Localization of 3D Anatomical Structures Using Random Forests and Discrete Optimization

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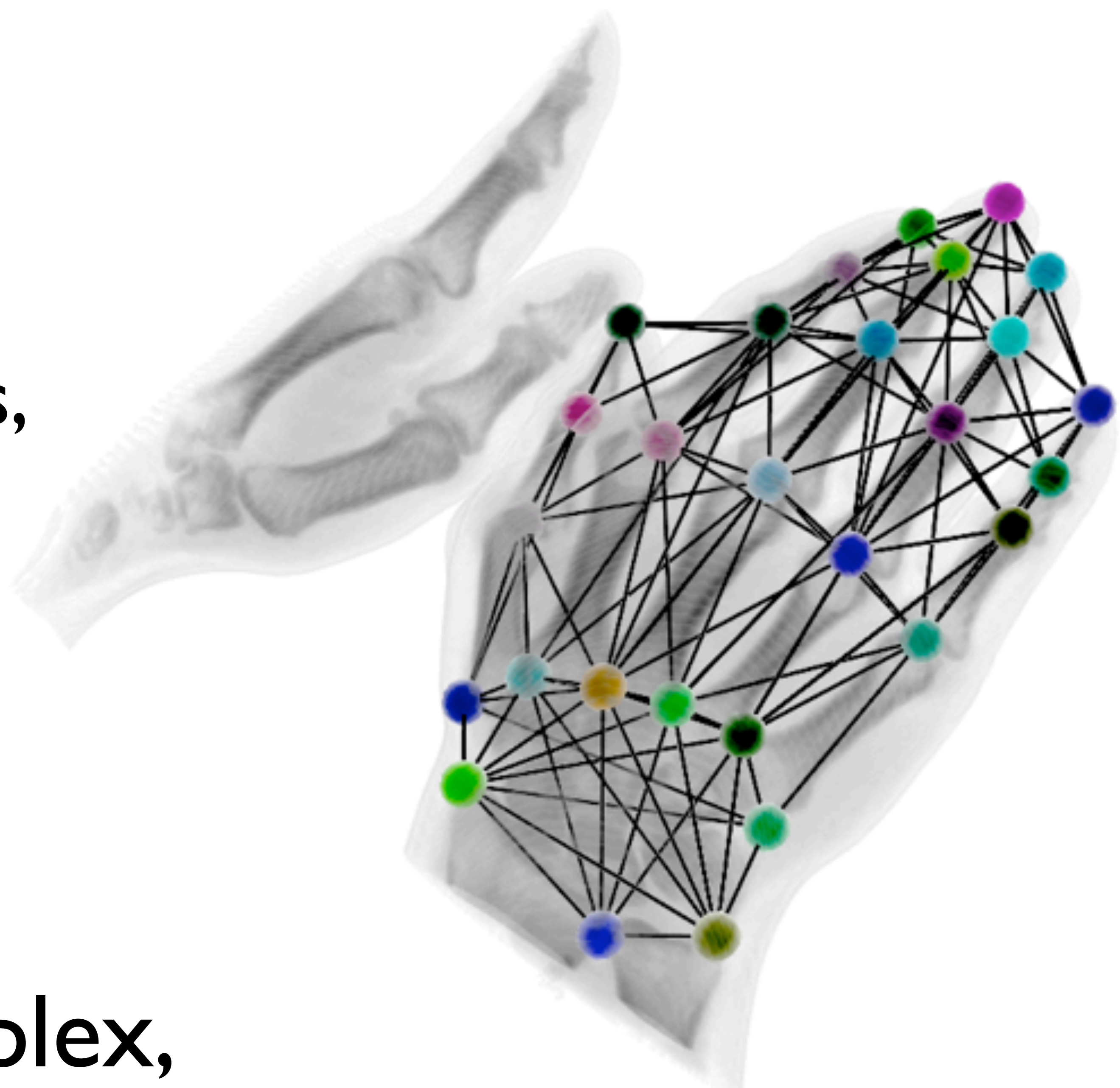
Motivation

- Most segmentation approaches require spatial initialization
  - ASM, AAM, GraphCuts, LevelSets
- Often application specific
- Localization of complex, self-similar structures

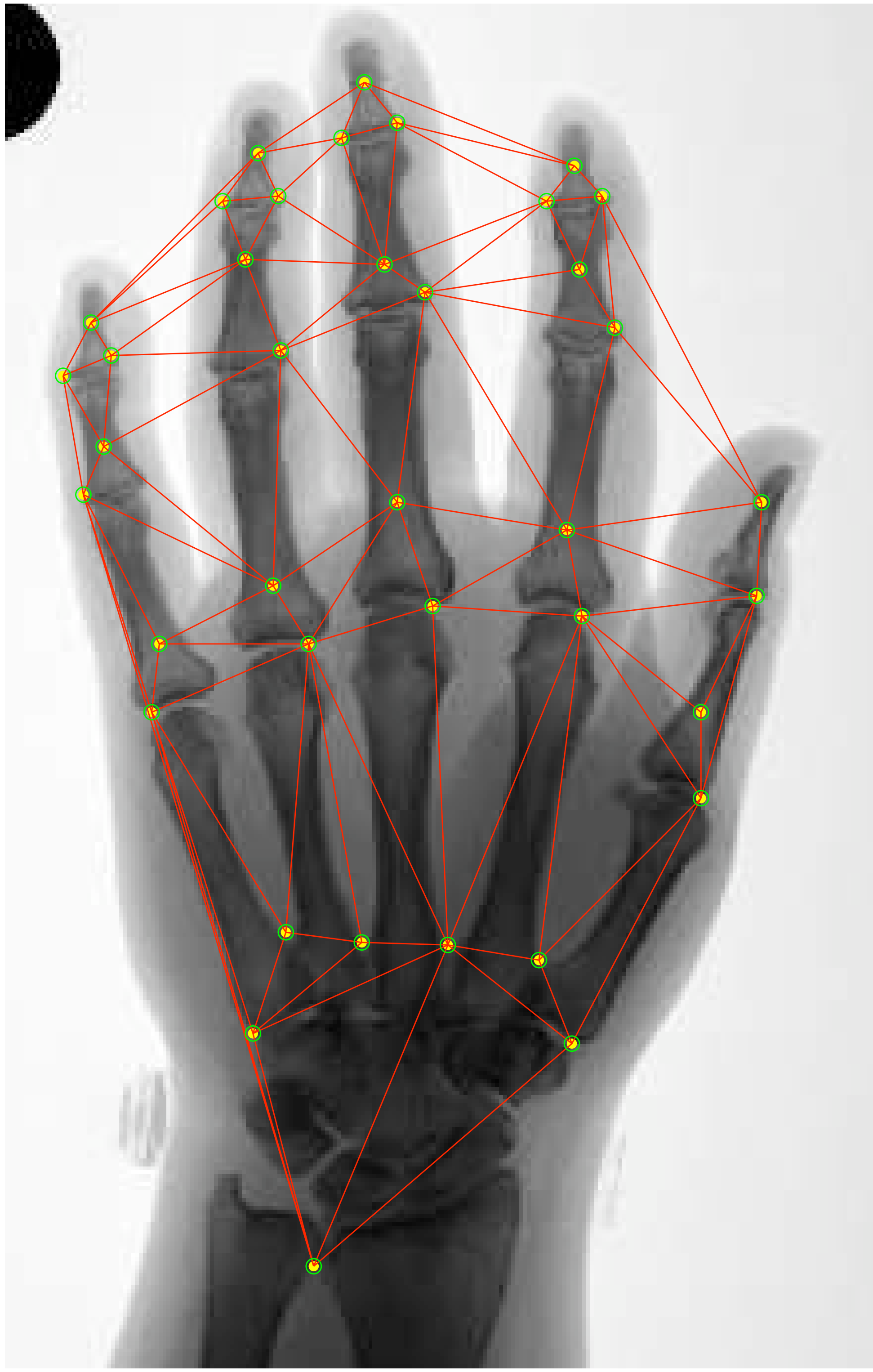


Localization Approaches

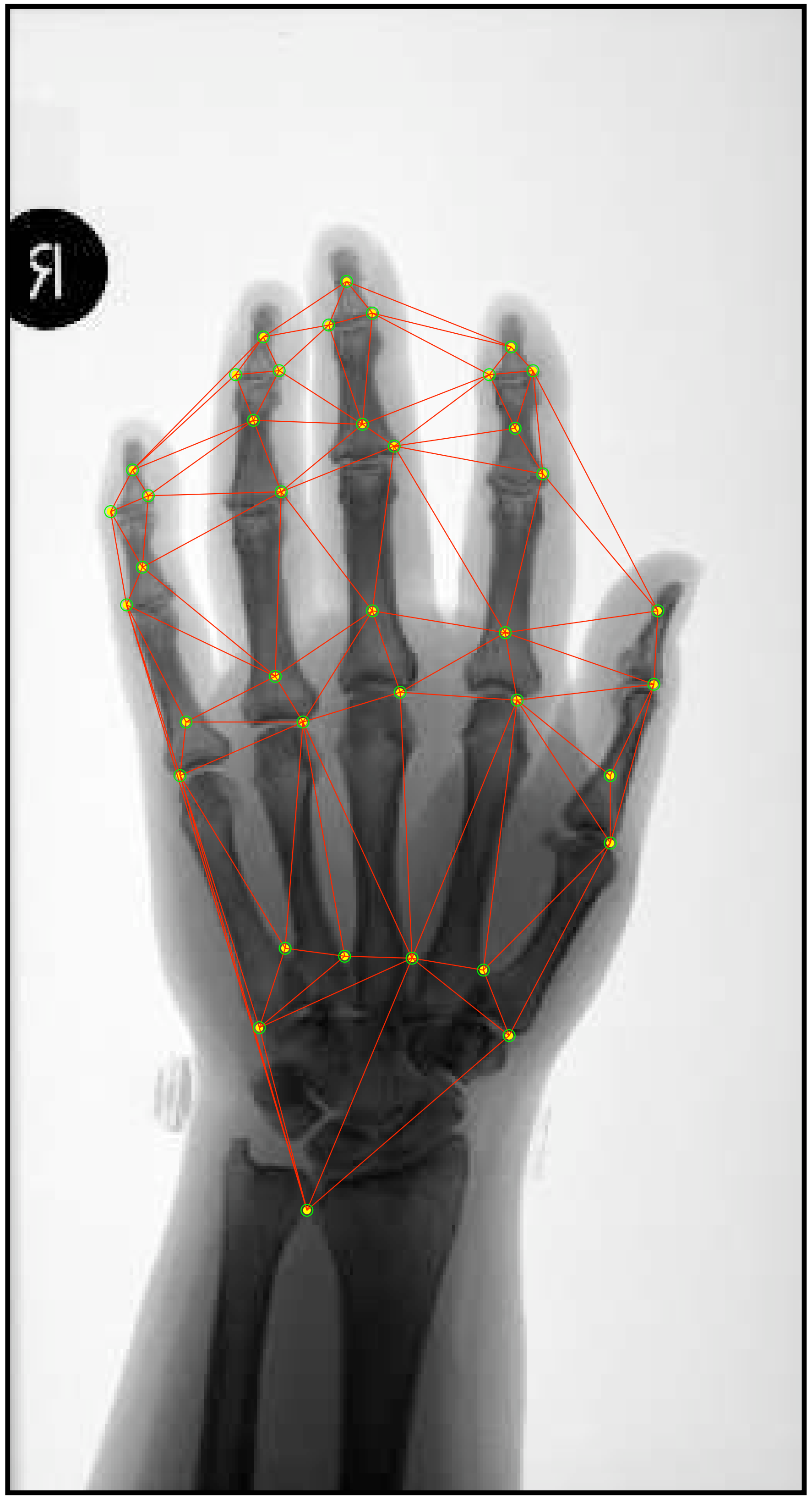
- Sparse MRF Appearance Models [Donner 2007,2010]
- Marginal Space Learning [Zheng 2009]
- Hierarchical Parsing [Seifert 2009]
- Random Forests [Criminisi 2009, Lempitsky 2009]
- A*-based optimization [Bergtholdt 2010]

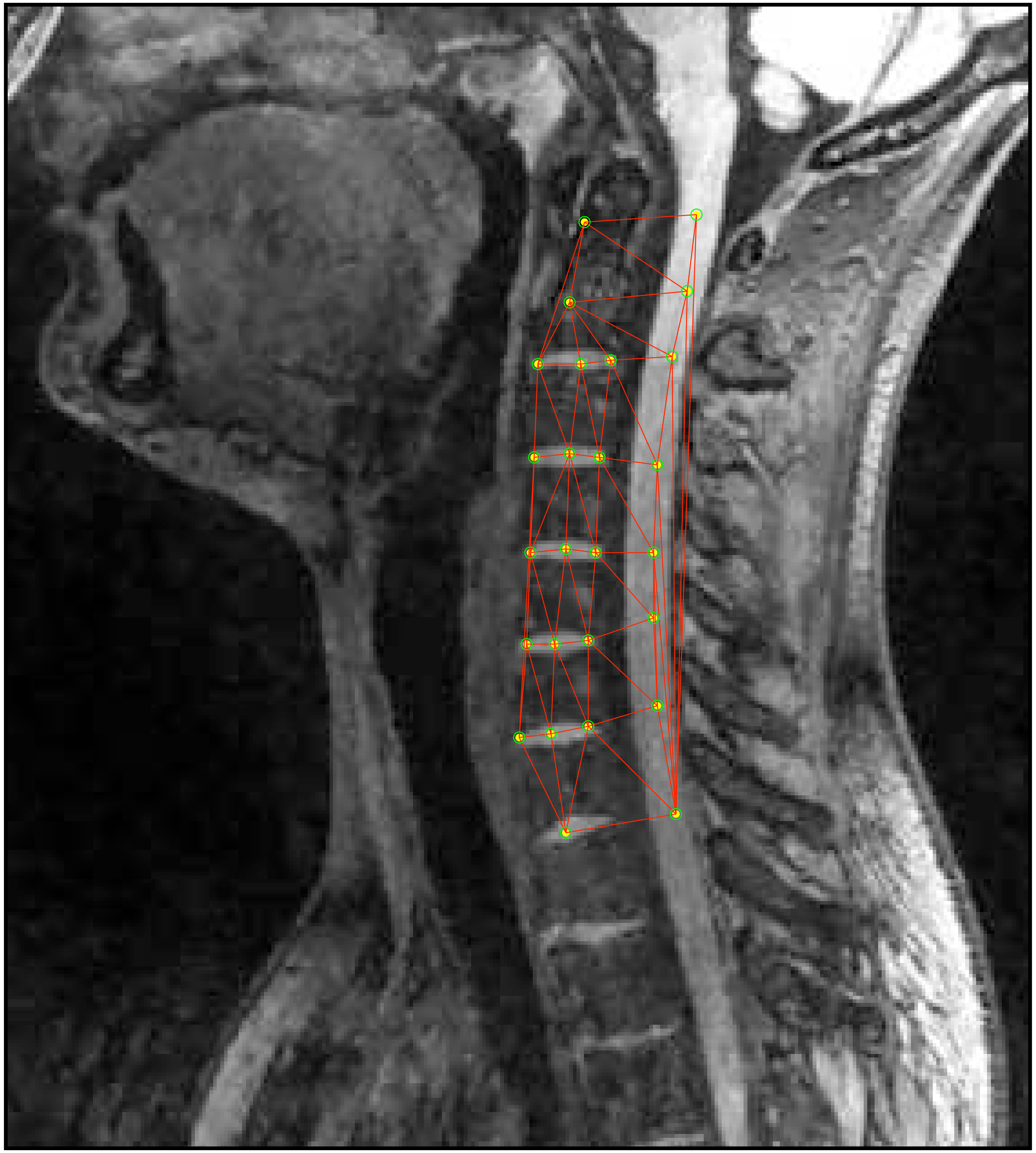
Sparse MRF Appearance Models

- Based on interest points
  - E.g. GVFpoints, Harris Corners
- Sparse Appearance Model
  - Elastic geometric model
  - Local descriptors around landmarks / edges
- Matching task formulated as MRF



Successful Matching



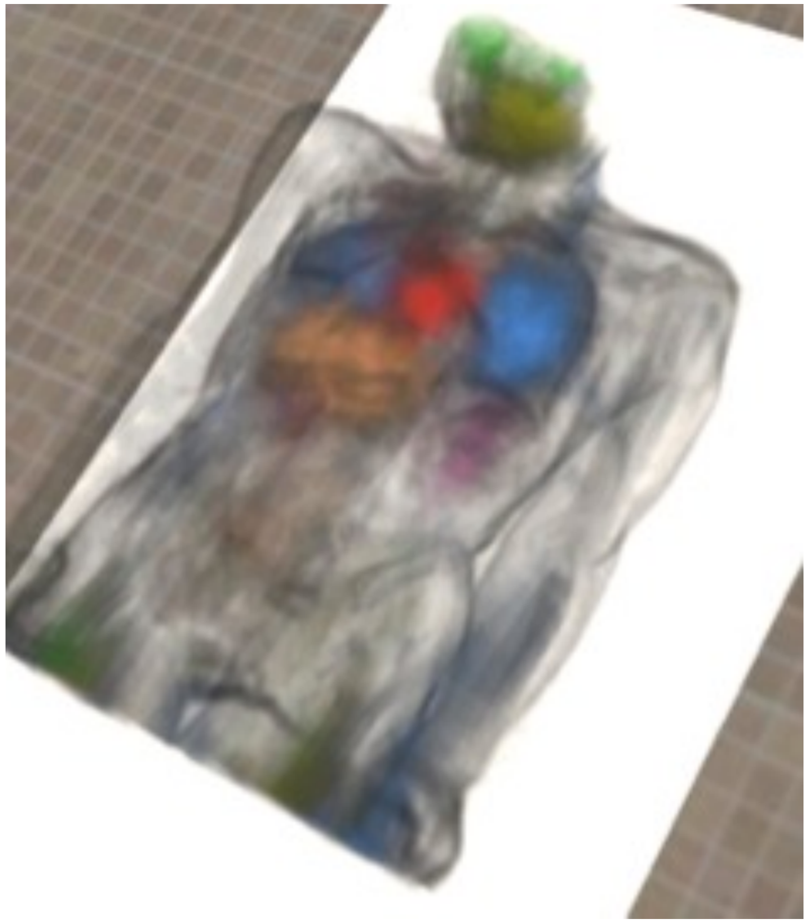


Problems in 3D

- Too many interest points
  - Corners or Symmetry to ambiguous
  - Multiple types of interest points?
- Local descriptors
  - How too choose?
  - *Which distance metric?*
- Size of MRF becomes intractable

Random Forest based Localization

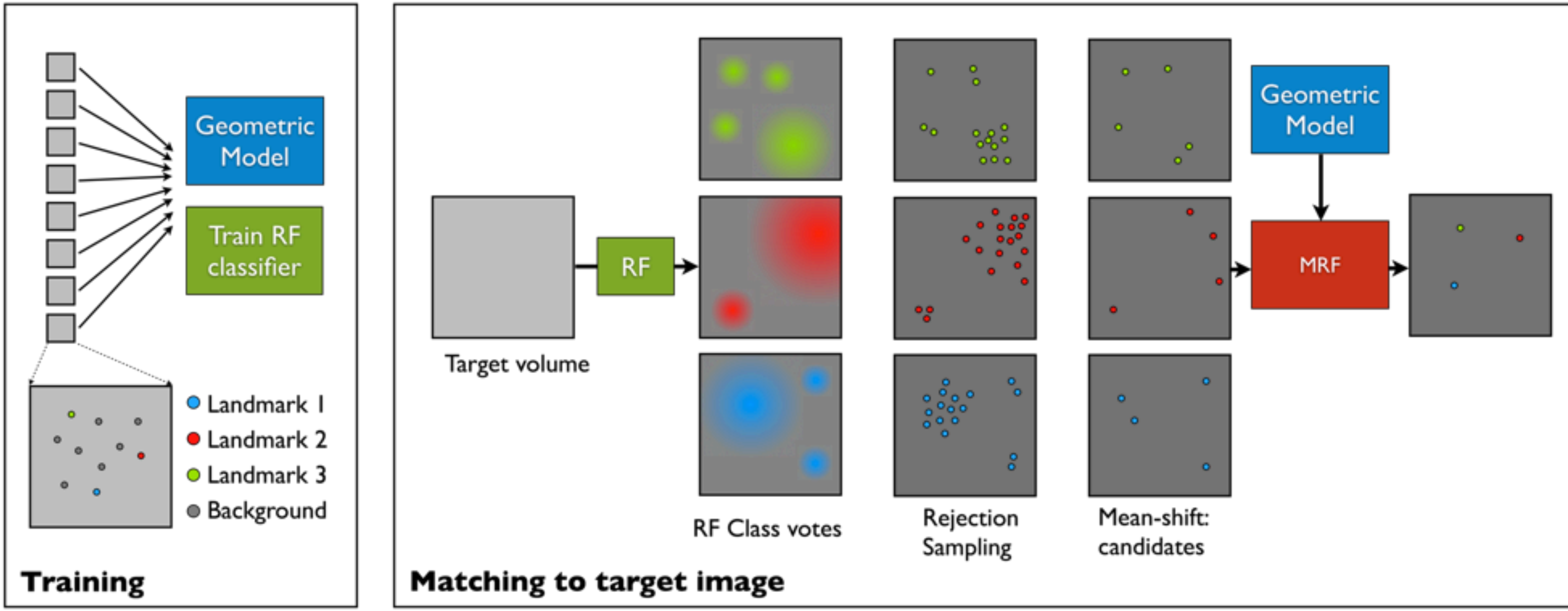
- Decision Forests with Long-Range Spatial Context for Organ Localization in CT Volumes
  [Criminisi 2009]
  - Haar-like features with random perturbation
  - Annotation trough bounding box
  - Fast GPU implementation
  - Focused on entire organs

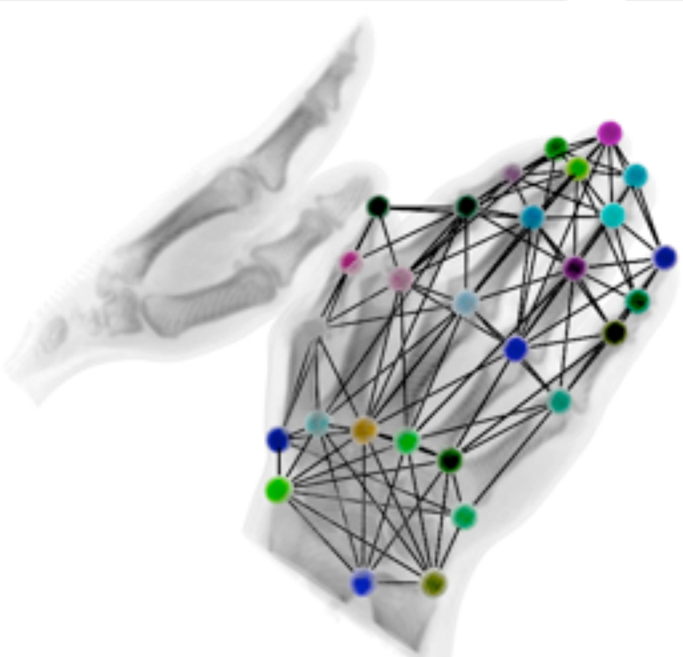


Proposed Approach

- Finding candidate points through classification
  - Haar-like features
  - Random forest classification
  - Meanshift on sampled classification probabilities: cluster centers as candidate points
- Probability estimation for MRF nodes/edges
  - Local support of candidate point
  - Edge probabilities from Gaussian distributions
  - Simplified MRF graph through sparsity of label/edge probabilities

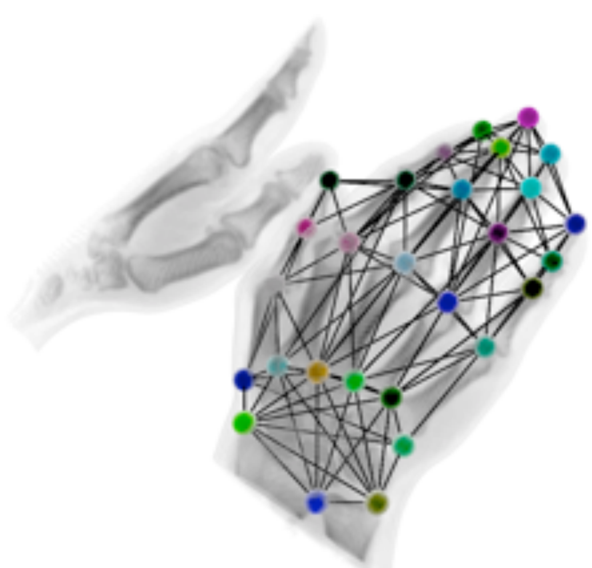
Flow Chart

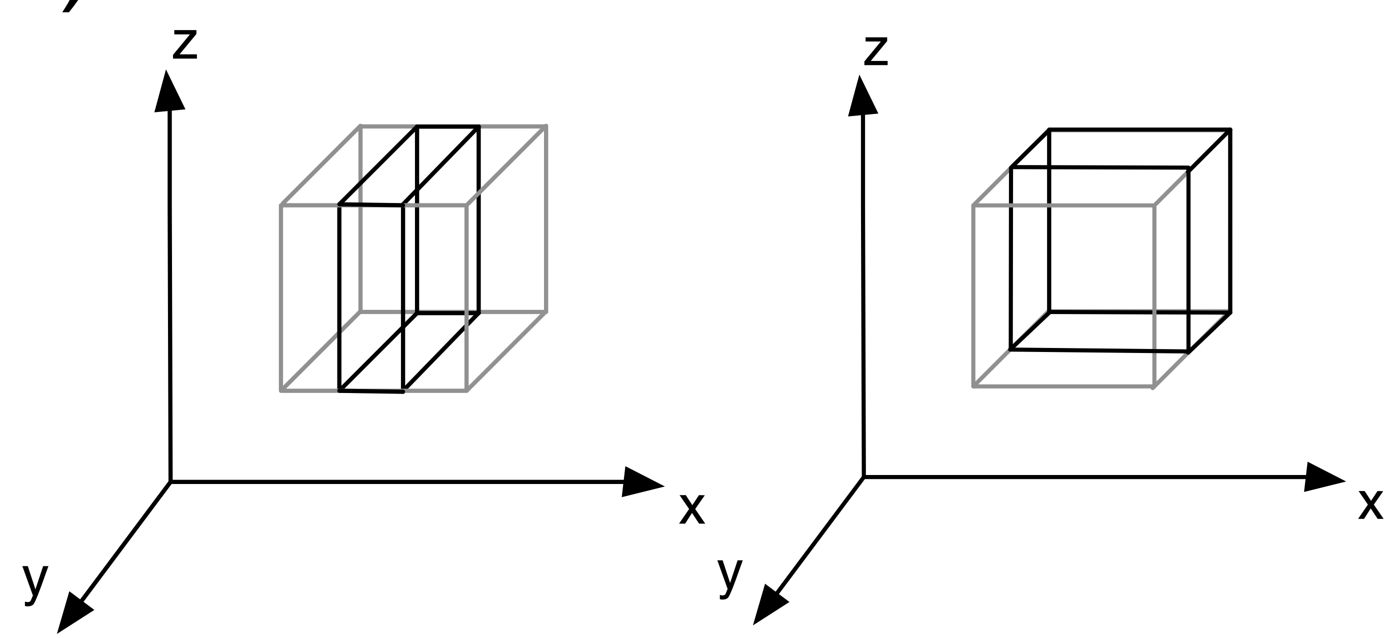

Geometric Model
Train RF classifier
Landmark 1
Landmark 2
Landmark 3
Background
Training
Target volume
RF
RF Class votes
Rejection Sampling
Mean-shift: candidates
Geometric Model
MRF
Matching to target image



Learning Candidate Point Detectors

- Landmarks selected in each training sample
- Features computed for all voxels within a 3 voxel radius
- Haar-like features, using integral volumes
- 7 Features (average, 3 edge, 3 ridge) on 3 scales (8, 16, 32 vx)



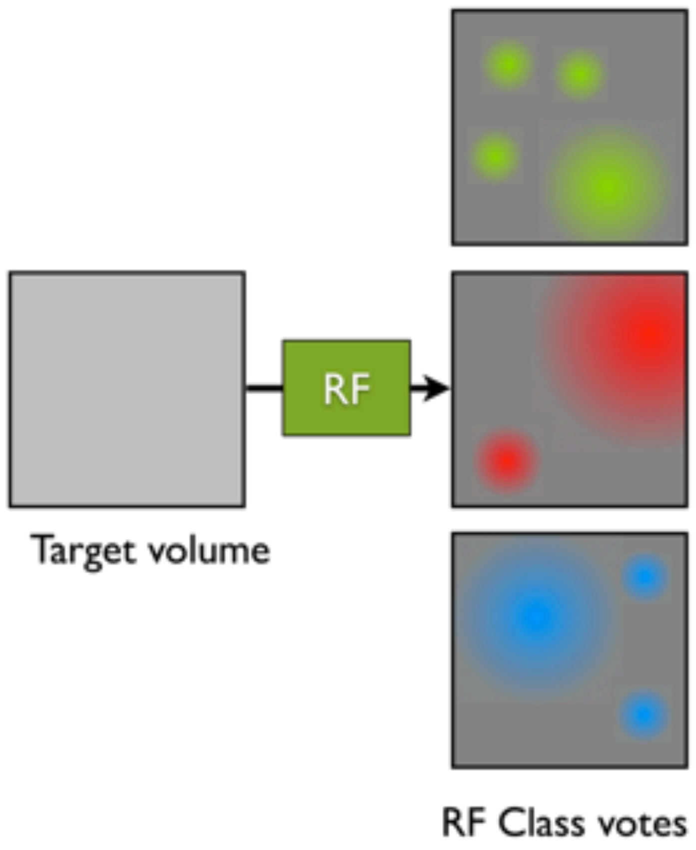


Random Forest Training

- One class per landmark
- + 1 background class, randomly sampled

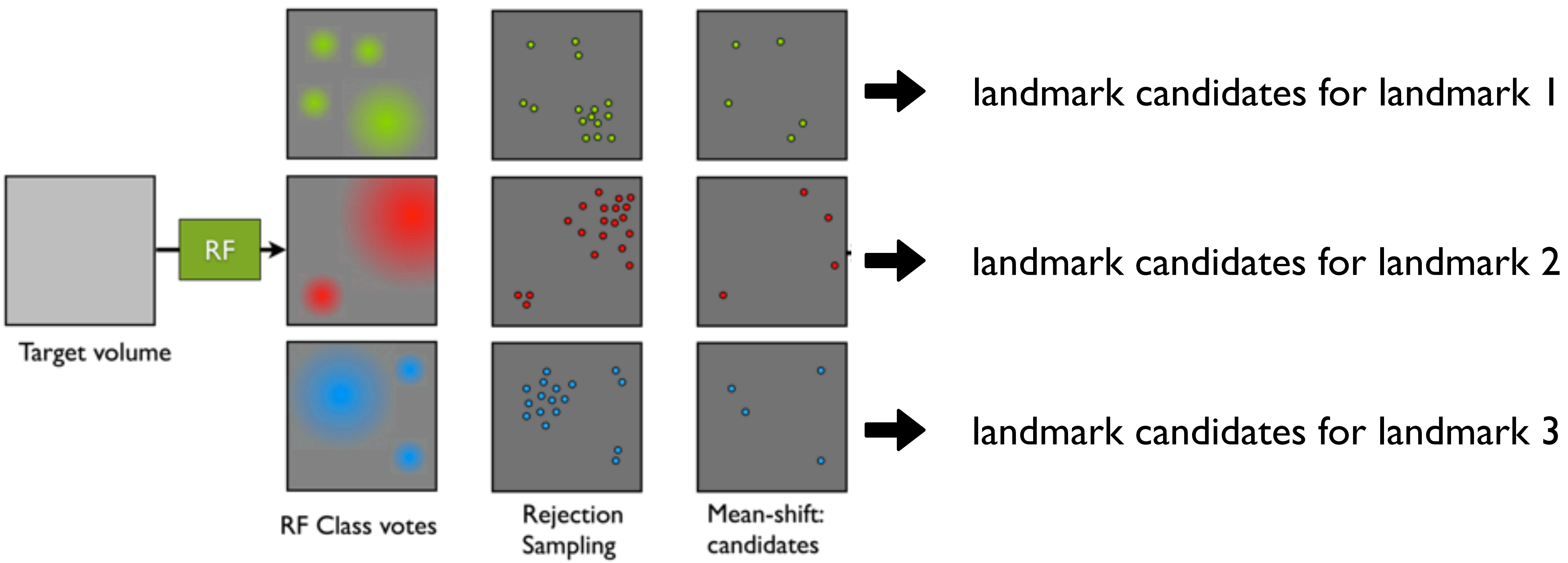
Random Forest Classification

- Vote count for each class = probability estimate for that landmark



Sampling & Mean Shift

- Rejection sampling from normalized vote counts
- Sum ofvotes per cluster = local support of the candidate



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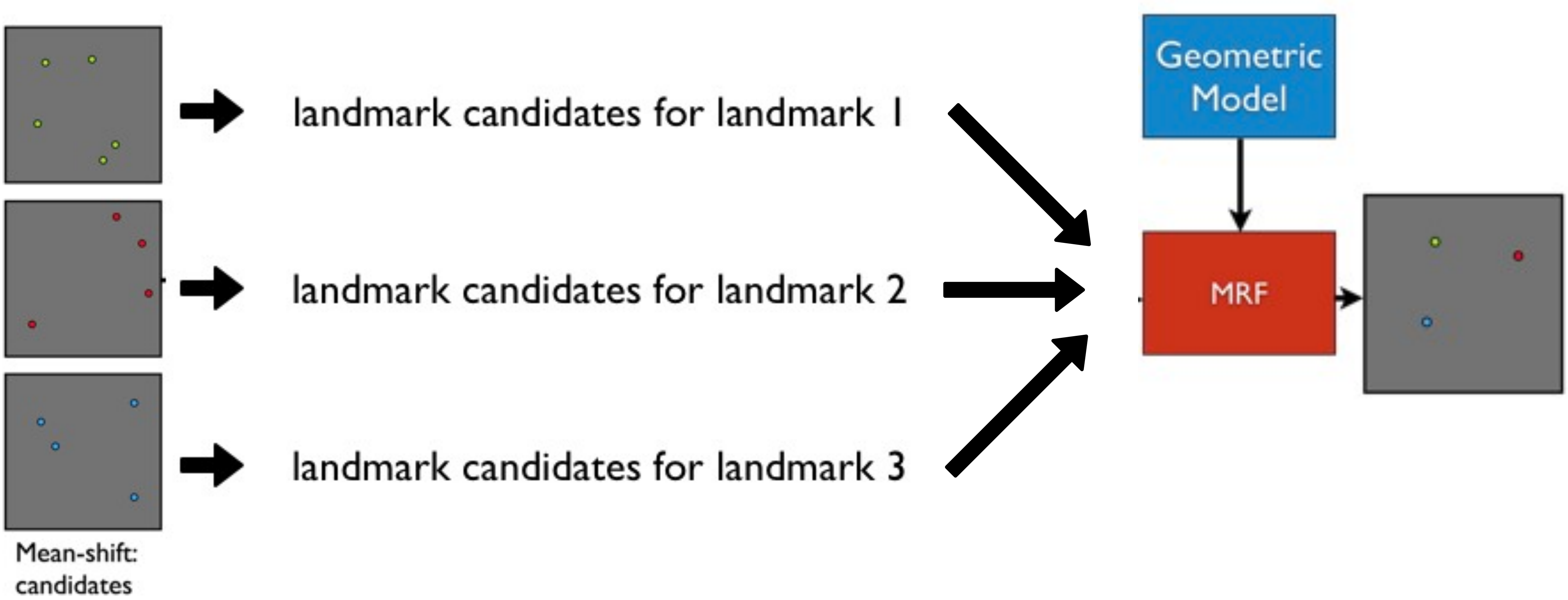
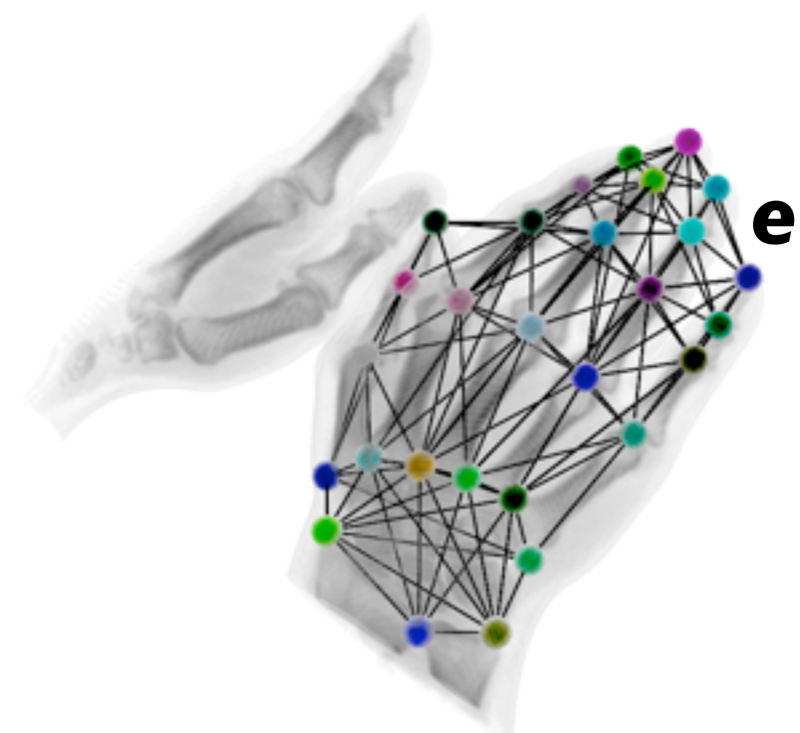
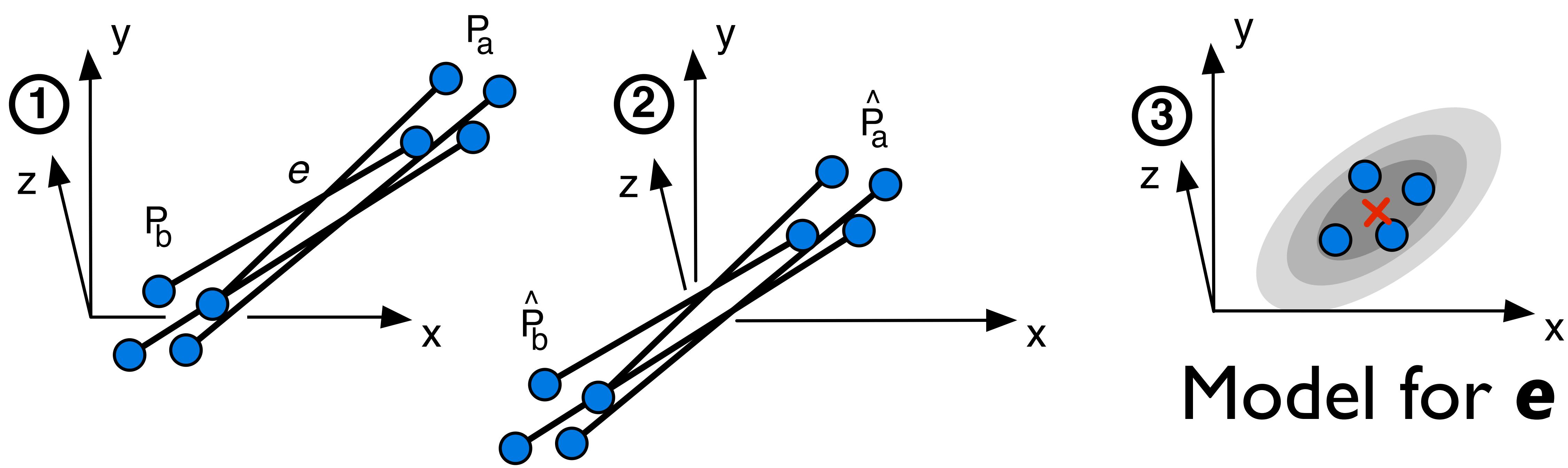


Geometric Model

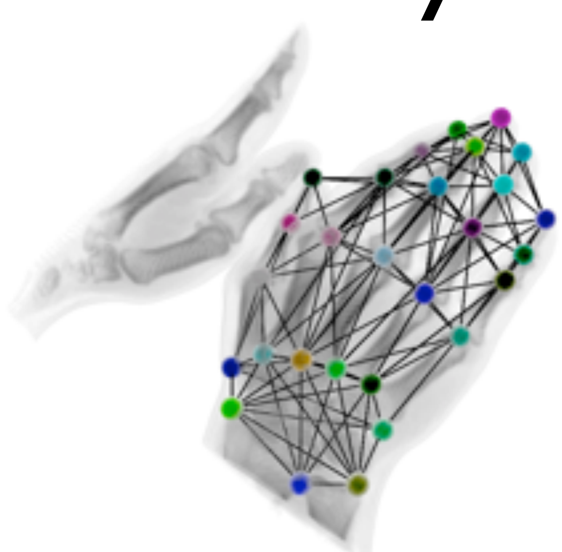
- Specified topology, following anatomical connectivity
- Estimate Gaussian distribution of length and orientation for each edge

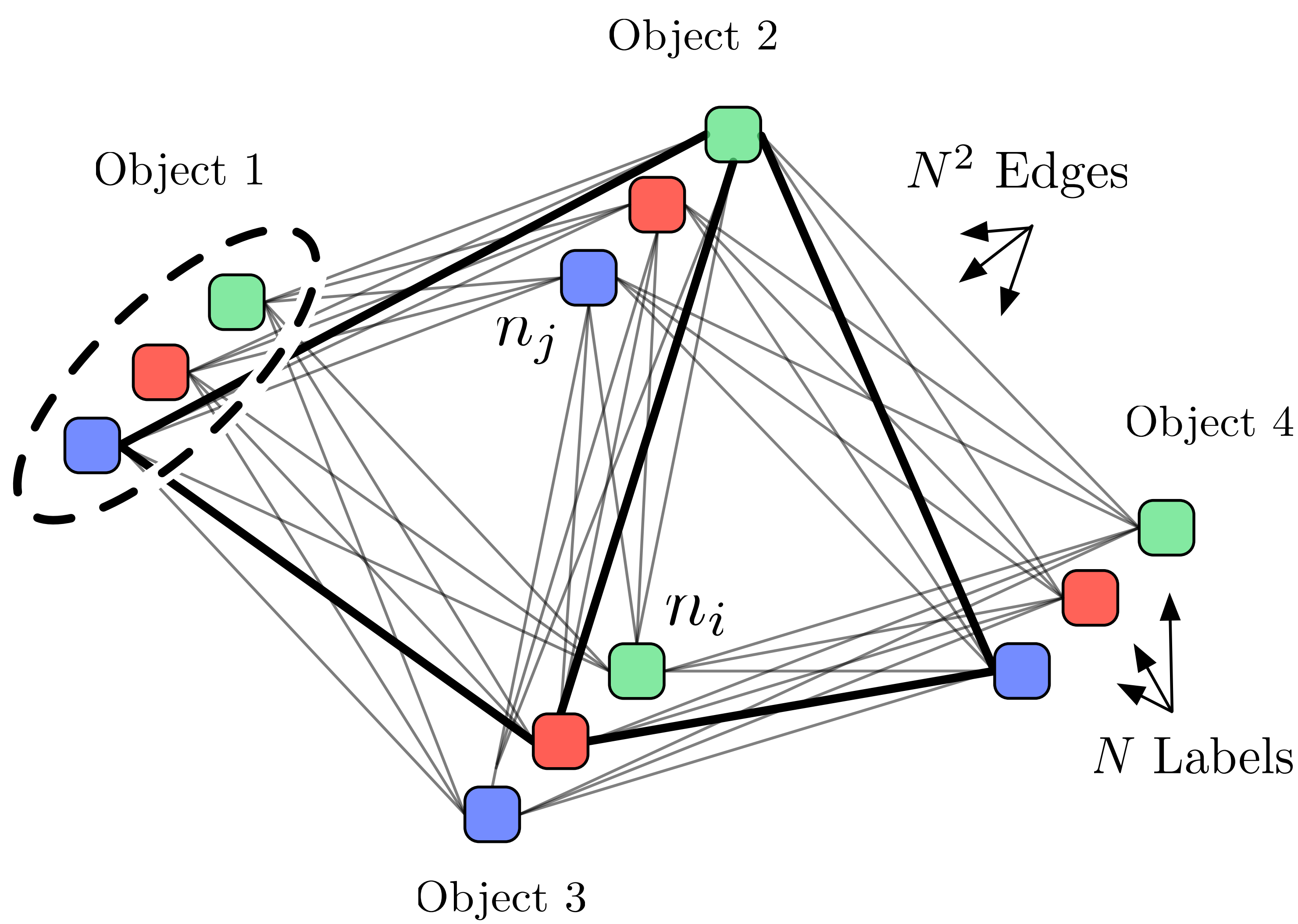




Constuct Markov Random Field

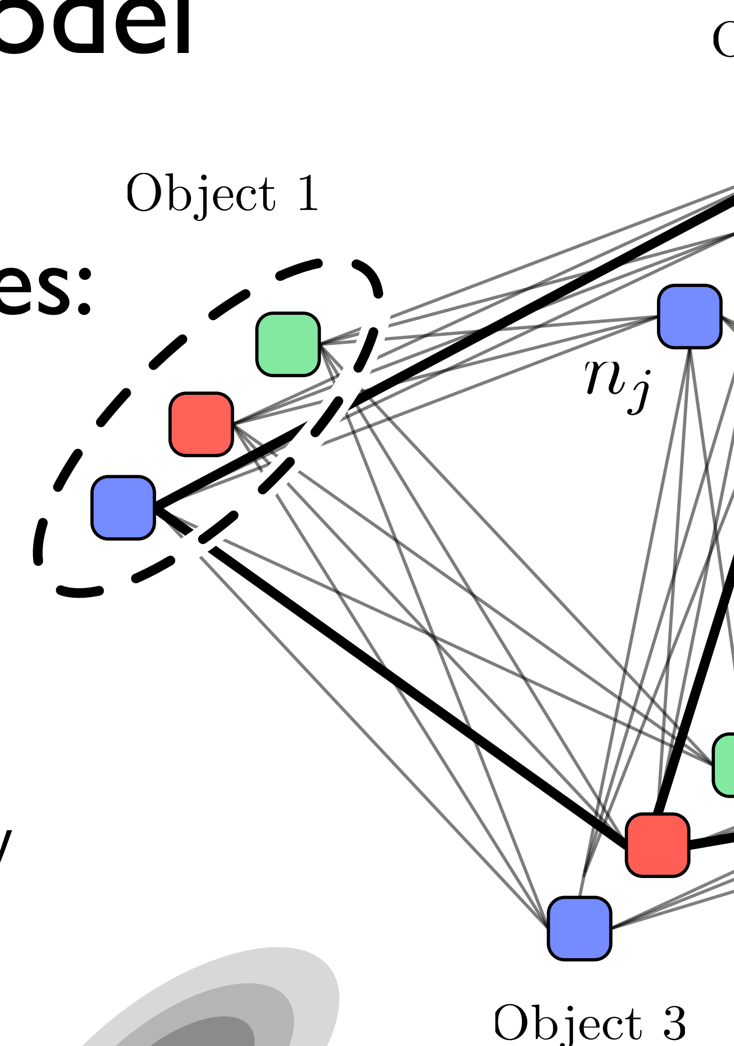
- Same topology as geometric model
- 28 Nodes, with N~28*50 labels representing the landmark candidates
- Lables:
  local support
- Edges:
  edge similarity

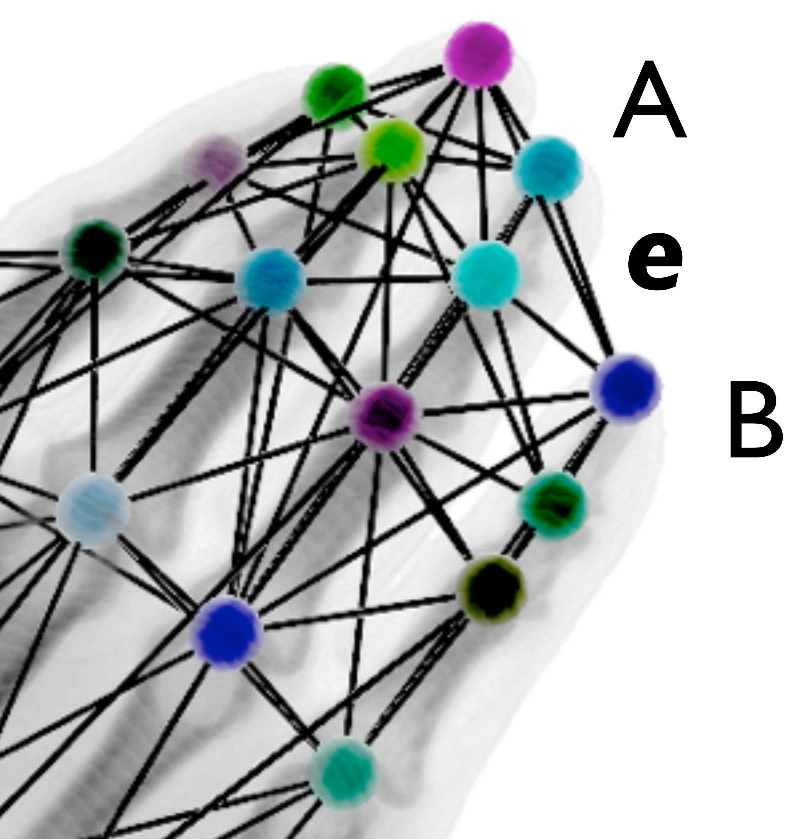


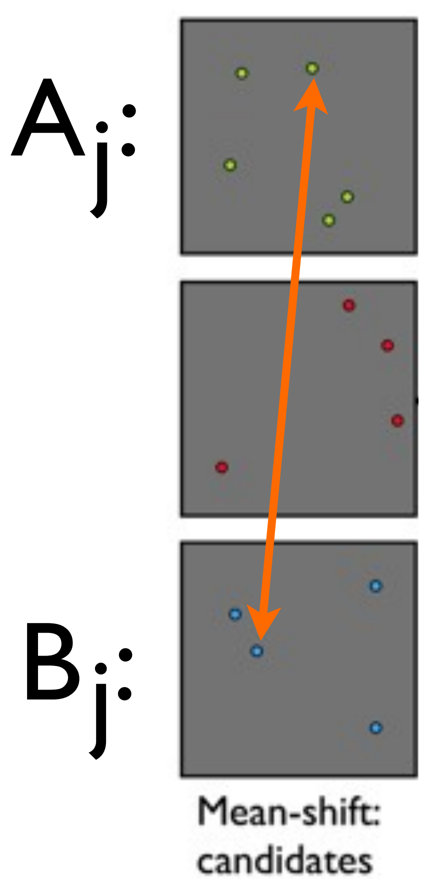


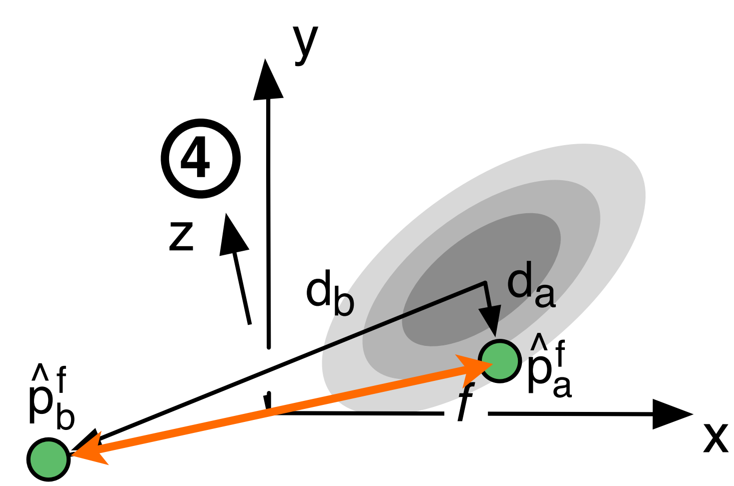
Edge similarities

- For each model edge **e** between model landmarks A and B:
  - For all pairs (A_j,B_j) of landmark candidates:
  - Similarity = max(p_a, p_b) of the non-normalized Gaussian model for **e**





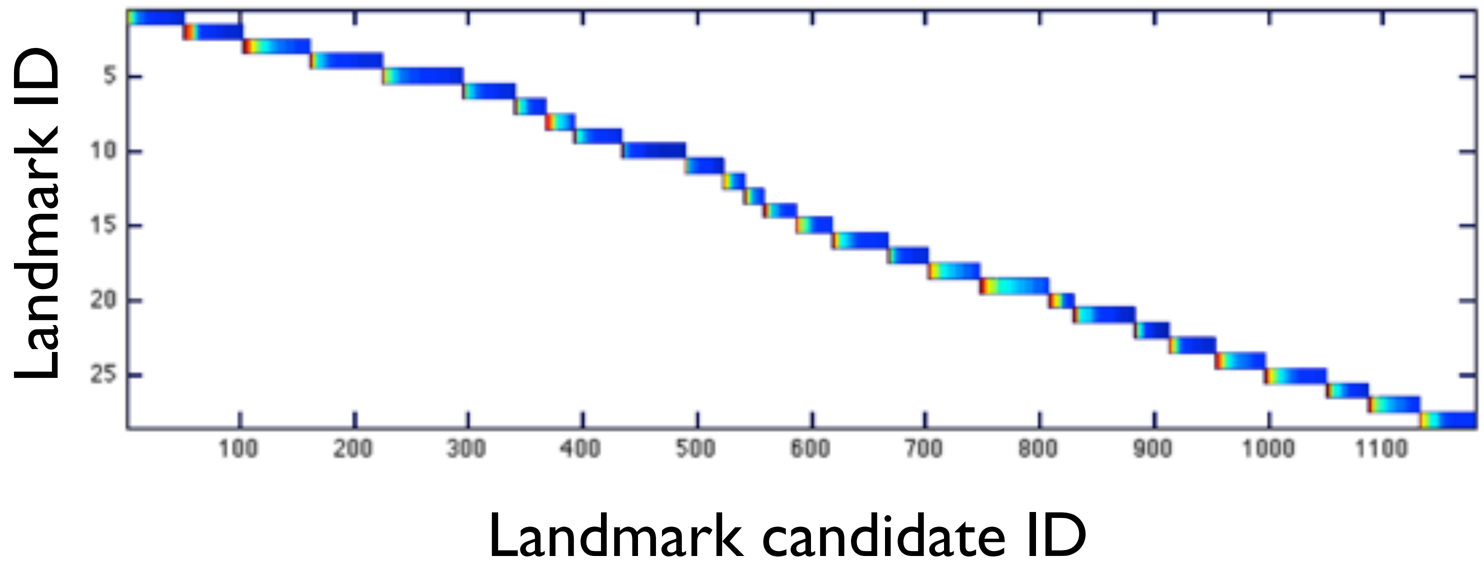




Model for **e**

Sparse MRF structure

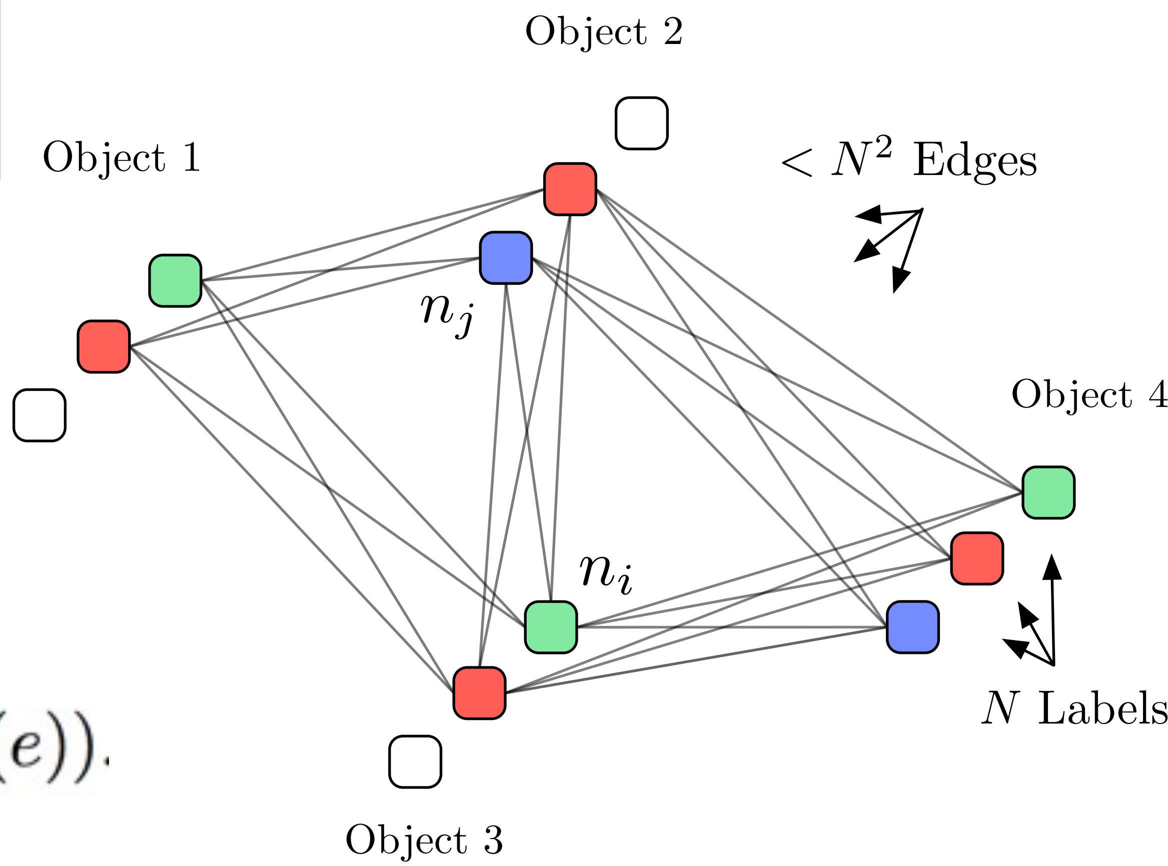
- Sparse point confidences



- Sparse edge structure:

$$Conf(\mathcal{S}) = \sum_{l=1\ldots L} \mathcal{L}(l, \mathcal{S}(l)) + \sum_{e=1\ldots E} \mathcal{E}(e, \mathcal{S}(e)).$$

$$\mathcal{S}^* = \underset{\mathcal{S}}{\operatorname{argmax}}\, Conf(\mathcal{S})$$

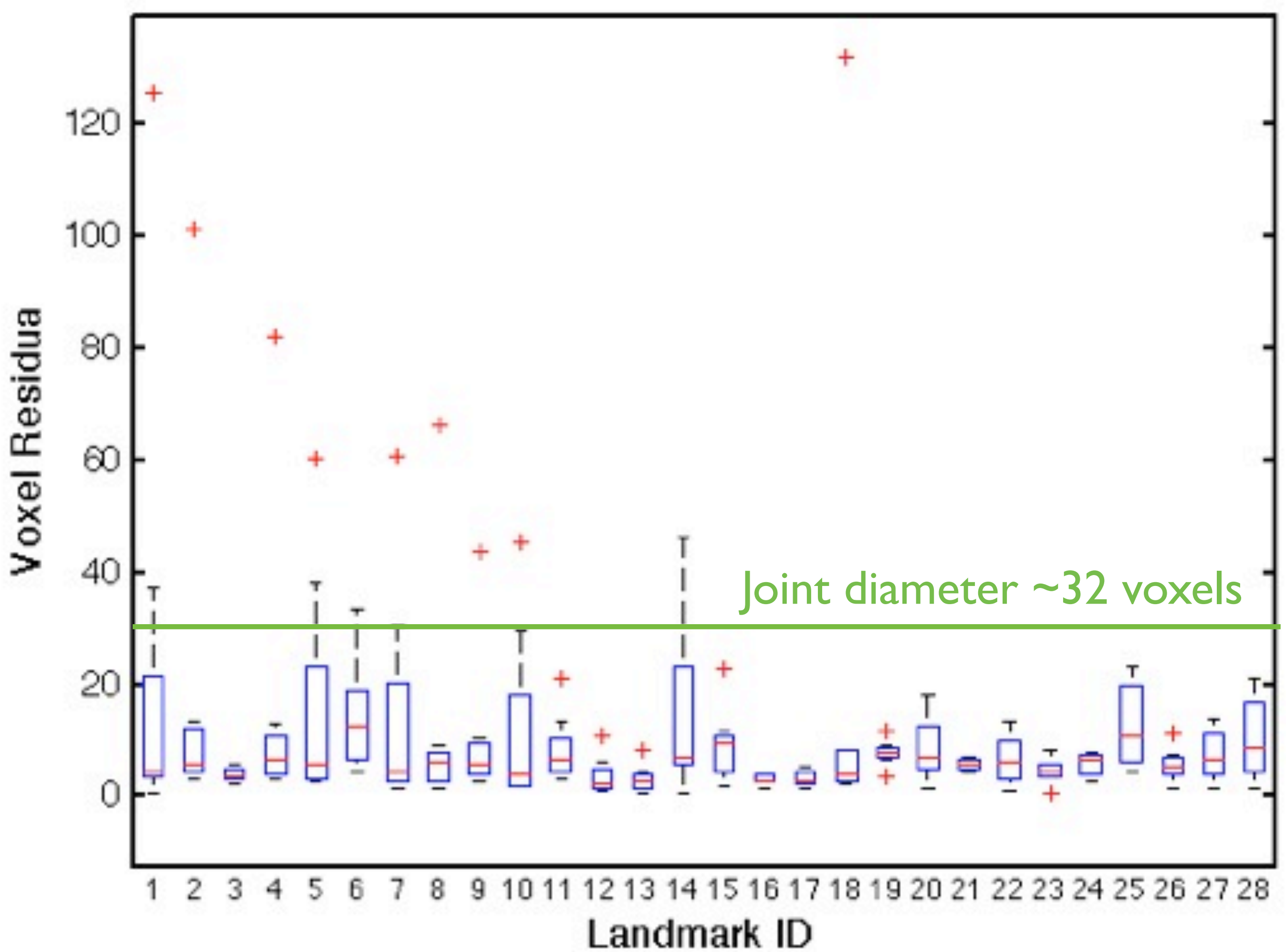


Experiments

- 8 high-resolution hand CTs
- $256 \times 384 \times 330$ voxels
- 28 landmarks selected in each training image
- 33500 training samples for the RF
- Leave-one-out cross validation

Results

- mean/median/std: 10.13 / 5.59 / 16.99 voxels



Distances of resulting localization to ground truth.

Sphere Radius = Median Error

Conlusion

- Simple method for localization of complex, self-similar anatomical structures
- Learned candidate detectors allow to cope with 3D data

Outlook

- Evaluation on other datasets (thorax MRI, whole body CT)
- Learning the graph topology - learn landmarks
- Evaluation of MRF solvers

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