DSAC – Differentiable RANSAC for Camera Localization

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Code and trained models:

Motivation

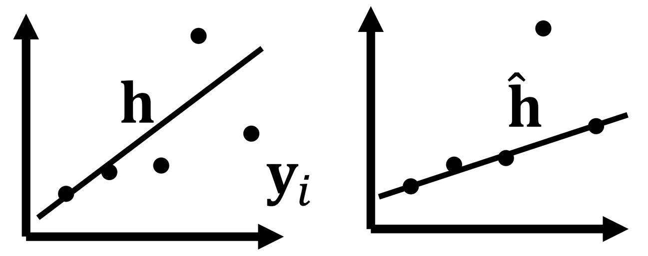
RANSAC (Random Sample Consensus) is an important algorithm in robust optimization. It cannot be used in deep learning pipelines because it is non-differentiable.

Our Goal: Use RANSAC in end-to-end learning.

RANSAC in a Nutshell:

1) Sample multiple hypotheses $\mathbf{h}_j$
2) Score each hypothesis: $s(\mathbf{h}_j)$
3) Take best one (and refine): $\hat{\mathbf{h}} = \boxed{\operatorname{argmax}_{\mathbf{h}_j} s(\mathbf{h}_j)}$

Not differentiable



Naïve Fit   RANSAC Fit

Contributions

- We explore **two ways** of making RANSAC differentiable: **soft** argmax **selection** and **probabilistic selection**.
- We put both options in a **new** end-to-end trainable **camera localization pipeline**.
- We show experimentally that **probabilistic selection is superior.** We call RANSAC with this option **DSAC**.
- We **exceed state-of-the-art** on camera localization **by 7.2%** (new results: by 12.8%).

Differentiable Alternatives to argmax

Our hypotheses depend on learnable parameters $\mathbf{w}$: $\mathbf{h}_j^{\mathbf{w}} \coloneqq \mathbf{h}_j(\mathbf{w})$

We wish to minimize the loss ℓ of selected hypotheses over training images I:

$$\widehat{\mathbf{w}} = \operatorname*{argmin}_{\mathbf{w}} \sum_I \ell(\hat{\mathbf{h}}^{\mathbf{w}})$$

$$\frac{\partial}{\partial \mathbf{w}} \ell(\hat{\mathbf{h}}^{\mathbf{w}}) = \frac{\partial \ell}{\partial \hat{\mathbf{h}}^{\mathbf{w}}} \frac{\partial \hat{\mathbf{h}}^{\mathbf{w}}}{\partial \mathbf{w}} \quad \text{but} \quad \frac{\partial}{\partial \mathbf{w}} \operatorname*{argmax}_{\mathbf{h}_j^{\mathbf{w}}} s(\mathbf{h}_j^{\mathbf{w}})$$

Selection depends on all hypotheses and all scores!

We define a softmax score distribution: $\boxed{P(j|\mathbf{w}) \coloneqq \exp\left(s(\mathbf{h}_j^{\mathbf{w}})\right) / \sum_k \exp(s(\mathbf{h}_k^{\mathbf{w}}))}$

Soft argmax Selection

$$\mathbf{h}_{\mathrm{SoftAM}}^{\mathbf{w}} = \sum_j P(j|\mathbf{w}) \mathbf{h}_j^{\mathbf{w}}$$

Soft, deterministic decision

Probabilistic Selection

$$\mathbf{h}_{\mathrm{DSAC}}^{\mathbf{w}} = \mathbf{h}_j^{\mathbf{w}}, \text{where } j \sim P(j|\mathbf{w})$$

Hard, probabilistic decision

Derivatives

Soft argmax **Selection:**

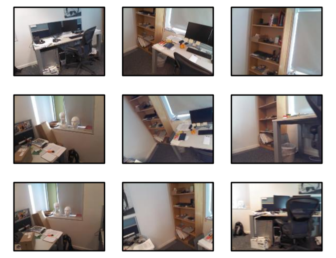
$$\frac{\partial}{\partial \mathbf{w}} \mathbf{h}_{\mathrm{SoftAM}}^{\mathbf{w}} = \sum_j \left(\mathbf{h}_j^{\mathbf{w}} \frac{\partial}{\partial \mathbf{w}} P(j|\mathbf{w}) + P(j|\mathbf{w}) \frac{\partial}{\partial \mathbf{w}} \mathbf{h}_j^{\mathbf{w}} \right)$$

Probabilistic Selection: We derive the expectation of the task loss.

$$\frac{\partial}{\partial \mathbf{w}} \mathbb{E}_{j \sim P(j|\mathbf{w})}\left[\ell(\mathbf{h}_j^{\mathbf{w}})\right] = \mathbb{E}_{j \sim P(j|\mathbf{w})}\left[\ell(\mathbf{h}_j^{\mathbf{w}}) \frac{\partial}{\partial \mathbf{w}} \log P(j|\mathbf{w}) + \frac{\partial}{\partial \mathbf{w}} \ell(\mathbf{h}_j^{\mathbf{w}})\right]$$

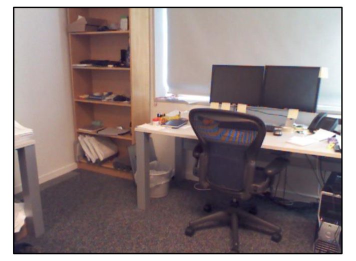
Application: Camera Localization

Training Data:



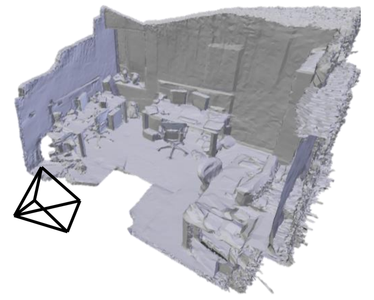
Annotated Images

Test Input:



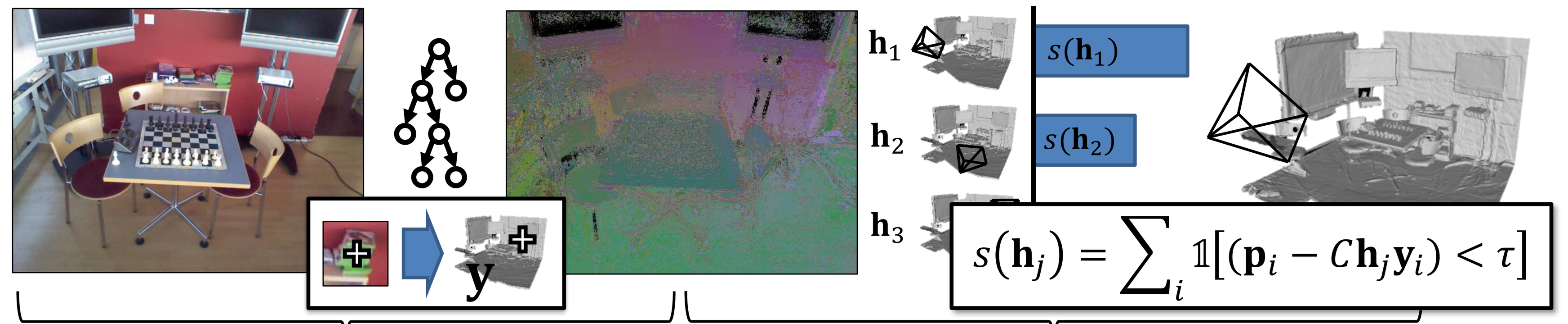
RGB Image

Test Output:



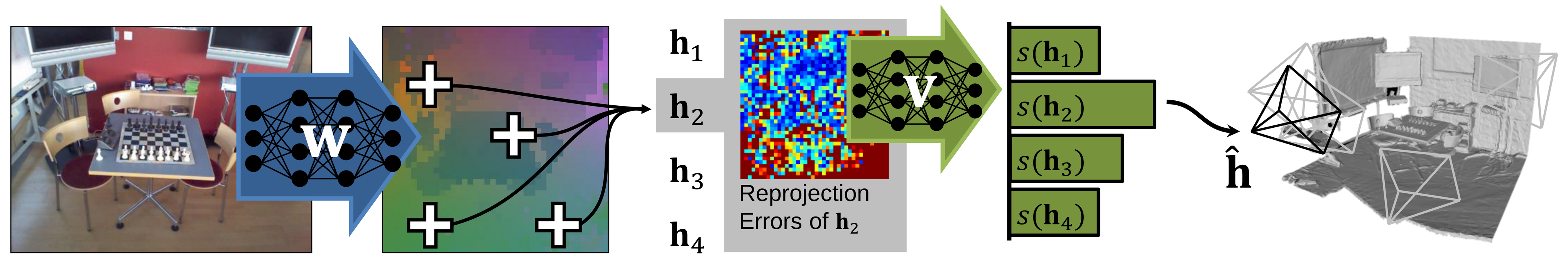
$\hat{\mathbf{h}}$: 6D Pose $\begin{cases} \text{3D Translation } \mathbf{t} \\ \text{3D Rotation } \boldsymbol{\theta} \end{cases}$

Previous Work: Scene Coordinate Regression [Sho13, Bra16]



Scene Coordinate Regression   RANSAC + Refinement

Our Pipeline



Input RGB | Scene Coordinate (**y**) Regression | Hypothesis Sampling | Scoring (s) | Hypothesis Selection | Refinement (**R**)

We learn two CNNs with parameters **w** and **v** jointly by minimizing:

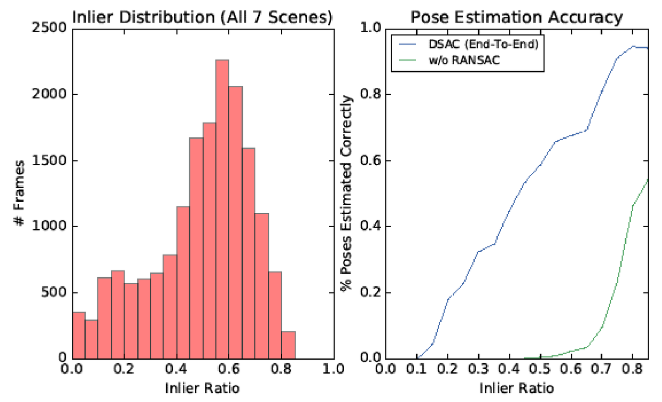
$$\mathbb{E}_{j \sim P(j|\mathbf{w},\mathbf{v})}\left[\ell(\mathbf{R}(\mathbf{h}_j^{\mathbf{w}}, \mathbf{w}), \mathbf{h}^*)\right], \text{with}$$
$$\ell(\mathbf{h}, \mathbf{h}^*) = \max(\measuredangle(\boldsymbol{\theta}, \boldsymbol{\theta}^*), \|\mathbf{t} - \mathbf{t}^*\|)$$

Experiments

Dataset: 7-Scenes [Sho13]

RGB-D images of 7 indoor scenes with pose annotations, 1k-5k training resp. test images. We use **only RGB** at test time.

Difficult frames of 7-Scenes.



Initialization: Componentwise Training

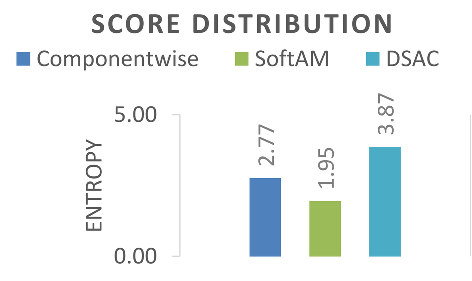
Scene Coordinate Regression: Generate ground truth scene coordinates $\mathbf{y}^*$ and minimize:

$$\widehat{\mathbf{w}} = \operatorname*{argmin}_{\mathbf{w}} \sum_i \|\mathbf{y}_i - \mathbf{y}_i^*\|.$$

Score Regression: Optimize a dummy score of hypotheses sampled around ground truth poses.

Results:

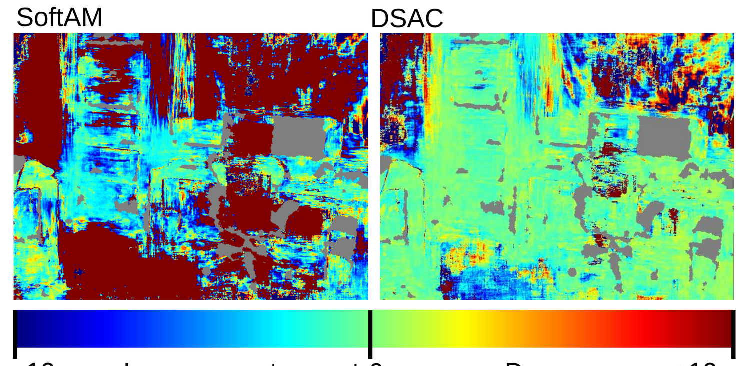
% Frames with Error <5°,5cm	Trained Componentwise	Trained End-to-End
Shotton et al. [Sho13]	38.6%	-
Brachmann et al. [Bra16]	55.2%	-
Ours, RANSAC	61.0%	-
Ours, SoftAM	61.6%	59.6% (-2.0%)
Ours, DSAC	60.3%	**62.4%** (+2.1%)



Input RGB   Scene Coordinate Ground Truth   Componentwise Training, Prediction

Change in Prediction Error after End-to-End Training w.r.t. Componentwise Training:

SoftAM   DSAC

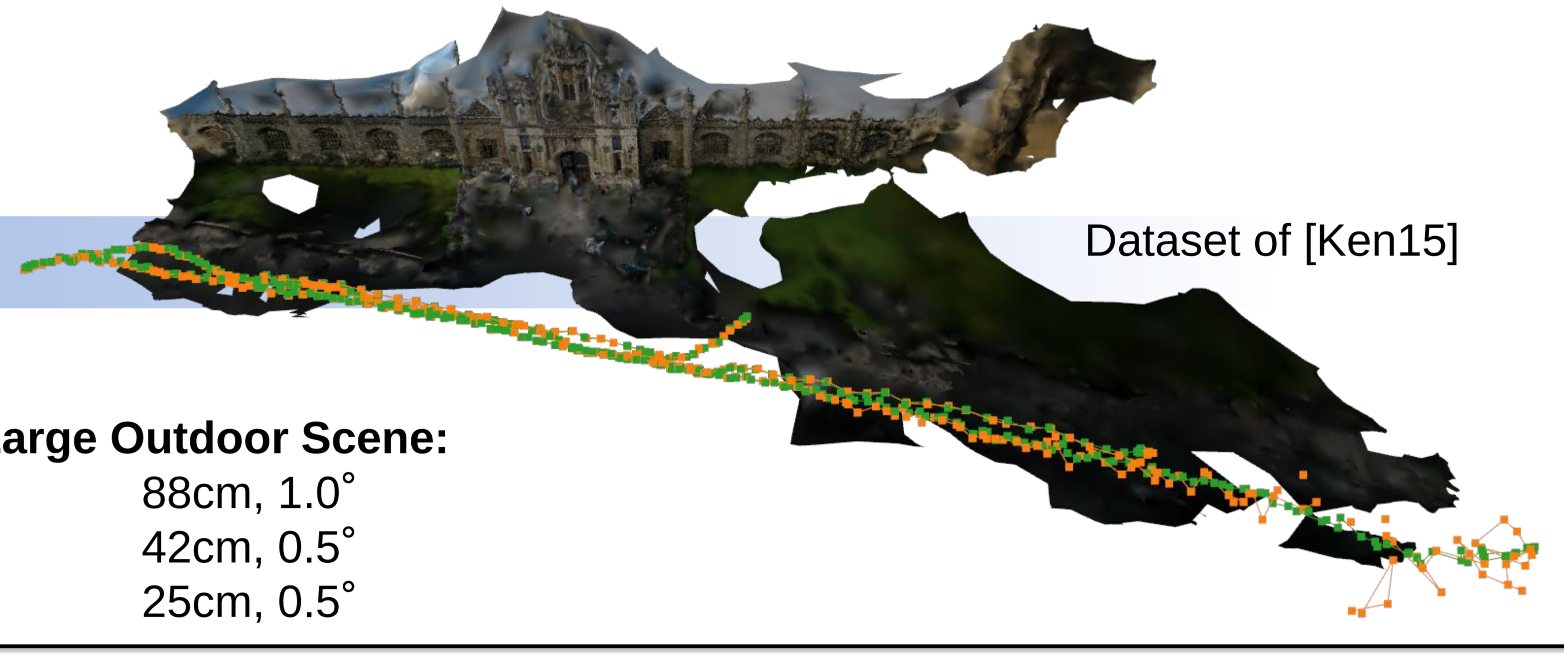


New Results

7-Scenes: 68.0%

Median Accuracy on a Large Outdoor Scene:

PoseNet [Ken17]:	88cm, 1.0°
Sparse Features [Sat16]:	42cm, 0.5°
Our Results:	25cm, 0.5°



Dataset of [Ken15]

[Sho13] "Scene Coordinate Regression Forests for Camera Relocalization in RGB-D Images", Shotton et al., CVPR'13
[Bra16] "Uncertainty-Driven 6D Pose Estimation of Objects and Scenes from a Single RGB Image", Brachmann et al., CVPR'16
[Ken15] "PoseNet: A Convolutional Network for Real-Time 6-DOF Camera Relocalization" Kendall et al., ICCV'15
[Ken17] "Geometric Loss Functions for Camera Pose Regression with Deep Learning" Kendall and Cipolla, CVPR 2017
[Sat16] "Efficient & Effective Prioritized Matching for Large-Scale Image-Based Localization" Sattler et al., PAMI 2016

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