CS231A

Computer Vision:

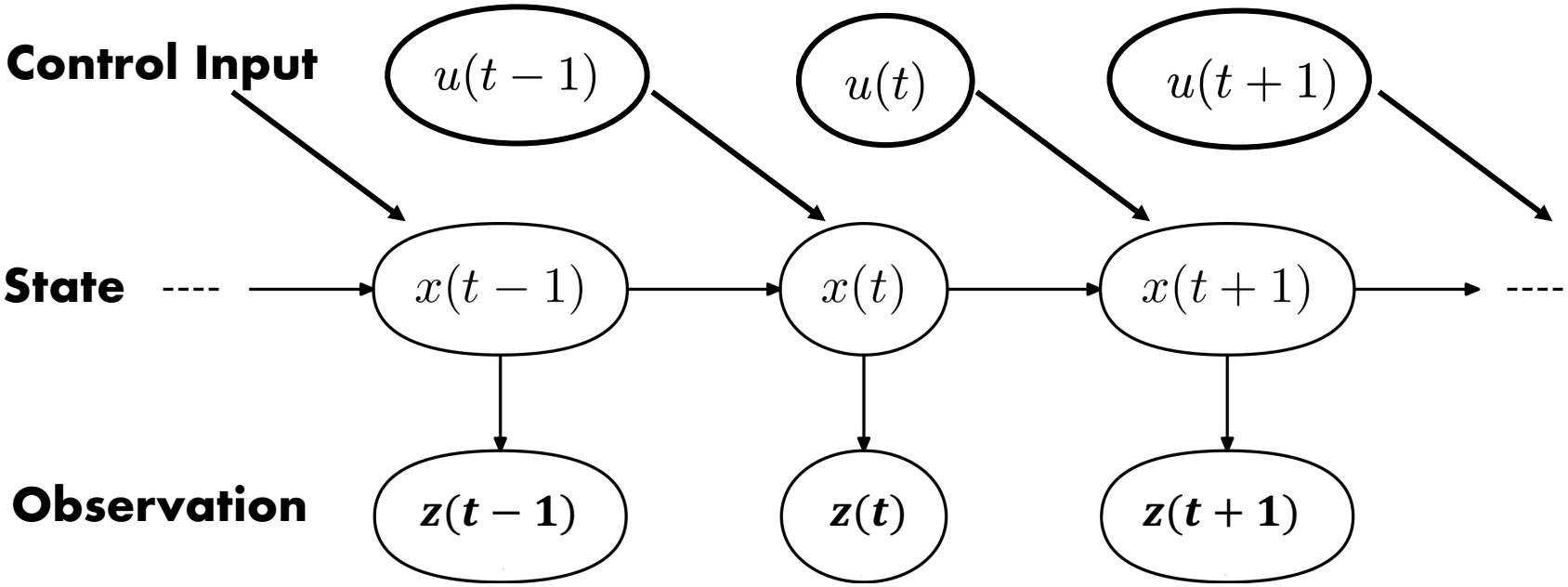
From 3D Reconstruction to Recognition

Neural Radiance Fields for Novel View Synthesis

Outline

- Recap: Kalman Filters
- Recap: Differentiable versus Generative Observation Models
- Representations for Novel View Synthesis
- Neural Radiance Fields

Graphical Model of System to Estimate



1: **Algorithm Bayes_filter**$(bel(x_{t-1}), u_t, z_t)$**:**
2: for all x_t do
3: $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1})\ bel(x_{t-1})\ dx$
4: $bel(x_t) = \eta\ p(z_t \mid x_t)\ \overline{bel}(x_t)$
5: endfor
6: return $bel(x_t)$

The Bayes Filter

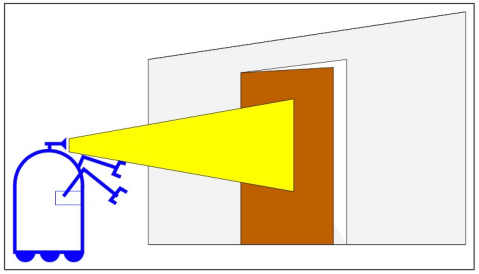


Figure 2.2 A mobile robot estimating the state of a door.

- Recursive filter for estimating x_t only from x_{t-1}, z_t and u_t and not from the ever-growing history $z_{1:t}, u_{1:t}$

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Transition/Dynamics model

Predict Step

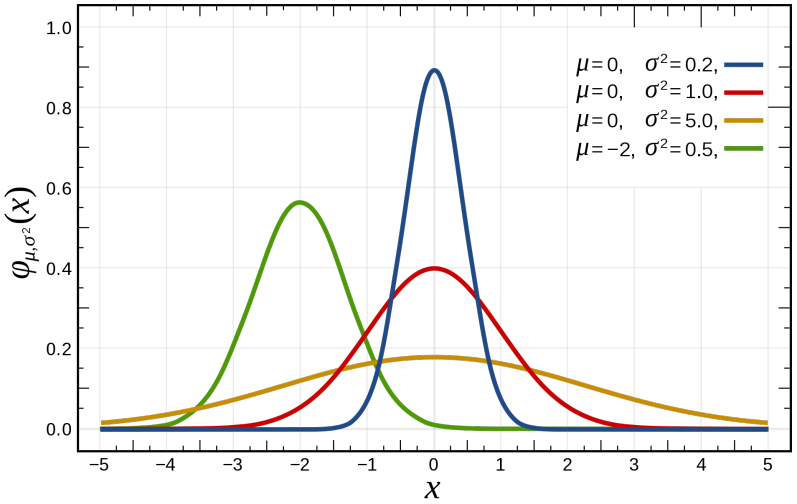
Update Step

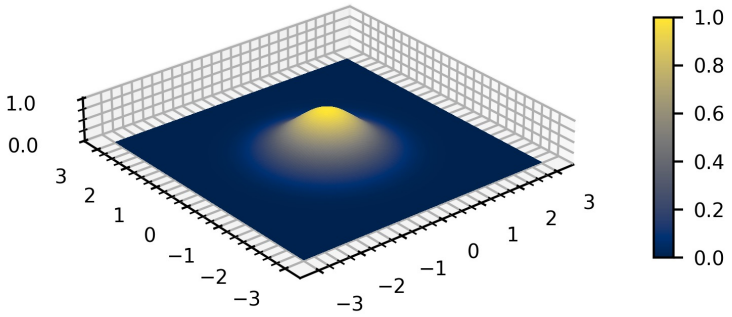
Measurement Model

Gaussian Filters - Kalman Filter

$$\mathbf{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

$$p(x) = \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\left\{-\tfrac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right\}$$





The Kalman Filter Algorithm

Algorithm Kalman_filter$(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$**:**

$$\bar{\mu}_t = A_t\, \mu_{t-1} + B_t\, u_t$$

$$\bar{\Sigma}_t = A_t\, \Sigma_{t-1}\, A_t^T + R_t$$

$$K_t = \bar{\Sigma}_t\, C_t^T (C_t\, \bar{\Sigma}_t\, C_t^T + Q_t)^{-1}$$

$$\mu_t = \bar{\mu}_t + K_t(z_t - C_t\, \bar{\mu}_t)$$

$$\Sigma_t = (I - K_t\, C_t)\, \bar{\Sigma}_t$$

return μ_t, Σ_t

Uncertainty increases

K = Kalman Gain $K \approx \frac{R}{Q}$

Uncertainty decreases

Algorithm Bayes_filter$(bel(x_{t-1}), u_t, z_t)$**:**

for all x_t do

$\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1})\, bel(x_{t-1})\, dx$ **Predict Step**

$bel(x_t) = \eta\, p(z_t \mid x_t)\, \overline{bel}(x_t)$ **Update Step**

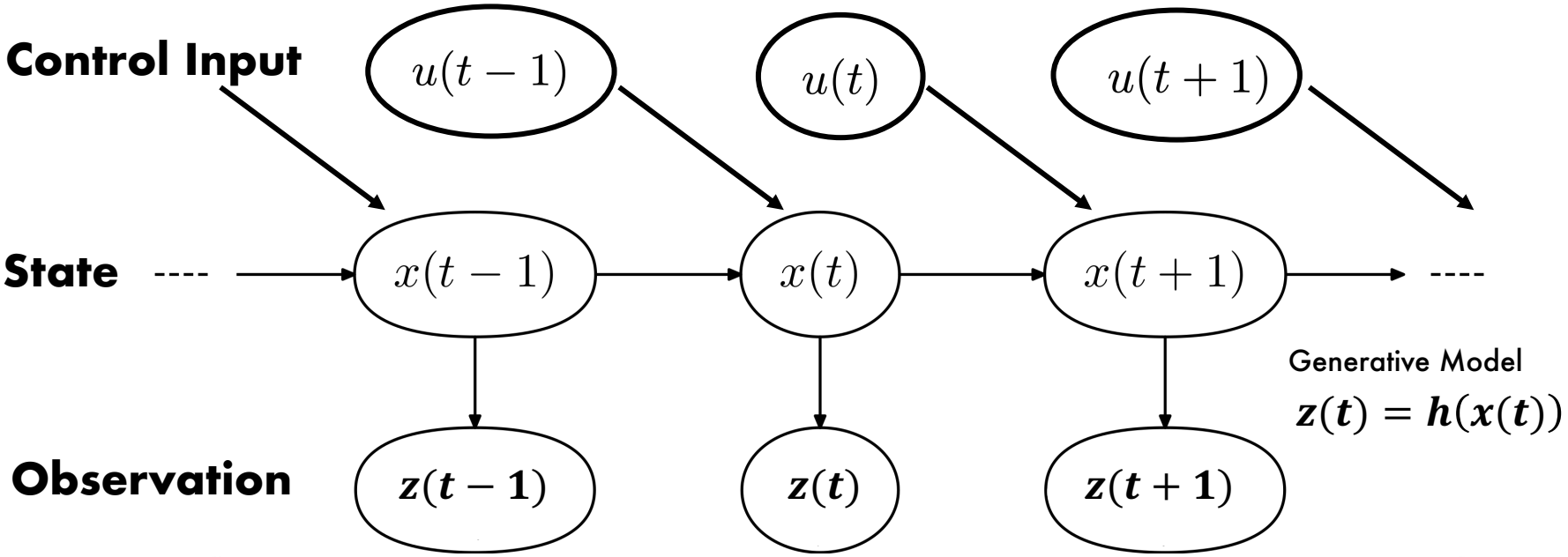
endfor

return $bel(x_t)$

If R large, then K is large. Update dominated by innovation.

If Q large, then K is small. Update dominated by prediction.

Graphical Model of System to Estimate



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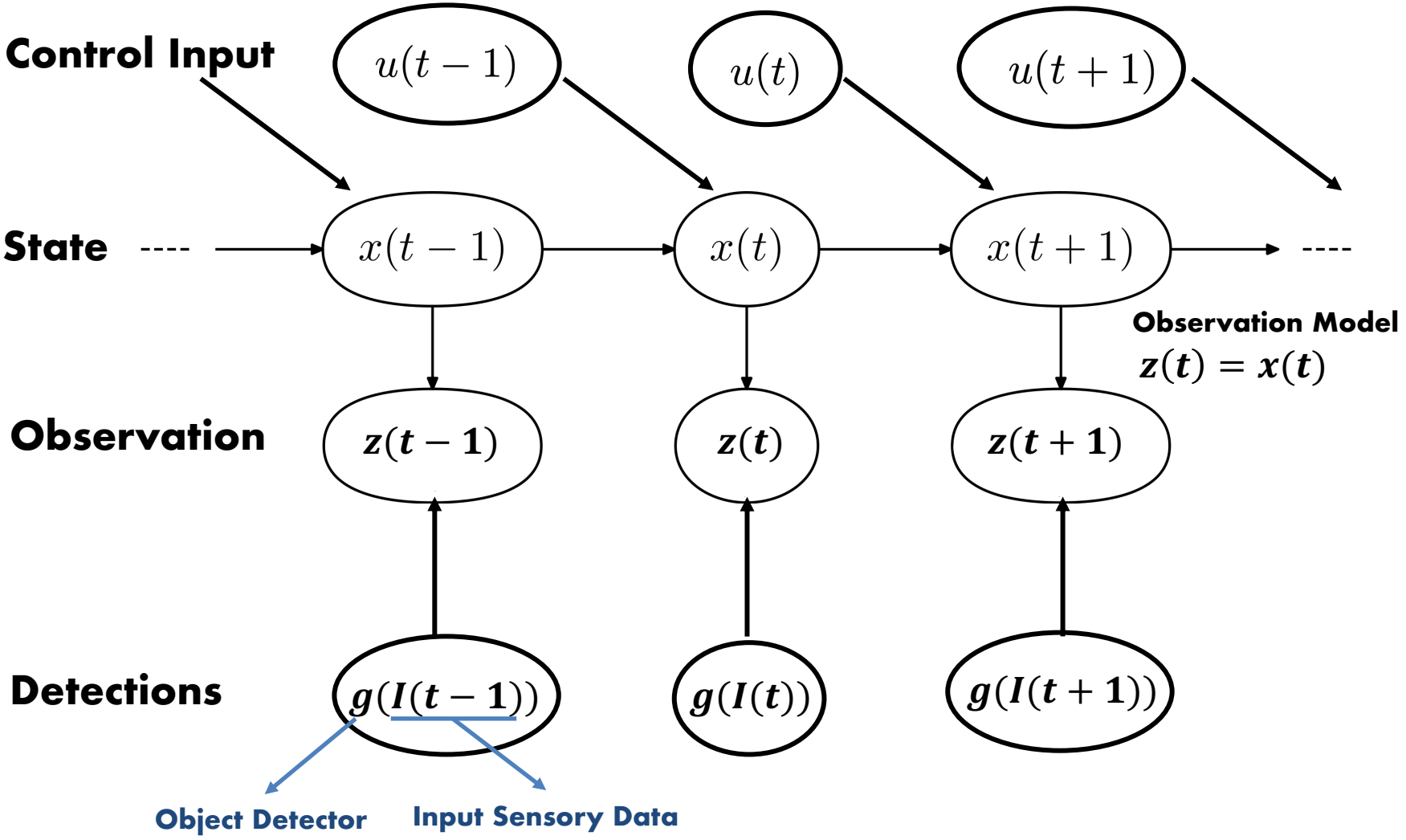
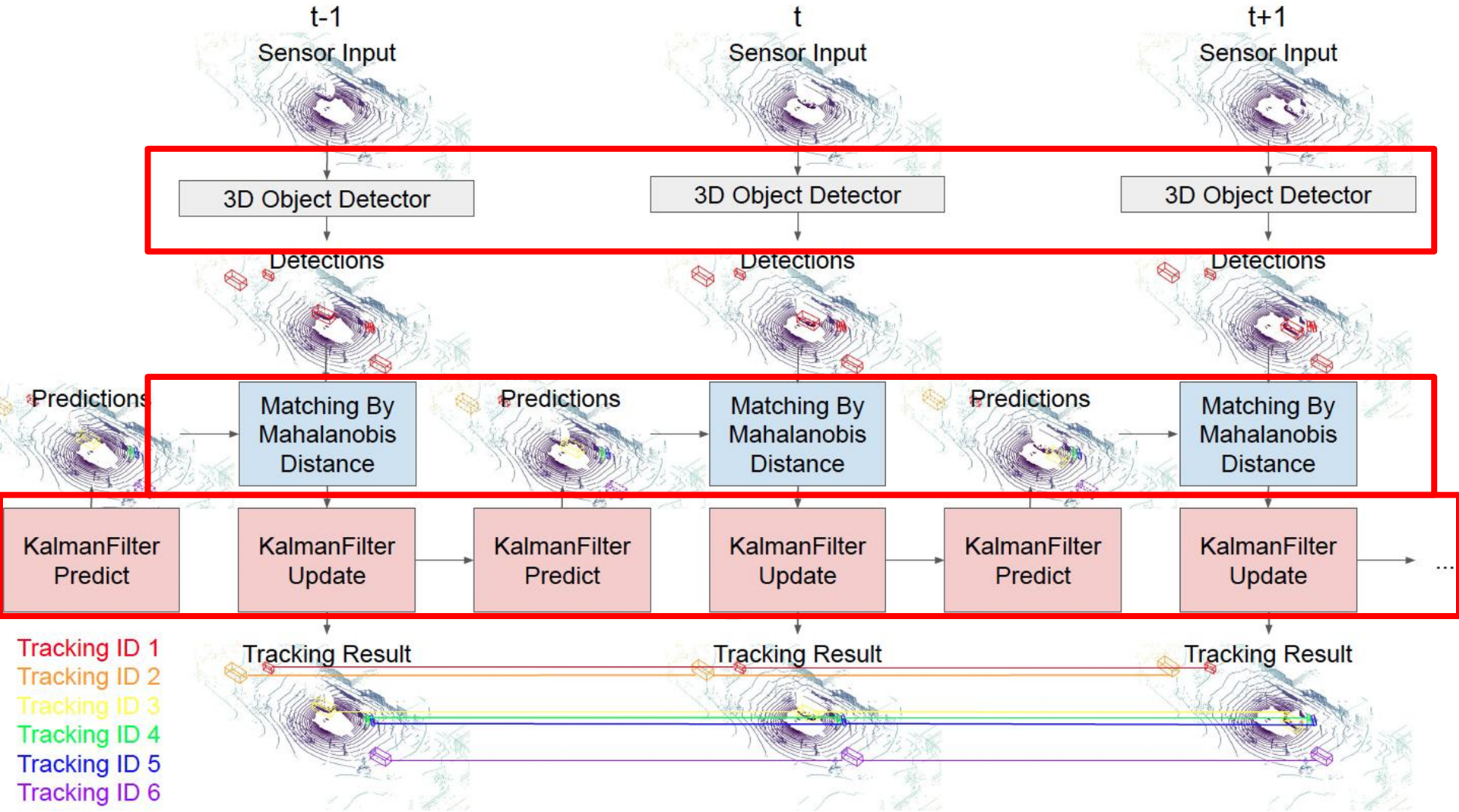
Tracking by Detection



Multi-Object Tracking by Detection

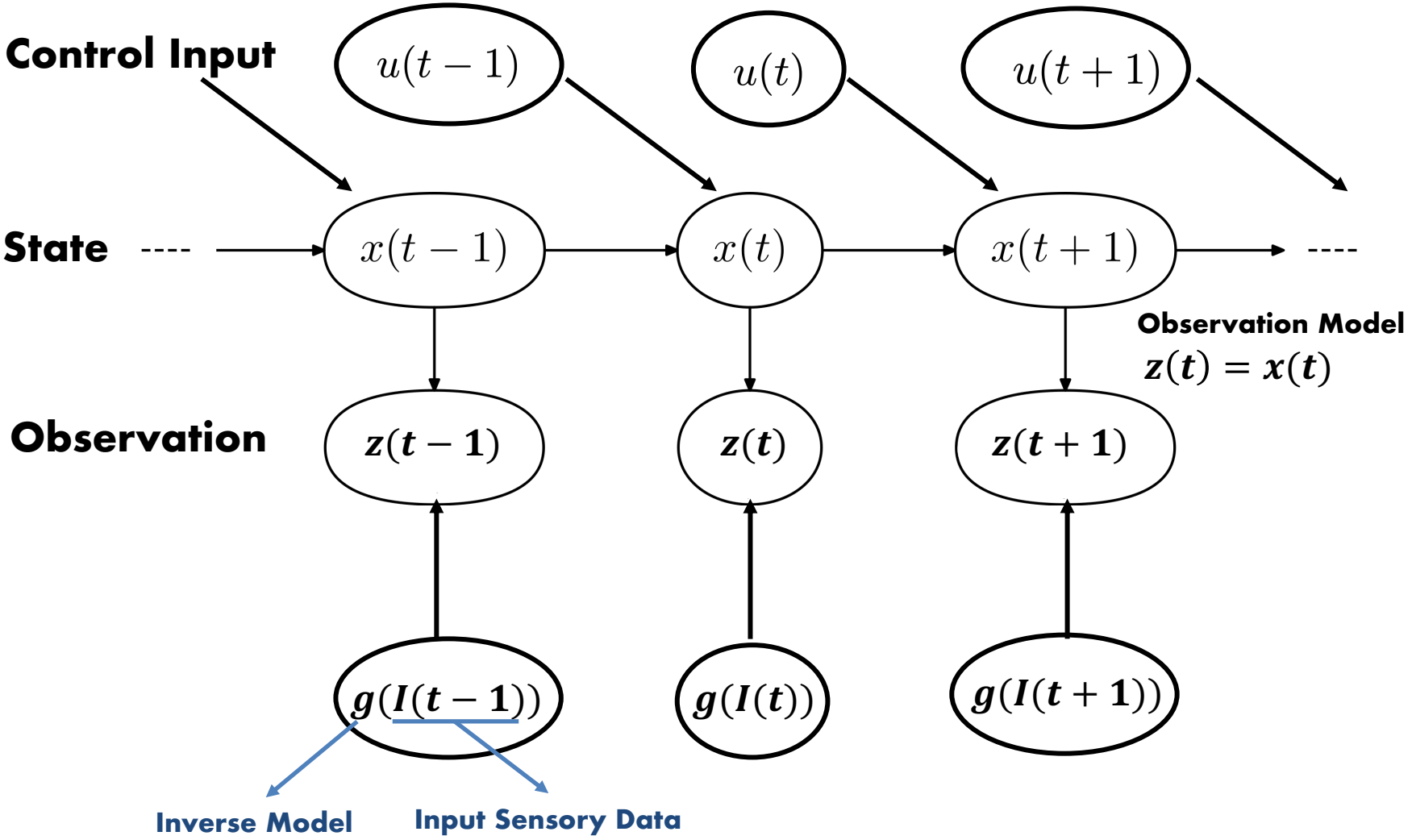


Priors and Hyperparameters

A lot of hardcoded knowledge!

- State Representation
- Models
  - Forward Model
    - State to next state
    - Action to next state
  - Measurement Model
- Probabilistic Properties
  - Process Noise
  - Measurement Noise

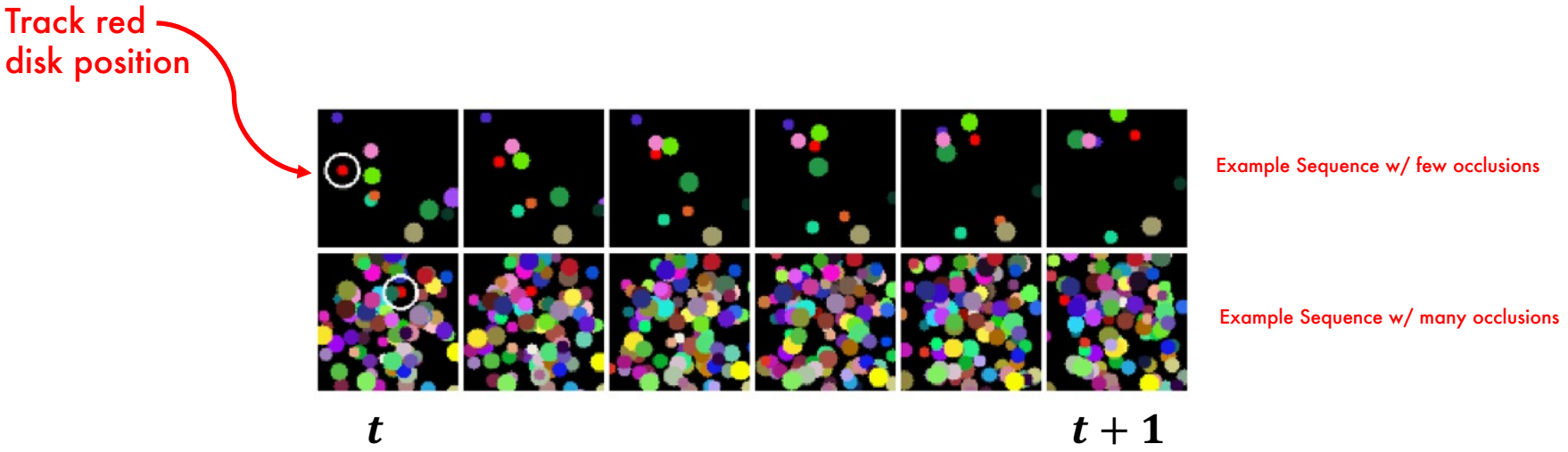
Differentiable Filtering



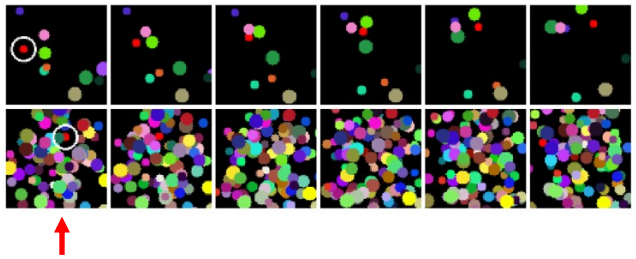
BackpropKF : Learning Discriminative Deterministic State Estimators. Haarnoja et al. NeurIPS 2016

- Differentiable version of the Kalman Filter
- Uses Images as observations; learns a sensors that outputs state directly

$$g(I_t) = z_t \approx x_t$$

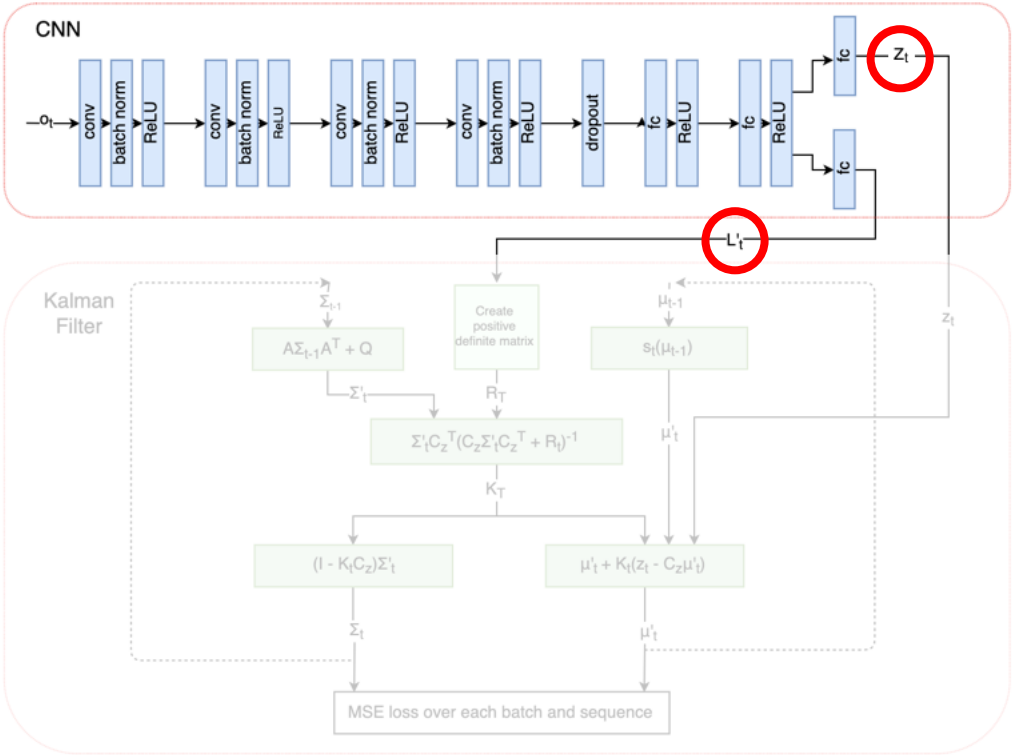


Differentiable Kalman Filter - Structure



R is high if red disk is occluded

$$g(I_t) = z_t \approx x_t$$



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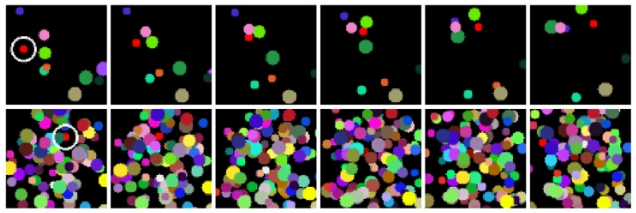
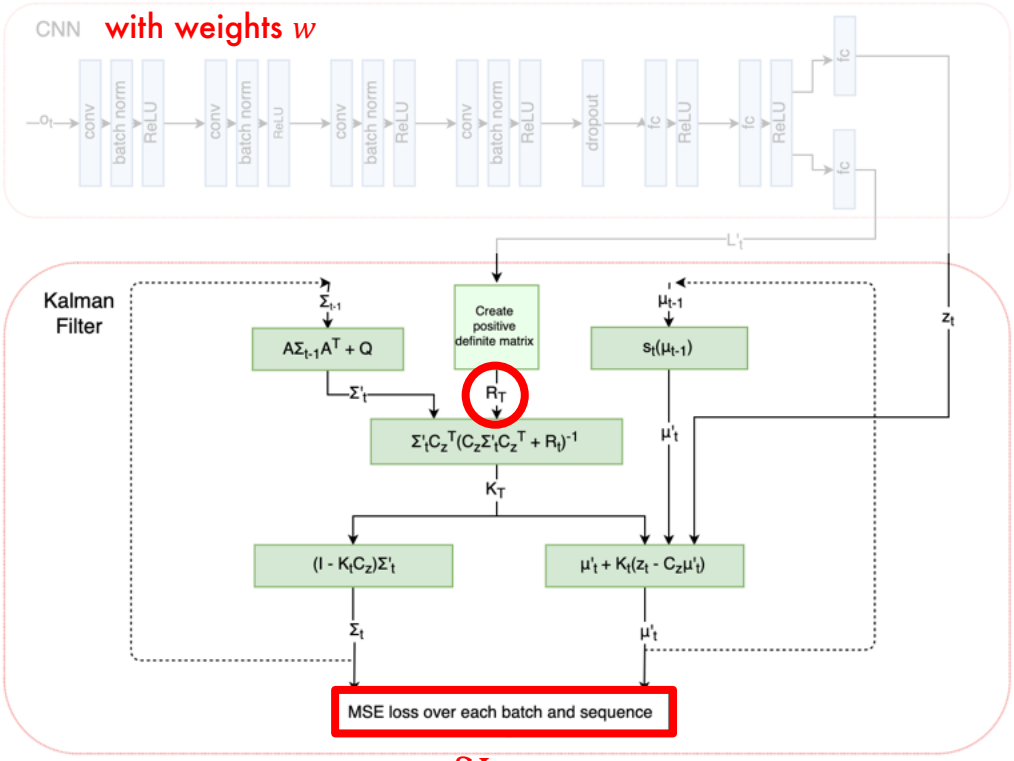
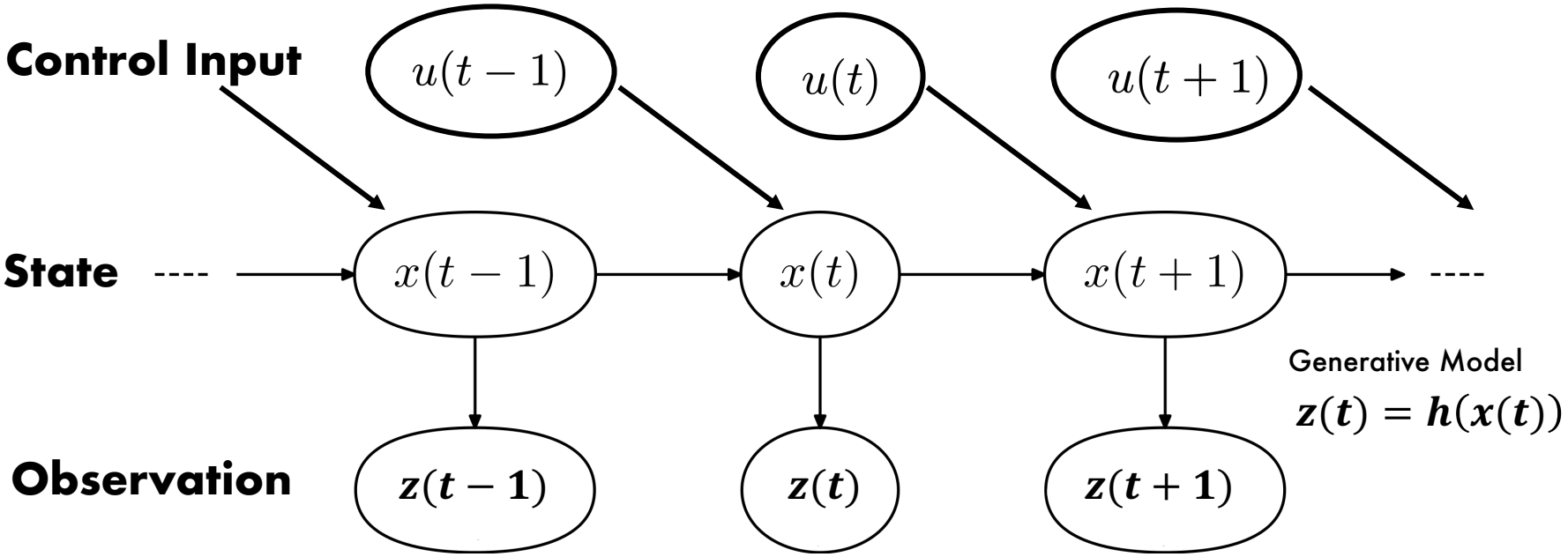


$$L'L^T = R$$



$$\frac{\delta Loss}{\delta w}$$

Graphical Model of System to Estimate



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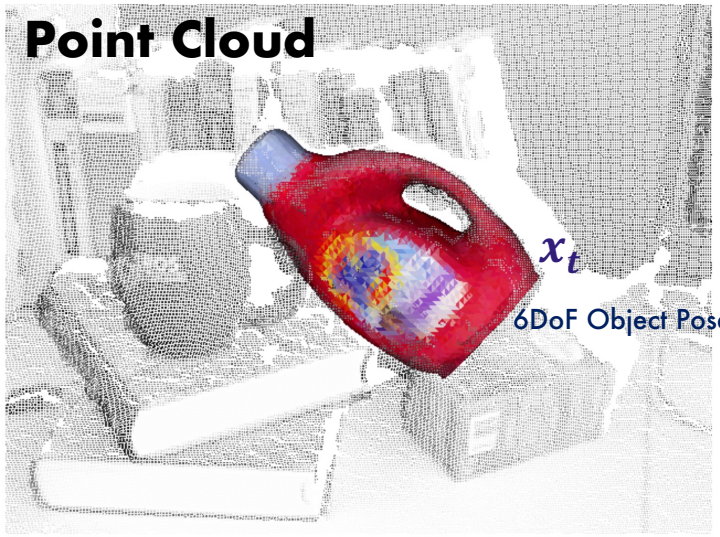
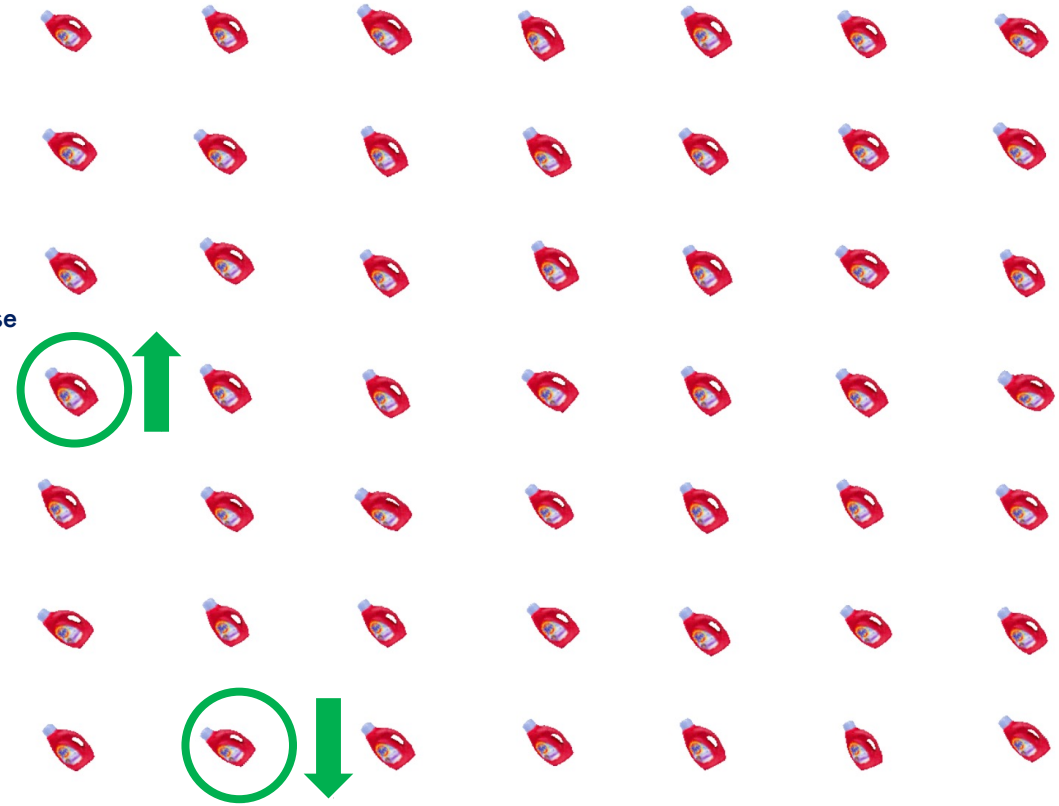
Example Observation model for 3D object





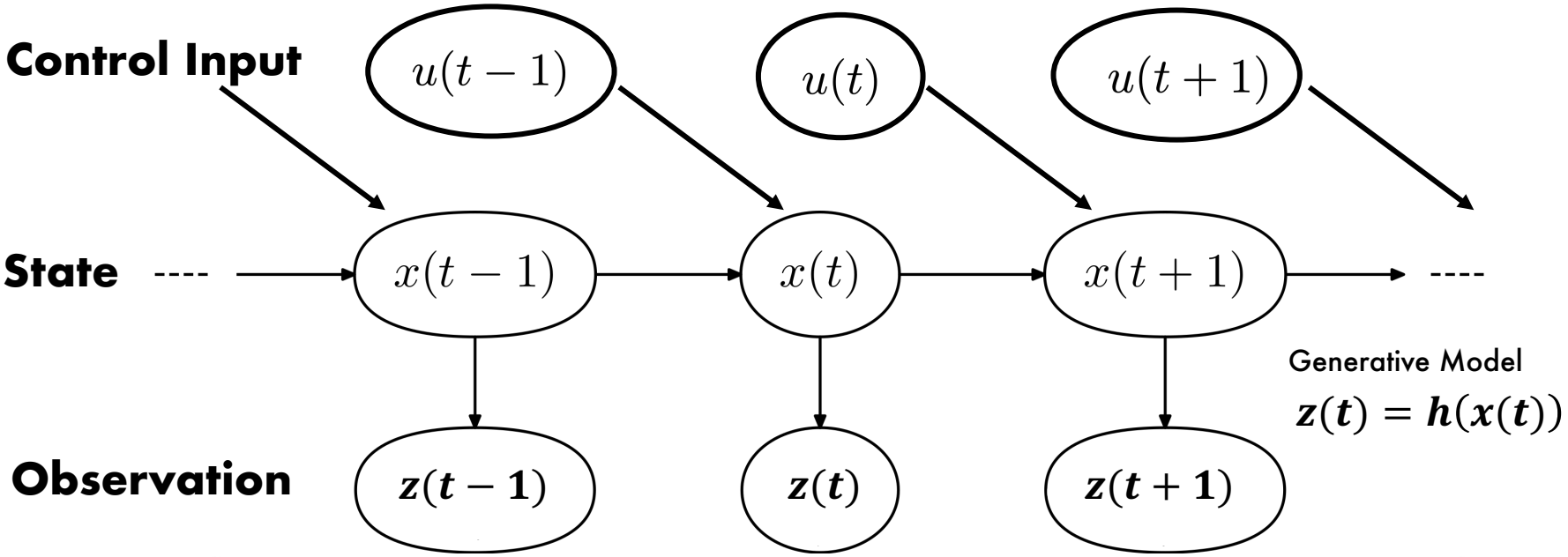
Algorithm Particle_filter$(\mathcal{X}_{t-1}, u_t, z_t)$**:**

$\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
for $m = 1$ to M do
  sample $x_t^{[m]} \sim p(x_t \mid u_t, x_{t-1}^{[m]})$
  $w_t^{[m]} = p(z_t \mid x_t^{[m]})$
  $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$
endfor
for $m = 1$ to M do
  draw i with probability $\propto w_t^{[i]}$
  add $x_t^{[i]}$ to $\mathcal{X}_t$
endfor
return $\mathcal{X}_t$

Importance Sampling

Changhyun Choi and Henrik I. Christensen. Rgb-d object tracking: A particle filter approach on gpu. In IROS, pages 1084–1091, 2013

Graphical Model of System to Estimate



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Novel view synthesis

- Can be an implementation of the generative observation model
- A scene learned from a few discrete views
  - Let's say you want to localize the camera relative to the scene in new poses
  - Track camera pose with filter

NeRF

Representing Scenes as Neural Radiance Fields for View Synthesis

ECCV 2020 Oral - Best Paper Honorable Mention

Ben Mildenhall* UC Berkeley
Pratul P. Srinivasan* UC Berkeley
Matthew Tancik* UC Berkeley
Jonathan T. Barron Google Research
Ravi Ramamoorthi UC San Diego
Ren Ng UC Berkeley

*Denotes Equal Contribution

The problem of novel view synthesis

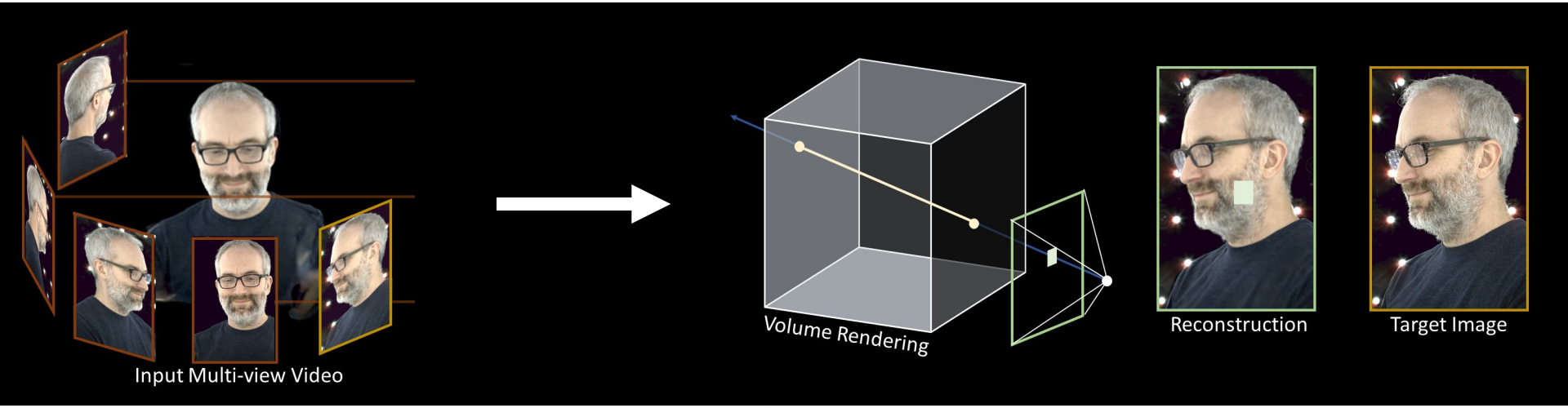
Inputs: sparsely sampled images of scene

Outputs: *new* views of same scene (rendered by our method)

2

Mildenhall et al. ECCV 2020. https://www.matthewtancik.com/nerf

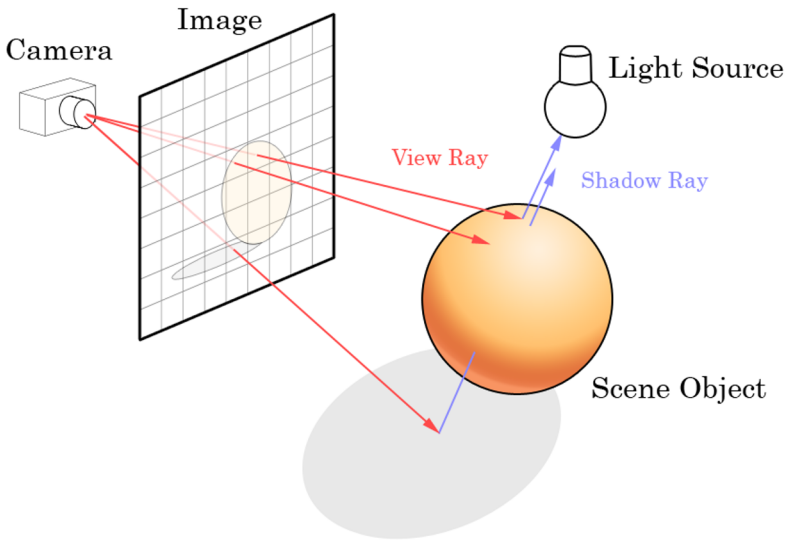
One Approach: Reconstruct 3D voxel grid RGB-alpha grid



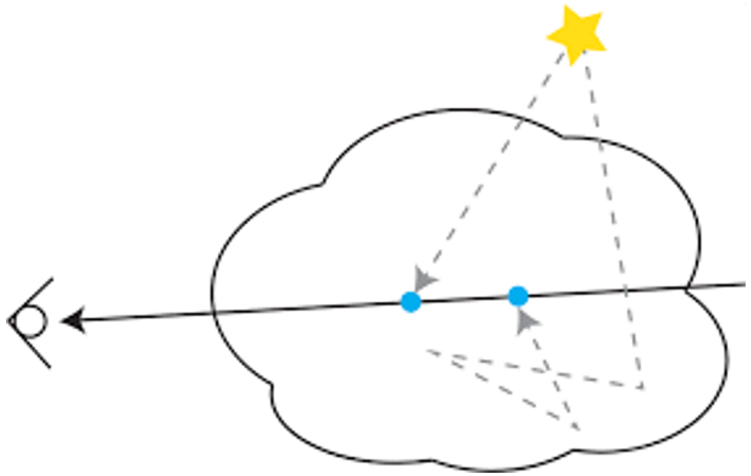
Multiview geometry for Reconstruction, Shape Carving, …

Neural Volumes, Lombardi et al. 2019

Ways to Render



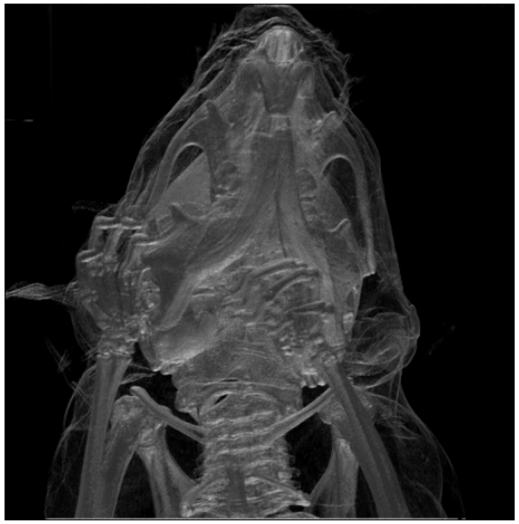
Surface rendering



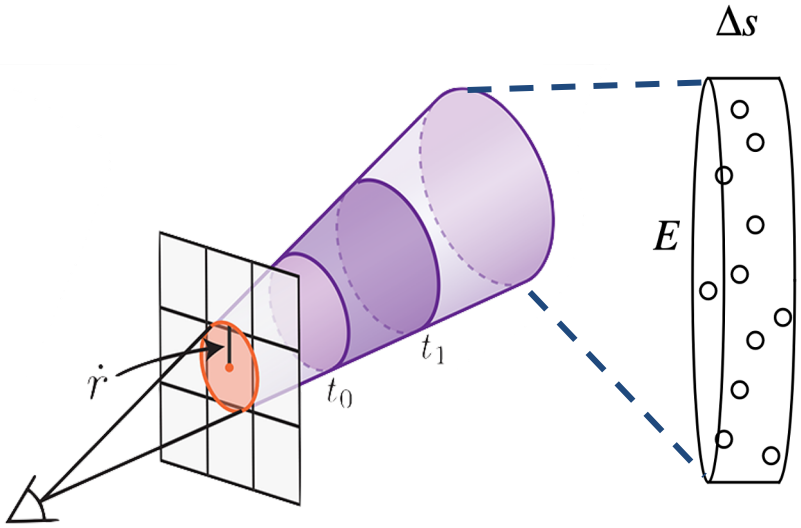
Volume rendering

Reasons to use volume rendering

- Show smoke / other diffuse effects in scene.
- Generating surfaces from 3D data can produce nasty artifacts; volume renderings are “soft.”
- Don’t need to reason about *where* surfaces are located to reflect light.



Physical model



- Ray defines a cylinder in space which contains particles.
- Particles can:
  - emit light
  - occlude light from behind them
  - reflect / scatter light from environment

Volume rendering equation

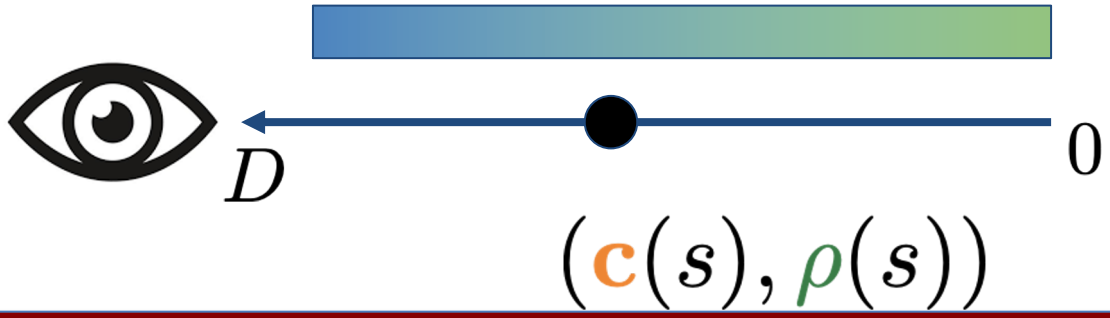
$$\mathbf{I}(D) = \mathbf{I}_0 T(0) + \int_0^D \mathbf{c}(s)\rho(s)T(s)ds$$

pixel color

radiance density

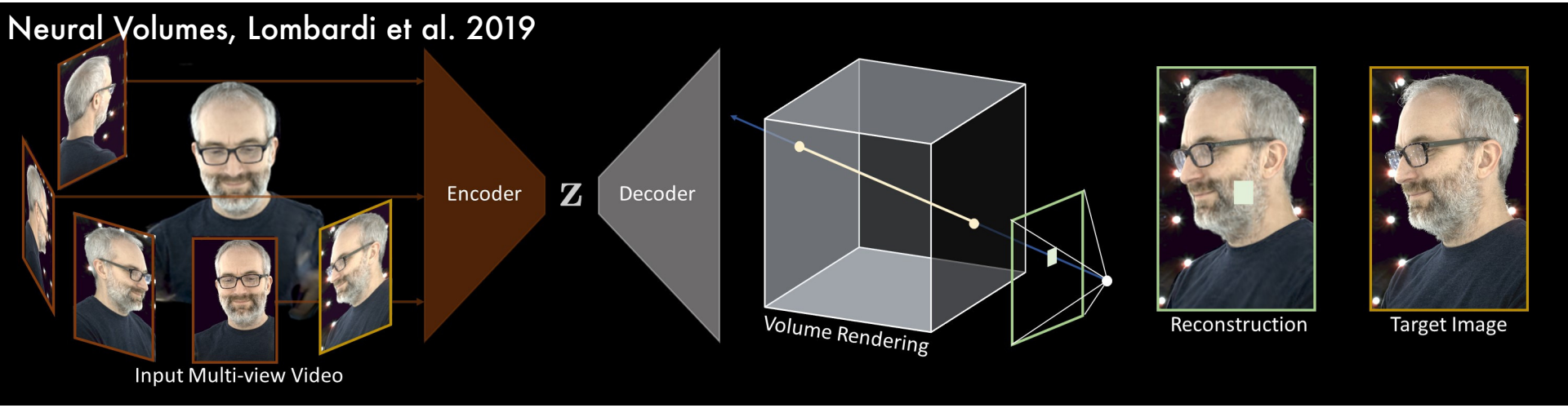
$$T(s) = \exp\left(-\int_s^D \rho(t)dt\right)$$

transparency

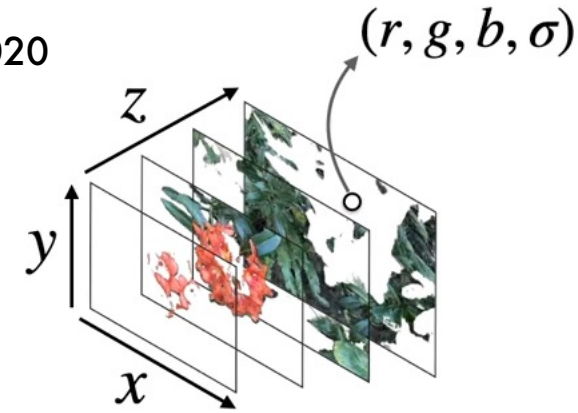


Predict 3D Voxel RGB-alpha Grid

Neural Volumes, Lombardi et al. 2019



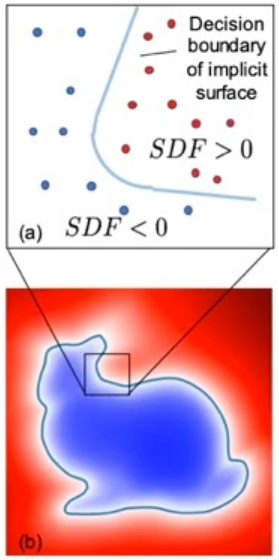
Single-View Multi-Plane Images, Tucker and Snavely, 2020



Pros and Cons of RGB-alpha volume rendering for view Synthesis

- Alpha Composition is trivially differentiable, plays nicely with gradient-based optimization
- Bad storage requirements for 3D grid

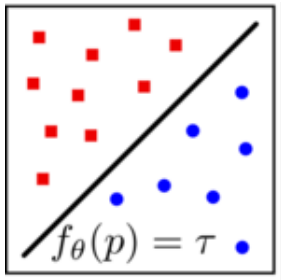
Neural networks as a shape representation



DeepSDF, Park et al. 2019

Supervised with 3D:
DeepSDF [Park et al. 2019],
Occupancy Networks [Mescheder et al. 2019],
Local Deep Implicit Functions [Genova et al. 2020],
Local Implicit Grids [Jiang et al. 2020]

Supervised with images:
Scene Representation Networks [Sitzmann et al. 2019],
Differentiable Volumetric Rendering [Niemeyer et al. 2020],
DIST [Liu et al. 2020]



Pros and Cons of Neural networks as a continuous shape representation

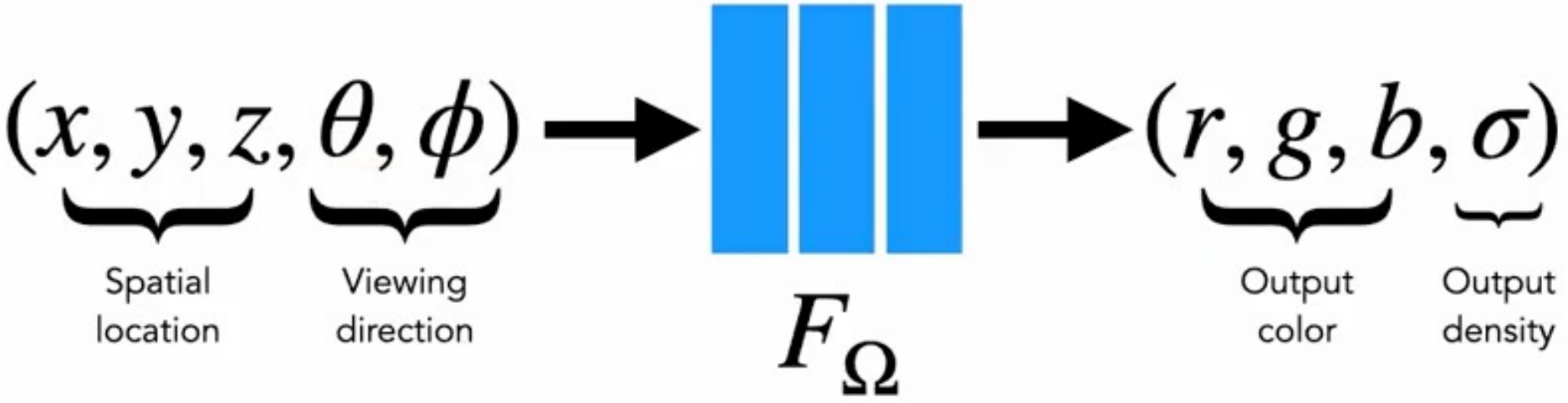
- Limited rendering model: Difficult to optimize (Shape as surface instead of volume)
- Highly compressible

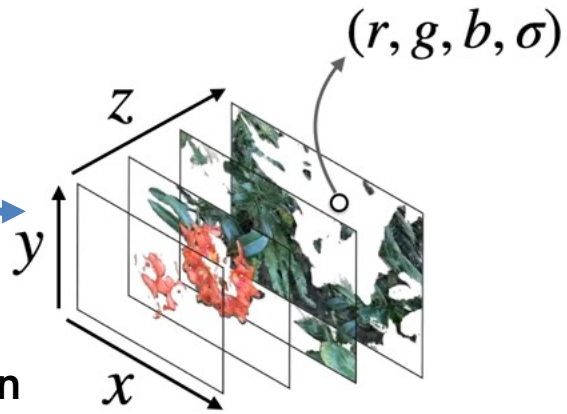
NeRF (neural radiance fields)

- Neural network as a volume representation using volume rendering to do view synthesis

- $(x, y, z, \theta, \phi) \rightarrow color, opacity$

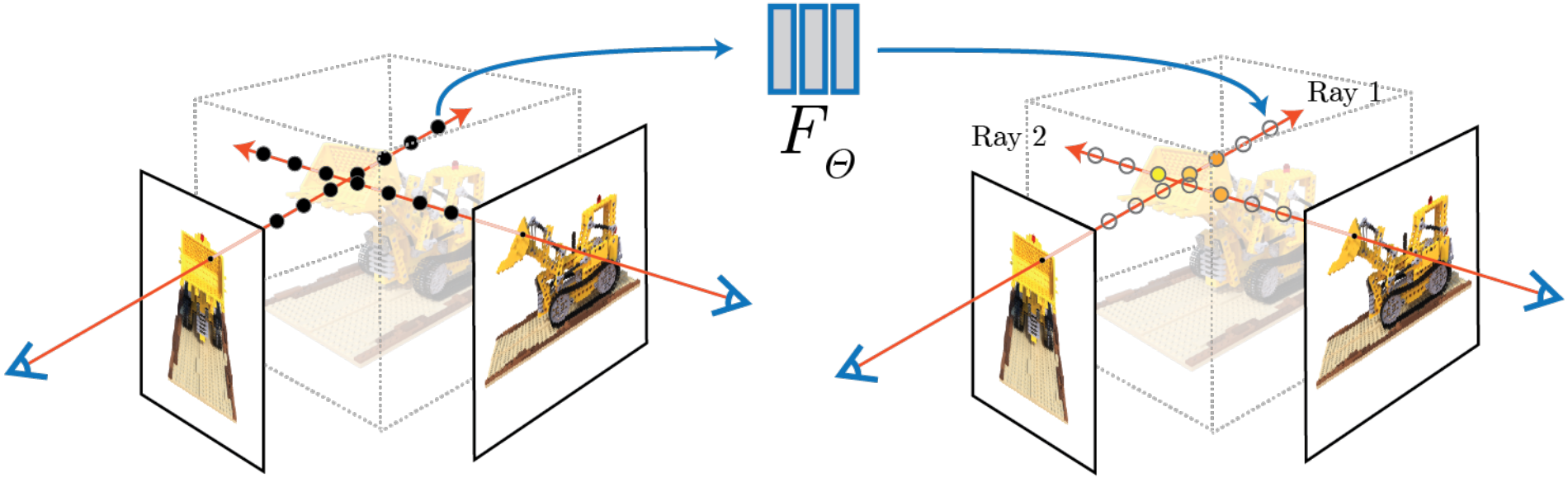
Represent a scene as a continuous 5D function





No need to instantiate Volume representation

Generate views with traditional volume rendering



Mildenhall et al. ECCV 2020. https://www.matthewtancik.com/nerf

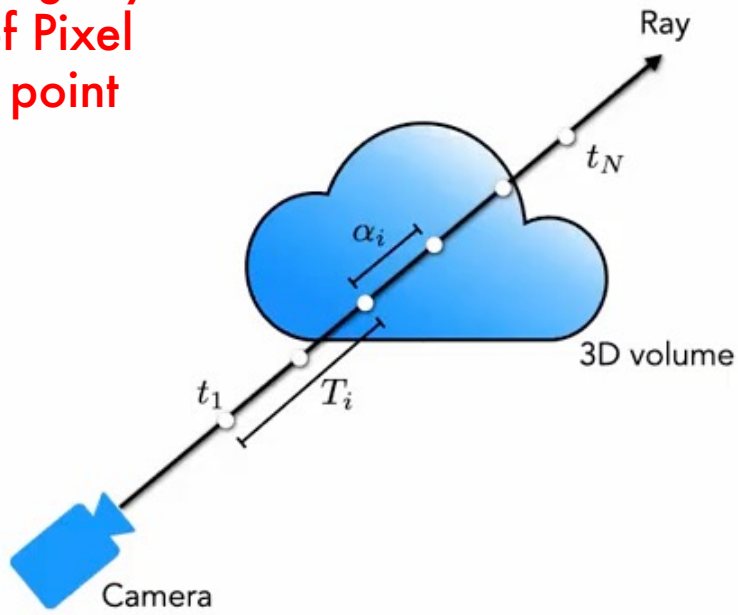
Generate views with traditional volume rendering

Rendering model for ray r(t) = o + td:

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

weights, colors

t = point along ray
C = Color of Pixel
c = color of point



How much light is blocked earlier along ray:

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

Transparency

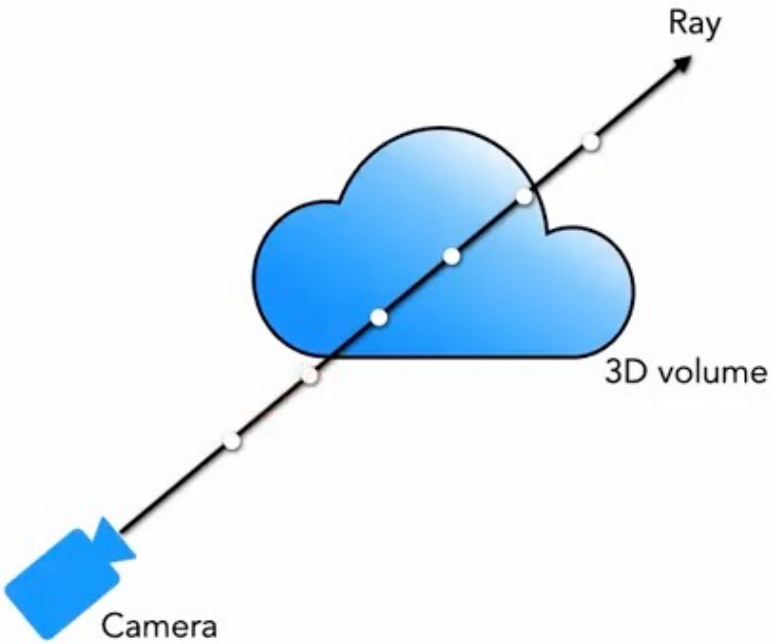
How much light is contributed by ray segment *i*:

$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$

Function of segment length δt_i and volume density σ

From Presentation by Matthew Tancik: Neural Radiance Fields for View Synthesis. 2020.

Can we allocate samples more efficiently? Two pass rendering

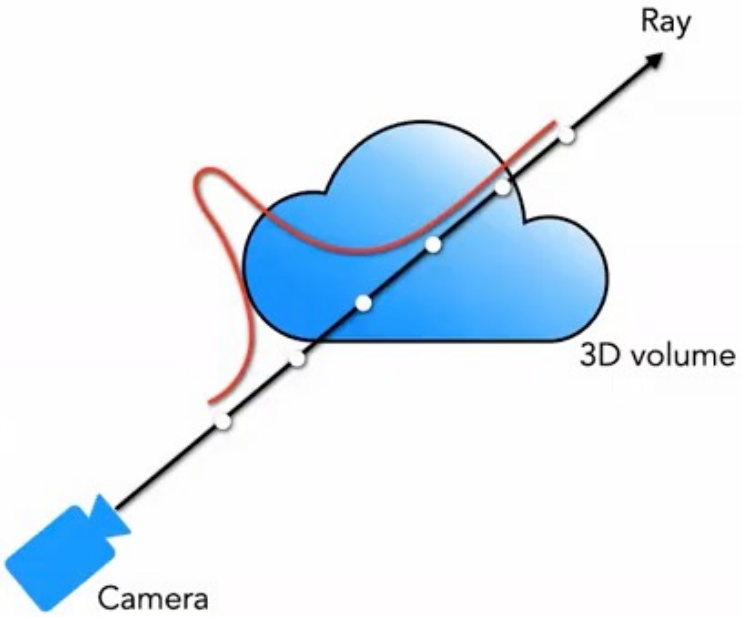


From Presentation by Matthew Tancik: Neural Radiance Fields for View Synthesis. 2020.

Two pass rendering: coarse

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

treat weights as probability distribution for new samples

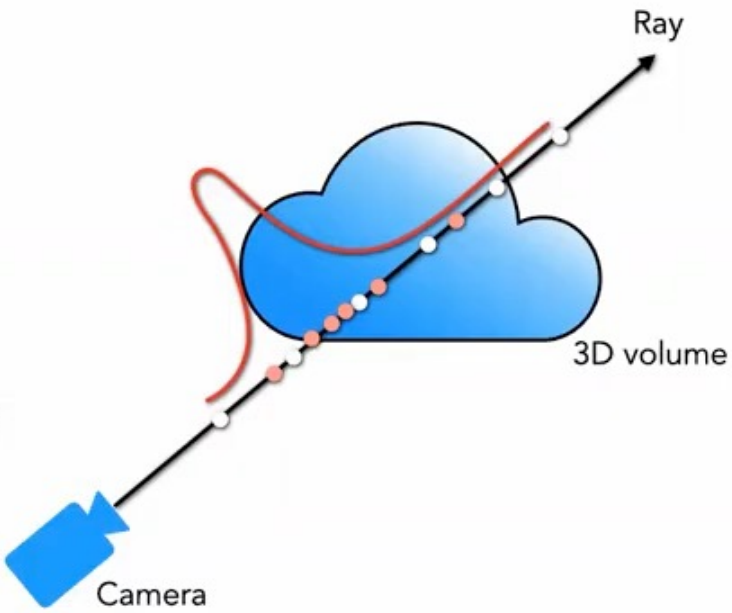


From Presentation by Matthew Tancik: Neural Radiance Fields for View Synthesis. 2020.

Two pass rendering: fine

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

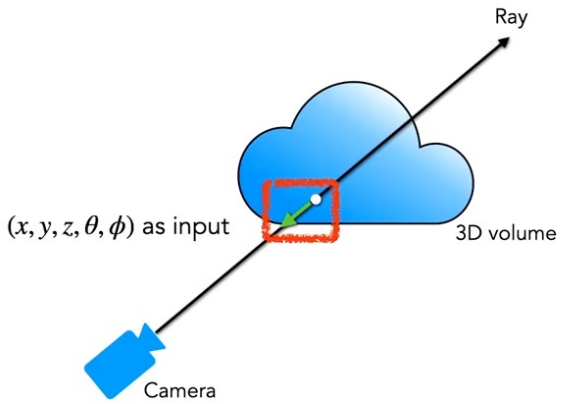
treat weights as probability distribution for new samples



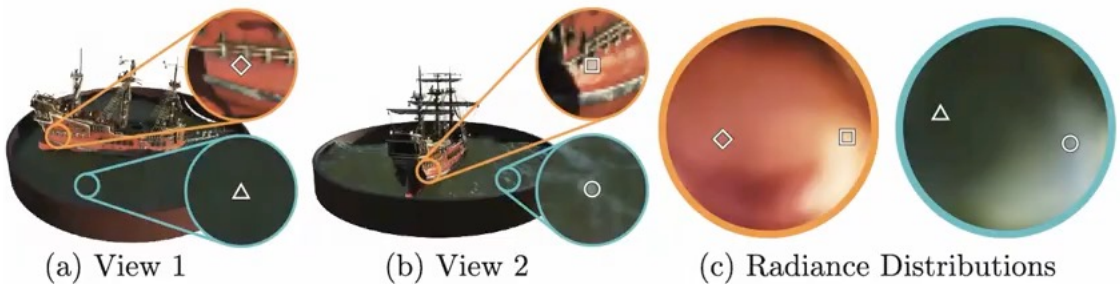
From Presentation by Matthew Tancik: Neural Radiance Fields for View Synthesis. 2020.

Viewing direction as input

- Color of any point varies as function of viewing direction, i.e. Radiance field
- If points are fixed but direction varies, the view dependent specularity comes out



17


(a) View 1 (b) View 2 (c) Radiance Distributions

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Volume rendering is trivially differentiable

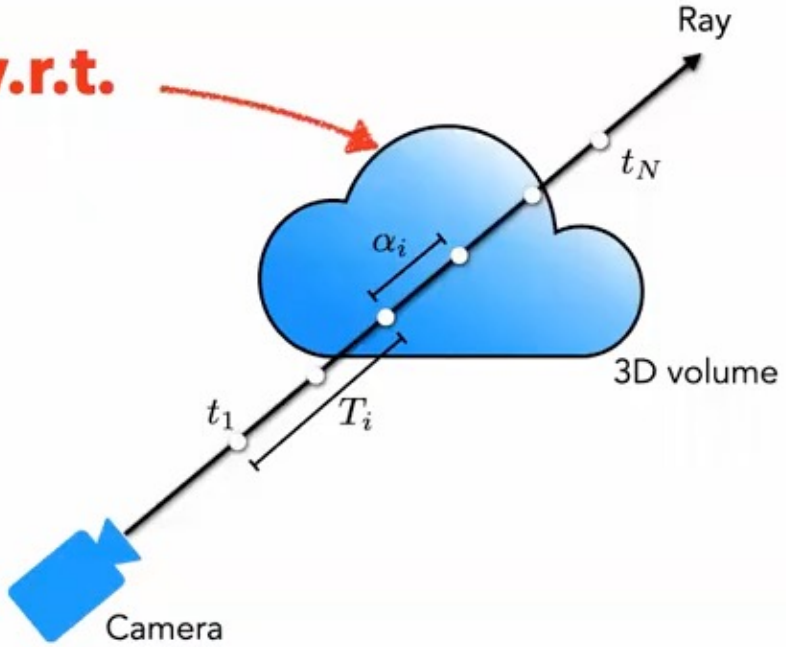
Rendering model for ray r(t) = o + td:

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

colors

weights

differentiable w.r.t.



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*:

$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$

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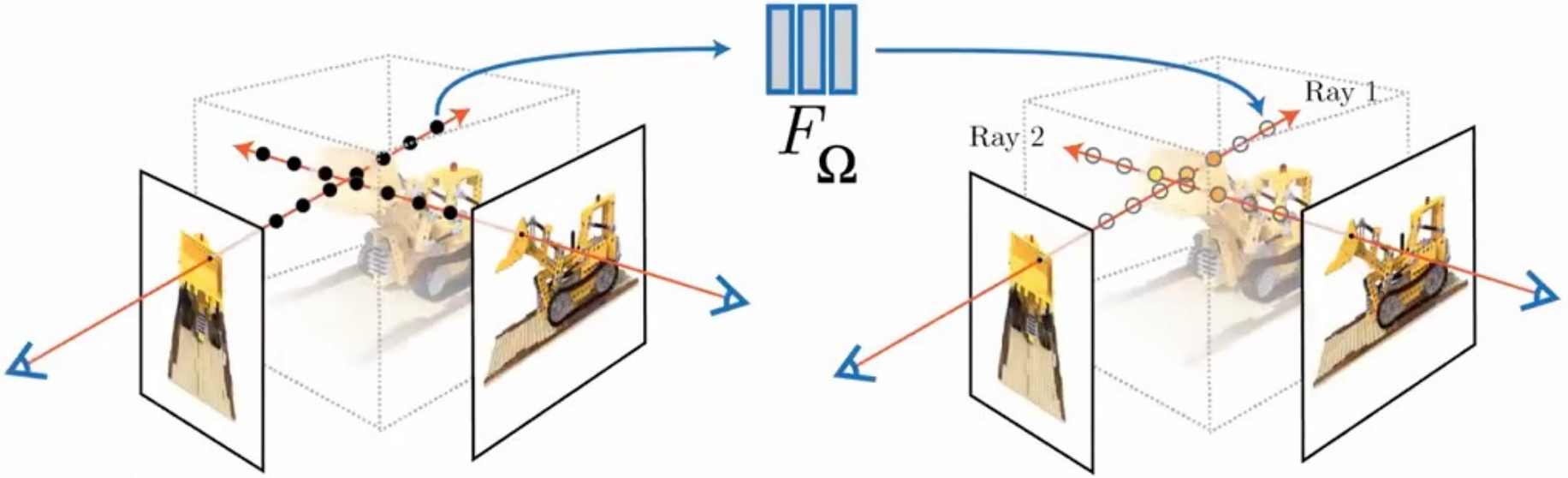
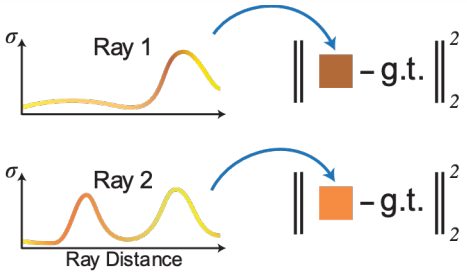
Optimize with gradient descent on rendering loss



$$\min_{\Omega} \sum_{i} \|\text{render}^{(i)}(F_\Omega) - I_{\text{gt}}^{(i)}\|^2$$



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Training network to reproduce all input views of the scene

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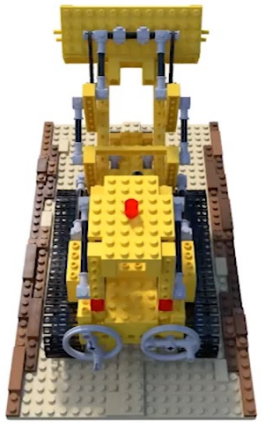
Results – Synthetic data





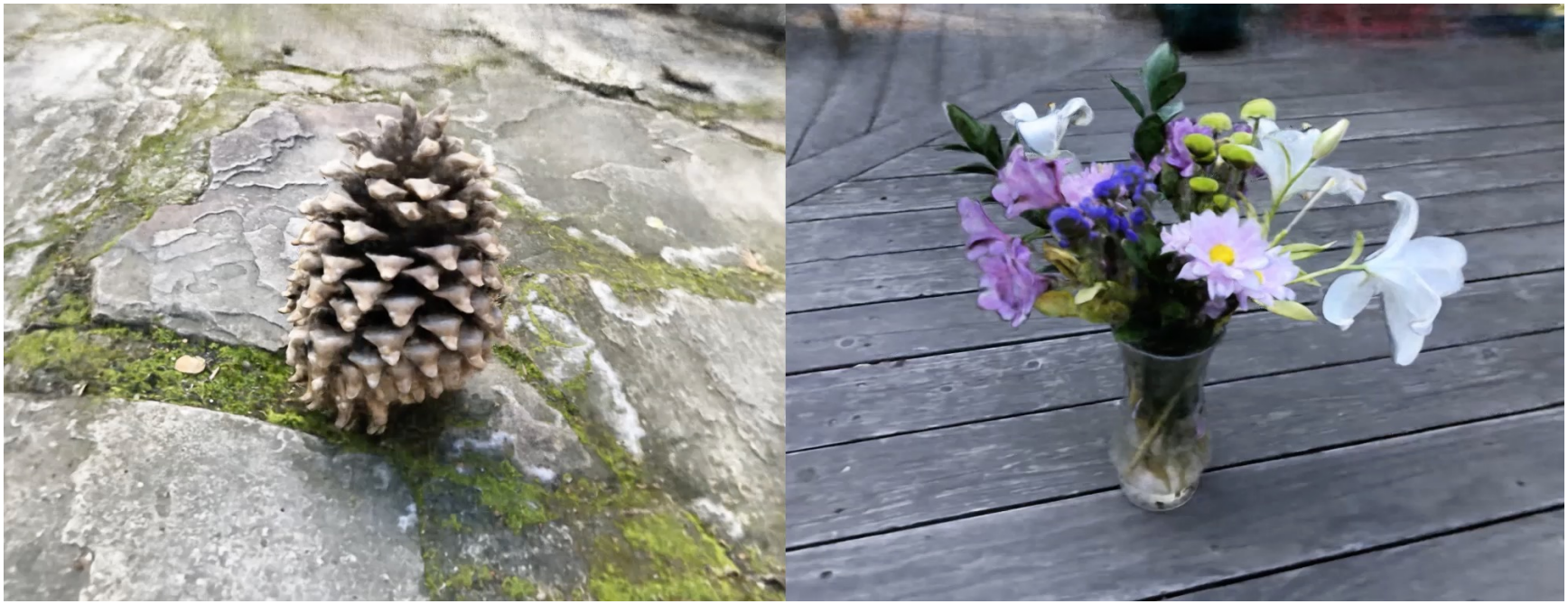
Results – View Dependent Appearance

Results – View Dependent Appearance

Results – Visualization Geometry

Results – Visualization Geometry

Results on Real Scenes



CS231A

Computer Vision:

From 3D Reconstruction to Recognition

Next lecture:

Neural Radiance Cont’ with applications to pose estimation and state estimation