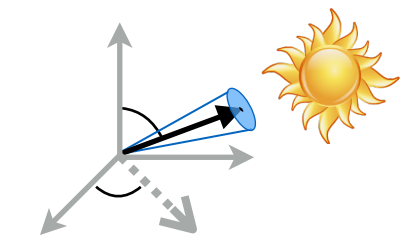


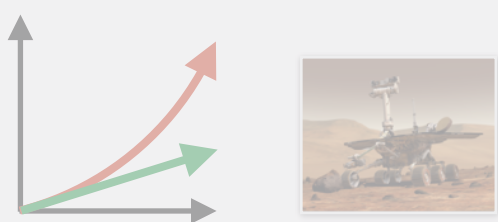
Reducing drift in VO by inferring sun direction using a Bayesian CNN

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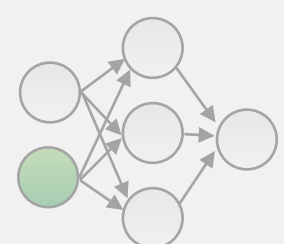
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Motivation



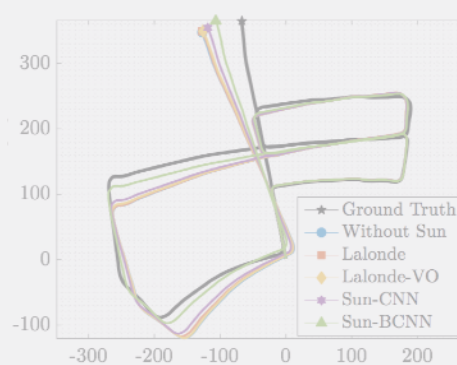
Approach



Training & Testing



Results



Conclusions

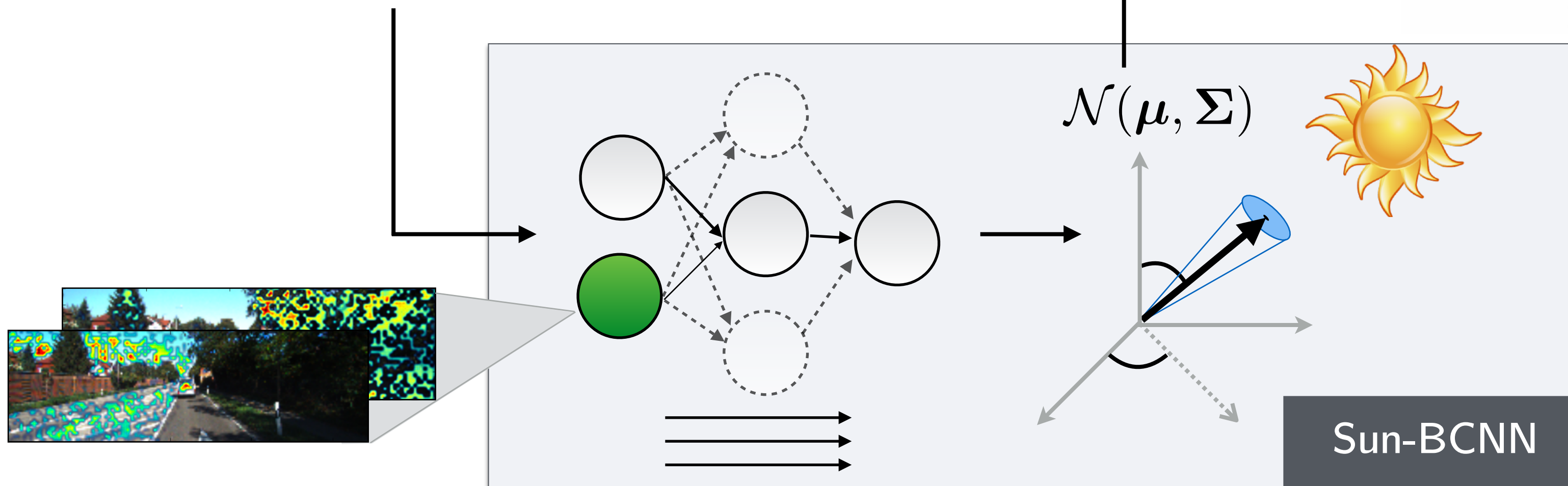
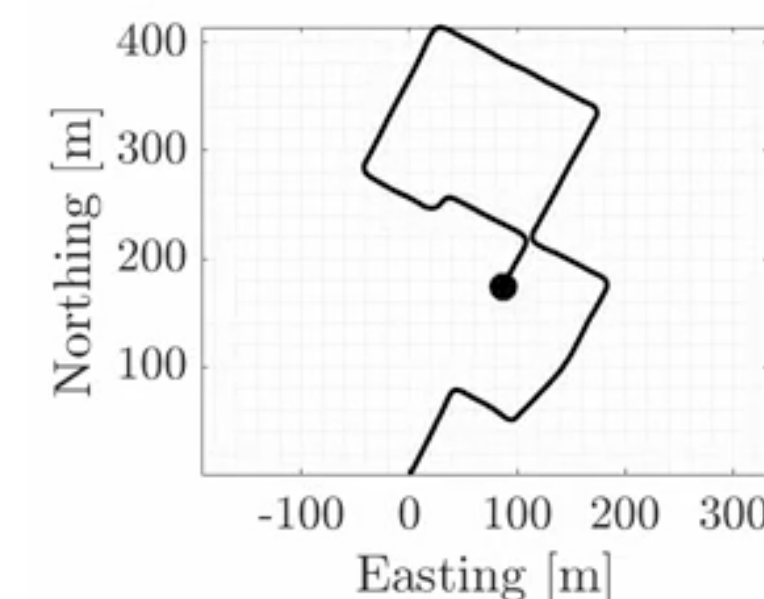


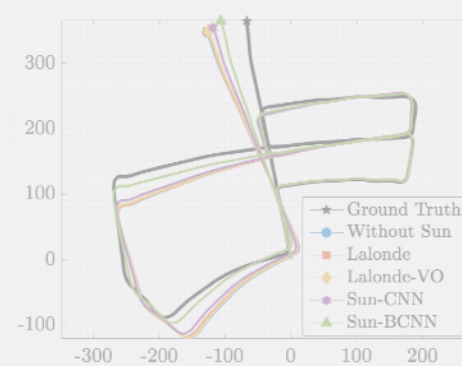
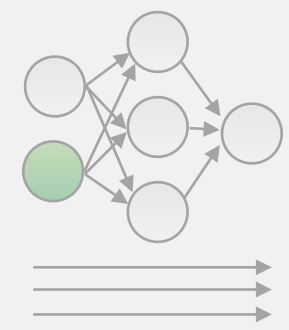
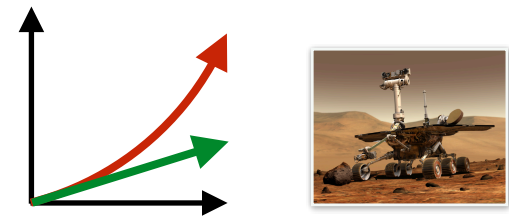
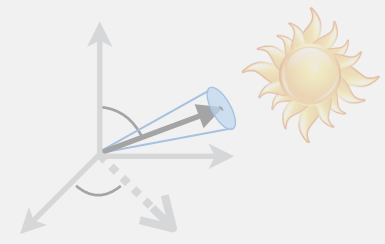
Sparse Feature Tracks



Stereo VO

Improved Localization





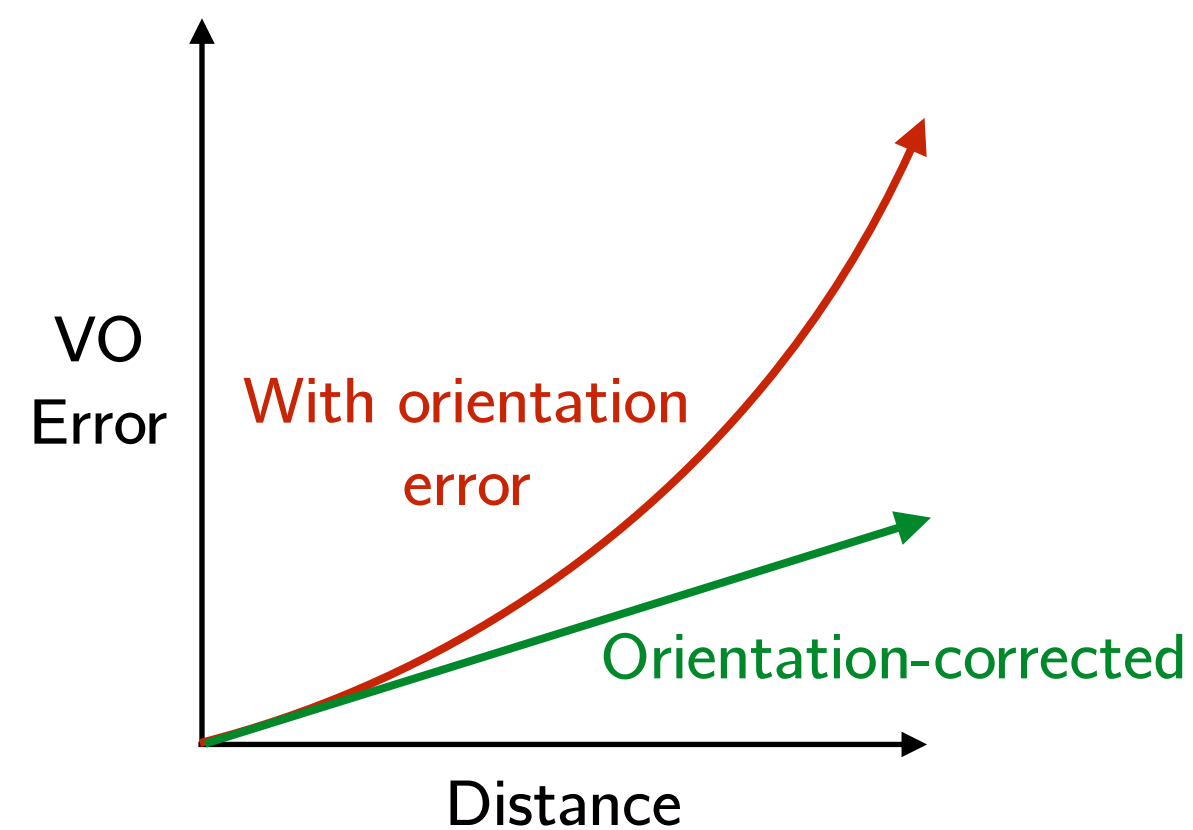
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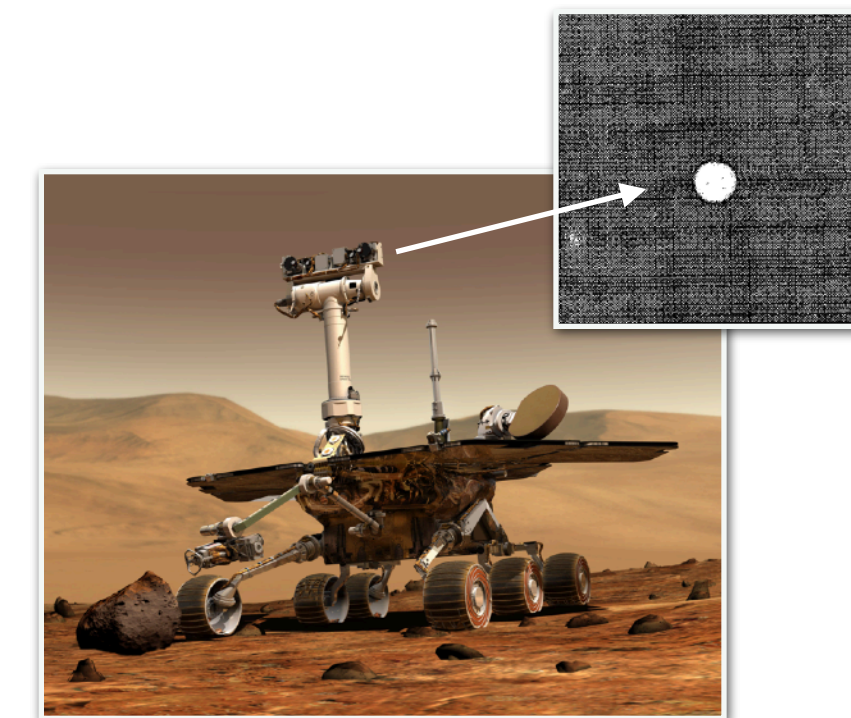
Error growth in visual odometry

VO is a dead-reckoning technique and suffers from super-linear error growth, largely due to accumulated orientation error

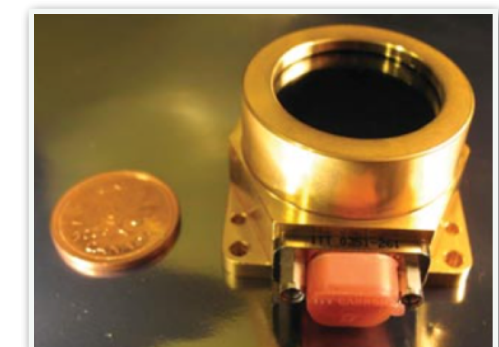


Correcting drift with absolute orientation

Drift can be reduced using orientation information from a sun sensor



Specially oriented camera (e.g., MERs)

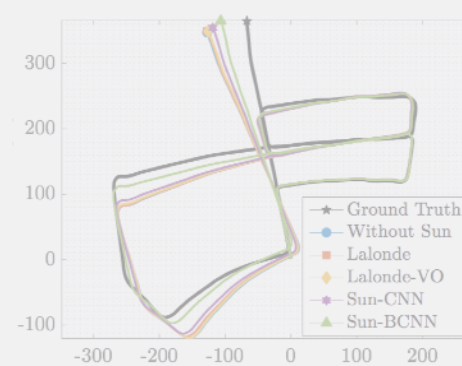
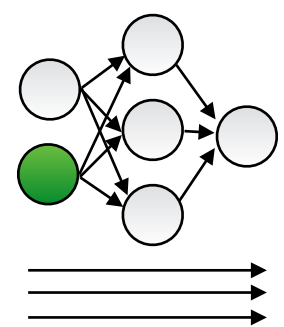
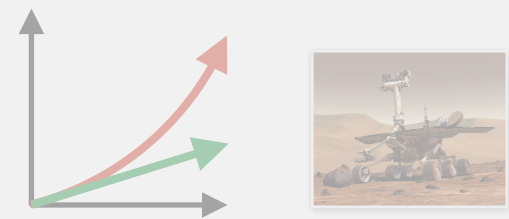
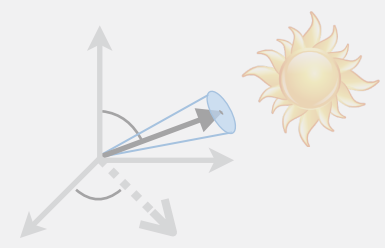


Specialized sun sensor



Can we use our existing image stream to infer the direction of the sun from environmental cues?





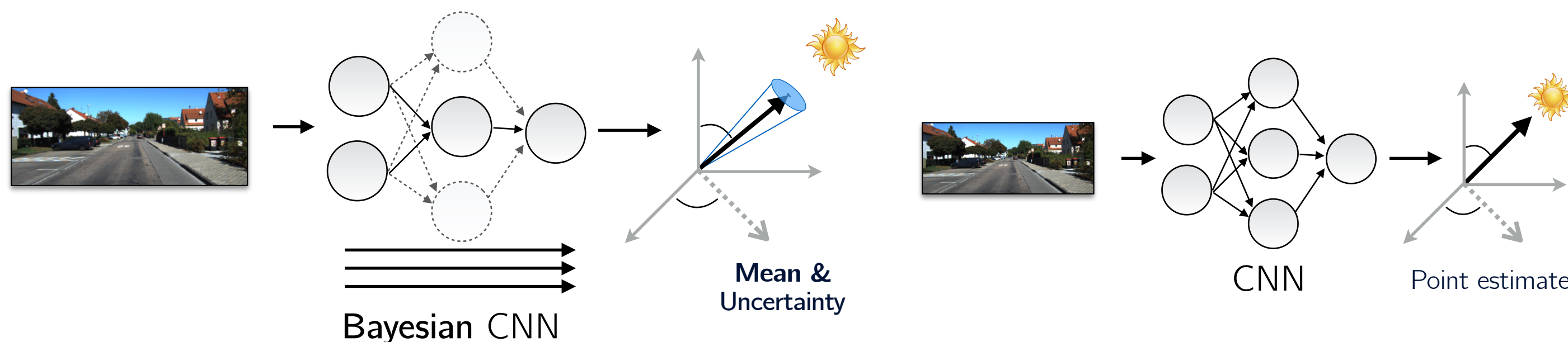
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Bayesian Convolutional Neural Networks

Using dropout to compute uncertainty

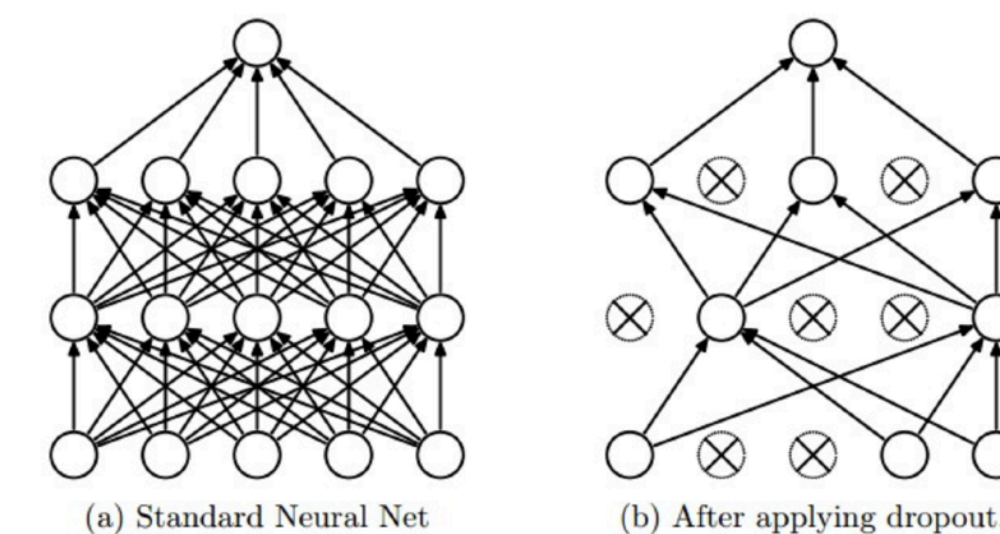


Key Insight Training with dropout → Variational Inference

- Given prior: $p(\mathbf{w}) \rightarrow p(\mathbf{w}|\mathbf{X}, \mathbf{S})$
(NN weights) (training images) (training targets)
- By defining variational distribution: $q(\mathbf{w}) \sim p(\mathbf{w}|\mathbf{X}, \mathbf{S})$
(matrix with K_i weights for layer i)
 $q(\mathbf{w}_i) = \mathbf{M}_i \text{diag} \left\{ \{b_j^i\}_{j=1}^{K_i} \right\}$
 $b_j^i \in \text{Bernoulli}(p_i)$ (dropout probability)
- Training with dropout is equivalent to minimizing the KL divergence between true posterior and variational distribution:
 $D_{\text{KL}}(p(\mathbf{w}|\mathbf{X}, \mathbf{S}) || q(\mathbf{w}))$
- At test time, sample variational distribution stochastically: (Monte Carlo dropout):
 Mean $\mathbb{E}(\hat{\mathbf{s}}_k^*) = \bar{\mathbf{s}}_k^* \approx \frac{1}{N} \sum_{n=1}^N \hat{\mathbf{s}}_k^*(\mathbf{x}^*, \mathbf{w}^n)$
 Covariance $\mathbb{E}(\hat{\mathbf{s}}_k^* \hat{\mathbf{s}}_k^{*T}) \approx \tau^{-1} \mathbf{1} + \frac{1}{N} \sum_{n=1}^N \hat{\mathbf{s}}_k^*(\mathbf{x}^*, \mathbf{w}^n) \hat{\mathbf{s}}_k^*(\mathbf{x}^*, \mathbf{w}^n)^T - \bar{\mathbf{s}}_k^* \bar{\mathbf{s}}_k^{*T}$
model precision

Dropout

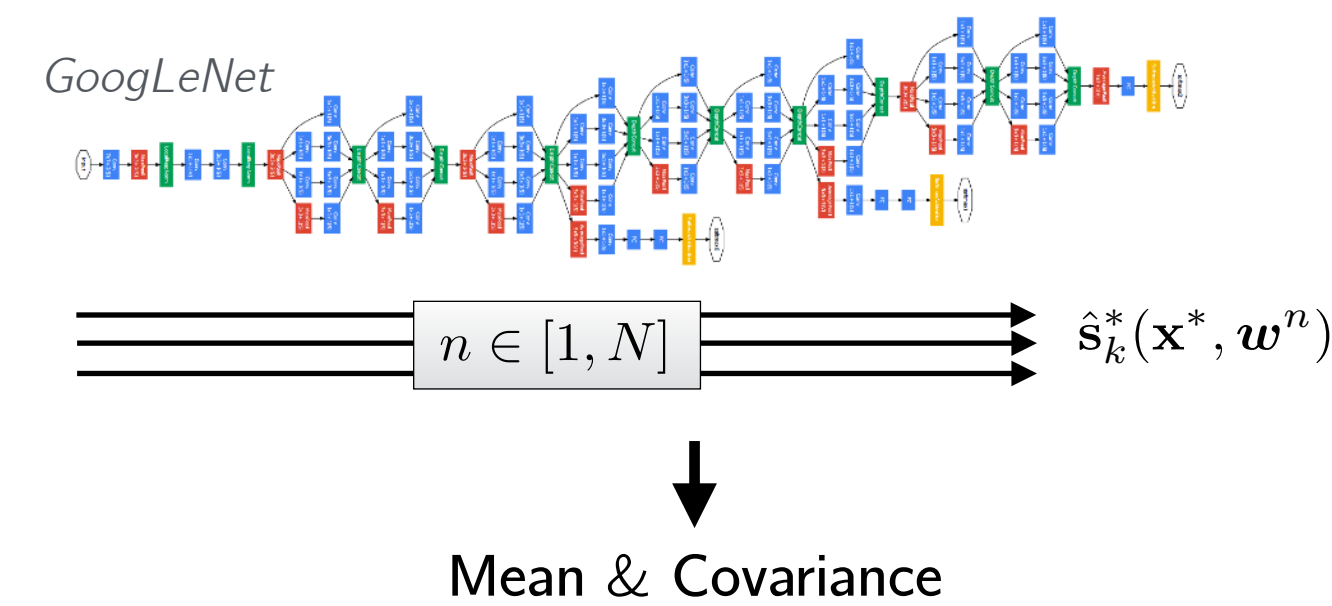
Originally developed to reduce overfitting

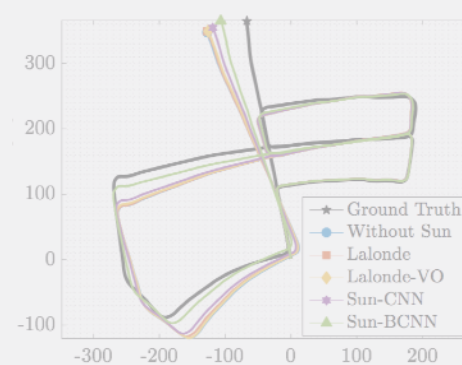
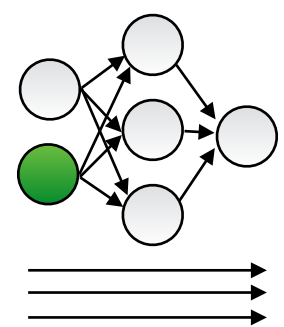
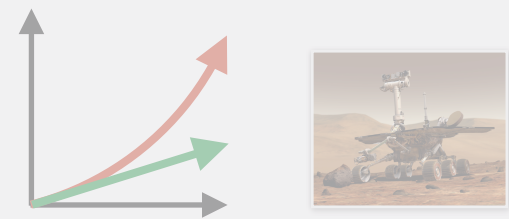
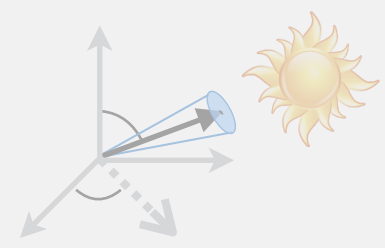


Applied only during training

Monte Carlo Dropout

Uncertainty through stochastic sampling using dropout during testing





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Sliding window sparse stereo visual odometry

Cost (to minimize)

$$\mathcal{J} = \mathcal{J}_{\text{reprojection}} + \mathcal{J}_{\text{prior}}$$

$$\mathcal{J}_{\text{reprojection}} = \sum_{k=k_1}^{k_2} \sum_{j=1}^J \mathbf{e}_{\mathbf{y}_{k,j}}^T \mathbf{R}_{\mathbf{y}_{k,j}}^{-1} \mathbf{e}_{\mathbf{y}_{k,j}}$$

$$\mathcal{J}_{\text{prior}} = \mathbf{e}_{\hat{\mathbf{T}}_{k_1,0}}^T \mathbf{R}_{\hat{\mathbf{T}}_{k_1,0}}^{-1} \mathbf{e}_{\hat{\mathbf{T}}_{k_1,0}}$$

Stereo observation model $\mathbf{y}_{k,j} = \mathbf{g}(\mathbf{p}_k^j) = \begin{bmatrix} u \\ v \\ d \end{bmatrix} = \begin{bmatrix} f_u p_{k,x}^j / p_{k,z}^j + c_u \\ f_v p_{k,y}^j / p_{k,z}^j + c_v \\ f_u b / p_{k,z}^j \end{bmatrix}$

Sun-aided visual odometry

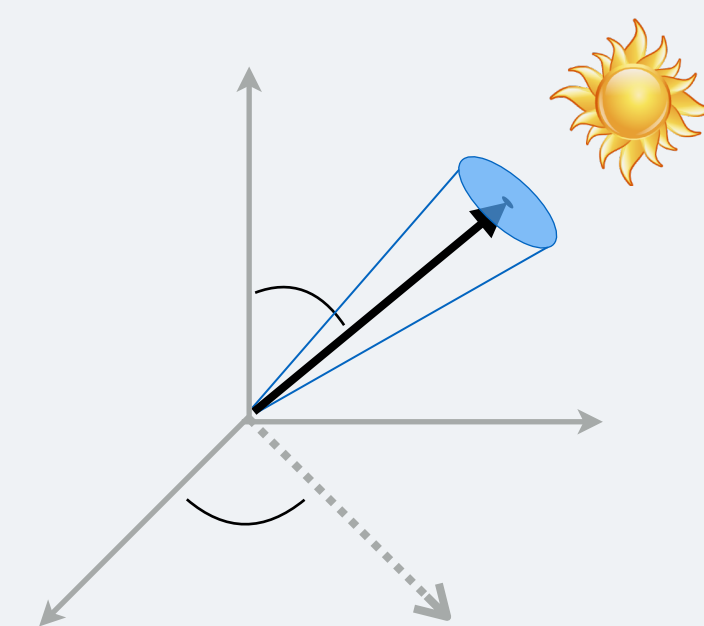
Cost (to minimize)

$$\mathcal{J} = \mathcal{J}_{\text{reprojection}} + \mathcal{J}_{\text{prior}} + \mathcal{J}_{\text{sun}}$$

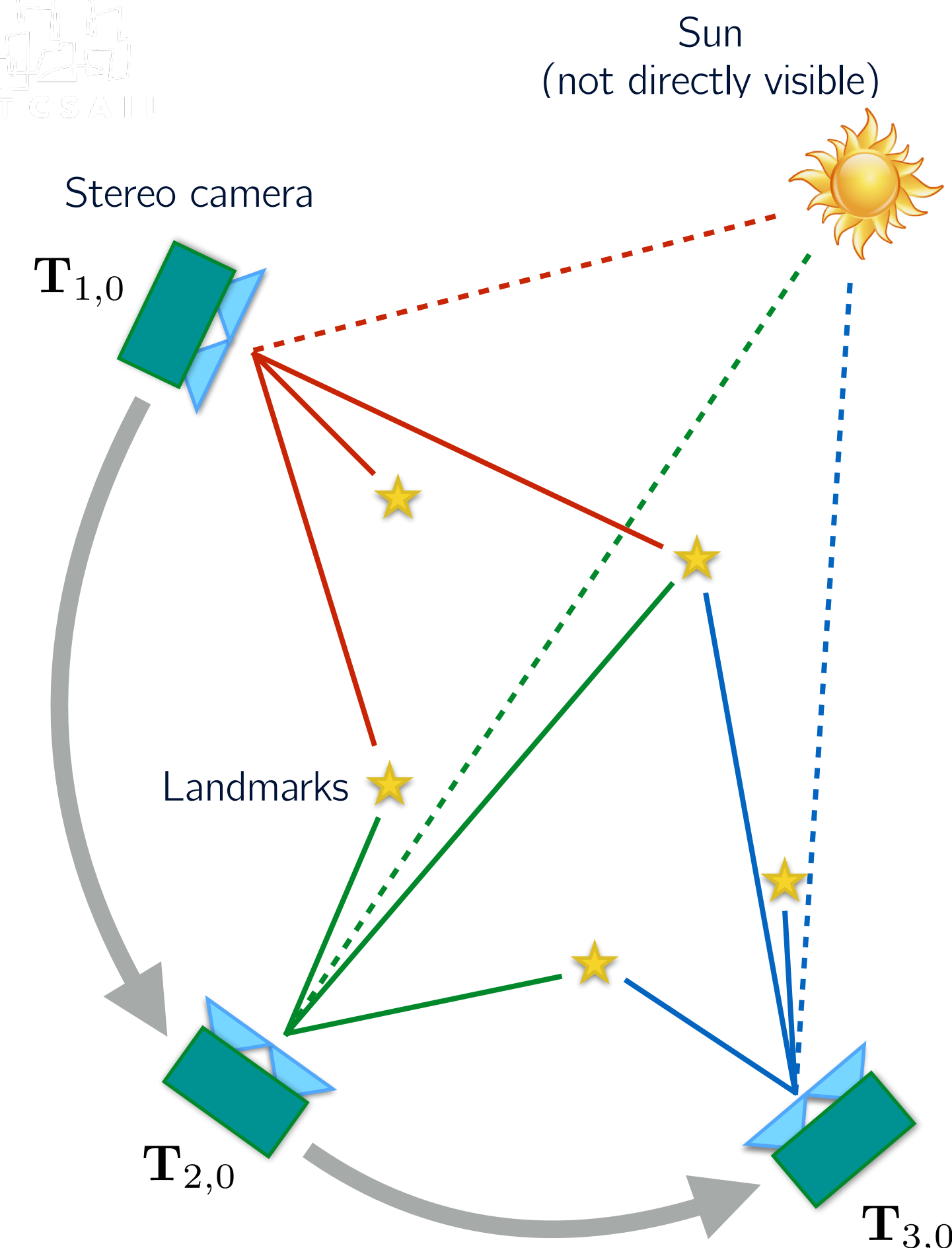
$$\mathcal{J}_{\text{sun}} = \sum_{k=k_1}^{k_2} \mathbf{e}_{\mathbf{s}_k}^T \mathbf{R}_{\mathbf{s}_k}^{-1} \mathbf{e}_{\mathbf{s}_k}$$

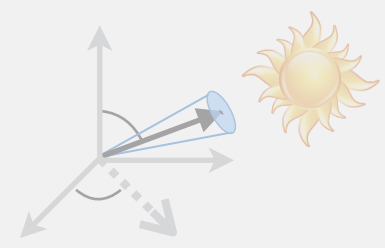
Sun observation model
(zenith-azimuth)

$$\begin{bmatrix} \theta \\ \phi \end{bmatrix} = \mathbf{f}(\mathbf{s}_k) = \begin{bmatrix} \text{acos}(-s_{k,y}) \\ \text{atan2}(s_{k,x}, s_{k,z}) \end{bmatrix}$$



Mean and uncertainty

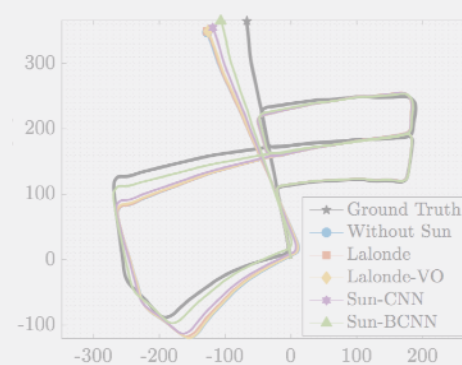
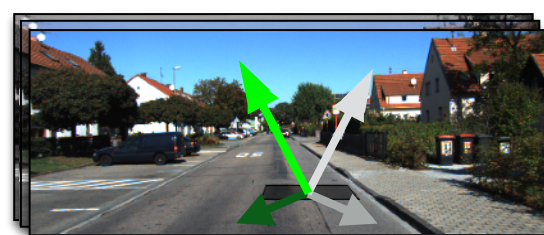
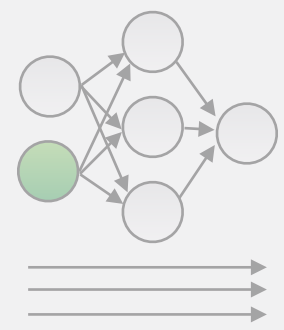
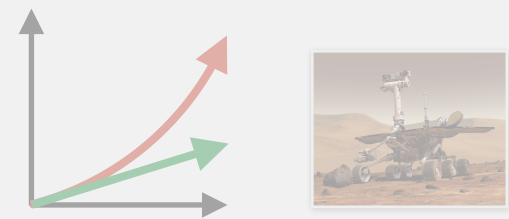




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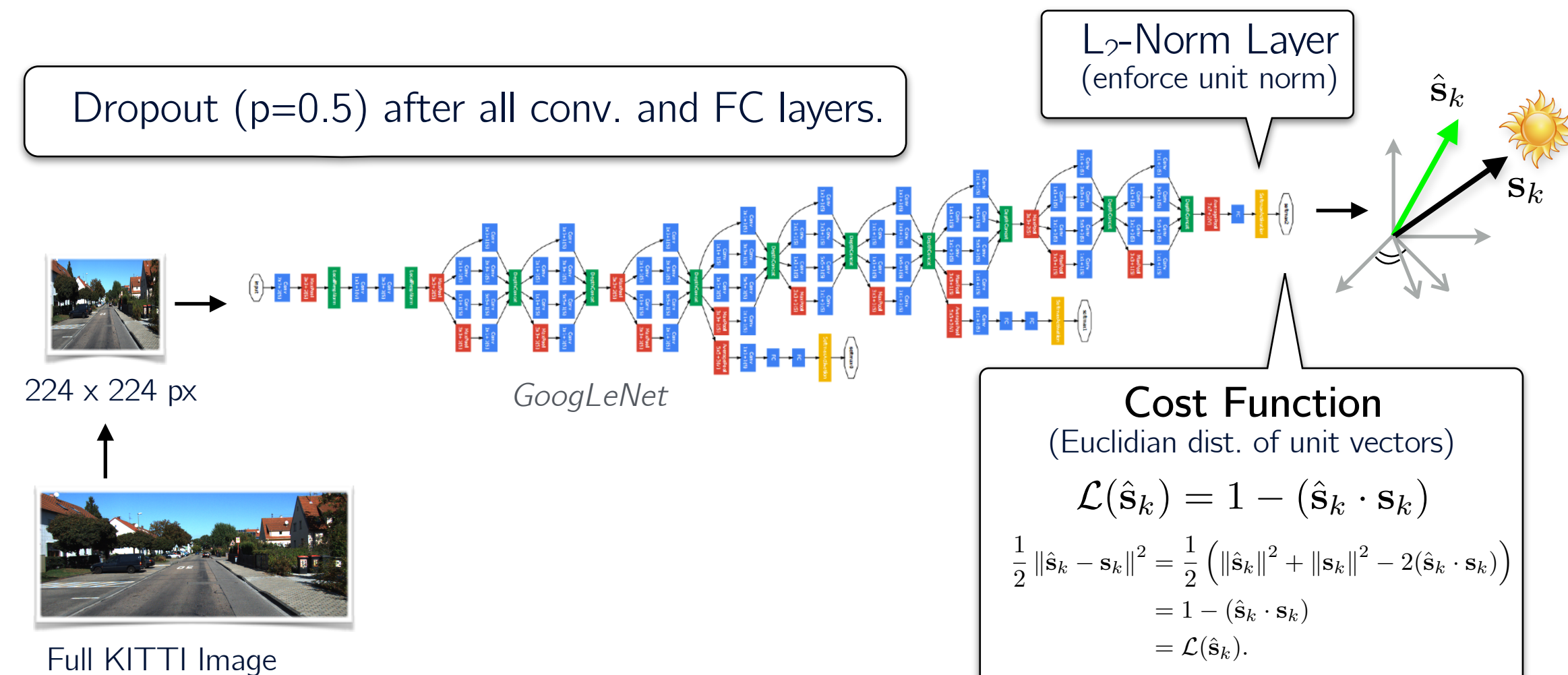
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Training & Testing

How to build a Sun-BCNN



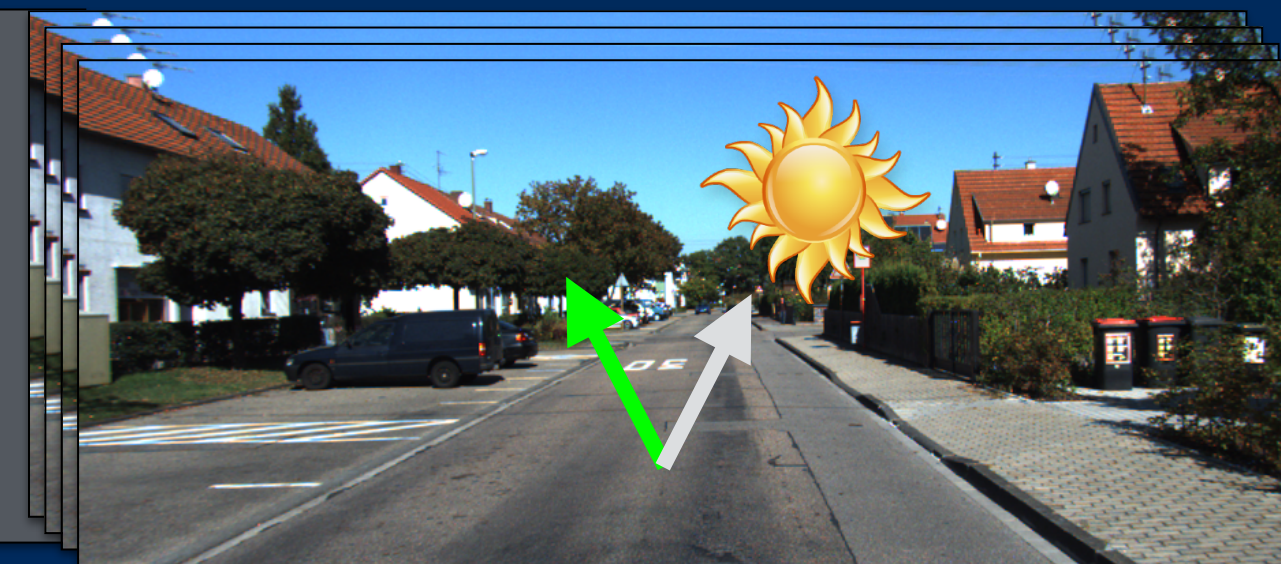
Testing

- 1 Compute $N=25$ stochastic samples using Monte-Carlo dropout.
 - 2 **Mean:** Compute mean vector, normalize, convert to azimuth and zenith
 - 3 **Covariance:** Convert to azimuth, zenith angles. Compute empirical covariance, add inverse model precision.
-

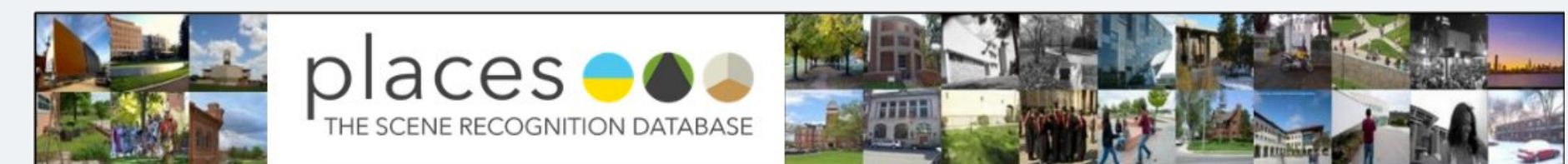
Dataset

KITTI Odometry Benchmark

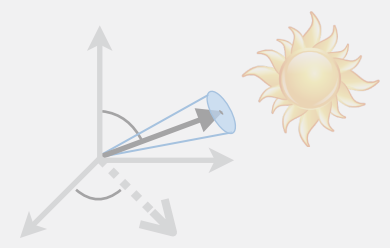
- 10 sequences
- 9/1 test/train split for each sequence
- 20k images per training set



Implementation Details



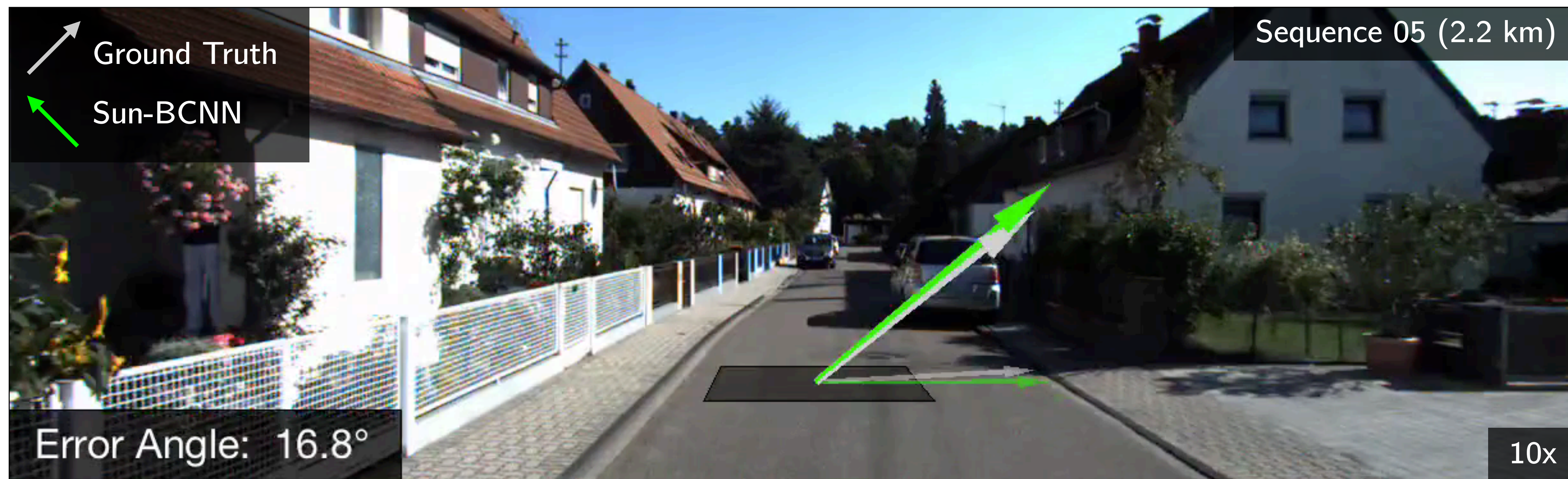
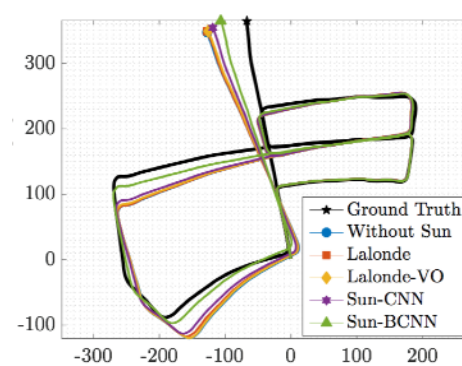
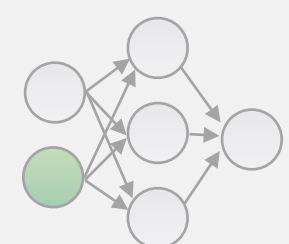
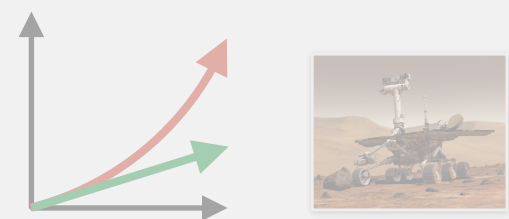
- Caffe Implementation
 - L2-Norm layers from Caffe SL
- Dropout after all convolutional and FC layers
 - $p = 0.5$
- GoogLeNet
 - Pre-trained on MIT Places
 - 224 x 224 RGB resized images
 - SGD, 1000 epochs, batch size of 64



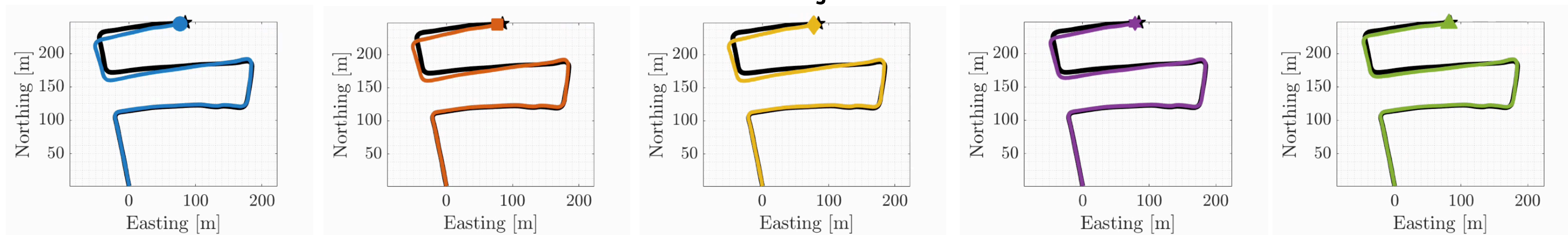
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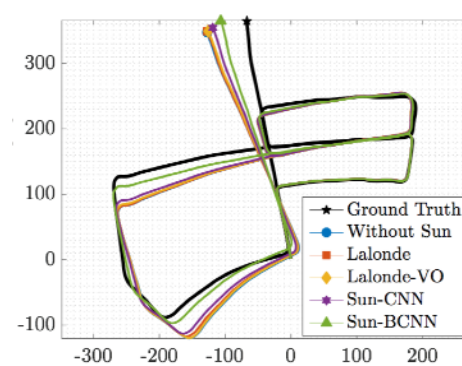
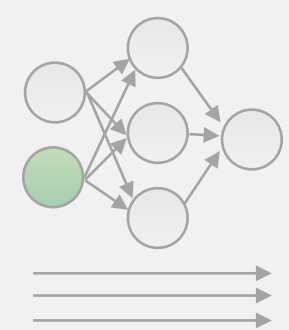
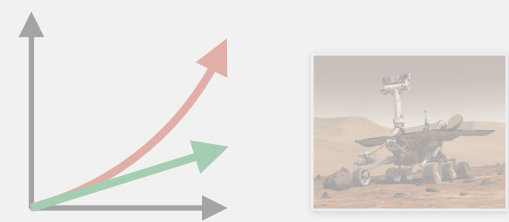
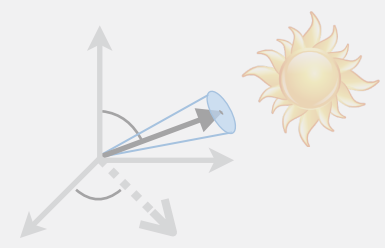
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VO Trajectories



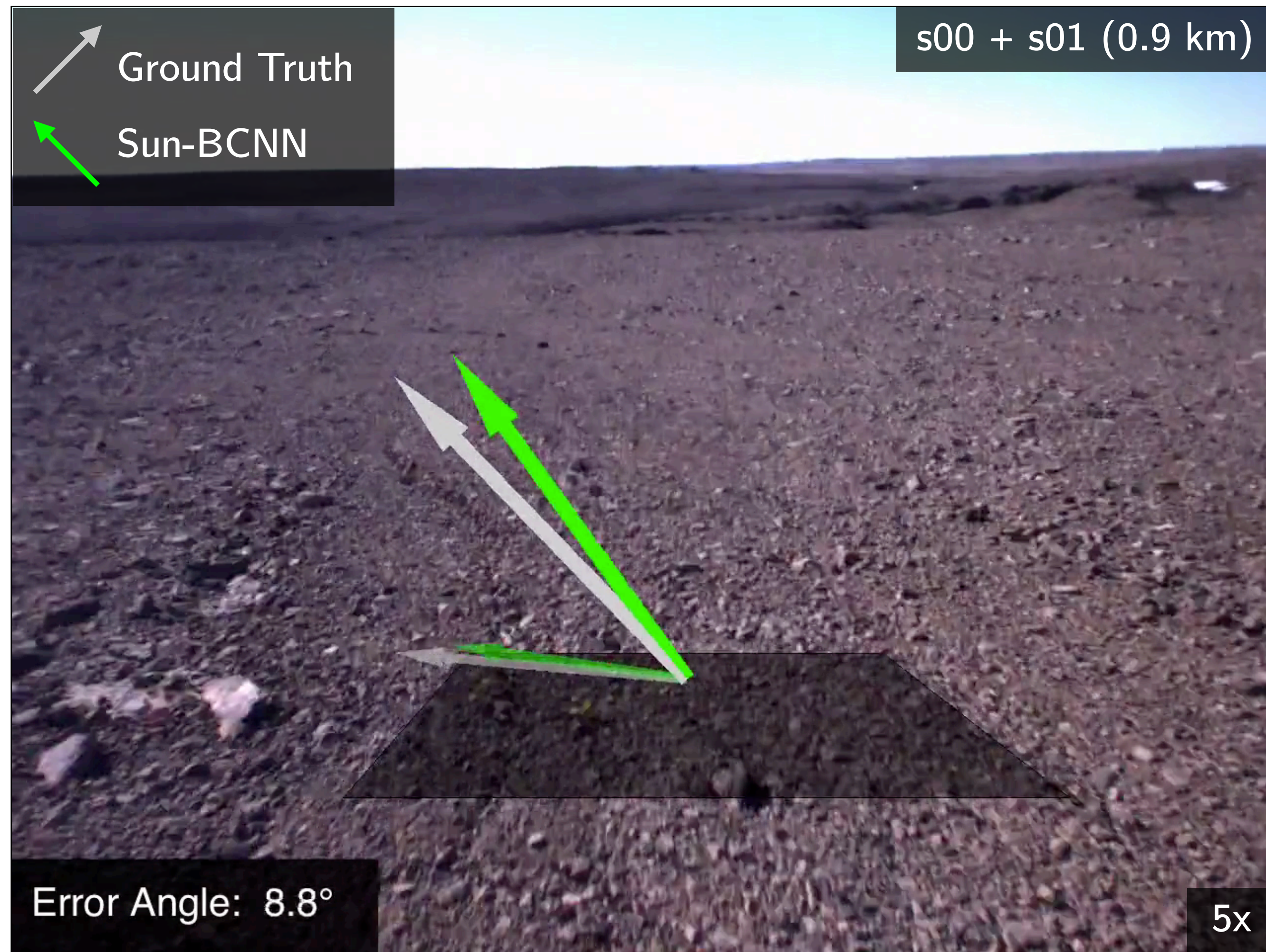
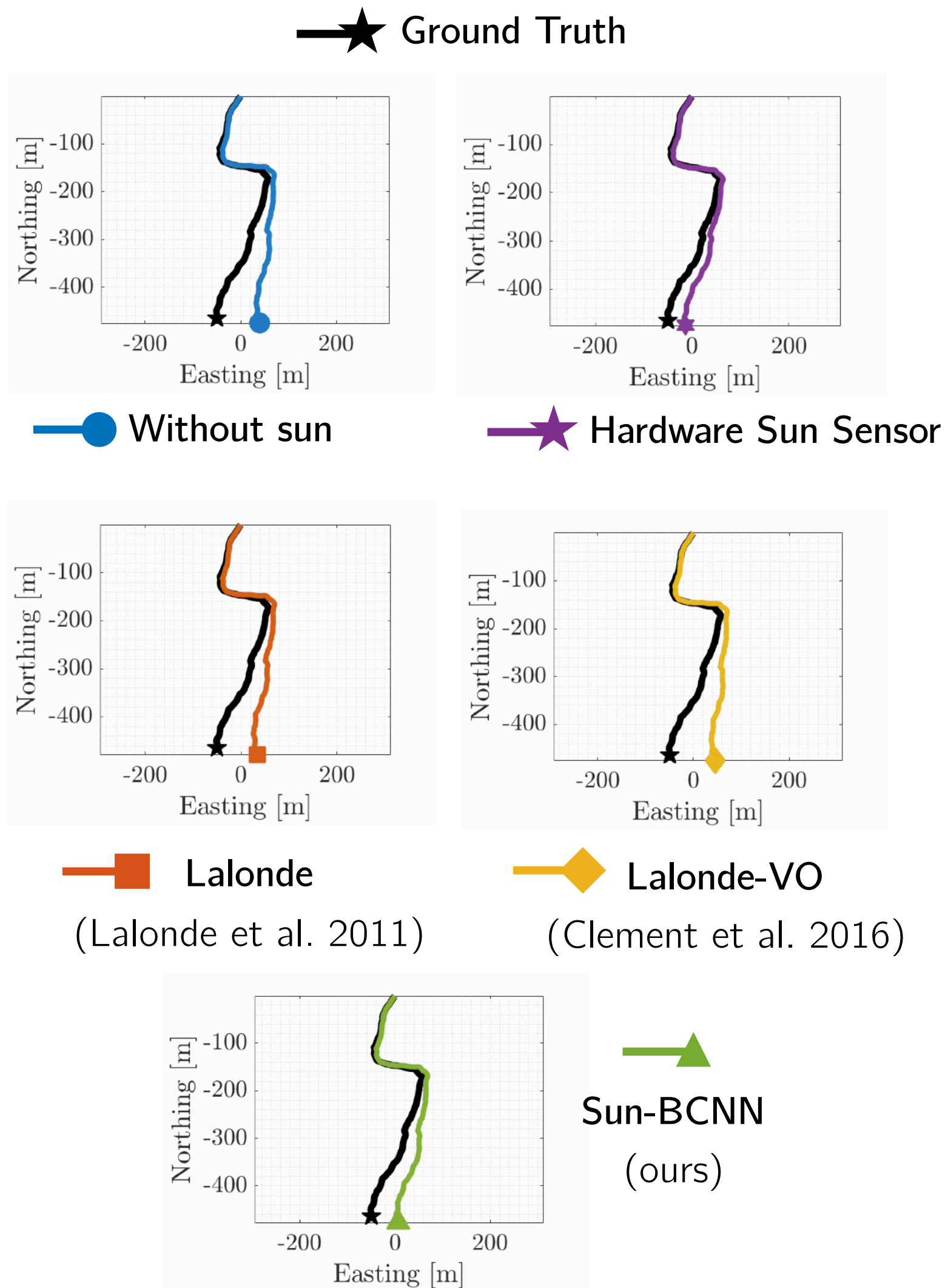
- Without sun
- Ground Truth
- Lalonde (Lalonde et al. 2011)
- Lalonde-VO (Clement et al. 2016)
- Sun-CNN (Ma et al. 2017)
- Sun-BCNN (ours)



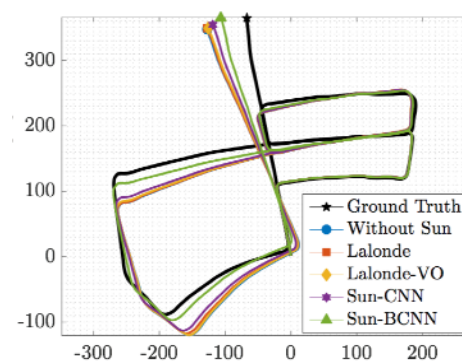
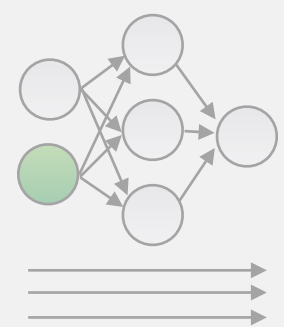
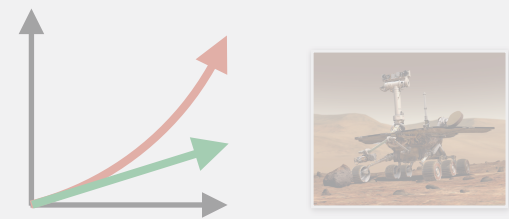
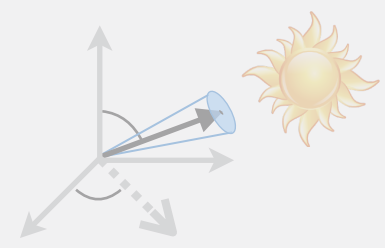
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P. Furgale, P. Carle, J. Enright, and T. D. Barfoot, "The Devon Island rover navigation dataset," IJRR, 2012.



Reducing drift in VO by inferring sun direction using a Bayesian CNN

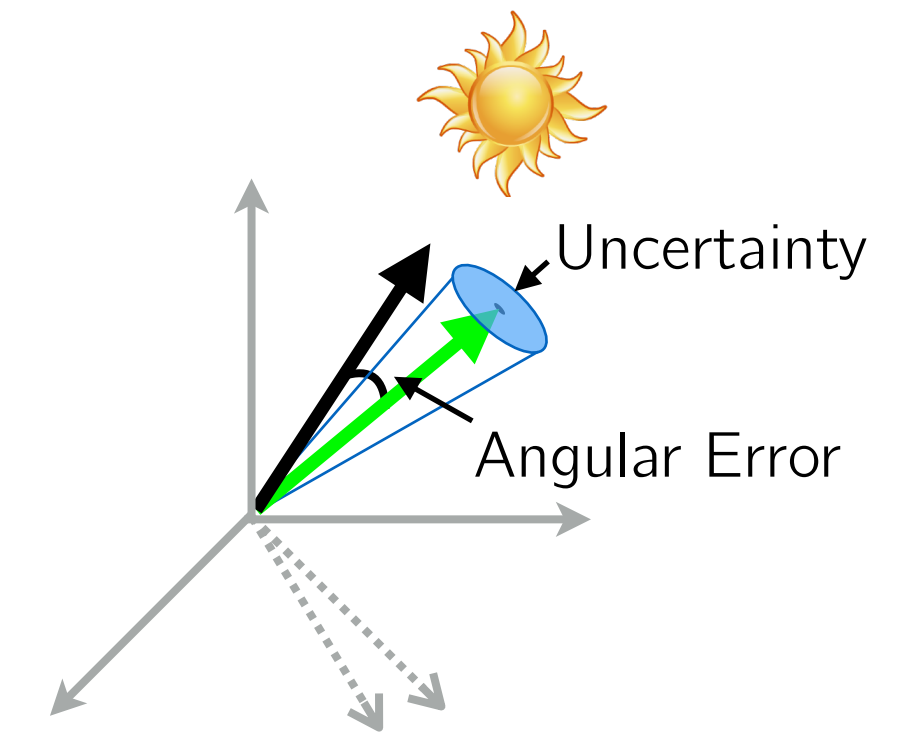
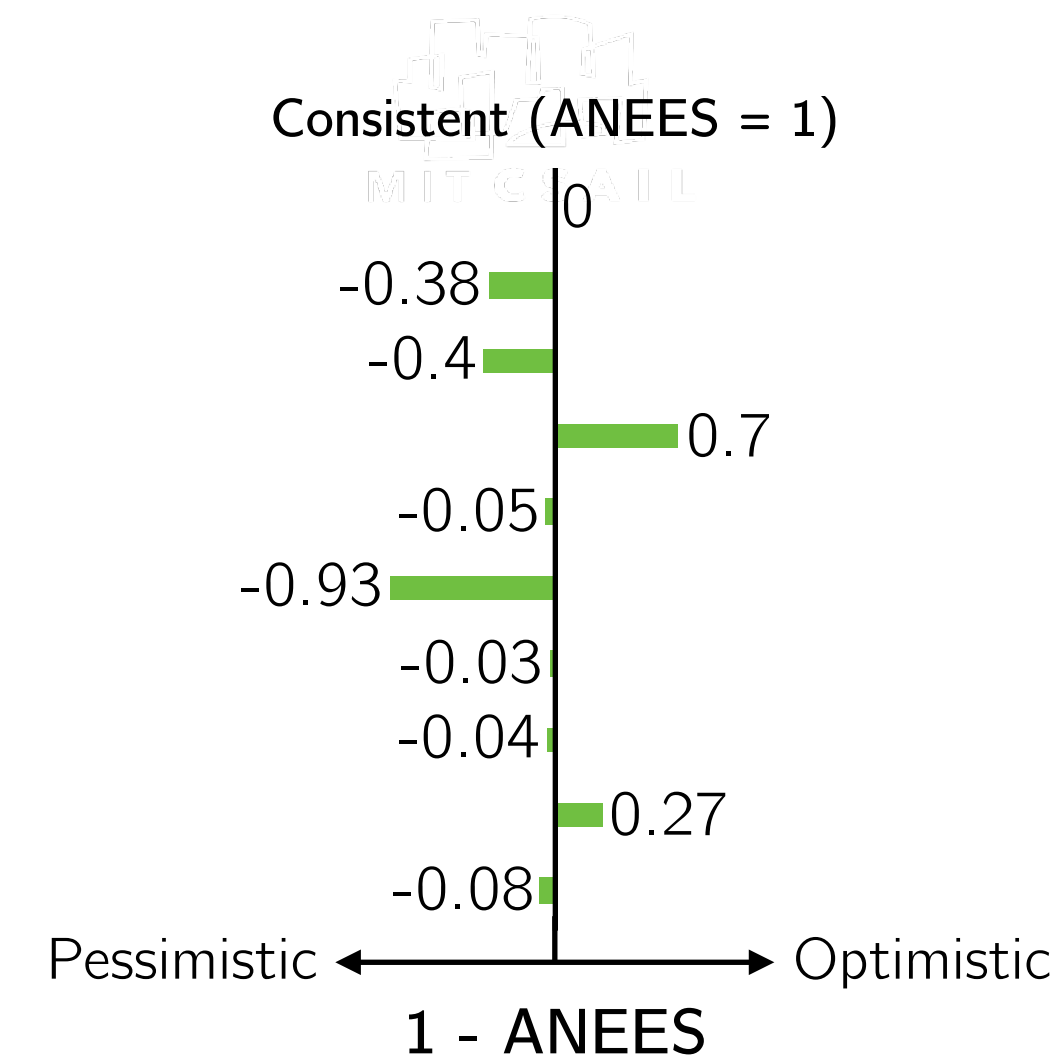
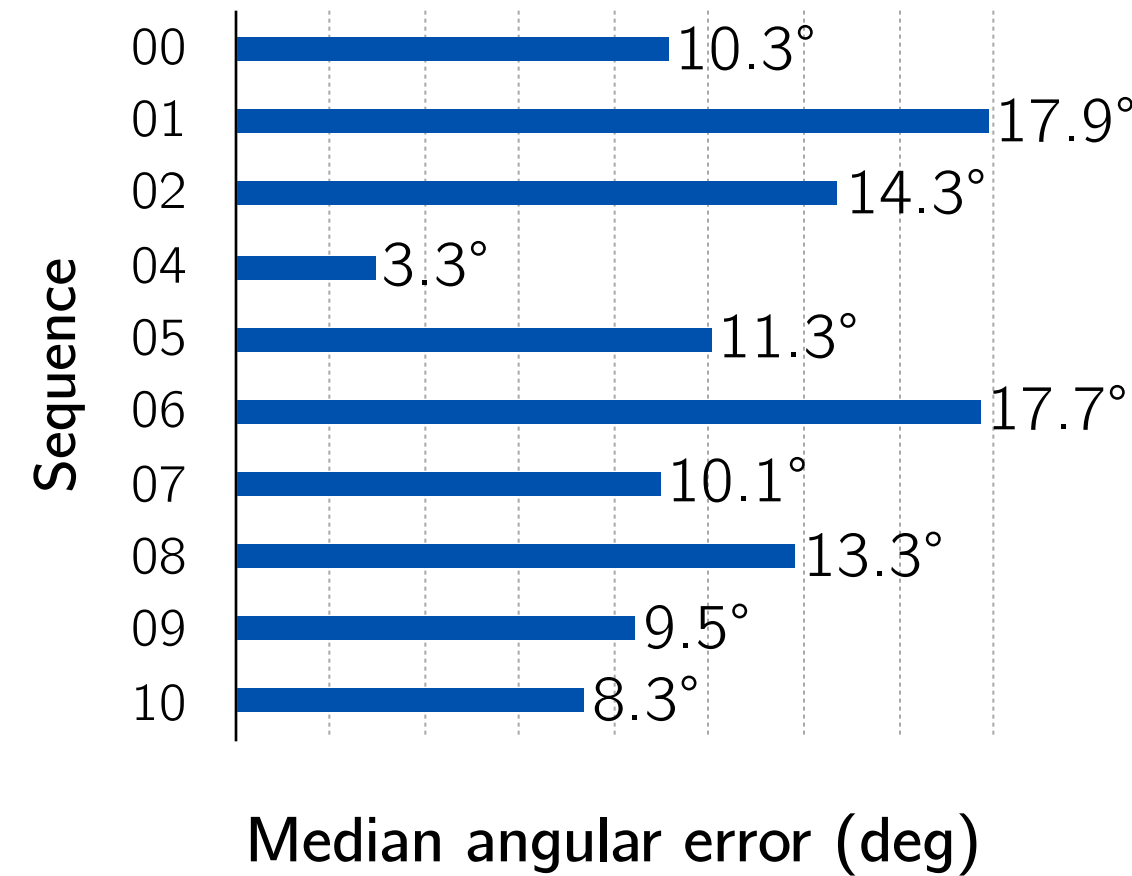
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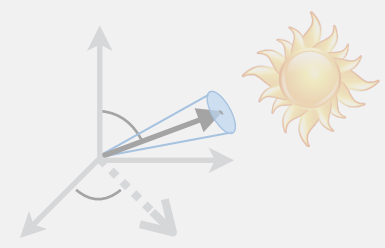
Testing on the KITTI Odometry Benchmark

Sun-BCNN:

- consistently achieves $< 18^\circ$ median angular error
- performs best with strong directional illumination cues
- struggles in ambiguous lighting conditions



Introduction

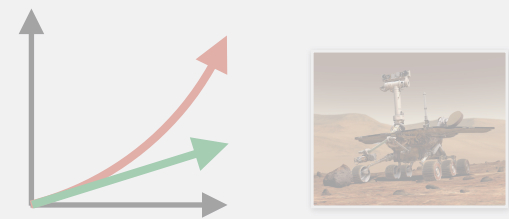


Reducing drift in VO by inferring sun direction using a Bayesian CNN

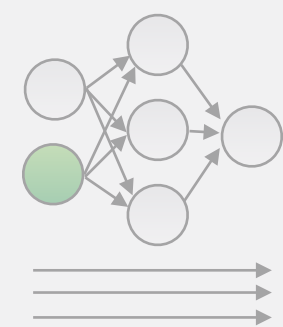
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Motivation



Approach



Future Work

- Incorporate temporal consistency (e.g. using RNN)
- Account for different cameras (e.g. by changing variables to remove effect of intrinsic calibration)



Acknowledgements



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UNIVERSITY OF TORONTO



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Journal Extension

Inferring Sun Direction to Improve Visual Odometry: A Deep Learning Approach

Valentin Peretroukhin¹, Lee Clement¹, and Jonathan Kelly¹

Abstract
We present a method to incorporate global orientation information from the sun into a visual odometry (VO) pipeline using only the existing image stream, where the sun is typically not visible. We leverage recent advances in Bayesian Convolutional Neural Networks (BCNNs) to train and implement a sun direction model (dubbed Sun-BCNN) that infers a three-dimensional sun direction vector from a single RGB image. Crucially, our method also computes a principled uncertainty associated with each prediction, using a Monte Carlo dropout scheme. We incorporate this uncertainty into a sliding window stereo visual odometry pipeline where accurate uncertainty estimates are critical for optimal data fusion. We evaluate our method on 21.6 km of urban driving data from the KITTI odometry benchmark, training set where it achieves a median error of approximately 12 degrees and yields improvements of up to 45% in translational ARMSSE and 52% in rotational ARMSSE compared to standard VO. We further evaluate our method on an additional 10 km of visual navigation data from the Devon Island Rover Navigation dataset, achieving a median error of less than 8 degrees and yielding similar improvements in estimation error. In addition to reporting on the accuracy of Sun-BCNN and its impact on VO, we analyze the sensitivity of our model to cloud cover, investigate the possibility of model transfer between urban and planetary analogue environments, and examine the impact of different methods for computing the mean and covariance of a norm-constrained vector on the accuracy and consistency of the estimated sun direction. An open source implementation of Sun-BCNN using Caffe is available at <https://github.com/utiasSTARS/sun-bcnn>.

Keywords
Orientation Estimation, Sun Sensing, Deep Learning, Visual Odometry, Robot Navigation

Introduction
A crucial competency of any autonomous mobile robot is the ability of the platform to estimate its own motion through its operating environment. While there exists a rich body of literature on the topic of motion estimation using a variety of techniques such as laser-based point cloud matching (Cox and Stach 2015) and visual-odometry (Lowe et al. 2015), ego-motion estimation is fundamentally a process of dead-reckoning and will accumulate unbounded error over time. This accumulated error, or drift, can be limited by incorporating global information into the motion estimation problem. This frequently takes the form of a globally consistent map, loop closure detection, or reliance on additional sensors such as GPS to make corrections to the estimated trajectory. In many situations, however, a globally consistent map may be unavailable or prohibitively expensive to compute, loop closures may not occur, or GPS may be unavailable or inaccurate. In such cases, it can be advantageous to rely on environmental cues such as the sun, which can easily provide global orientation information since it is easily detectable and its apparent motion in the sky is well described by ephemeris models.

For visual odometry (VO) in particular, the addition of global orientation information can limit the growth of drift error to be linear rather than exponential with distance travelled (Khan et al. 2003). Sun based orientation corrections have been successfully used in planetary

Figure 1. Our method uses a Bayesian Convolutional Neural Network (BCNN) to estimate the direction of the sun, and also produce a principled uncertainty estimate for each prediction. We incorporate this virtual sun sensor into a stereo visual odometry pipeline to reduce estimation error.

Figure 2. Sun-BCNN architecture diagram showing input image, feature extraction, and output sun direction vector.

Figure 3. Comparison of trajectories: Ground Truth (blue), Without Sun (red), Lalonde (green), Lalonde-VO (orange), Sun-CNN (purple), and Sun-BCNN (yellow). Sun-BCNN shows significantly reduced drift compared to other methods.

GitHub

utiasSTARS / sun-bcnn

Bayesian CNN Sun Detector

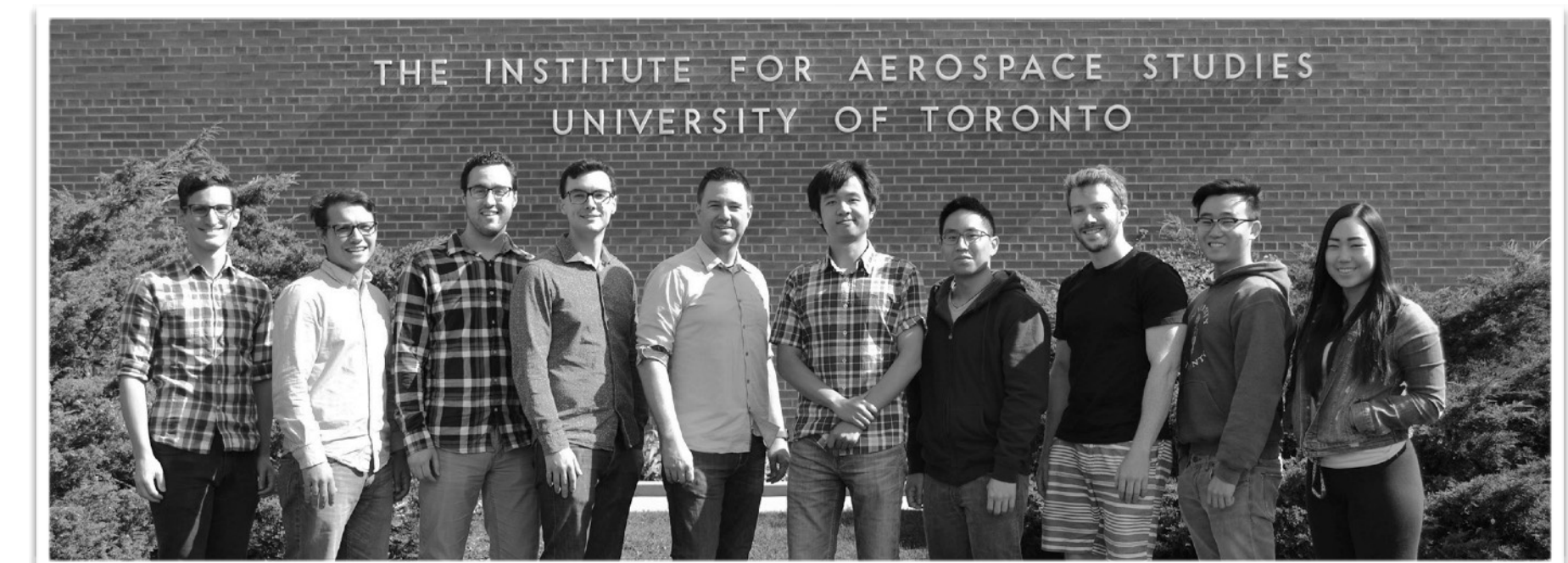
23 commits | 1 branch | 0 releases | 2 contributors

valentinp Added link to forked version of Caffe-si 8 months ago

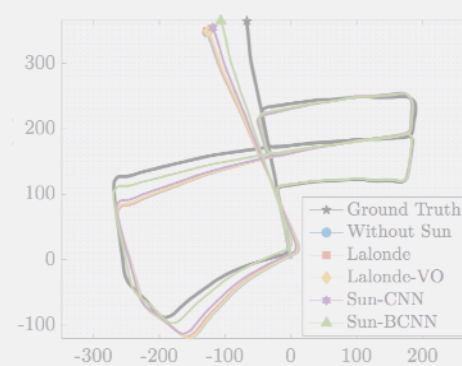
- caffe-files Cleaned up ground truth files into CSVs, and added training instructions 8 months ago
- kitti-groundtruth-data Cleaned up ground truth files into CSVs, and added training instructions 8 months ago
- scripts Added both covariance options to the testing python file 8 months ago
- .gitignore DS_store banished 8 months ago
- README.md Added link to forked version of Caffe-si 6 months ago
- sun-bcnn.png Added gitignore and resized readme image 8 months ago

Sun-BCNN

Bayesian Convolutional Neural Network to infer Sun Direction from a single RGB image, trained on the KITTI dataset [1].



Results



Conclusions

IJRR Special Issue on ISER
Invited, under review

Caffe implementation of Sun-BCNN
github.com/utiasSTARS/sun-bcnn

