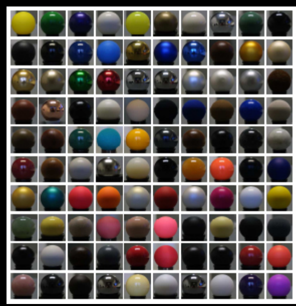
Measurement and Data-driven BRDFs



70001 – Advanced Computer Graphics: Photographic Image Synthesis

Abhijeet Ghosh

Lecture 12, Feb. 16th 2024

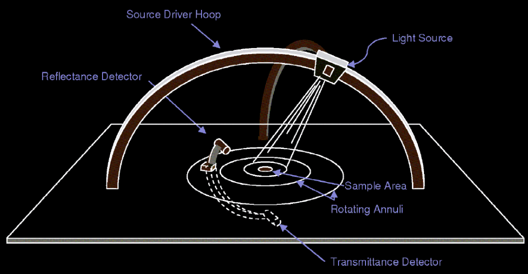
1

BRDF Measurement

- Analytical models have limitations
  - describe specific kinds of surfaces
  - appropriate parameters not easy to obtain!
- Measurement of BRDFs a solution
  - direct usage as tabulated data
  - fit to analytic models or basis functions

2

Dense Measurements

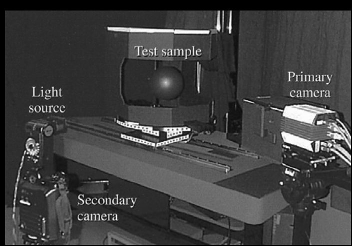


- Gonioreflectometer
  - Source and sensor with arc rotation, sample on turntable
  - Cornell, CUReT, NIST databases
  - Missing measurements interpolation!

3

Image-based Measurements

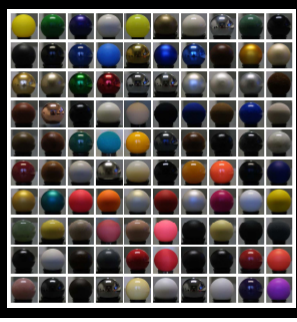
Isotropic



[Marschner et al. 00]

[Matusik et al. 03]

- Spherical sample for isotropic BRDFs
  - 1 photograph → all reflectance directions
  - lightsource rotation along 1 axis

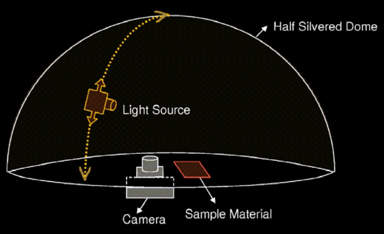


100 isotropic BRDFs
MERL database

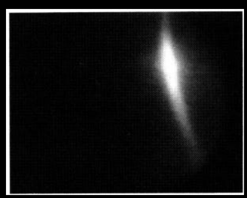
4

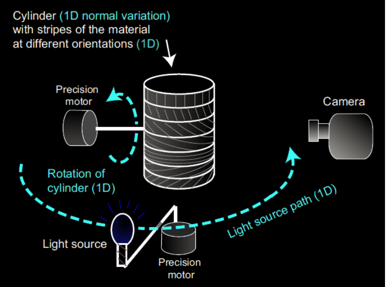
Image-based Measurements

Anisotropic

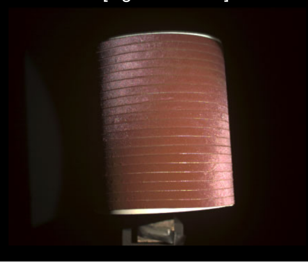


[Ward 92]



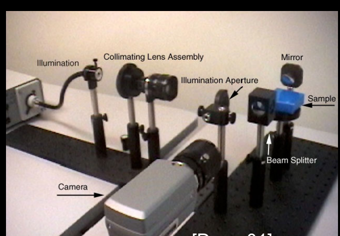


[Ngan et al. 05]

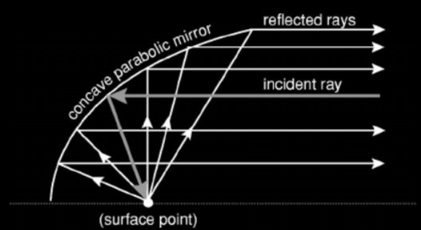


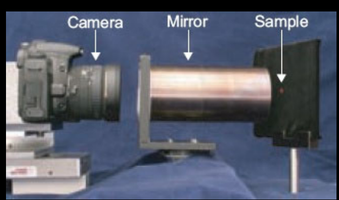
Catadioptric Measurements

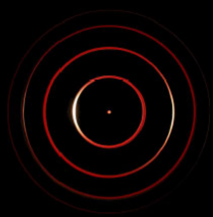
Parabolic mirror



[Dana 01]



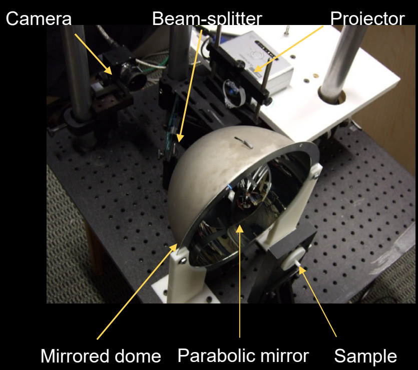




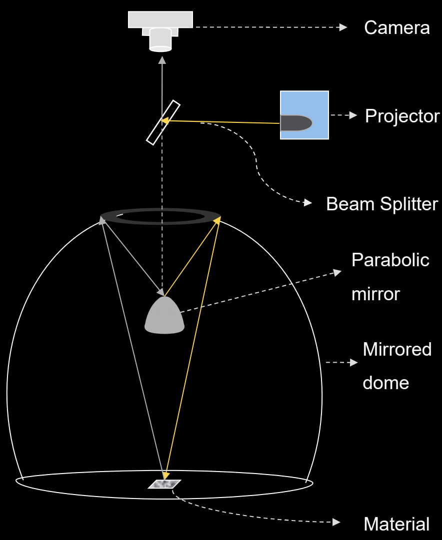
Radial imaging system with a cylindrical mirror

[Kuthirummal&Nayar 06]

Catadioptric Measurements

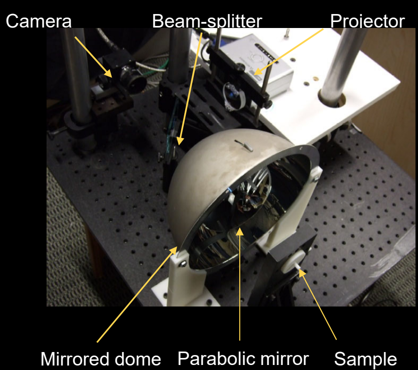


[Ghosh et al. 07]

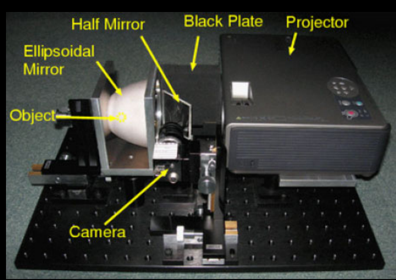


7

Catadioptric Measurements



[Ghosh et al. 07]

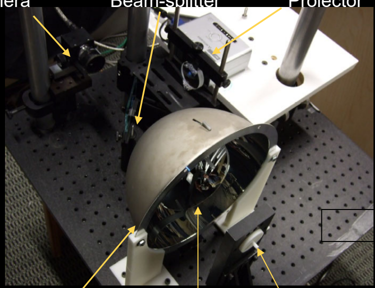


[Mukaigawa et al. 07]

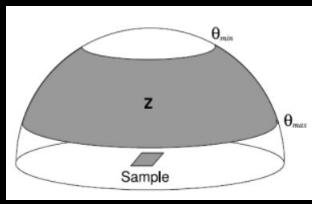
– Mukaigawa et al. point sample the BRDF
– Ghosh et al. project basis functions

8

Basis Illumination



[Ghosh et al. 07]



Measurement Zone

$$z_k(\omega_o) = \int_{\mathbf{Z}} Z_k(\omega_i) f_r(\omega_i, \omega_o) \cos\theta_i \, d\omega_i.$$

Camera Illumination

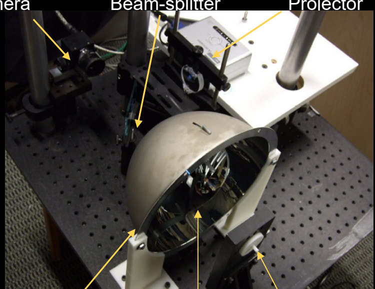
$$\hat{f}_r(\omega_i, \omega_o) = f_r(\omega_i, \omega_o) \cos\theta_i \approx \sum_k Z_k(\omega_i) z_k(\omega_o),$$

BRDF approximation

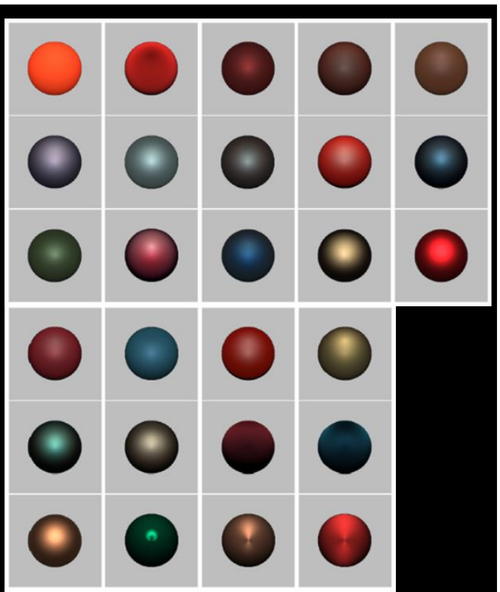
- Orthonormal Zonal basis functions Z_k (related to spherical harmonics)
- Coeffiecients of BRDF z_k in the basis recorded

9

Basis Illumination



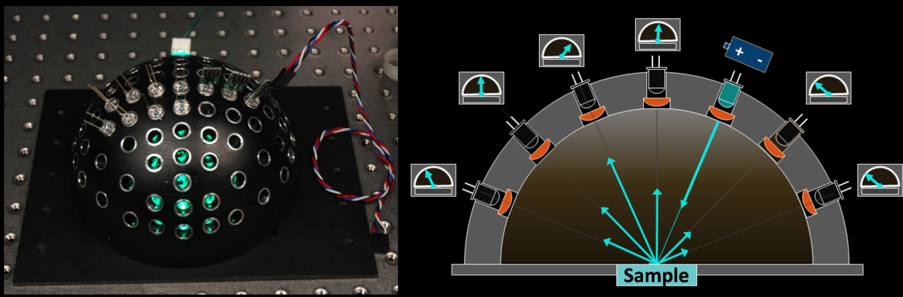
[Ghosh et al. 07]



- Zonal basis functions (related to spherical harmonics)
- Coeffiecients of BRDF in the basis recorded

10

LED-based Measurement



[Ben-Ezra et al. 08]

- LEDs as emitters as well as sensors!
- Parallel measurements – O(N) instead of O(N^2)

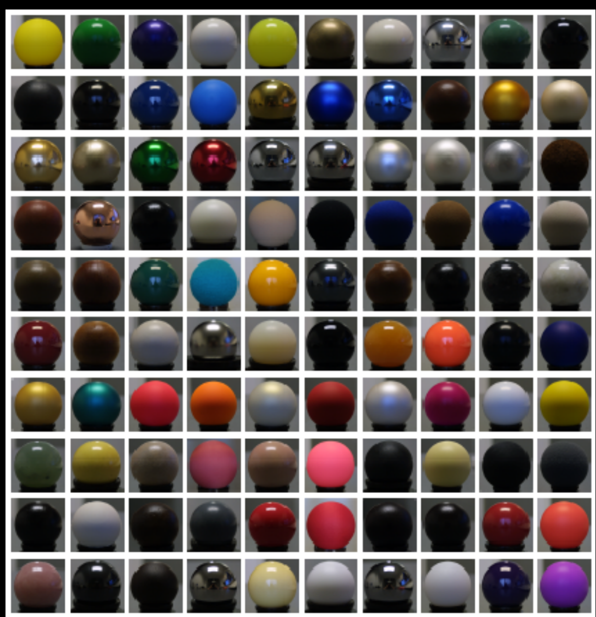
11

Data-driven BRDF Representation

More than 100 different BRDFs

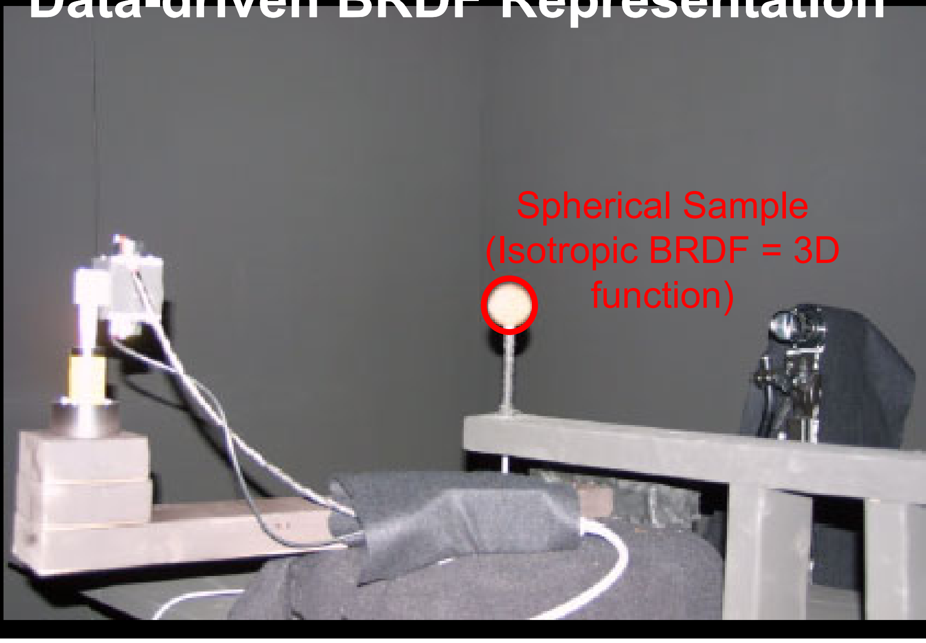
(MERL database)

20-80M Reflectance Measurements per Material



12

Data-driven BRDF Representation

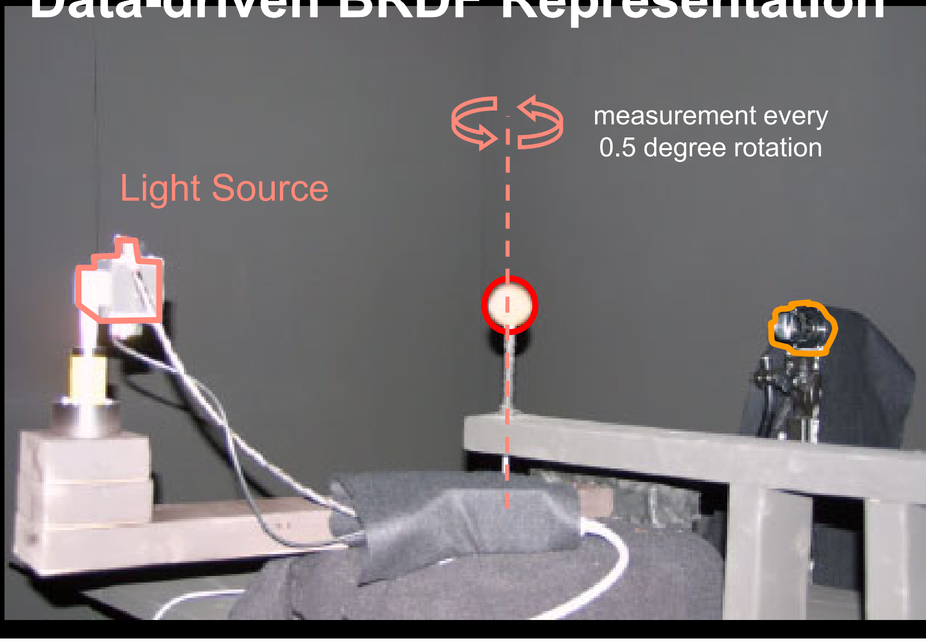


13

Data-driven BRDF Representation

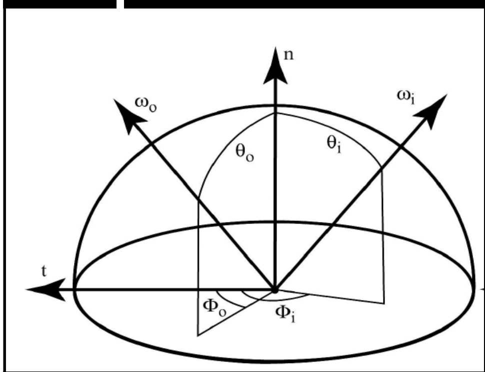
14

Data-driven BRDF Representation



15

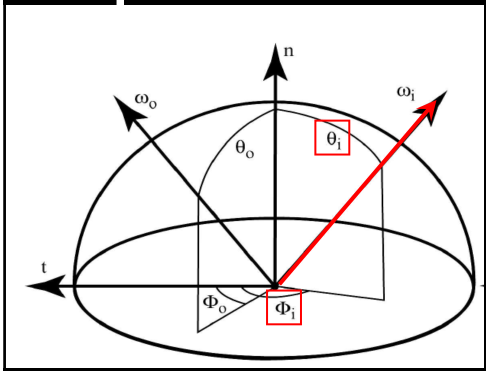
Reparameterization



Standard

16

Reparameterization

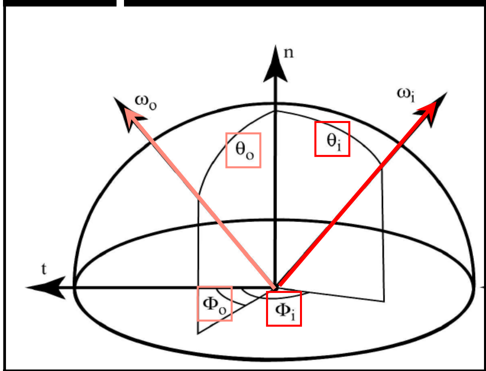


Standard

Incident: $\omega_i = (\theta_i, \Phi_i)$

17

Reparameterization

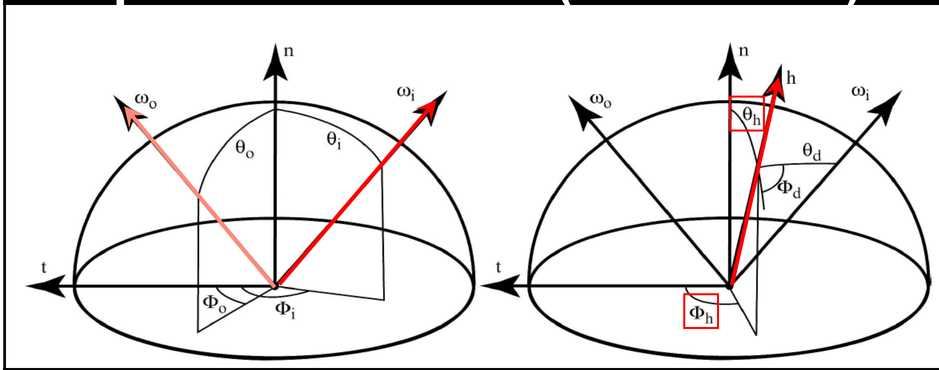


Standard

Incident: $\omega_i = (\theta_i, \Phi_i)$
Exitant: $\omega_o = (\theta_o, \Phi_o)$

18

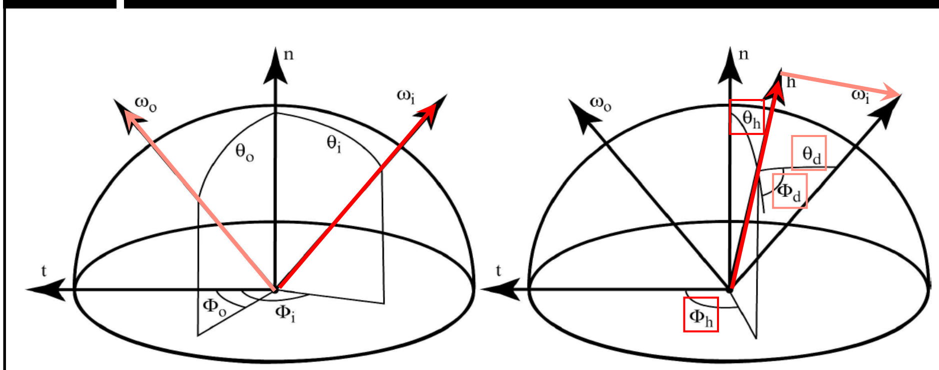
Reparameterization (half-vector)



Standard	Rusinkiewicz
Incident: $\omega_i = (\theta_i, \Phi_i)$ Exitant: $\omega_o = (\theta_o, \Phi_o)$	Halfway: $\omega_h = (\theta_h, \Phi_h)$

19

Reparameterization



Standard	Rusinkiewicz
Incident: $\omega_i = (\theta_i, \Phi_i)$ Exitant: $\omega_o = (\theta_o, \Phi_o)$	Halfway: $\omega_h = (\theta_h, \Phi_h)$ Difference: $\omega_d = (\theta_d, \Phi_d)$

20

Reparameterization

Advantage:

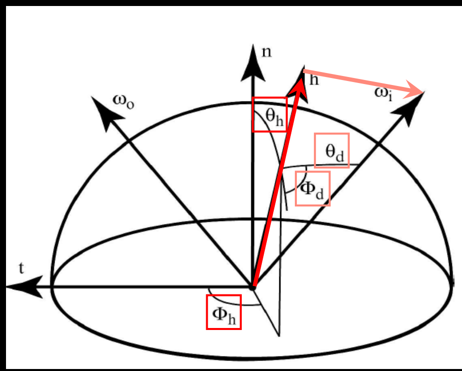
Specular highlight

⇩

Around halfway vector

⇩

$\omega_h = 0$



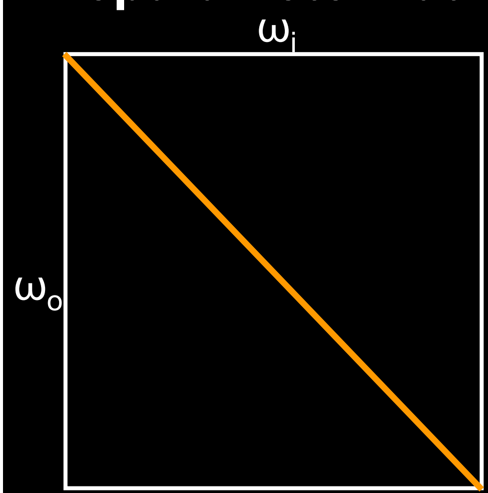
Rusinkiewicz

Halfway: $\omega_h = (\theta_h, \Phi_h)$

Difference: $\omega_d = (\theta_d, \Phi_d)$

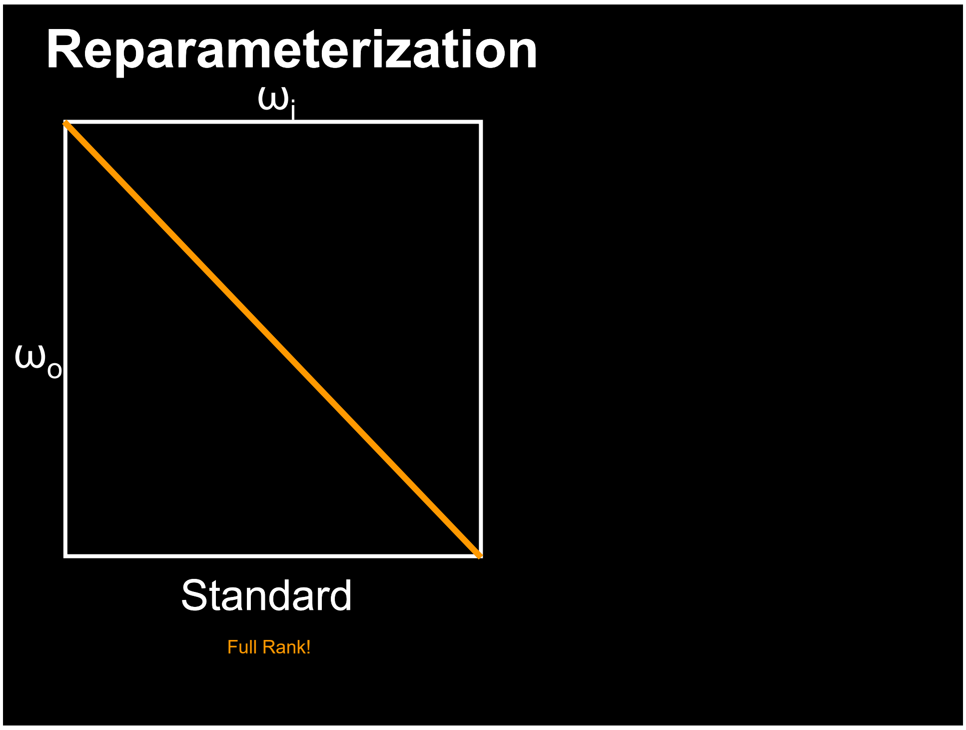
21

Reparameterization

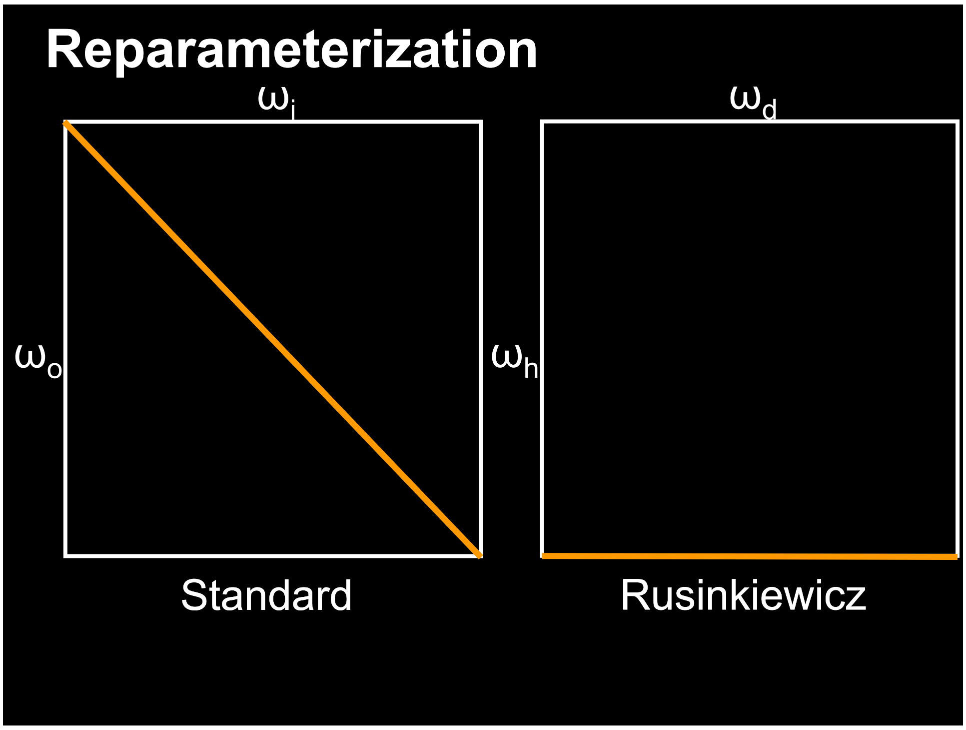


Standard

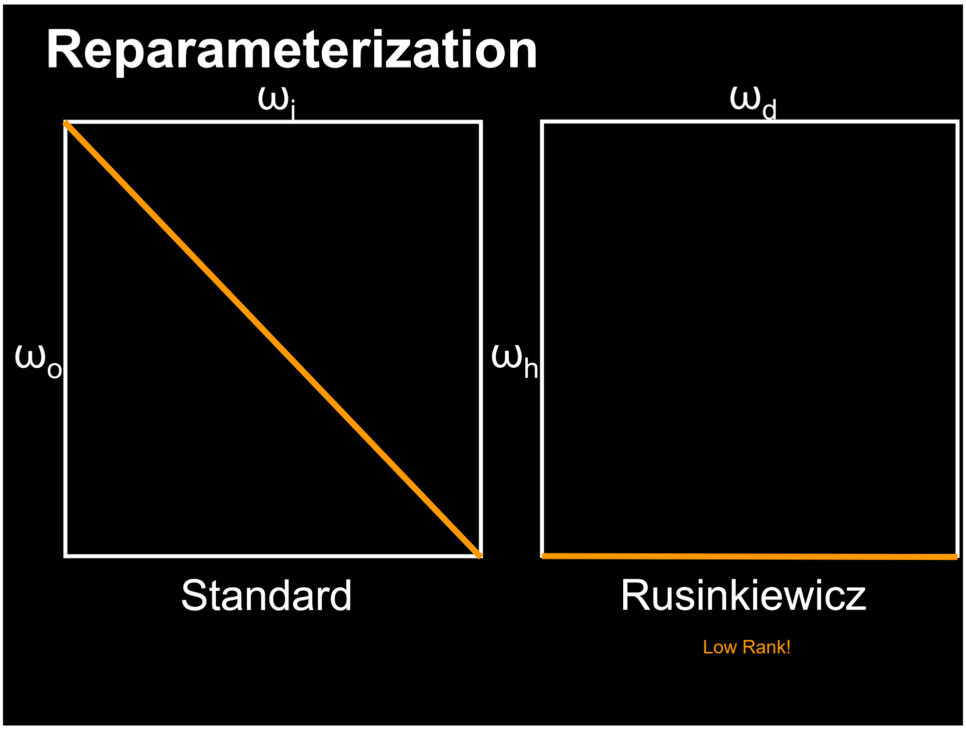
22


Reparameterization
ω_i
ω_o
Standard
Full Rank!

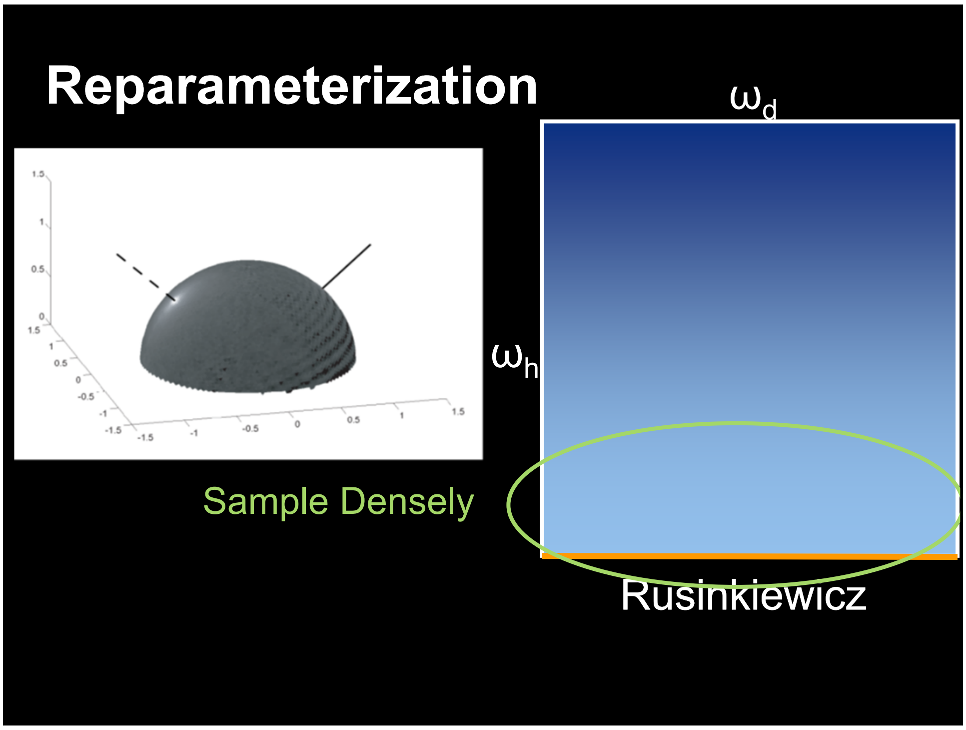
23


Reparameterization
ω_i
ω_d
ω_o
ω_h
Standard
Rusinkiewicz

24


Reparameterization
ω_i
ω_d
ω_o
ω_h
Standard
Rusinkiewicz
Low Rank!

25


Reparameterization
ω_d
ω_h
Sample Densely
Rusinkiewicz

26

Reparameterized data

Tabulated: 90 (θ_h) x 90 (θ_d) x 360 (φ_d)

- Easy to use in rendering system
- Halve the number of φ bins by enforcing reciprocity!

$$f(\theta_h, \theta_d, \phi_d) = f(\theta_h, \theta_d, \phi_d + \pi)$$

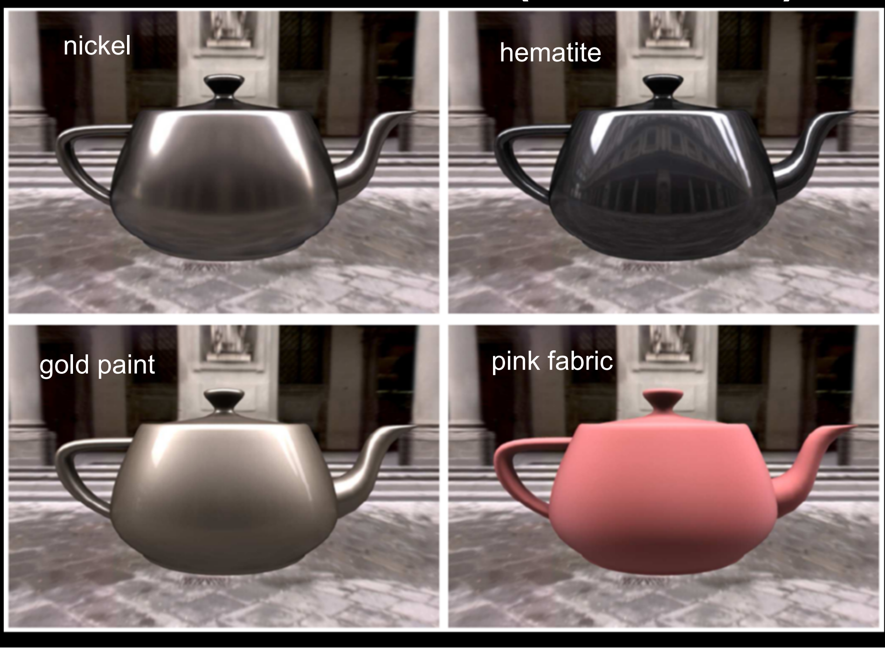
  – 90 (θ_h) x 90 (θ_d) x 180 (φ_d)

Disadvantages:

- Requires 17Mb / BRDF
- 12 Hours to capture

27

Direct Visualization (Tabulated)



28

Data-driven BRDF Representations

Data-driven Analysis

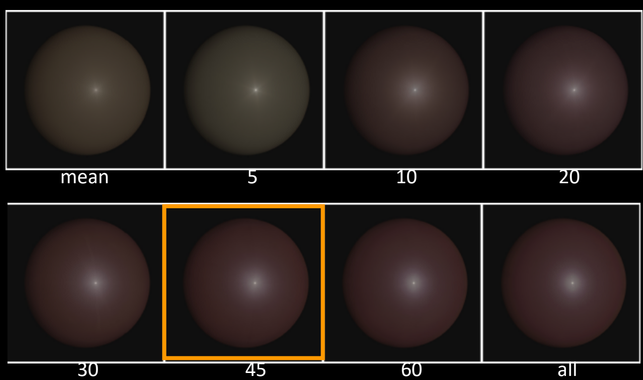
- Linear Data Analysis (PCA)
- Non-linear Data Analysis
- BRDFs as data driven basis

[Matusik et al. 2003]

29

Linear Data Analysis (PCA)

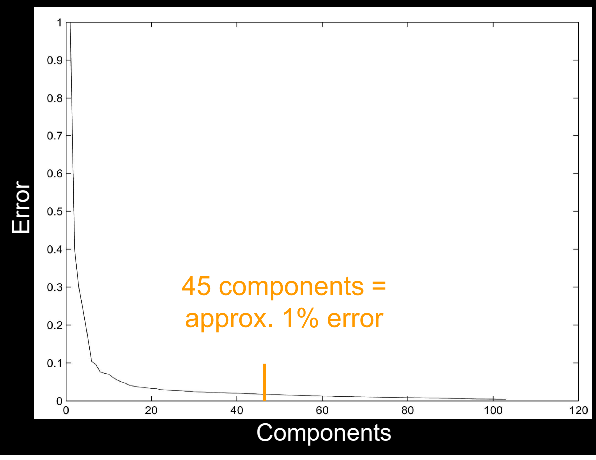
- Linearize each BRDF in a (long) vector
- Apply PCA on **all** these vectors
- Keep n largest principal vectors



30

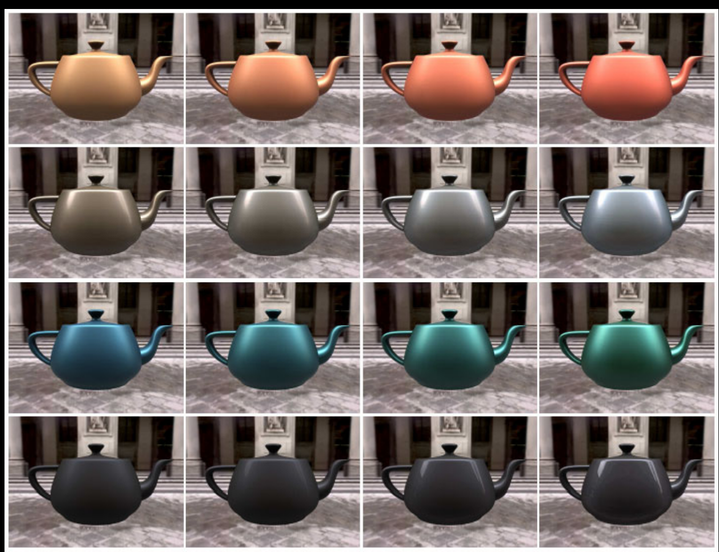
Linear Data Analysis (PCA)

- Linearize each BRDF in a (long) vector
- Apply PCA on **all** these vectors
- Keep n largest principal vectors



31

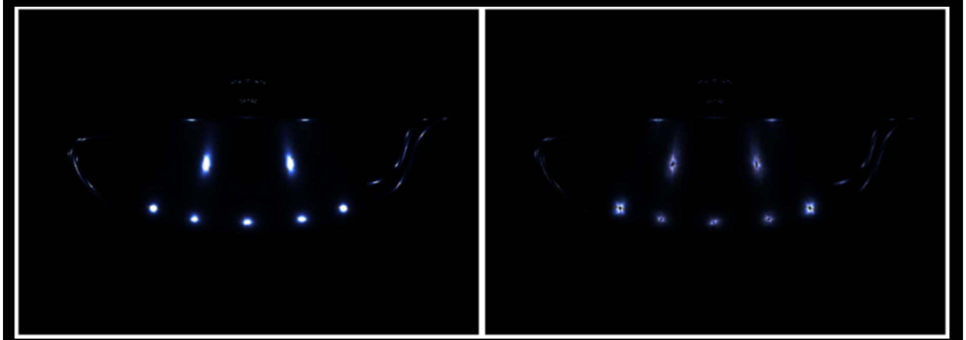
PCA space exploration



32

Problem: non-physical BRDFs

45D space contains non-physical BRDFs

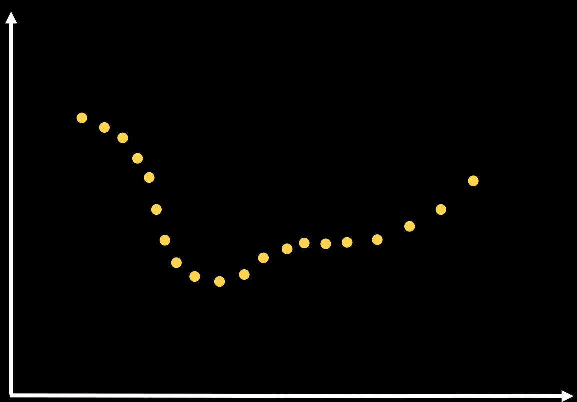


Measured BRDF
(point A in 45D space)

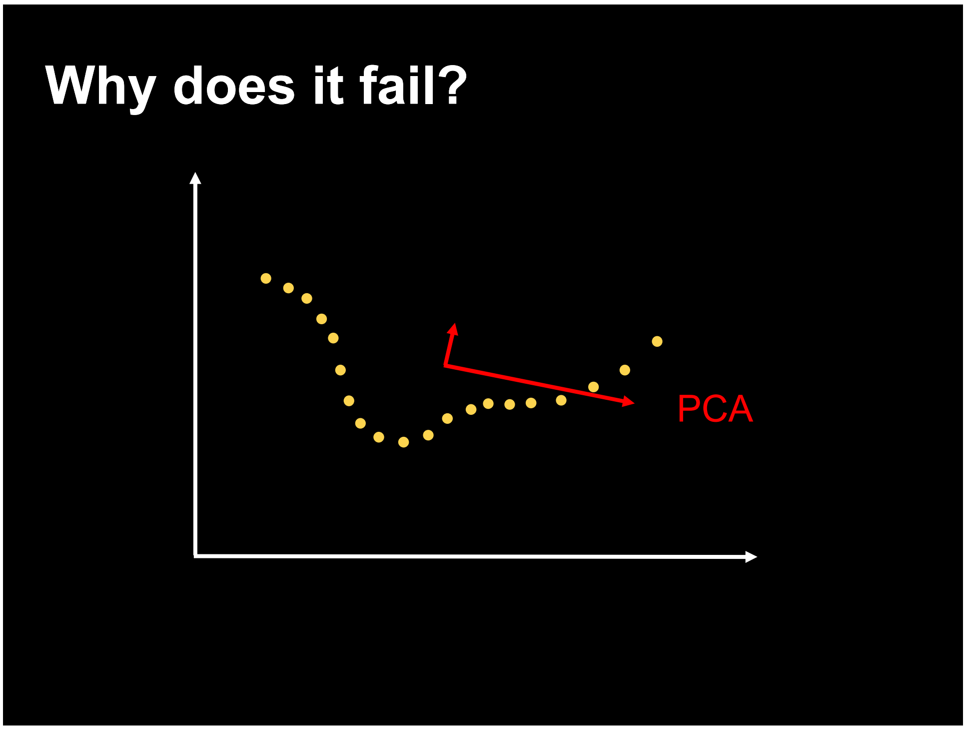
Non-physical BRDF
(point close to A in 45D space)

33

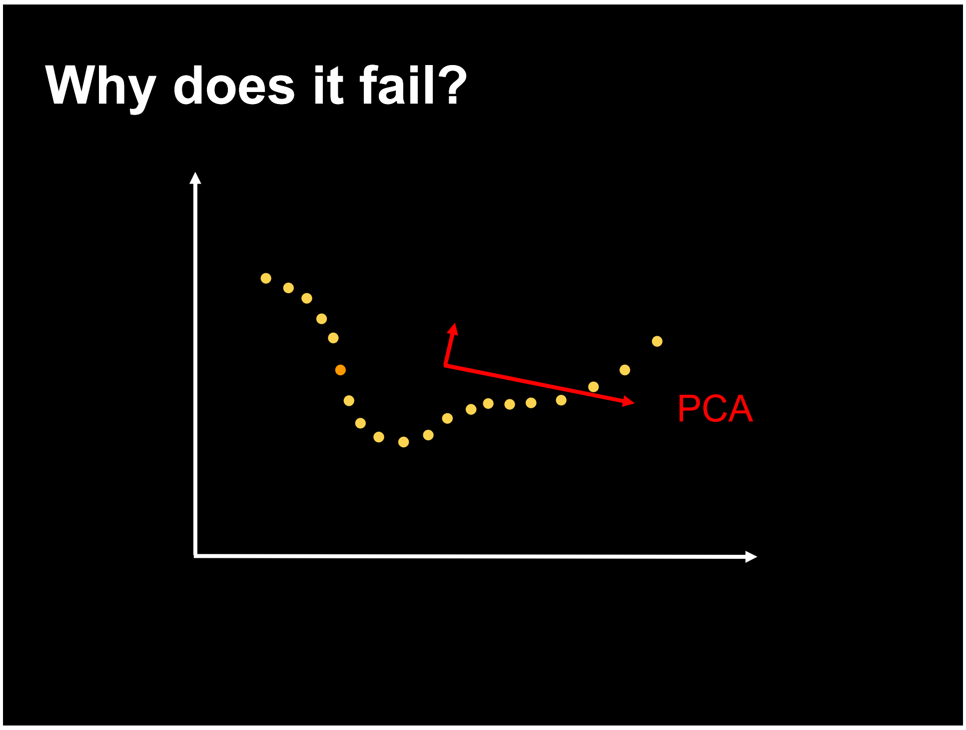
Why does it fail?



34

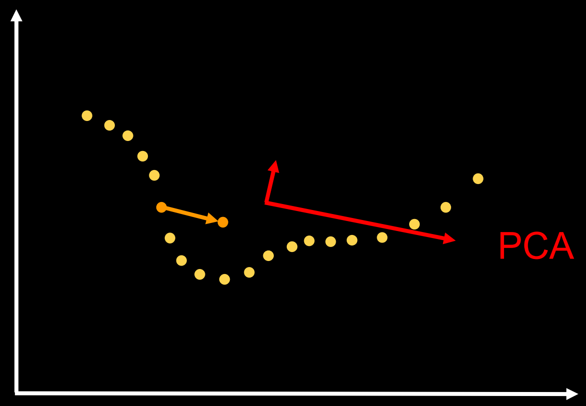


35



36

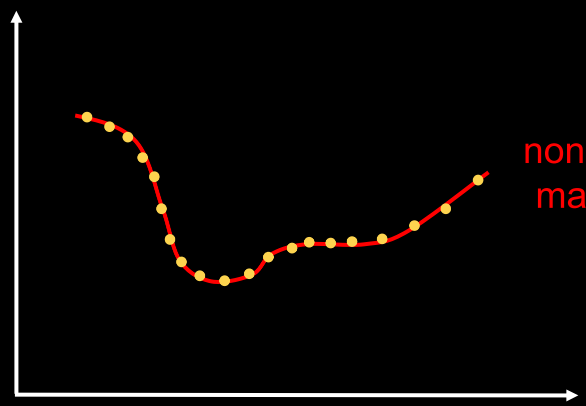
Why does it fail?



Move a little => fall outside measured space

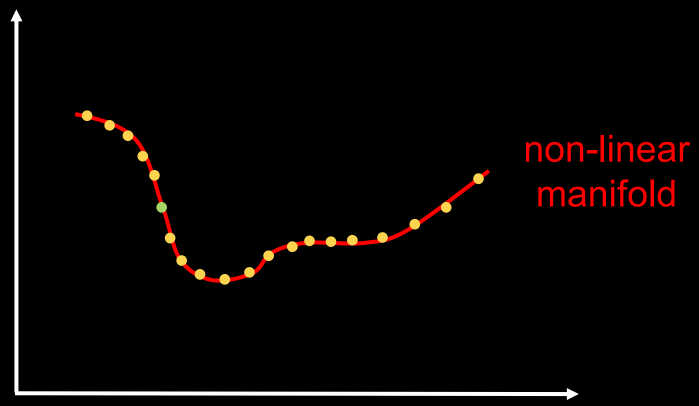
37

Why does it fail?



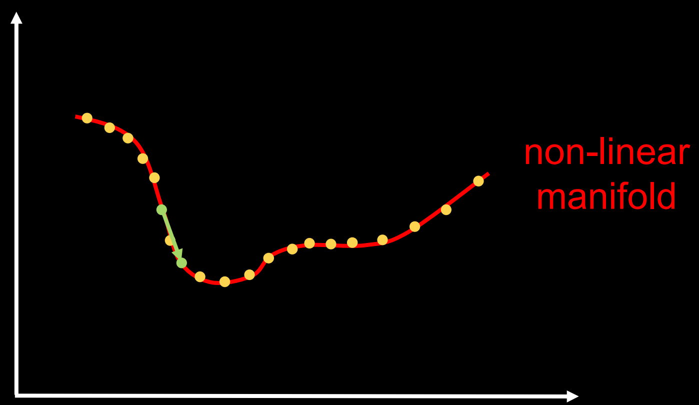
38

Why does it fail?



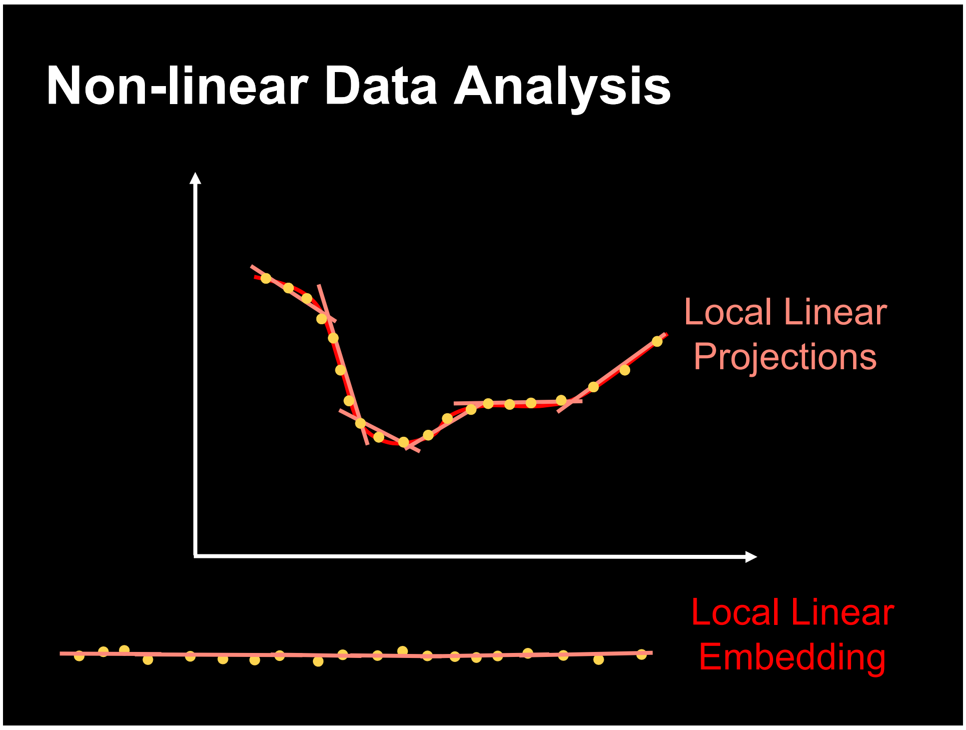
39

Why does it fail?

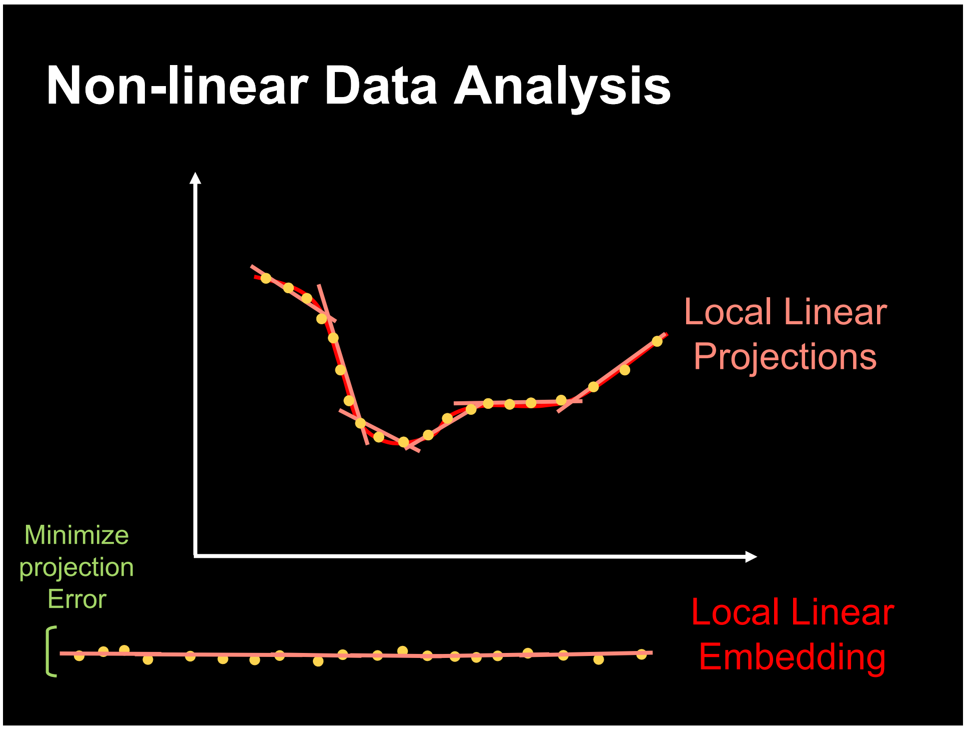


Only move over manifold!

40


Non-linear Data Analysis
Local Linear
Projections
Local Linear
Embedding

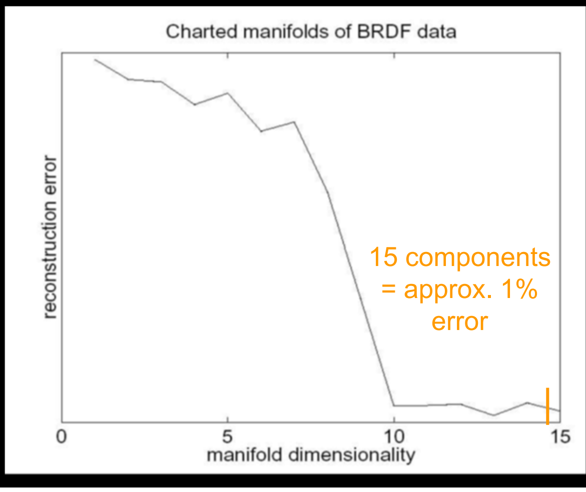
41


Non-linear Data Analysis
Local Linear
Projections
Minimize
projection
Error
Local Linear
Embedding

42

Non-linear Data Analysis

Charter Method [Brand 2003]: kernel-based mixtures of projections that minimizes distortions of local neighborhoods



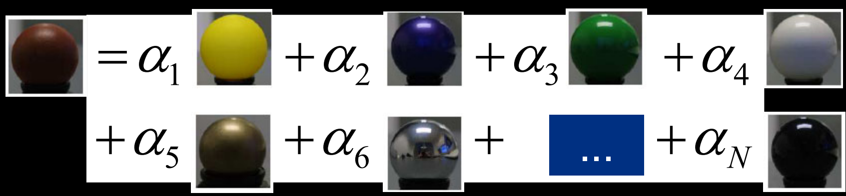
43

Non-linear manifold exploration

44

BRDFs as Basis Functions

Representing a new BRDF as a linear combination of the 100 measured BRDFs



45

Solution

Linear equation: b = Pa

b = linearized BRDF (4M x 1) (new data)

P = matrix of all BRDFs (4M x 100) (MERL database)

a = unknowns (100 x 1)

Hugely over-constrained

(many more knowns than unknowns)

46

Alternate randomized solution

- 800 rows from the original P (randomly selected)

b' = P'a

b' = 800 x 1 vector

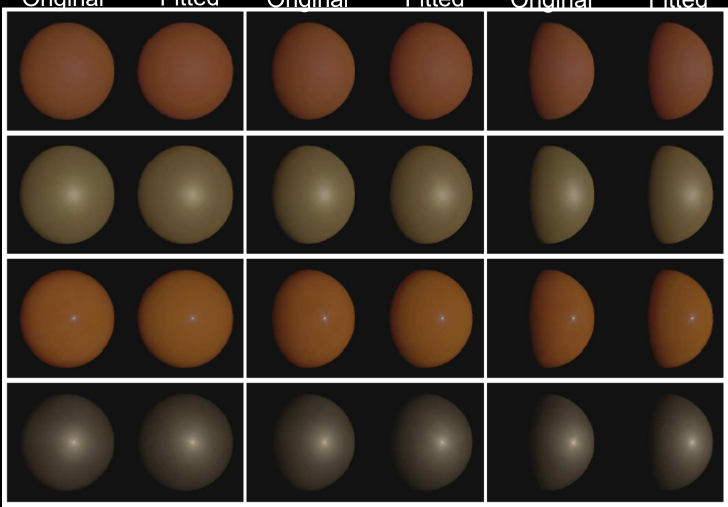
P' = 800 x 100 vector

a = 100 x 1 vector

- 800 (ω_i, ω_o) samples (measurements)

47

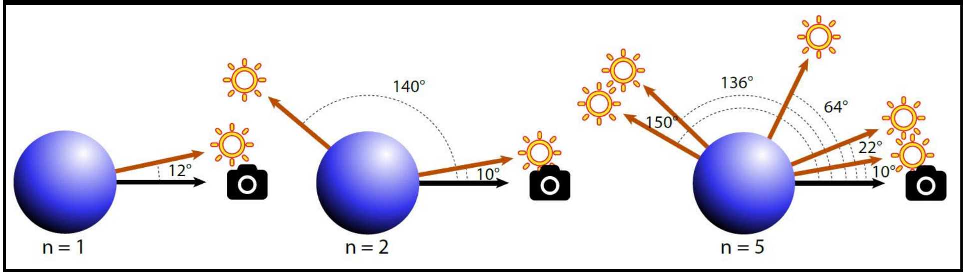
BRDFs as Basis Functions



BRDFs based on 800 samples

48

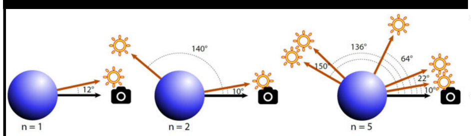
Optimal BRDF sampling [Neilson et al. 15]



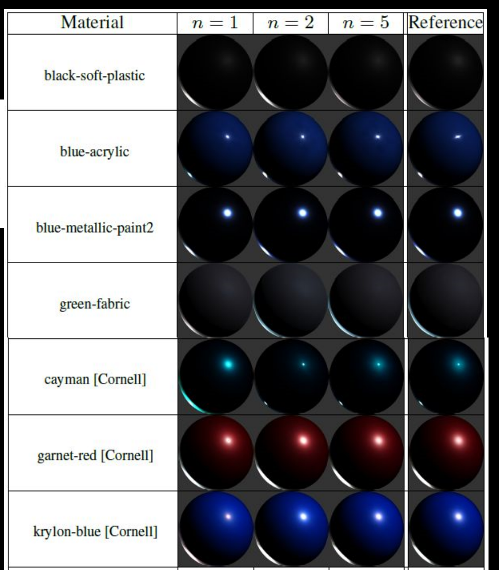
- Up to 5 views sufficient for spherical samples
- Fitting based on projection to space spanned by 100 MERL BRDFs

49

Optimal BRDF sampling [Neilson et al. 15]



Suggested minimal measurements



Material	$n = 1$	$n = 2$	$n = 5$	Reference
black-soft-plastic				
blue-acrylic				
blue-metallic-paint2				
green-fabric				
cayman [Cornell]				
garnet-red [Cornell]				
krylon-blue [Cornell]				

50

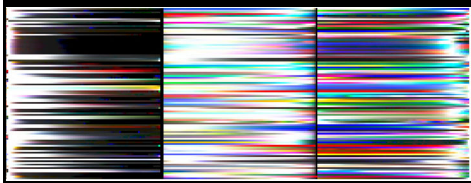
[Bagher et al. 16]

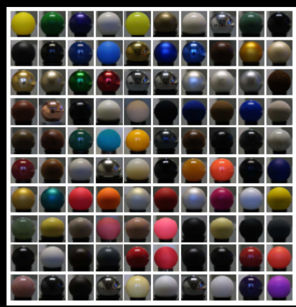
Data-driven microfacet model

$$\rho_M(\theta_h, \theta_d, \phi_d) = \rho_d + \rho_s \left(\frac{D(\theta_h)\, F(\theta_d)\, G(\theta_i)\, G(\theta_o)}{\cos\theta_i\, \cos\theta_o} \right)$$

Product of three separate 1-D factors:

$D(\theta_h)$, $F(\varphi_d)$, $G(\theta_{i,o})$



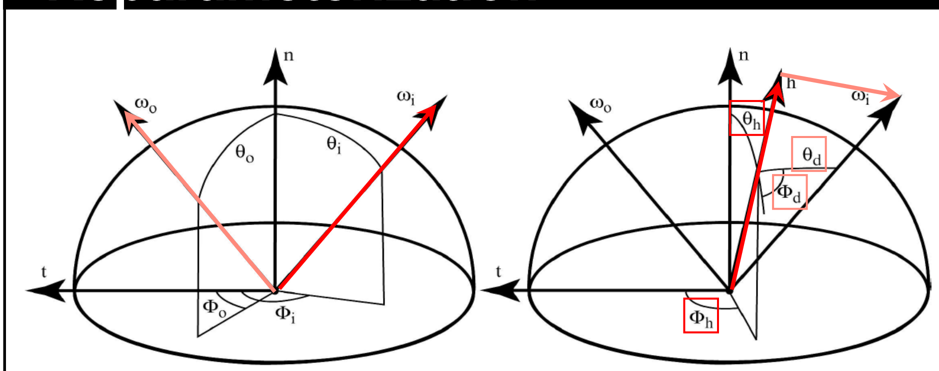


100 isotropic BRDFs

MERL database

51

Reparameterization



Standard | Rusinkiewicz

Incident: $\omega_i = (\theta_i, \Phi_i)$
Exitant: $\omega_o = (\theta_o, \Phi_o)$

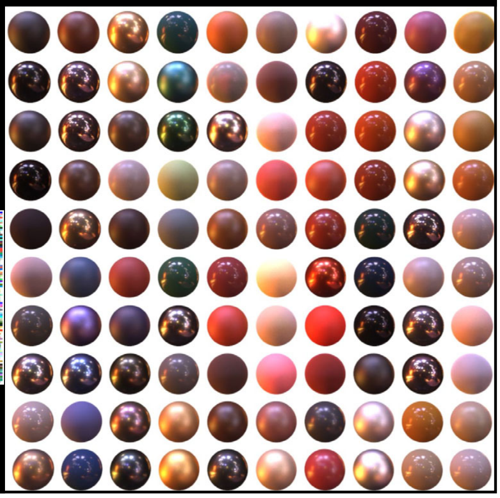
Halfway: $\omega_h = (\theta_h, \Phi_h)$
Difference: $\omega_d = (\theta_d, \Phi_d)$

52

[Bagher et al. 16]

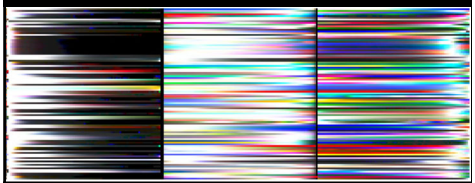
Data-driven microfacet model

$$\rho_M(\theta_h, \theta_d, \phi_d) = \rho_d + \rho_s \left(\frac{D(\theta_h)\, F(\theta_d)\, G(\theta_i)\, G(\theta_o)}{\cos\theta_i\, \cos\theta_o} \right)$$



Product of three separate 1-D factors:

$D(\theta_h)$, $F(\varphi_d)$, $G(\theta_{i,o})$

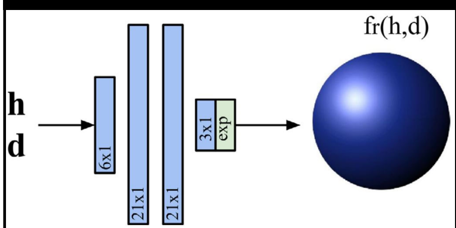


Massive compression while preserving accuracy compared to analytic model fits

53

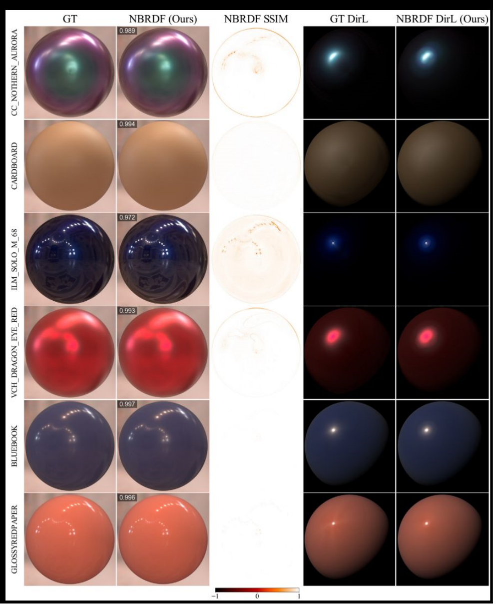
Neural BRDF

[Strajman et al. 21]



N-BRDF neural network MLP

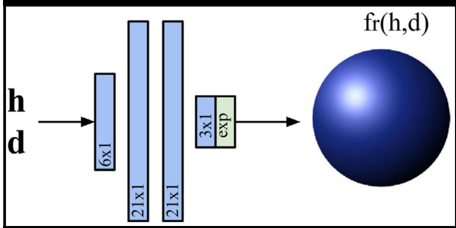
- Non-linear encoding
- ReLU activations and exponential output
- Network size: 6 x 21 x 21 x 3 = 675 weights
- High accuracy of representation of measured BRDFs!



54

NBRDF interpolation

[Strajman et al. 21]



N-BRDF neural network MLP

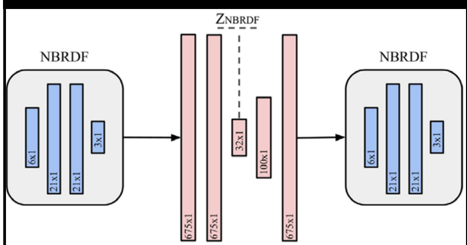
- Non-linear encoding
- ReLU activations and exponential output
- Network size: 6 x 21 x 21 x 3 = 675 weights

Direct interpolation of 675 weights of two N-BRDFs
(Aluminium and Blue Fabric)

55

NBRDF autoencoder

[Strajman et al. 21]



N-BRDF autoencoder MLP

- 675 NBRDF weights flattened into 1D input vector
- ZNBRDF autoencoder representation
  - reduced latent code: 32 weights

Improved interpolation using 32 weights of ZNBRDF latent code

56