

Deep Learning for Fluoroscopic Feature Detection

Mid Point Presentation

Liujiang Yan

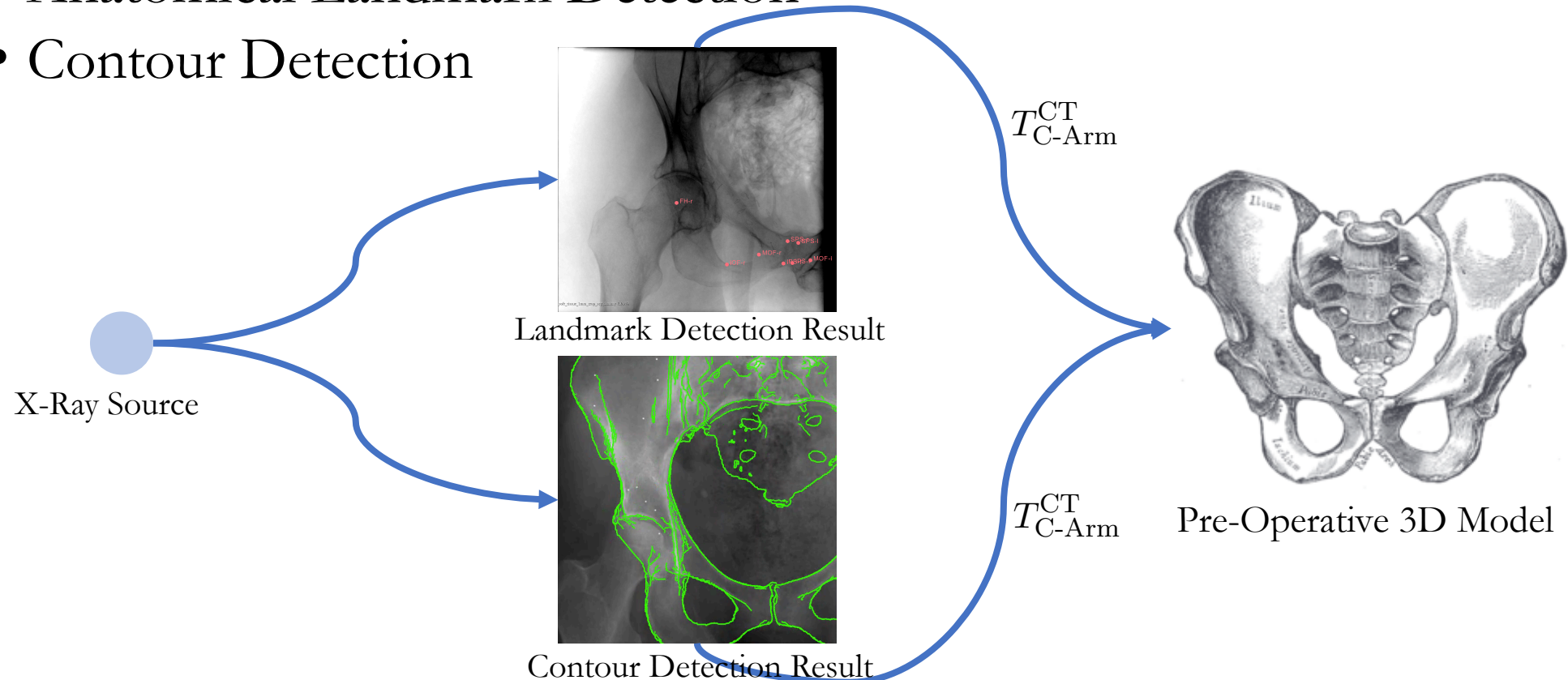
Mentor: Robert Grupp, Professor Russell Taylor





Motivation

- Feature Detection for 2D-3D Registration
 - Anatomical Landmark Detection
 - Contour Detection





Pipeline Summary

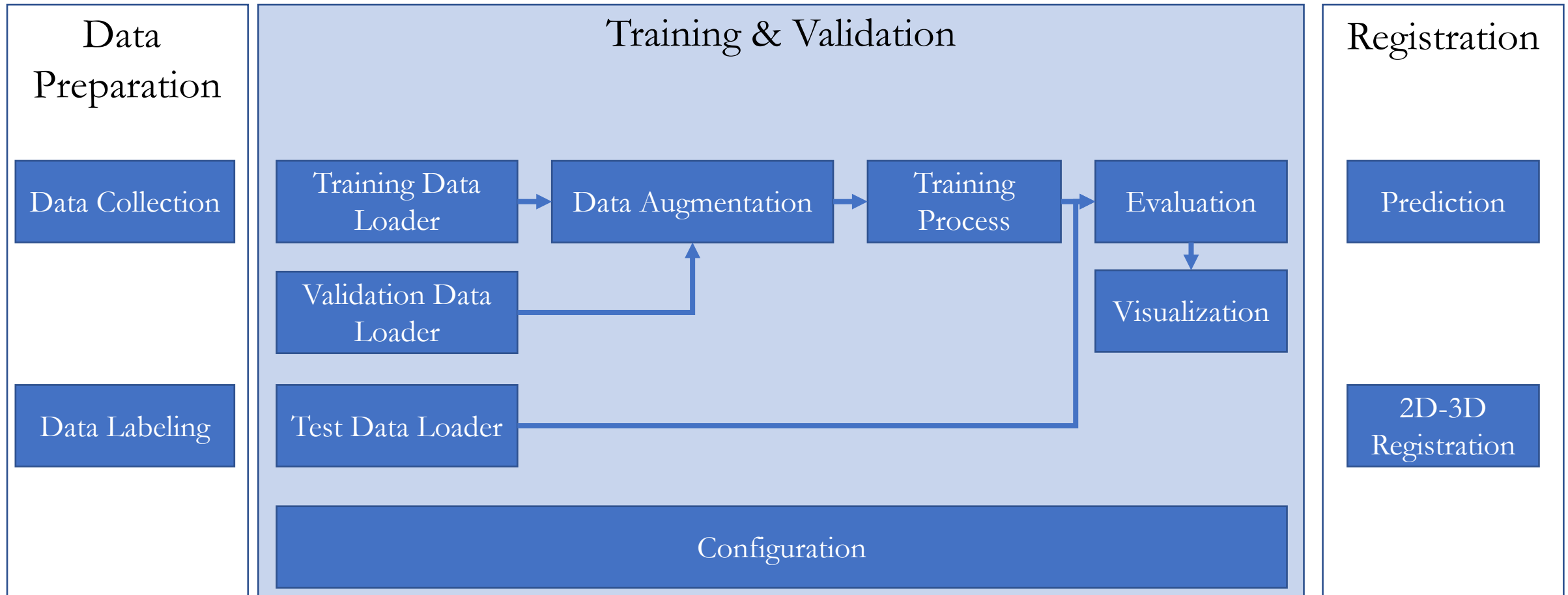
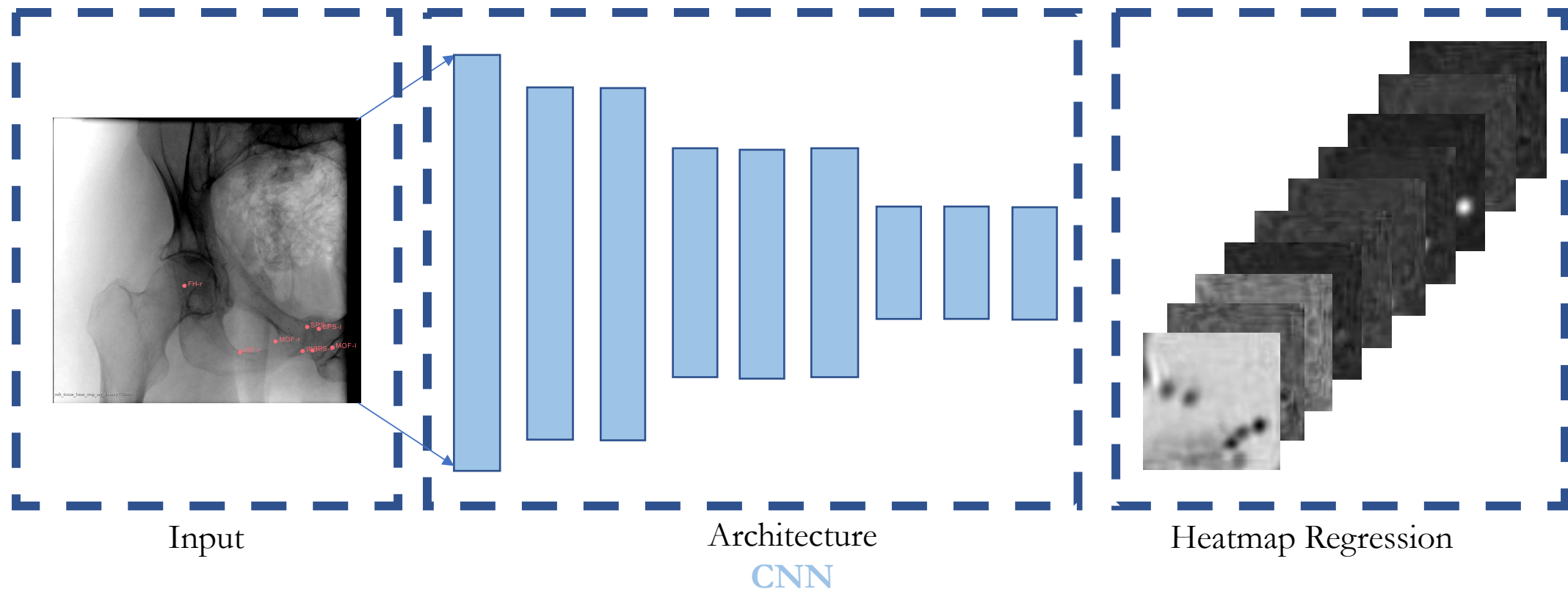


Fig. Pipeline Layout



Approach - Heatmap Regression

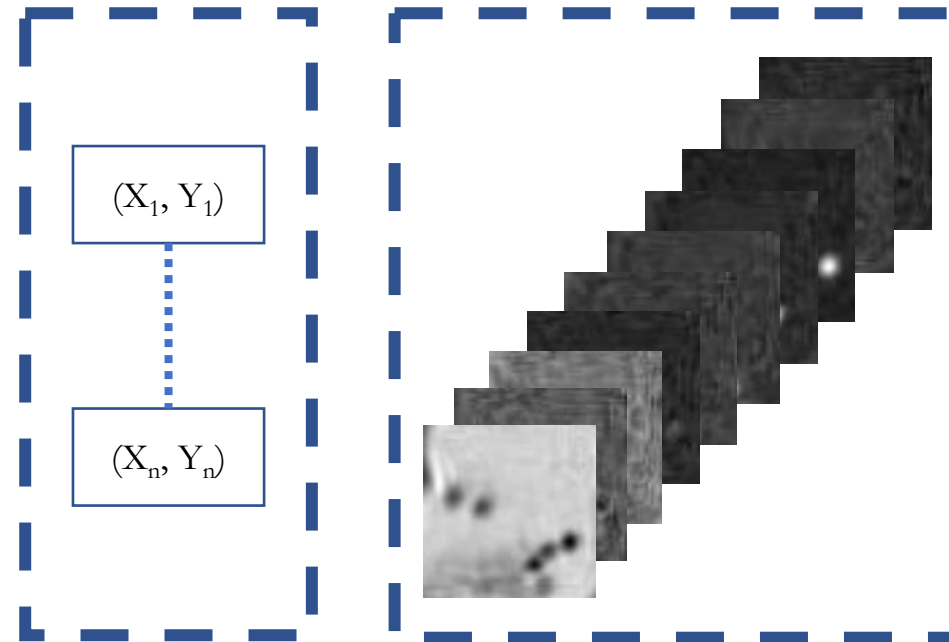
- Problem identification: fixed number key point detection
- Heatmap: Intensity given by Gaussian distribution with position as mean





Approach

Why regress heatmap instead of position? What is the tradeoff?



Position Regression

Heatmap Regression

Network Architecture

- Convolutional Pose Machine
- Multi Stage Model
- Intermediate Supervision

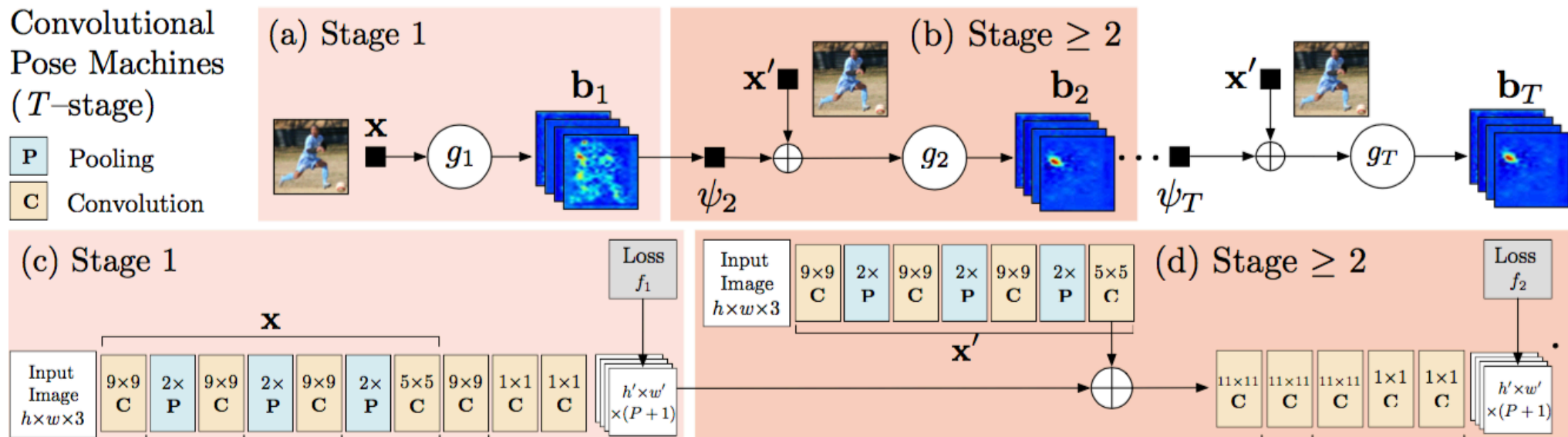


Fig. Convolutional Pose Machine^[1]

Network Architecture

- Convolutional Pose Machine
- Multi Stage Model
- Intermediate Supervision

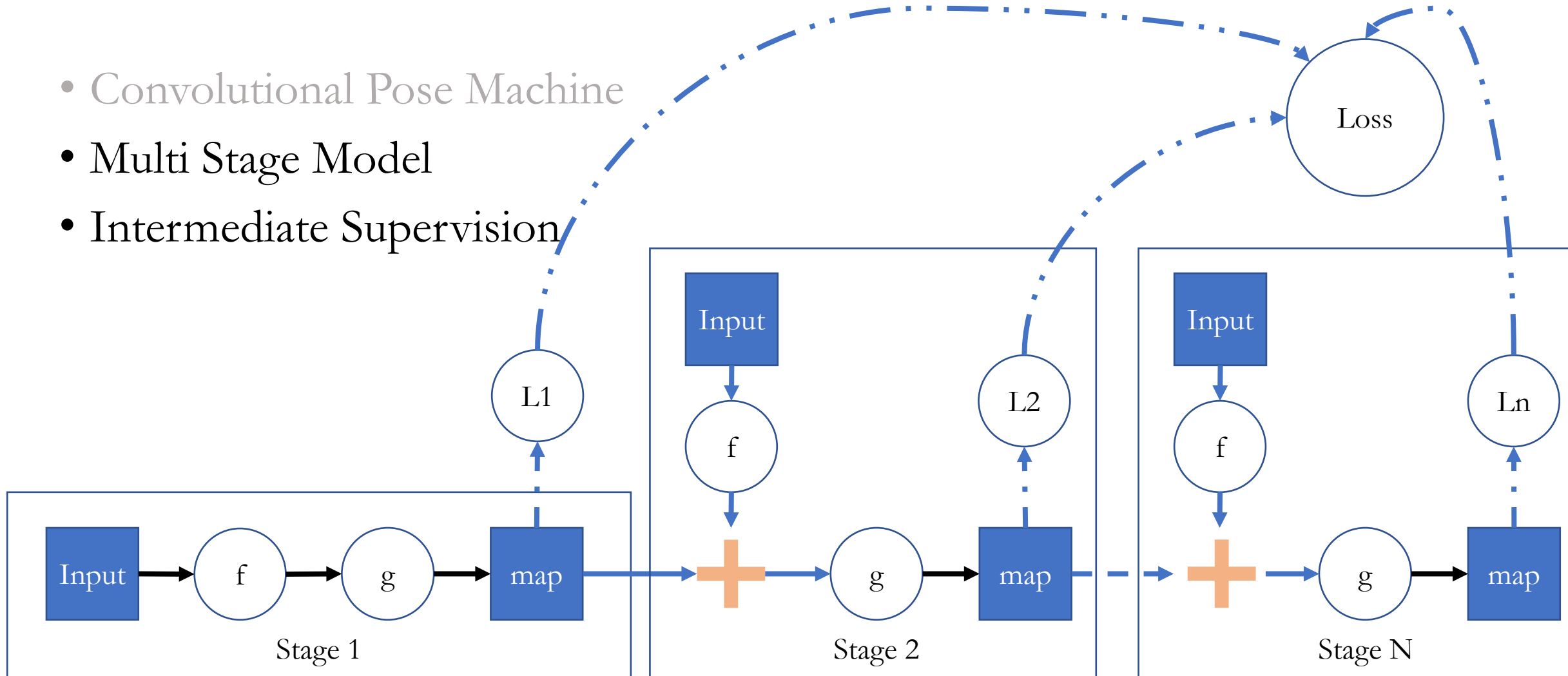


Fig. Architecture Details

Hyperparameters - Stage Number

- More stages:
 - Larger parameter space; larger receptive field;
 - Overfitting; Harder to train; Takes more time and memory;

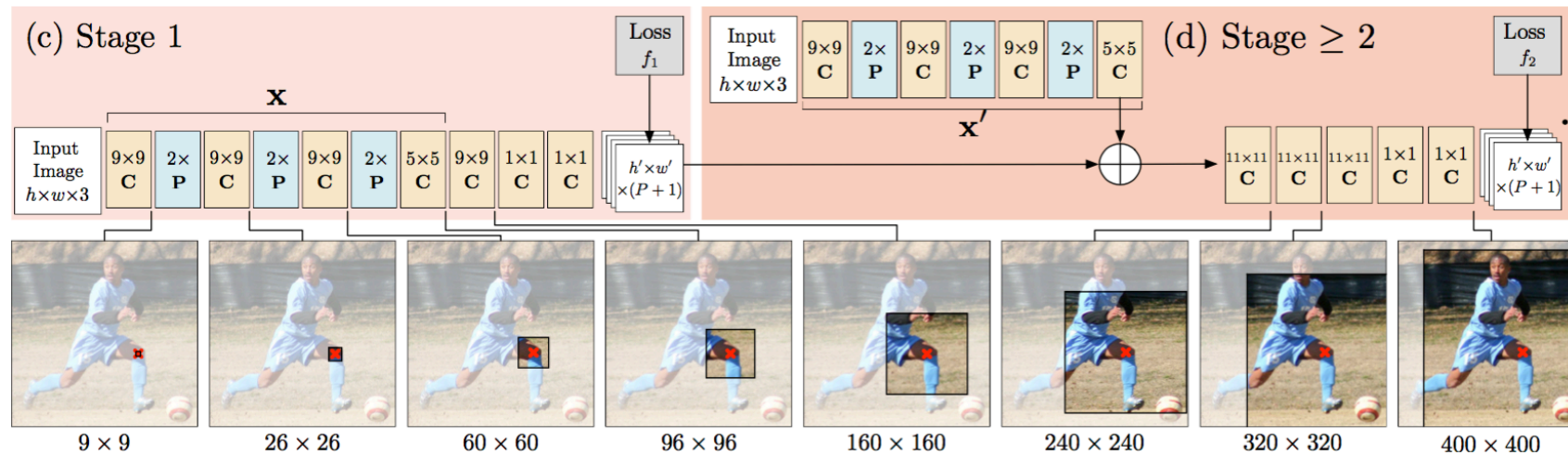


Fig. Convolutional Pose Machine^[1]

[1] Wei, Shih-En, et al. "Convolutional pose machines." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016.

Hyperparameters - Heatmap

- Output Size:
 - Larger size means more accurate localization; More resources to train;
- Gaussian Variance:
 - Larger variance means more information; less accurate localization;

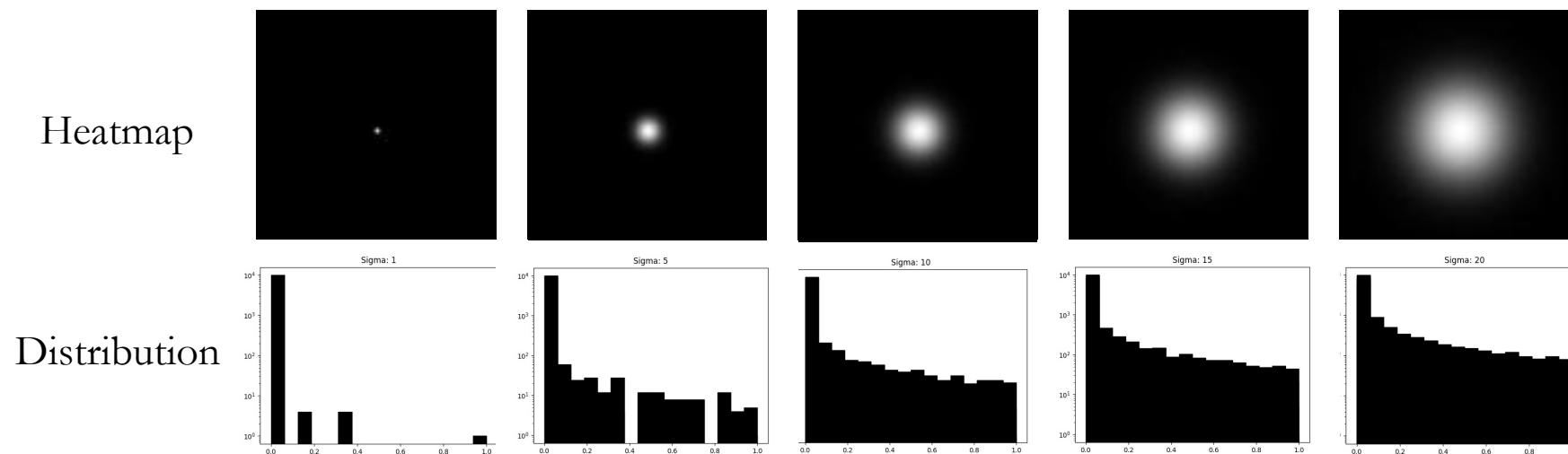
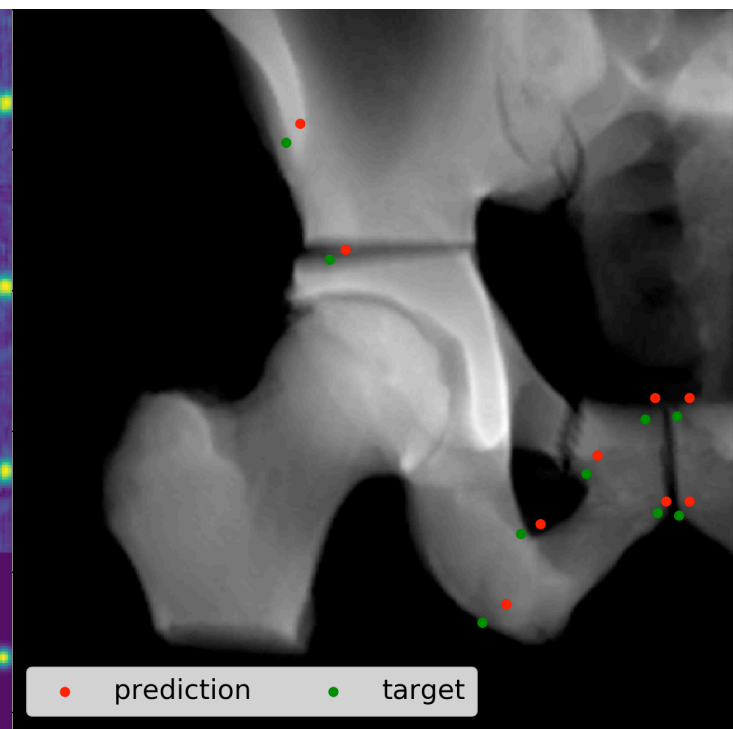
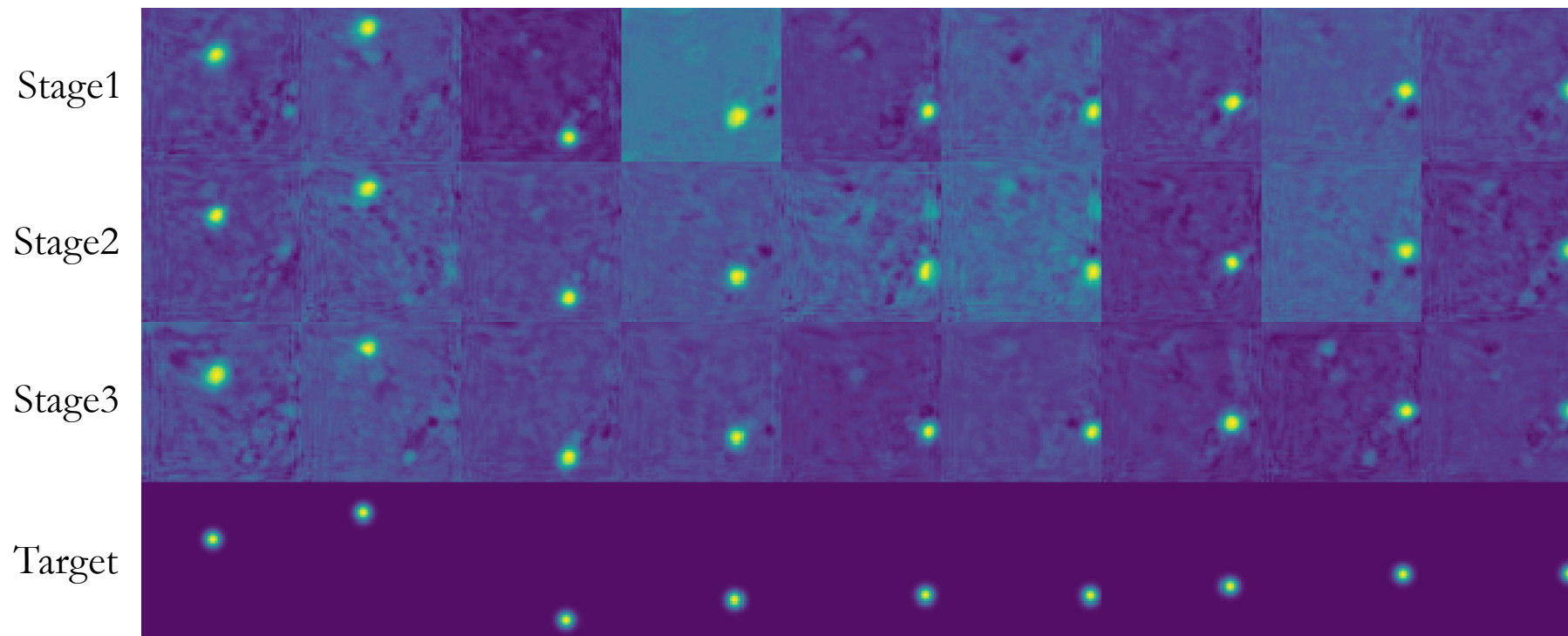


Fig. Heatmap with different variance and corresponding intensity histogram



Evaluation and Visualization

- Multistage Visualization - Intuition
- 2D Error Plot - Quantitative Analysis
- Good Prediction / Bad Prediction - Case Study





Evaluation and Visualization

- Multistage Visualization - Intuition
- 2D Pixel Error Plot - Quantitative Analysis
 - Discretization: 10x downsample
 - Measure in original image size (768 by 768);
 - Heatmap size (63 by 63);
- Good Prediction / Bad Prediction - Case Study



Evaluation and Visualization

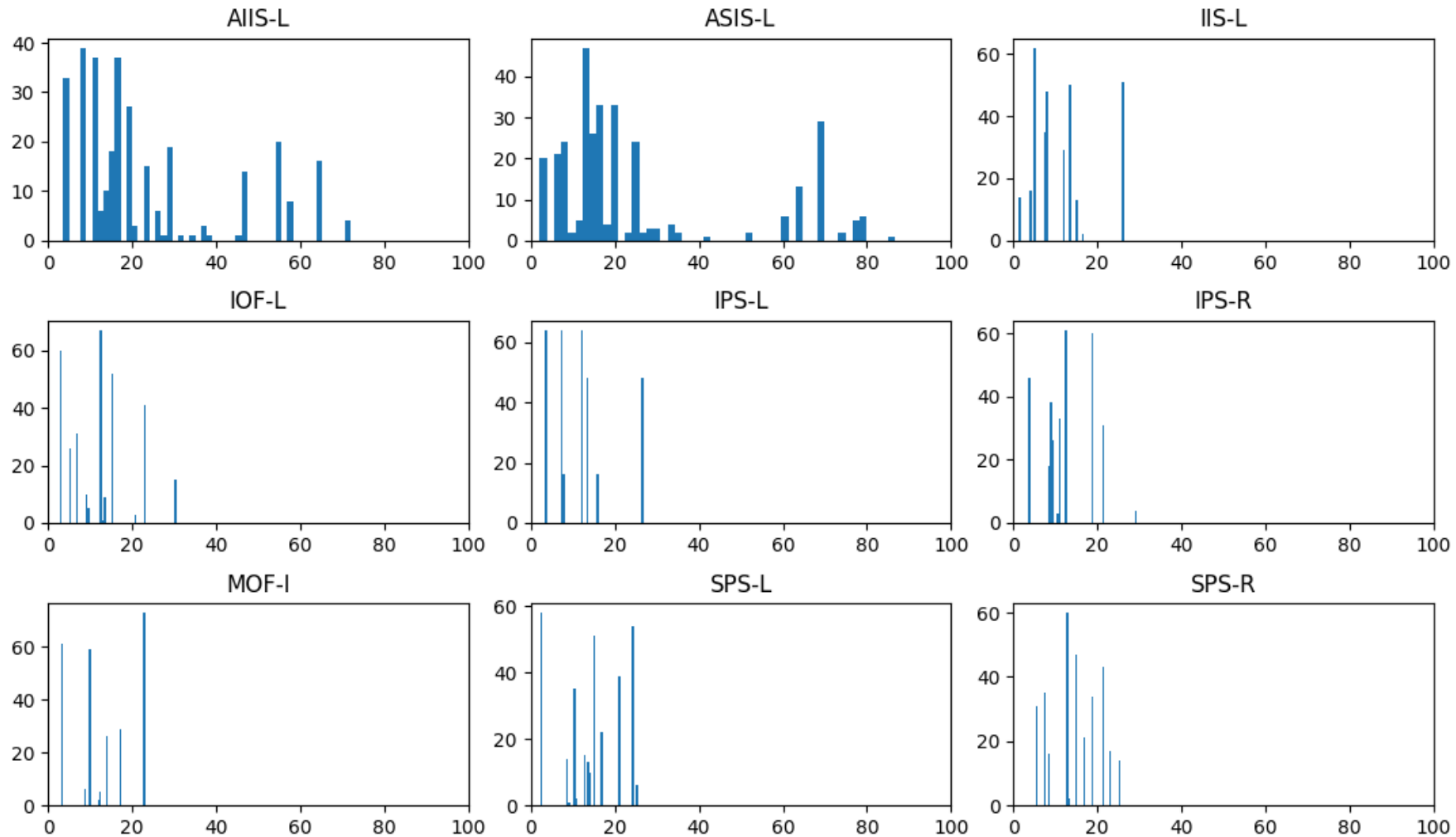


Fig. 2D Pixel Error

Evaluation and Visualization

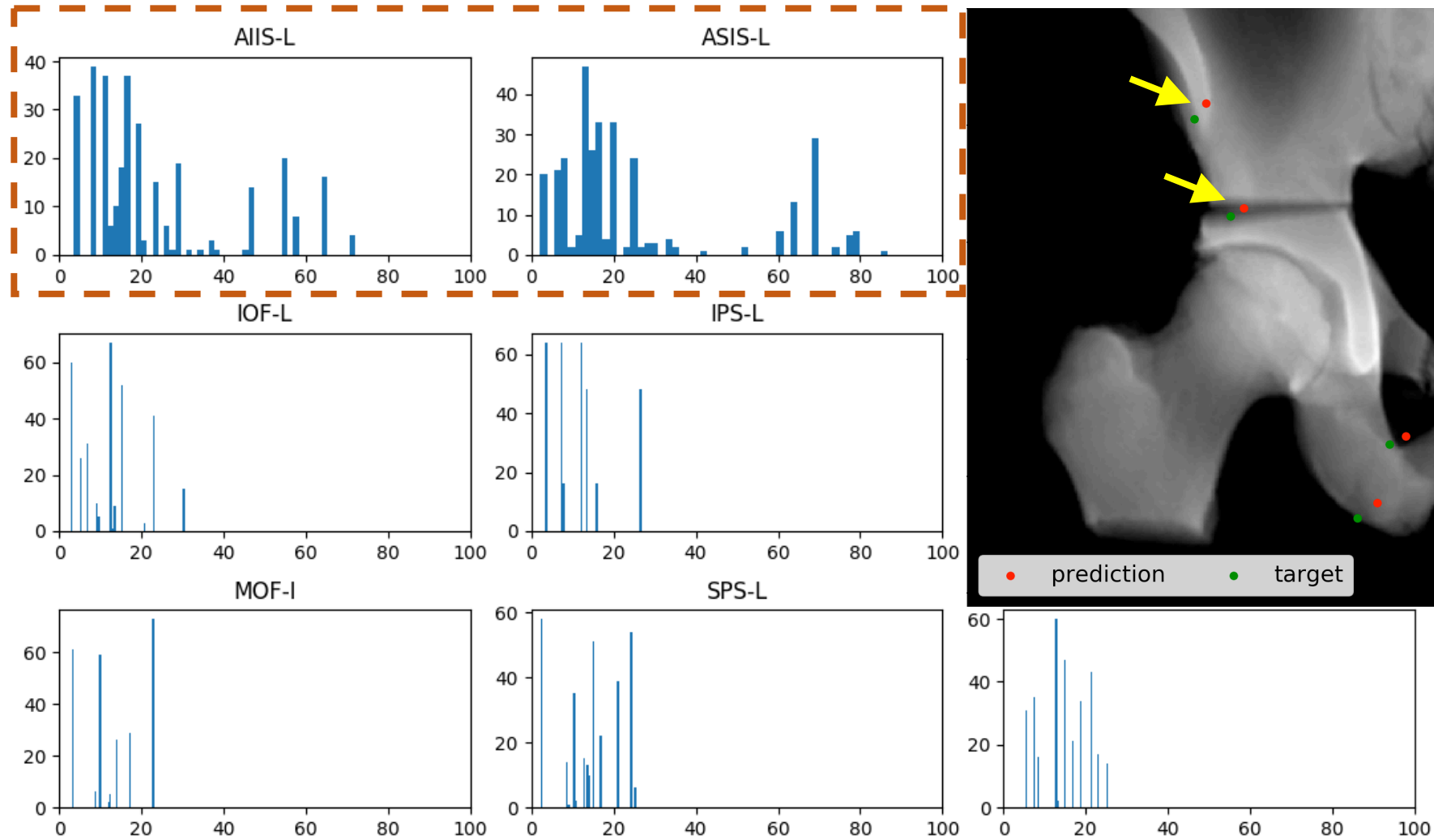
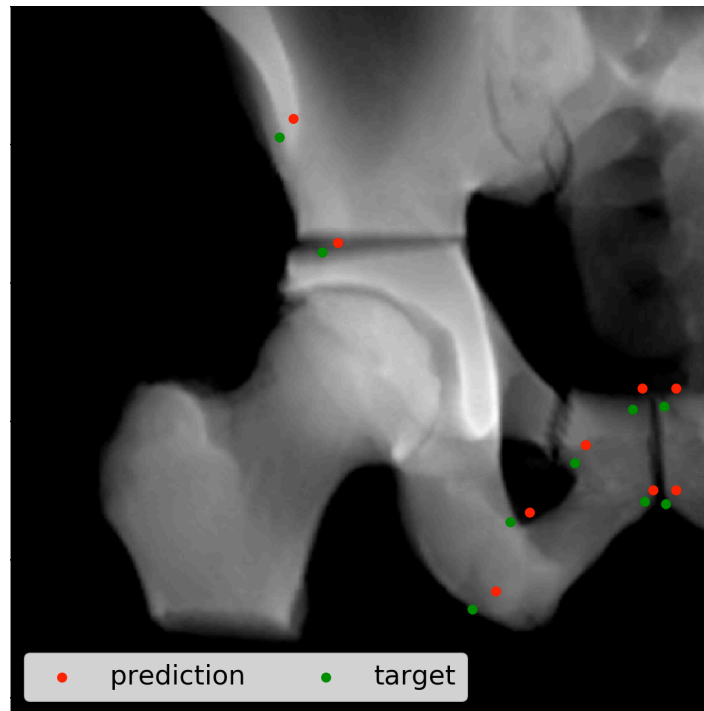
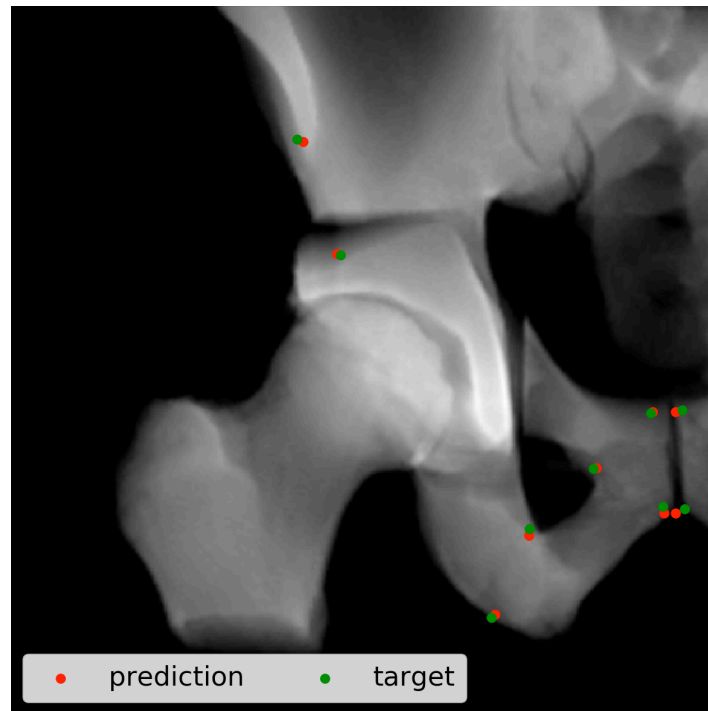


Fig. 2D Pixel Error



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Limitations & Data Augmentation

- Intra-operation scenario: Tool in the view
- Hard to synthesize samples with tool in the view



Fig. Tool in the view



Limitations & Data Augmentation

- Intra-operation scenario: Tool in the view
- Random Mask (shape; size; location; rotation; brightness)
 - Input: mask some connected region with random constant value;
 - Target: keep all landmarks visible;

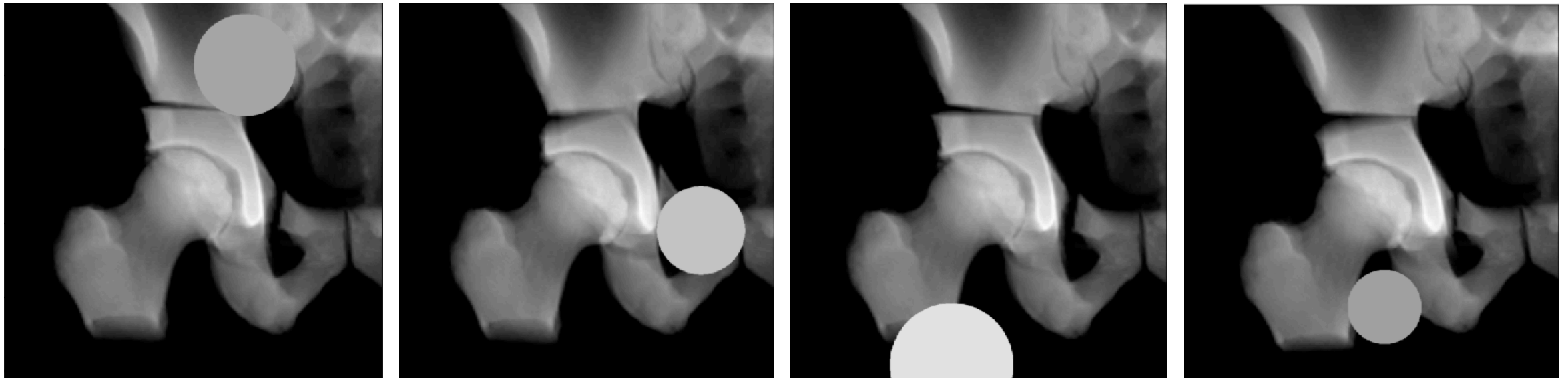
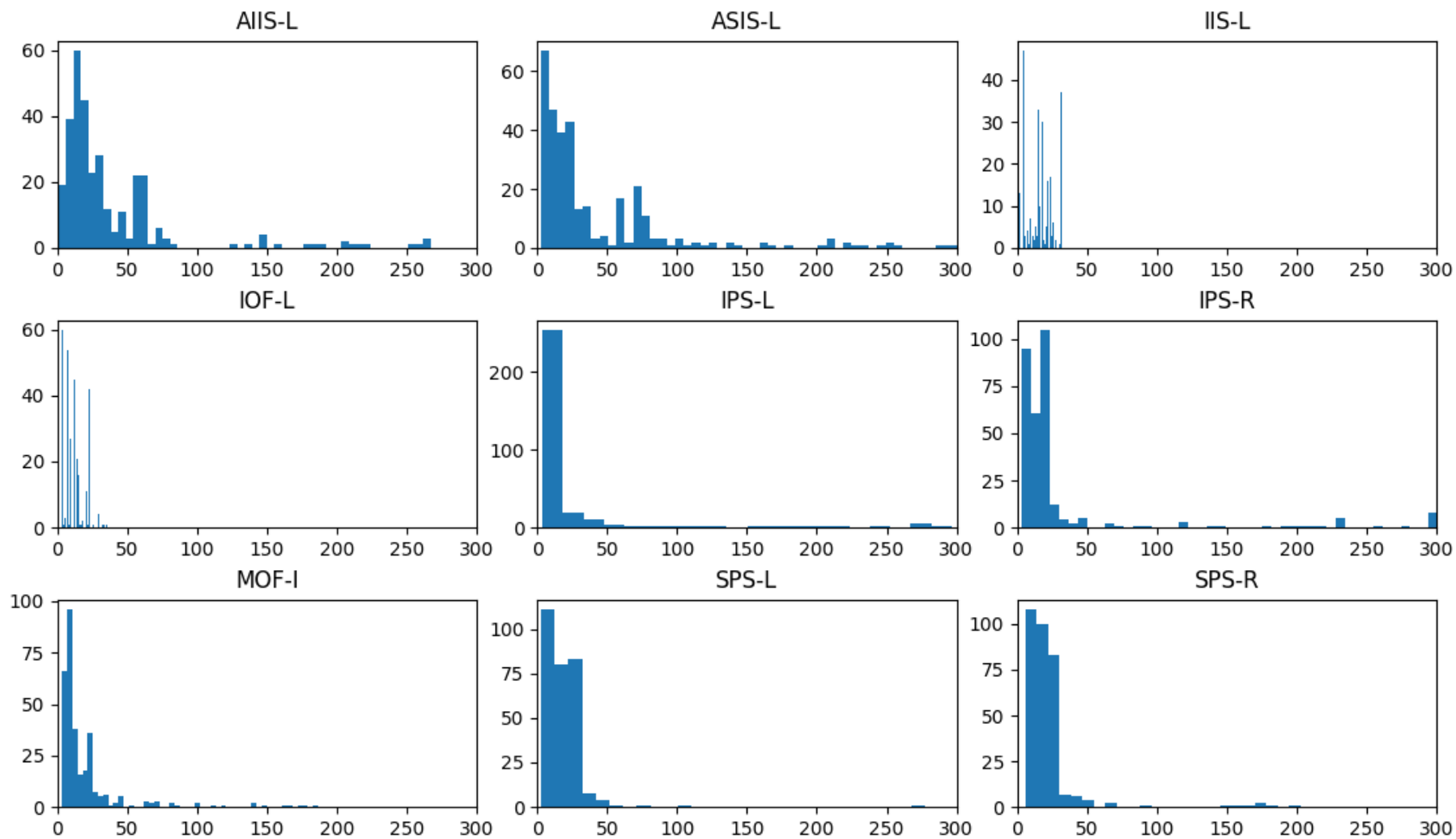


Fig. Samples with Random Mask (not necessarily circular)



Spatial Error Plot

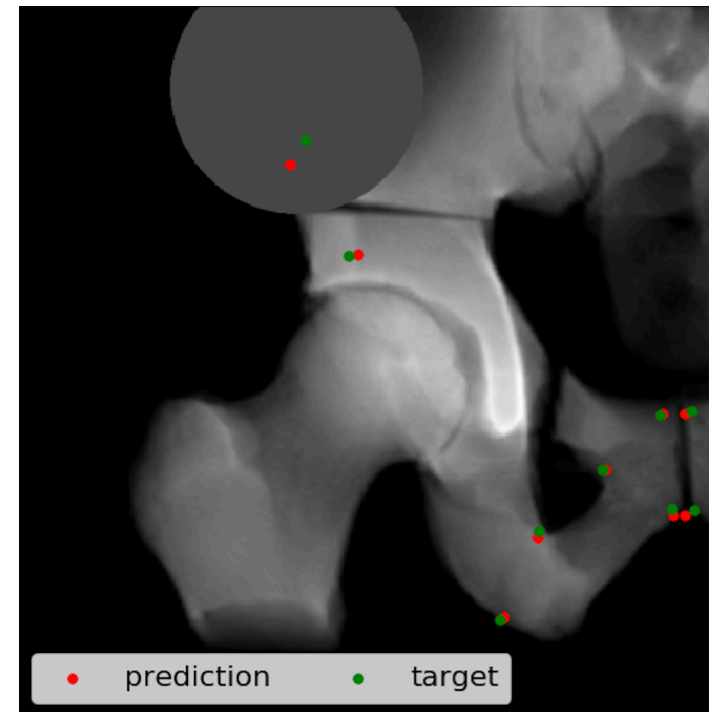
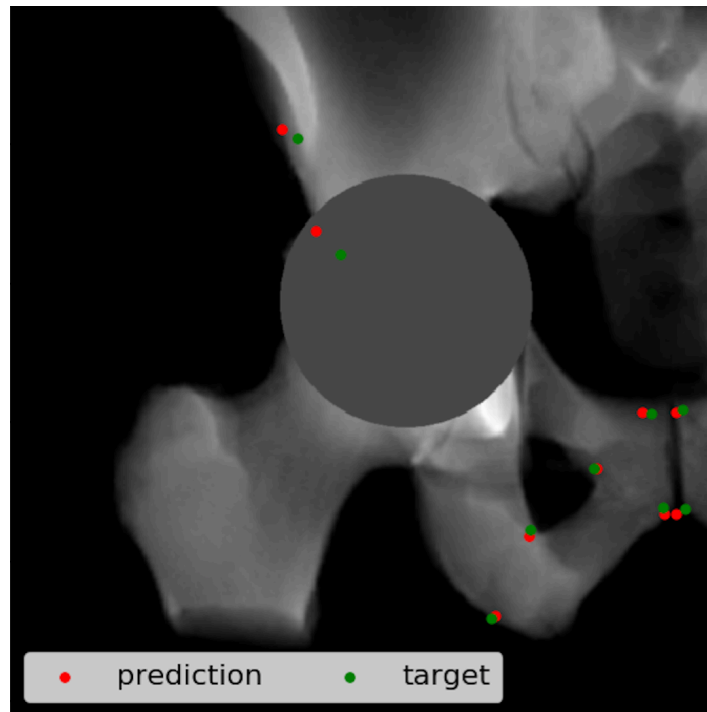


Landmark Spatial Error (**With Mask**)



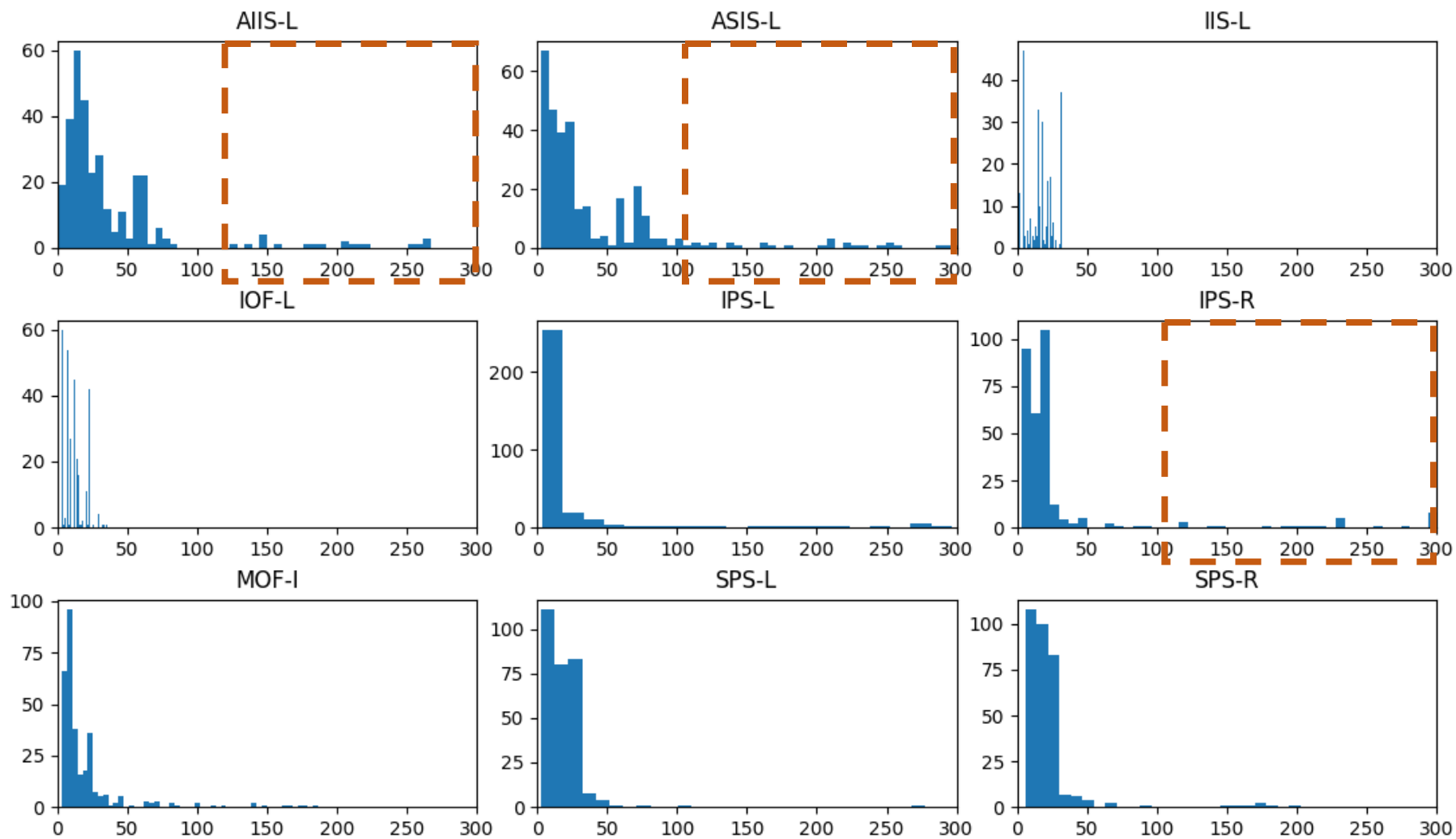
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Spatial Error Plot

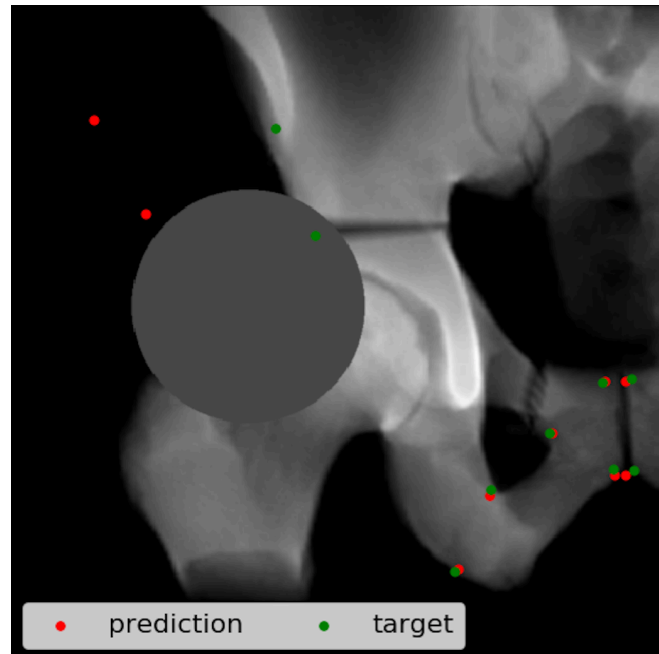


Landmark Spatial Error (With Mask)



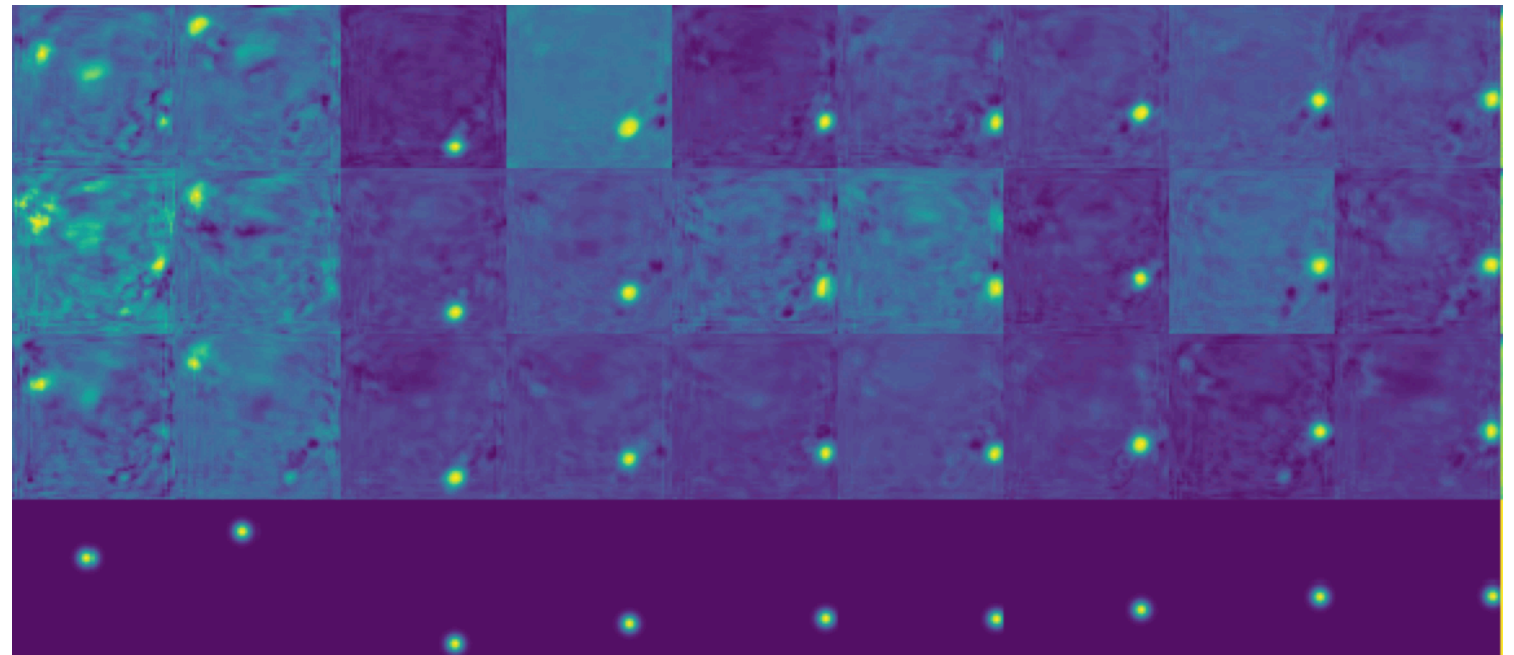
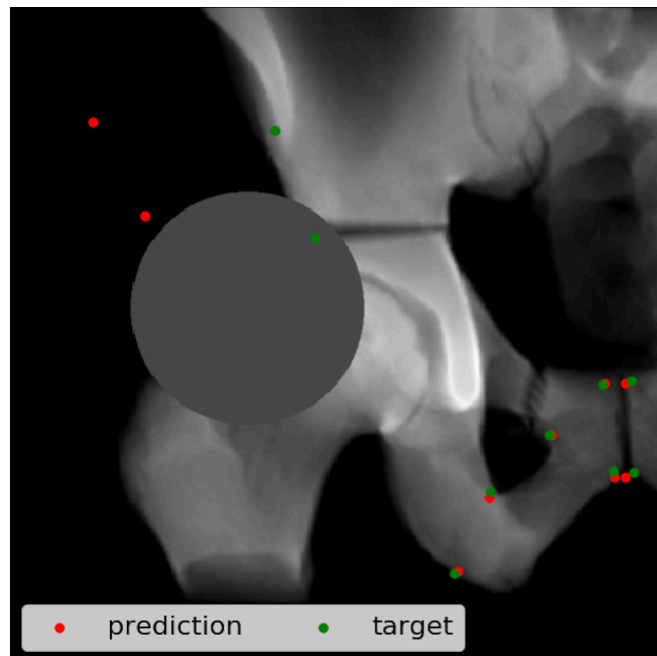
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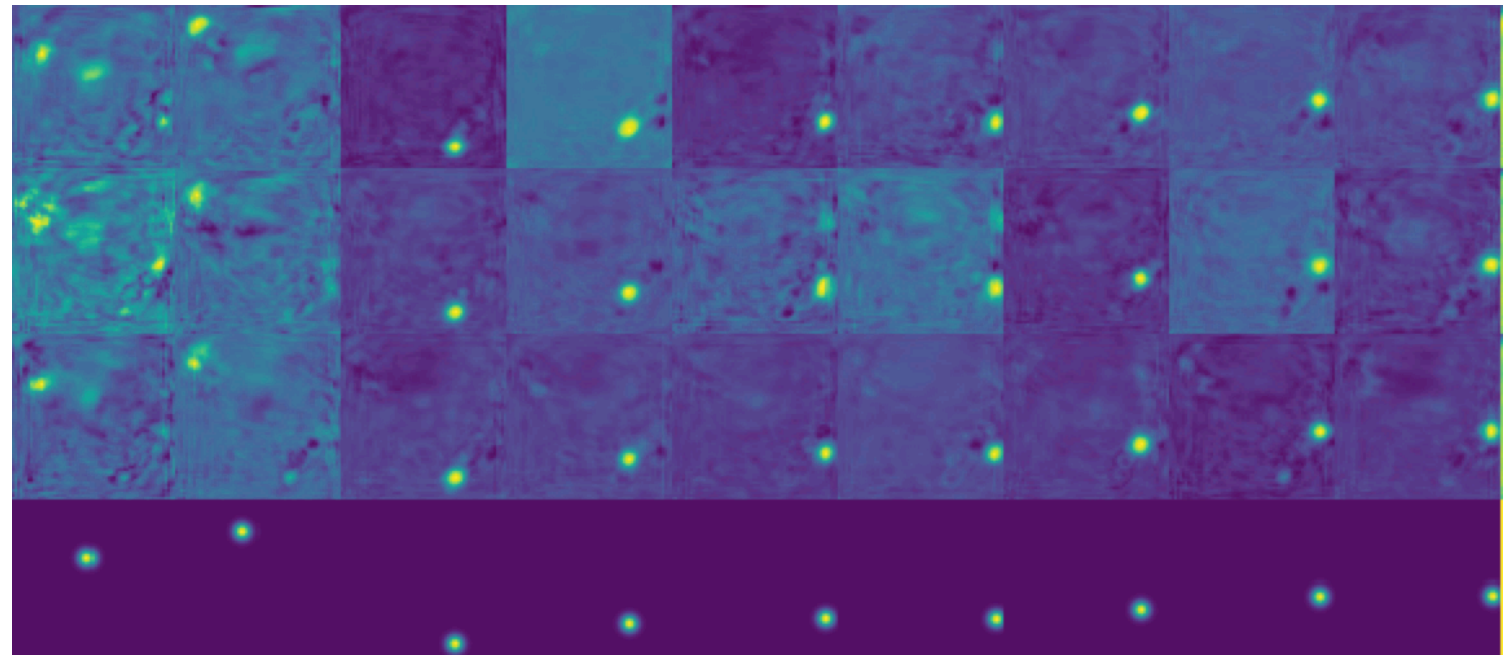
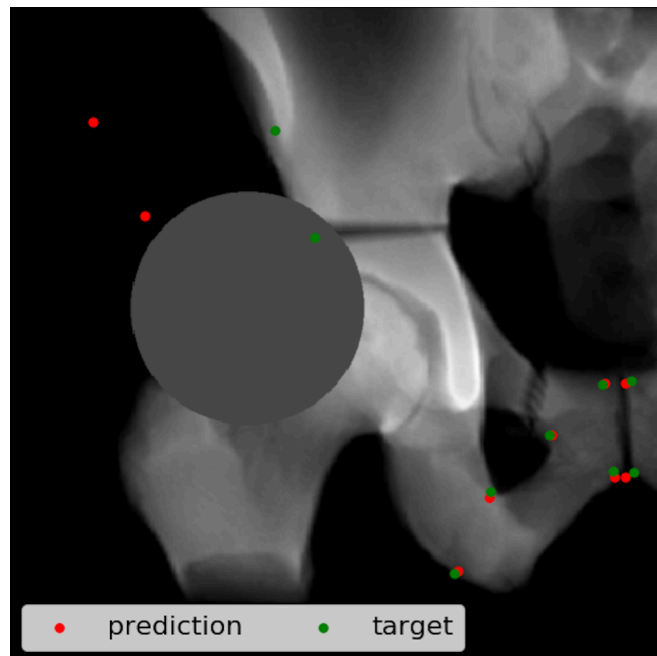
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Why regress heatmap instead of position

- Heatmap gives uncertainty measure about the prediction
- Heatmap generation is essentially the prior about the annotation





Why regress heatmap instead of position

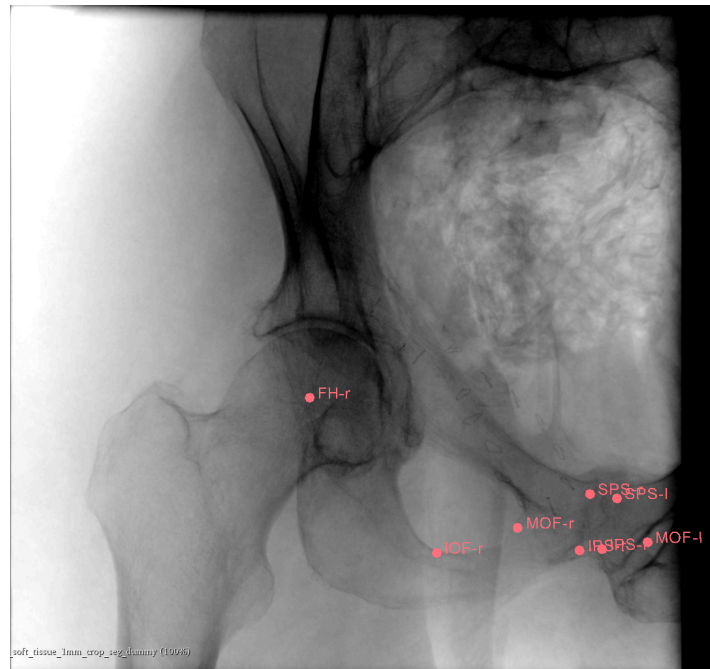
- Heatmap gives uncertainty measure about the prediction
- Heatmap generation is essentially the prior about the annotation
- Could be used for detecting outliers
- 2D-3D registration by utilizing the distribution of 2D prediction
 - Let the prediction of landmark is given by $\mathcal{N}(\mu; \Sigma)$
 - The objective function could be derived by Mahalanobis distance

$$\arg \min_{\theta \in SE(3)} \sum_i \frac{1}{2} [P_{2D}^i - \mathcal{P}(P_{3D}^i; \theta)]^T \Sigma^{-1} [P_{2D}^i - \mathcal{P}(P_{3D}^i; \theta)]$$



Dependencies

- Simulated dataset with soft tissue / Real dataset
- Simulated dataset with contour annotated
- 2D-3D registration methods



Real X-Ray Data

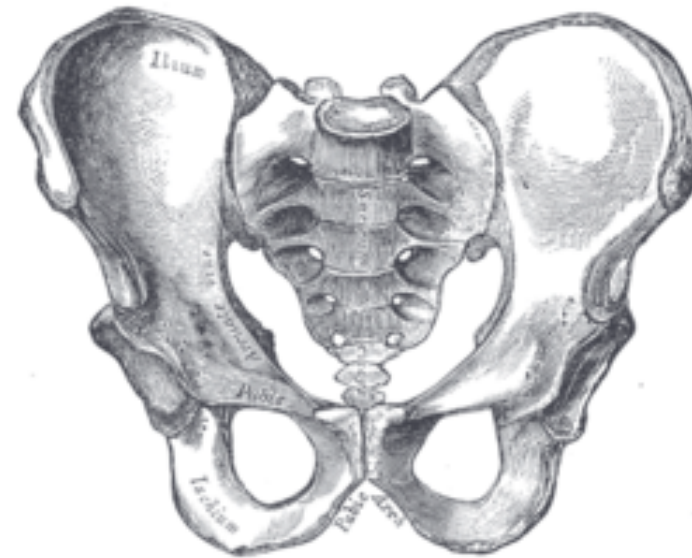
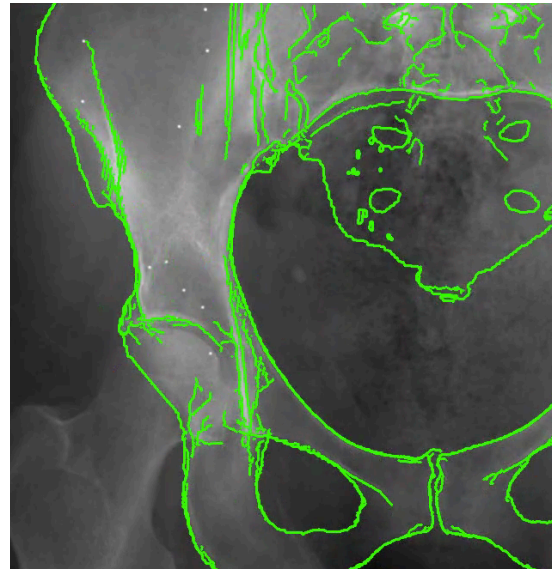


Simulated X-Ray Data



Dependencies

- Simulated dataset with soft tissue / Real dataset
- Simulated dataset with contour annotated
- 2D-3D registration methods



Dependencies

- Simulated dataset with soft tissue / Real dataset
- Simulated dataset with contour annotated
- 2D-3D registration methods
 - Evaluate performance by comparing the led registration result.

$$\arg \min_{\theta \in SE(3)} \sum_i \frac{1}{2} \left\| \mathbf{p}_{2D}^{(i)} - \mathcal{P}(\mathbf{p}_{3D}^{(i)}; \theta) \right\|_2^2$$



Conclusion

- Minimum deliverable achieved; Ongoing works on medium / maximum;
- Developed landmark detection pipeline using PyTorch;
- Tuned convolutional pose machine architecture;
- Perform data augmentation to address tool in the view problem;
- Evaluated and visualized results for further analysis;
- Need more training data (landmark, contour) for further experiment;
- Need registration method for evaluation.

Thank you for listening.