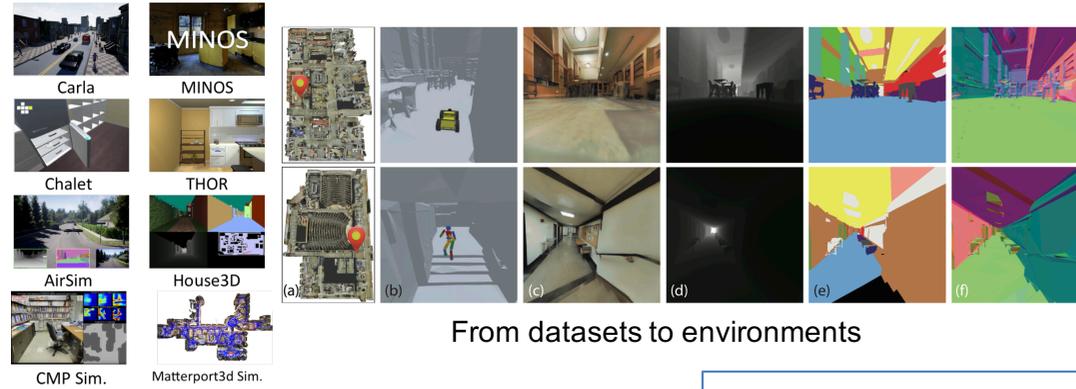


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<http://gibsonenv.stanford.edu>

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Introduction



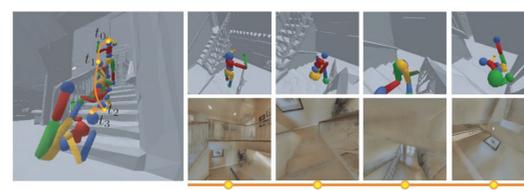
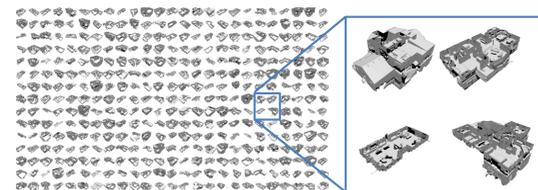
From datasets to environments

- Learning in **real world**: slow, fragile
- Learning in **simulation**: generalization difficulties: (1) photorealism (2) semantic distribution mismatch

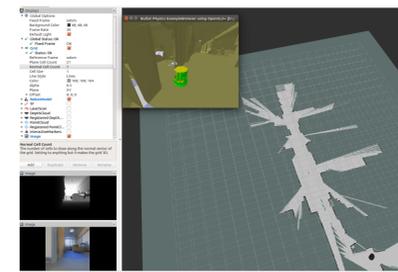
we propose

Gibson Environment

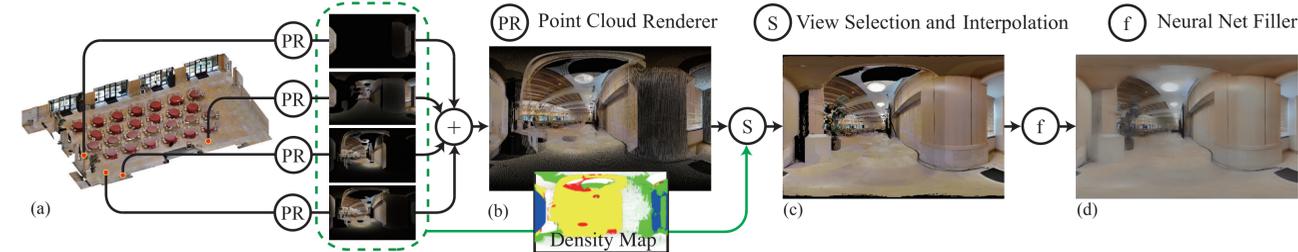
1. Database: real-world RGBD panoramas
2. Physics engine: PyBullet



3. View synthesis: Neural Network filler and Goggle mechanism (Method Section)
4. ROS integration & Gym integration



Rendering Engine



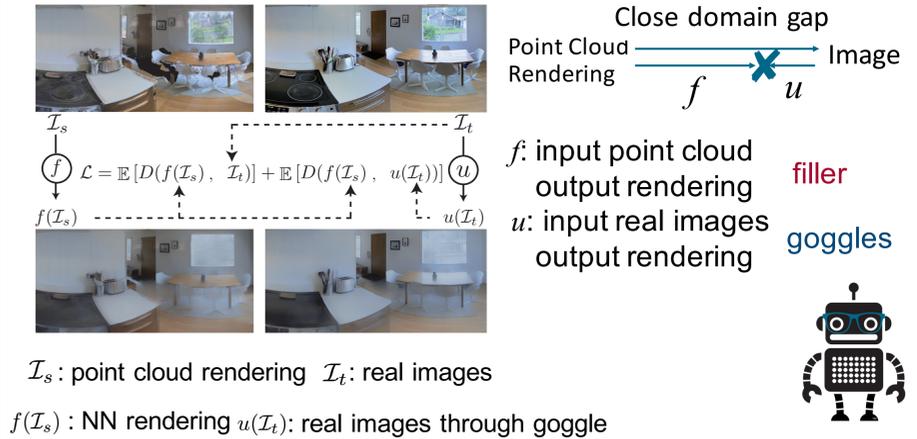
Our rendering engine has 3 stages:

1. (a)->(b) Point cloud rendering: **reproject** points to new view
2. (b)->(c) View selection: adaptively **select** view to retrieve points from; Interpolation: **interpolate** rendered points to image
3. (c)->(d) Neural network: **fill** holes and fix geometry issues

Training techniques:

- Color matching loss
- Stochastic identity initialization
- Perceptual loss for $D(I_1, I_2)$

Goggle Mechanism



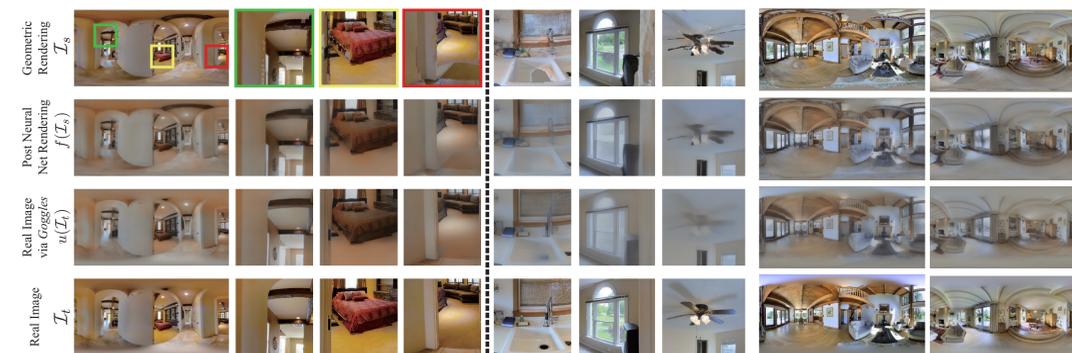
Experimental Results

Dataset comparison

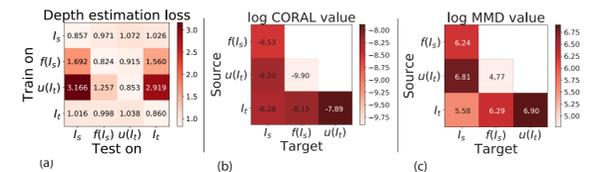
Dataset	Gibson	SUNCG	Matterport3D
Number of Spaces	572	45622	90
Total Coverage m^2	211k	5.8M	46.6K
SSA	1.38	0.74	0.92
Nav. Complexity	5.98	2.29	7.80
Real-World Transfer Err	0.92 [§]	2.89 [†]	2.11 [†]

View Synthesis

Qualitative Results



Transferring to Real World Results



Example tasks in Gibson



Conclusions and Limitations

We propose Gibson Environment for developing real world perception for active agents.

Limitations (future work):

- Dynamic contents
- Manipulation



Source code <https://github.com/StanfordVL/GibsonEnv>



Download Gibson dataset: <http://gibsonenv.stanford.edu>

Browser dataset online:

<http://gibsonenv.stanford.edu/database/>