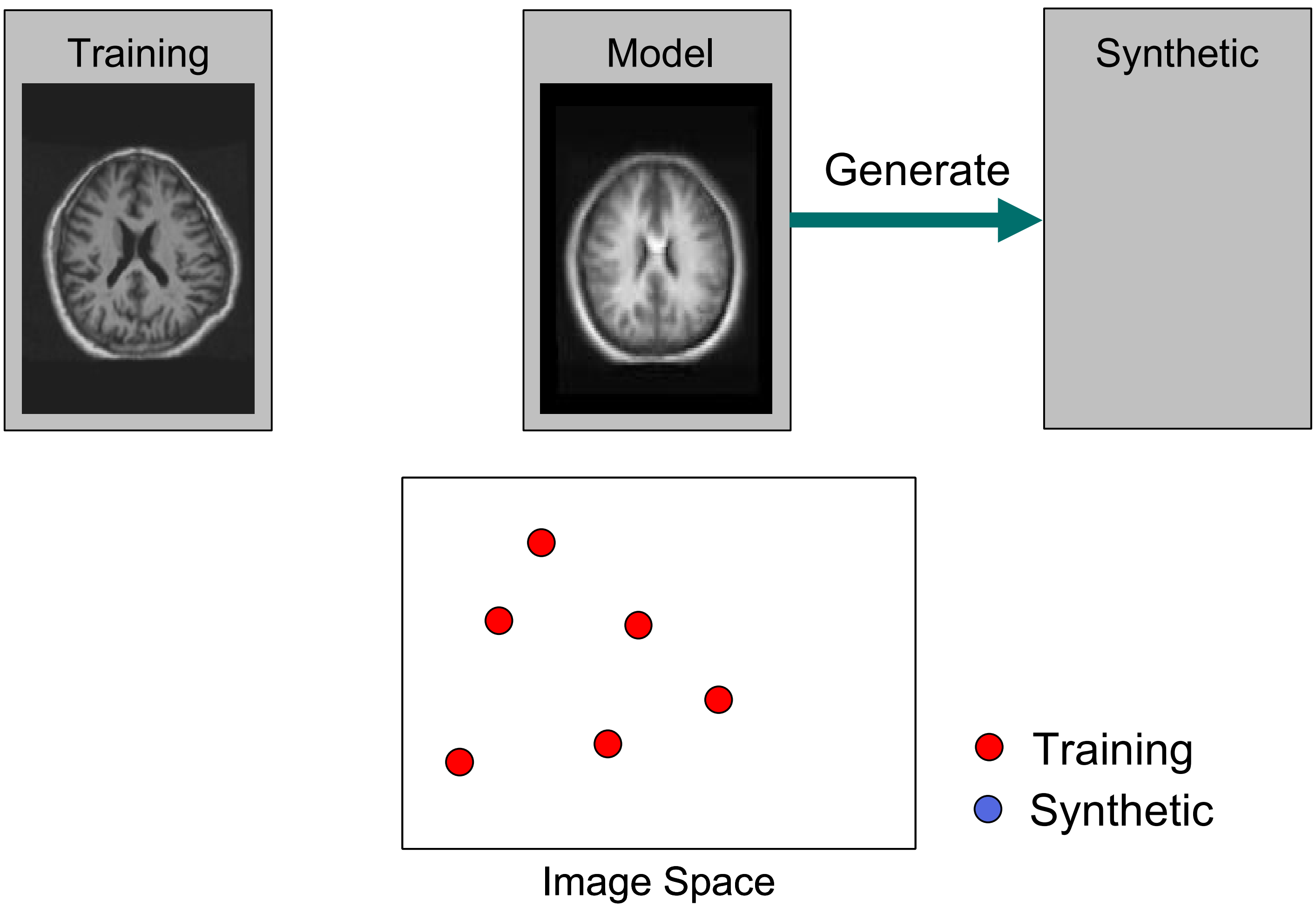


Image Space

Training and Synthetic Images



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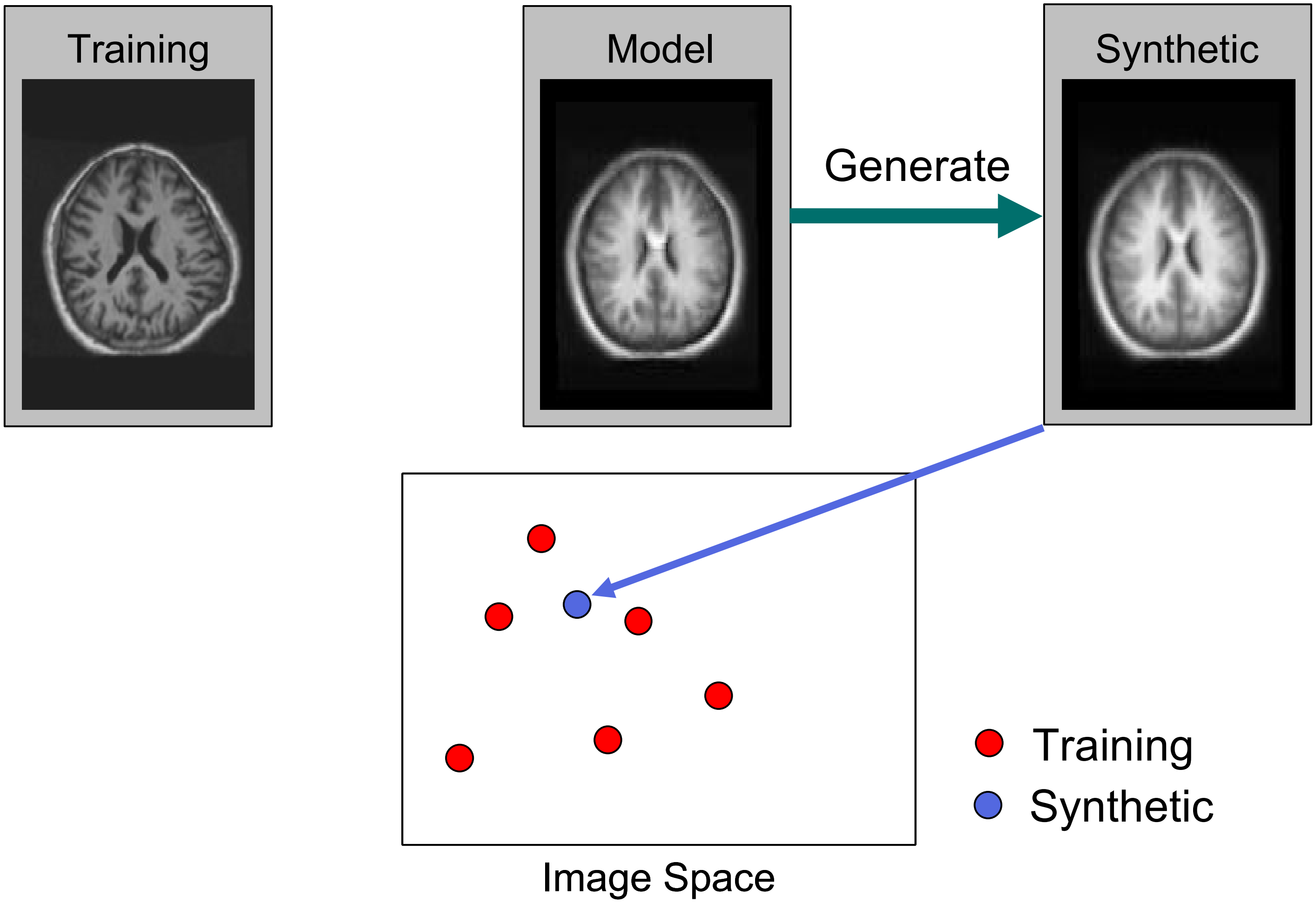

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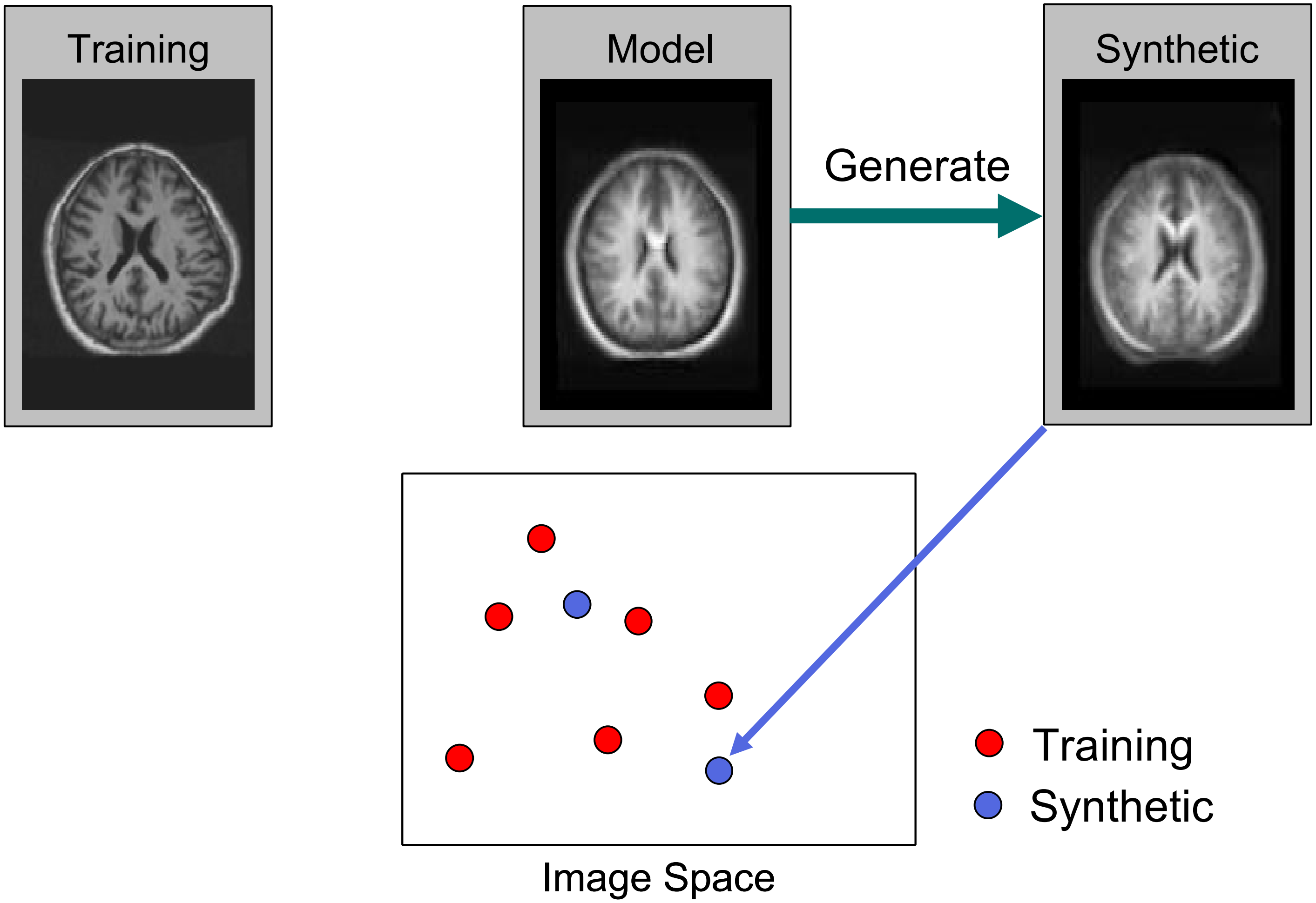

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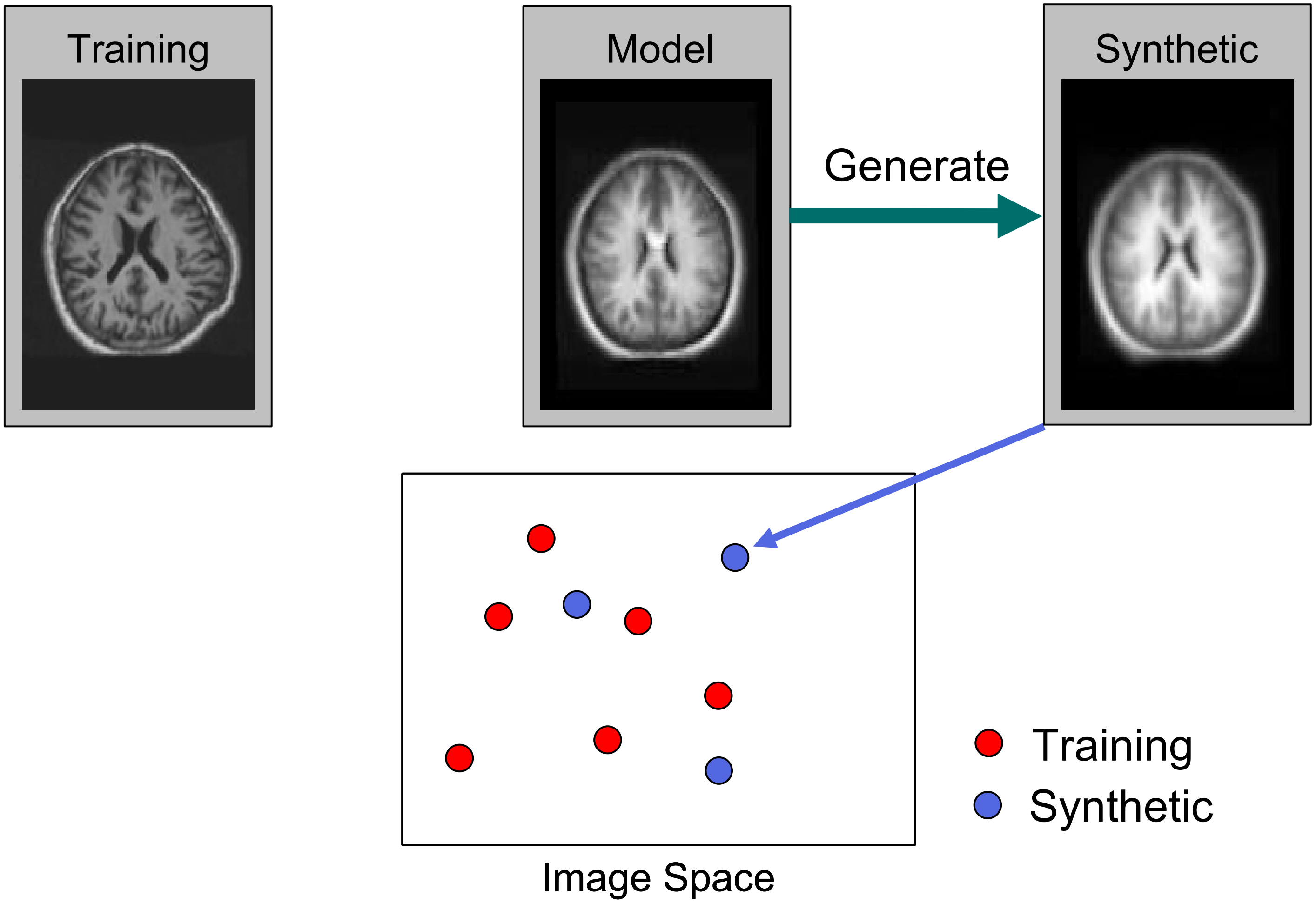

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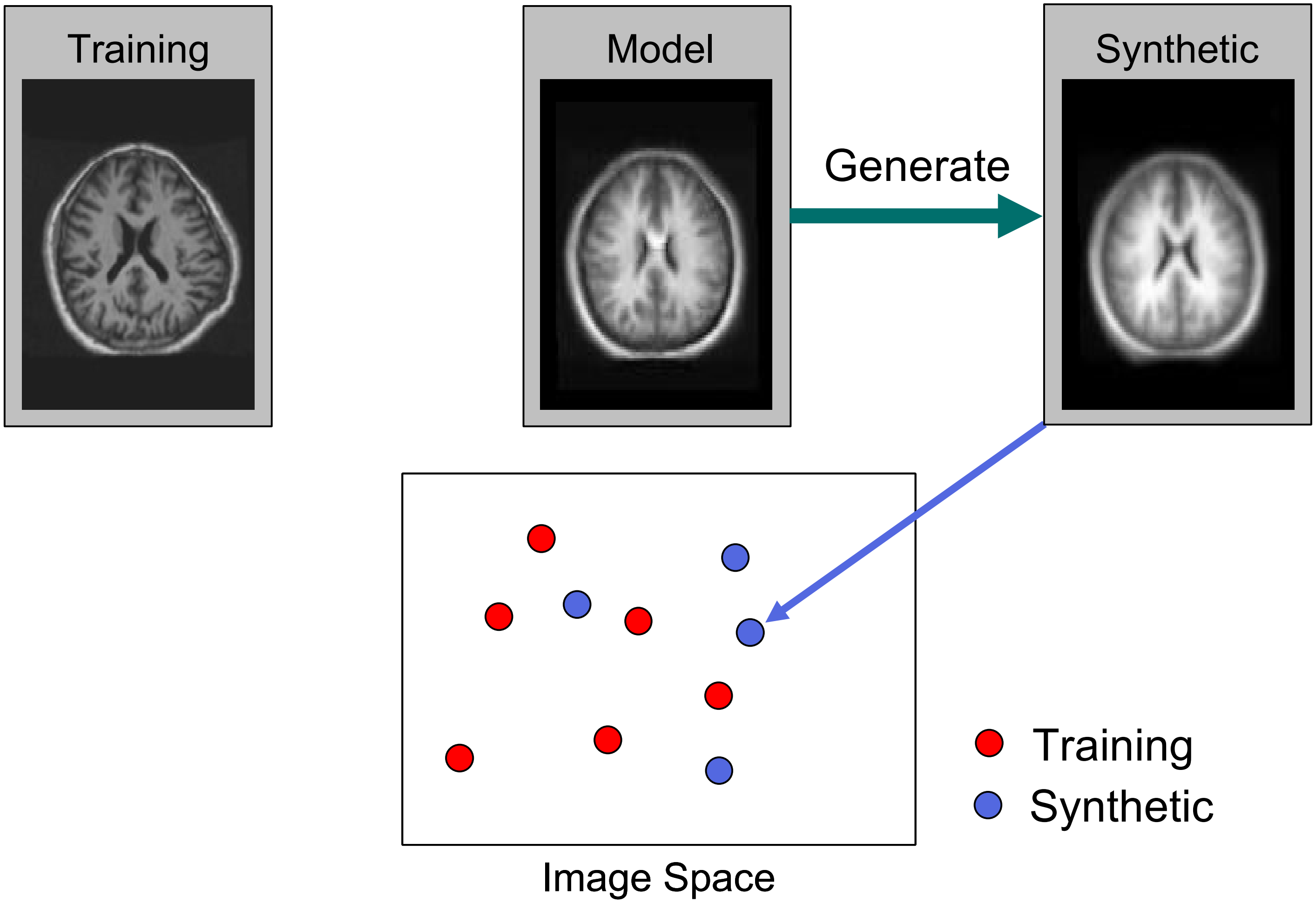

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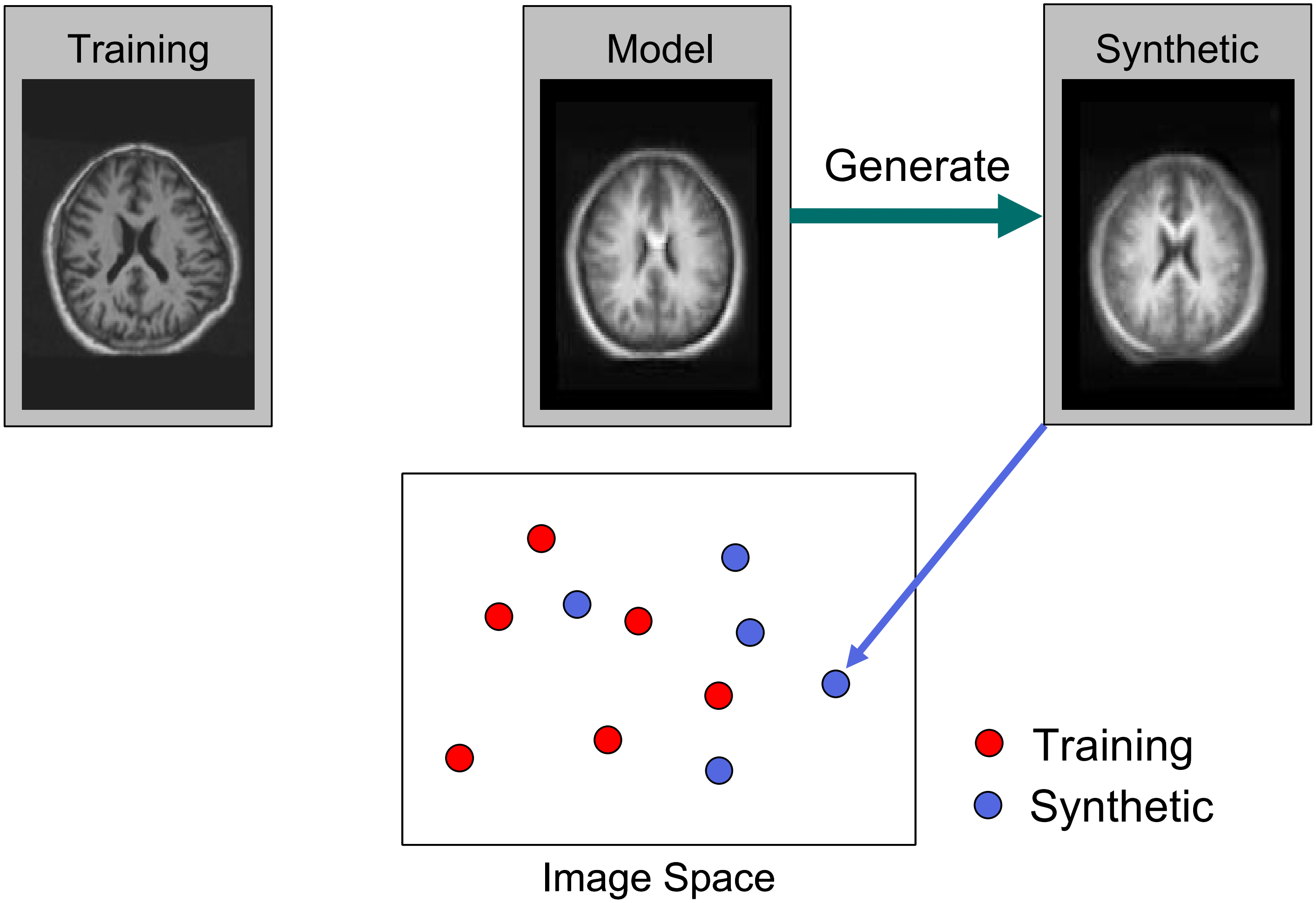

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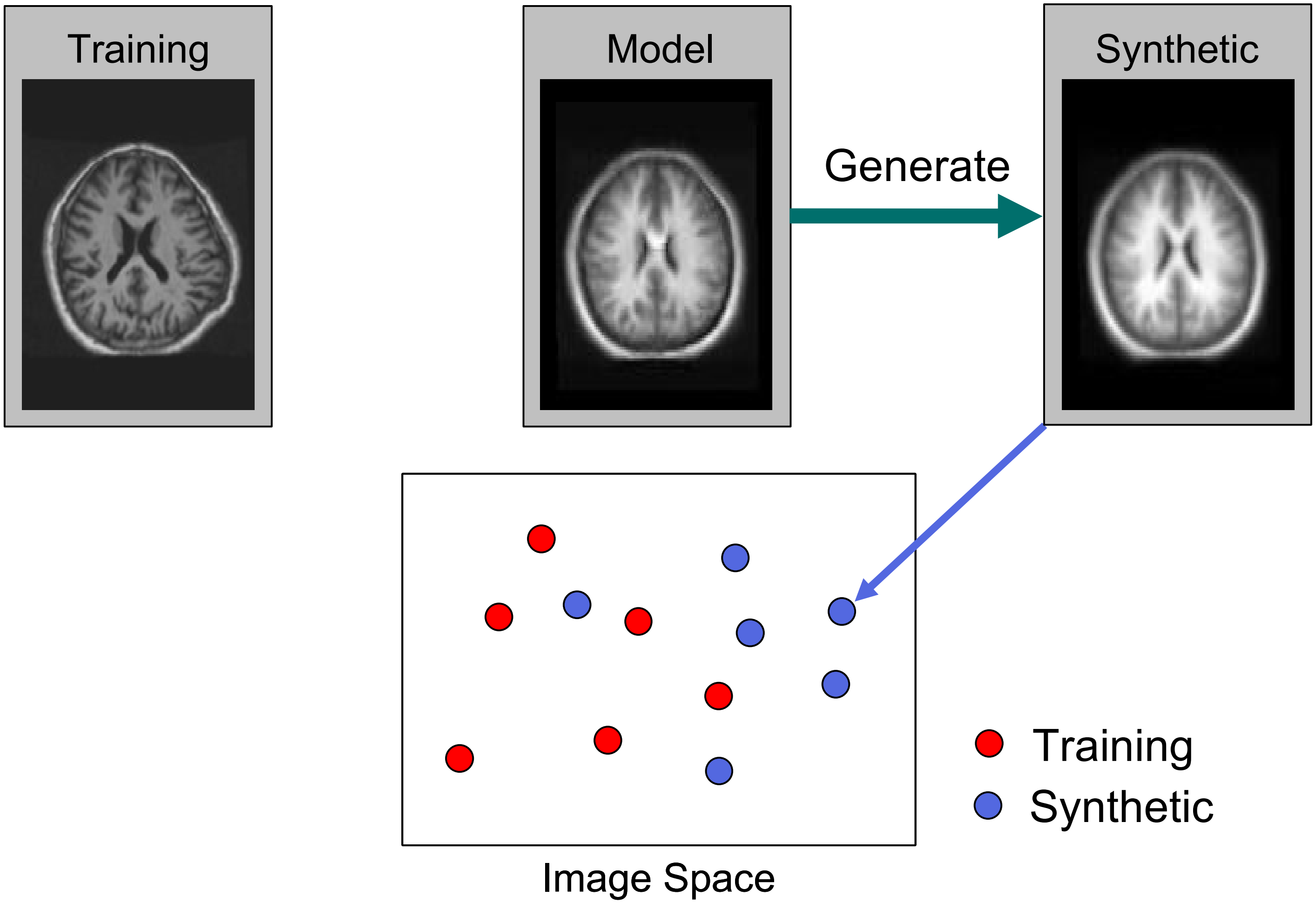

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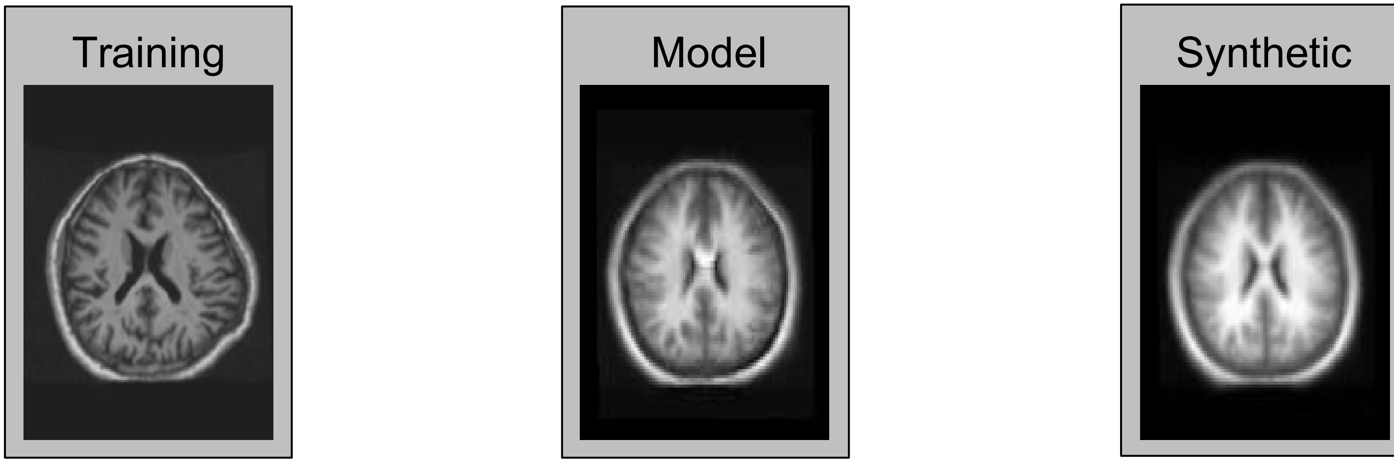

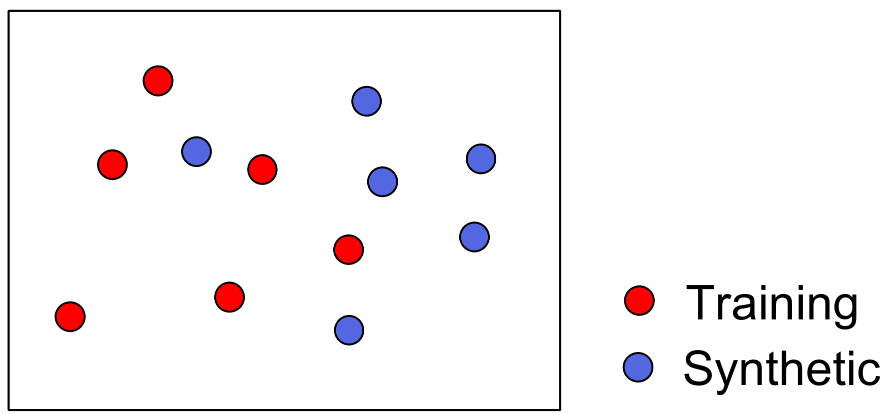

Image Space

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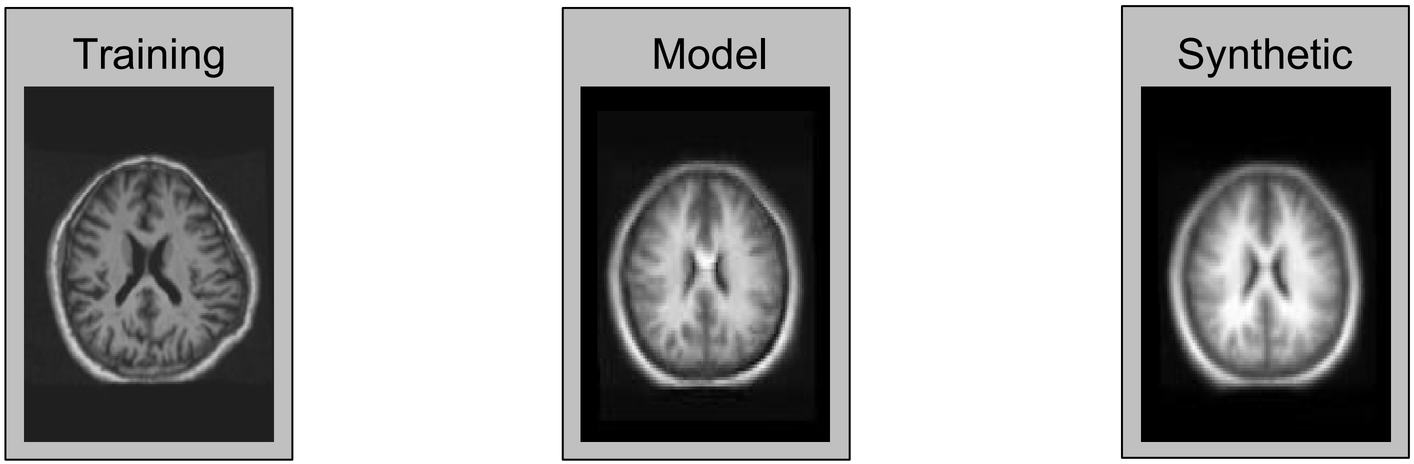
Training and Synthetic Images



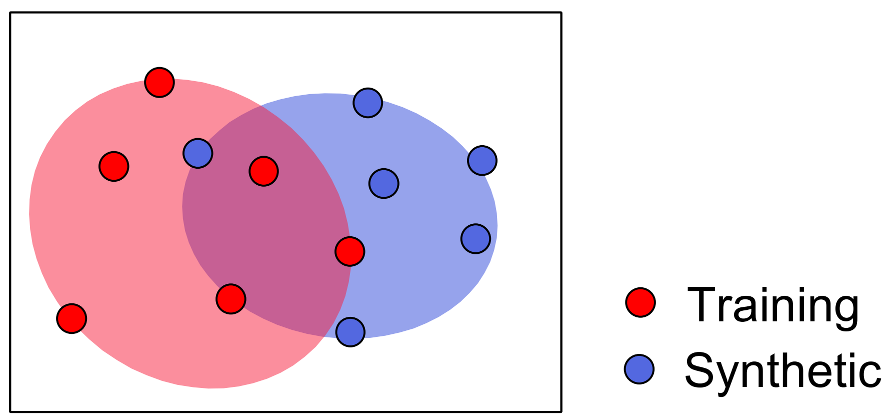
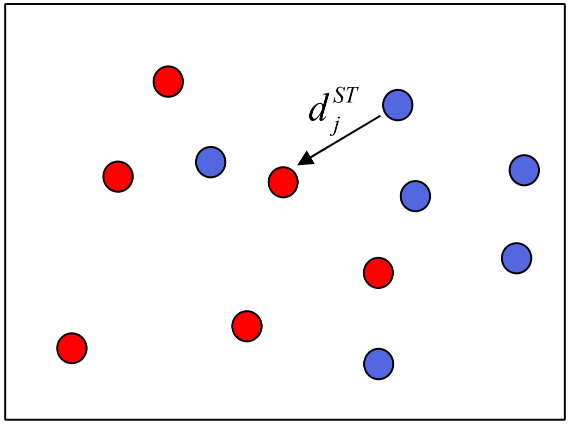


Image Space

Model Quality



Training

Synthetic

Given measure d of image distance

$$Specificity = \sum_{j=1}^{m} \left| d_j^{ST} \right| \Big/ m$$

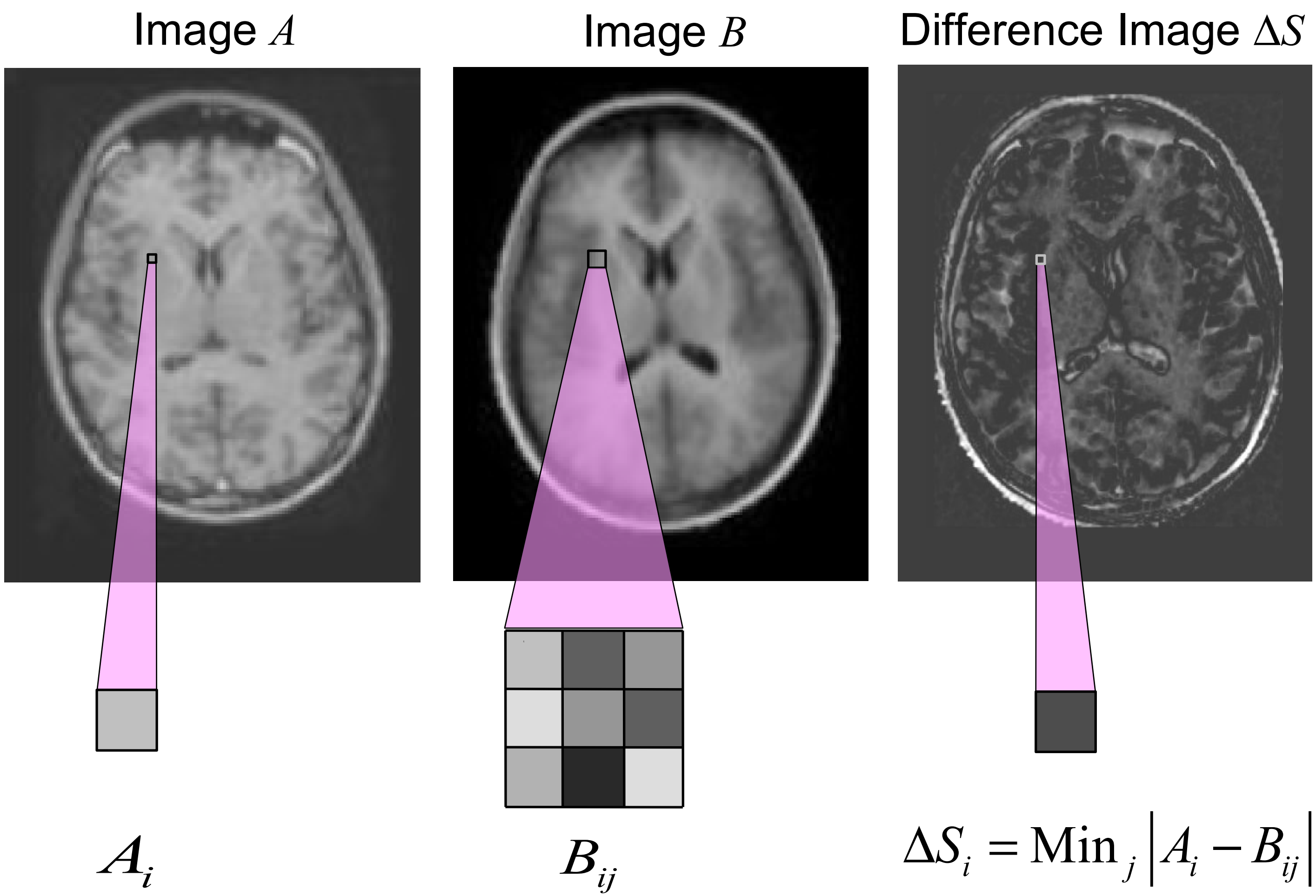
Mean distance to nearest training image

- Euclidean or shuffle distance d between images
- Better models have smaller distances, d
- Plot [-*Specificity*], which decreases as model degrades

Measuring Inter-Image Distance

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

Shuffle Distance



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

Varying Shuffle Radius

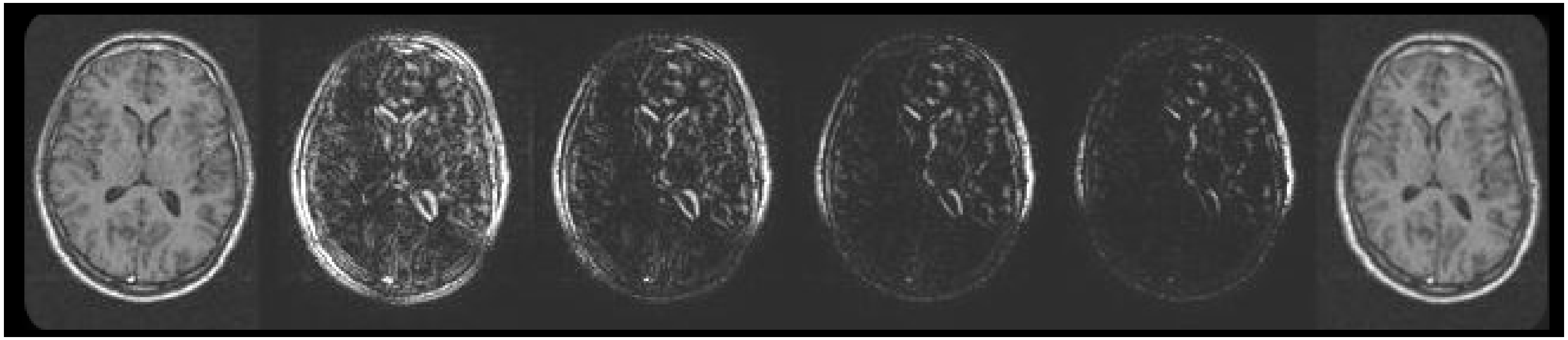


Image A r = 1 r = 1.5 r = 2.1 r = 3.7 Image B

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Validation Experiments

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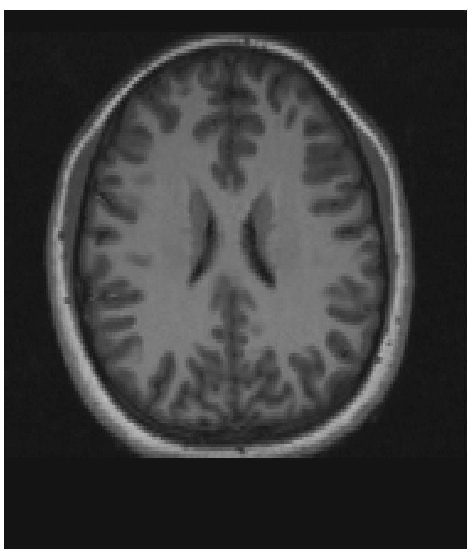
Experimental Design

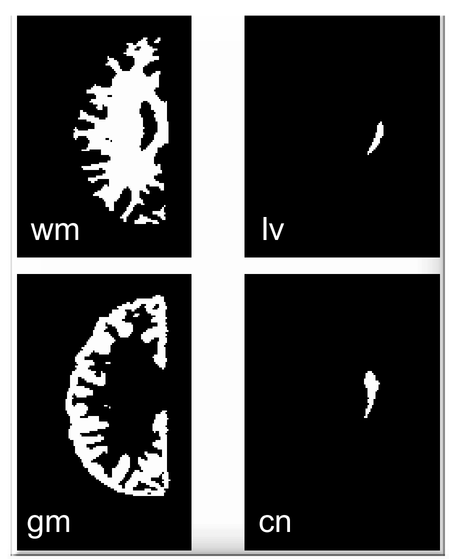
- MGH dataset (37 brains)
- Selected 2D slice
- Initial ‘correct’ NRR
- Progressive perturbation of registration
  - 10 random instantiations for each perturbation magnitude
- Comparison of the two different measures
  - overlap
  - model-based

Brain Data

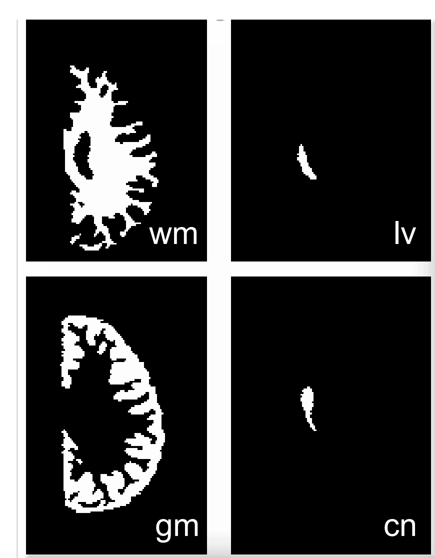
- Eight labels per image
  - L/R white/grey matter
  - L/R lateral ventricle
  - L/R caudate nucleus



Image



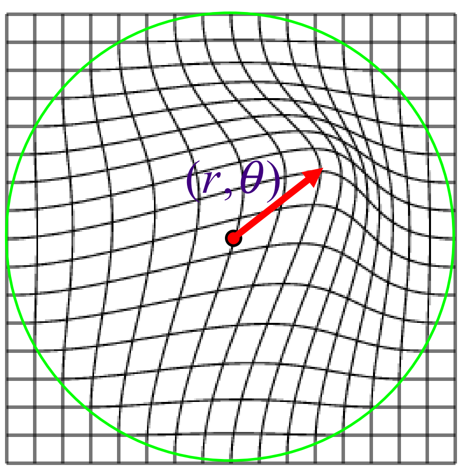
LH Labels



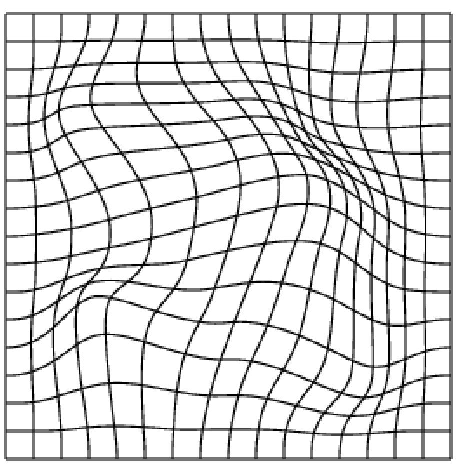
RH Labels

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

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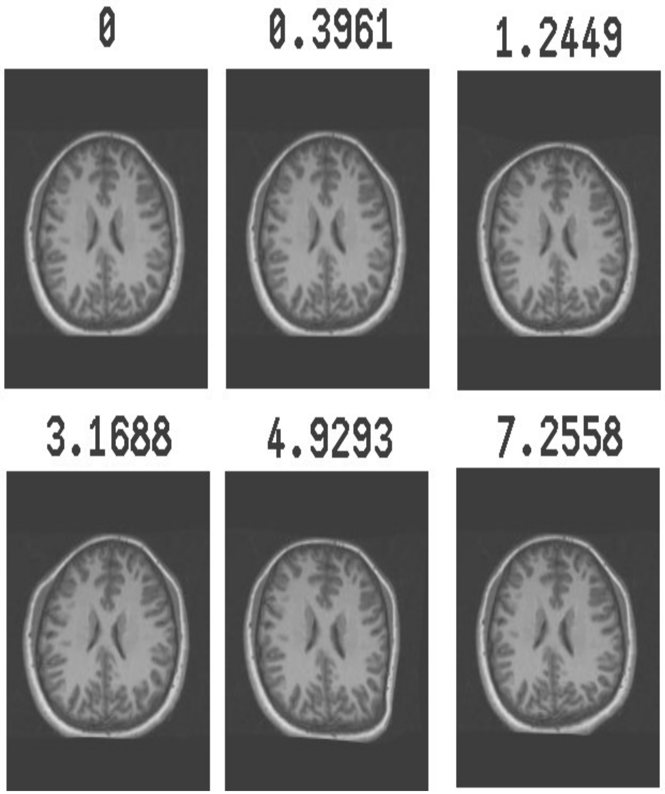
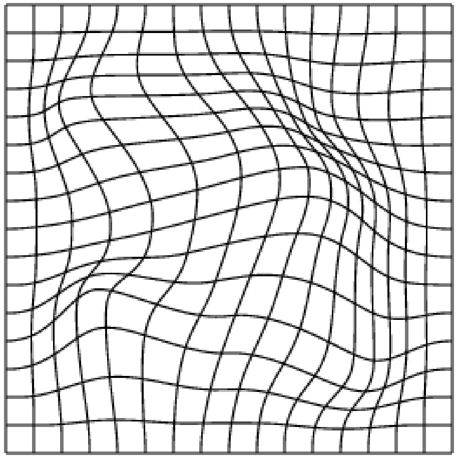
Examples of Perturbed Images



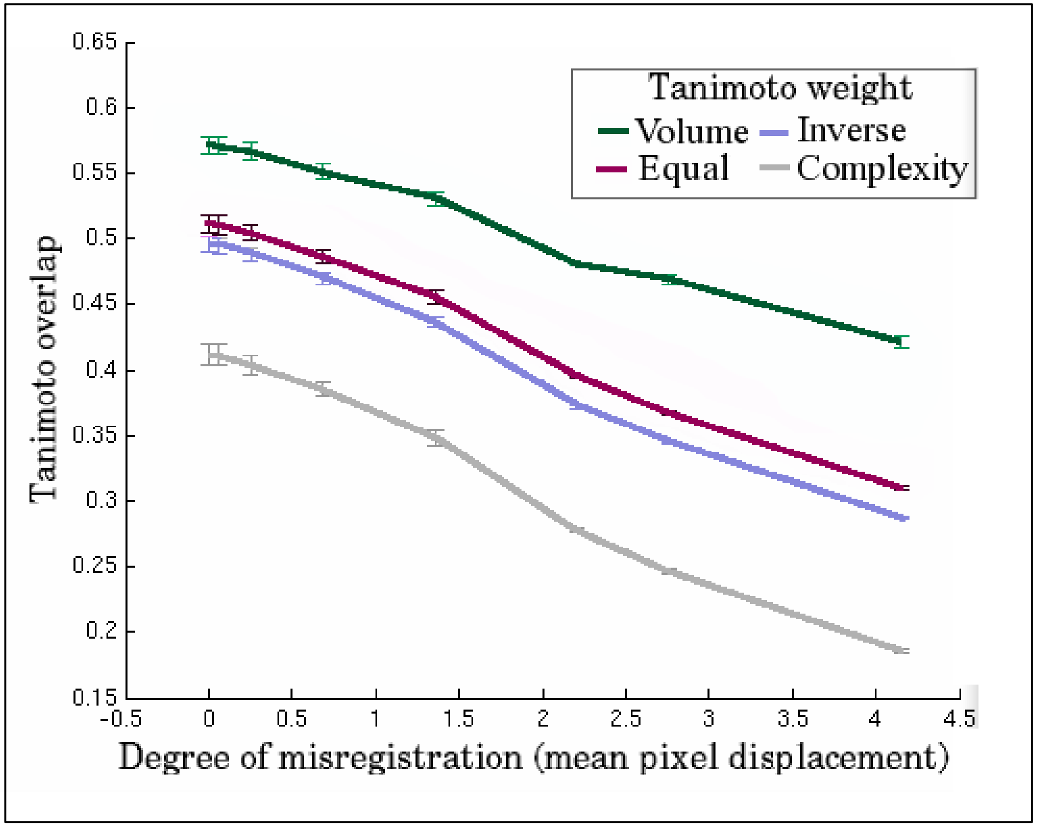
Increasing mean pixel displacement



Example warp

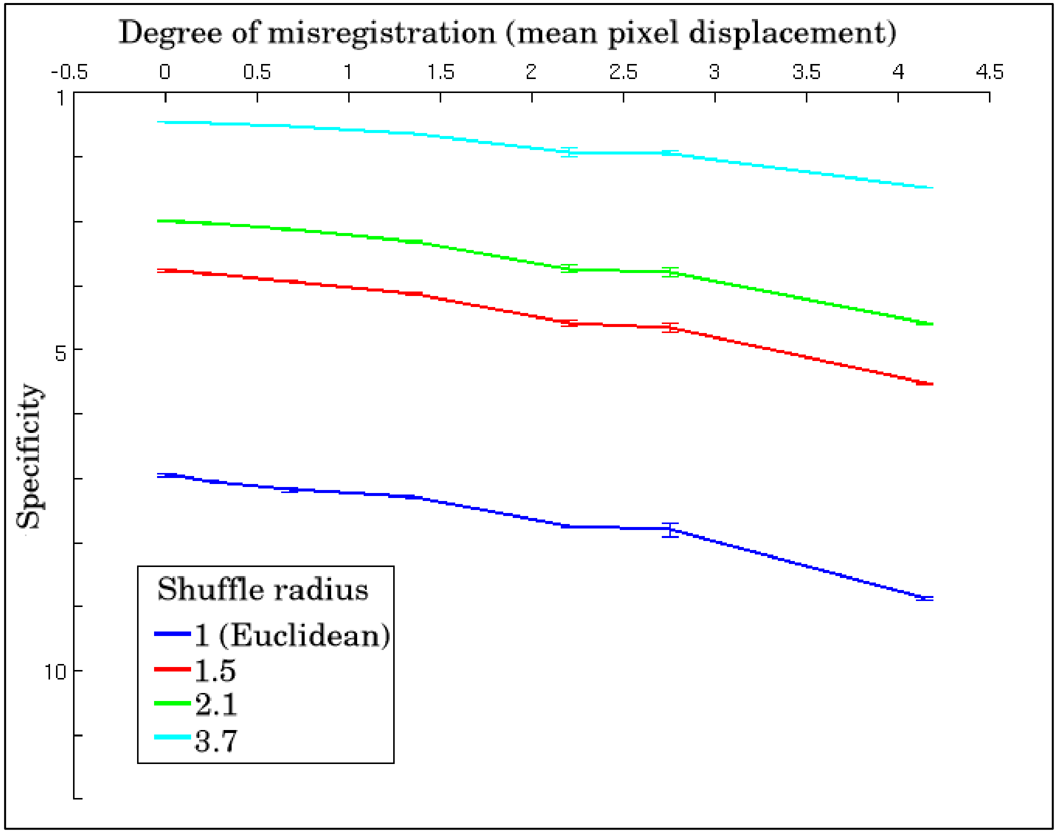
Results – Generalised Overlap

- Overlap decreases monotonically with misregistration



Results – Model-Based

- [-*Specificity*] decreases monotonically with misregistration



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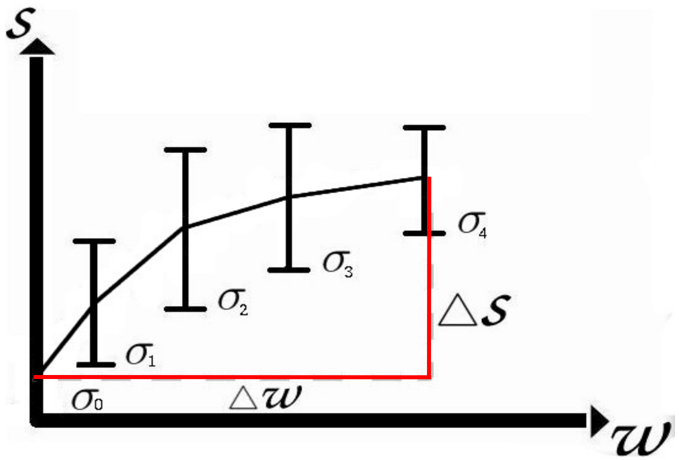
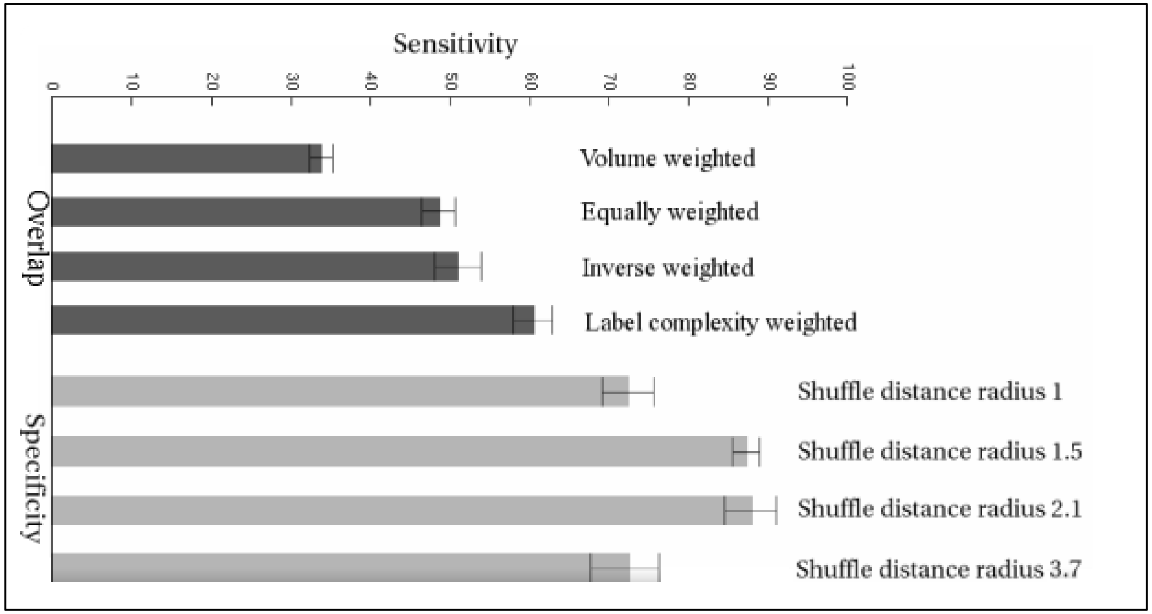
Results – Comparison

- 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



Results – Sensitivities

- Sensitivity
  - ability to detect small changes in registration
  - high sensitivity good



- Specificity more sensitive than overlap

Further Tests – Noise

- A measure of robustness to noise is sought
- Validation experiments repeated with noise applied
  - each image has up to 10% white noise added
  - two instantiations of set perturbation are used
- Results indicate that the model-based method is robust
  - changes in Generalisation and Specificity remain detectable
  - curves remain monotonic
  - noise can potentially exceed 10%

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Practical Application

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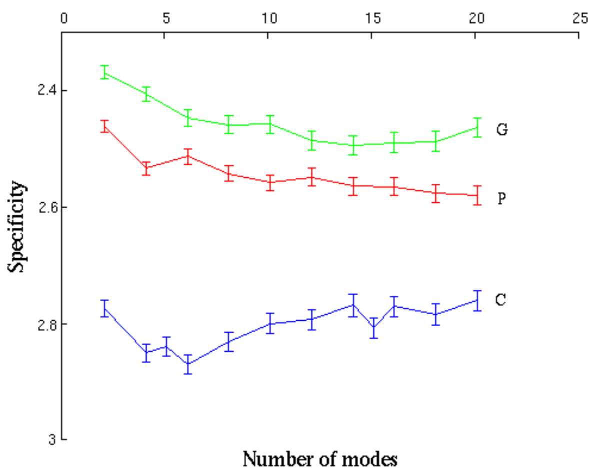
Practical Application

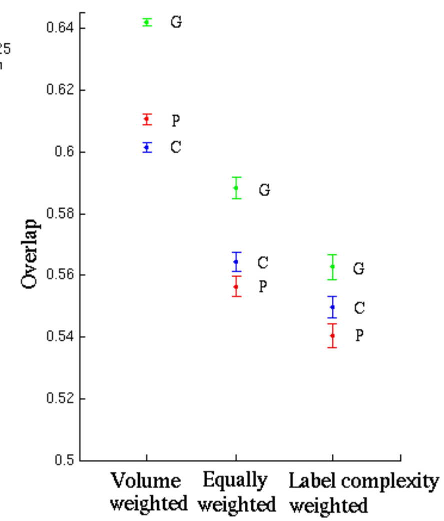
- 3 registration algorithms compared
  - Pair-wise registration
  - Group-wise registration
  - Congealing
- 2 brain datasets used
  - MGH dataset
  - Dementia dataset
- 2 assessment methods
  - Model-based (Specificity)
  - Overlap-based

Practical Application - Results

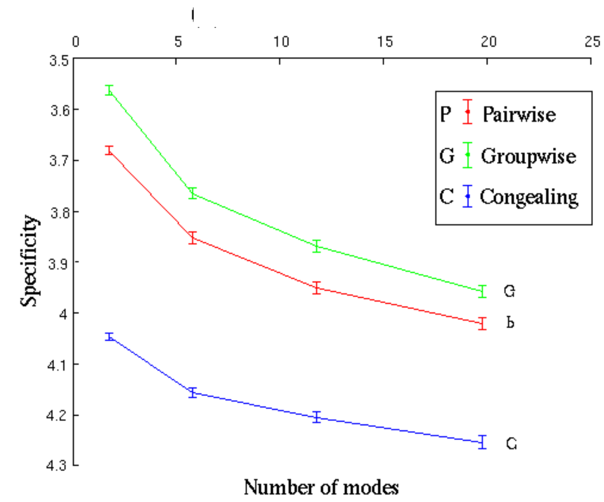
- Results are consistent
- Group-wise > pair-wise > congealing



MGH Data



MGH Data



Dementia Data

Extension to 3-D

- 3-D experiments
- Work in progress
  - validation experiments laborious to replicate
  - comparison of 4-5 NRR algorithms
- Fully-annotated IBIM data
- Results can be validated by measuring label overlap

Conclusions

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