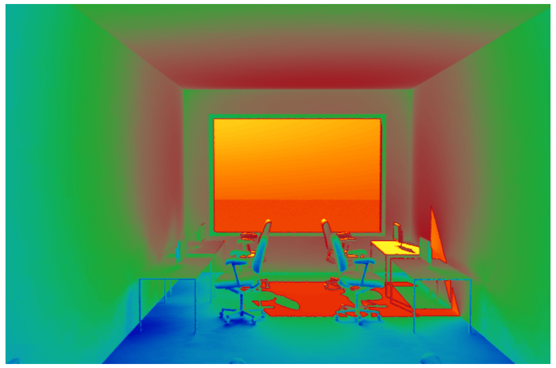
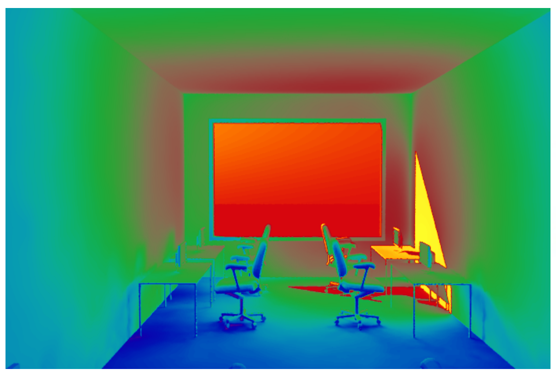
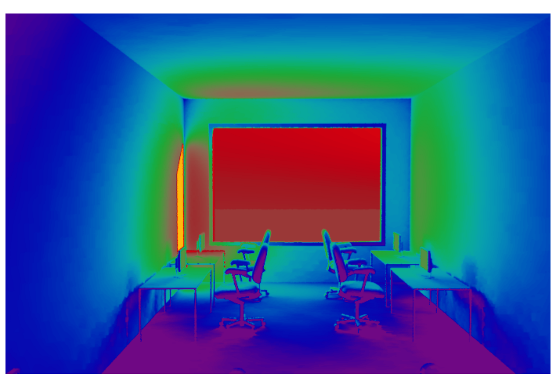
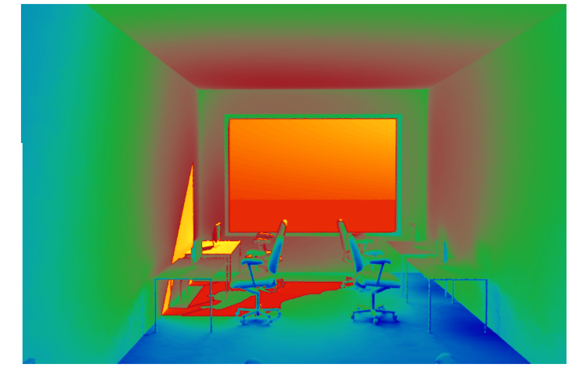
COMPUTING LONG-TERM DAYLIGHTING SIMULATIONS FROM HIGH DYNAMIC RANGE PHOTOGRAPHS USING *DEEP NEURAL NETWORKS*

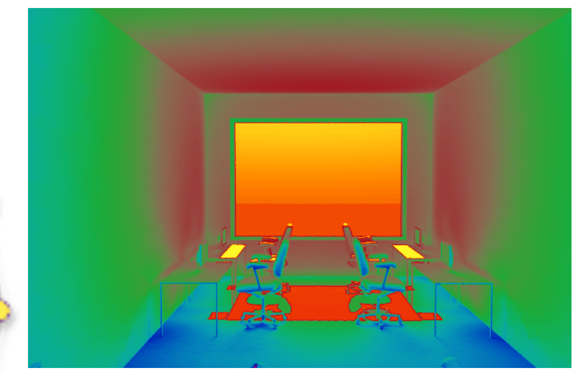
EARLY RESULTS

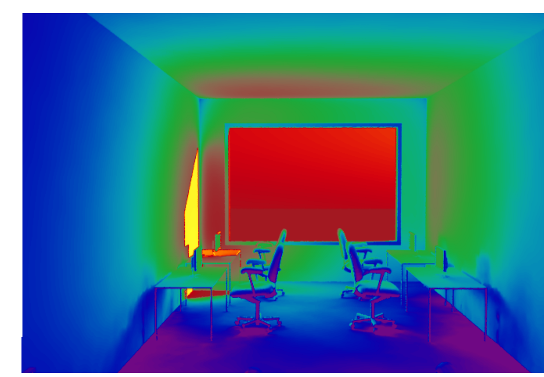












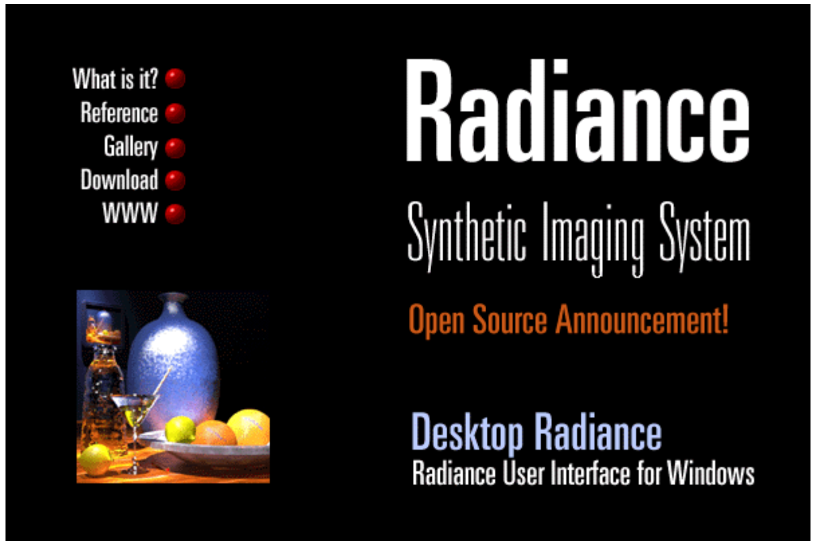
Yue Liu[1], Mehlika Inanici[1], Alex Colburn[2]

Email: *yueliu@uw.edu*

[1] University of Washington, College of Built Environments

[2] Zillow Group, 3D Vision Research

16th International Radiance Workshop, Oregon, 22. 08, 2017


What is it?
Reference
Gallery
Download
WWW
Radiance
Synthetic Imaging System
Open Source Announcement!
Desktop Radiance
Radiance User Interface for Windows

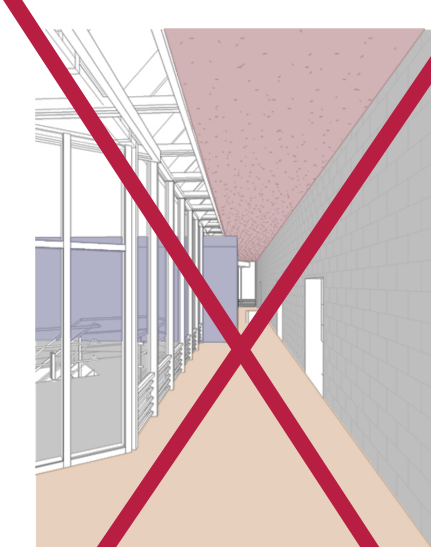
Content

- Background and Motivation
- Methodology
  - HDR imagery
  - Deep Neural Networks
- Results
- Conclusion and Future Work

Motivation

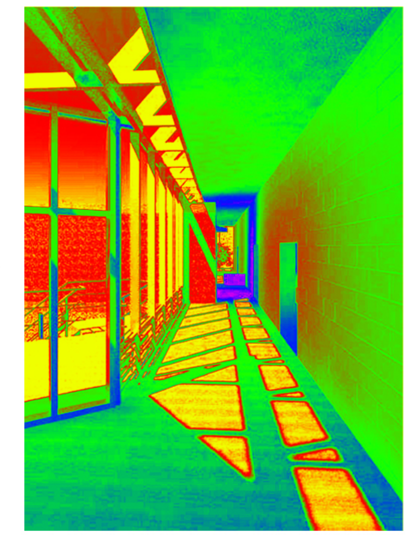
Traditional Long-term Lighting Simulation Approach for Existing Spaces:

Scene



~~Light Model~~

Rendering Images



Light Analysis

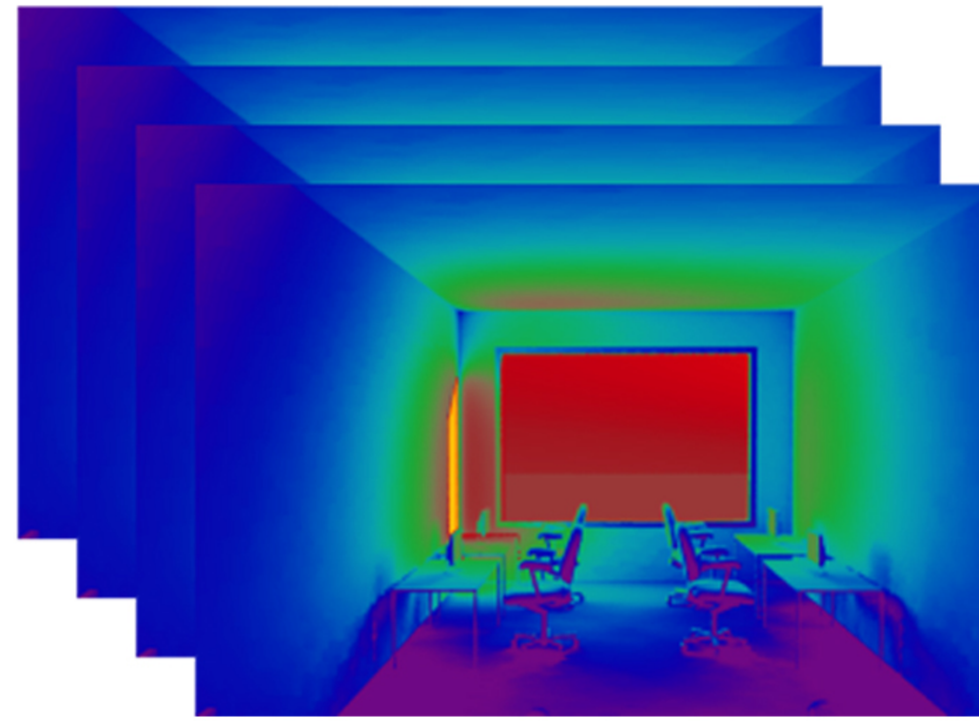
Geometry Measurement + Material Measurement

Motivation

What if we can capture…

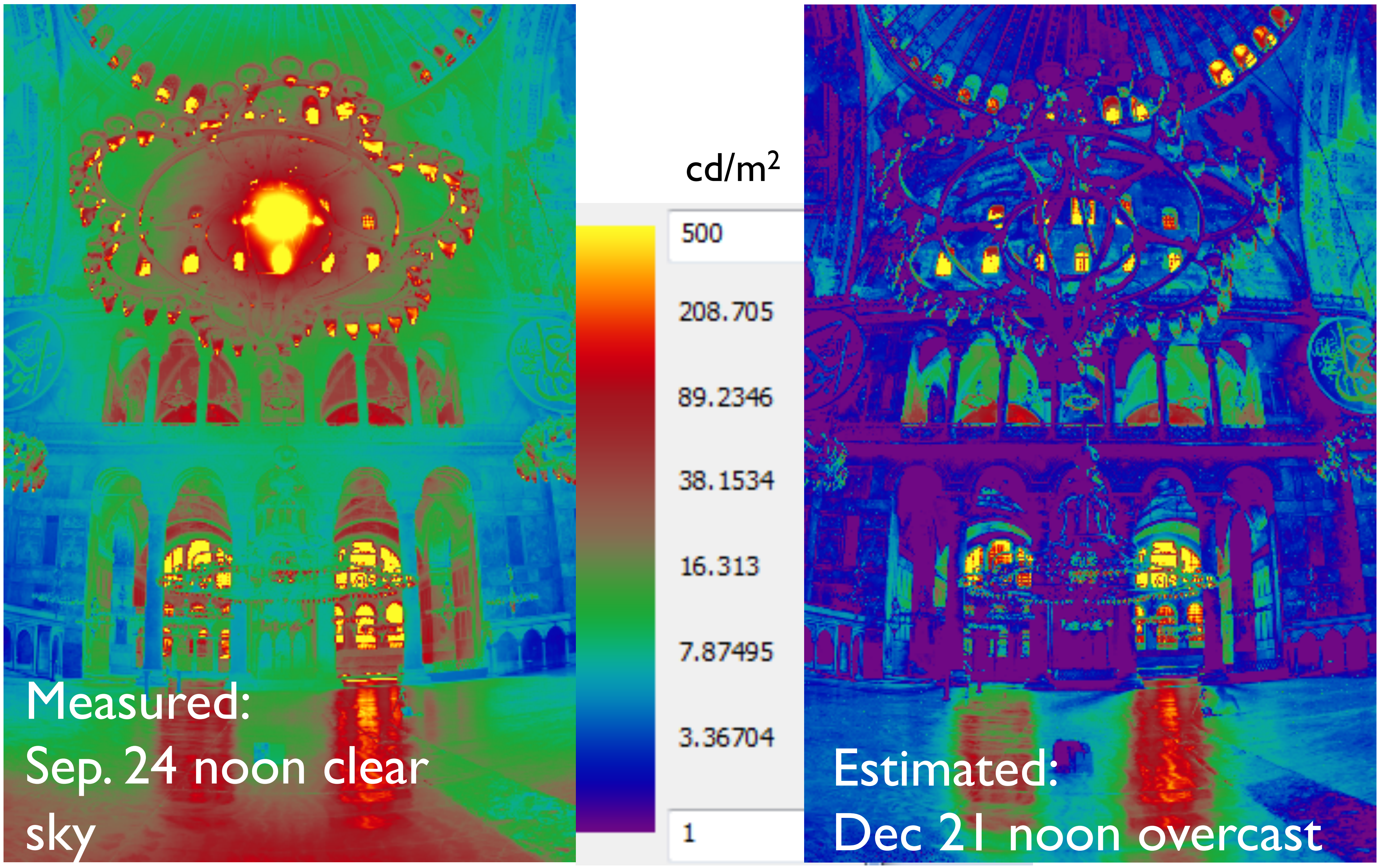
… HDR images in a limited time frame

?



… and use this information to predict long-term performance….

Previous work:



Short-term to Long-term Lighting Predictions

Mehlika Inanici, Dynamic Daylighting Simulations from Static High Dynamic Range Imagery Using Extrapolation and Daylight Coefficient Methodologies, Proceedings of IBPSA Conference, 2013.

Motivation

Ground Truth Images Reconstructed Images Error maps

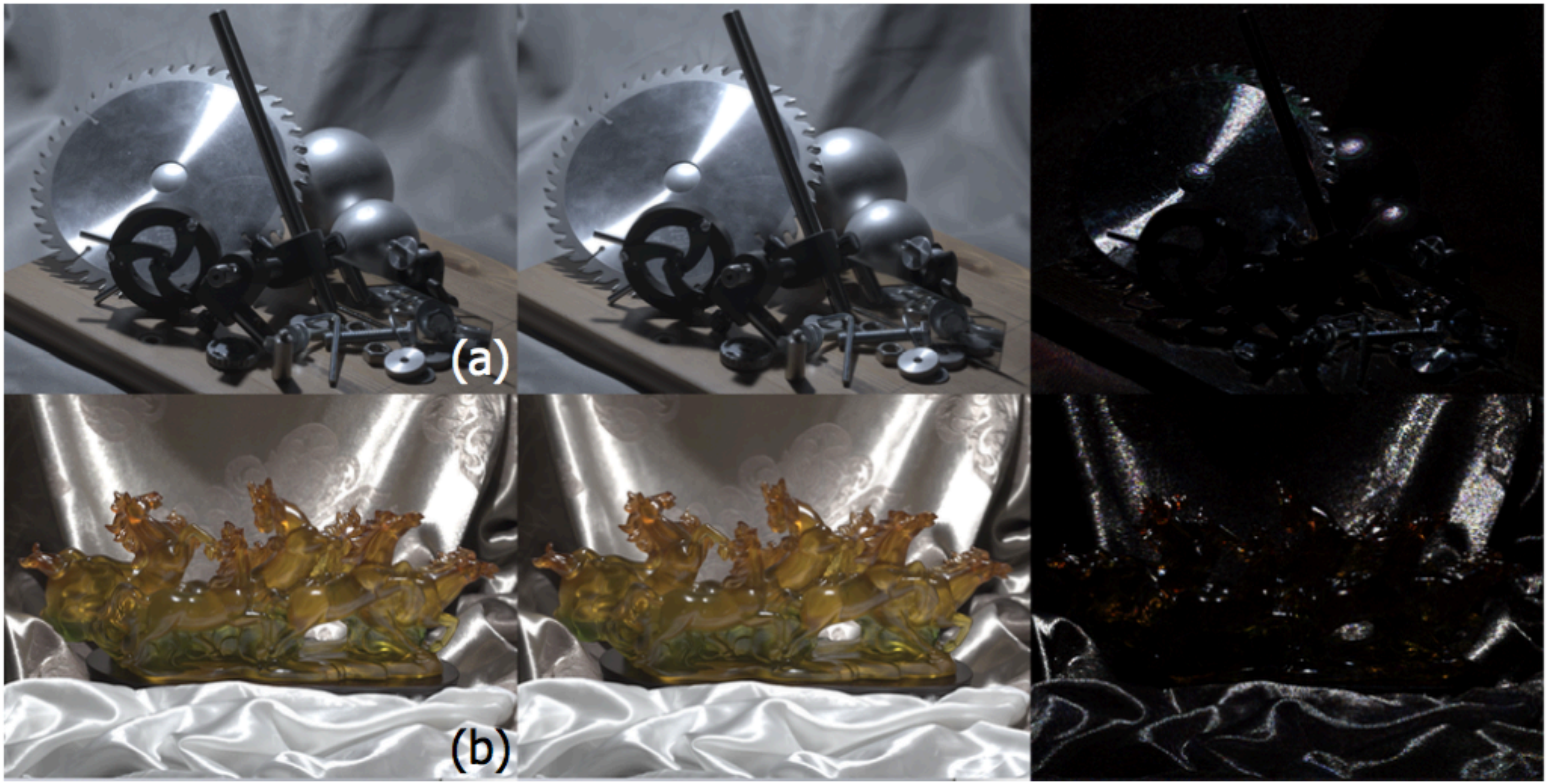


Image Based Relighting

Peiran Ren, Yue Dong, Stephen Lin, Xin Tong, Baining Guo, Image Based Relighting Using Neural Networks, ACM SIGGRAPH, 2015.

Methodology: Light Transport Matrix

Outgoing Radiance
(Np image pixels)

Lighting condition
(Ns light sources)

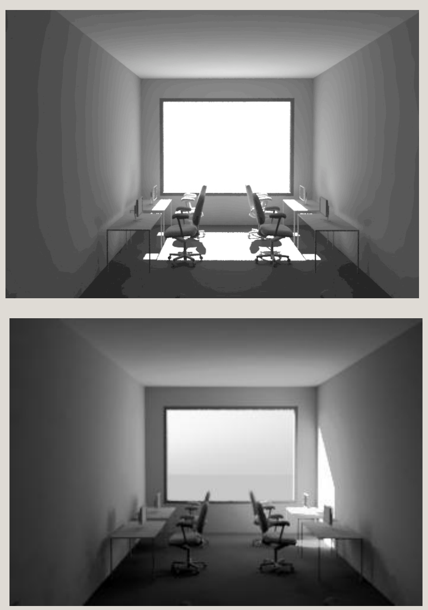
$$I = \boxed{M} * L$$

Light Transport
Matrix (Np * Ns)

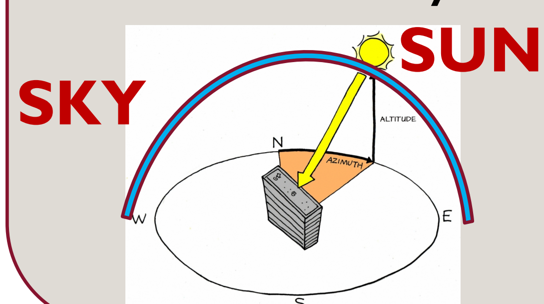
Research Framework

User Input:

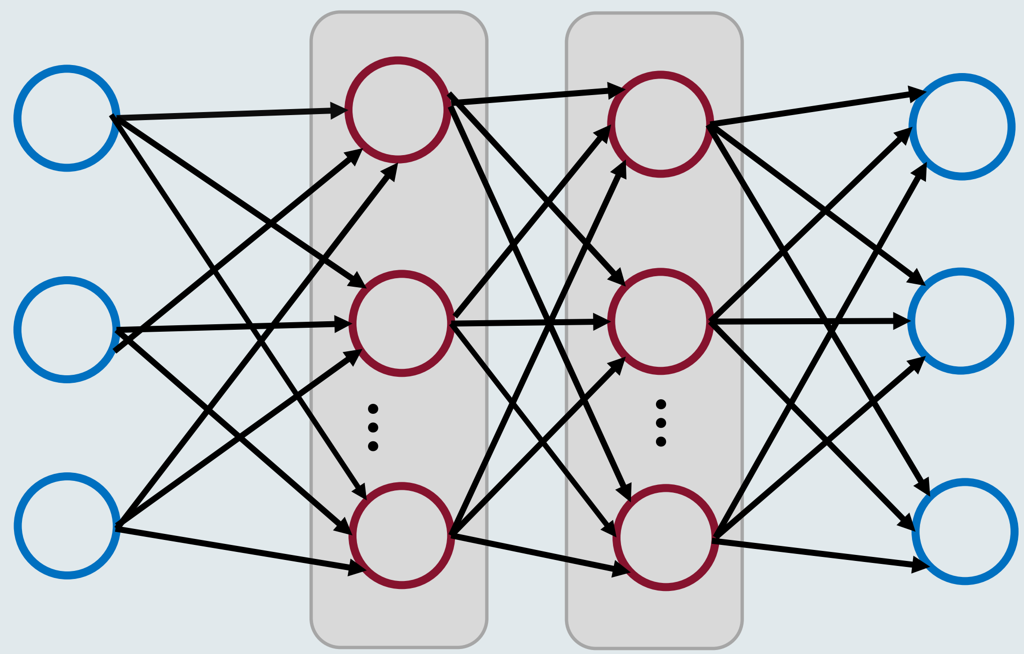
HDR images in a limited time frame



Labeled images with parameters of sun and sky

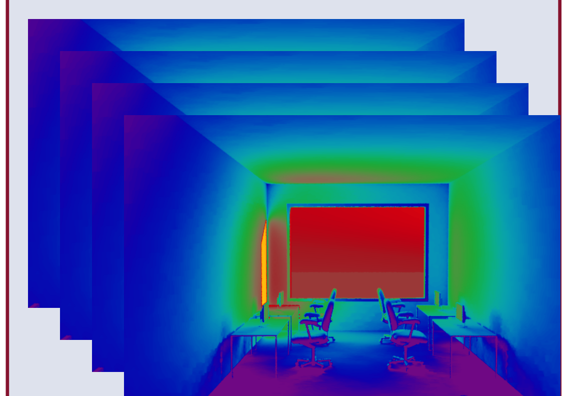


Model Light Transport Matrix Using Neural Networks:



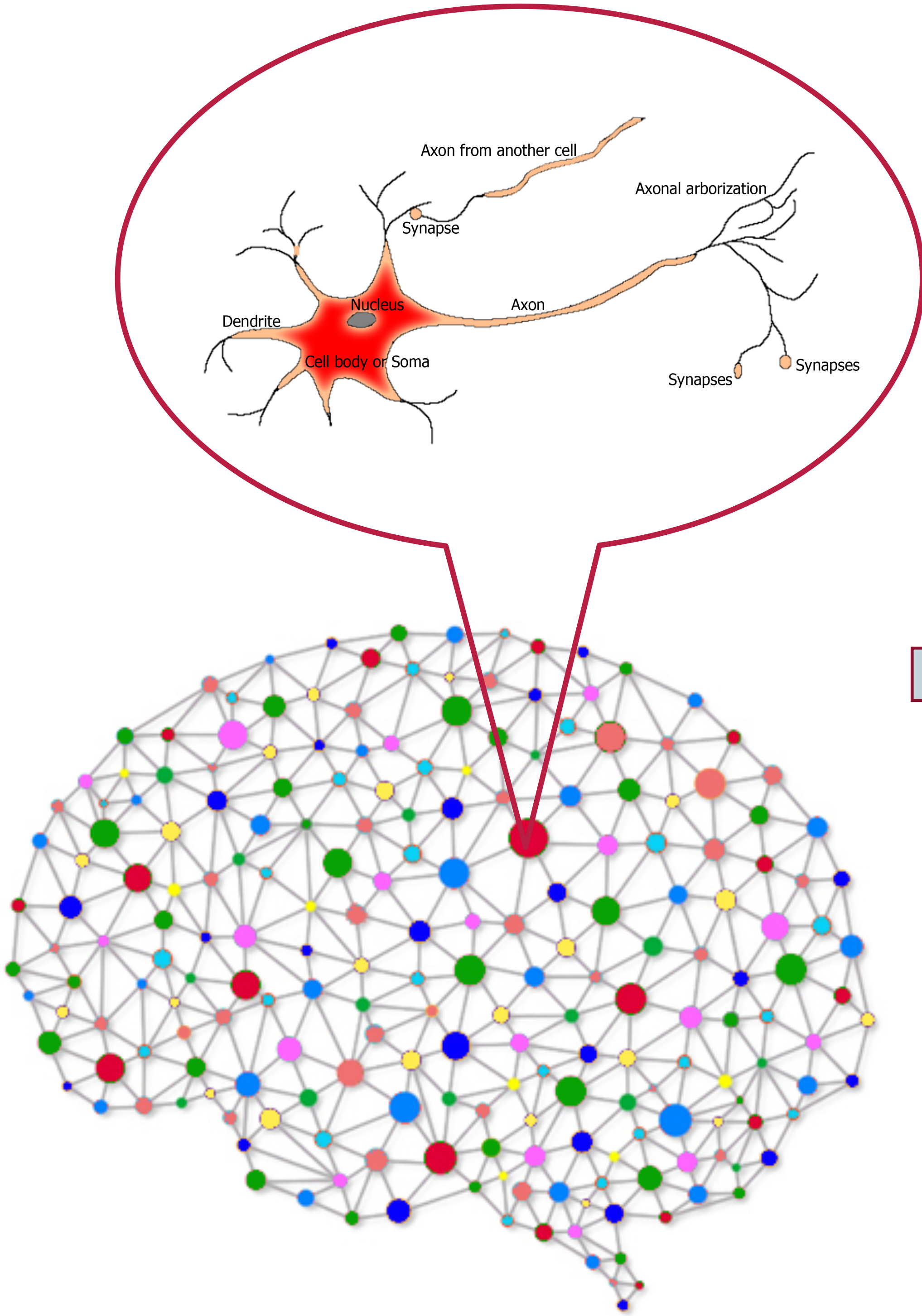
Output:

Images with luminance information for any time of the day (over a whole year) given the parameters of sun and sky



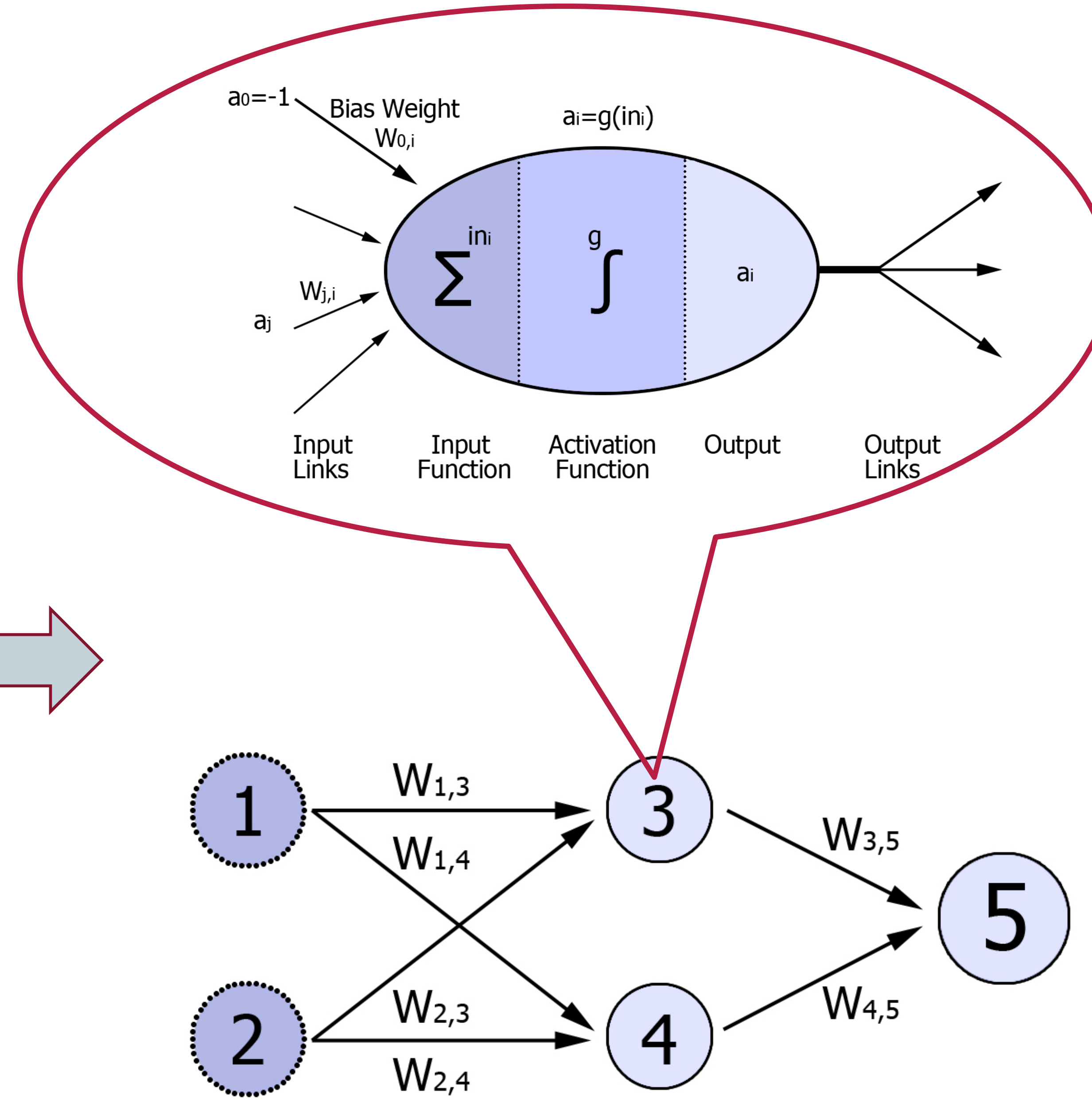
Methodology: Neural Networks

Inspiration: human brain



Small computational units with simple low-bandwidth communication

Realization: neural network



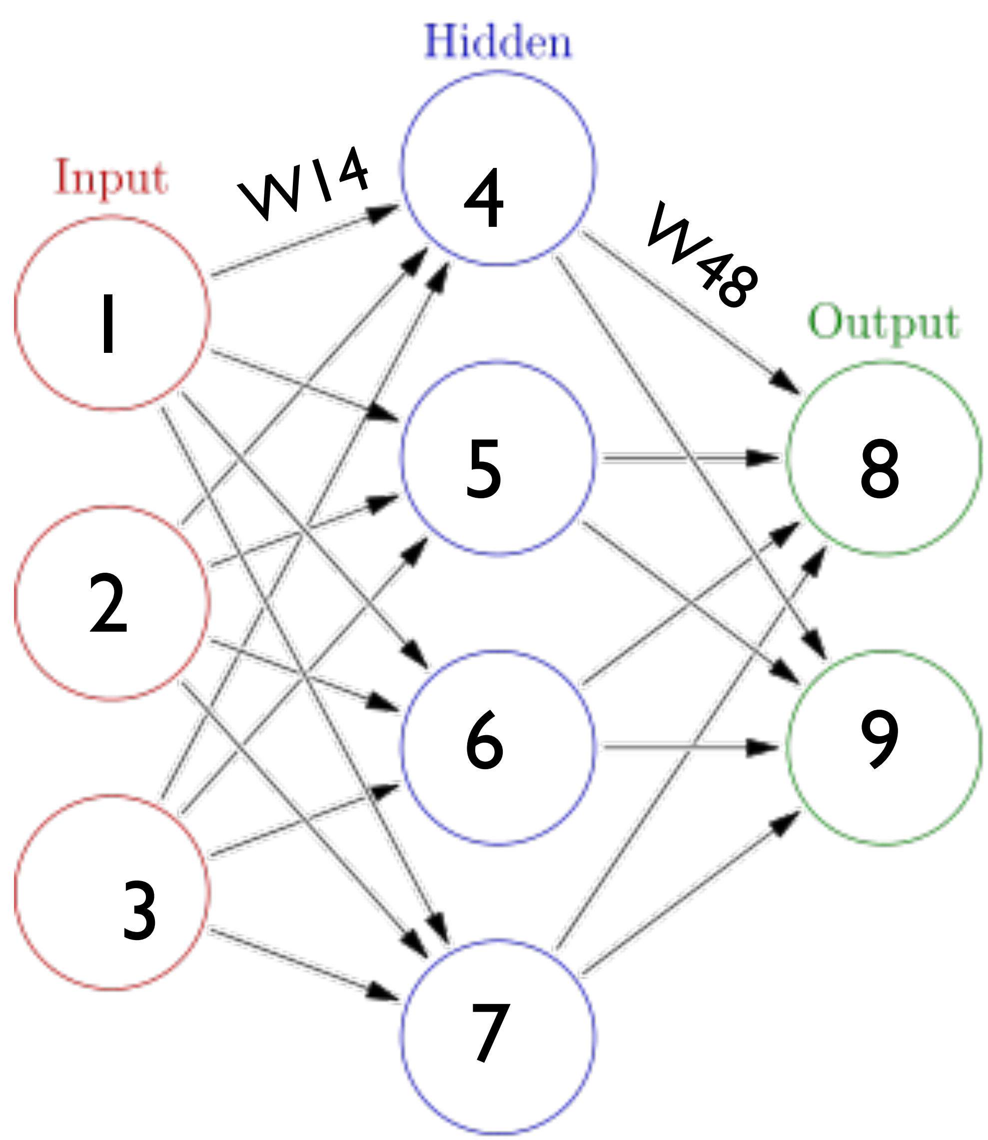
$$a_5 = g(W_{3,5}.a_3 + W_{4,5}.a_4)$$
$$= g(W_{3,5}.g(W_{1,3}.a_1 + W_{2,3}.a_2) + W_{4,5}.g(W_{1,4}.a_1 + W_{2,4}.a_2))$$

Units connected by *directed weighted links*

Methodology: Neural Networks Learning

Key Idea:

Algorithms Iteratively adjusts *weights* to reduce *error* (difference between network output and target output)



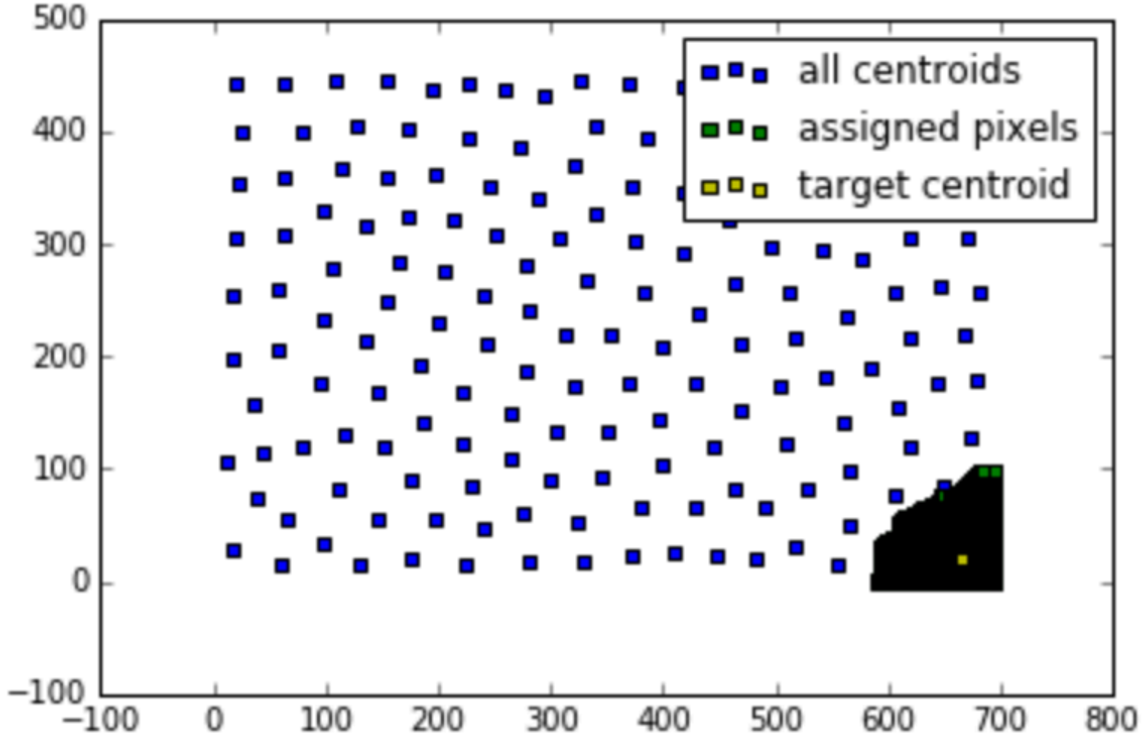
Methodology – Adaptive Fuzzy Clustering

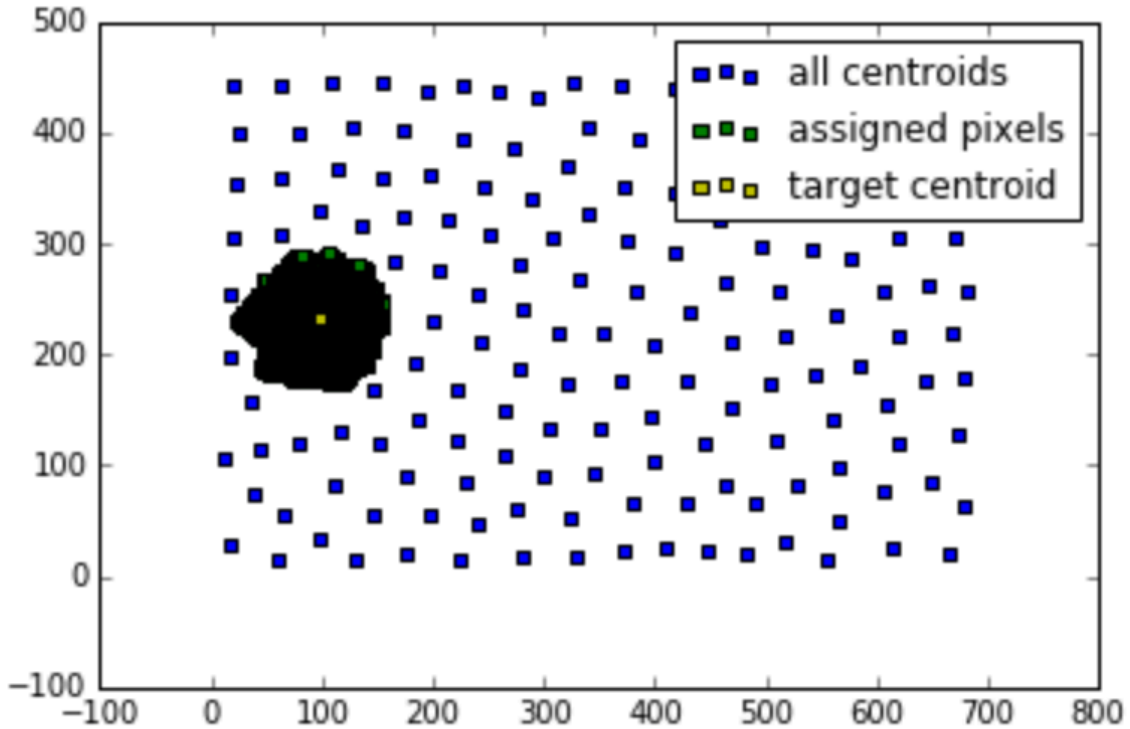
"Adaptive" Feature

- 4 Levels of Clustering

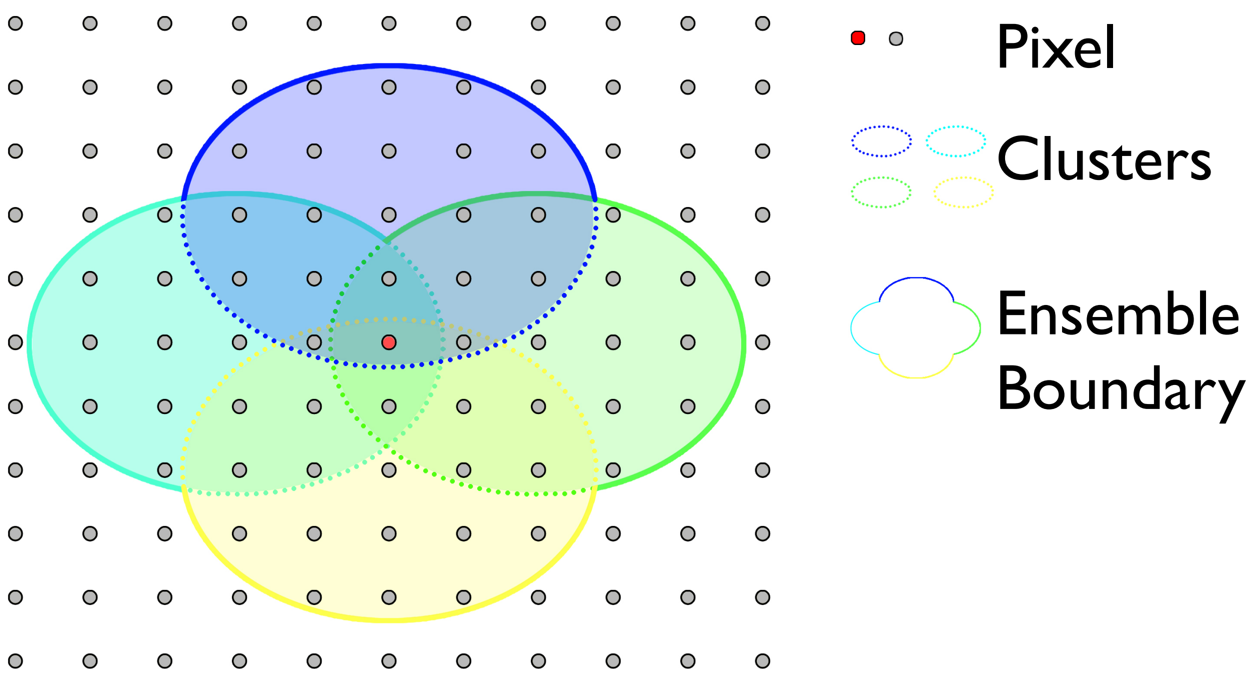
Methodology – Adaptive Fuzzy Clustering

"Fuzzy" Feature

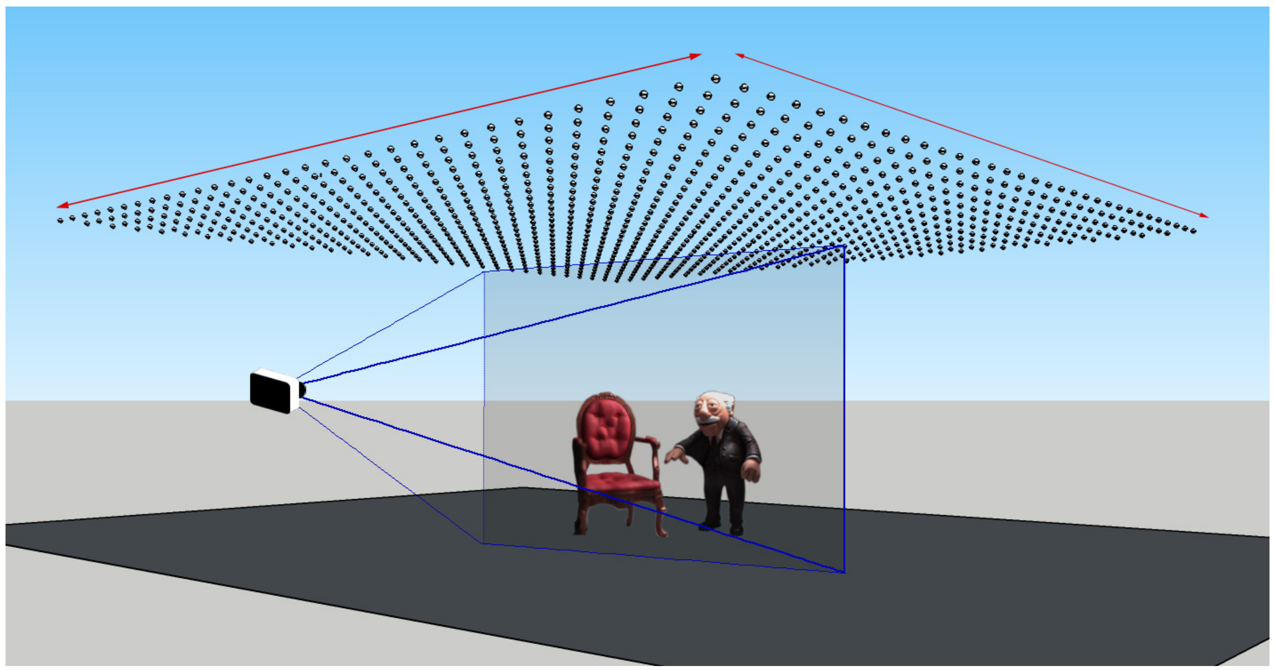




Optimized Way:
Fuzzy Clustering

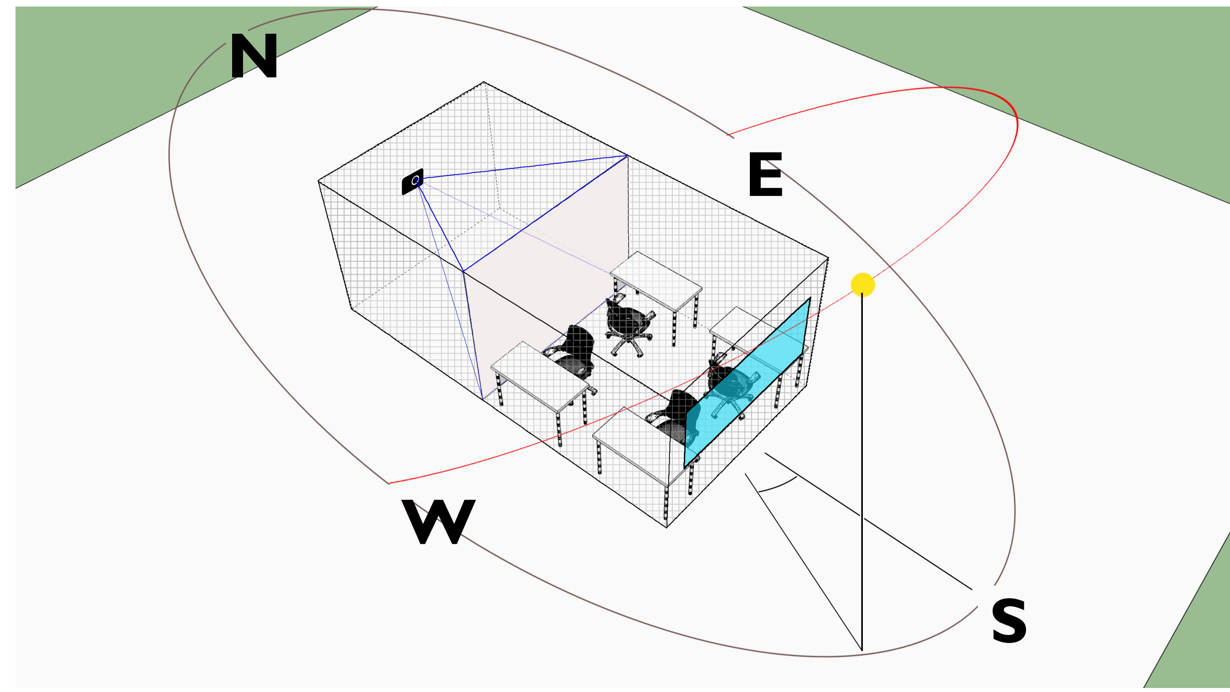


Experiment Settings: Two Groups of Data



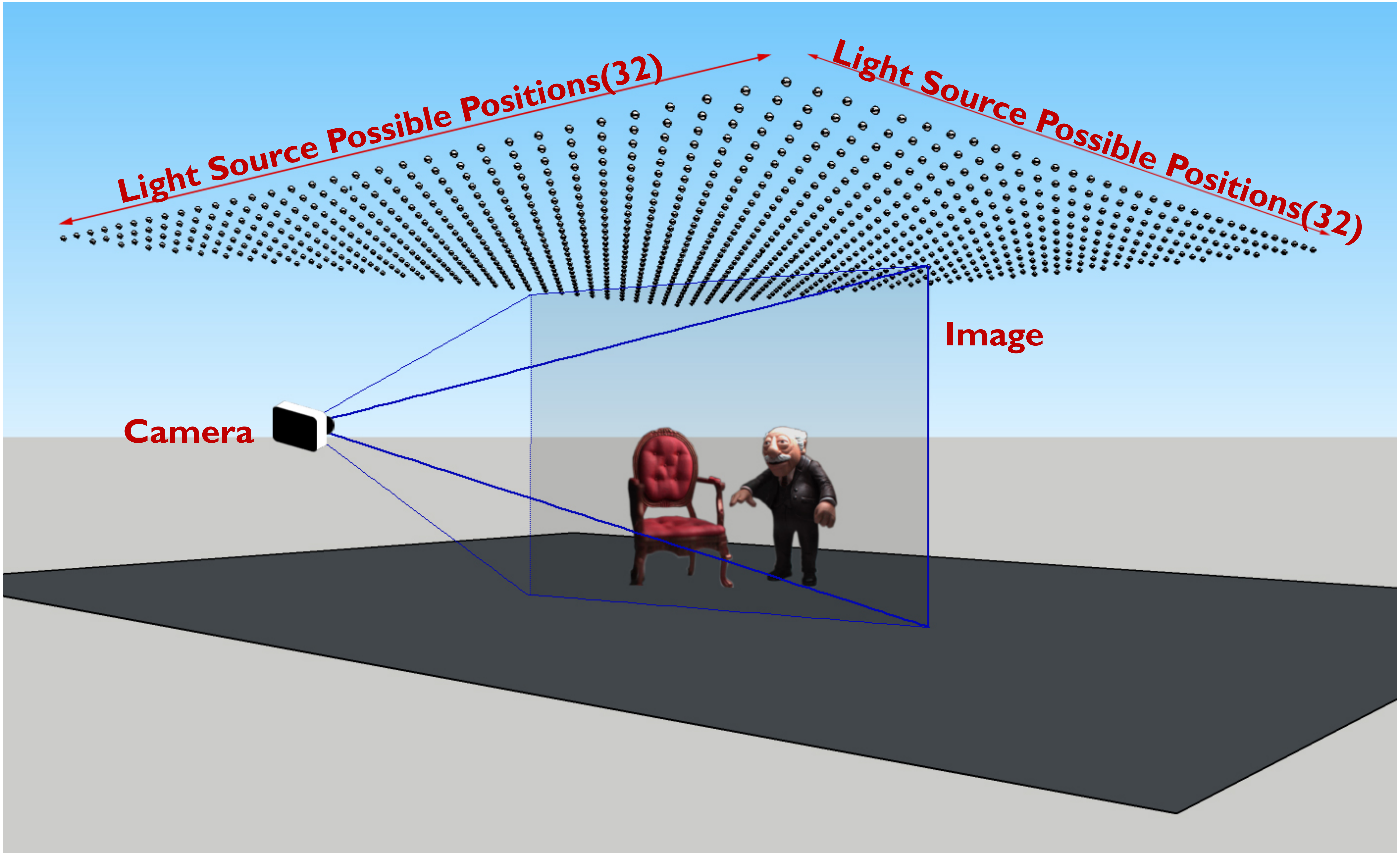
Waldorf

Optical Computing for Fast Light Transport Analysis
Matthew O'Toole and Kiriakos N. Kutulakos.
ACM SIGGRAPH Asia, 2010.

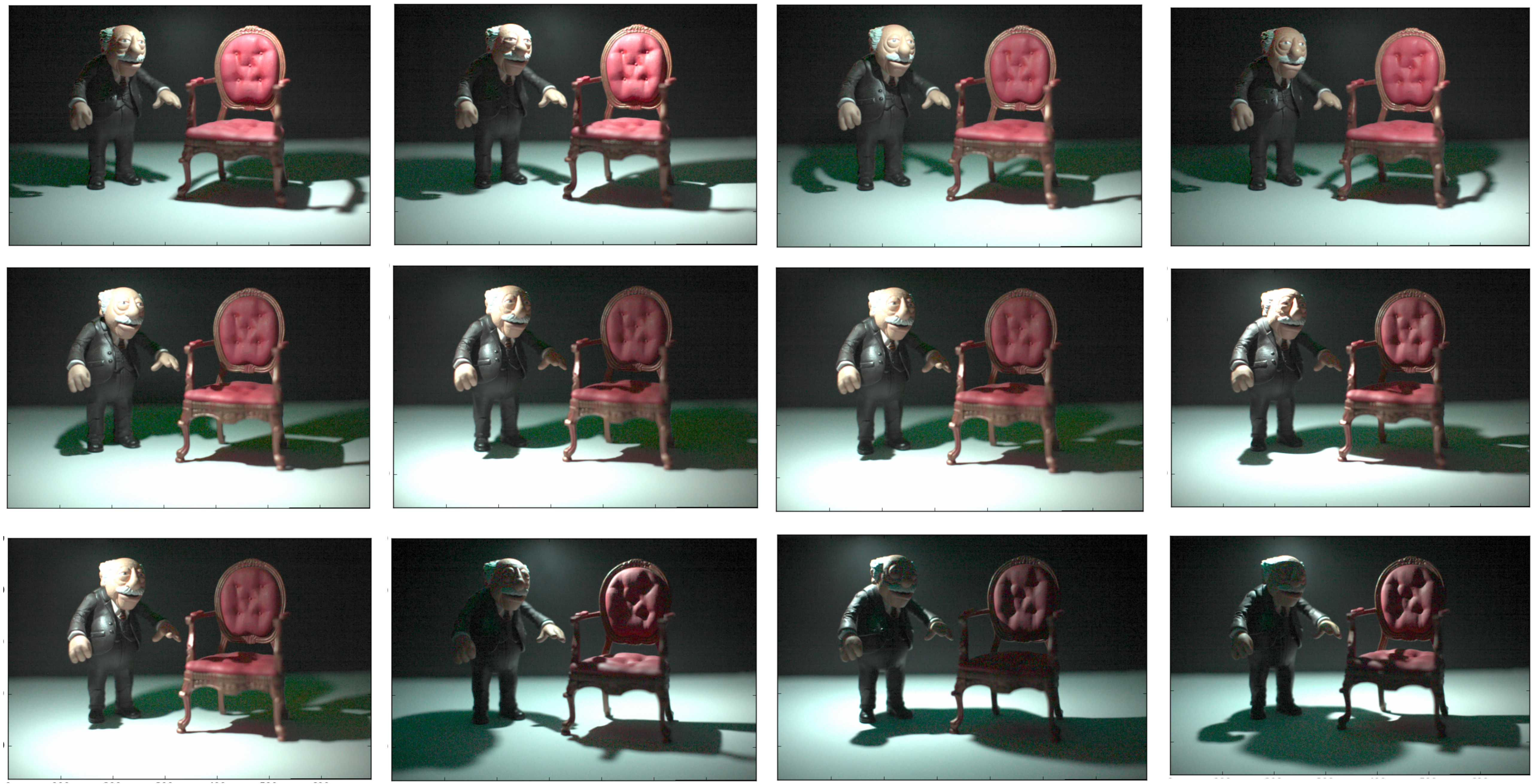


Office simulations generated using Radiance

Case 1: Waldorf Data

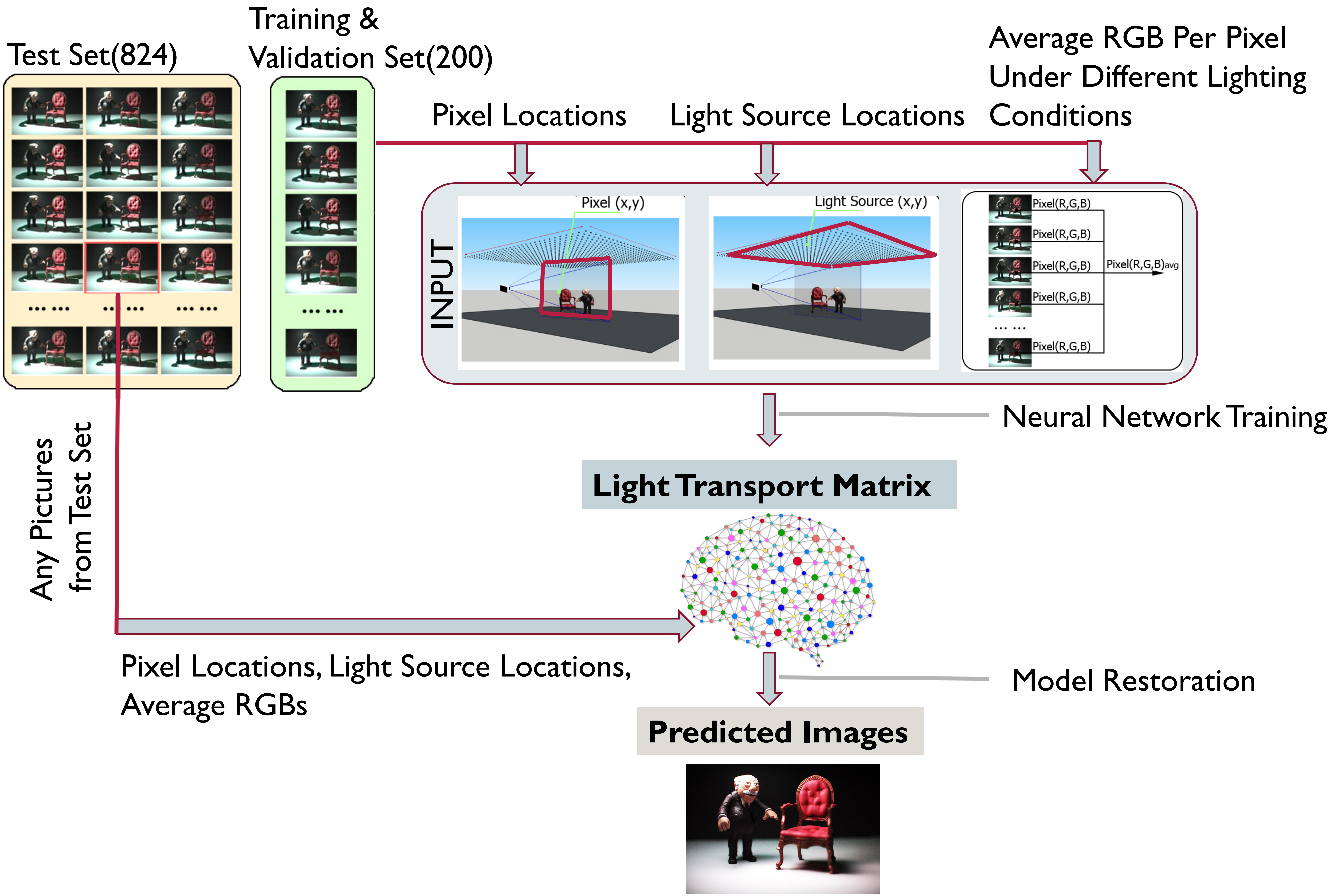


Case 1: Waldorf Data



Optical Computing for Fast Light Transport Analysis
Matthew O'Toole and Kiriakos N. Kutulakos. ACM SIGGRAPH Asia, 2010.

Case 1: Input and Output



Case 1: Preliminary Results

Original Image

Predicted Image

- Based on 200 out of 1024 images as input data
- Average error rate $\varepsilon_{average}$ = **0.03**

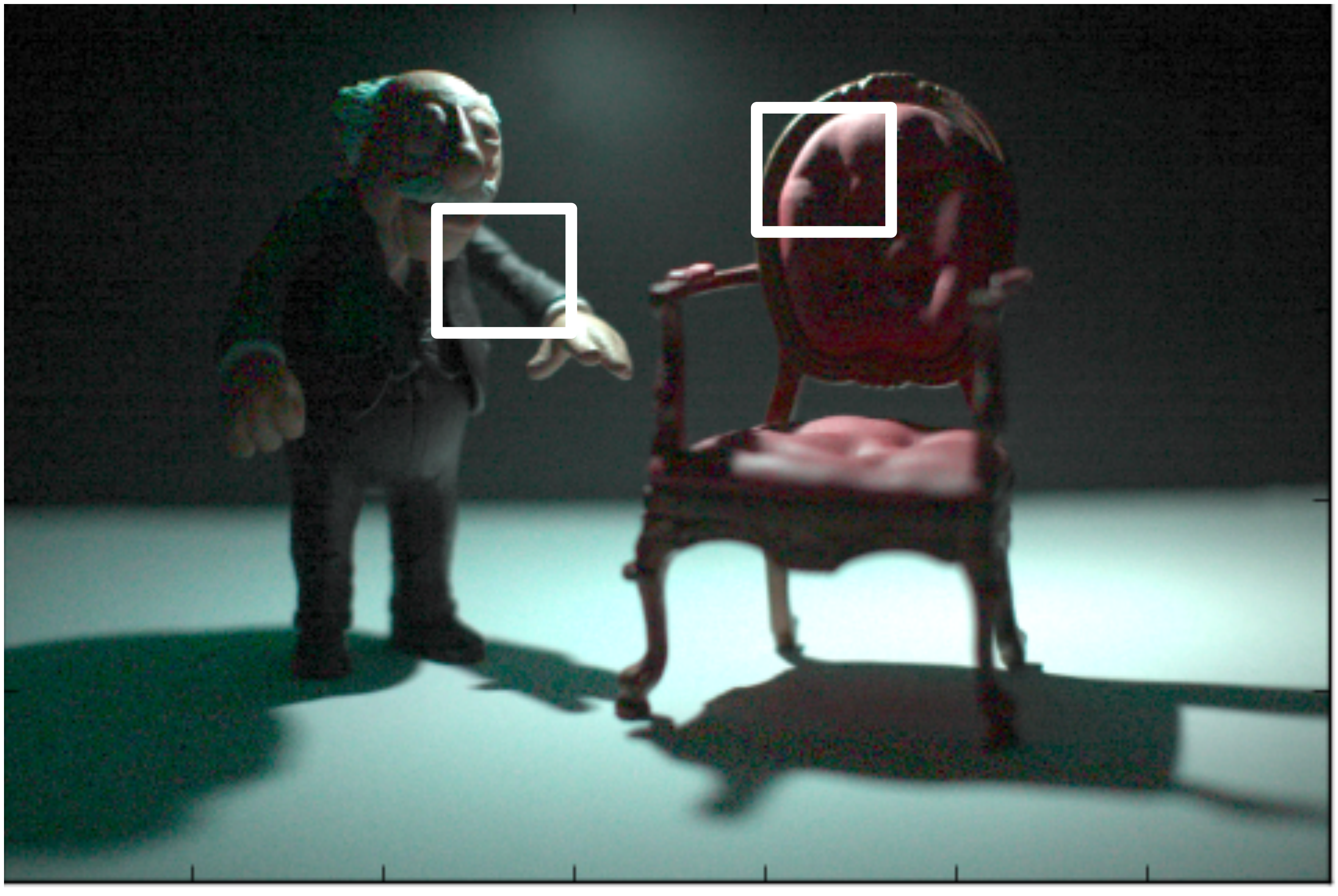
$$\varepsilon = \sqrt{\frac{\sum_j \|I_j - \widetilde{I}_j\|^2}{\sum_j \|I_j\|^2}}$$

Where:

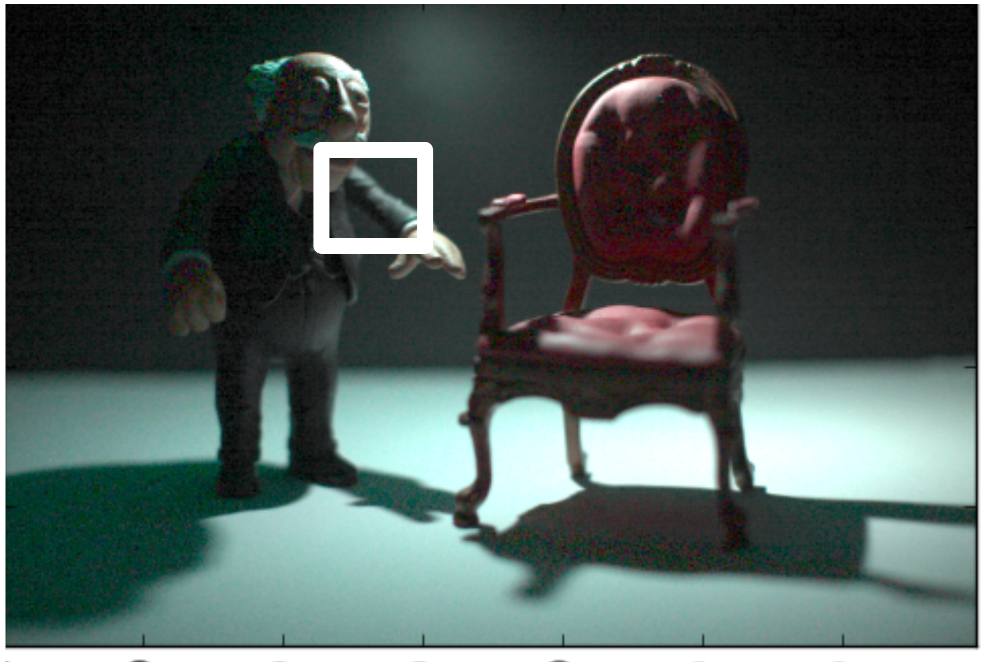
I_j : RGB of ground truth light transport marix M(., j)

$\widetilde{I}_j$: RGB of reconstructed light transport matrix M(., j)

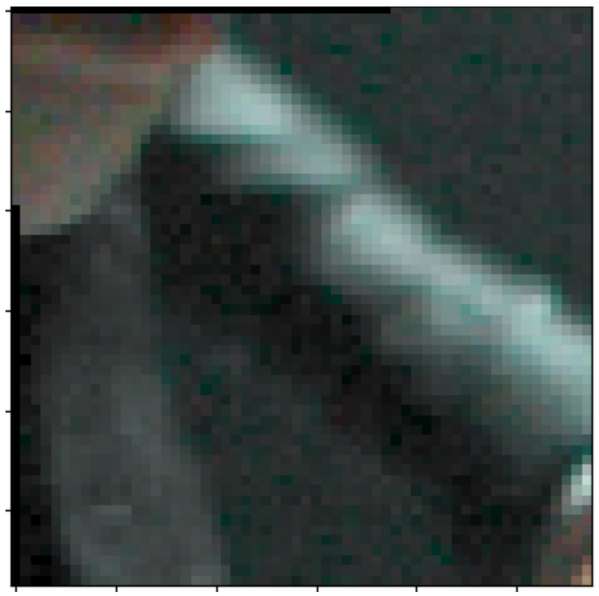
Case 1: Preliminary Results



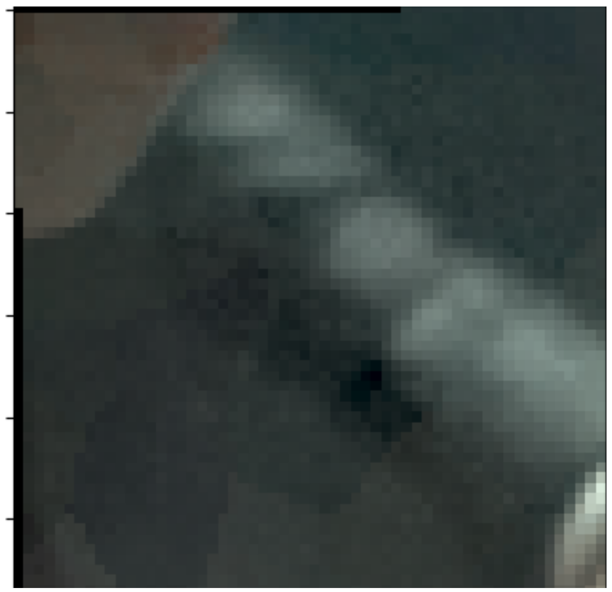
Case 1: Preliminary Results



Set 1

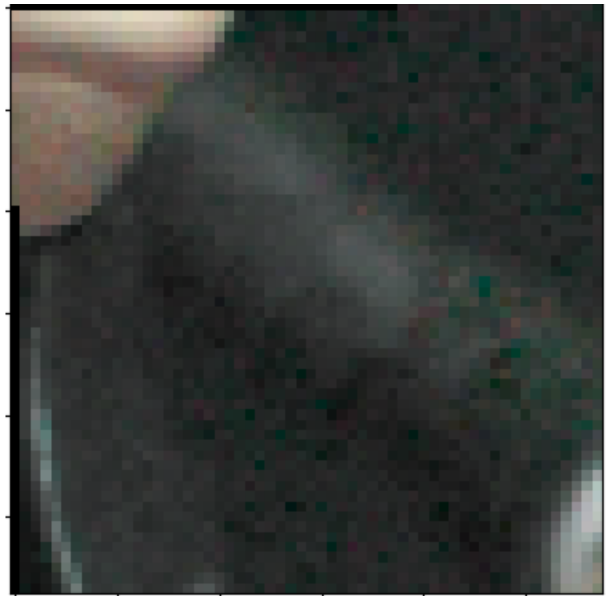


Ground truth



Predicted

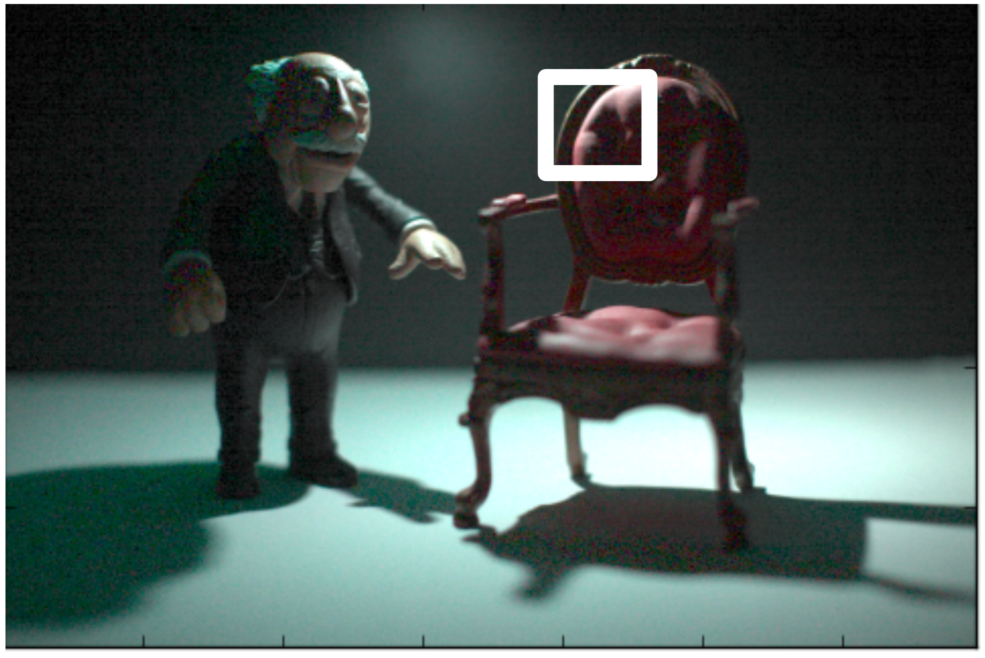
Set 2



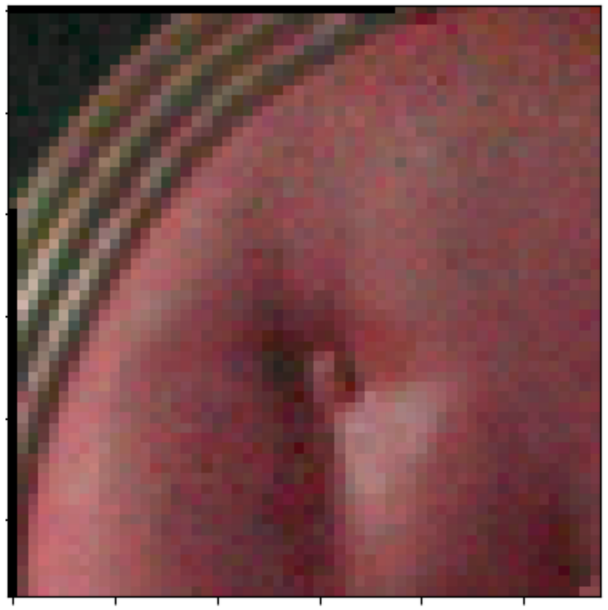
Ground truth

Predicted

Case 1: Preliminary Results



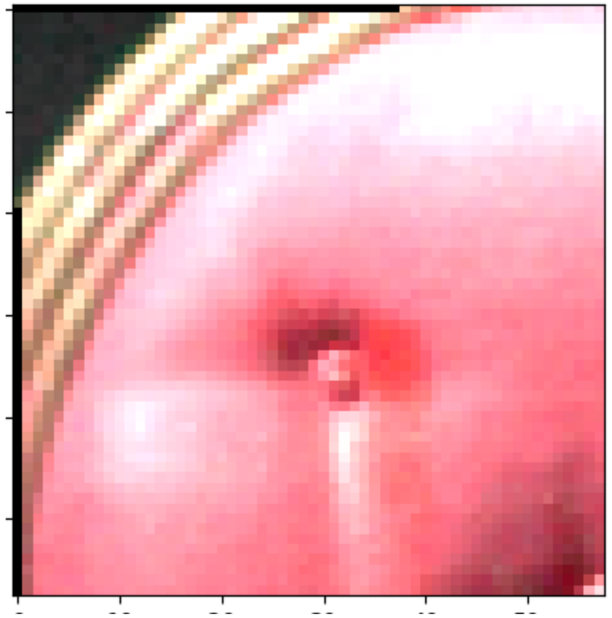
Set 1



Ground truth

Predicted

Set 2

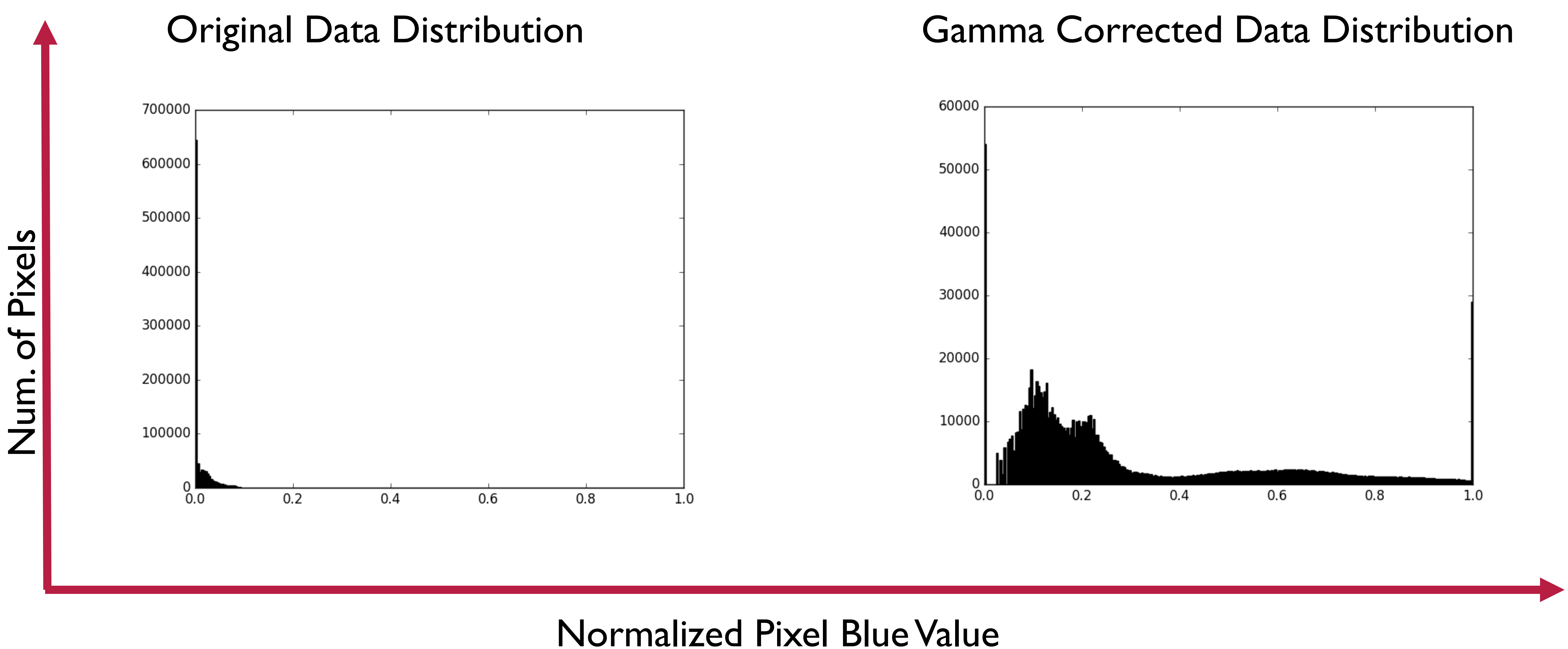


Ground truth

Predicted

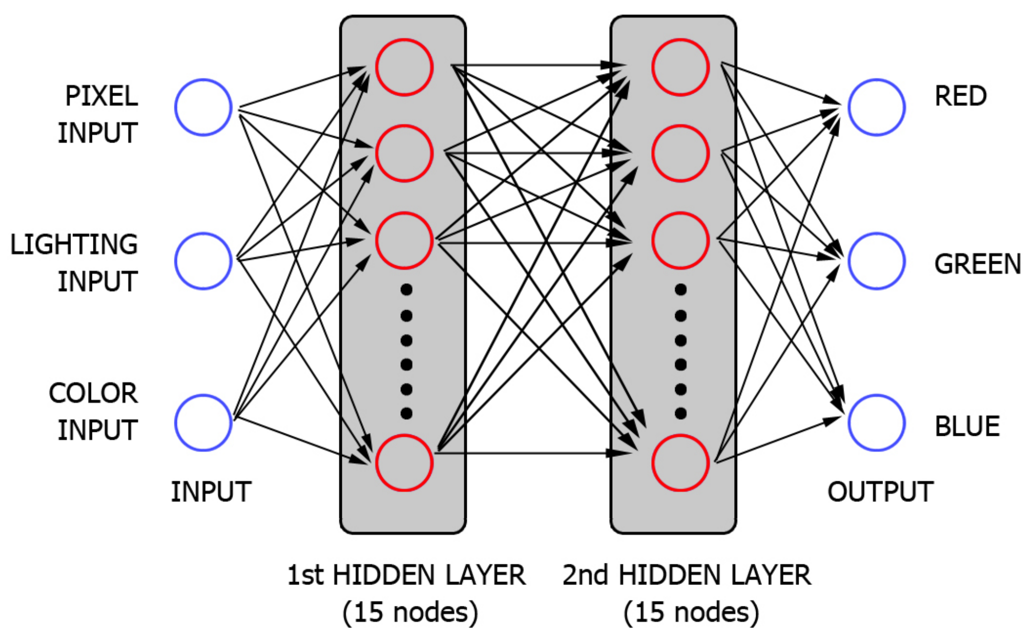
Case 1: Observation and Improvements

1. Pre-processing Data: Gamma Correction

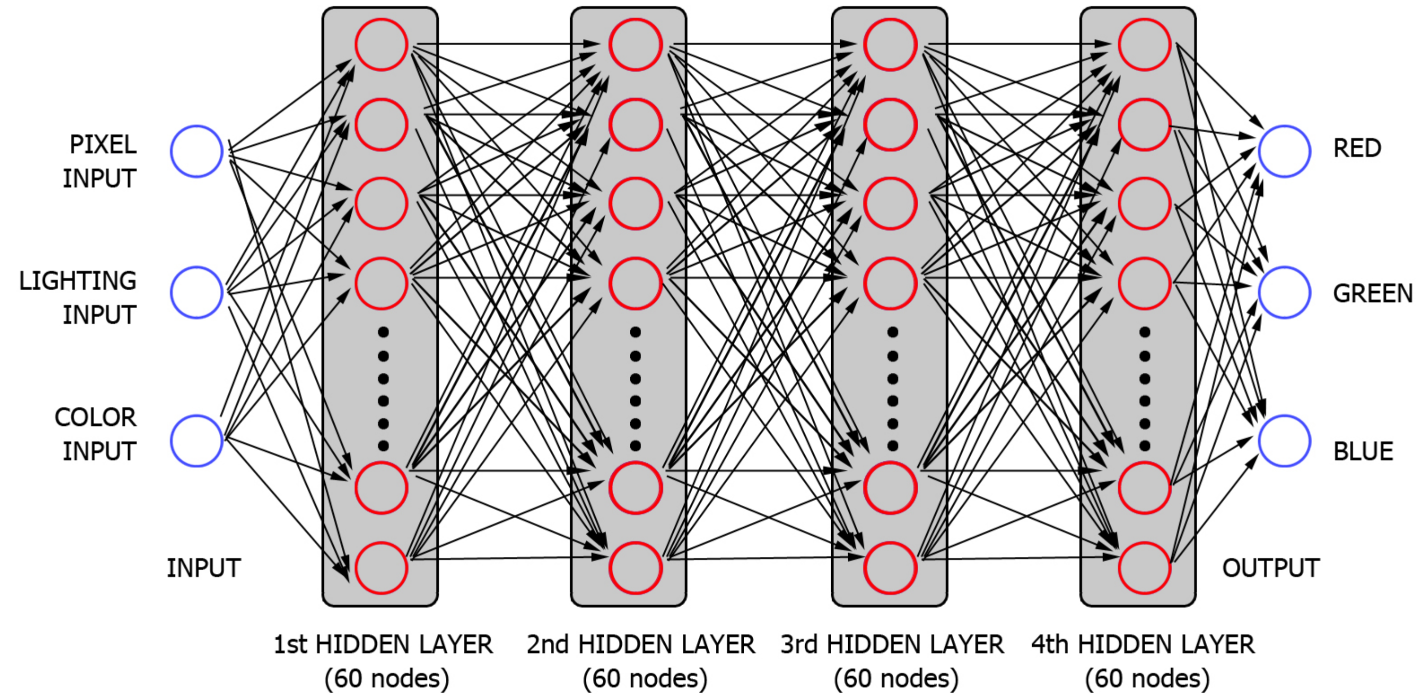


Case 1: Observation and Improvements

2. Improved Neural Network Structure



Original Neural Network



Deeper and Wider Neural Network

* Pre-processed Images without any Post-processing

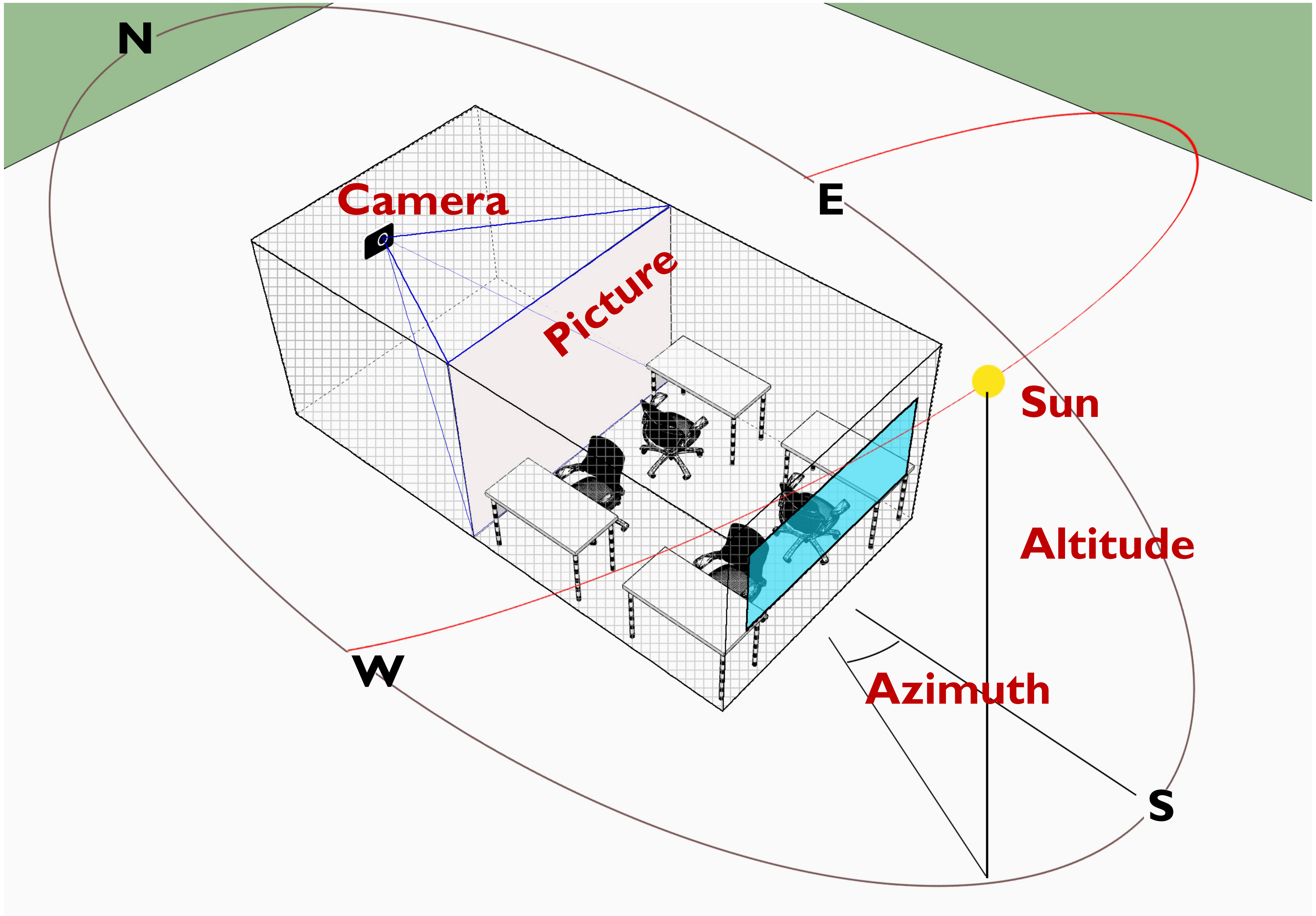
Case 1: Observation and Improvements

Improved Accuracy

Original Image

Predicted Image

Case 2: Radiance Generated Data

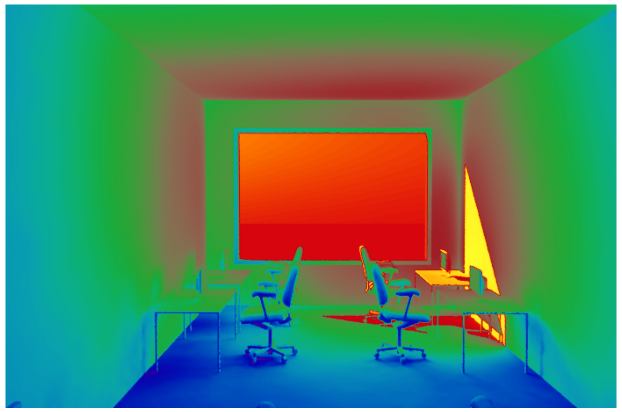


Room Information	
Room Type	Office
Window Orientation	South
Location	Seattle
Time	9/21

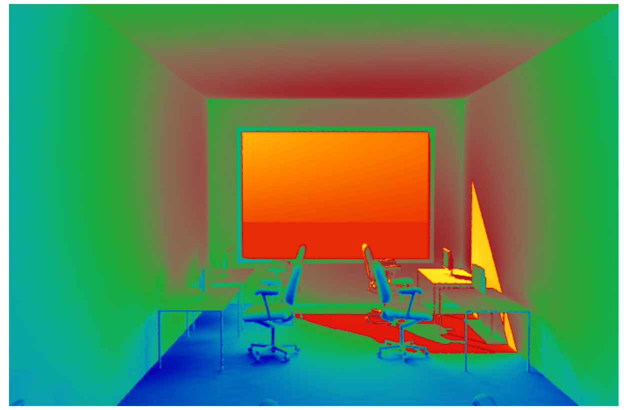
Rendering Settings	
Sky Type	CIE Clear with Sun
Rendering Quality	High
Image Size	348 * 230

Image Frequency
Every 3 minutes, from 9am – 6pm,
200 images in total.

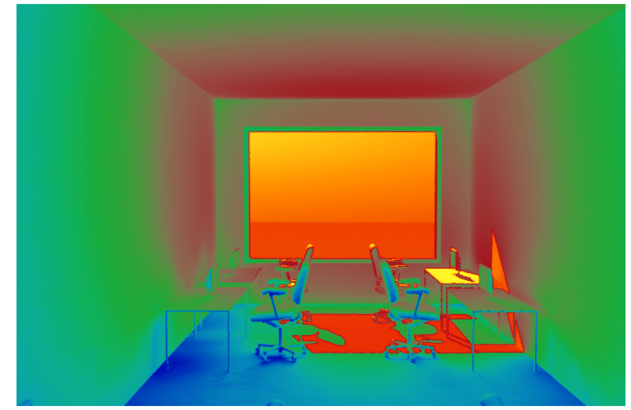
Case 2: Radiance Generated Data



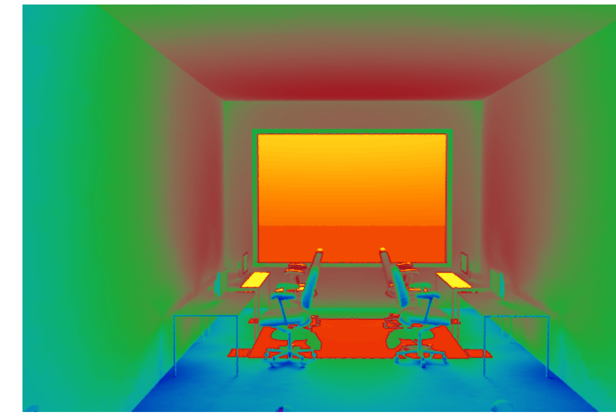
09am



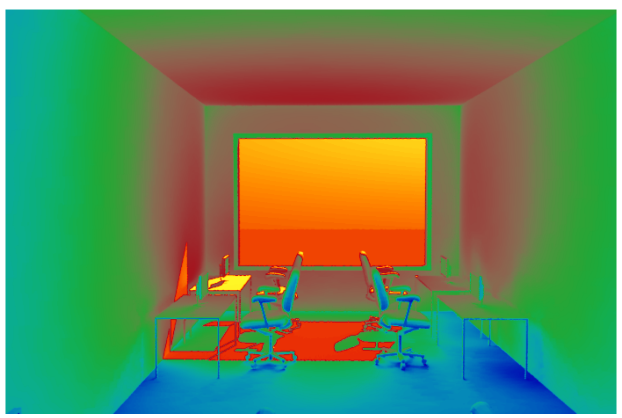
10am



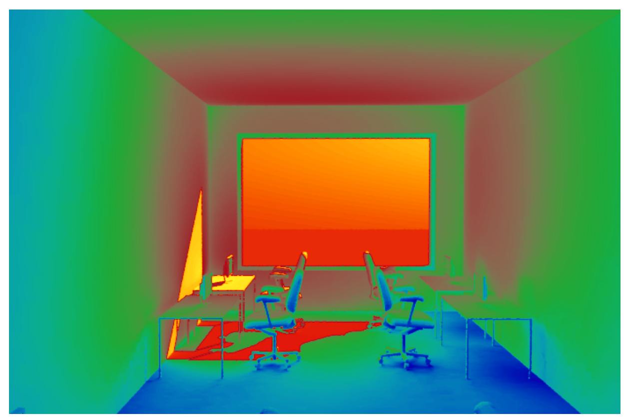
11am



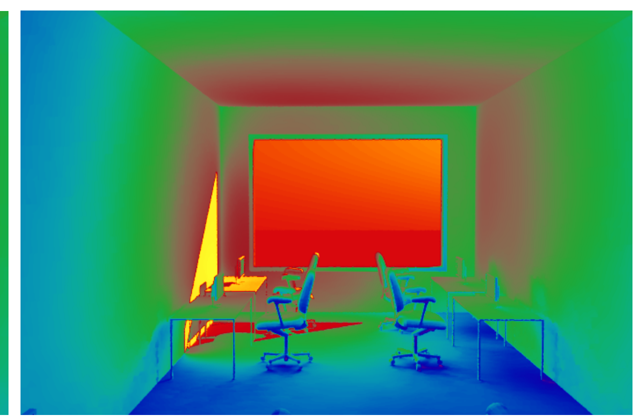
12pm



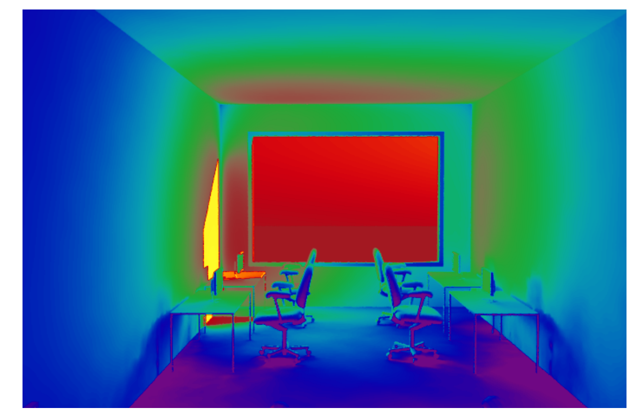
1pm



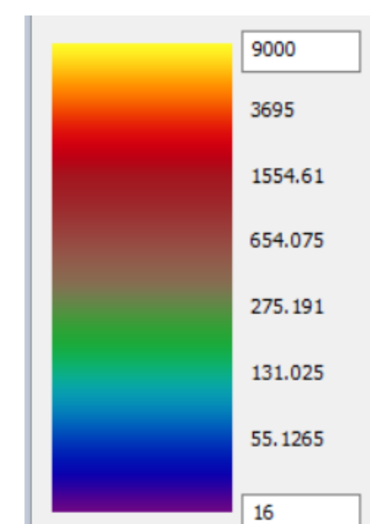
2pm



3pm

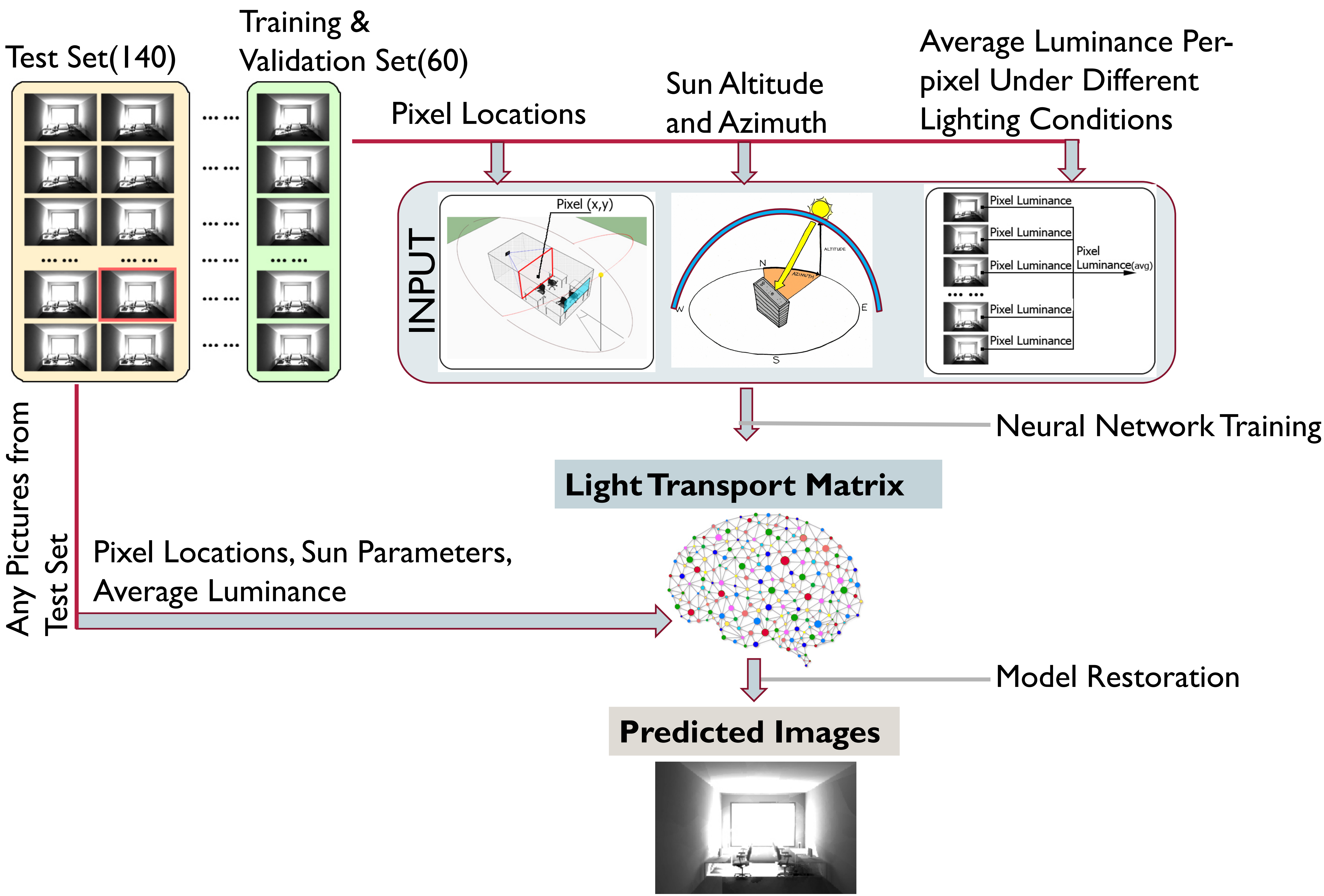


4pm



Variation in One Day
On September 21st

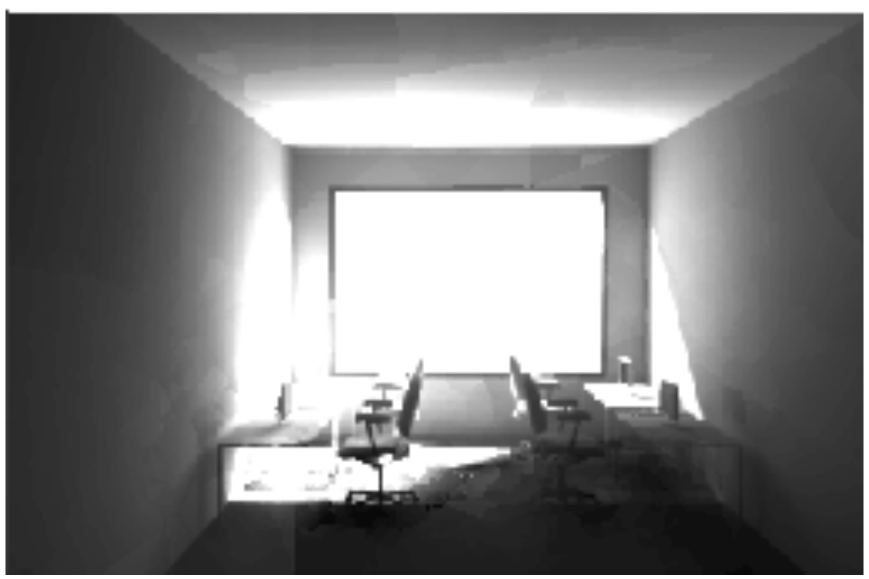
Case 2: Input and Output



Case 2: Preliminary Results

Original Image

Predicted Image



- Based on 60 out of 200 images as input data
- Average error rate $\varepsilon_{average}$ = **0.02**

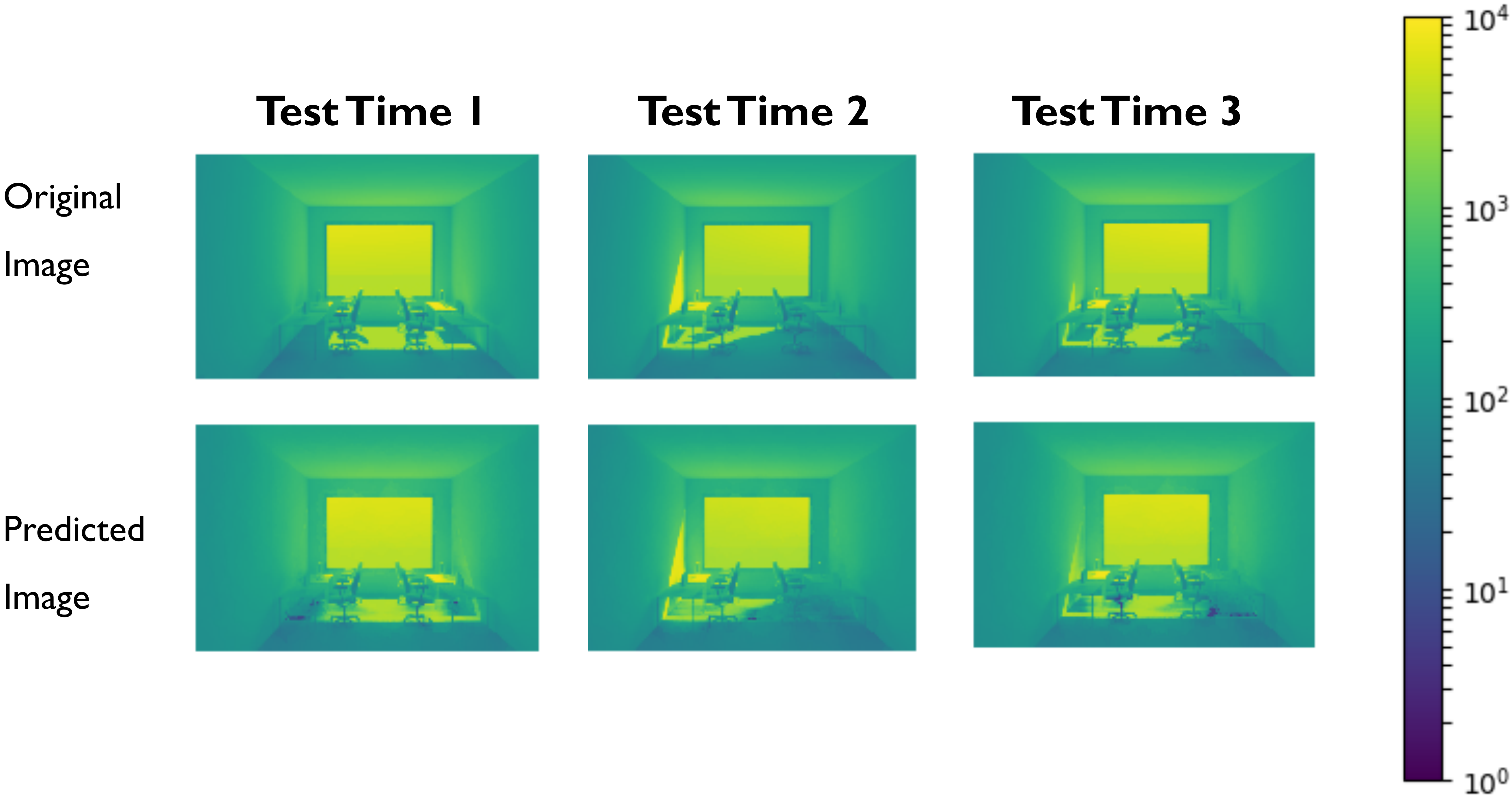
$$\varepsilon = \sqrt{\frac{\sum_j \|I_j - \tilde{I}_j\|^2}{\sum_j \|I_j\|^2}}$$

Where:

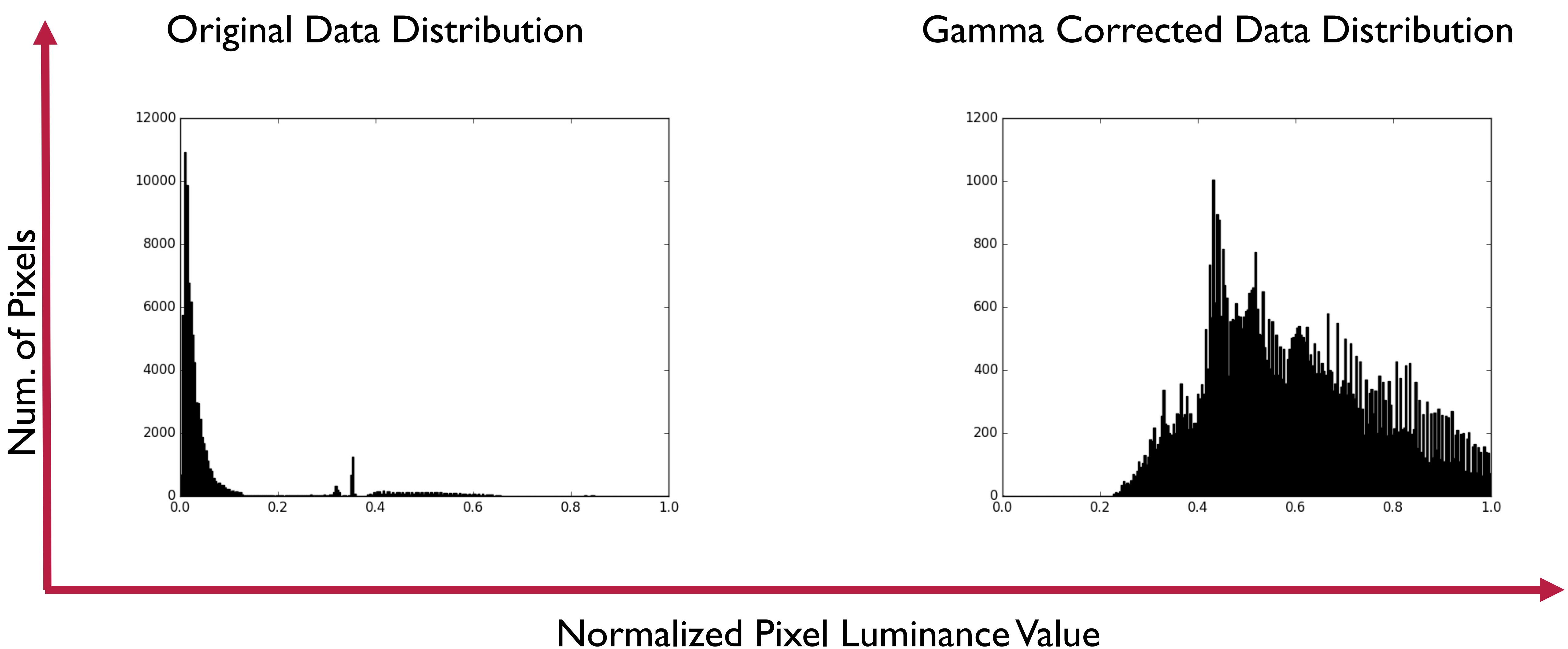
I_j : RGB of ground truth light transport marix M(., j)

$\tilde{I}_j$: RGB of reconstructed light transport matrix M(., j)

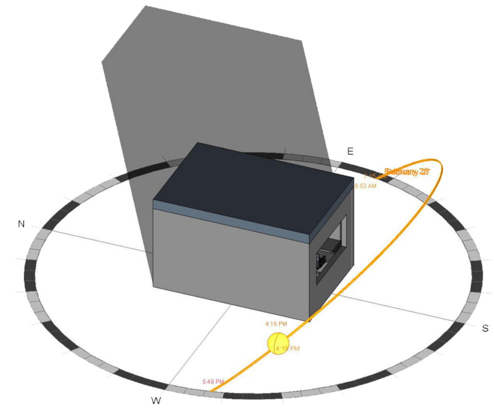
Case 2: Preliminary Results

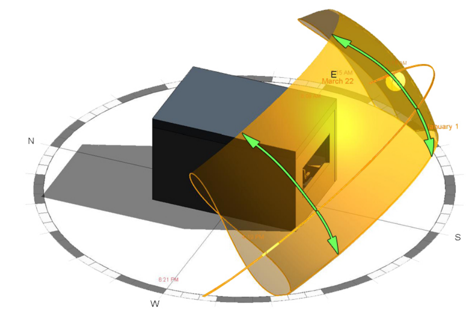


Case 2: Observation and Improvements



Future Work





- Add sky complexity
- Test accuracy on long term predictions
- Improve the neural network models to achieve better accuracy and efficiency
- Test using real HDR captures of the scene (field test)

Conclusion

- Deep Neural Networks(DNNs) Show Promise for Architectural Lighting Research
- Applications
  - Evaluations of existing spaces
  - Remodeling and adaptive reuse
  - Can be used for complicated lighting simulations in the future

Acknowledgement

- Microsoft Azure
- Zillow Group
- National Supercomputing Center in Changsha
- IES Robert Thunen Memorial Scholarships

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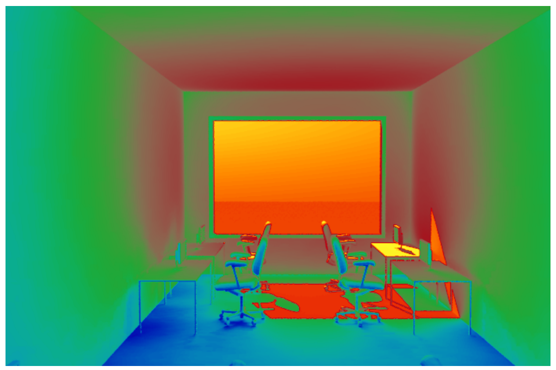
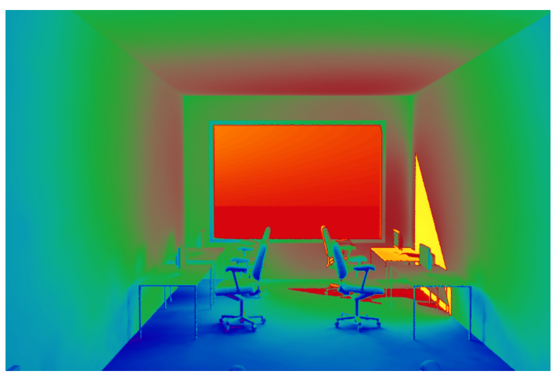
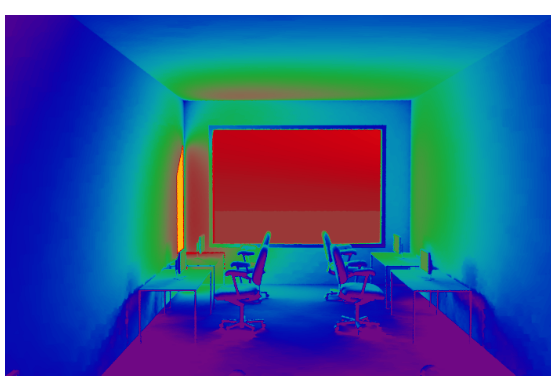
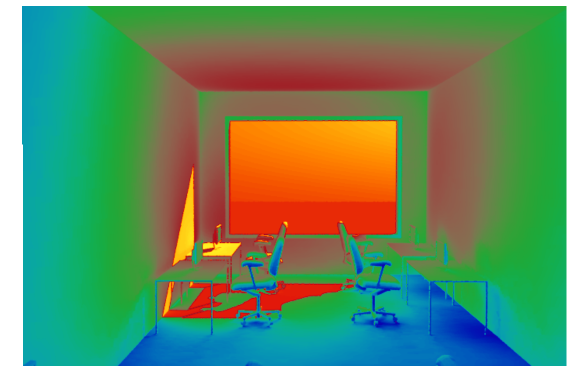
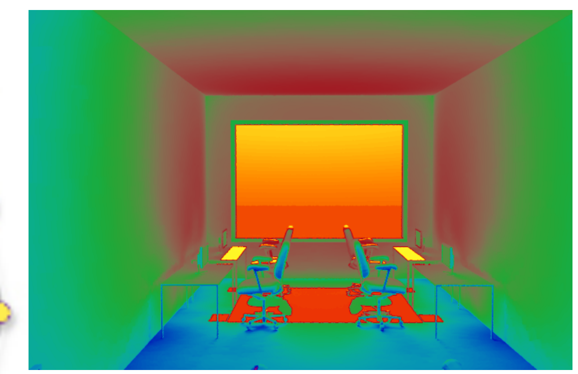
EARLY RESULTS

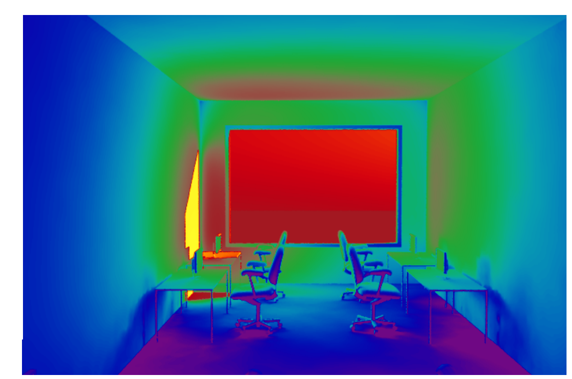












Thank you!

Email: yueliu@uw.edu