

Image-Based Rendering

CSE 274, Lecture 1: Keynote and Logistics

Ravi Ramamoorthi

<http://www.cs.ucsd.edu/~ravir>



1

Instructor

Ravi Ramamoorthi <http://www.cs.ucsd.edu/~ravir>

- PhD Stanford, 2002 [with Pat Hanrahan, 2020 Turing Award]
- “*Spherical Harmonic Lighting*” widely used in games (e.g. Halo series), movies (e.g. Avatar), etc. (Adobe, ...)
- At Columbia 2002-2008, UC Berkeley 2009-2014
- “*Monte Carlo denoising*” inspired raytracing offline, real-time; consults at NVIDIA
- At UCSD since Jul 2014: Director, Center for Visual Computing
- “*NeRF: Neural Radiance Fields for View Synthesis*” widely cited IBR technique
- Awards for research: White House PECASE (2008), SIGGRAPH Significant New Researcher (2007), ACM Fellow (2018), Two Frontiers Science Awards (23,24)
- <https://www.youtube.com/watch?v=qpyCxqXGe7I>
- Computer Graphics online MOOC (CSE 167x) finalist for two edX Prizes.

2

Outline of Lecture

- Lecture: *Image-Based Rendering: From View Synthesis to Neural Radiance Fields and Beyond* (originally Eurographics Keynote Apr 24)
- Logistics of course

3

Virtual Experiences of Real-World Scenes



4

Input Images

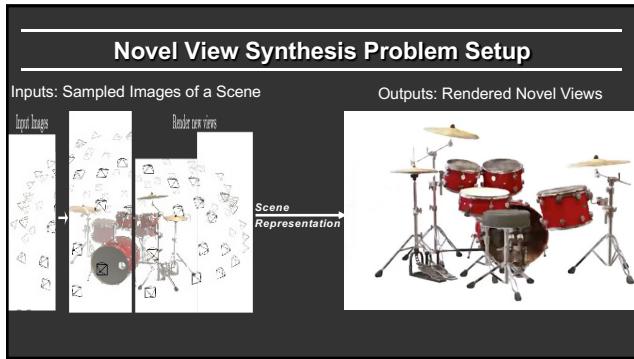


5

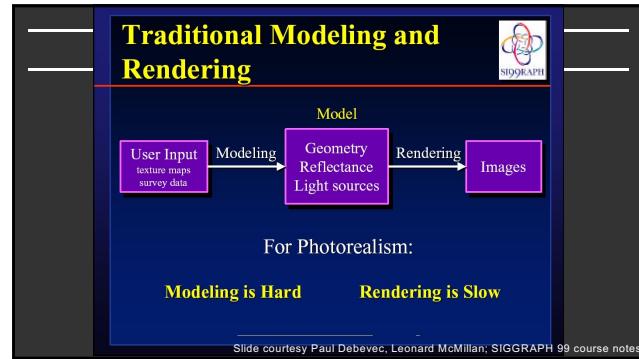
Output Virtual Experience



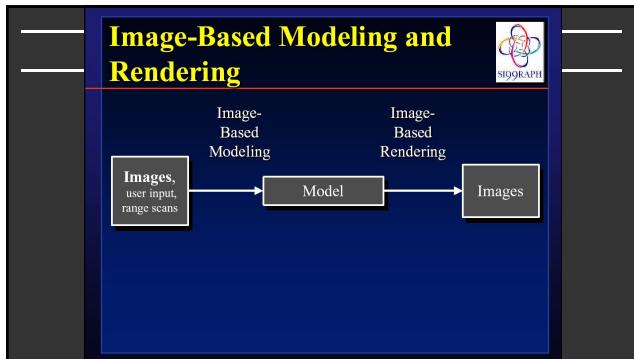
6



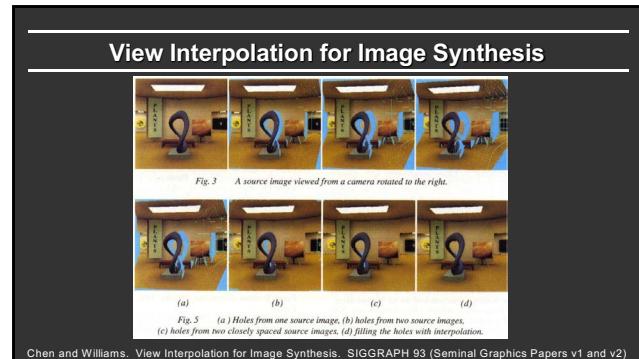
7



8



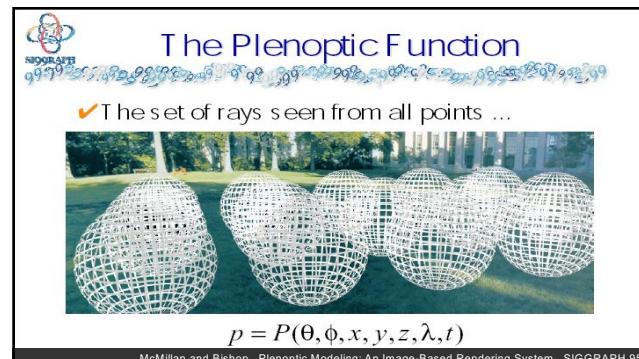
9



10



11



12

Light Fields

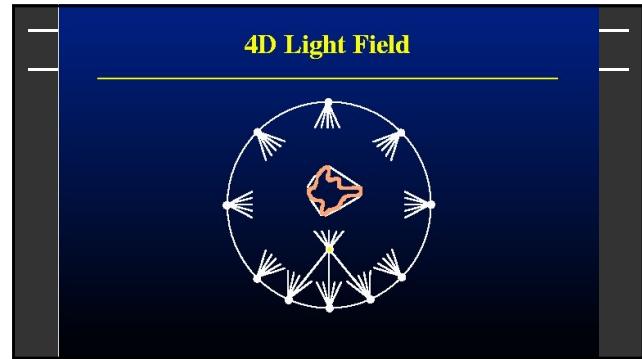
Gershun's and Moon's idea of a light field:

Radiance as a function of a ray or line: $L(x, y, z, \theta, \phi)$

- In “free space” (no occluders) 5D reduces to 4D
 - Exterior of the convex hull of an object
 - Interior of an environment
- Images are 2D slices
 - Insert acquired imagery
 - Extract image from a given viewpoint

From Levoy and Hanrahan. Light Field Rendering. SIGGRAPH 96

13



14

Surface Light Fields and Reflectance Fields

Wood et al. Surface Light Fields for 3D Photography. SIGGRAPH 00

Debevec et al. Acquiring the Reflectance Field of a Human Face. SIGGRAPH 00

15

Seminal Graphics Papers: Pushing the Boundaries

6 Imaging and Vision

View Interpolation for Image Synthesis 401
S. I. Chen and L. Williams Article 45:423–432

Photorealistic Modeling: An Image-Based Rendering System 403
L. Williams and G. Bishop Article 46:433–440

Light Field Rendering 405
M. Levoy and P. Hanrahan Article 47:441–452

The Lumigraph 407
S. J. Gortler, R. Grzeszczuk, R. Szeliski and M. F. Cohen Article 48:453–464

Modeling and Rendering Architecture from Photographs: A Hybrid Geometry-and-Image-Based Approach 409
P. J.Debevec, C. J. Taylor and J. Malik Article 49:465–474

Acquiring the Reflectance Field of a Human Face 411
P. J. Debevec, C. J. Taylor, H.-P. K. Blok, W. Sarokin and M. Segal Article 50:475–486

Surface Light Fields for 3D Photography 413
D. N. Wood, S. I. Adams, K. Adlunger, B. Curless, T. Duchamp, D. H. Salesin and W. Stuetzle Article 51:487–496

Unstructured Lumigraph Rendering 415
C. J. Taylor, M. Boult, L. McMillan, S. Gortler and M. Cohen Article 52:497–504

Fast Separation of Direct and Global Components of a Scene Using High-Frequency Illumination 417
S. K. Nayar, G. Krishnan, M. D. Grossberg and R. Raskar Article 53:505–514

Photo Tourist: Exploring Photo Collections in 3D 419
N. Snavely, C. M. Seitz and R. Szeliski Article 54:515–528

SIGGRAPH AWARD WINNERS (SNR, CGA, COONS)

- Williams: Coons 03
- (an interesting story)
- Levy CGA96; Hanrahan: CGA93, Coons03, Turing20
- Gortler: SNR 02; Szeliski: CGA 11; Cohen: CGA 98, Coons 19
- Debevec: SNR 01; (Malik: NAE 11)
- Debevec: SNR 01
- Salesin: CGA 00
- Gortler: SNR 02; Cohen: CGA 98, Coons 19
- Raskar: CGA 17; (Nayar: NAE 08)
- Snavely: SNR 14; Szeliski: CGA 11

16

View Synthesis till mid 2010s: Classical Geometry

- Reconstruct (implicit) 3D geometry of scene

Penner and Zhang 2017

17

View Synthesis in mid 2010s: Deep Learning

- Deep learning but still implicit geometry

Elvnn et al. 2016; Kalantari et al. 2016

18

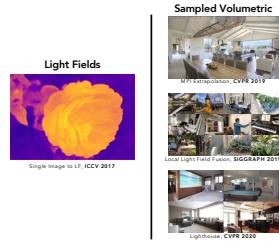
View Synthesis end 2010s: Deep Learning + MPis

- Multi-Plane Images (Szeliski Golland 99, Zhou 18): Sampled Volume Representation



Mildenhall, Srinivasan et al. 2019

19



Slide courtesy Pratul Srinivasan

20

PREDICTING SCENE DEPTHS AND LIGHT FIELD FROM SINGLE IMAGE

- Input: single image

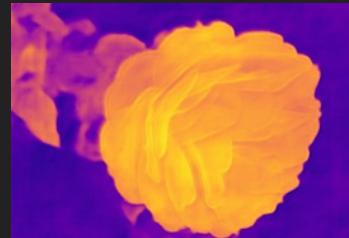


Synthesizing a 4D RGBD Light Field from a Single Image, Srinivasan et al. (ICCV 2017)

21

PREDICTING SCENE DEPTHS AND LIGHT FIELD FROM SINGLE IMAGE

- Output: dense multiview depths



Synthesizing a 4D RGBD Light Field from a Single Image, Srinivasan et al. (ICCV 2017)

22

PREDICTING SCENE DEPTHS AND LIGHT FIELD FROM SINGLE IMAGE

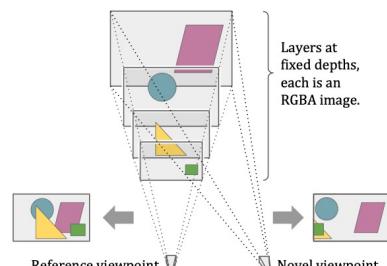
- Output: local light field



Synthesizing a 4D RGBD Light Field from a Single Image, Srinivasan et al. (ICCV 2017)

23

Representing scenes with frustum-sampled RGBA layers (a.k.a. Multi-plane Image or MPI)



Stereo Magnification, Zhou et al. 2018

24

Casual Capture for Light Field Synthesis



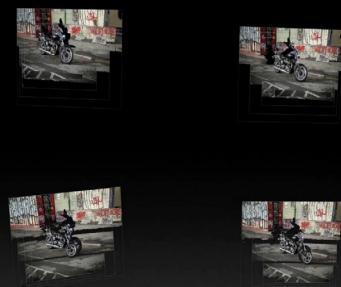
25

Promote each sampled view to local light field



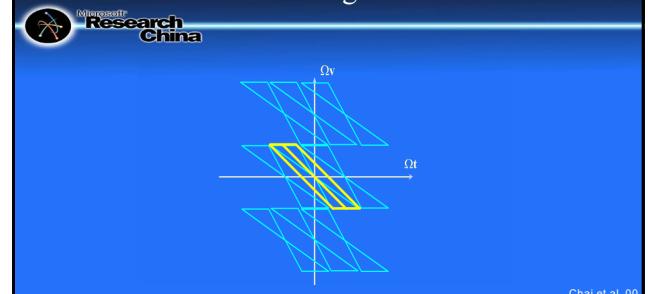
26

Blend nearby local light fields to render novel views



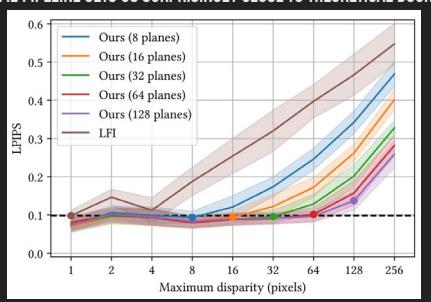
27

Light Field Reconstruction



28

ML PIPELINE GETS US SURPRISINGLY CLOSE TO THEORETICAL BOUND

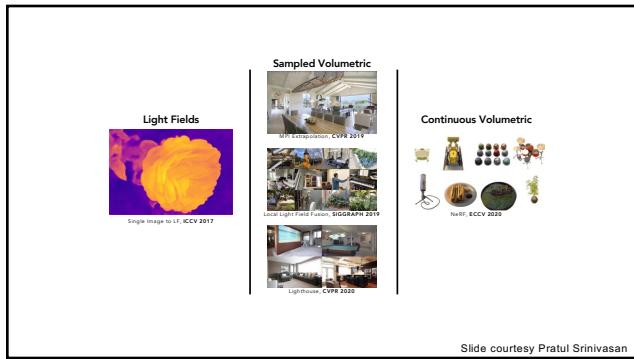


29

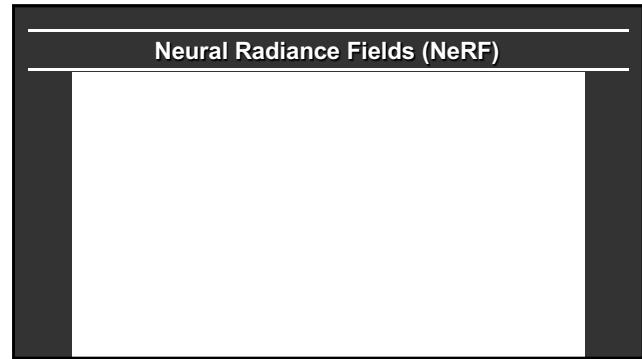
Local Light Field Fusion



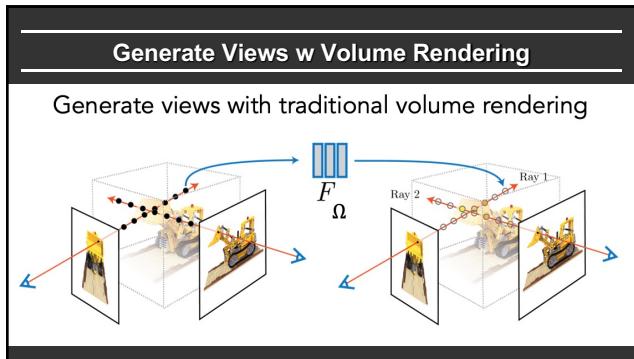
30



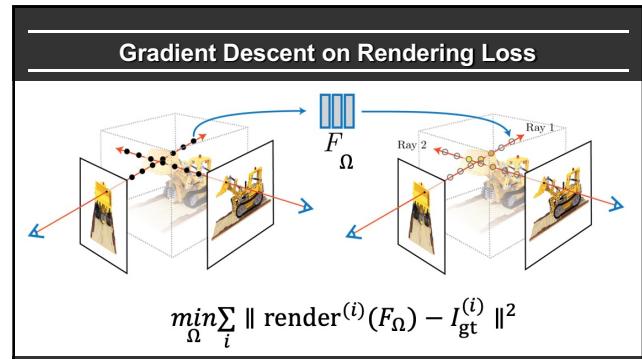
31



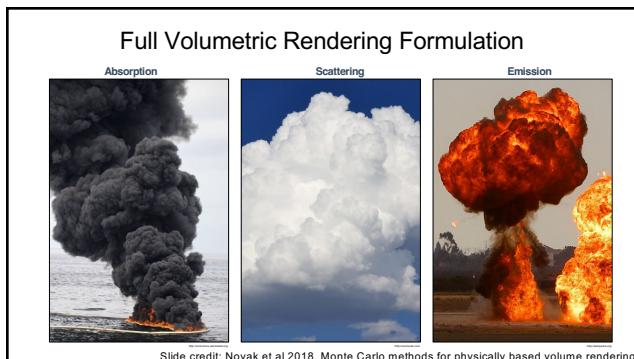
32



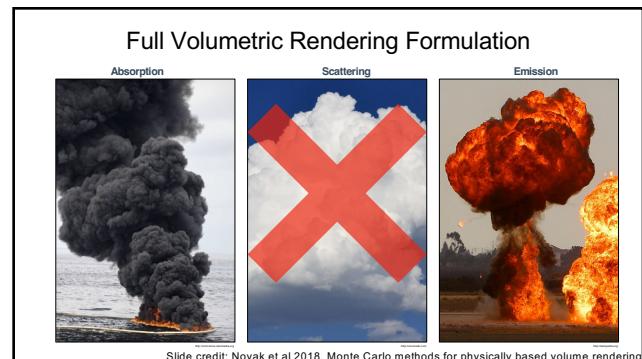
33



34



35



36

Summary: volume rendering integral estimate

Rendering model for ray $r(t) = \mathbf{a} + t\mathbf{d}$:

$$\mathbf{c} \approx \sum_{i=1}^n T_i \alpha_i \mathbf{c}_i$$

colors
weights

How much light is blocked earlier along ray:

$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

How much light is contributed by ray segment i :

$$\alpha_i = 1 - \exp(-\sigma_i \delta_i)$$

Use neural network to replace large N-d array



(r, g, b, σ)

versus

$$(x, y, z, \theta, \phi) \longrightarrow \text{Neural Network} \longrightarrow (r, g, b, \sigma)$$

F_Ω

37

38

Preserve High-Frequency Features



Ground truth image



Neural network output without high frequency mapping



Neural network output with high frequency mapping

Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains. Tancik et al. Neurips 20

39

More detail than implicit scene MLP

SRN [Sitzmann et al. 2019]



NeRF



Nearest Input

40

Results



41

View-Dependent w Directional Dependence



42

Detailed Scene Geometry, Occlusion



44

Detailed Scene Geometry, Occlusion



45

NeRFs in the Metaverse



46

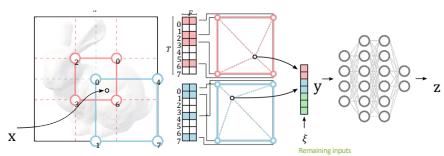
2022: NVIDIA Instant NGP – Real Time NeRFs

TIME Magazine Named NVIDIA Instant NeRF a Best Invention of 2022



47

Multiresolution Hash Encoding



48

Reducing compute-per-sample: learned hash grids (Instant NGP)



49

3D Gaussian Splats for Radiance Fields



Kerbl, Kopanas, Leimkuhler, Drettakis 23; EG Distinguished Career Award 24

50

NeRFs for Digital Twins



51

NeRFs for Landscapes



Instant NeRF (@ionstenhens85 on Twitter); slide courtesy Thomas Müller

52

NeRFs for Furry Volumes



Instant NeRF (@vibrantmechul on Twitter); slide courtesy Thomas Müller

53

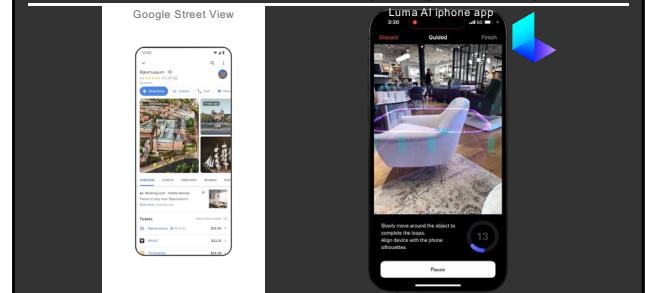
NeRFs + Language Models

- Text-based editing with large language models (Haque et al.)

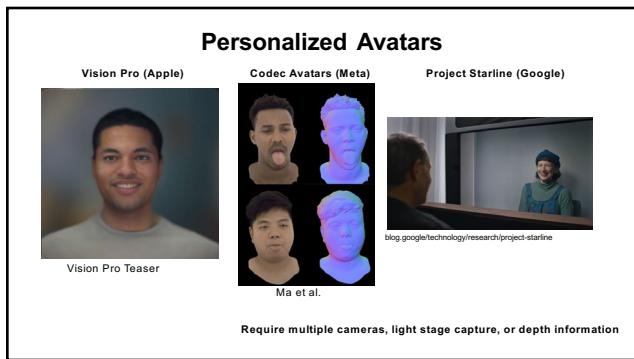


54

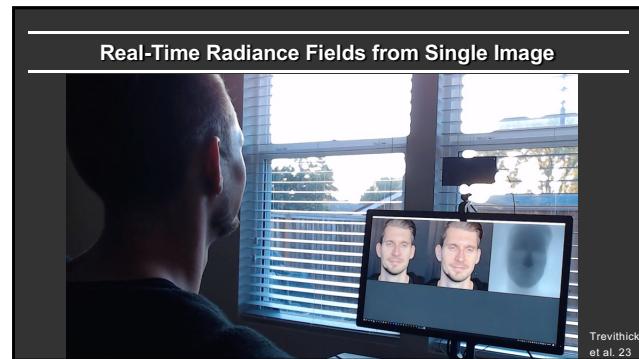
NeRFs in Production (Google, Luma)



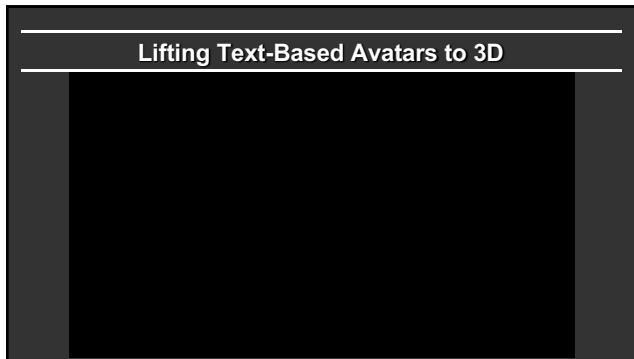
55



56



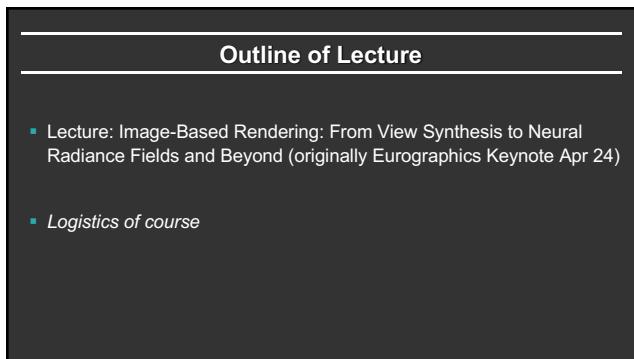
57



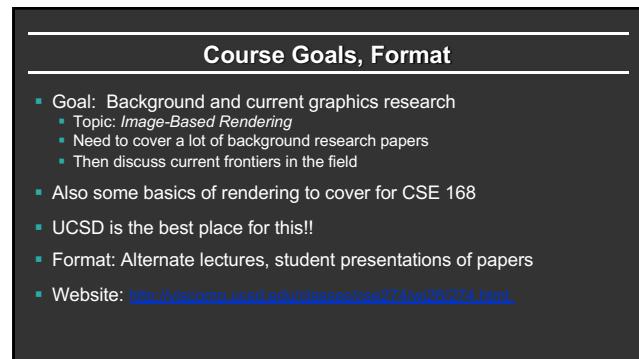
58



59



60



61

Course Logistics

- No textbooks. Required readings are papers online (and some handouts)
 - Handouts at <http://viscomp.ucsd.edu/classes/cse274/w26/readings>
- Office hours: after class or email. My contact info is on my webpage: <http://www.cs.ucsd.edu/~ravir>
- Zoom: <https://ucsd.zoom.us/mv/ravir11> (if we need to move to remote instruction temporarily or permanently)
- TA: Nithin Raghavan n2raghavan@ucsd.edu. Office hours: see website or email for another time.
- Should count for PhD, MS, BS electives in graphics and vision, see me if there is a problem or you need a certification

62

Requirements

- Pass-Fail (2 units)
 - Show up to class regularly
 - Present 1 or 2 paper(s) if needed
 - Prefer you do this rather than just sit in
- Grades (4 units)
 - Attend class, participate in discussions
 - Present 1 or 2 papers (please do this well)
 - If class is large, groups of 2 can present 1 paper
 - Project (key part of grade)

63

Project

- Wide flexibility if related to course. Can be done groups of 2
 - Default: Implement (part of) one of papers and produce an impressive demo for image-based rendering or view synthesis
 - See/e-mail me re ideas
 - Best projects will go beyond simple implementation (try something new, some extensions)
- ML support only through basic DSMLP or AWS Educate through UCSD
 - We may have some old GPUs but largely on own (or do non-ML project)
- Alternative (less desirable): Summary of 3+ papers in an area
 - Best projects will explore links/framework not discussed by authors, and suggest future research directions

64

Prerequisites

- Strong interest in graphics, vision, want to learn about image-based rendering
- Computer graphics experience (167 or equivalent)
 - Experience with rendering not required; first few weeks will cover basics. But also doesn't hurt, consider UCSD online CSE 168. And computer vision.
- Course will move quickly
 - Covering recent and current active research
 - Some material quite technical
 - Considerable background material is covered
 - Assume some basic knowledge
 - Many topics. Needn't fully follow each one, but doing so is most rewarding.

65

Assignment this week

- E-mail me (ravir@cs.ucsd.edu) [only if not done already]
 - Name, e-mail, status (Senior, PhD etc.)
 - Will you be taking course grades or P/F
 - Background in graphics/any special comments
 - *Optional for all: Papers you'd like to present FCFS (only those that say "presented by students")*

66

Questions?

67