On the uncertainty of self-supervised monocular depth estimation

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1. Problem Definition

Goal: joint depth prediction and uncertainty estimation from a single input image.

Key Contributions:

- A comprehensive evaluation of uncertainty estimation approaches tailored for **self-supervised** monocular depth estimation.
- An in-depth study of how different self-supervised strategies impacts on both uncertainty and depth.
- A new **Self-Teaching** paradigm to model uncertainty, crucial in the case of unknown camera poses during training.

2. Self-supervised monocular depth estimation

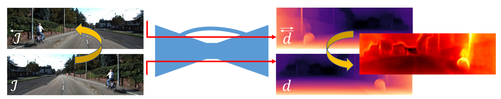
Supervision from hard to source ground truth labels can be replaced by an **image reconstruction loss** $\mathcal{L}_{ss}$ [1]. Given an input image $\mathcal{I}$ and a second frame $\mathcal{I}^{\dagger}$, a warped image $\tilde{\mathcal{I}}$ is obtained as a function π of intrinsics K, $K^{\dagger}$, relative pose $(R|t)$, $\mathcal{I}^{\dagger}$ and estimated depth d.

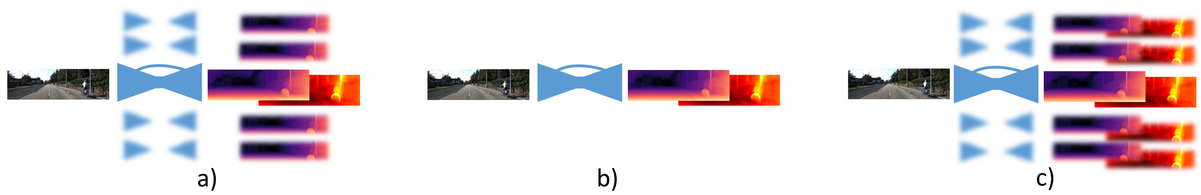
$$\mathcal{L}_{ss} = \mathcal{F}(\tilde{\mathcal{I}}, \mathcal{I}) = \alpha \cdot \frac{1 - \text{SSIM}(\tilde{\mathcal{I}}, \mathcal{I})}{2} + (1-\alpha) \cdot |\tilde{\mathcal{I}} - \mathcal{I}| \quad \text{with} \quad \tilde{\mathcal{I}} = \pi(\mathcal{I}^{\dagger}, K^{\dagger}, R|t, K, d)$$

Supervision can be sourced from K frames $\tilde{\mathcal{I}}$ selecting the minimum for each pixel q as $\mathcal{L}_{ss}(q) = \min_{i \in [0..K]} \mathcal{F}(\tilde{\mathcal{I}}_i(q), \mathcal{I}(q))$. The K frames can be acquired together with $\mathcal{I}$ by means of a single moving camera (M), a stereo rig (S) or both (MS). If $\mathcal{I}, \tilde{\mathcal{I}}$ are taken by a single camera, relative pose $(R|t)$ is unknown and thus estimated together with d.

3. Uncertainty estimation for self-supervised monocular estimation

Uncertainty from flipping. By estimating two depth maps d and $\overleftarrow{d}$ for image $\mathcal{I}$ and its horizontally flipped counterpart $\overleftarrow{\mathcal{I}}$, a naive uncertainty can be obtained as $|d - \overleftrightarrow{d}|$ by flipping back $\overleftarrow{d}$, similarly to the post-processing proposed in [2] (**Post**)





Uncertainty estimation strategies can be classified as follows [3]:

a) Empirical estimation. These methods sample a subset of all possible networks and estimate uncertainty as the **variance** $\sigma^2(d)$ over their predictions. Examples: MC Dropout (**Drop**), Bootstrapped Ensemble (**Boot**), Snapshots Ensemble (**Snap**).

b) Predictive estimation. This category aims at encoding uncertainty as a function of network parameters and the input image by means of a **predictive** model. Examples: Learned Reprojection (**Reproj**), Log-likelihood maximization (**Log**). This latter, traditionally used when ground truth is available, can be adapted to the self-supervised case as follows [4]

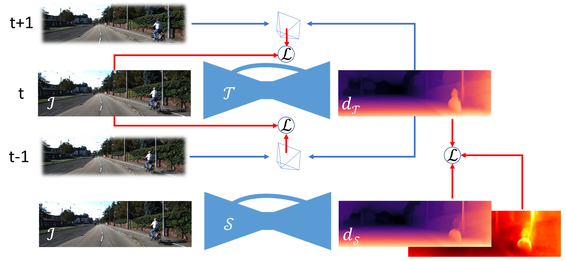
$$\mathcal{L}_{Log} = \frac{\min_{i \in [0..K]} \mathcal{F}(\tilde{\mathcal{I}}_i(q), \mathcal{I}(q))}{\sigma(d)} + \log \sigma(d)$$

c) Bayesian estimation. It models uncertainty by marginalizing over all possible network weights rather than choosing a point estimate. An approximation [5] is obtained combining **empirical** and **predictive** techniques (for instance, **Boot+Log**).

4. Self-teaching

In case of unknown pose (M, MS), predictive methods such as Log jointly model uncertainty for both estimated depth and pose. Indeed, $\mathcal{L}_{\text{Log}}$ is computed over $\mathcal{F}(\tilde{\mathcal{I}}, \mathcal{I})$, for which $\tilde{\mathcal{I}}$ is obtained as a function π of unknown variables d and $(R|t)$. Thus, we propose a **Self-Teaching** scheme (**Self**), training a student instance $\mathcal{S}$ to mimic the distribution sourced from a teacher model $\mathcal{T}$ trained with self-supervision

$$\mathcal{L}_{Self} = \frac{|\mu(d_{\mathcal{S}}) - d_{\mathcal{T}}|}{\sigma(d_{\mathcal{S}})} + \log \sigma(d_{\mathcal{S}})$$



5. Experiments & Results

- We train 10 new variants of MonoDepth2 [1] implementing different uncertainty modelling strategies.
- We train on 192×640 resized images, with batch size 12 for 20 epochs with M, S and MS supervision and evaluate on the Eigen test split with improved ground truth, defined in [6].
- For depth, we measure Abs Rel, RMSE (Lower is better) and $\delta < 1.25$ (Higher is better). For uncertainty, we measure the Area Under Sparsification Error (AUSE) and Area Under Random Gain (AURG).
- **Self-teaching** consistently improves depth estimation. When pose is unknown (M,MS) it outperform Log.

Depth evaluation:

Method	#Trn	#Par	#Fwd	Abs Rel	RMSE	$\delta < 1.25$	Abs Rel	RMSE	$\delta < 1.25$	Abs Rel	RMSE	$\delta < 1.25$
				(M)			(S)			(MS)		
Monodepth2 [1]	1×	1×	1×	0.090	3.942	0.914	0.085	3.942	0.912	0.084	3.739	0.918
Monodepth2-*Post* [1]	1×	1×	2×	0.088	3.841	0.917	0.084	3.777	**0.915**	**0.082**	**3.666**	**0.919**
Monodepth2-*Drop*	1×	1×	N×	0.101	4.146	0.892	0.129	4.908	0.819	0.172	5.885	0.679
Monodepth2-*Boot*	N×	N×	1×	0.092	3.821	0.911	0.085	**3.772**	0.914	0.086	3.787	0.910
Monodepth2-*Snap*	1×	N×	1×	0.091	3.921	0.912	0.085	3.849	0.912	0.085	3.806	0.914
Monodepth2-*Repr*	1×	1×	1×	0.092	3.936	0.912	0.085	3.873	0.913	0.084	3.828	0.913
Monodepth2-*Log*	1×	1×	1×	0.091	4.052	0.910	0.085	3.860	**0.915**	0.083	3.790	0.916
Monodepth2-*Self*	(1+1)×	1×	1×	**0.087**	3.826	**0.920**	0.084	3.835	**0.915**	0.083	3.682	**0.919**
Monodepth2-*Boot+Log*	N×	N×	1×	0.092	3.850	0.910	0.085	3.777	0.913	0.086	3.771	0.911
Monodepth2-*Boot+Self*	(1+N)×	N×	1×	0.088	**3.799**	0.918	0.085	3.793	0.914	0.085	3.704	0.915
Monodepth2-*Snap+Log*	1×	1×	1×	0.092	3.961	0.911	**0.083**	3.833	0.914	0.084	3.828	0.914
Monodepth2-*Snap+Self*	(1+1)×	1×	1×	0.088	3.832	0.919	0.086	3.859	0.912	0.085	3.715	0.916

Uncertainty evaluation:

Method	Abs Rel		RMSE		$\delta \geq 1.25$		Abs Rel		RMSE		$\delta \geq 1.25$		Abs Rel		RMSE		$\delta \geq 1.25$	
	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG	AUSE	AURG
	(M)						(S)						(MS)					
Monodepth2-*Post*	0.044	0.012	2.864	0.412	0.056	0.022	0.036	0.020	2.523	0.736	0.044	0.034	0.036	0.018	2.498	0.655	0.044	0.031
Monodepth2-*Drop*	0.065	0.000	2.568	0.944	0.097	0.002	0.103	-0.029	6.163	-2.169	0.231	-0.080	0.103	-0.027	7.114	-2.580	0.303	-0.081
Monodepth2-*Boot*	0.058	0.001	3.982	-0.743	0.084	-0.001	0.028	0.029	2.291	0.964	0.031	0.048	0.028	0.030	2.269	0.985	0.034	0.049
Monodepth2-*Snap*	0.059	-0.001	3.979	-0.639	0.083	-0.002	0.028	0.029	2.252	1.077	0.030	0.051	0.029	0.028	2.245	1.029	0.033	0.047
Monodepth2-*Repr*	0.051	0.008	2.972	0.381	0.069	0.013	0.040	0.017	2.275	1.074	0.050	0.030	0.046	0.010	2.662	0.635	0.062	0.018
Monodepth2-*Log*	0.039	0.020	2.562	0.916	0.044	0.038	0.022	0.036	0.938	2.402	**0.018**	0.061	0.028	0.029	1.714	**1.562**	0.028	0.050
Monodepth2-*Self*	0.030	0.026	2.009	1.266	0.030	0.045	0.022	0.035	1.679	1.642	0.022	0.056	**0.022**	0.033	**1.654**	1.515	**0.023**	0.052
Monodepth2-*Boot+Log*	0.038	0.021	2.449	0.820	0.046	0.037	**0.020**	**0.038**	**0.807**	**2.455**	**0.018**	**0.063**	0.030	0.028	1.962	1.282	0.032	0.051
Monodepth2-*Boot+Self*	**0.029**	**0.028**	**1.924**	**1.316**	**0.028**	**0.049**	0.023	0.035	1.646	1.628	0.021	0.058	0.023	0.033	1.688	1.494	**0.023**	**0.056**
Monodepth2-*Snap+Log*	0.038	0.022	2.385	1.001	0.043	0.039	0.021	0.037	0.891	2.426	**0.018**	0.061	0.030	0.027	2.032	1.272	0.032	0.048
Monodepth2-*Snap+Self*	0.031	0.026	2.043	1.230	0.030	0.045	0.023	0.035	1.710	1.623	0.023	0.058	0.023	**0.034**	1.684	1.510	**0.023**	0.055

References

[1] C. Godard et al., "Digging into self-supervised monocular depth estimation" (ICCV 2019)

[2] C. Godard et al., "Unsupervised Monocular Depth Estimation with Left-Right Consistency" (CVPR 2017)

[3] E. Ilg et al., "Uncertainty Estimates and Multi-Hypotheses Networks for Optical Flow" (ECCV 2018)

[4] M. Klodt and A. Vedaldi, "Supervising the new with the old: learning SFM from SFM" (ECCV 2018)

[5] R. M. Neal, "Bayesian learning for neural networks" (Springer Science & Business Media)

[6] F. Aleotti et al., "Generative adversarial networks for unsupervised monocular depth prediction" (ECCVW 2018)

Links

Paper

GitHub Code

Youtube Video

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