

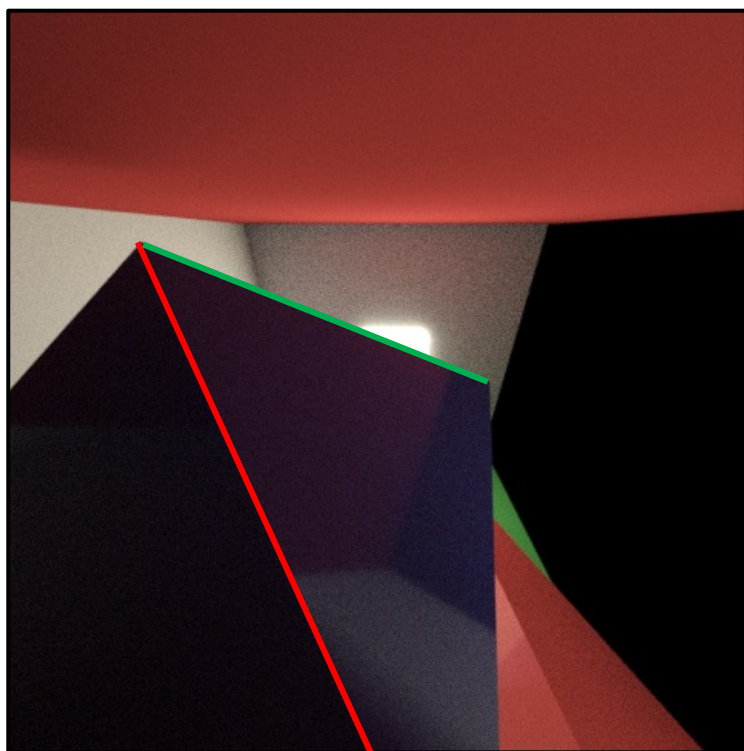
UNBIASED WARPED-AREA SAMPLING FOR DIFFERENTIABLE RENDERING

UCSD CSE 272
Advanced Image Synthesis

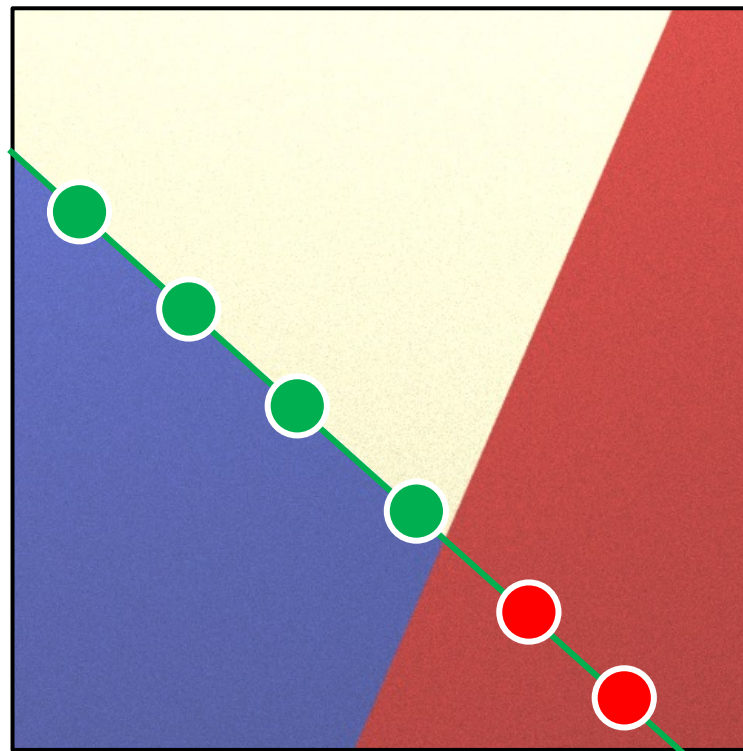
Tzu-Mao Li

with slides from Sai Bangaru

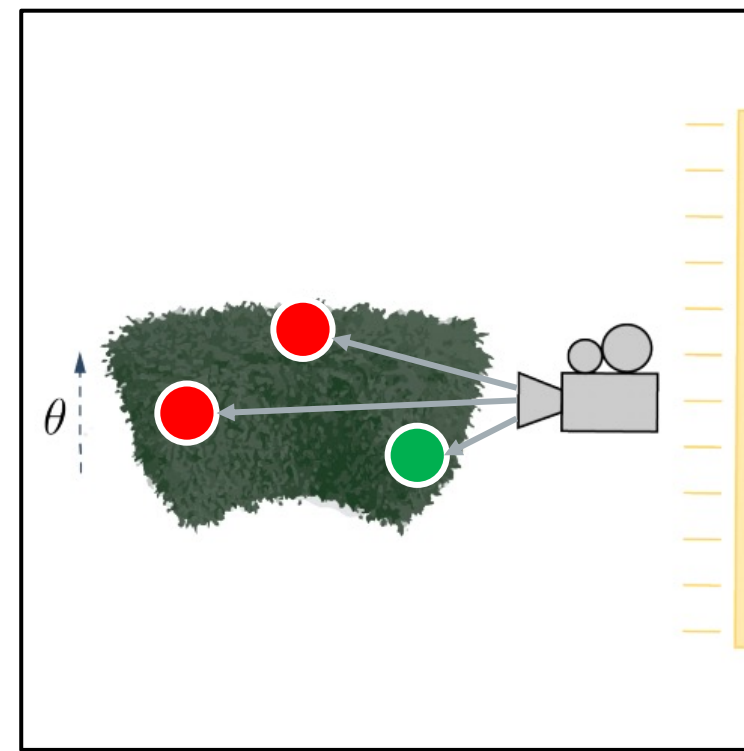
CHALLENGES: EDGE SAMPLING IS HARD!



Silhouette classification

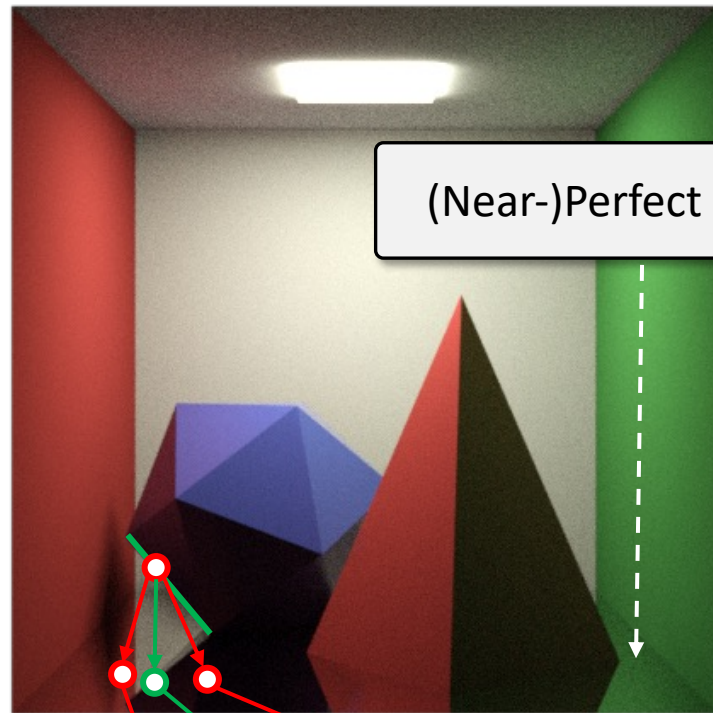


Occlusion

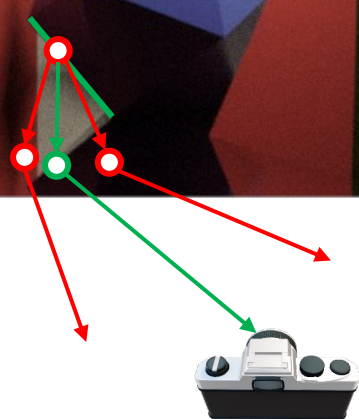


Depth complexity

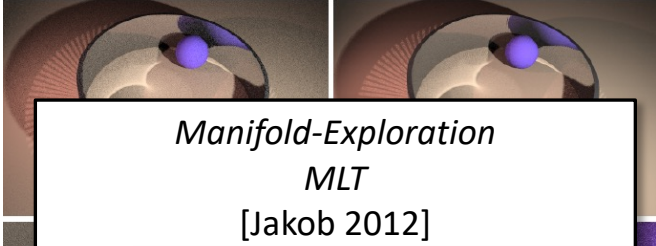
EDGE SAMPLING HAS TROUBLE WITH SPECULAR REFLECTIONS



(Near-)Perfect Mirror

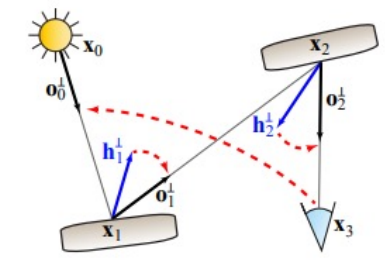


Rendering Caustics

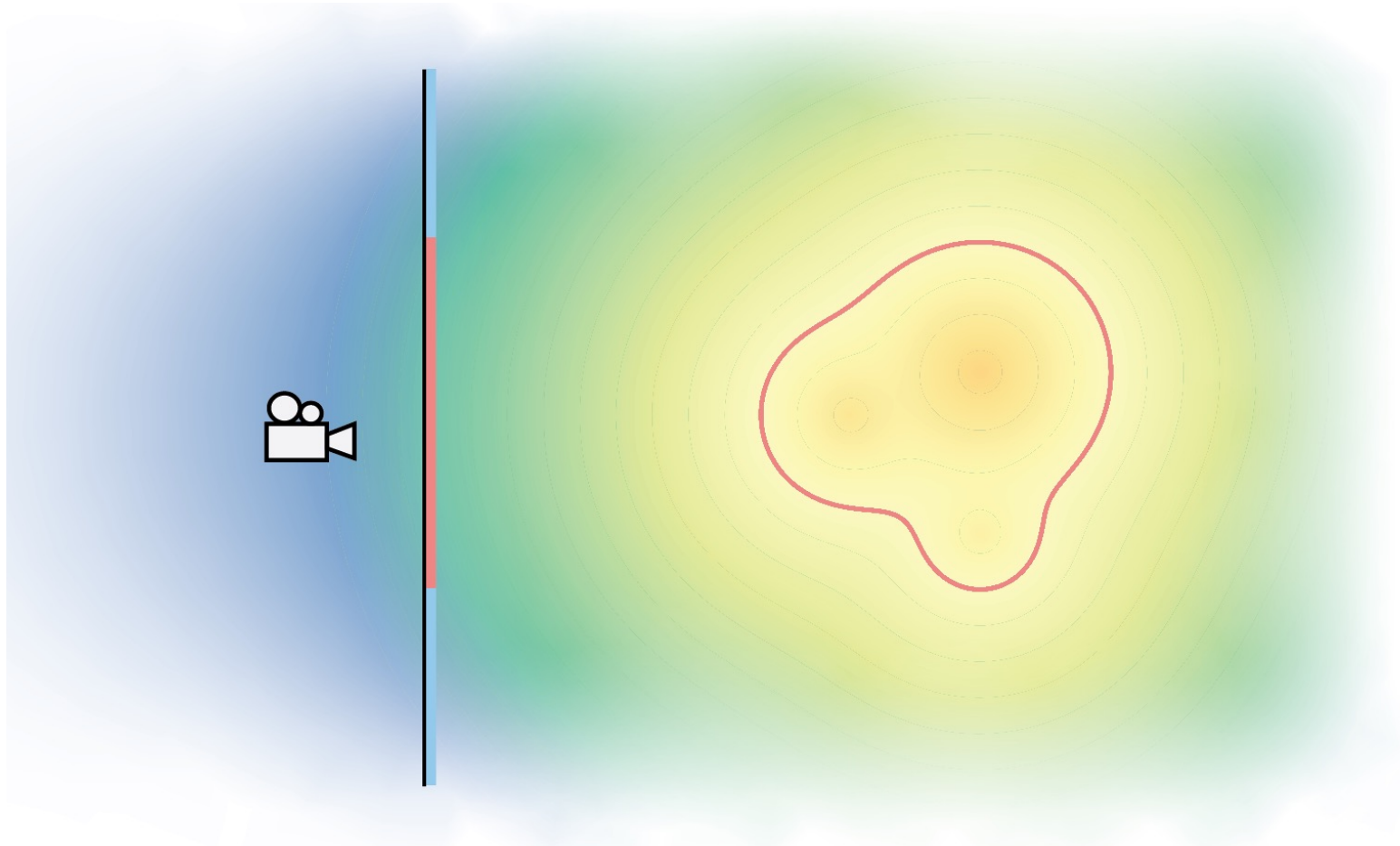


*Manifold-Exploration
MLT
[Jakob 2012]*

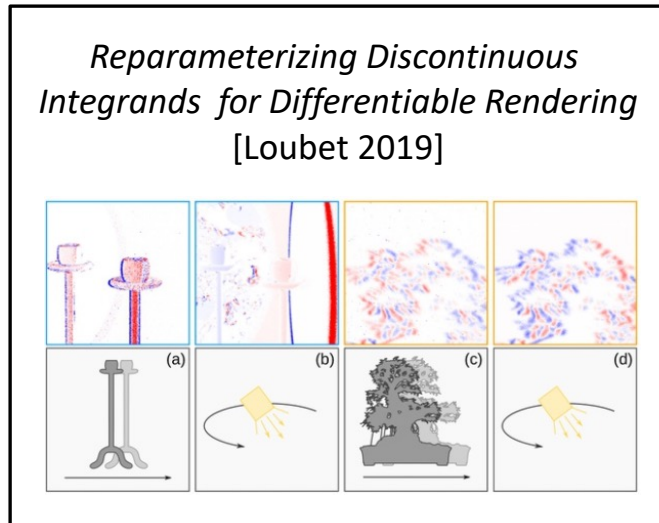
*Natural Constraint Representation
for MLT
[Kaplanyan 2014]*



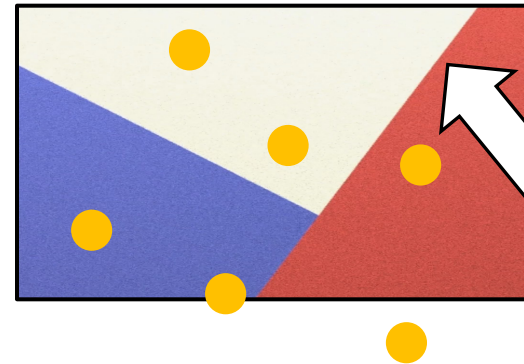
SILHOUETTE EXTRACTION IS DIFFICULT FOR IMPLICIT REPRESENTATIONS



CAN WE DESIGN AN UNBIASED AREA SAMPLING METHOD?



Transform samples with θ . Avoids discontinuities.



Heuristic Approximation!
May not work for all samples.

OUR APPROACH

CONVERTING EDGE SAMPLES TO AREA SAMPLES

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

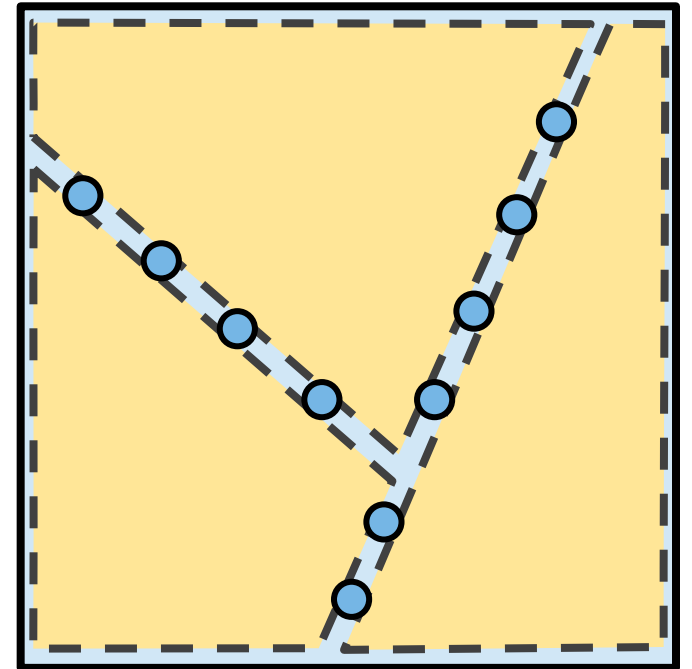
is estimated through edge samples ●

Goal: Rewrite

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

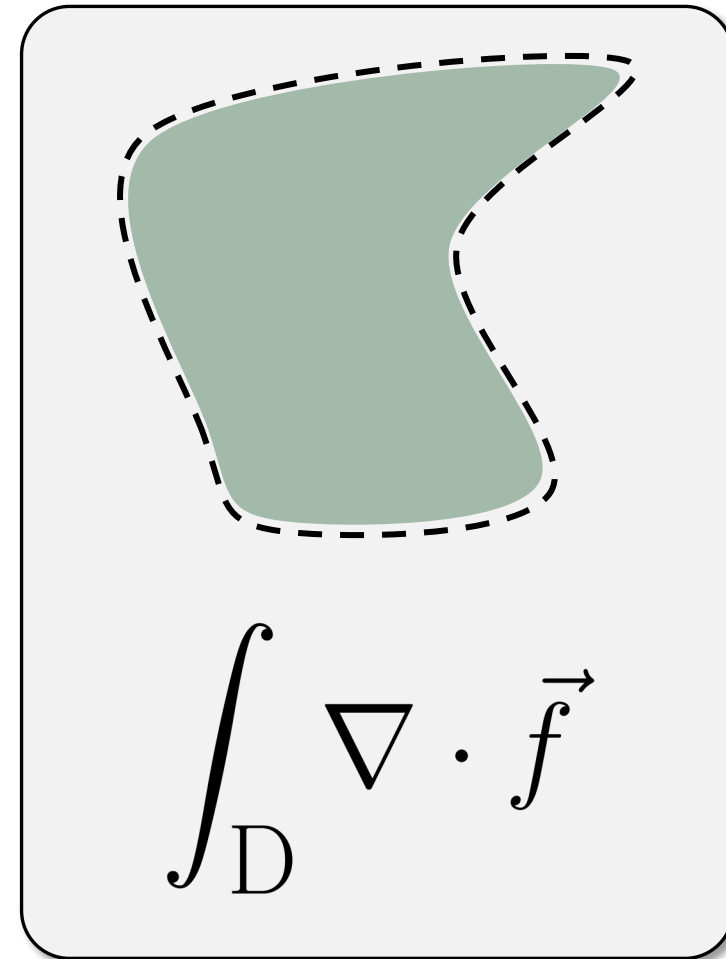
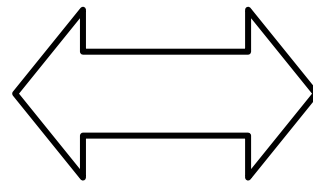
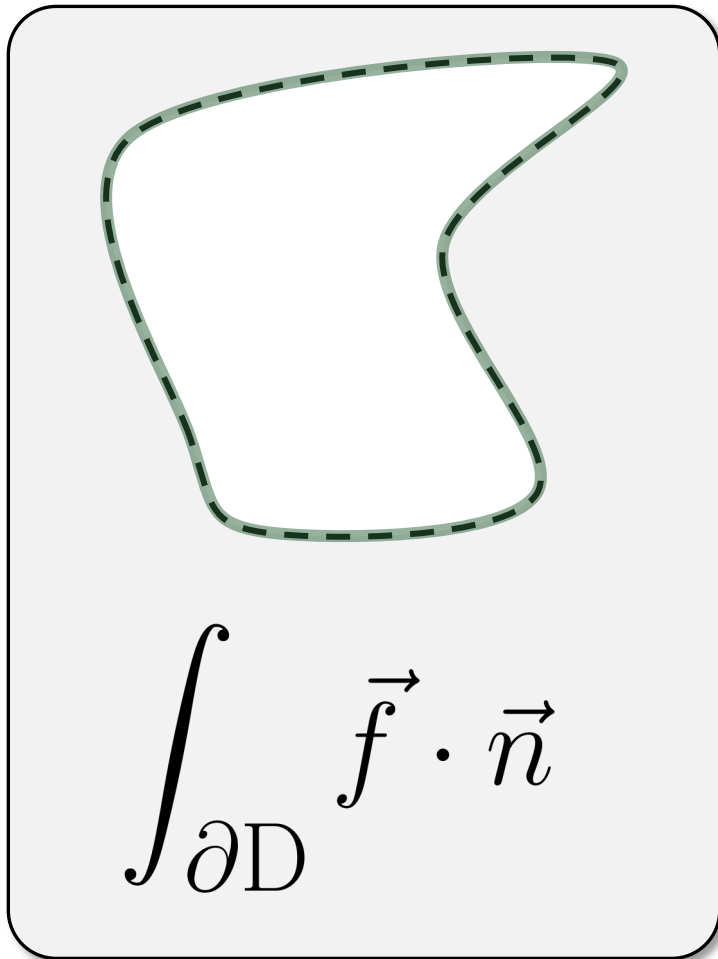
into area integral

$$\int_D g$$



THE DIVERGENCE THEOREM

[Gauss 1813]

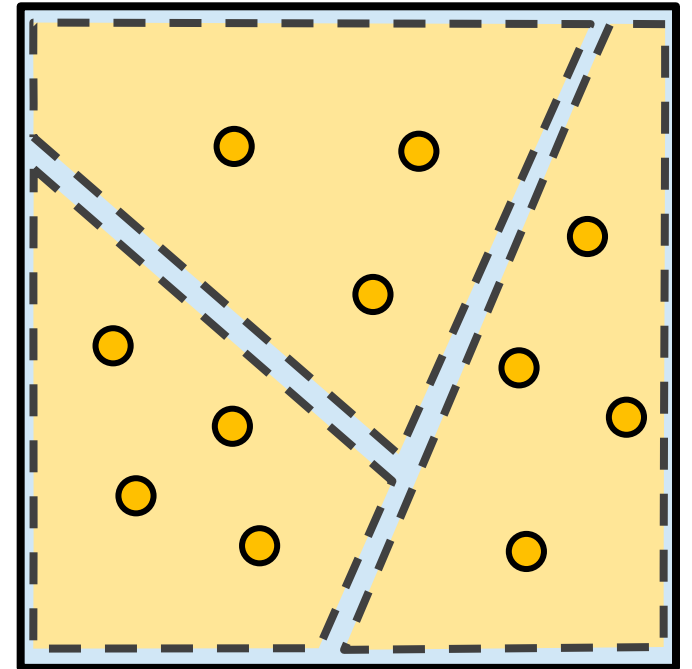


APPLYING THE DIVERGENCE THEOREM TO THE EDGE INTEGRAL

Goal: Rewrite $\int_{\partial D} f \vec{v} \cdot \vec{n}$ into area integral $\int_D g$

Solution: Rewrite $\int_{\partial D} f \vec{v} \cdot \vec{n}$ into $\int_D \nabla \cdot (\vec{v}_\theta f)$

$\int_D \nabla \cdot (\vec{v}_\theta f)$ can be estimated through area samples ●



QUICK RECAP

- Used *Reynolds transport theorem* to find the boundary integral

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

- Rewrote

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

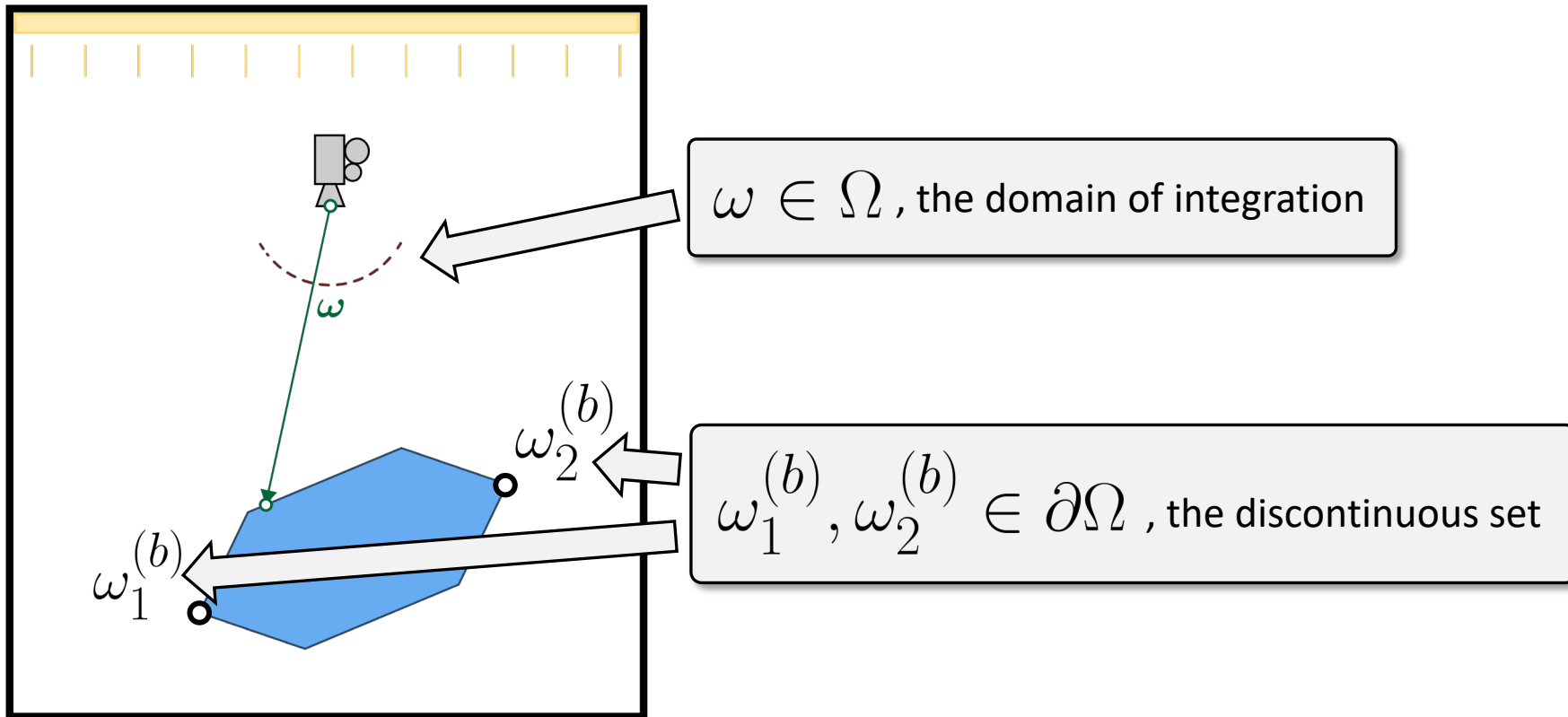
to

$$\int_D \nabla \cdot (\vec{v}_\theta f)$$

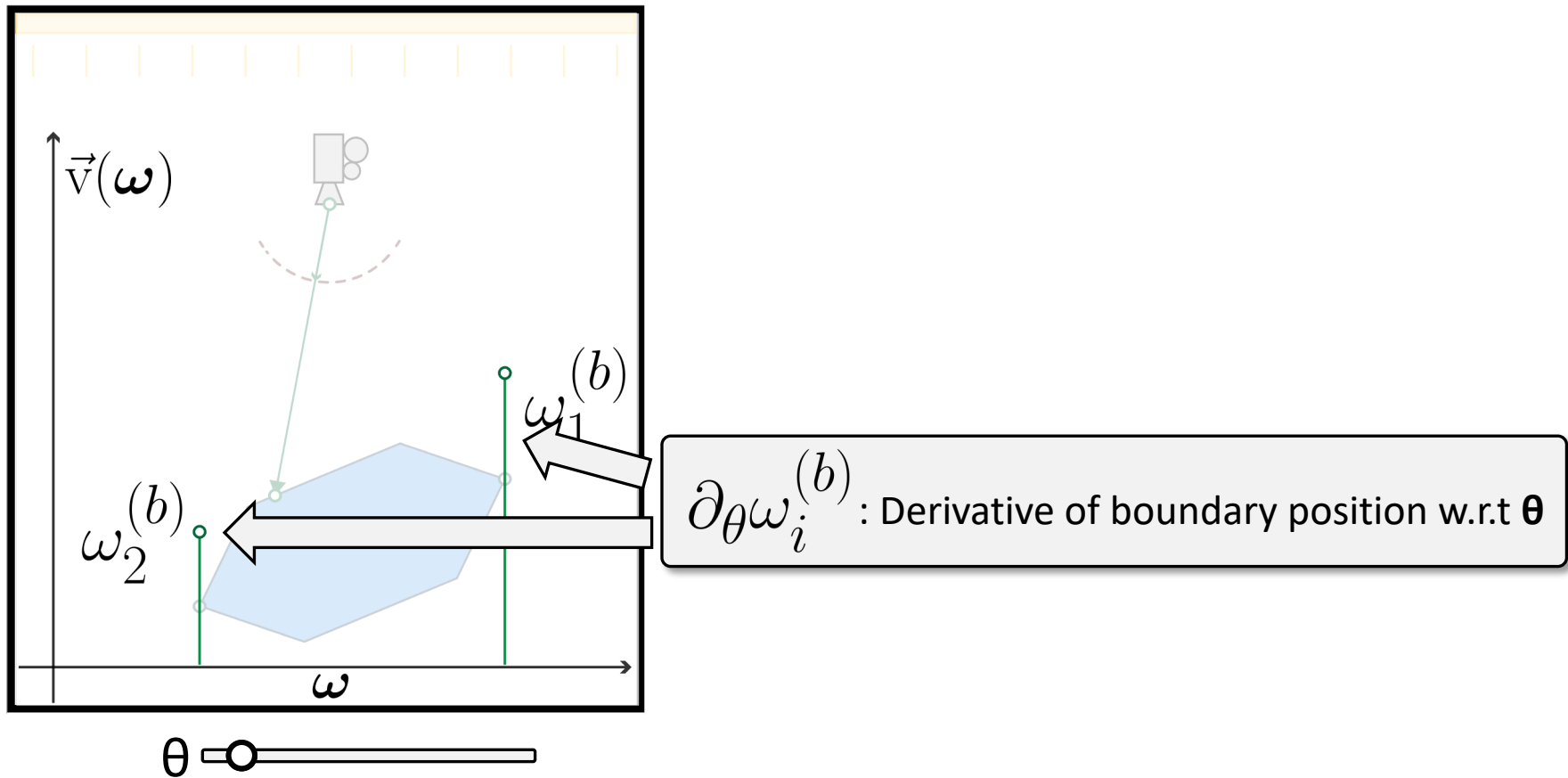
using the *divergence theorem*.

- Have to define the *vector field* \vec{v}_θ over domain D

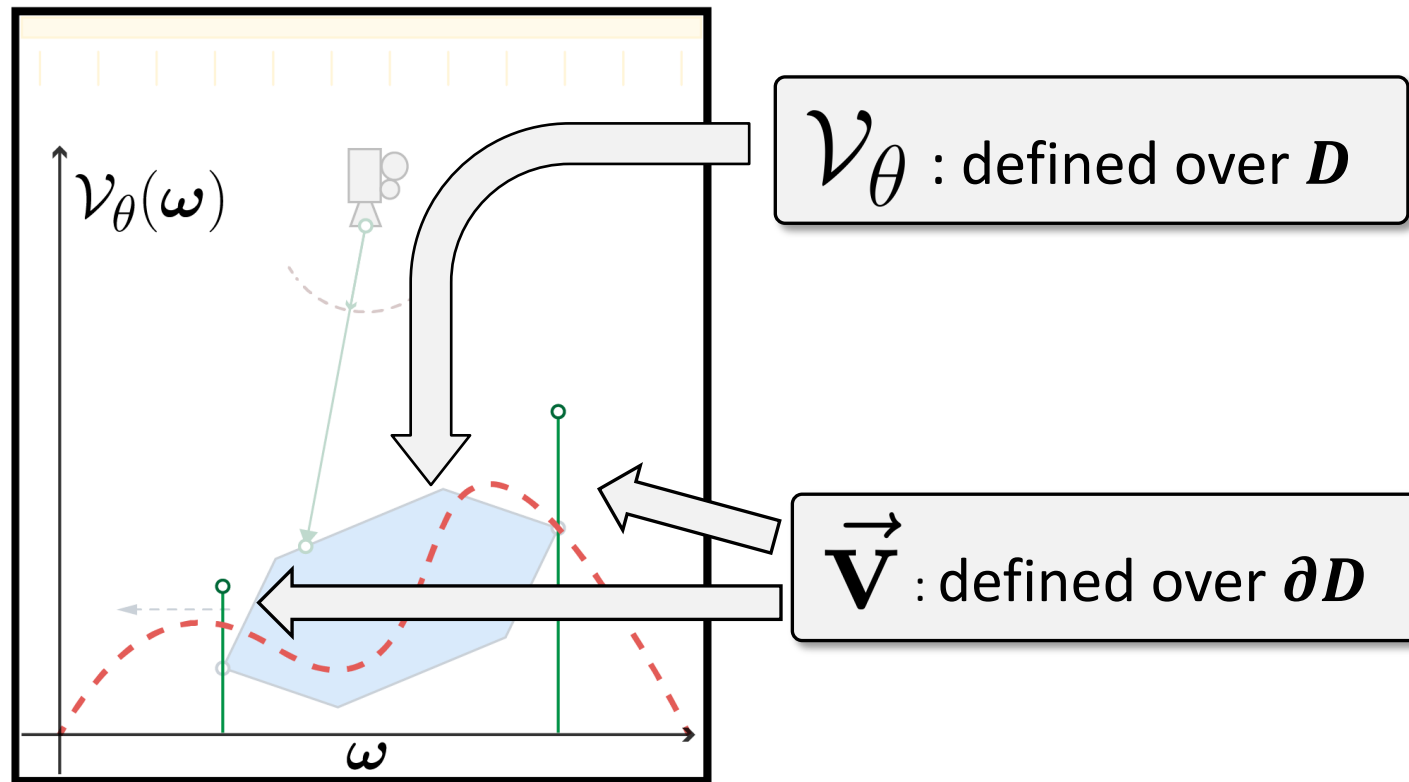
A 2D EXAMPLE SCENE



VELOCITY \vec{v} : THE BOUNDARY DERIVATIVE

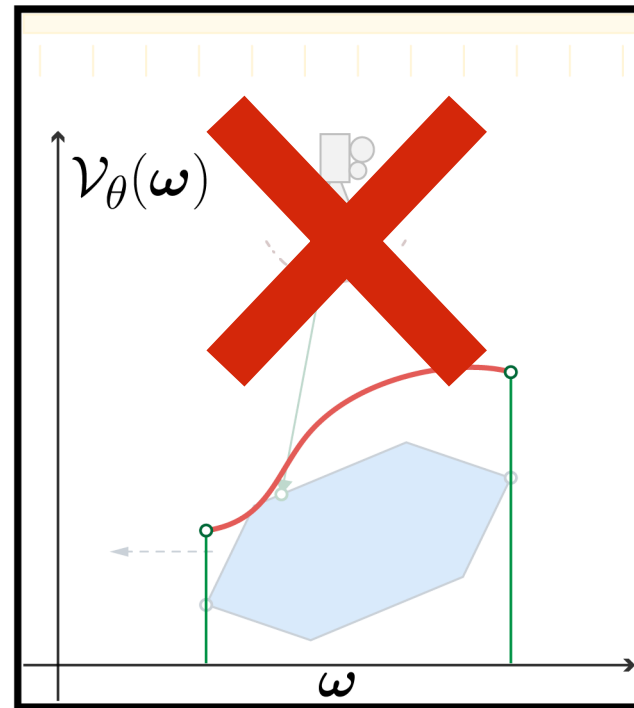
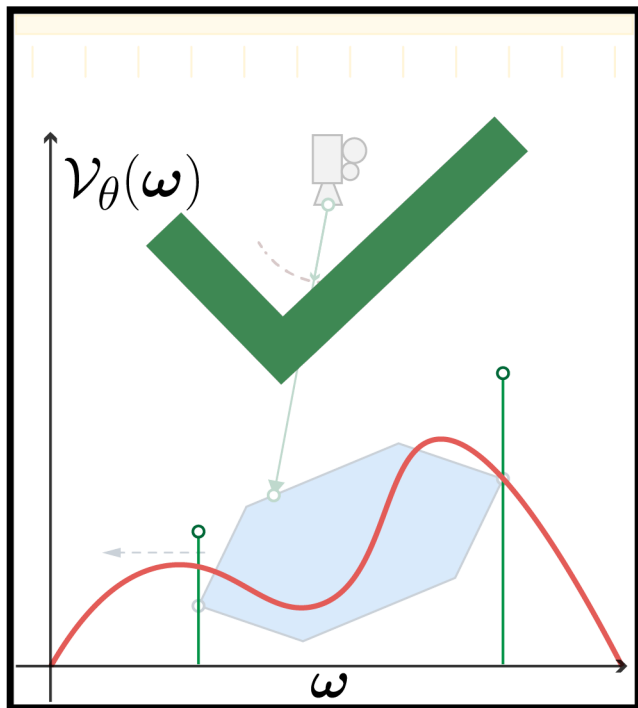


WARP FIELD \mathcal{V}_θ : EXTENSION OF \vec{V} TO ALL POINTS



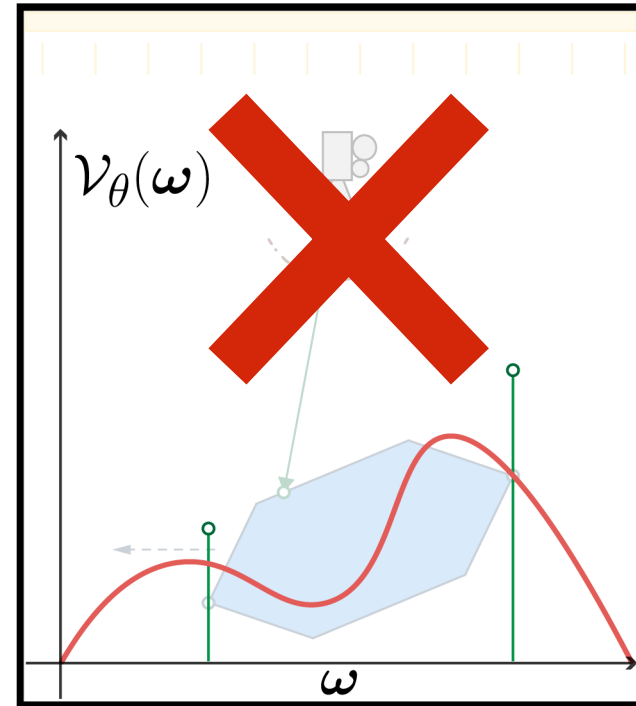
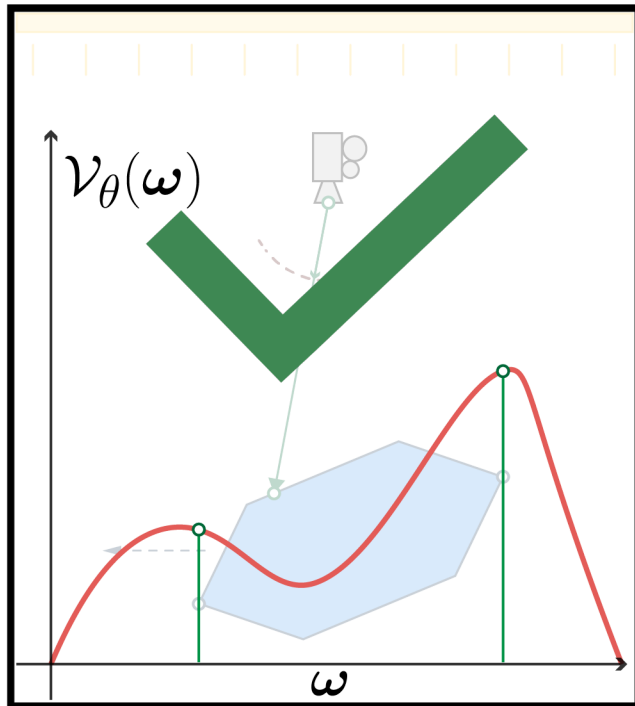
VALIDITY OF \vec{V}_θ

Rule 1: Continuous

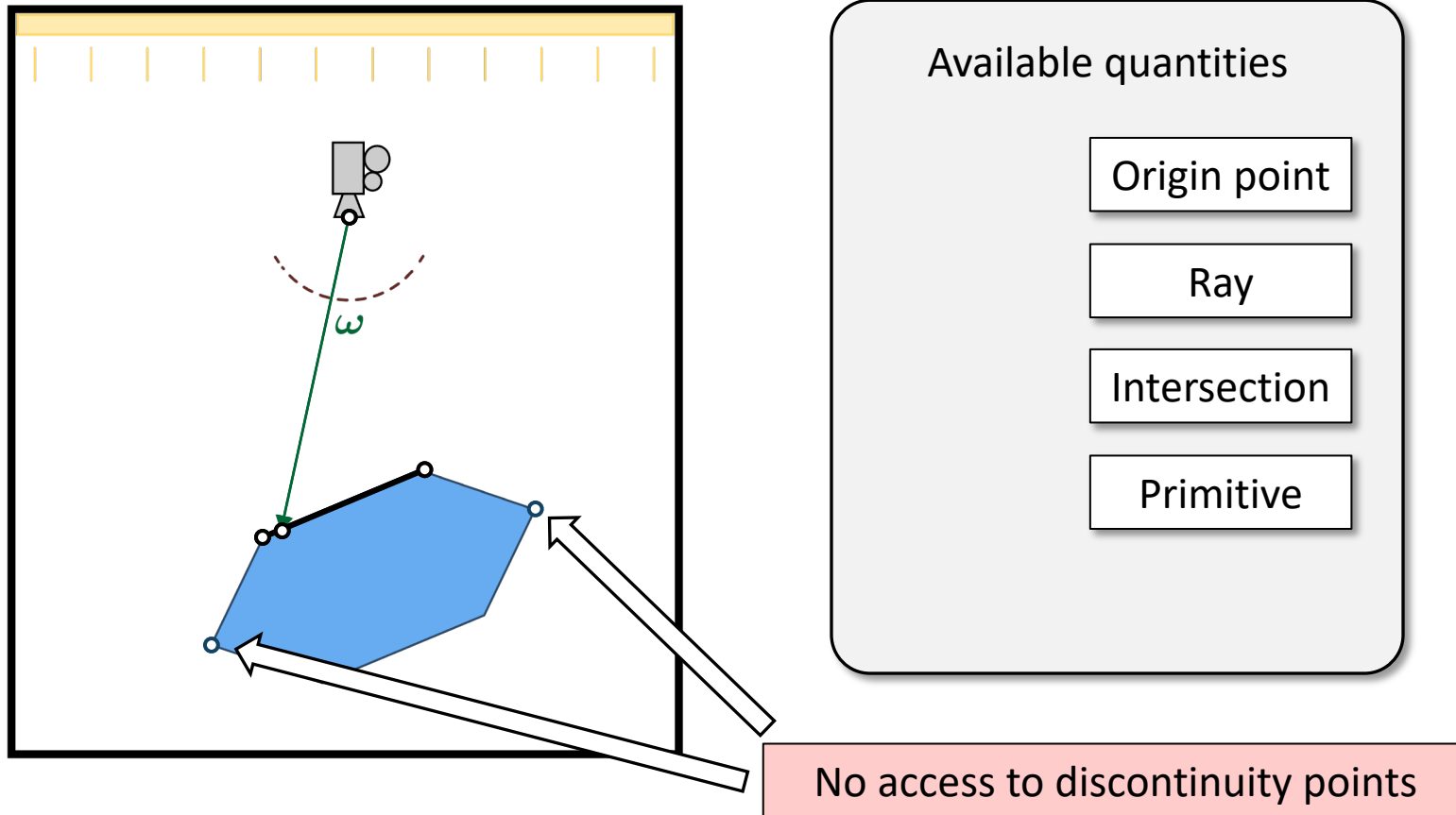


VALIDITY OF \vec{V}_θ

Rule 2: Boundary Consistent



INTERPOLATION WITHOUT KNOWLEDGE OF BOUNDARIES



CONSTRUCTING \vec{V}_θ

Attempt 1 \longrightarrow Find $\partial_\theta \omega$ through *implicit derivative*

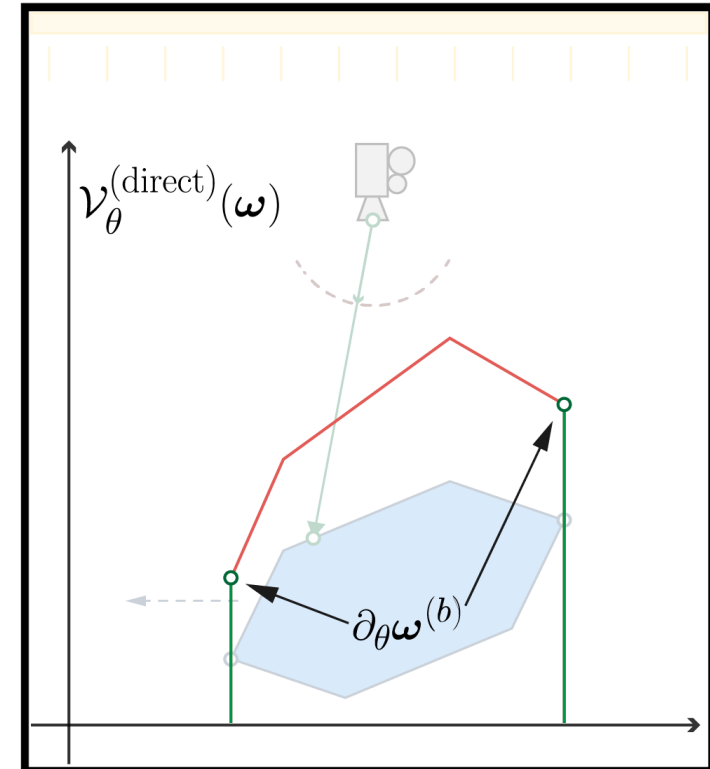
(Incorrect)

$$\mathbf{y} = \text{INTERSECT}(\omega, \theta) \implies \partial_\theta \omega = \frac{\partial_\omega \mathbf{y}}{\partial_\theta \mathbf{y}}$$

At all points (not just boundaries)

+ Boundary consistent

- Not continuous



CONSTRUCTING \vec{V}_θ

Attempt 2 \longrightarrow Filter *Attempt 1* with a Gaussian filter

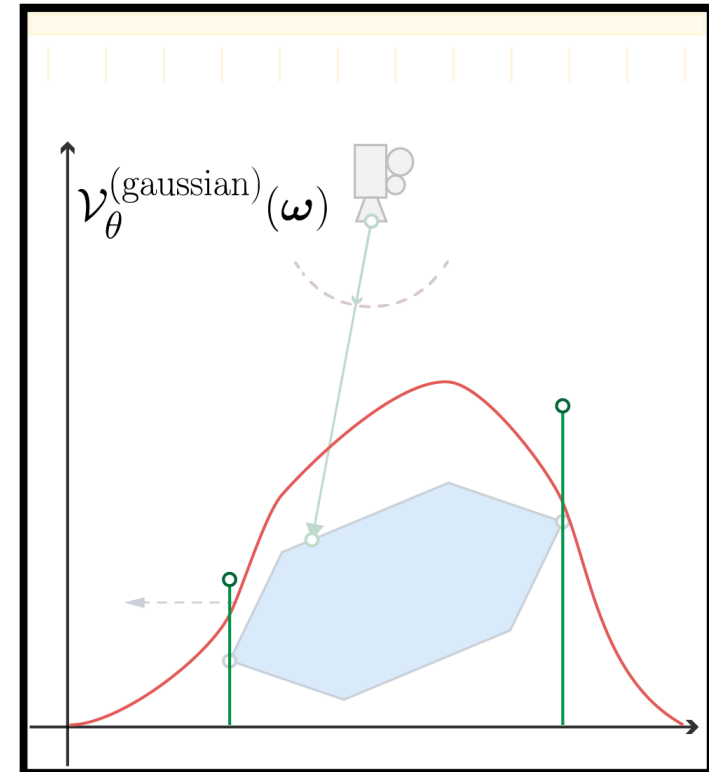
(Incorrect)

$$\int_{\Omega'} k(\omega, \omega') \frac{\partial_{\omega} \mathbf{y}}{\partial_{\theta} \mathbf{y}}$$

$k(.,.) = \text{Gaussian filter}$

+ Continuous

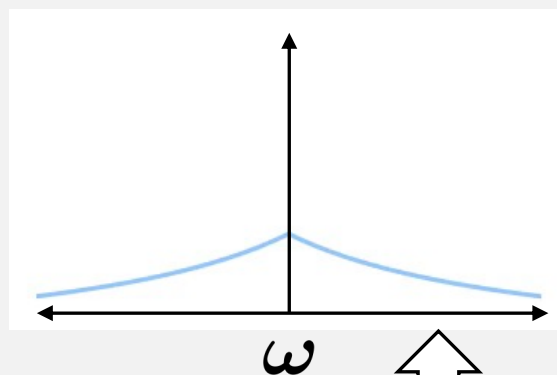
- Not boundary consistent



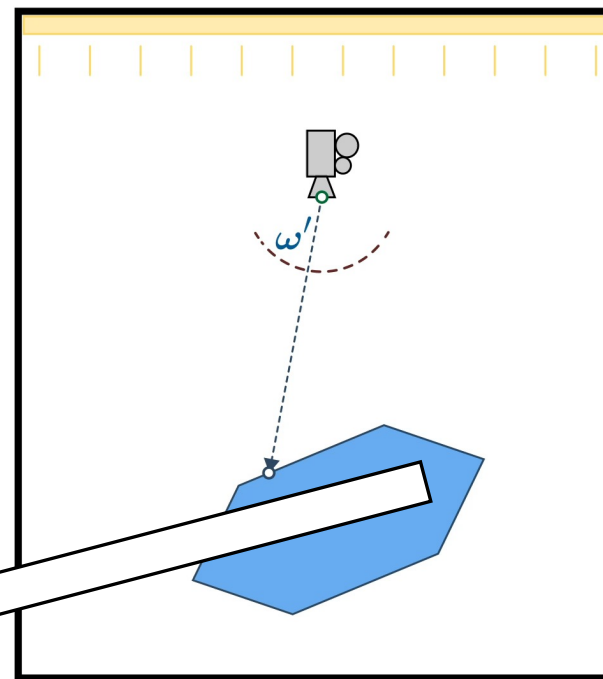
BOUNDARY-AWARE WEIGHTING

Goal: Find weights $k(\omega, \omega')$ s.t. $\vec{V}_\theta = \frac{\partial \omega \mathbf{y}}{\partial \theta \mathbf{y}}$ at boundaries.

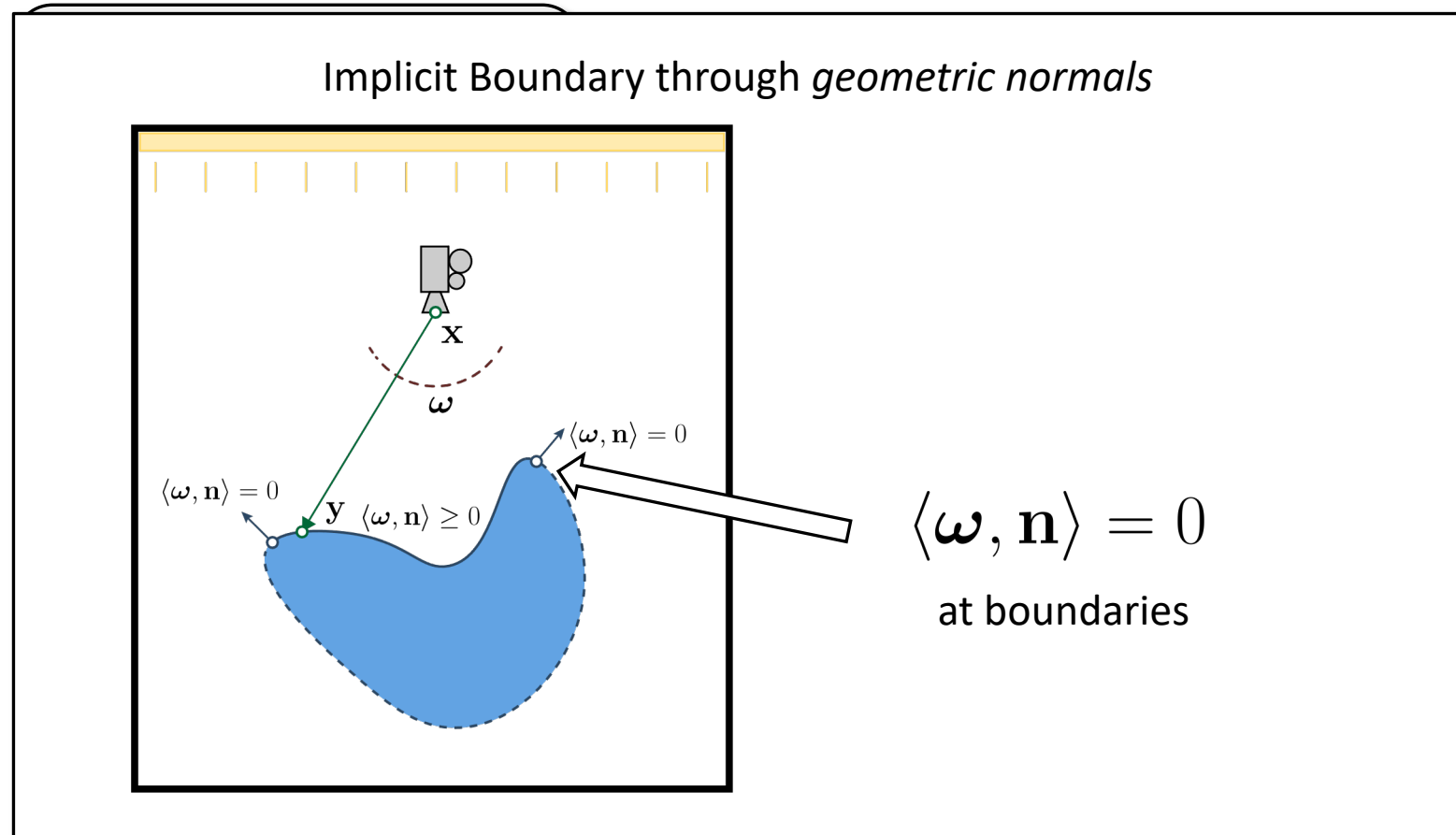
Ideal weighting function



Approach Dirac delta near boundaries



BOUNDARY-AWARE WEIGHTING



boundary sampling)

boundary
(g)

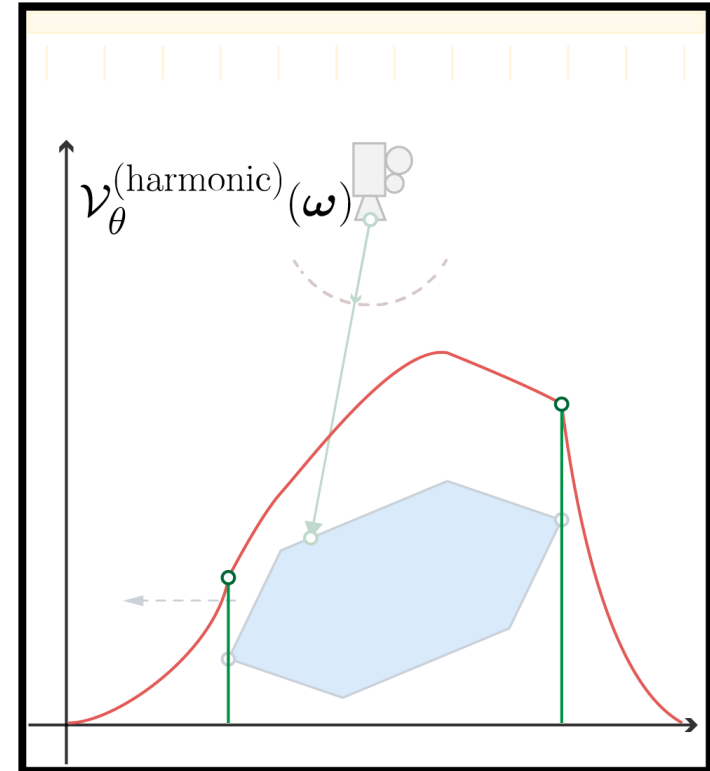
CONSTRUCTING \vec{V}_θ

Our Approach \longrightarrow Filter *Attempt 1* with harmonic weights

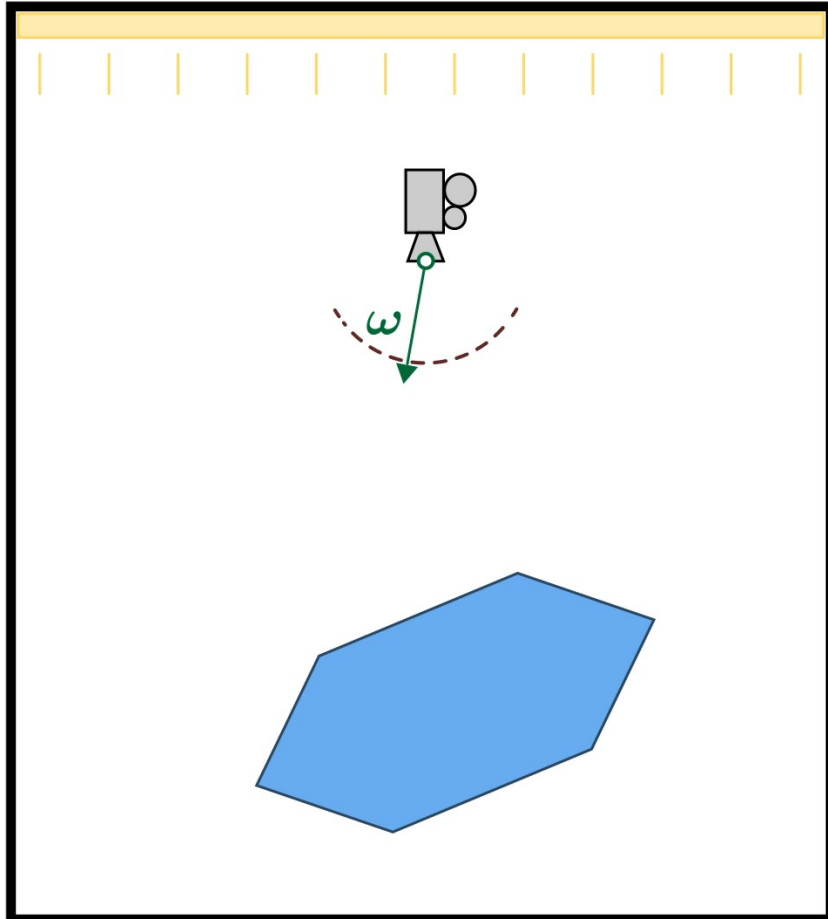
$$k(\omega, \omega') = \frac{1}{\boxed{D(\omega, \omega')} + \boxed{B(\omega')}}}$$

Distance function Boundary test

+ Boundary consistent
+ Continuous



COMPUTING \vec{V}_θ



1. Sample **path** using path tracer *(N paths)*

For each bounce:

2. Sample **auxiliary** rays *(N' rays)*

3. Compute boundary term **B()** locally

4. Compute weight **k(.,.)** and $\partial_\theta \omega$

5. Find weighted mean

QUICK RECAP

- Used *Reynolds transport theorem* to find the boundary integral

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

- Rewrote

$$\int_{\partial D} f \vec{v} \cdot \vec{n}$$

to

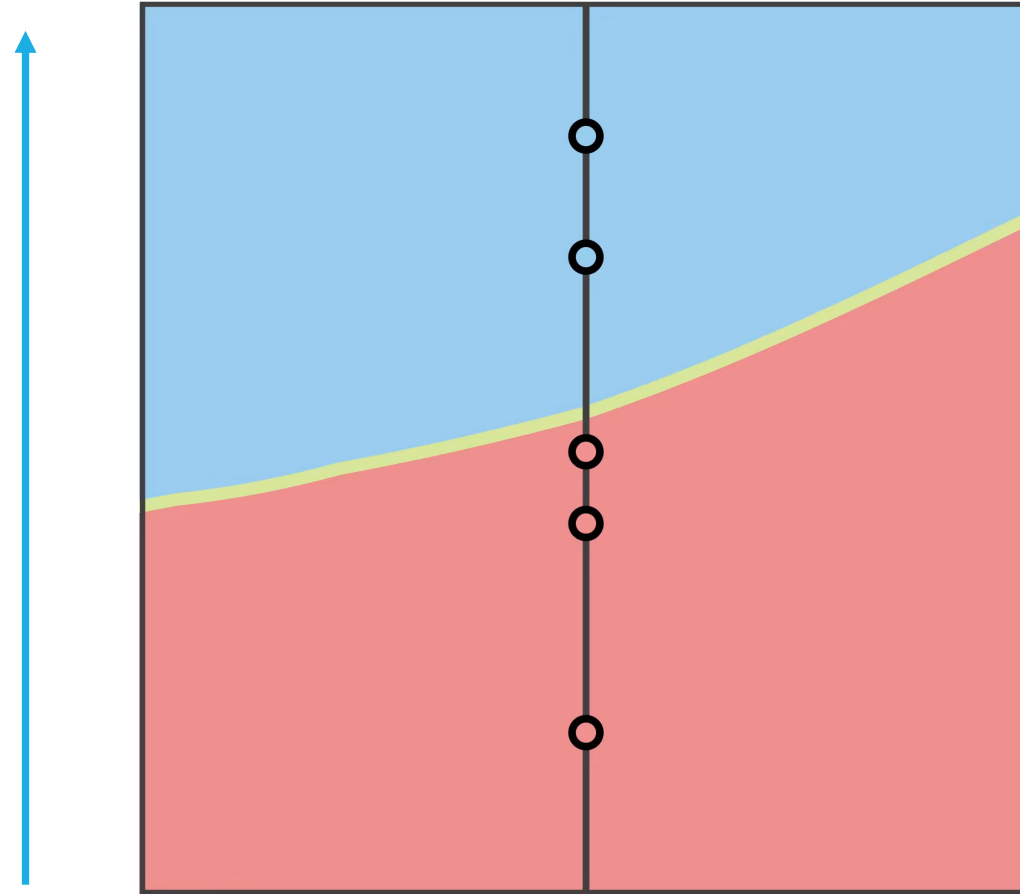
$$\int_D \nabla \cdot (\vec{v}_\theta f)$$

using the *divergence theorem*.

- Estimate **consistent** and **continuous** \vec{v}_θ over domain D using auxiliary rays

MORE INTUITION: WARP-AREA SAMPLING CAN BE SEEN AS A CHANGE OF VARIABLE

integration variable u



differentiating parameter θ

TRANSFORM SAMPLES

$$u = T(u'; \theta)$$

MORE INTUITION: WARP-AREA SAMPLING
CAN BE SEEN AS A CHANGE OF VARIABLE

$$\frac{\partial}{\partial \theta} \int_D f \, du = \int_D f_\theta + \nabla \cdot (\vec{v}_\theta f) \, du$$

MORE INTUITION: WARP-AREA SAMPLING
CAN BE SEEN AS A CHANGE OF VARIABLE

$$\begin{aligned} \frac{\partial}{\partial \theta} \int_D f \, du &= \int_D f_\theta + \nabla \cdot (\vec{\nu}_\theta f) \, du \\ &= \int_D \frac{\partial}{\partial \theta} (f(T(u'; \theta)) J_T) \, du' \end{aligned}$$

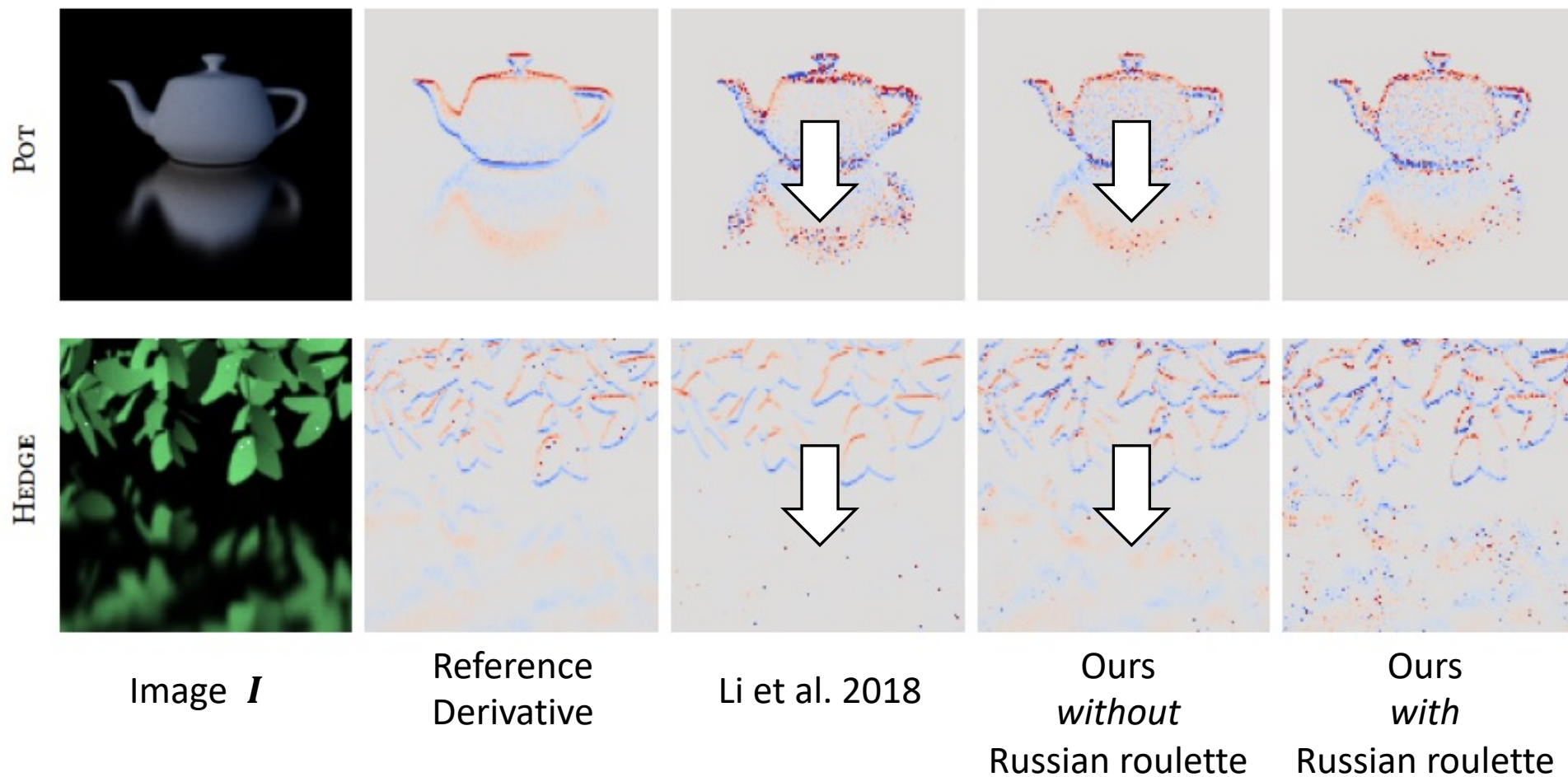
MORE INTUITION: WARP-AREA SAMPLING
CAN BE SEEN AS A CHANGE OF VARIABLE

$$\begin{aligned}\frac{\partial}{\partial \theta} \int_D f \, du &= \int_D f_\theta + \nabla \cdot (\vec{\mathcal{V}}_\theta f) \, du \\ &= \int_D \frac{\partial}{\partial \theta} (f(T(u'; \theta)) J_T) \, du'\end{aligned}$$

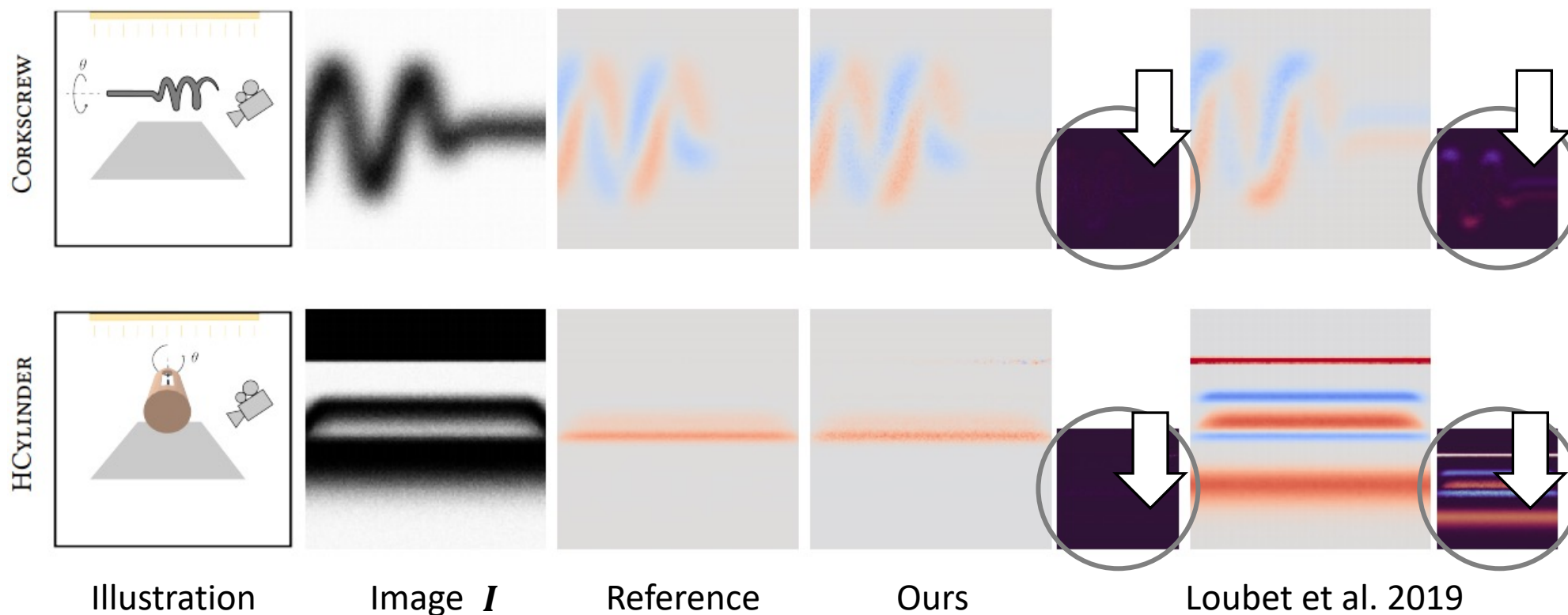
$$T = u' + (\theta - \theta_0) \mathcal{V}_\theta$$

RESULTS

VARIANCE COMPARISON WITH EDGE-SAMPLING

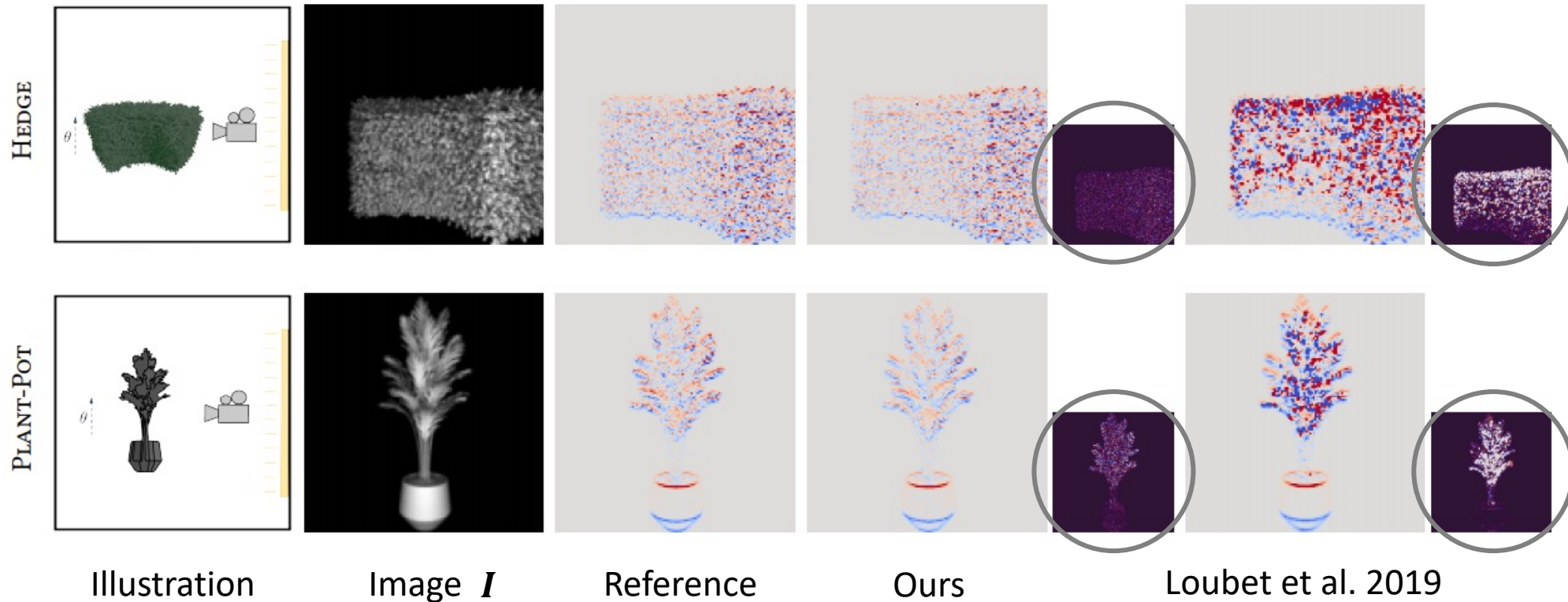


BIAS COMPARISON WITH REPARAMETERIZATION



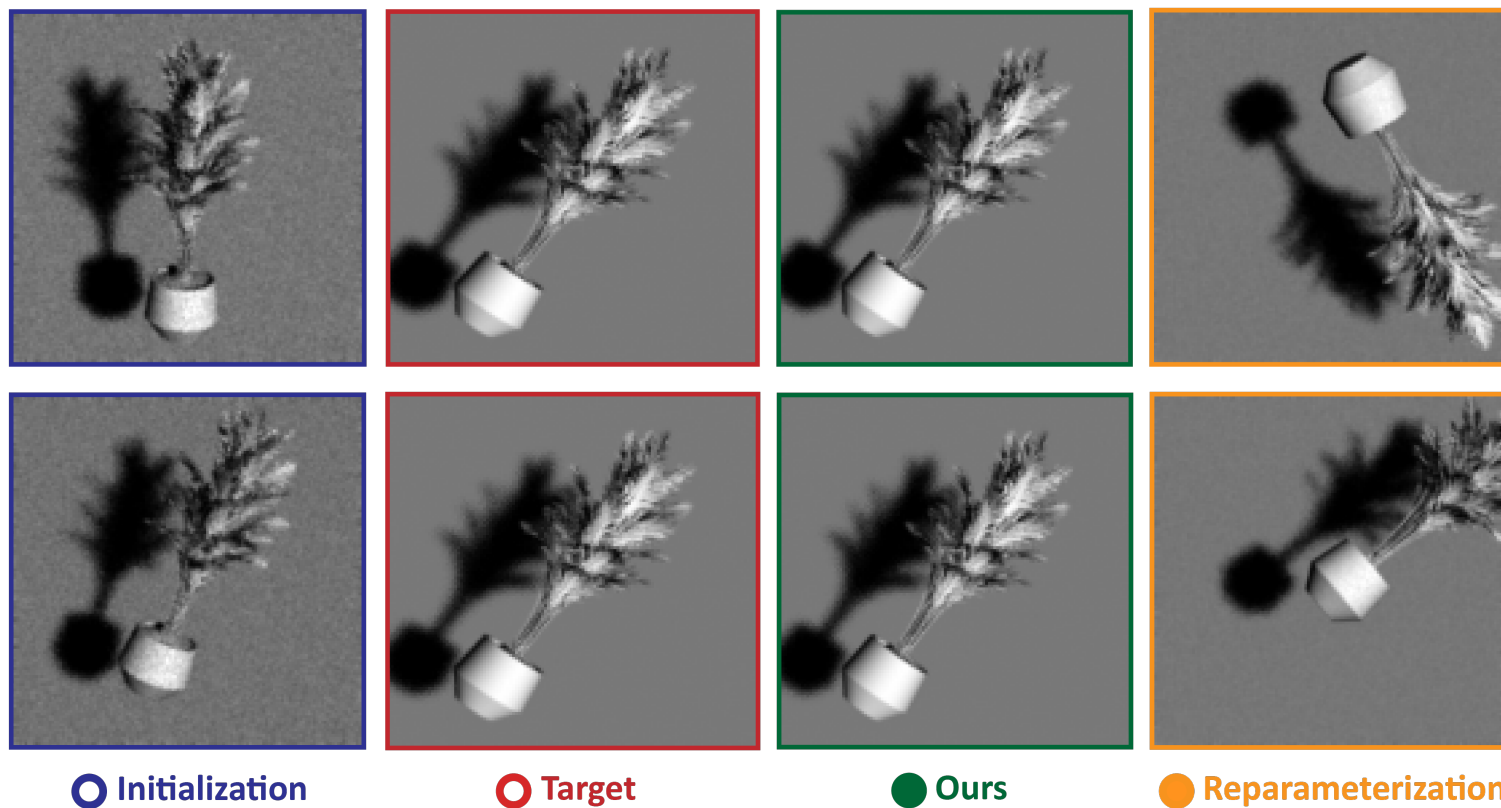
Rotating cylindrical objects present a complicated scenario for area-sampling

BIAS COMPARISON WITH REPARAMETERIZATION

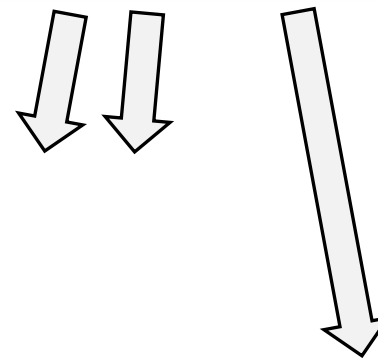


Extremely complex geometry like foliage can cause heuristic to fail

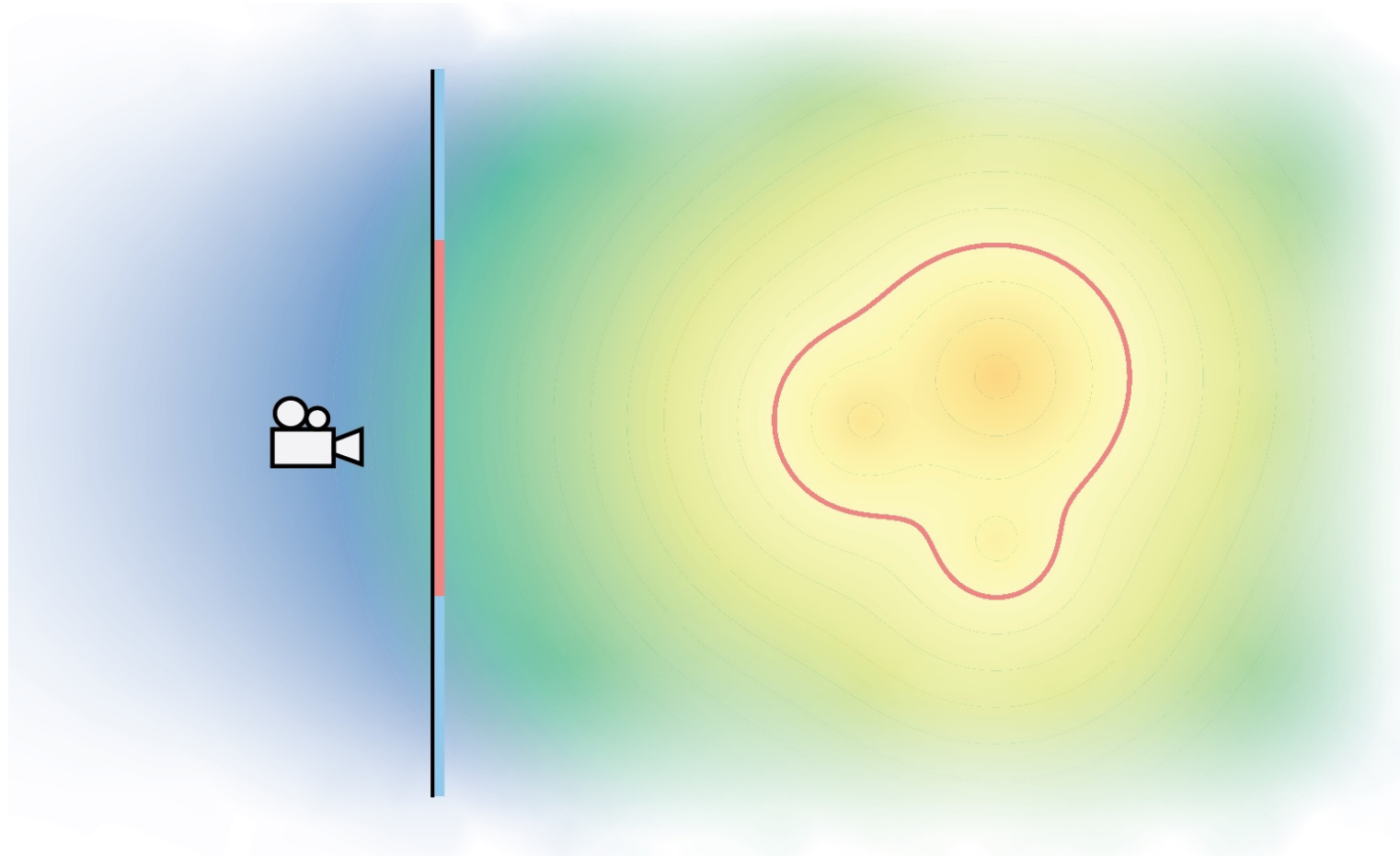
POSE ESTIMATION CAN FAIL WITH BIASED GRADIENTS



Multiple Initializations



WARPED-AREA SAMPLING CAN BE USED FOR SIGNED DISTANCE FIELDS RENDERING



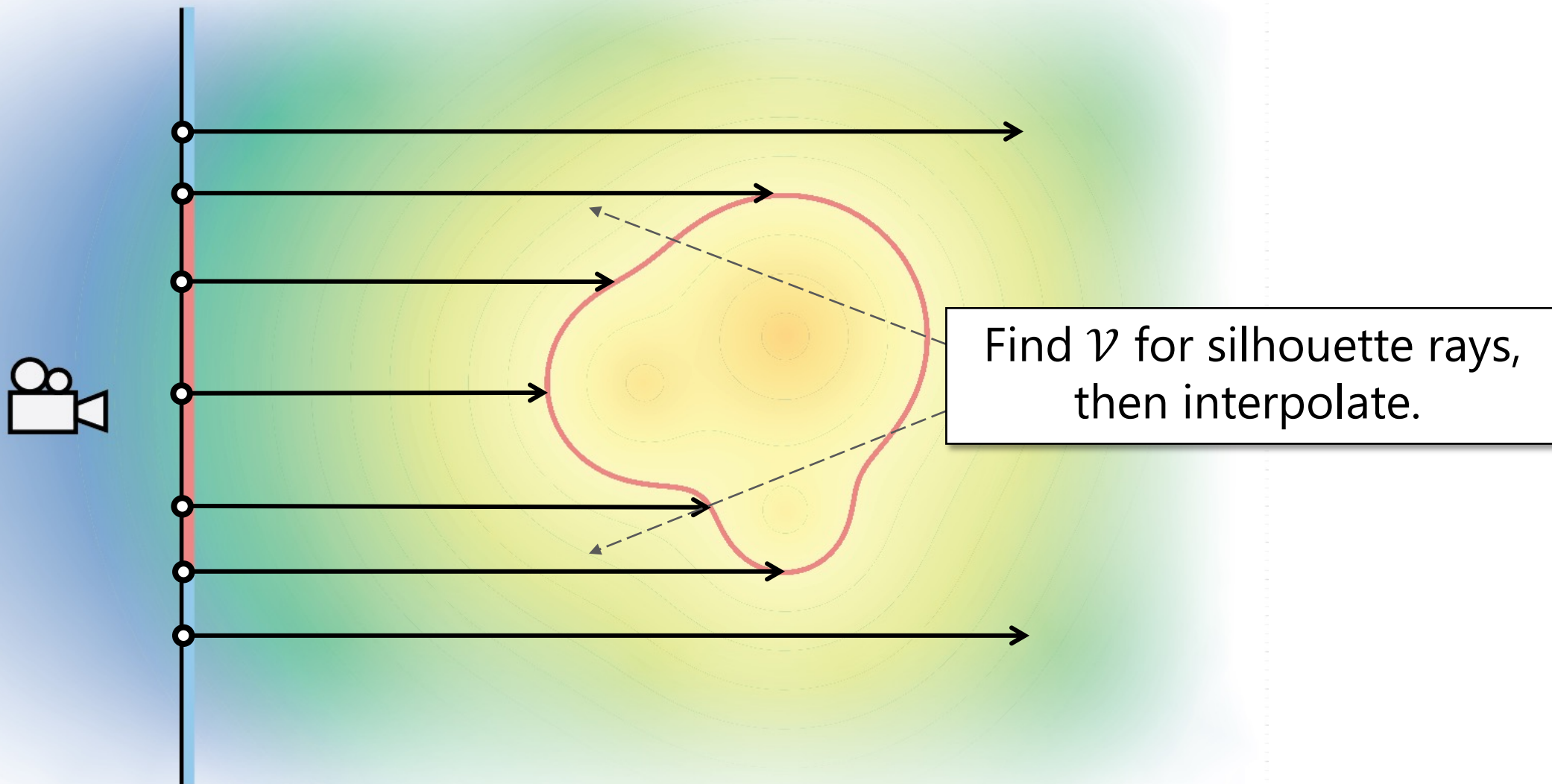
Differentiable Signed Distance Function Rendering

DELIO VICINI, École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
SÉBASTIEN SPEIERER, École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
WENZEL JAKOB, École Polytechnique Fédérale de Lausanne (EPFL), Switzerland

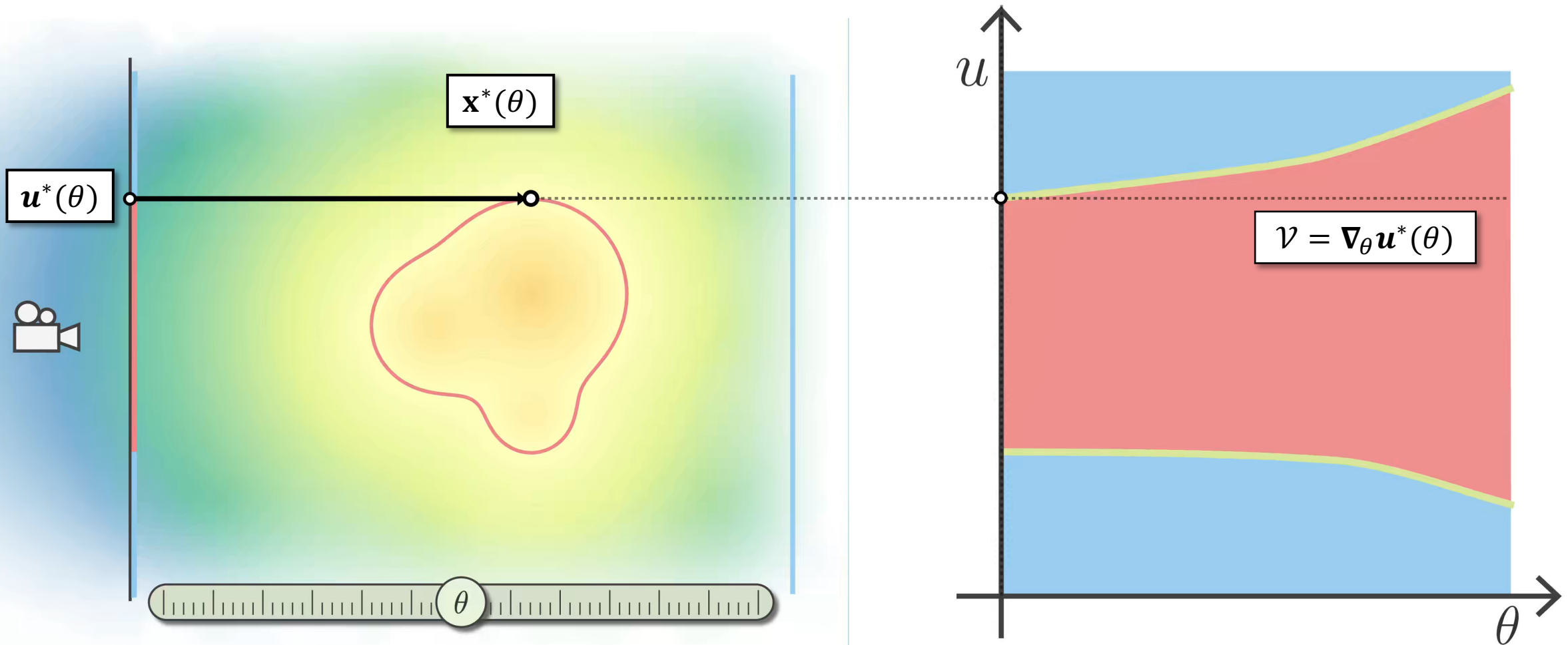
Differentiable Rendering of Neural SDFs through Reparameterization

Sai Praveen Bangaru MIT CSAIL USA sbangaru@mit.edu	Michaël Gharbi Adobe Research USA mgharbi@adobe.com	Tzu-Mao Li UC San Diego USA tzli@ucsd.edu	Fujun Luan Adobe Research USA fluan@adobe.com	Kalyan Sunkavalli Adobe Research USA sunkaval@adobe.com
Miloš Hašan Adobe Research USA mihasan@adobe.com	Sai Bi Adobe Research USA sbi@adobe.com	Zexiang Xu Adobe Research USA zexu@adobe.com	Gilbert Bernstein MIT CSAIL & UC Berkeley USA gilbo@berkeley.edu	Frédo Durand MIT CSAIL USA fredo@mit.edu

Computing A Consistent $\mathcal{V}(u)$ For An Arbitrary SDF



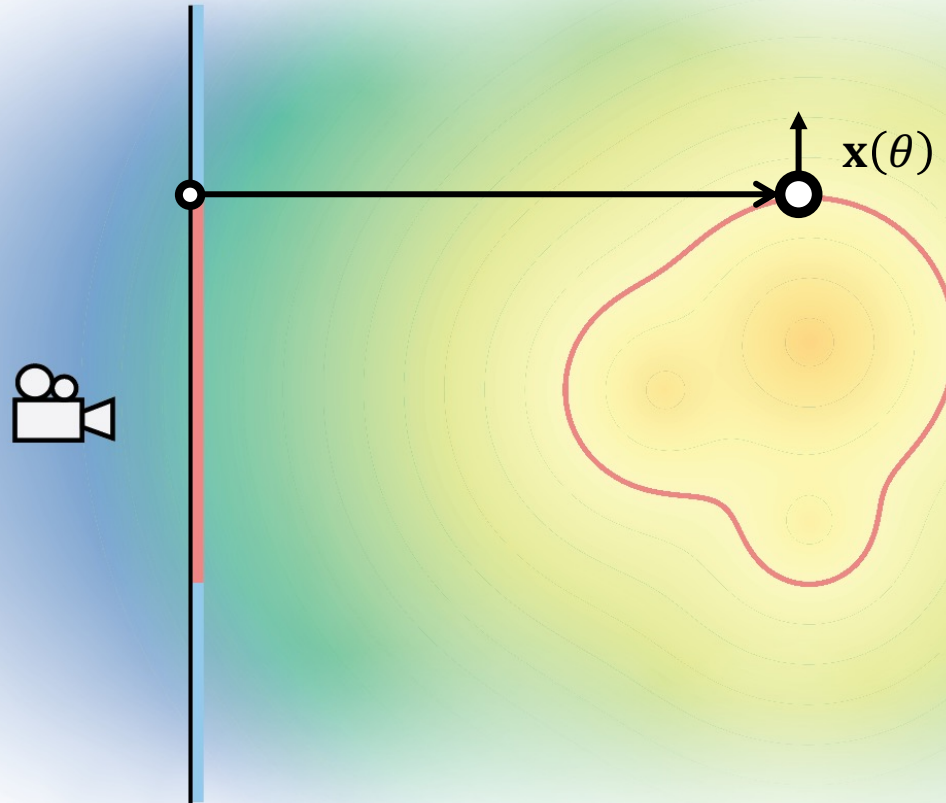
Computing \mathcal{V} By Differentiating The Silhouette Position u^*



Computing \mathcal{V} : Implicit Fn. Theorem + Chain Rule

1. Compute $\nabla_{\theta} \mathbf{x}^*(\theta)$ using implicit fn. theorem:

Derivative of any point in SDF can be computed by differentiating SDF function \mathbf{f}

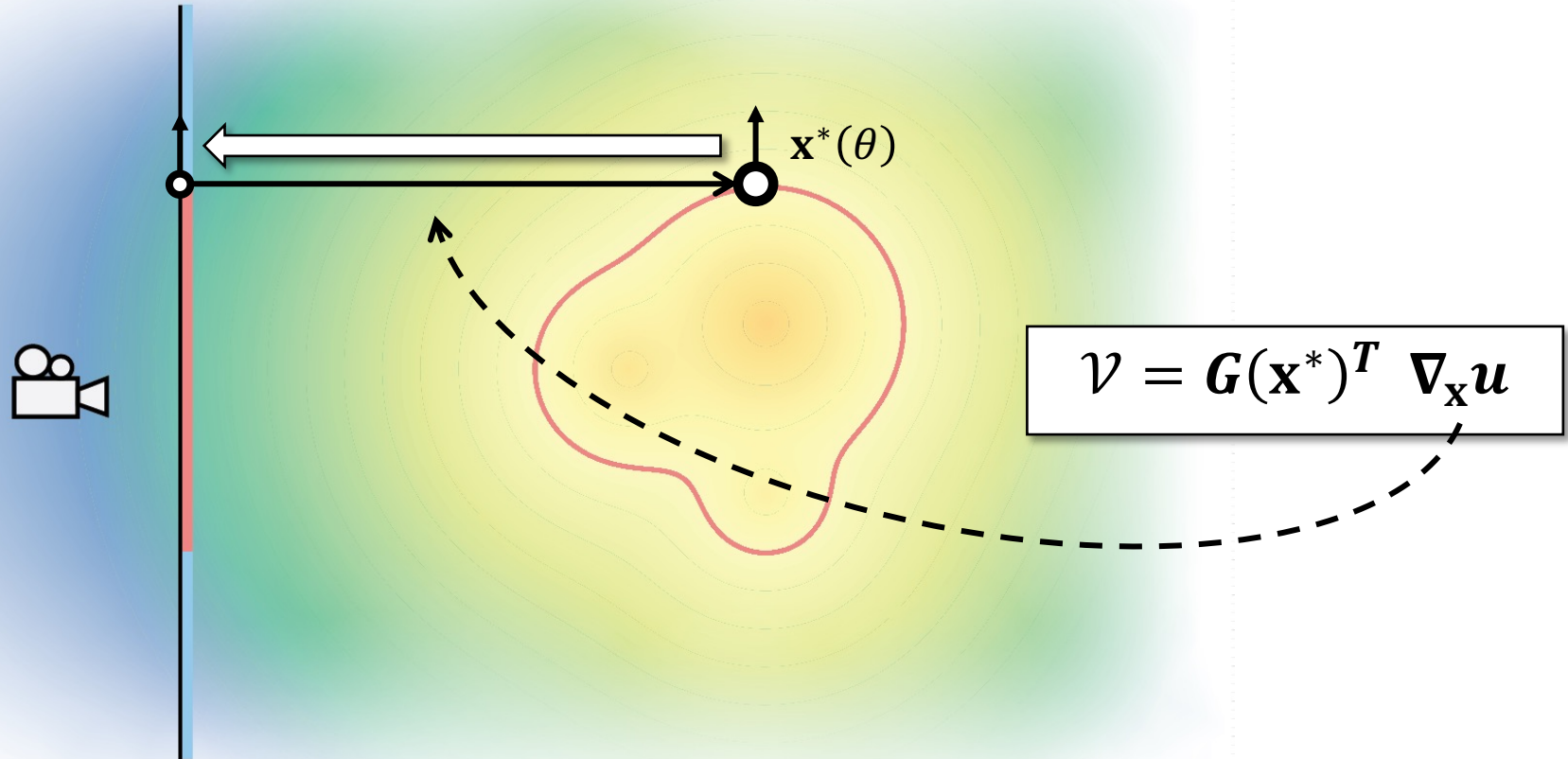


$$\nabla_{\theta} \mathbf{x}(\theta) = \nabla_{\theta} f(\mathbf{x}; \theta) \cdot \hat{\mathbf{n}}$$

$$= \mathbf{G}(\mathbf{x})$$

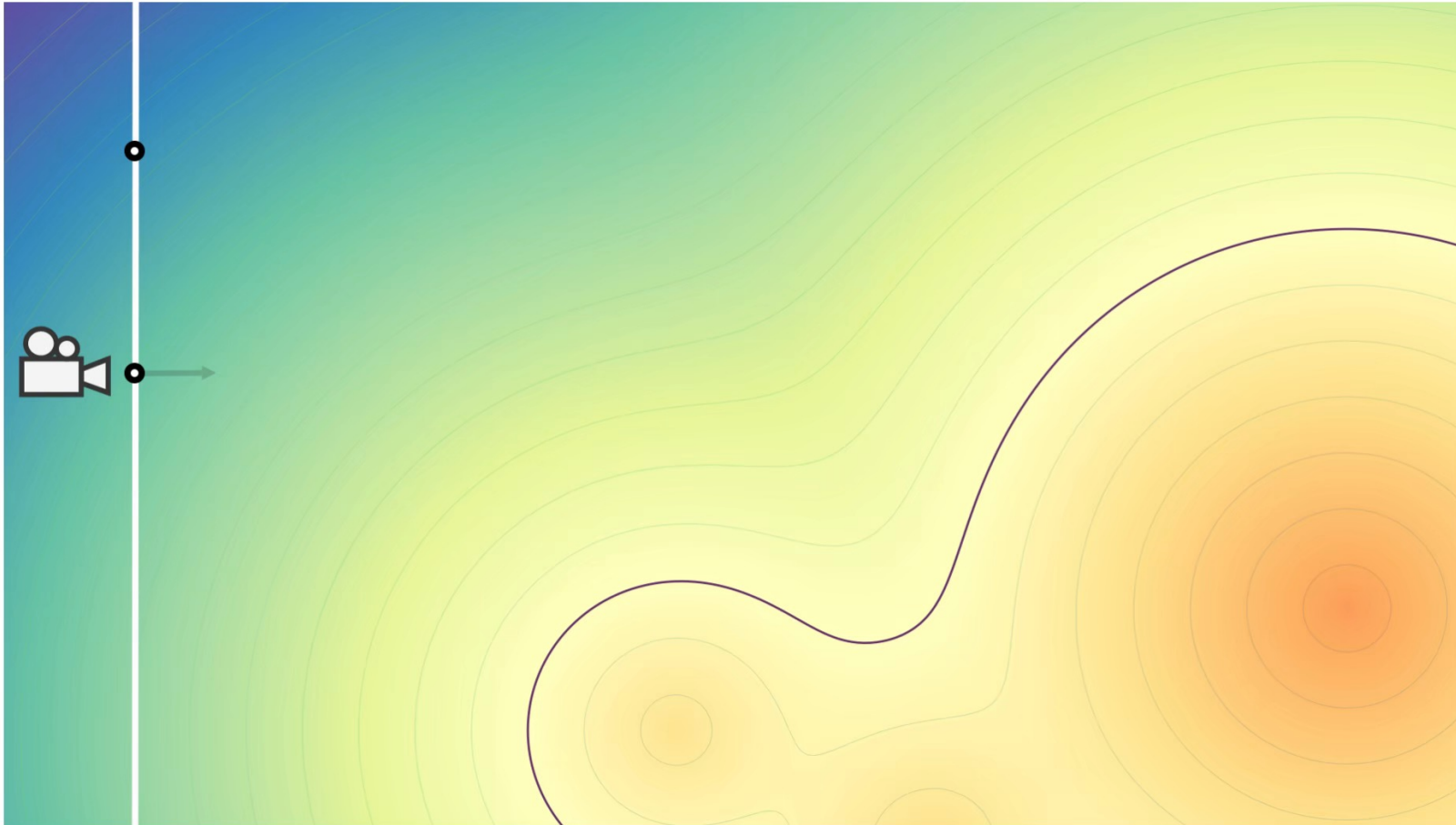
Computing \mathcal{V} : Implicit Fn. Theorem + Chain Rule

1. Compute $\nabla_{\theta} \mathbf{x}^*(\theta)$ using Implicit Fn. Theorem:
2. Propagate $G(\mathbf{x}^*)$ to sample space through chain rule ($u \rightarrow \mathbf{x}$):



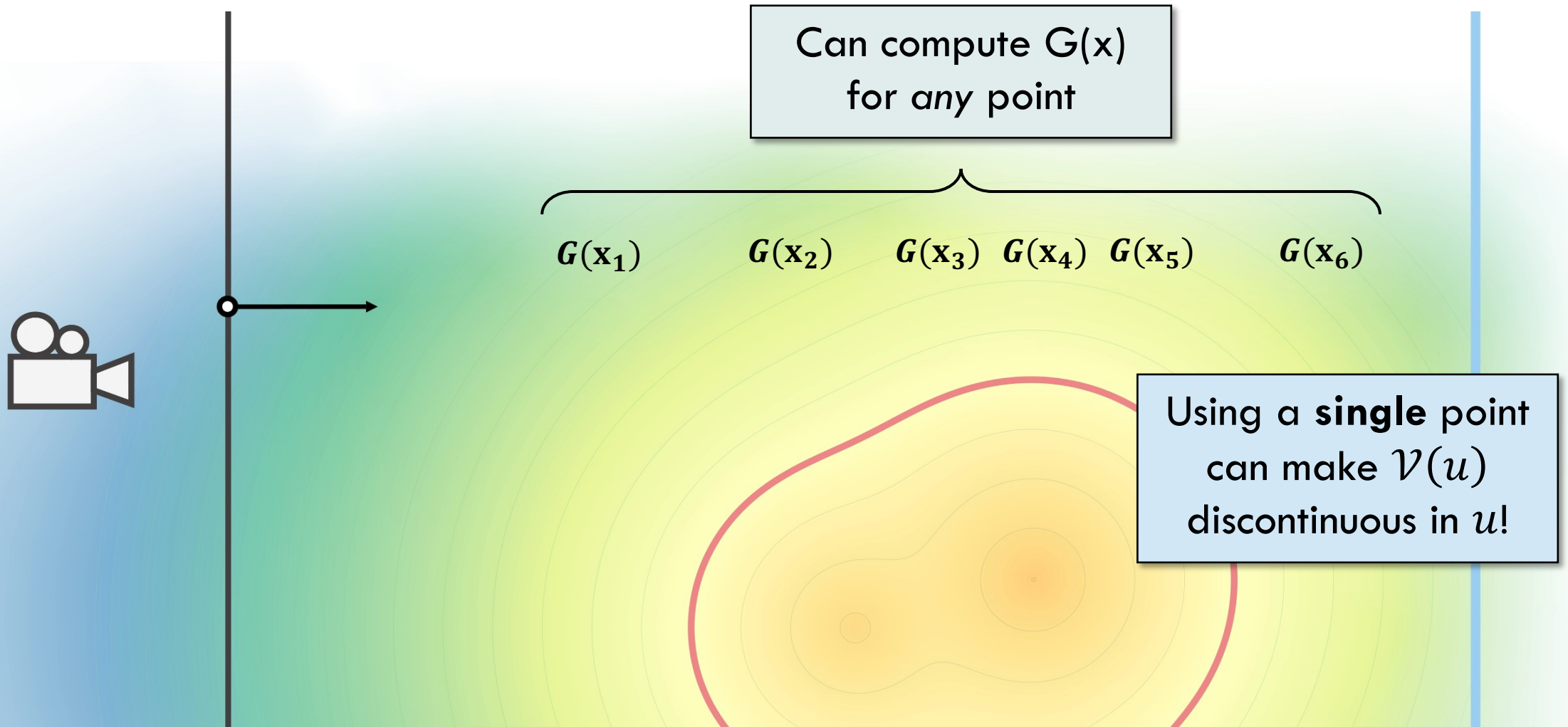
Computing $\mathcal{V}(u)$ For An Arbitrary Ray

Ray-SDF Intersection: Sphere Tracing



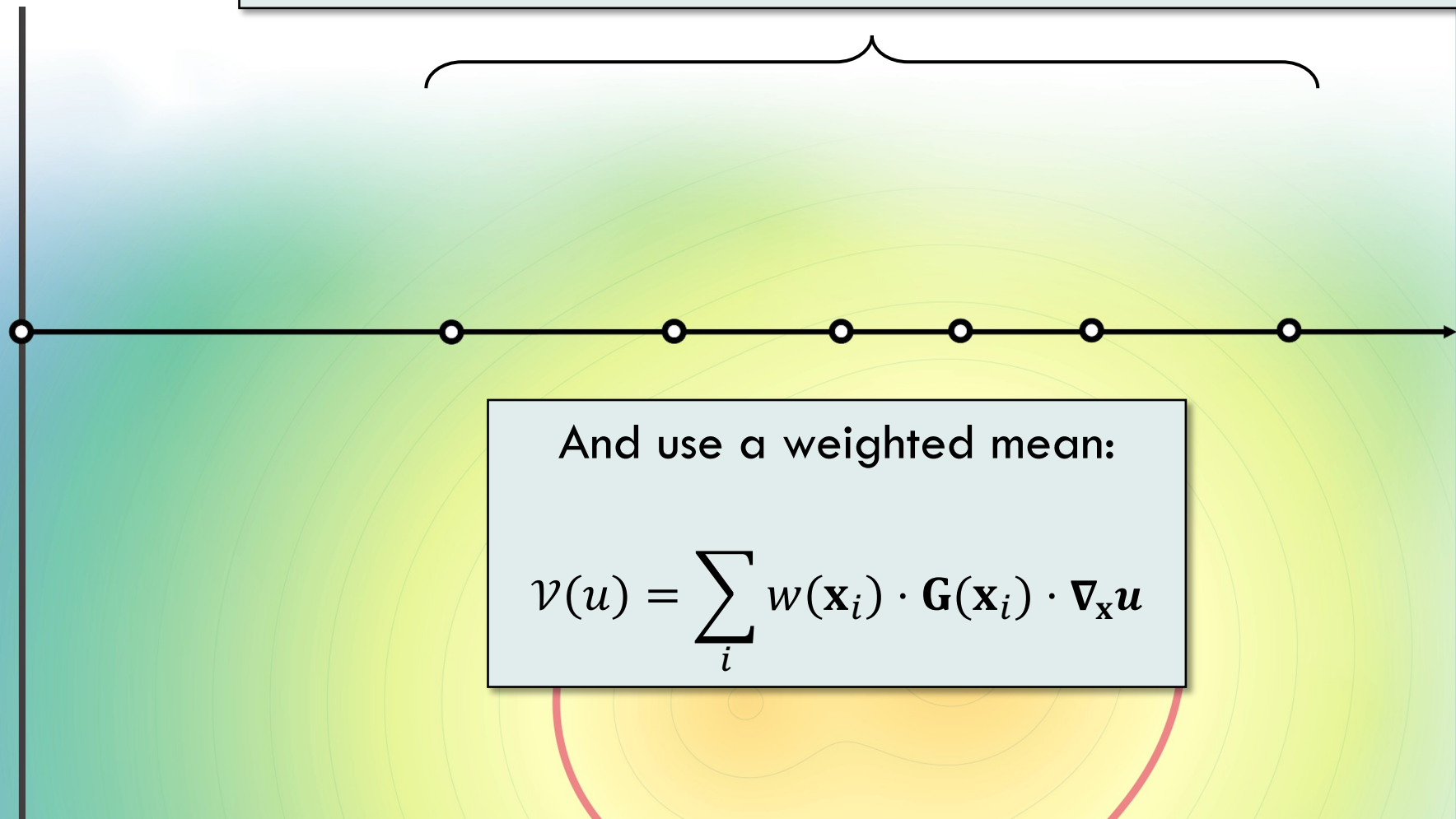
about
ette rays?

Can Compute $\mathcal{V}(u)$ using the Geometry Derivative $G(\mathbf{x})$ of any Sphere Tracer point



Computing $\mathcal{V}(u)$ as Weighted Mean of $G(\mathbf{x})$ over Sphere Tracer Points

Solution: Compute silhouette weights $w(\mathbf{x})$



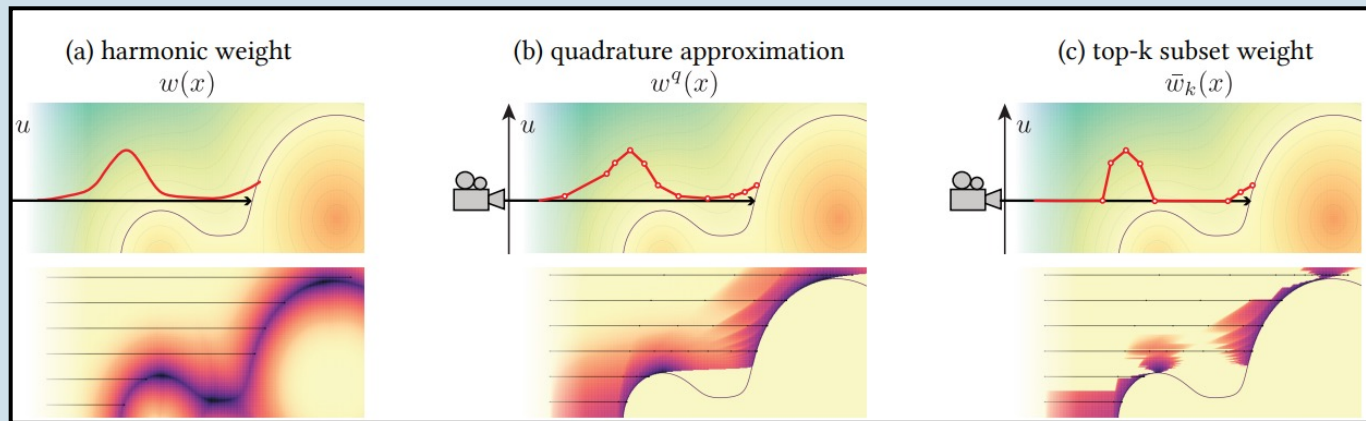
And use a weighted mean:

$$\mathcal{V}(u) = \sum_i w(\mathbf{x}_i) \cdot \mathbf{G}(\mathbf{x}_i) \cdot \nabla_{\mathbf{x}} u$$

Weighted-Mean $\mathcal{V}(u)$ Is Both Consistent And Continuous

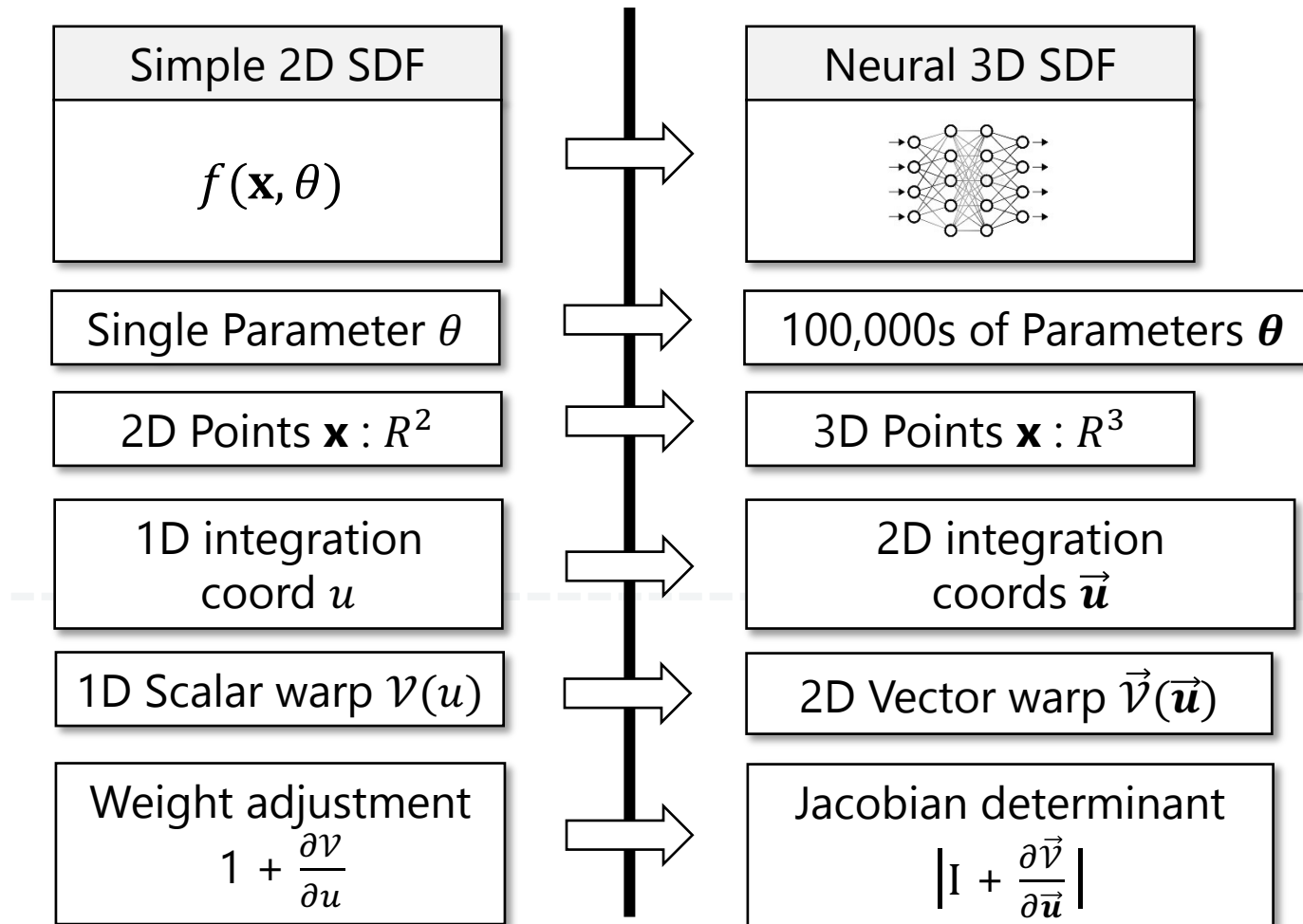
✓ Continuous

See **Paper**: Harmonic & Quadrature Weighting

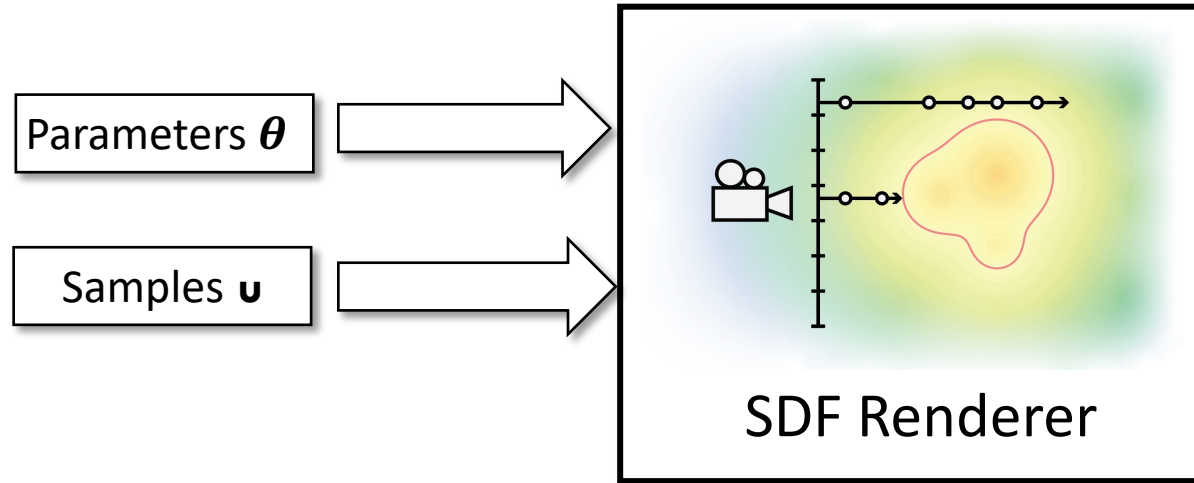


PROJECT PAGE

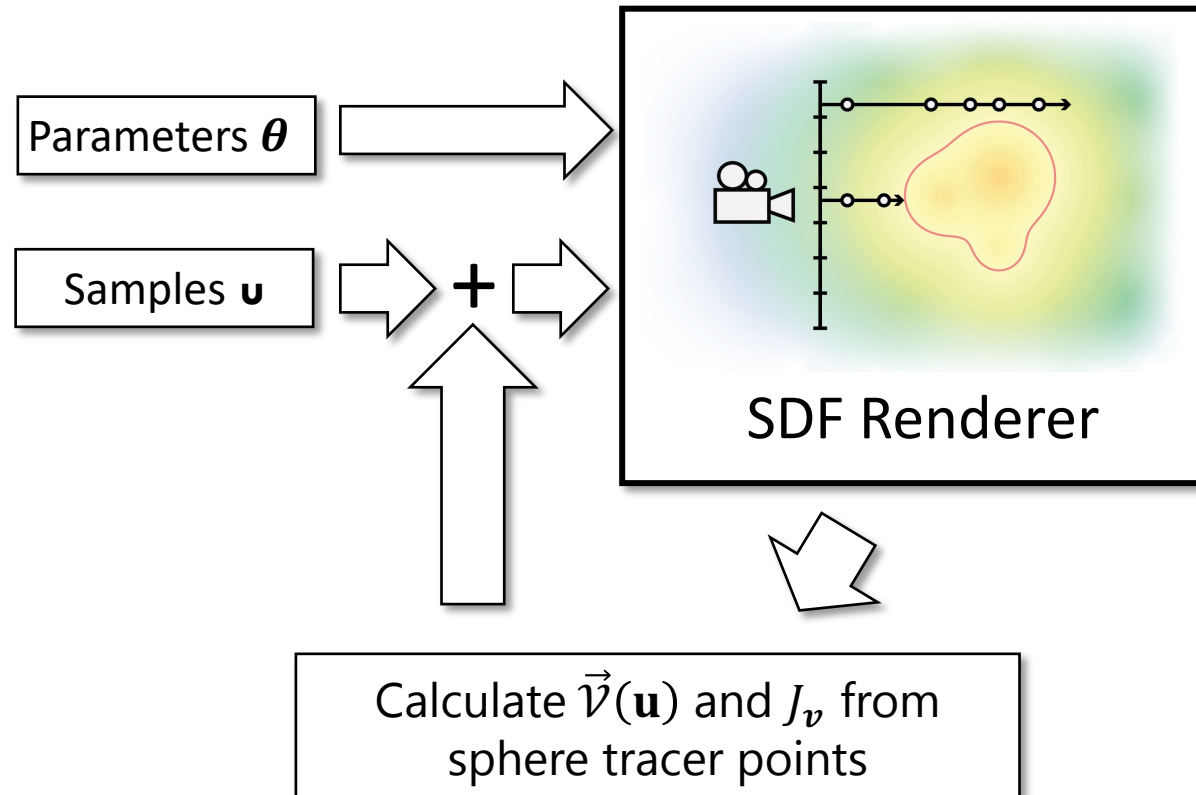
Scaling Up From Simple 2D To Neural 3D



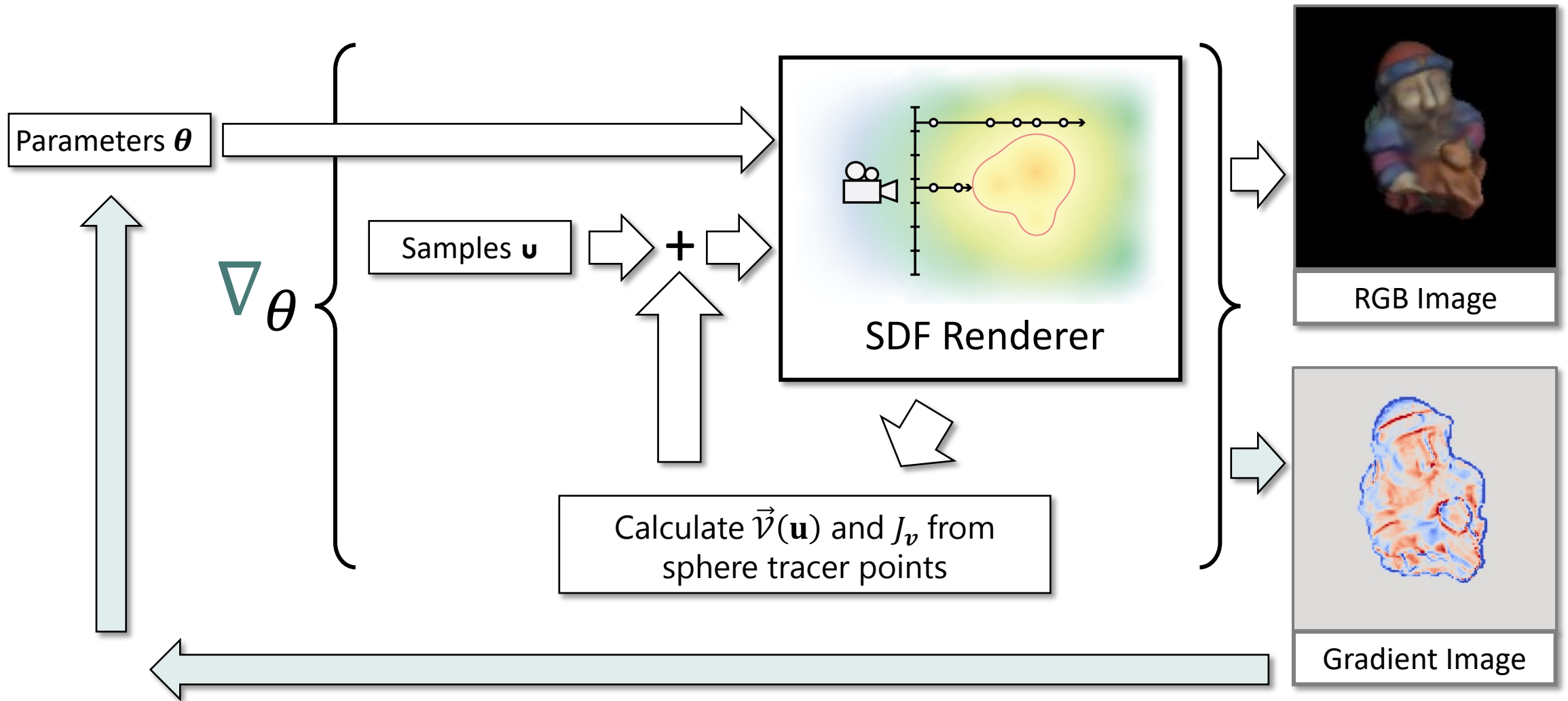
Putting It All Together: First, Render SDF As Usual



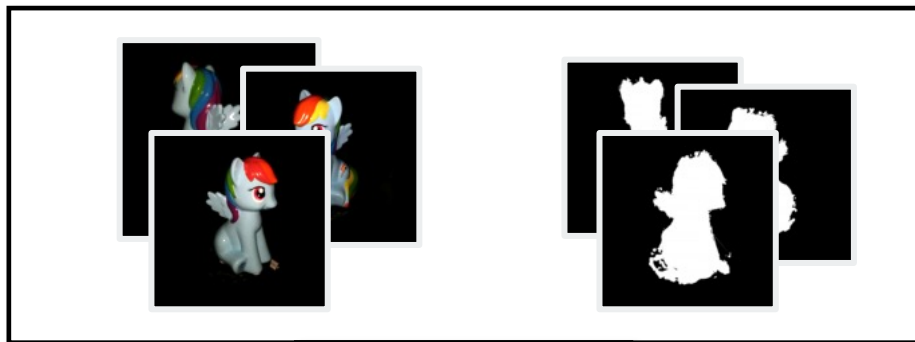
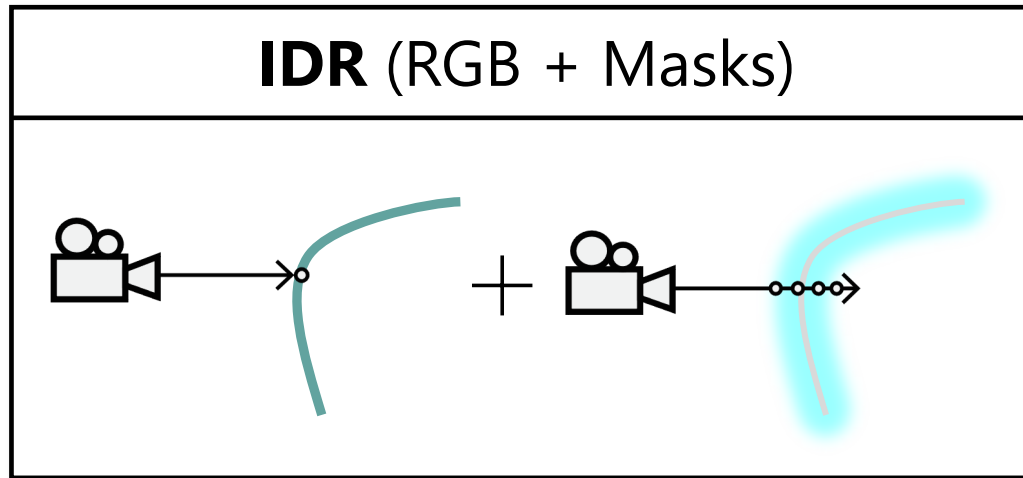
Putting It All Together: Then, Reparameterize Samples



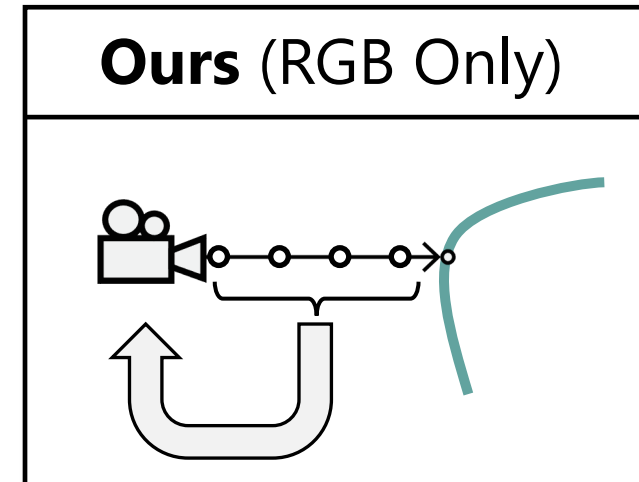
Putting It All Together: Finally, Differentiate With AD



Comparisons Against IDR (Yariv et al. 2020): A Sharp-Surface Model With Segmentation Mask Inputs

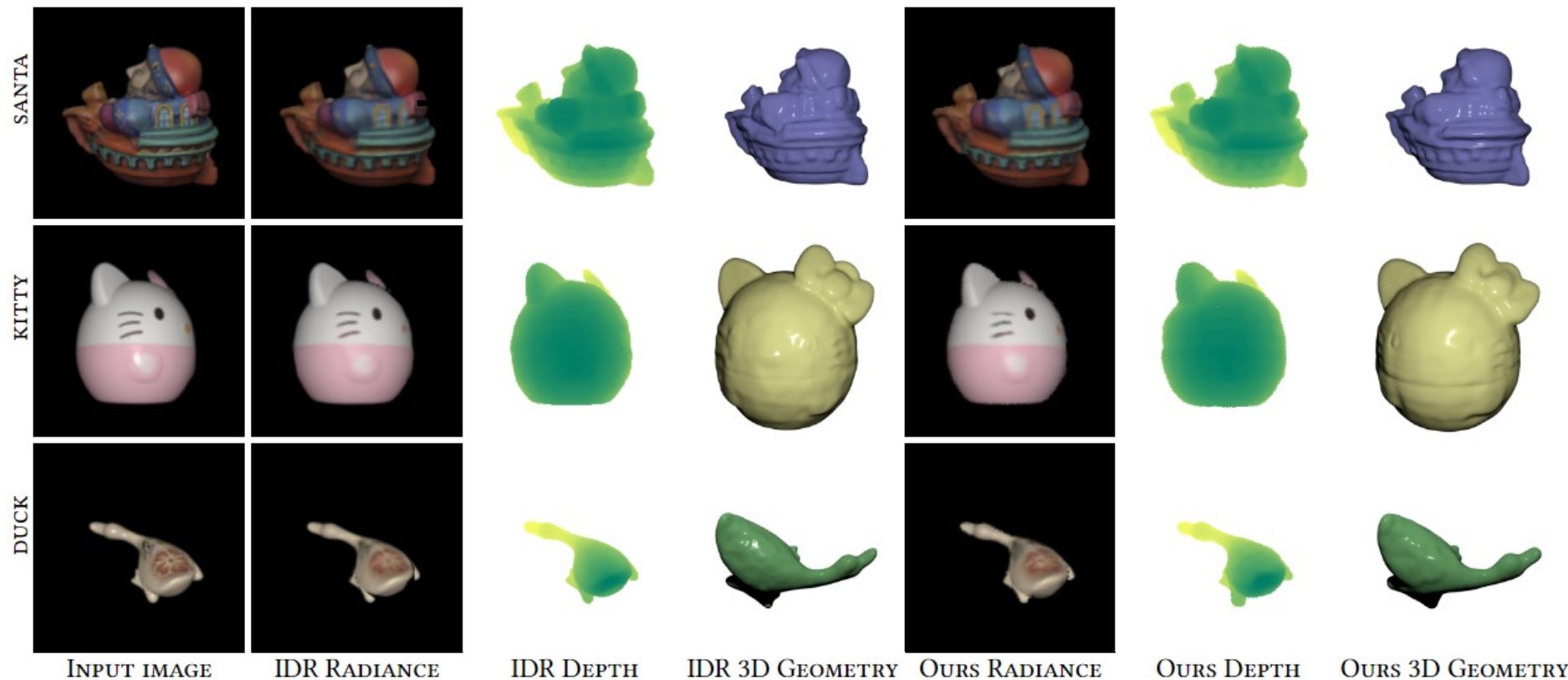
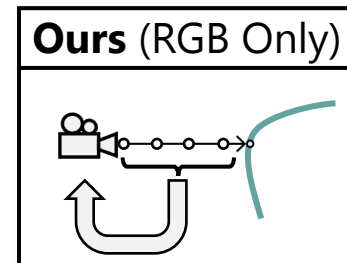
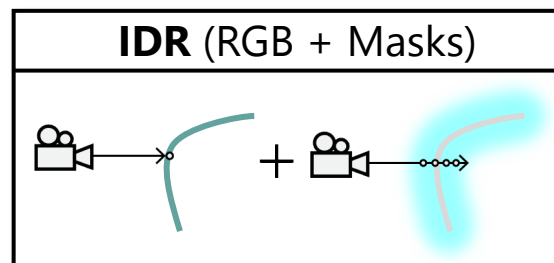


INPUTS

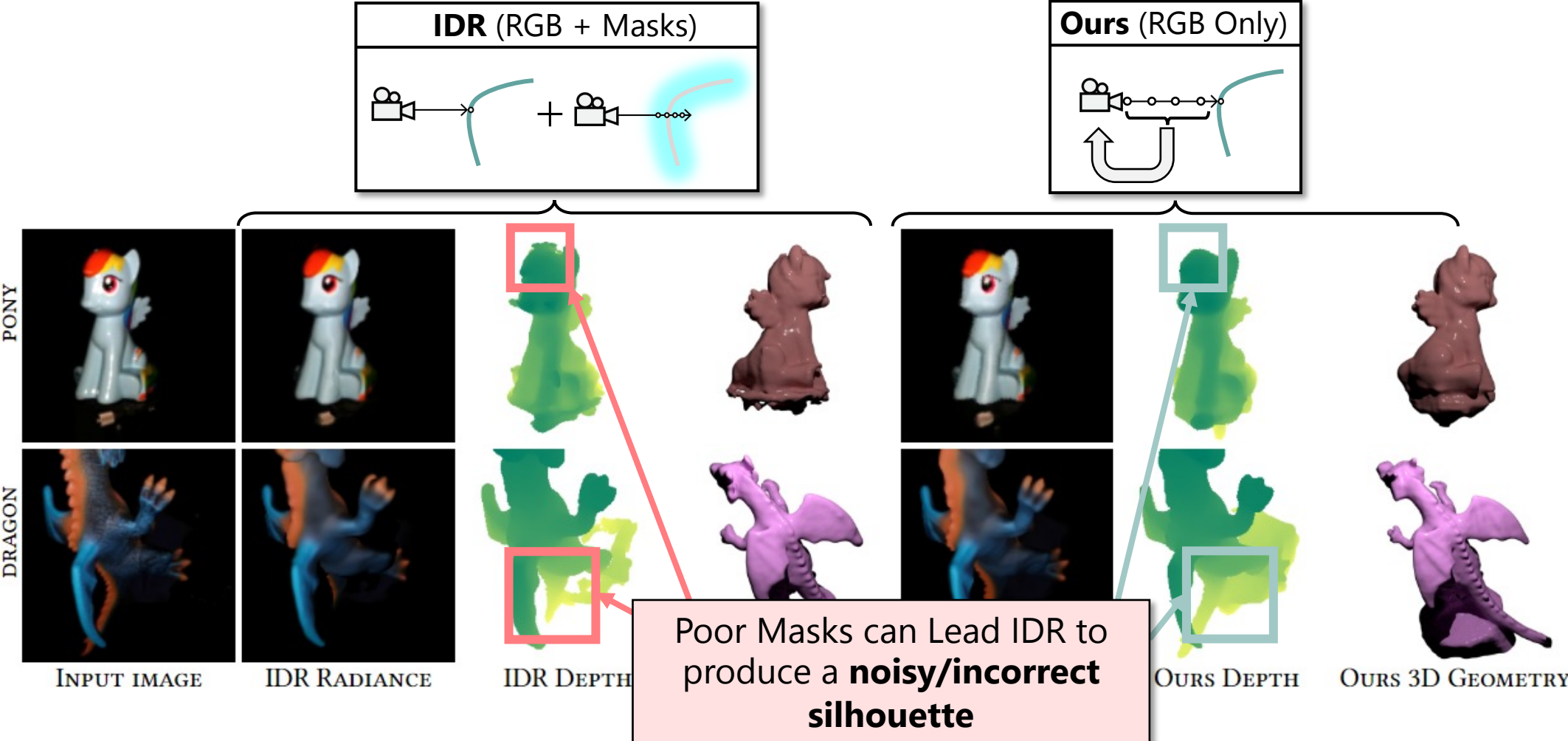


INPUTS

Reconstructions On-Par With IDR *Without* Using Masks

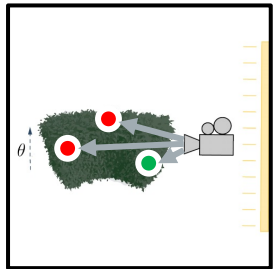


Cleaner Reconstructions Than IDR On Real Data with Poor Segmentation Masks

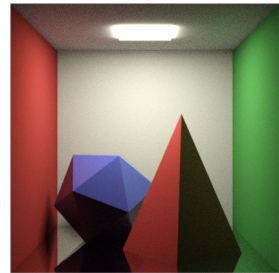


CONCLUSIONS

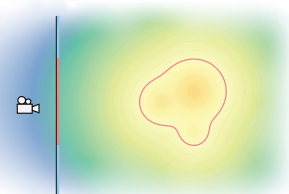
Problem With Edge Sampling



Depth complexity

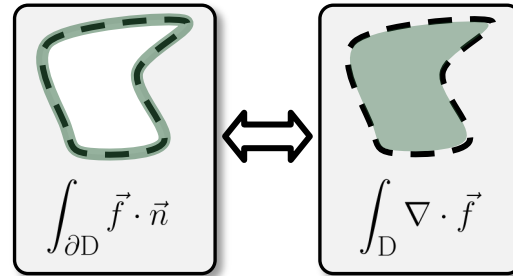


Specularities

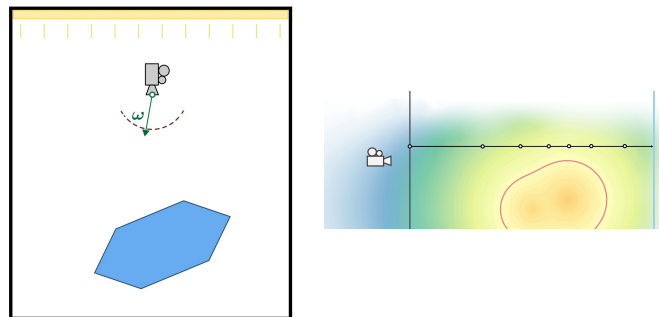


Implicit Representations

Warped-Area Sampling



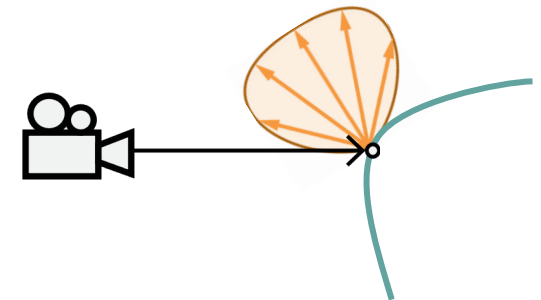
Convert to Area Sampling



On-the-fly Warp Field Estimation

Future Directions

More SDFs in Physically-based Pipelines



Boundary-Aware Reparameterization For Other Domains

