

# Participating media



# Course announcements

- Programming assignment 4 posted, due Friday 4/9 at 23:59.
  - How many of you have looked at/started/finished it?
  - Any questions?
- Take-home quiz 6 due tonight.
- Take-home quiz 7 will be posted tonight.
- Details about final project proposals will be posted today.
  - Proposals due April 16<sup>th</sup>.
  - Extra office hours to discuss topics.
- Vote on Piazza for recitation hours.
- Suggest on Piazza topics for this week's reading group.



# Graphics faculty candidate talk



- Speaker: **Mina Lukovic** (MIT)
- Title: **Transforming design and fabrication with computational discovery**
- Abstract: Recent advances in material science and computational fabrication provide promising opportunities for product design, mechanical and biomedical engineering, medical devices, robotics, architecture, art, and science. Engineered materials and personalized fabrication are revolutionizing manufacturing culture and having a significant impact on various scientific and industrial products. As new fabrication technologies emerge, effective computational tools are needed to fully exploit the potential of computational fabrication.

In this talk, I argue that computer science and mathematical models are essential for advancing and accelerating design practices and harnessing the potential of novel fabrication technologies. My aim is to transform the design workflow with computational tools and artificial intelligence and change “what?” and “how?” we can fabricate. I will discuss how the insights from differential geometry can help us understand existing materials and create new materials with specific performance. I will further demonstrate how grammars and deep learning can be combined for the autonomous discovery of terrain-optimized robots. Finally, I will show a data-efficient machine learning algorithm for optimal experiment design. Although different in methodologies, all these projects follow the same design pipeline and tackle two critical challenges: (i) providing tools for inverse design and (ii) accelerating design and fabrication with sophisticated algorithms.

# Graphics lab meeting talk



- Speaker: **Pratul Srinivasan** (Google Research)
- Title: **Extending Neural Radiance Fields**
- Abstract: Neural volumetric scene representations such as Neural Radiance Fields (NeRF) have spurred exciting progress across many inverse rendering tasks. However, there is still a long way to go before NeRF-like representations can be used instead of more traditional representations in graphics pipelines. I'll be talking about our recent work to extend NeRF to support anti-aliasing during rendering, real-time rendering, and relighting.



# Overview of today's lecture

- Wrap-up BRDFs.
- Participating media.
- Scattering material characterization.
- Volume rendering equation.
- Ray marching.
- Volumetric path tracing.
- Delta tracking.

# Slide credits

Most of these slides were directly adapted from:

- Wojciech Jarosz (Dartmouth).



# Fog

---



[Steve Lacey](#)

# Clouds & Crepuscular rays

---





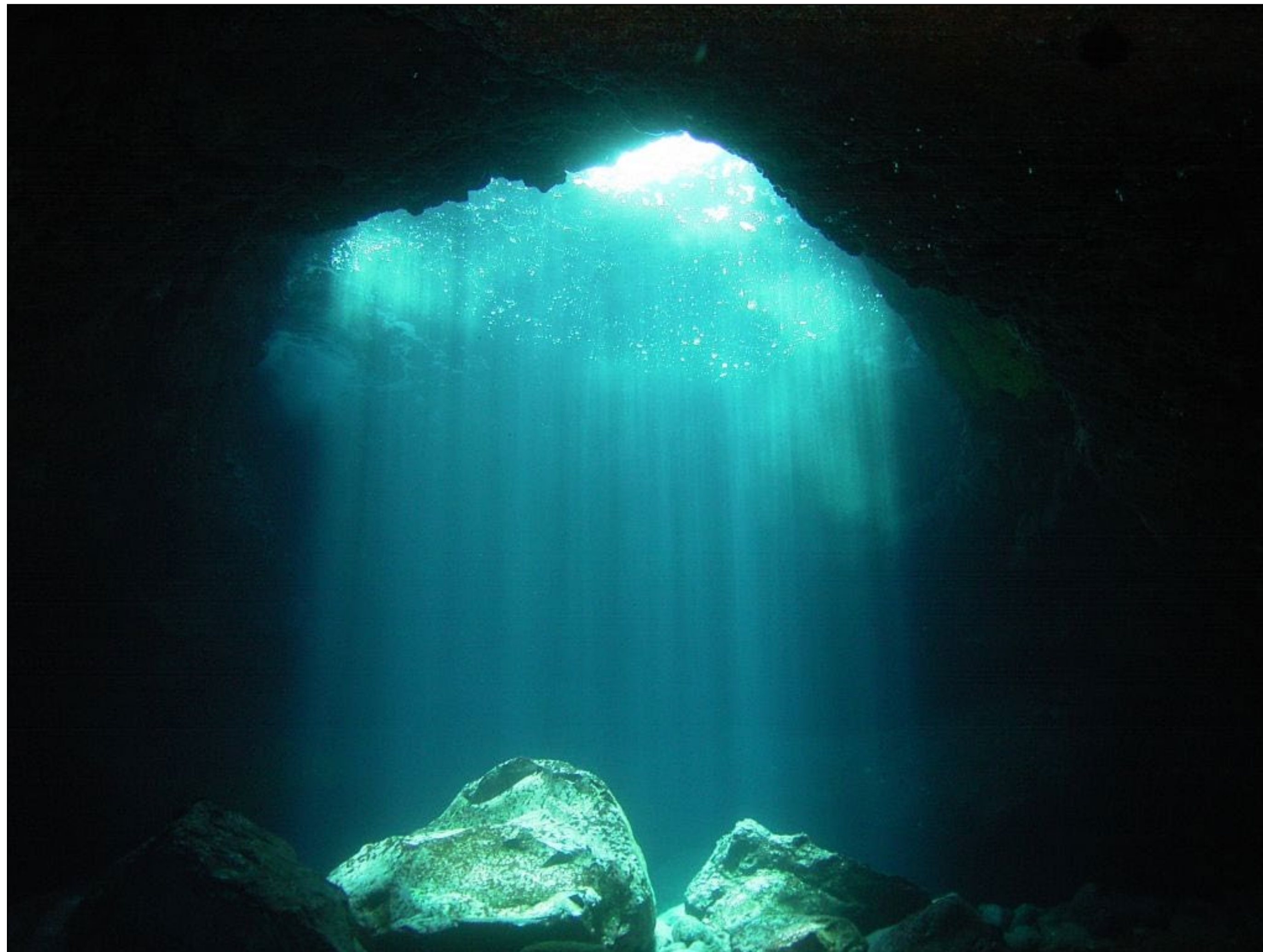
# Fire

---



# Underwater

---





# Surface or Volume?

---









# Antelope Canyon, Az.

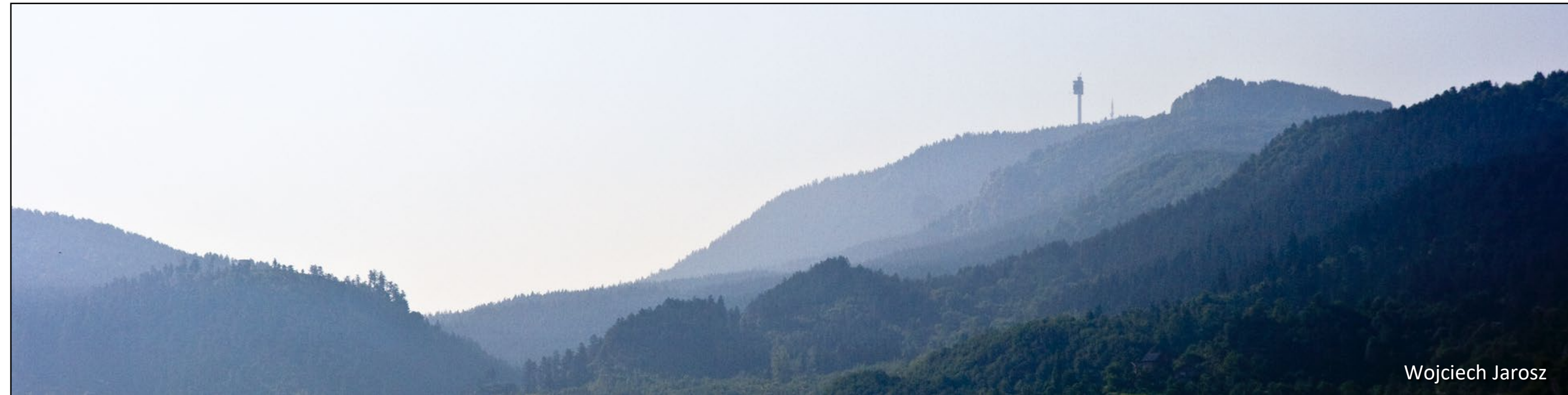
---



Wojciech Jarosz

# Aerial (Atmospheric) Perspective

---





# Leonardo da Vinci (1480)

---



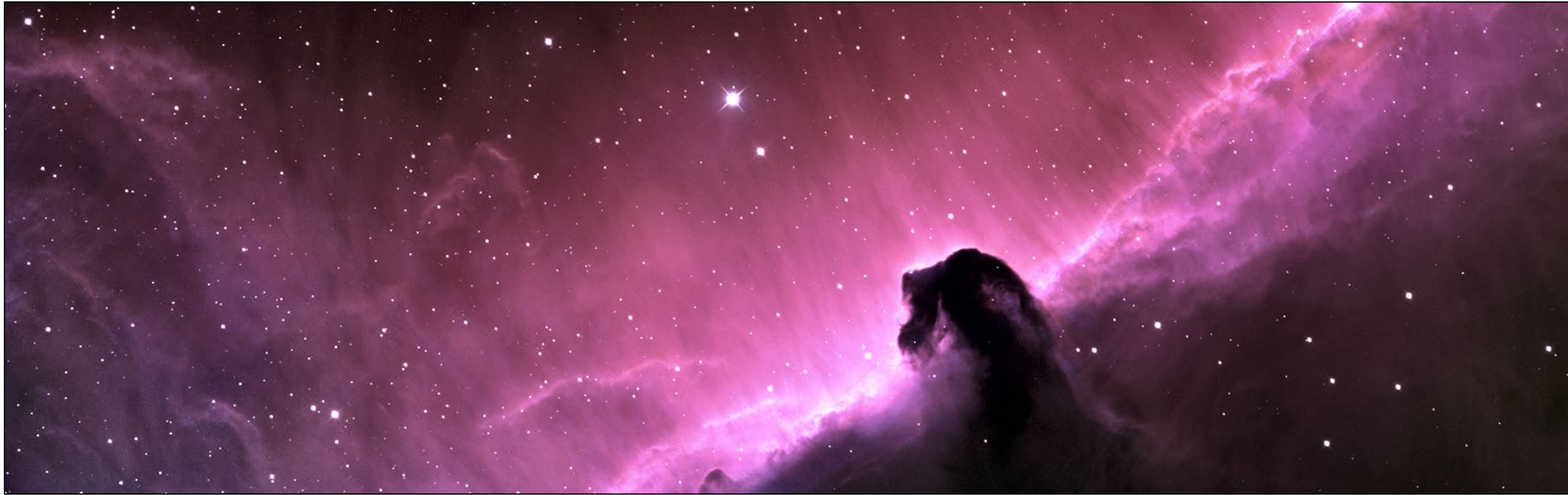
*Thus, if one is to be five times as distant, make it five times bluer.*

—Treatise on Painting, Leonardo Da Vinci, pp 295, circa 1480.



# Nebula

---





# Emission

---



# Absorption

---





# Scattering

---



# Defining Participating Media

---

Typically, we do not model particles of a medium explicitly (wouldn't fit in memory, completely impractical to ray trace)

The properties are described statistically using various coefficients and densities

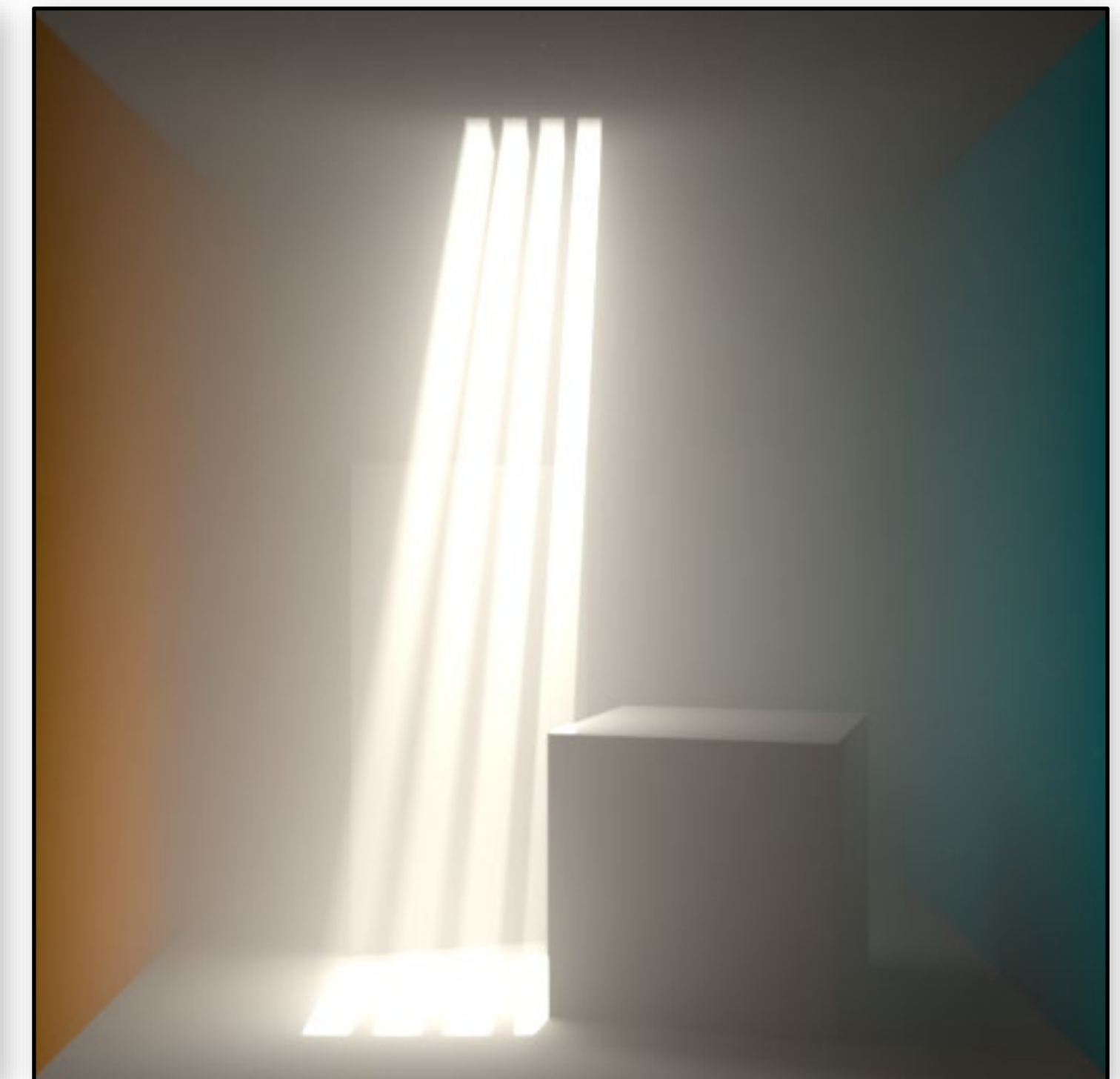
- Conceptually similar idea as microfacet models

# Defining Participating Media

---

Homogeneous:

- Infinite or bounded by a surface or simple shape



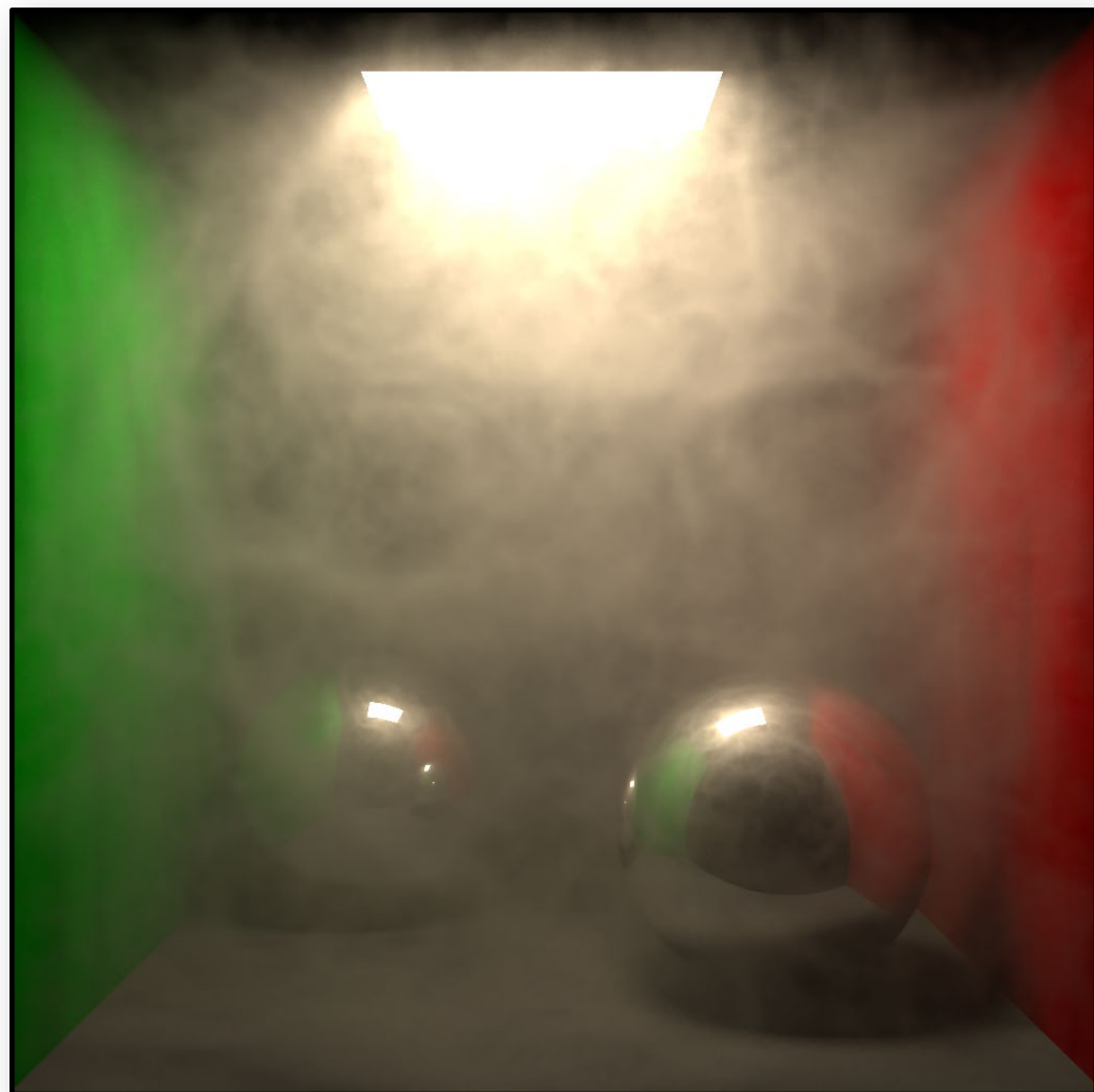


# Defining Participating Media

---

Heterogeneous (spatially varying coefficients):

- Procedurally, e.g., using a noise function
- Simulation + volume discretization, e.g., a voxel grid



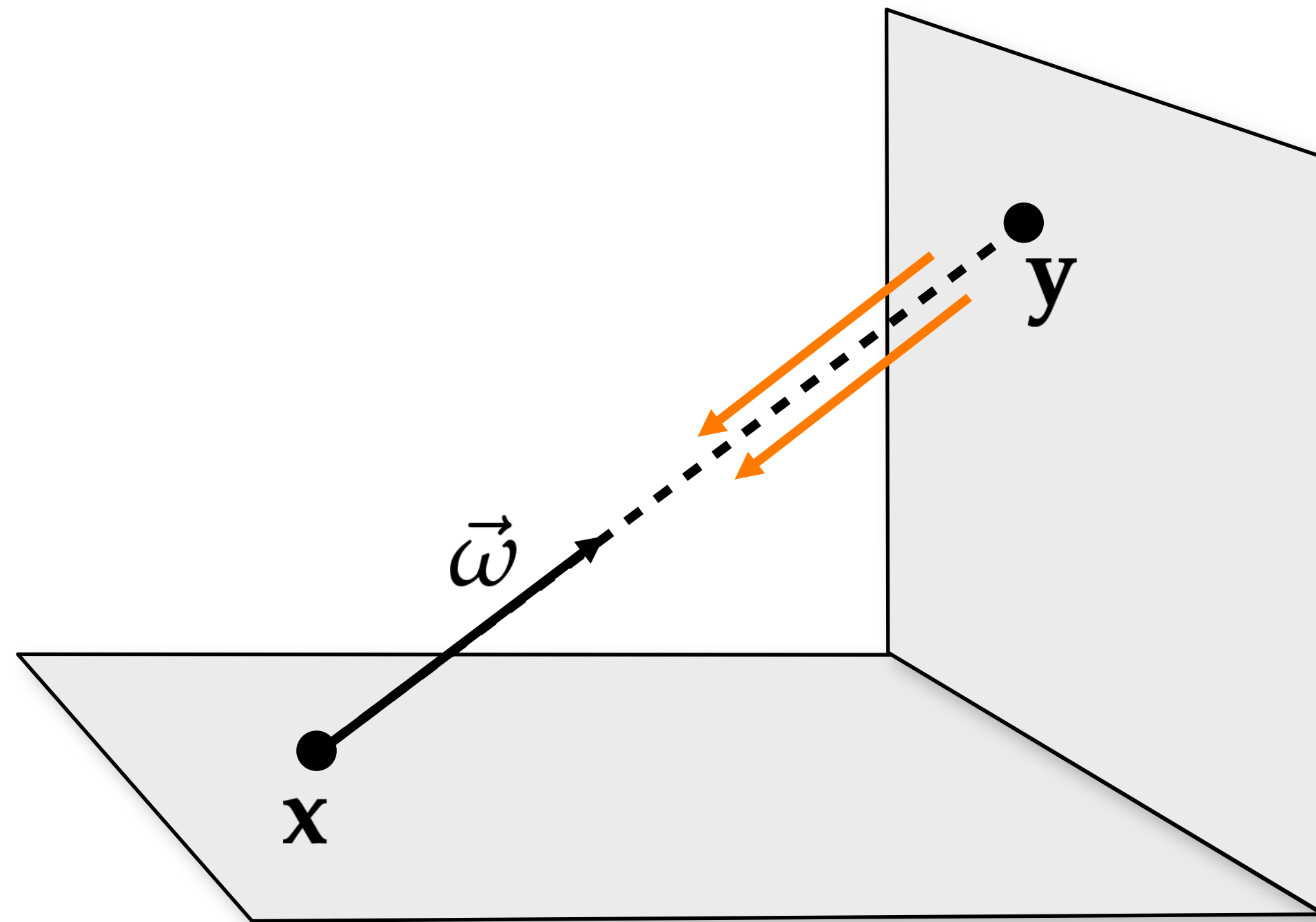
# Radiance

---

The main quantity we are interested in for rendering is radiance

Previously: radiance *remains constant* along rays between surfaces

$$L_i(\mathbf{x}, \vec{\omega}) = L_o(\mathbf{y}, -\vec{\omega})$$
$$\mathbf{y} = r(\mathbf{x}, \vec{\omega})$$



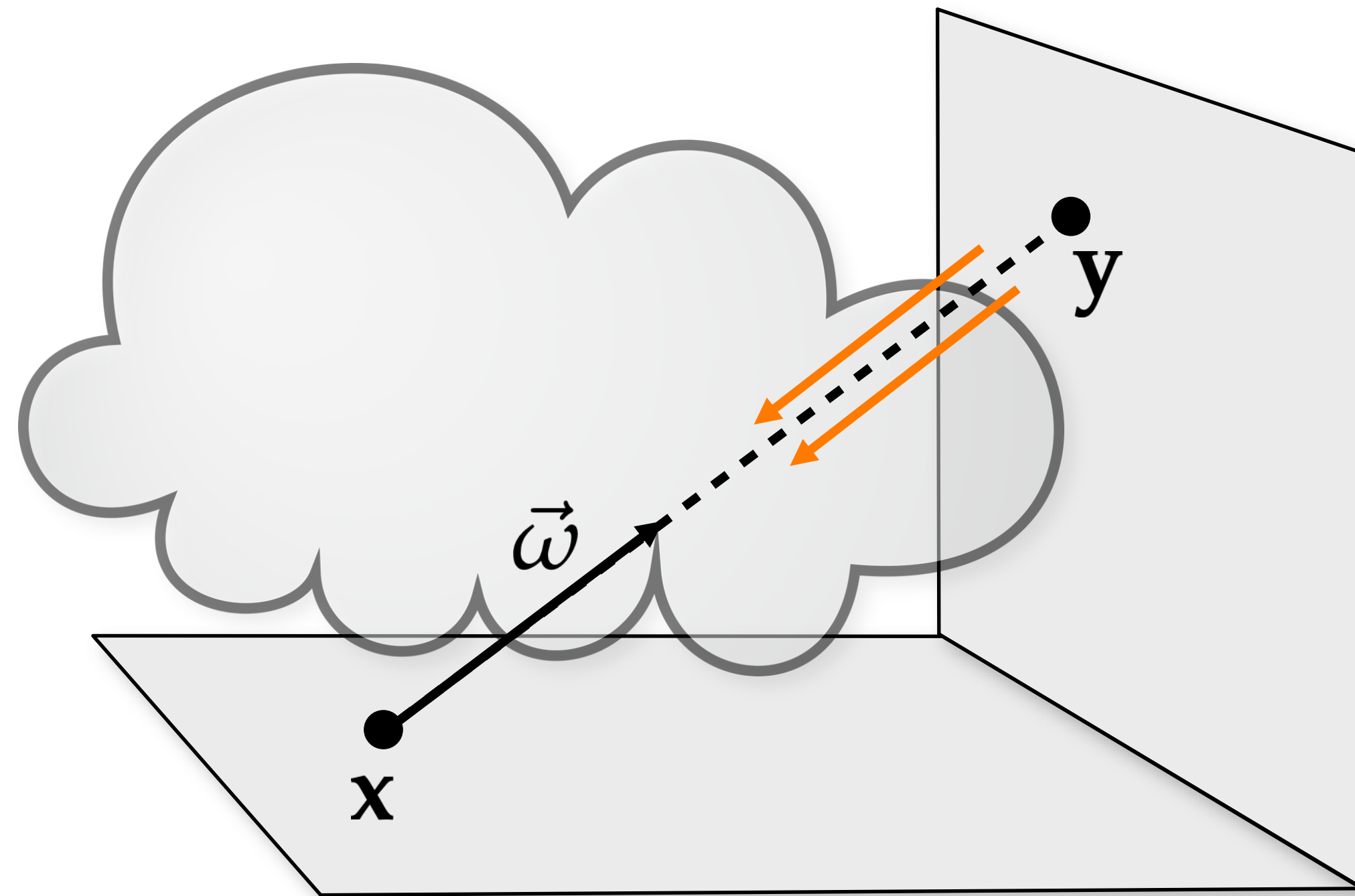


# Radiance

The main quantity we are interested in for rendering is radiance

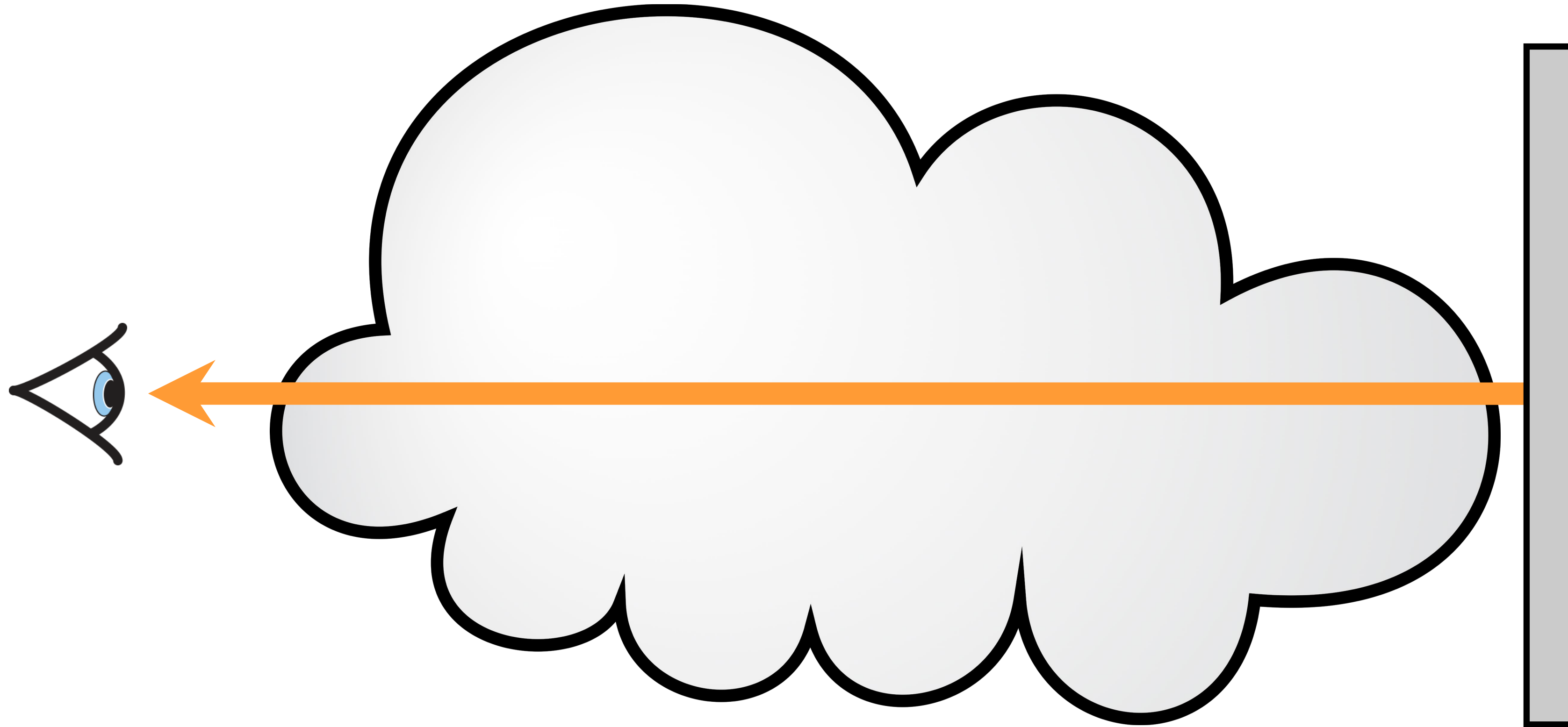
Now: radiance may *change* along rays between surfaces

$$L_i(\mathbf{x}, \vec{\omega}) \neq L_o(\mathbf{y}, -\vec{\omega})$$
$$\mathbf{y} = r(\mathbf{x}, \vec{\omega})$$



# Participating Media

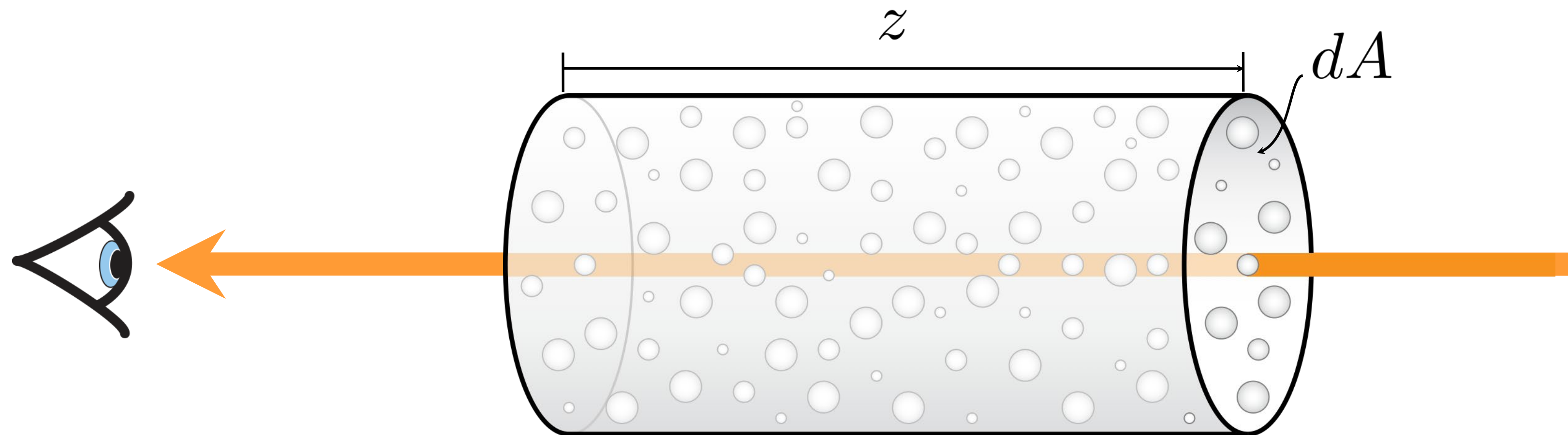
---





# Differential Beam

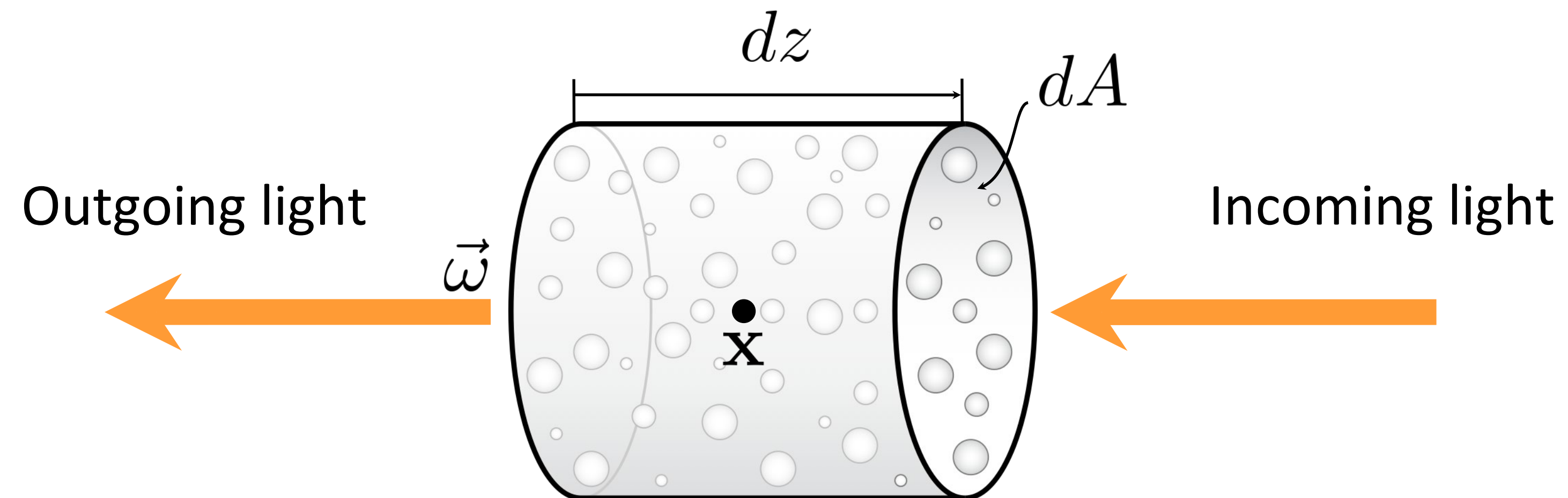
---



How much light is *lost/gained* along the differential beam due to interactions of light with the medium?

# Differential Beam Segment

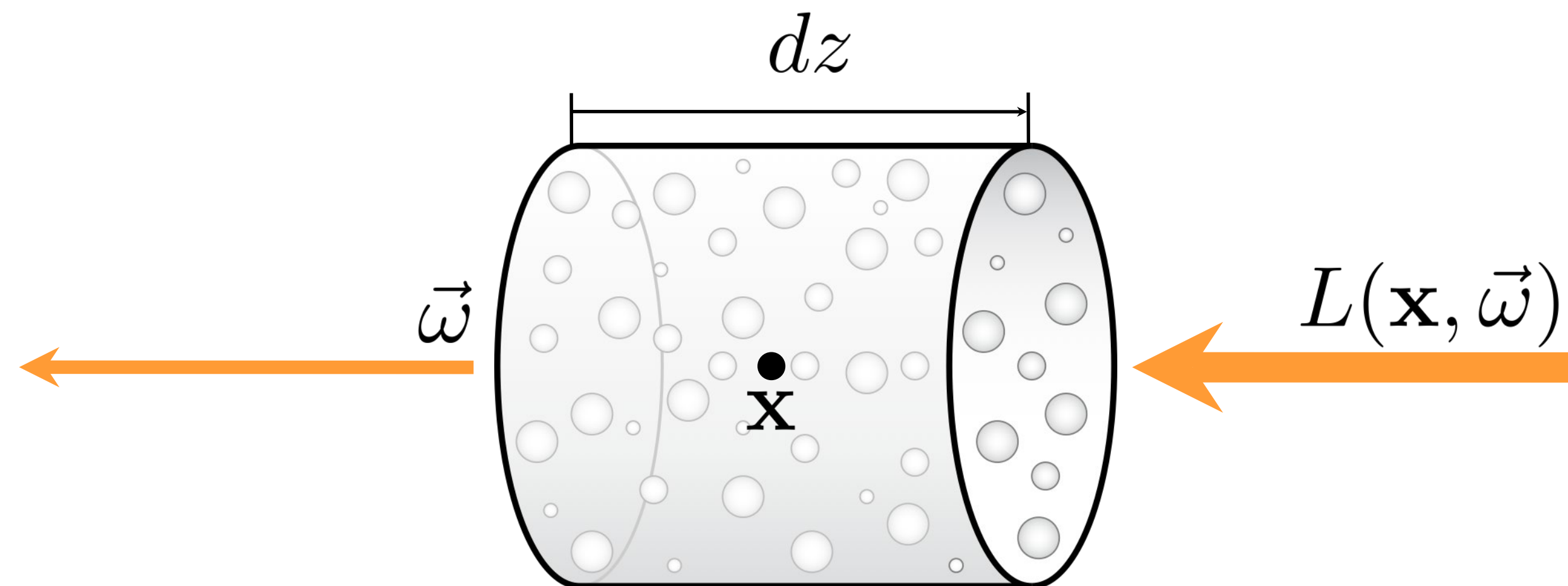
---





# Absorption

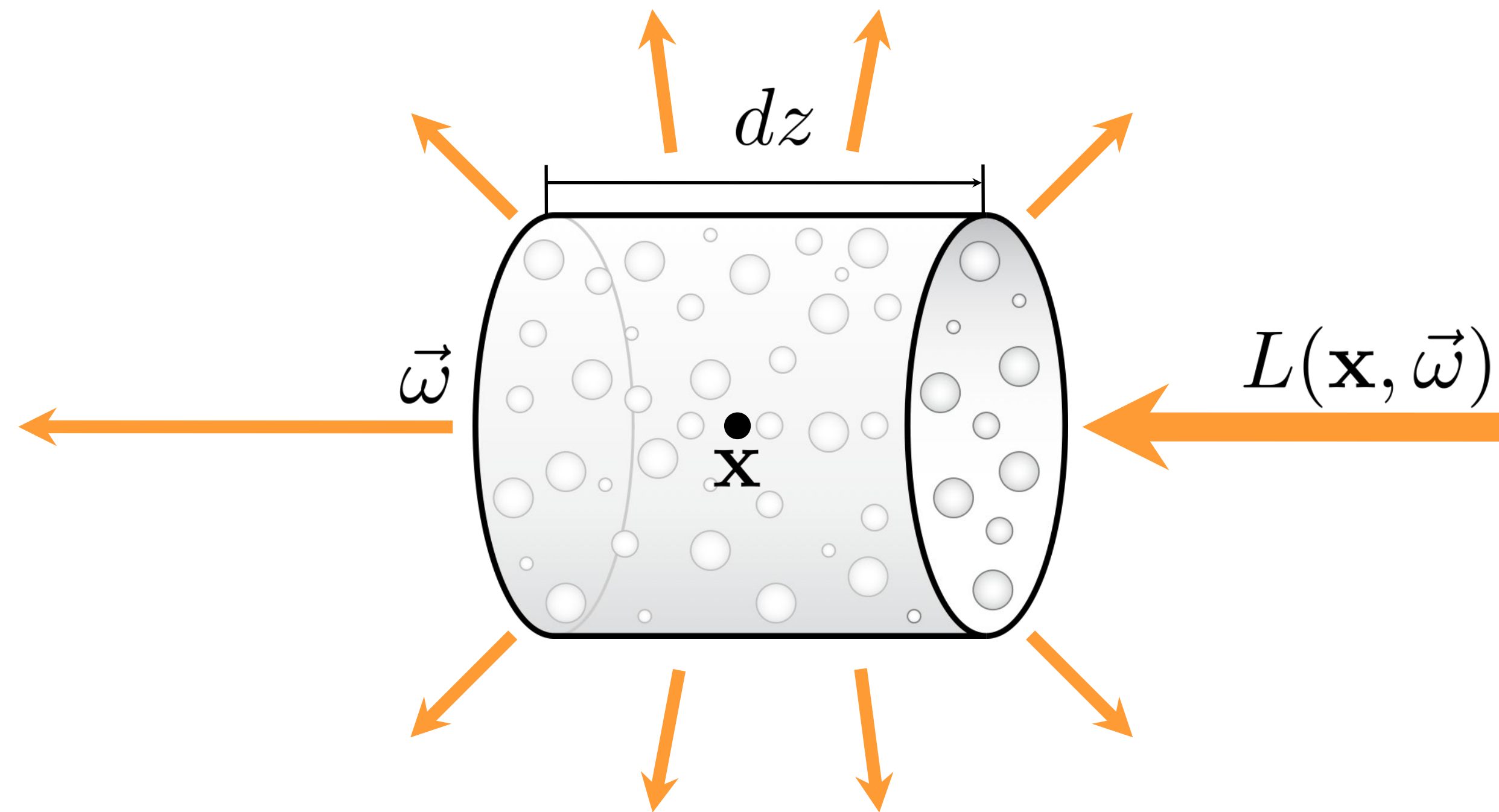
---



$$dL(\mathbf{x}, \vec{\omega}) = -\sigma_a(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz$$

$\sigma_a(\mathbf{x})$  : absorption coefficient  $[m^{-1}]$

# Out-scattering



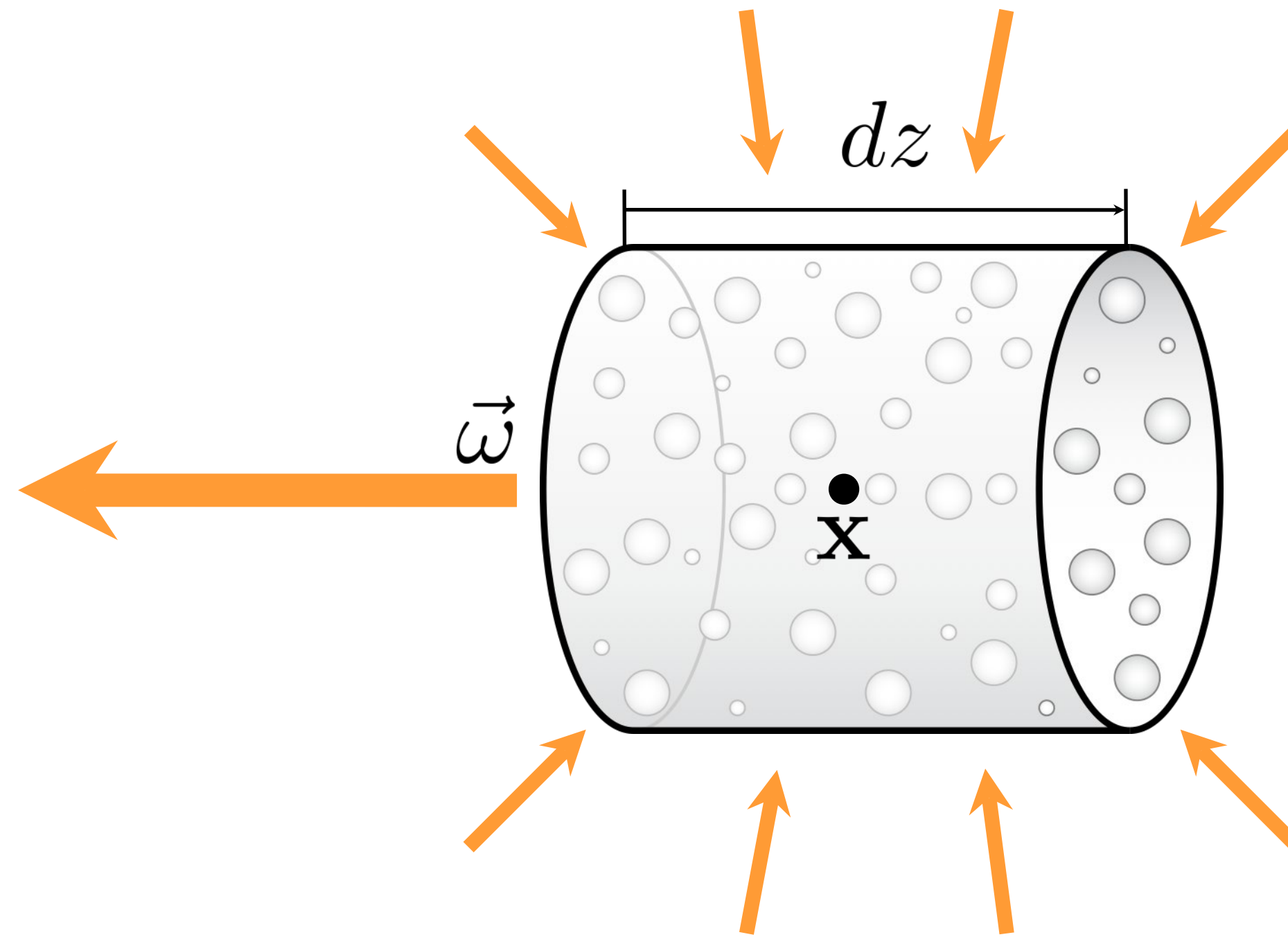
$$dL(\mathbf{x}, \vec{\omega}) = -\sigma_s(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz$$

$\sigma_s(\mathbf{x})$  : scattering coefficient  $[m^{-1}]$



# In-scattering

---



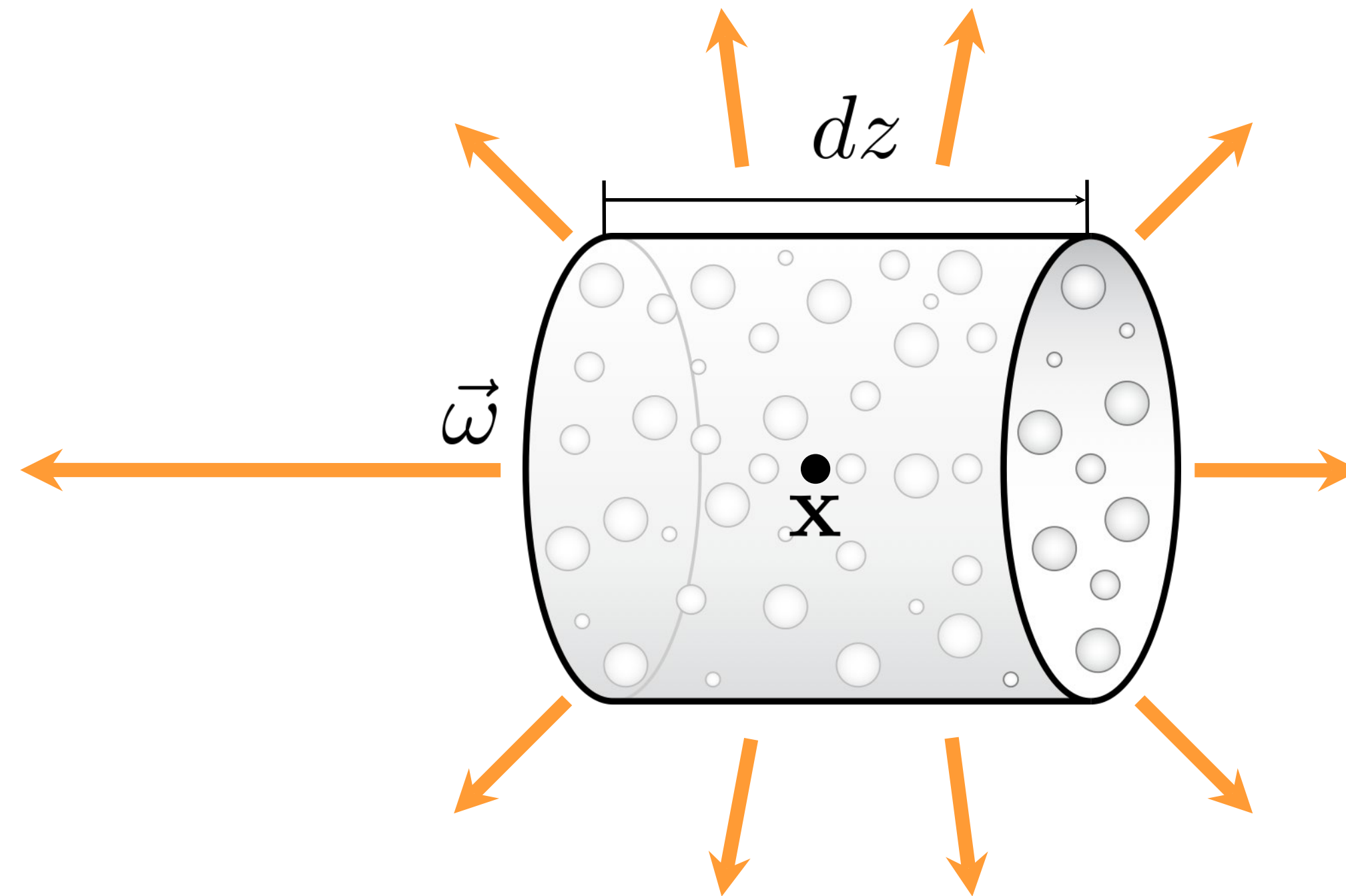
$$dL(\mathbf{x}, \vec{\omega}) = \sigma_s(\mathbf{x}) L_s(\mathbf{x}, \vec{\omega}) dz$$

$\sigma_s(\mathbf{x})$  : scattering coefficient  $[m^{-1}]$

$L_s(\mathbf{x}, \vec{\omega})$  : in-scattered radiance

# Emission

---



$$dL(\mathbf{x}, \vec{\omega}) = \sigma_a(\mathbf{x}) L_e(\mathbf{x}, \vec{\omega}) dz$$

\*Sometimes modeled without the absorption coefficient just by specifying a “source” term

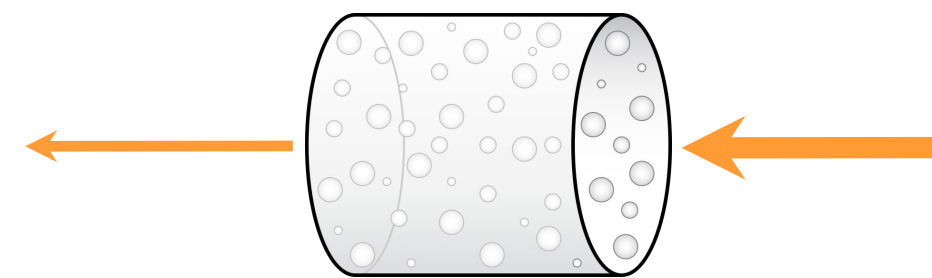
$\sigma_a(\mathbf{x})$  : absorption coefficient  $[m^{-1}]$

$L_e(\mathbf{x}, \vec{\omega})$  : emitted radiance

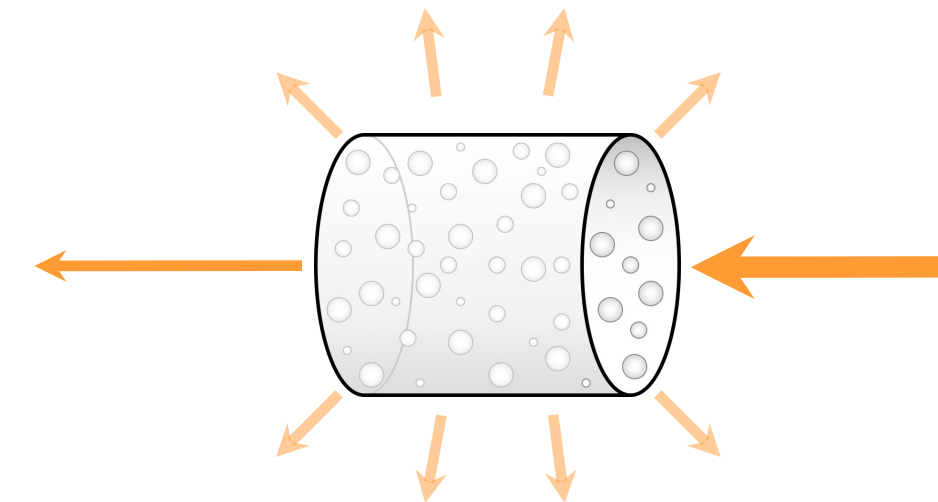


# Radiative Transfer Equation (RTE)

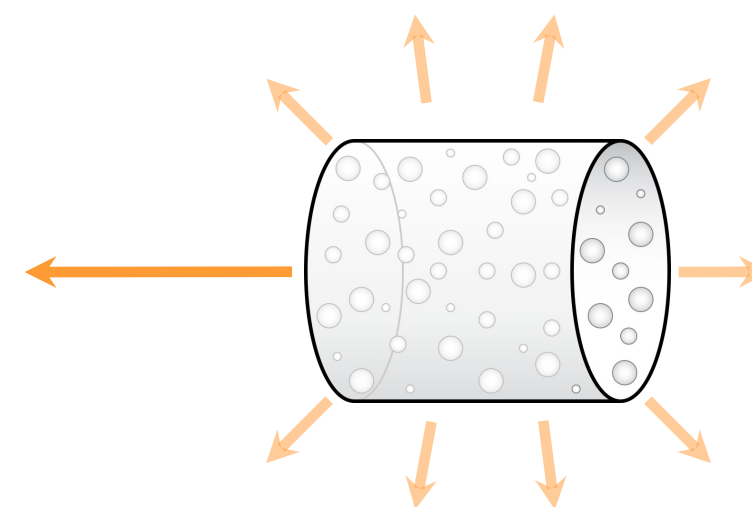
Absorption



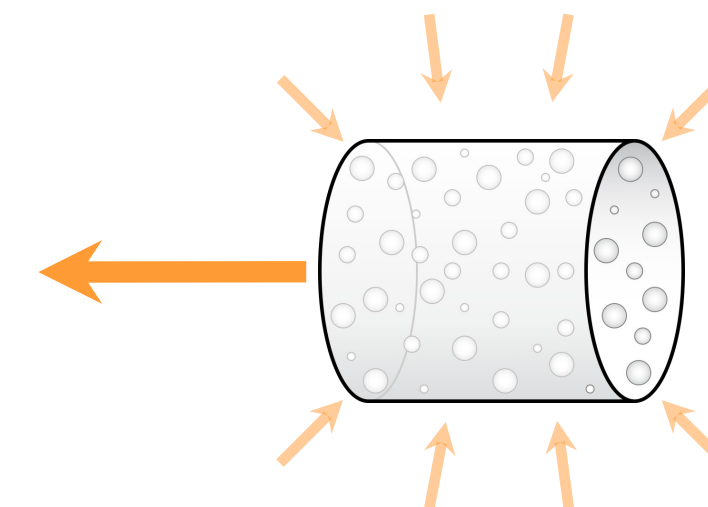
Out-scattering



$$dL(\mathbf{x}, \vec{\omega}) = \underbrace{-\sigma_a(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz}_{\text{Losses}} \underbrace{-\sigma_s(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz}_{\text{Losses}} + \underbrace{\sigma_a(\mathbf{x})L_e(\mathbf{x}, \vec{\omega})dz}_{\text{Gains}} + \underbrace{\sigma_s(\mathbf{x})L_s(\mathbf{x}, \vec{\omega})dz}_{\text{Gains}}$$



Emission



In-scattering

# Losses (Extinction)

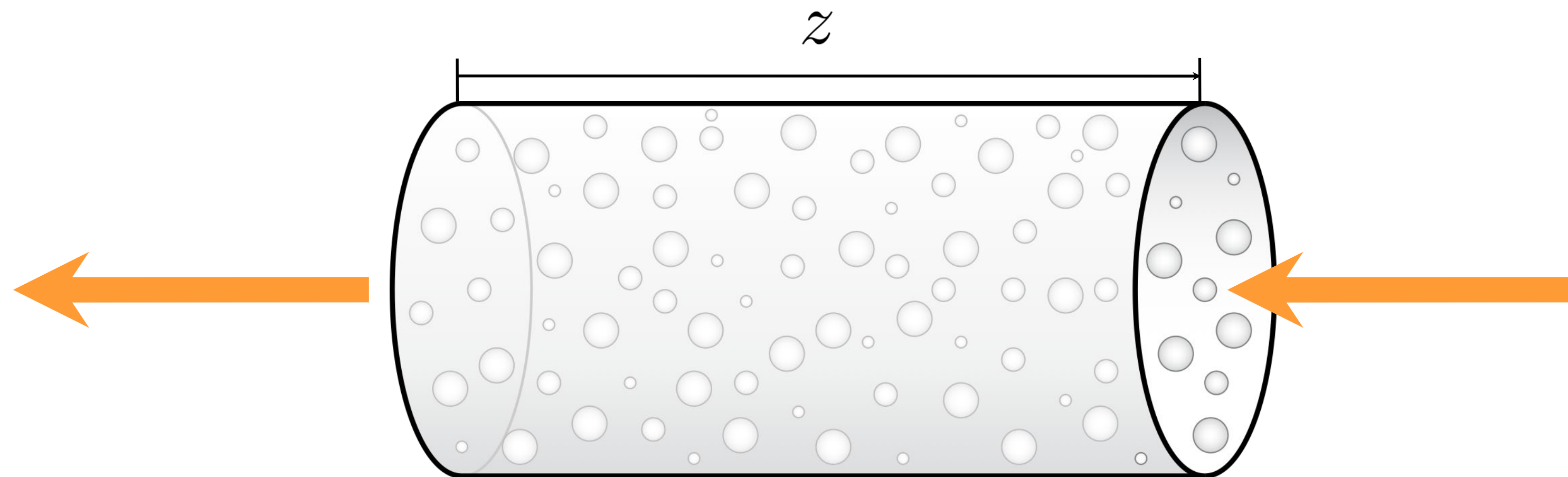
---

Absorption

Out-scattering

$$\begin{aligned} dL(\mathbf{x}, \vec{\omega}) &= -\sigma_a(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz - \sigma_s(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz \\ &= -\sigma_t(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz \end{aligned}$$

$\sigma_t(\mathbf{x})$  : extinction coefficient  $[m^{-1}]$   
: total loss of light per unit distance



What about a beam with a finite length?



# Extinction Along a Finite Beam

---

$$dL(\mathbf{x}, \vec{\omega}) = -\sigma_t(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz \quad // \text{ Assume constant } \sigma_t(\mathbf{x}), \text{ reorganize}$$

$$\frac{dL(\mathbf{x}, \vec{\omega})}{L(\mathbf{x}, \vec{\omega})} = -\sigma_t dz \quad // \text{ Integrate along beam from 0 to } z$$

$$\ln(L_z) - \ln(L_0) = -\sigma_t z$$

$$\ln\left(\frac{L_z}{L_0}\right) = -\sigma_t z \quad // \text{ Exponentiate}$$

$$\frac{L_z}{L_0} = e^{-\sigma_t z}$$

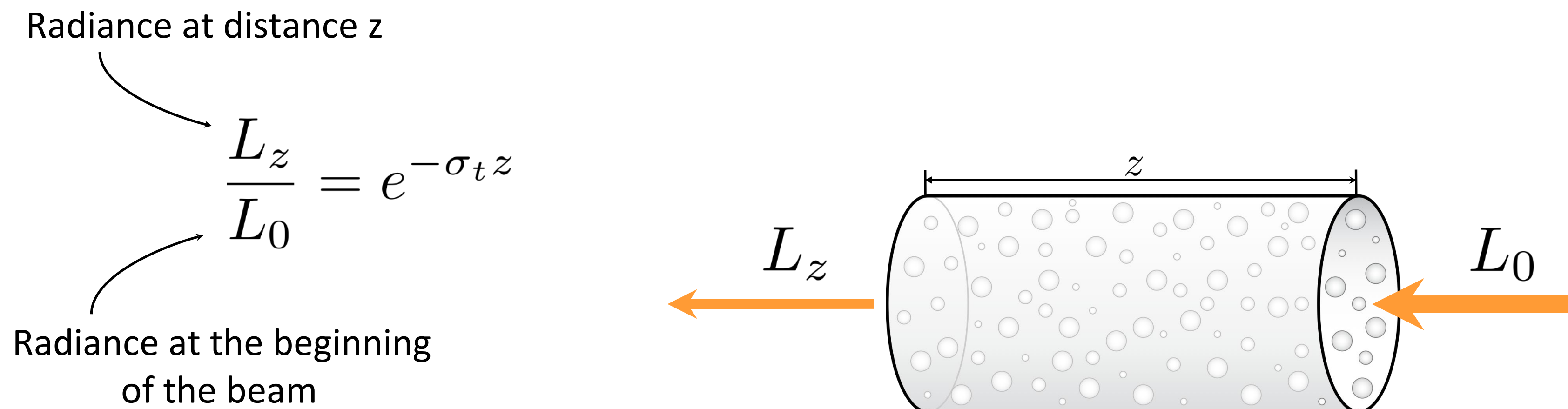
# Beer-Lambert Law

---

Expresses the remaining radiance after traveling a finite distance through a medium with constant extinction coefficient

The fraction is referred to as the *transmittance*

Think of this as fractional visibility between points





# Transmittance

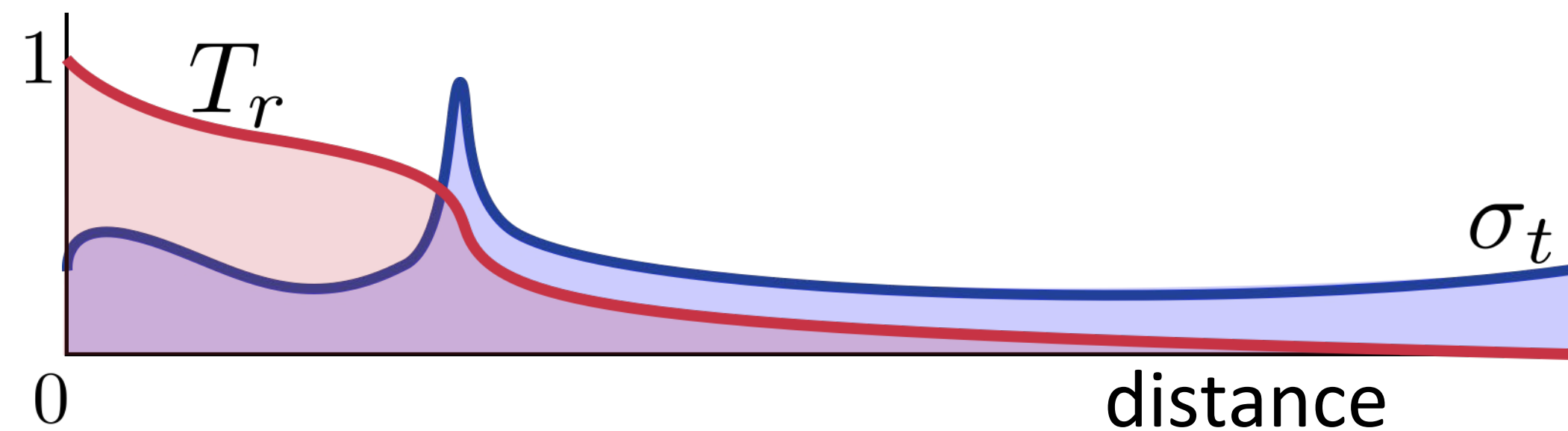
Homogeneous volume:

$$T_r(\mathbf{x}, \mathbf{y}) = e^{-\sigma_t \|\mathbf{x} - \mathbf{y}\|}$$

Heterogeneous volume (spatially varying  $\sigma_t$ ):

$$T_r(\mathbf{x}, \mathbf{y}) = e^{-\int_0^{\|\mathbf{x} - \mathbf{y}\|} \sigma_t(t) dt}$$

↖  
Optical thickness



# Transmittance

---

Homogeneous volume:

$$T_r(\mathbf{x}, \mathbf{y}) = e^{-\sigma_t \|\mathbf{x} - \mathbf{y}\|}$$

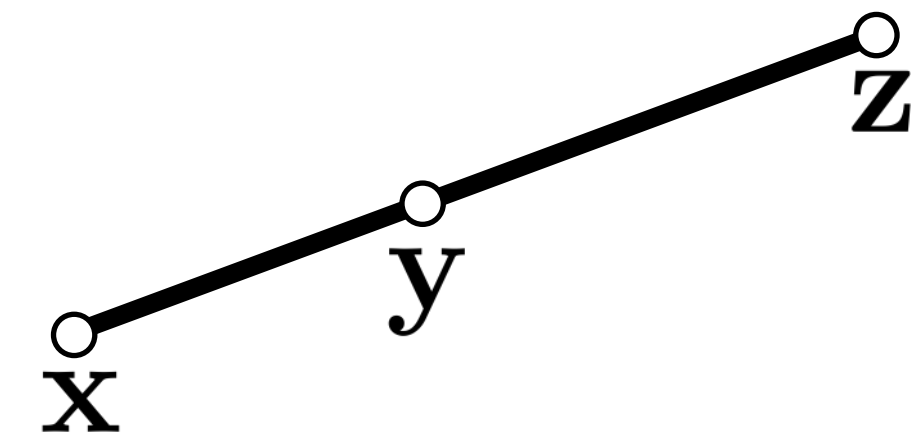
Heterogeneous volume (spatially varying  $\sigma_t$ ):

$$T_r(\mathbf{x}, \mathbf{y}) = e^{-\int_0^{\|\mathbf{x} - \mathbf{y}\|} \sigma_t(t) dt}$$

↖ Optical thickness

Transmittance is multiplicative:

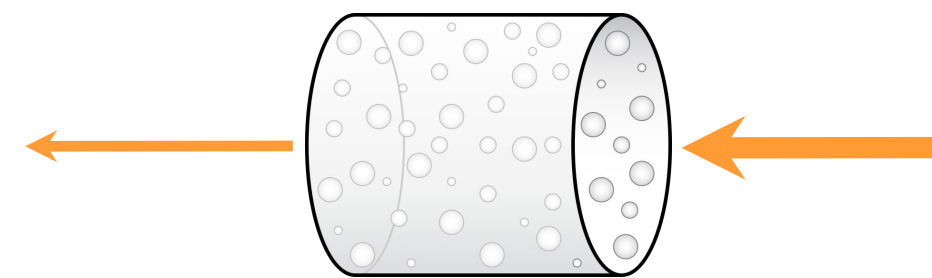
$$T_r(\mathbf{x}, \mathbf{z}) = T_r(\mathbf{x}, \mathbf{y}) T_r(\mathbf{y}, \mathbf{z})$$



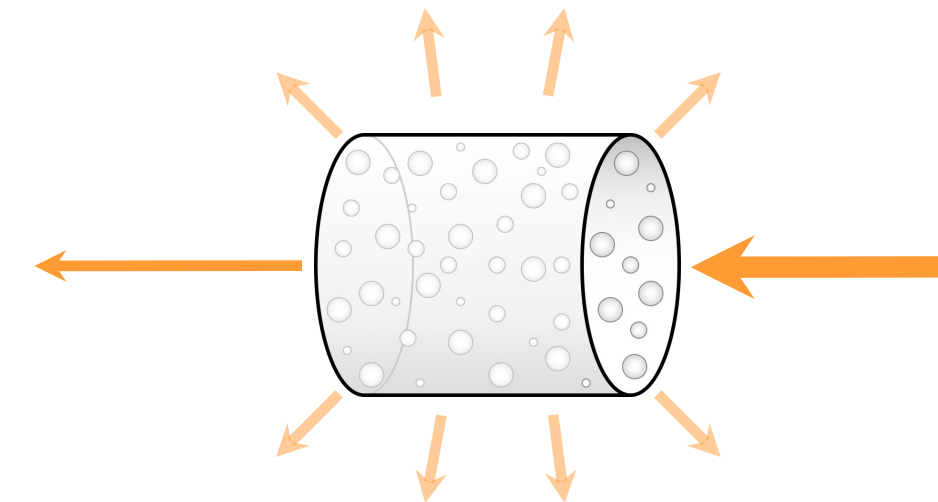


# Radiative Transfer Equation (RTE)

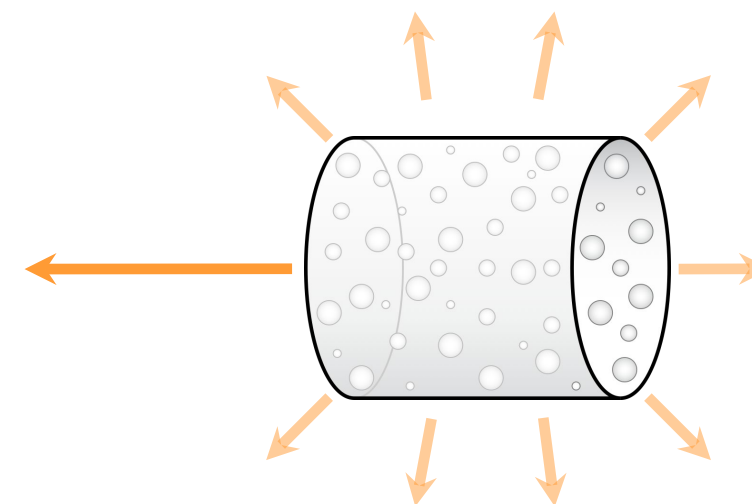
Absorption



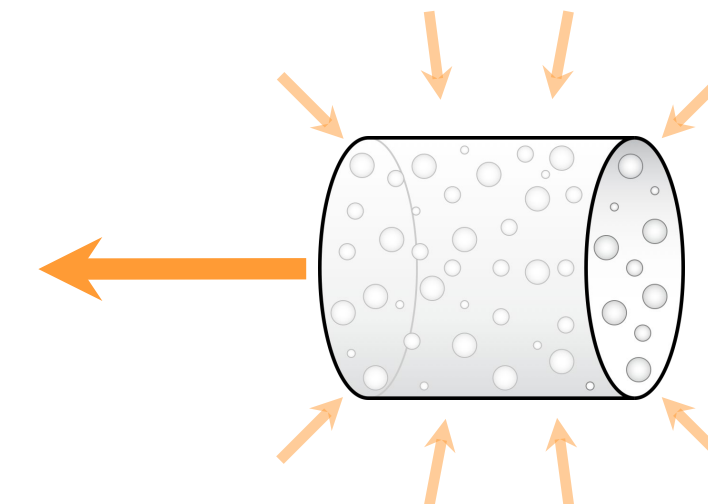
Out-scattering



$$dL(\mathbf{x}, \vec{\omega}) = -\sigma_a(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz - \sigma_s(\mathbf{x})L(\mathbf{x}, \vec{\omega})dz \\ + \sigma_a(\mathbf{x})L_e(\mathbf{x}, \vec{\omega})dz + \sigma_s(\mathbf{x})L_s(\mathbf{x}, \vec{\omega})dz$$



Emission

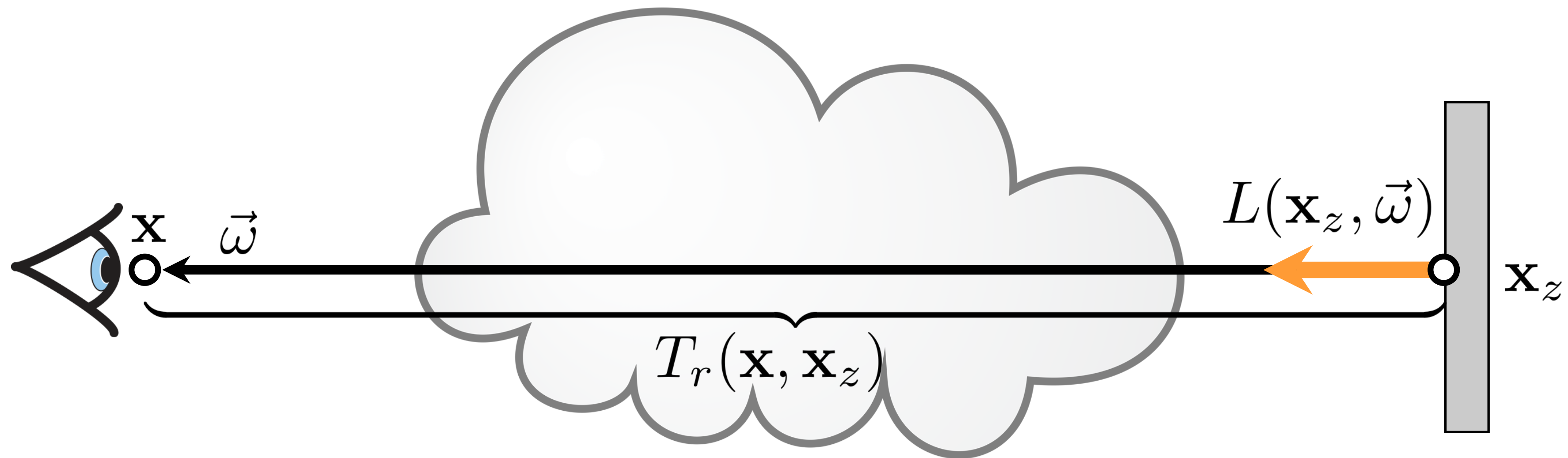


In-scattering

# Volume Rendering Equation

$$L(\mathbf{x}, \vec{\omega}) = T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})$$

Reduced (background) surface radiance

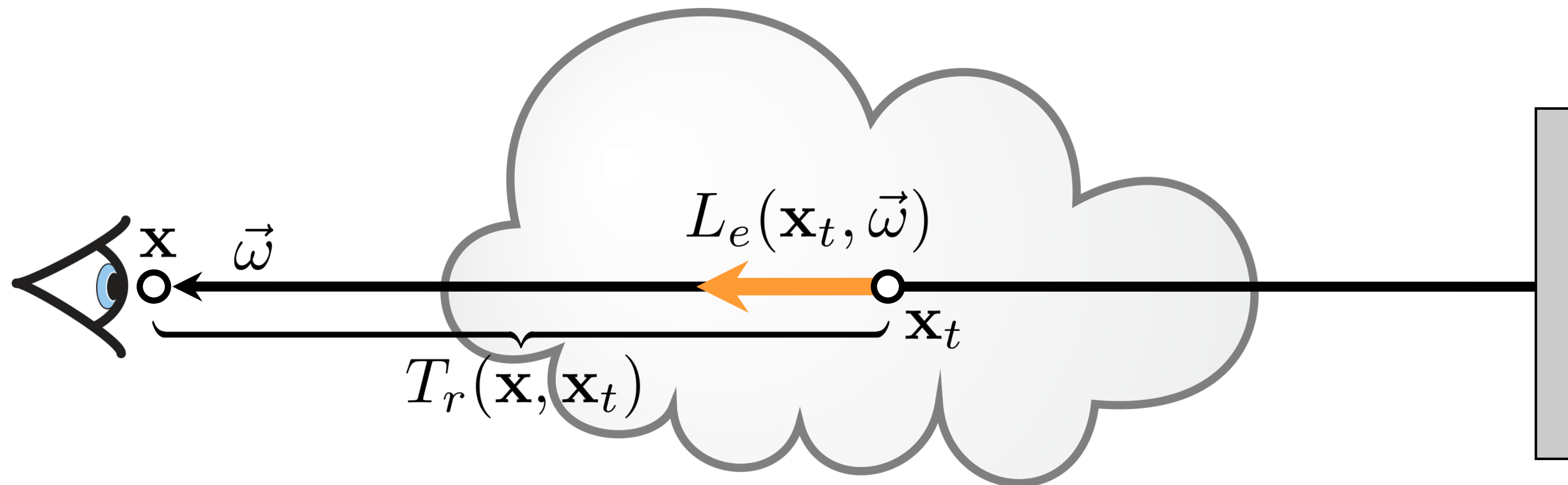




# Volume Rendering Equation

$$L(\mathbf{x}, \vec{\omega}) = T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega}) + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt$$

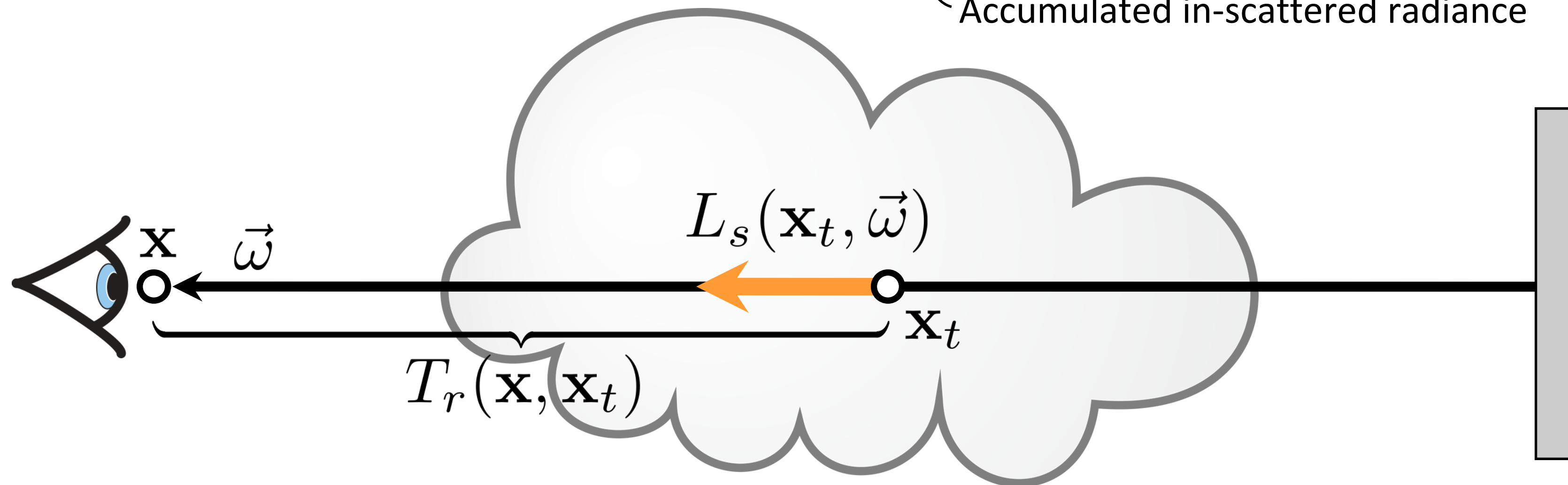
Accumulated emitted radiance



# Volume Rendering Equation

$$\begin{aligned} L(\mathbf{x}, \vec{\omega}) = & T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega}) \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt \\ & + \boxed{\int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) dt} \end{aligned}$$

Accumulated in-scattered radiance

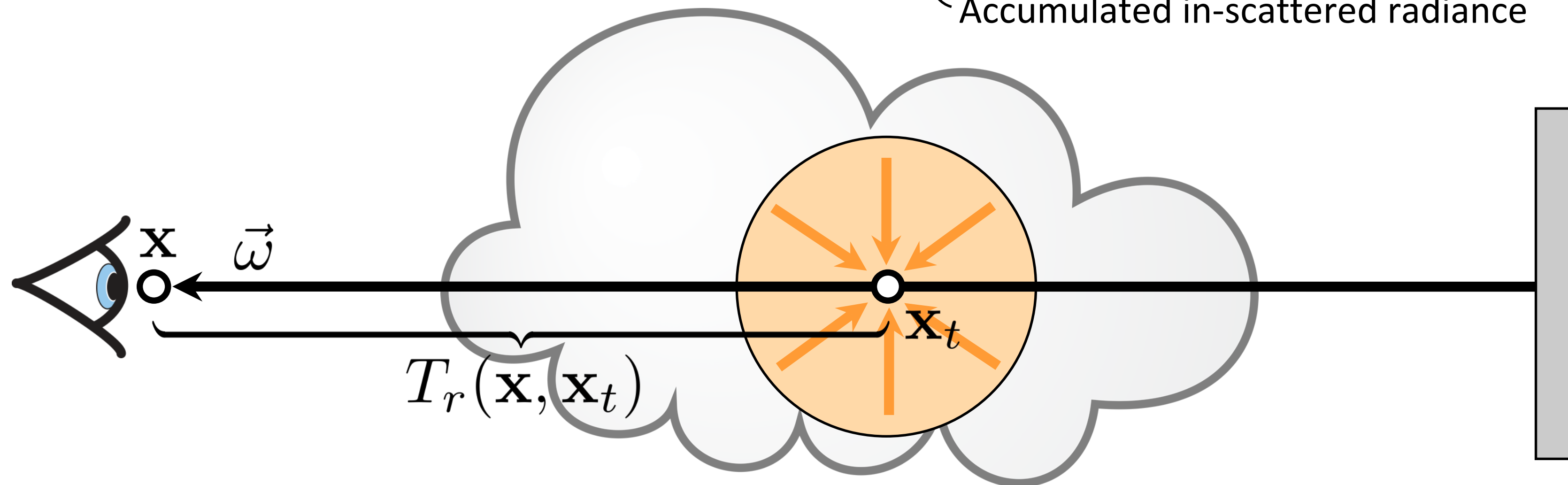




# Volume Rendering Equation

$$\begin{aligned} L(\mathbf{x}, \vec{\omega}) = & T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega}) \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) L_i(\mathbf{x}_t, \vec{\omega}') d\vec{\omega}' dt \end{aligned}$$

Accumulated in-scattered radiance



# Volume Rendering Equation

---

$$\begin{aligned} L(\mathbf{x}, \vec{\omega}) = & T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega}) \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) L_i(\mathbf{x}_t, \vec{\omega}') d\vec{\omega}' dt \end{aligned}$$



# Scattering in Media

# Phase Function $f_p$

---

Describes distribution of scattered light

Analog of BRDF but for scattering in media

Integrates to unity (unlike BRDF)

$$\int_{S^2} f_p(\mathbf{x}, \vec{\omega}', \vec{\omega}) d\vec{\omega}' = 1 \quad \text{Why do we have this property?}$$

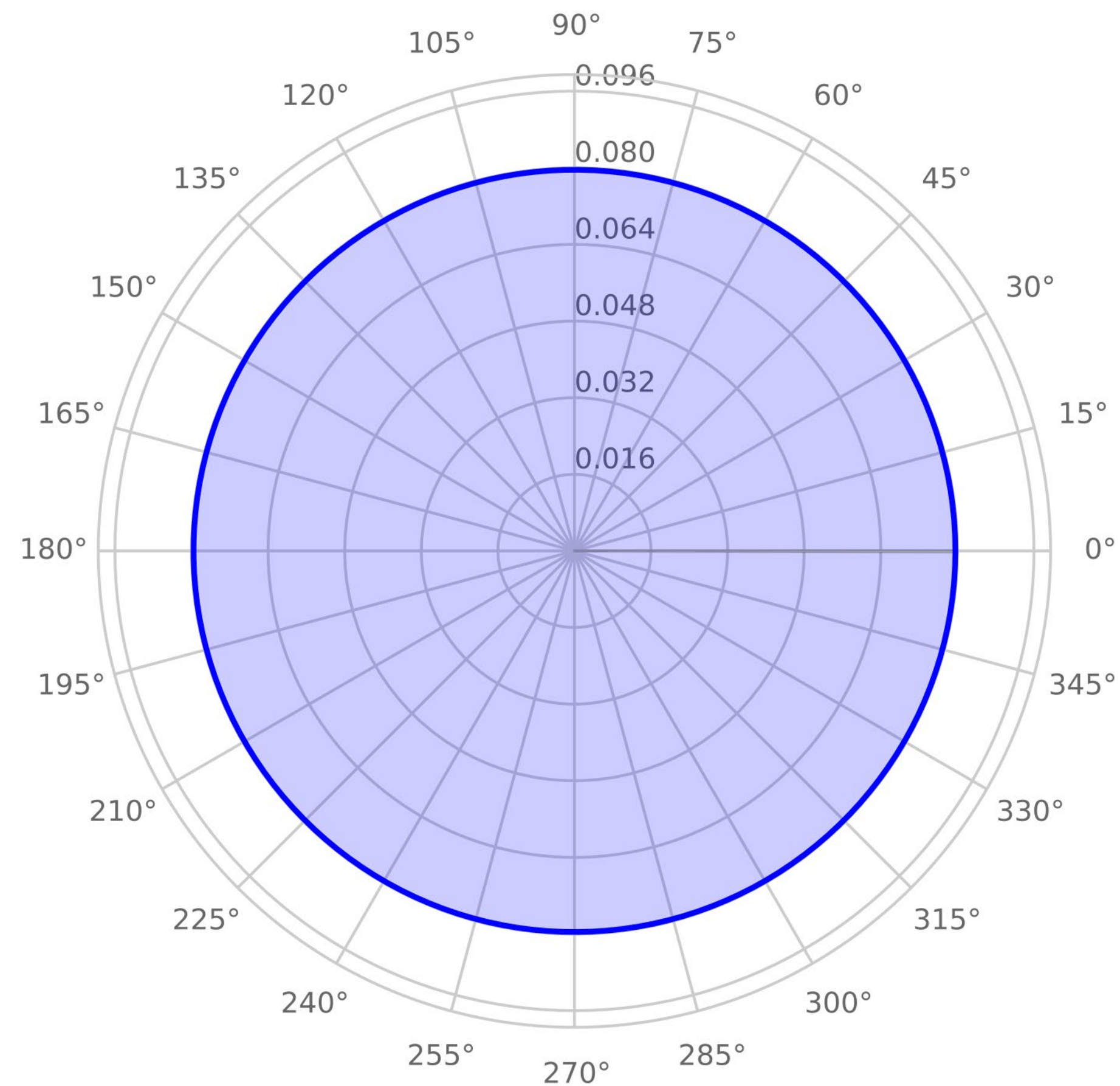
\*We will use the same convention that phase function direction vectors always *point away* from the shading point  $\mathbf{x}$ . Many publications, however, use a different convention for phase functions, in which direction vectors “follow” the light, i.e. one direction points *towards*  $\mathbf{x}$  and the other *away* from  $\mathbf{x}$ . When reading papers, be sure to clarify the meaning of the vectors to avoid misinterpretation.

# Isotropic Scattering

Uniform scattering, analogous to Lambertian BRDF

$$f_p(\vec{\omega}', \vec{\omega}) = \frac{1}{4\pi}$$

Where does this value come from?





# Anisotropic Scattering

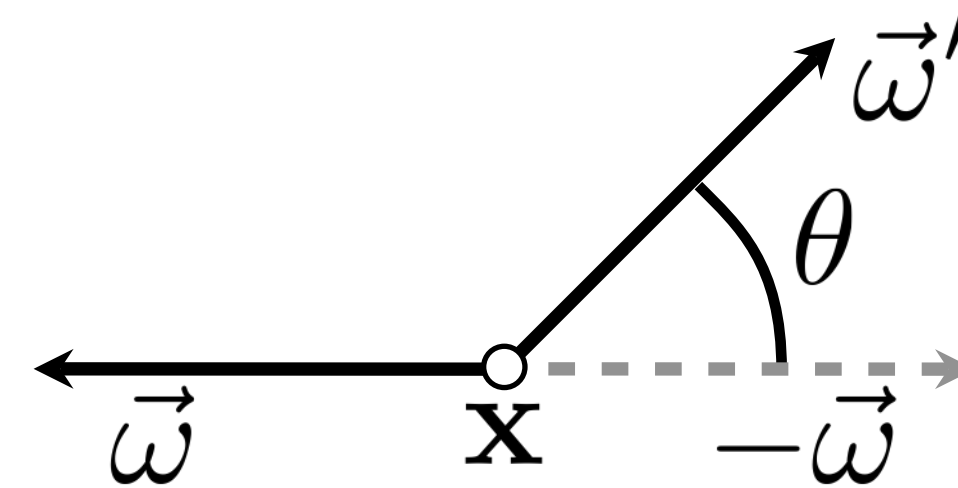
---

Quantifying anisotropy ( $g$ , “average cosine”):

$$g = \int_{S^2} f_p(\mathbf{x}, \vec{\omega}', \vec{\omega}) \cos \theta \, d\vec{\omega}'$$

where:

$$\cos \theta = -\vec{\omega} \cdot \vec{\omega}'$$



$g = 0$  : isotropic scattering (on average)

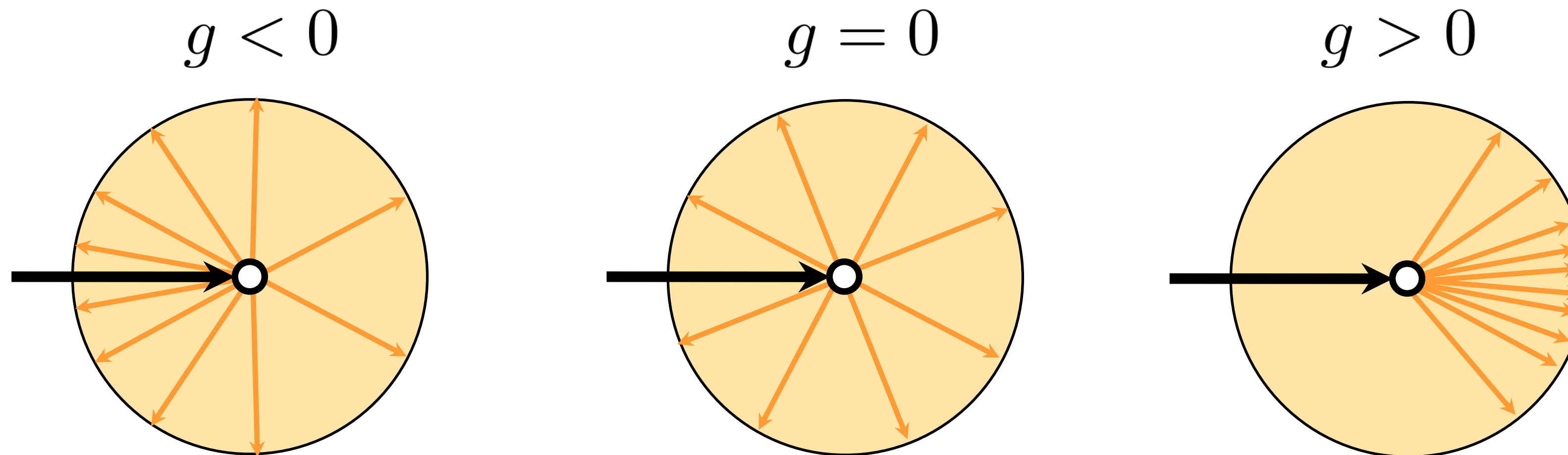
$g > 0$  : forward scattering

$g < 0$  : backward scattering

# Henyey-Greenstein Phase Function

Anisotropic scattering

$$f_{p\text{HG}}(\theta) = \frac{1}{4\pi} \frac{1 - g^2}{(1 + g^2 - 2g \cos \theta)^{3/2}}$$

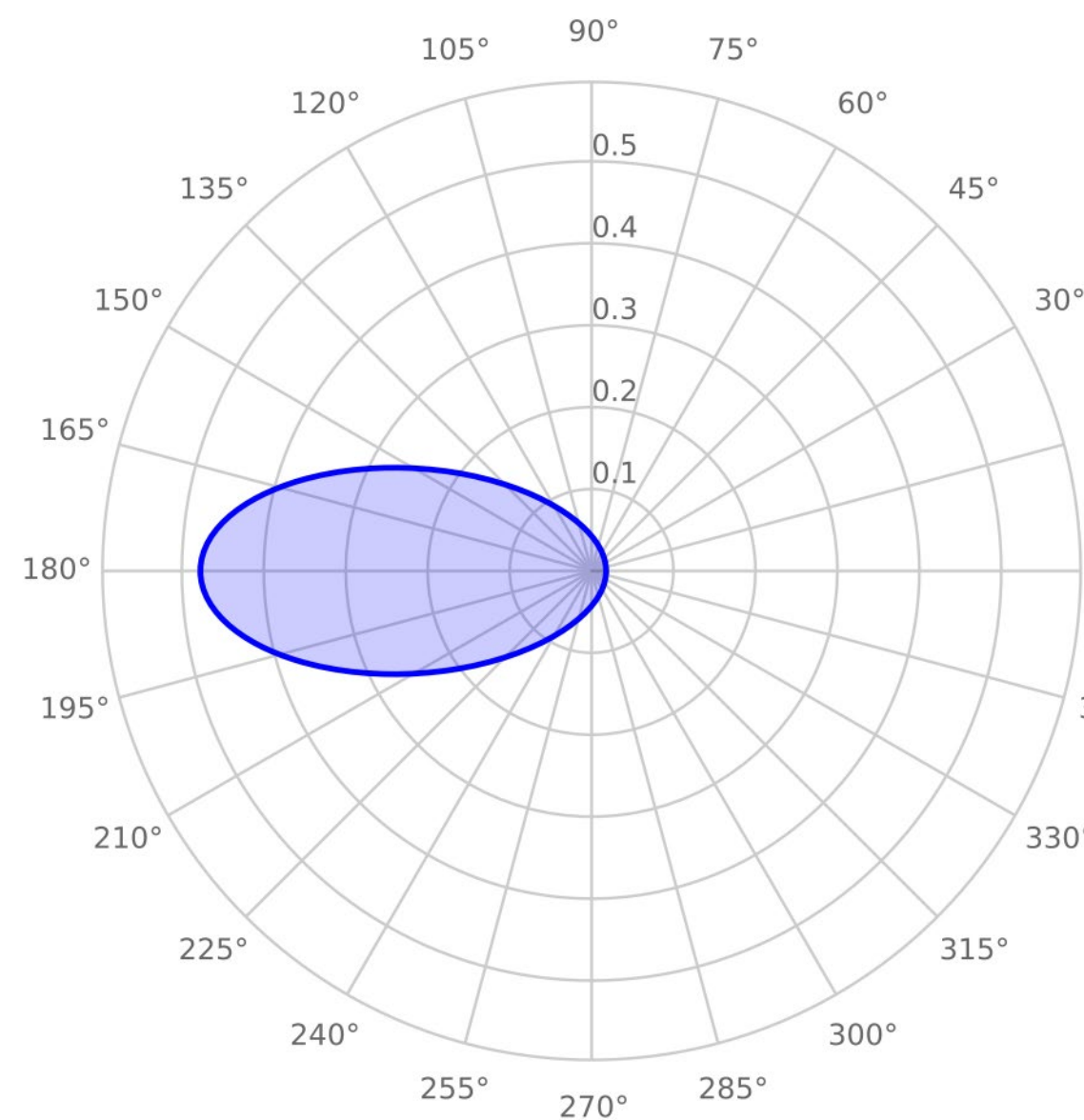


# Henyey-Greenstein Phase Function

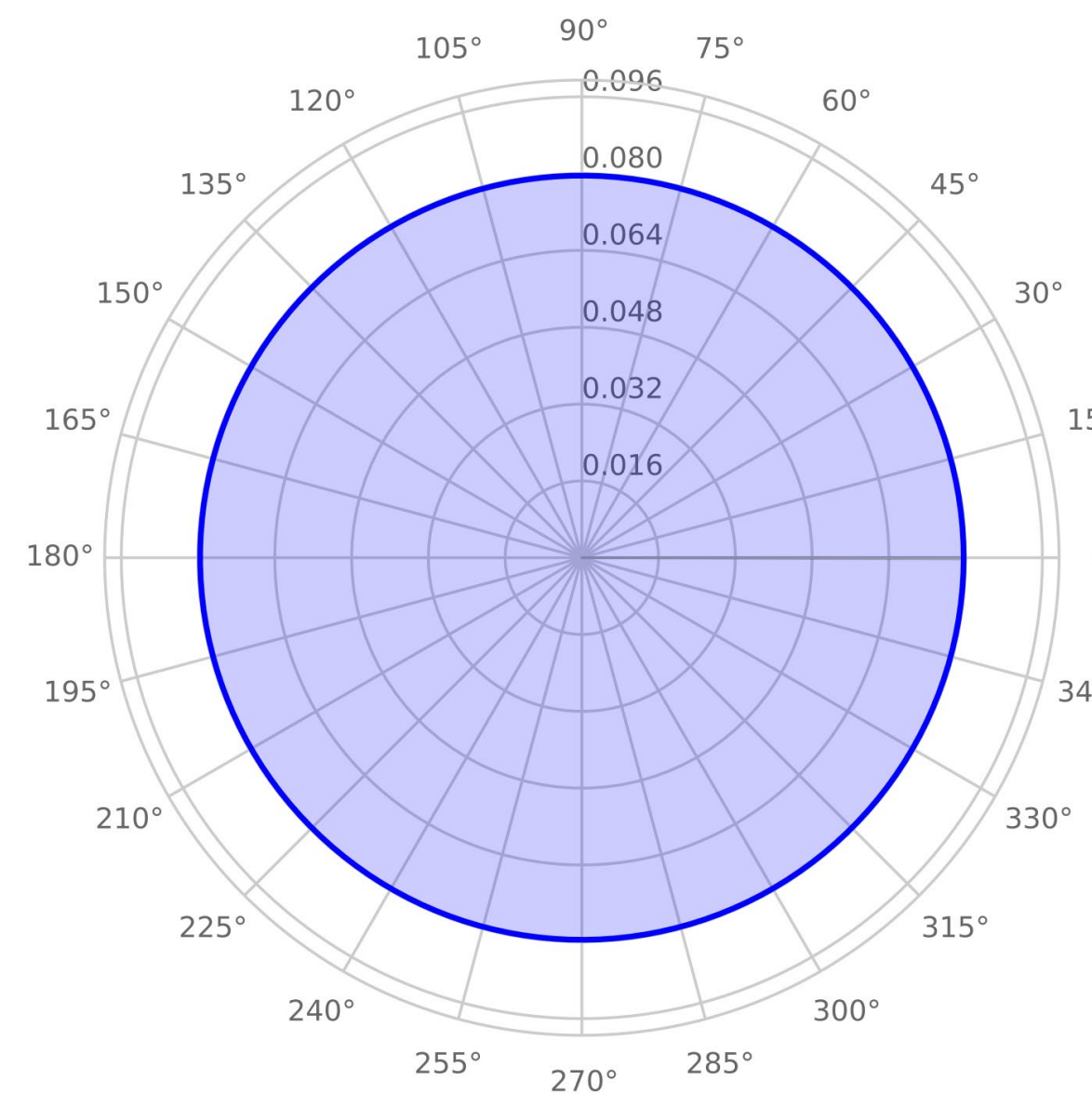
## Anisotropic scattering

$$f_{p\text{HG}}(\theta) = \frac{1}{4\pi} \frac{1 - g^2}{(1 + g^2 - 2g \cos \theta)^{3/2}}$$

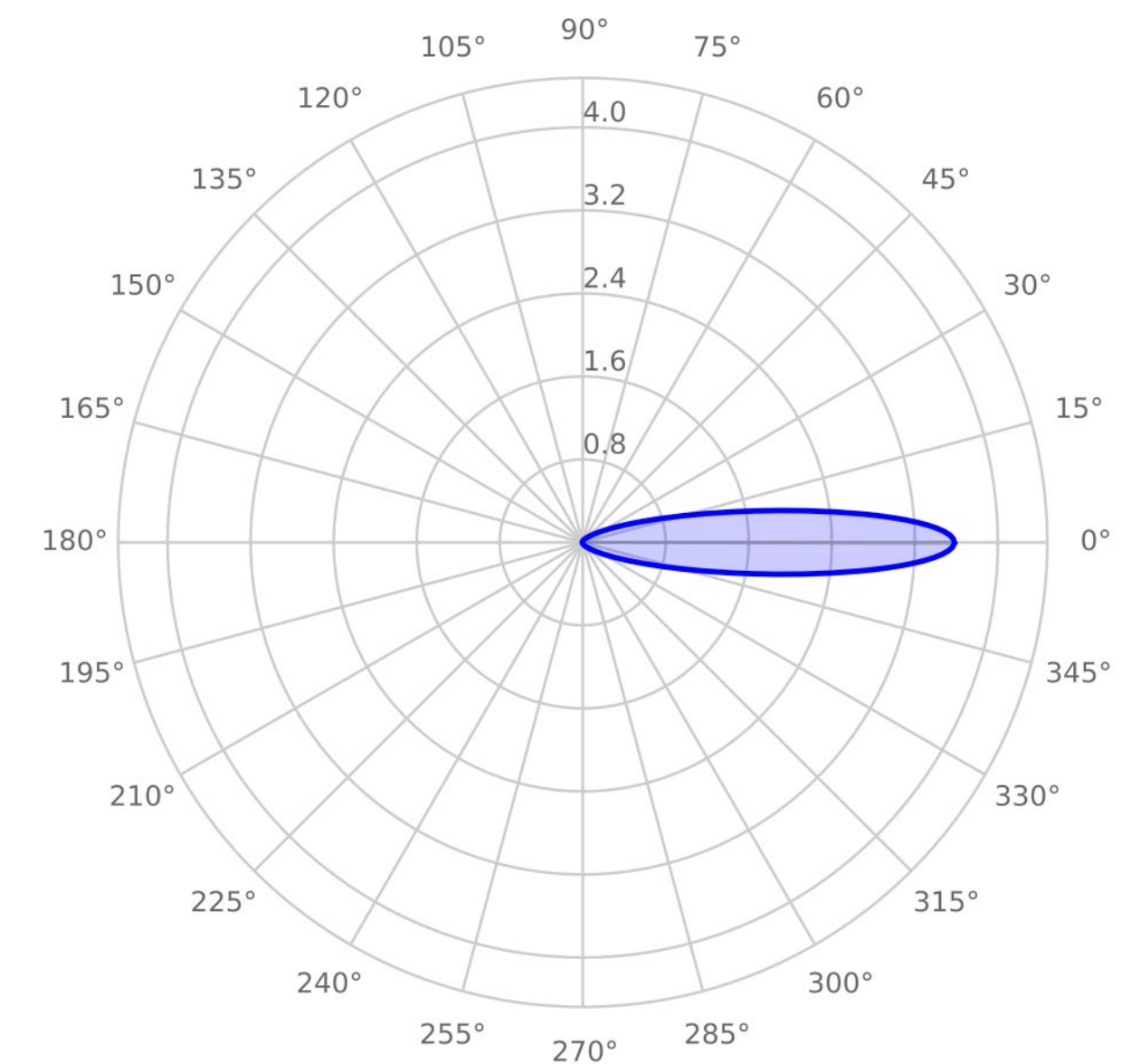
$$g = -0.5$$



$$g = 0$$

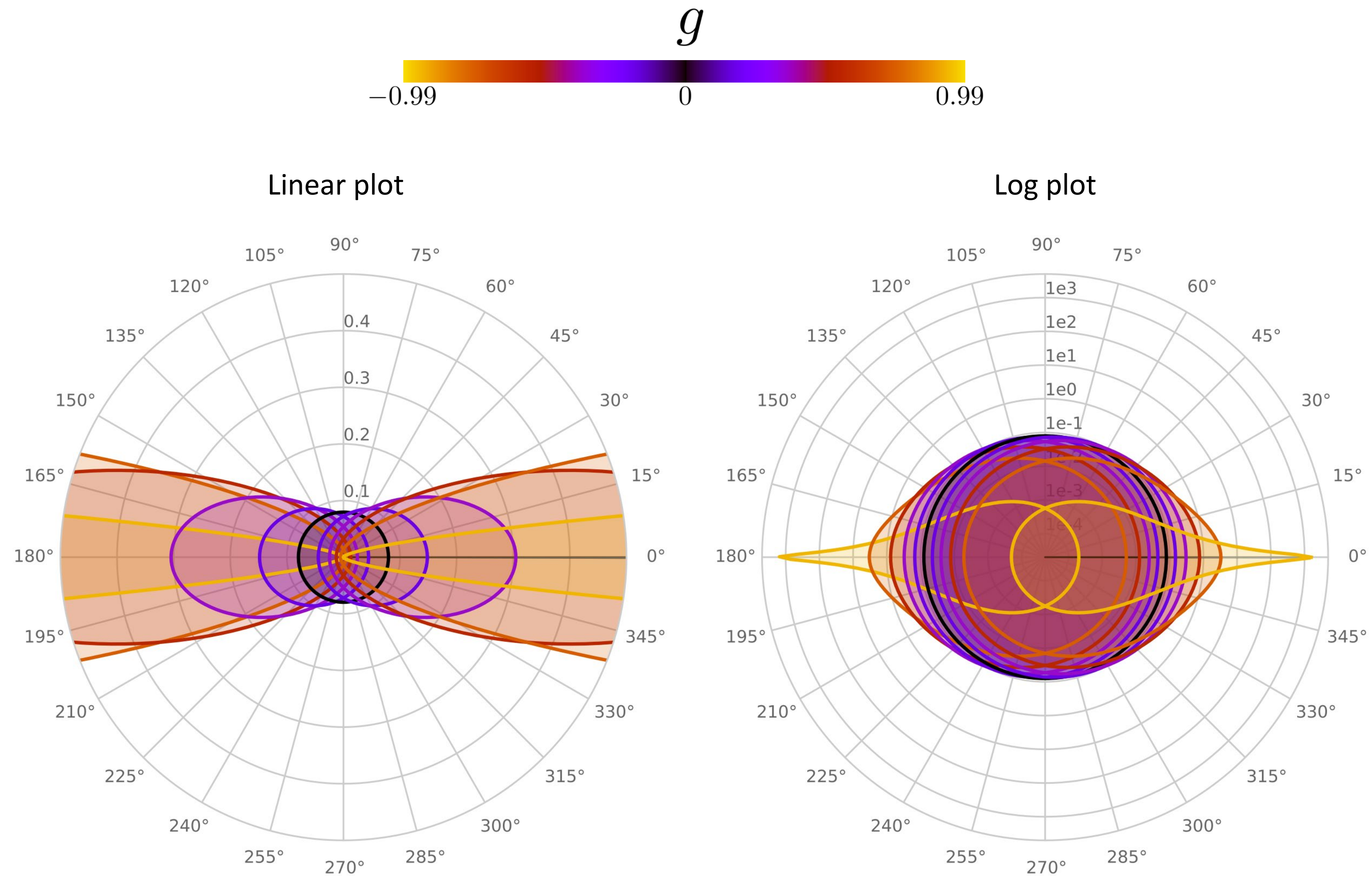


$$g = 0.8$$





# Henyey-Greenstein Phase Function



# Henyeey-Greenstein Phase Function

---

Empirical phase function

Introduced for intergalactic dust

Very popular in graphics and other fields

# Schlick's Phase Function

---

Empirical phase function

Faster approximation of HG

$$f_{p\text{Schlick}}(\theta) = \frac{1}{4\pi} \frac{1 - k^2}{(1 - k \cos \theta)^2}$$
$$k = 1.55g - 0.55g^3$$

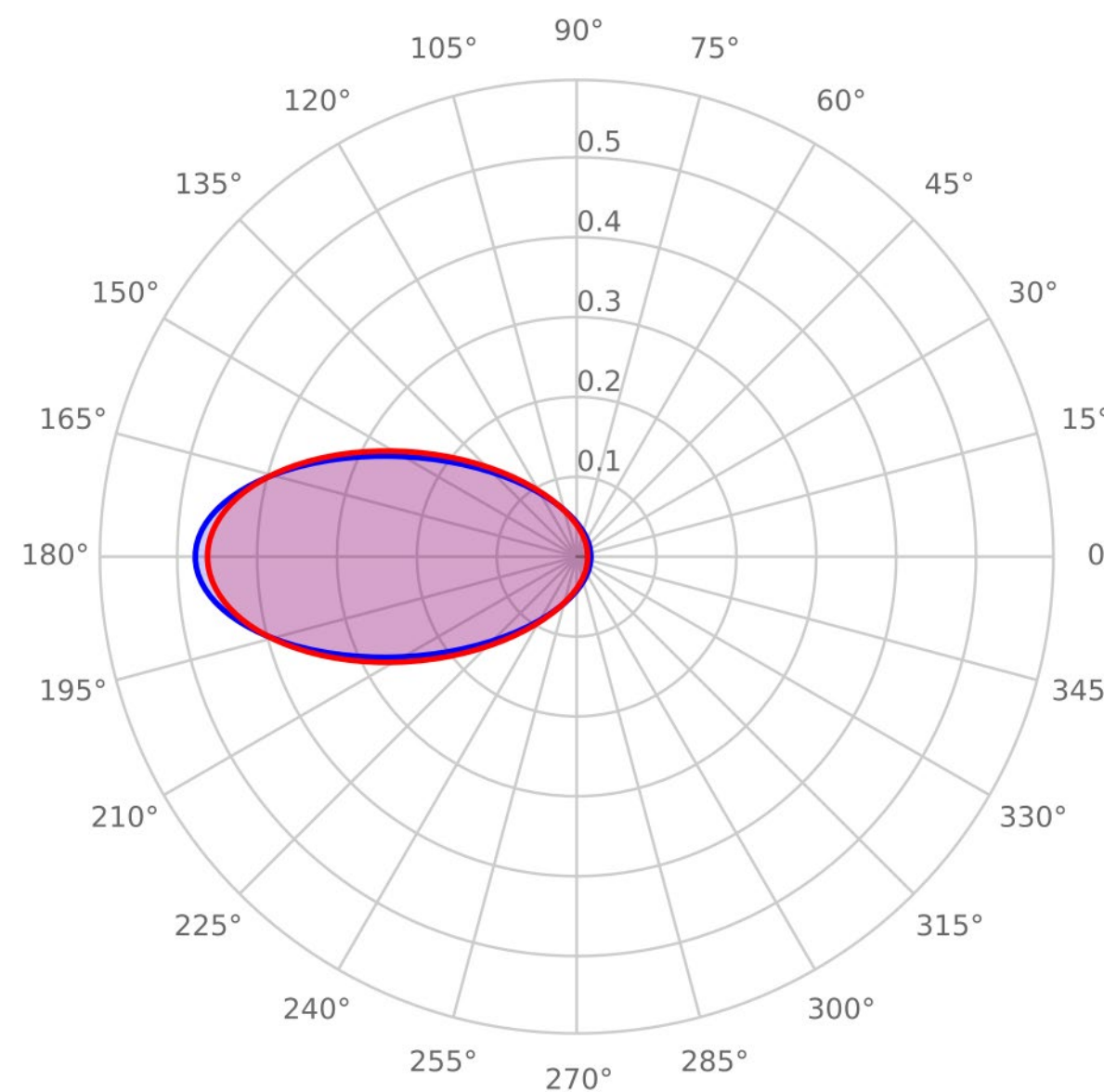


# Schlick's Phase Function

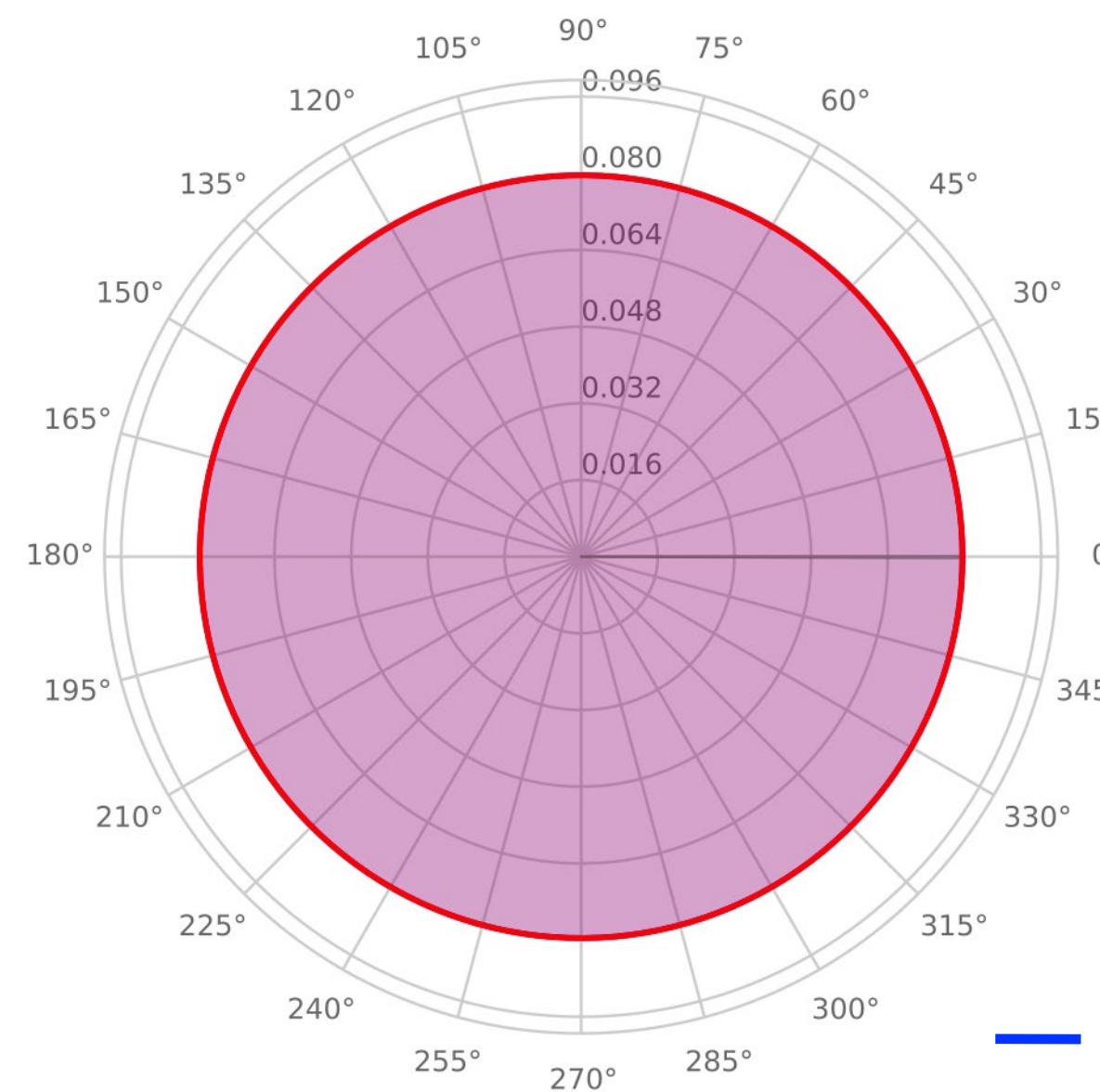
Empirical phase function

Faster approximation of HG

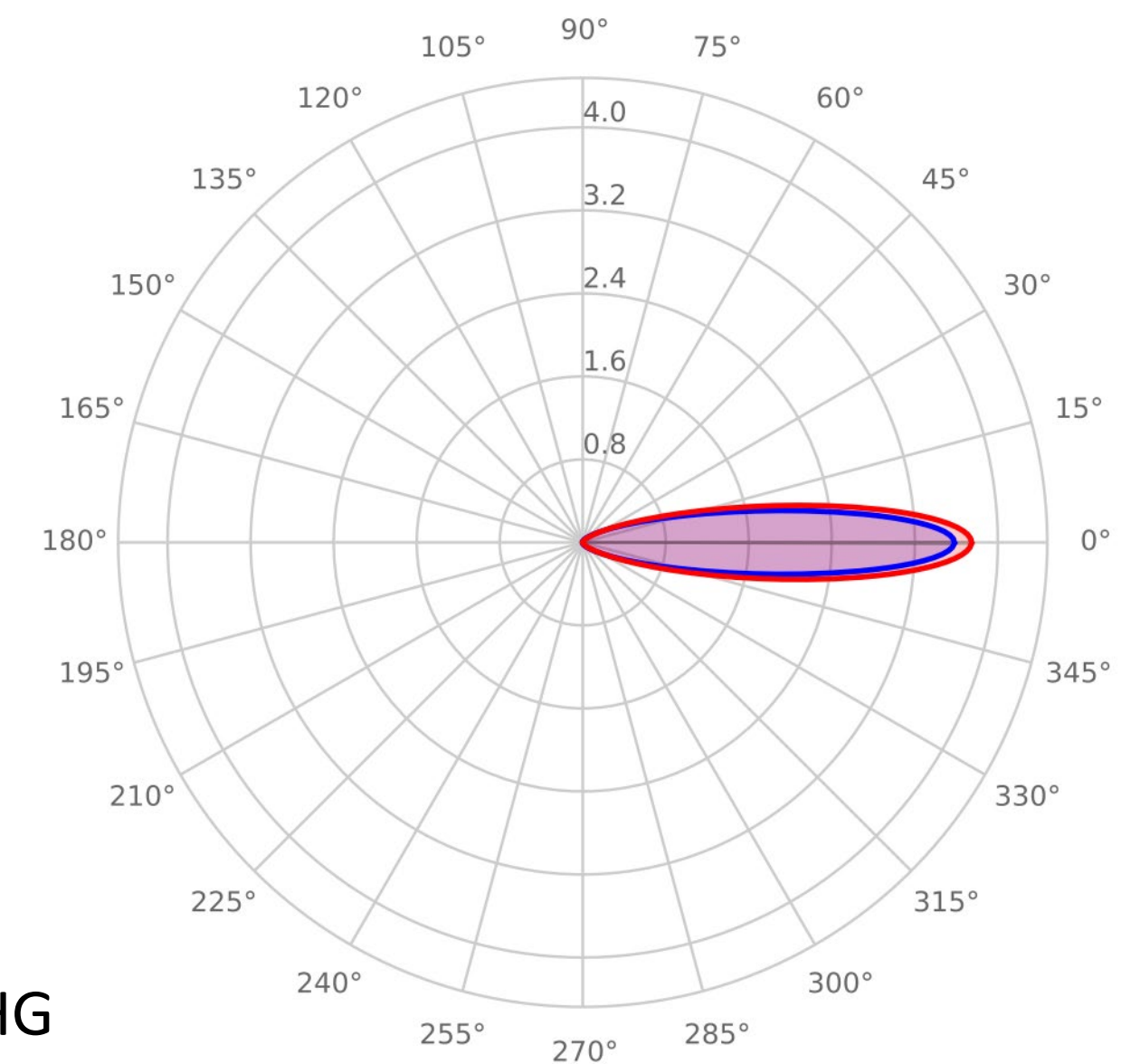
$$g = -0.5 \quad k = -0.706$$



$$g = 0 \quad k = 0$$



$$g = 0.8 \quad k = 0.96$$



— HG  
— Schlick

# Lorenz-Mie Scattering

---

If the diameter of scatterers is on the order of light wavelength, we cannot neglect the wave nature of light

Solution to Maxwell's equations for scattering from any spherical dielectric particle

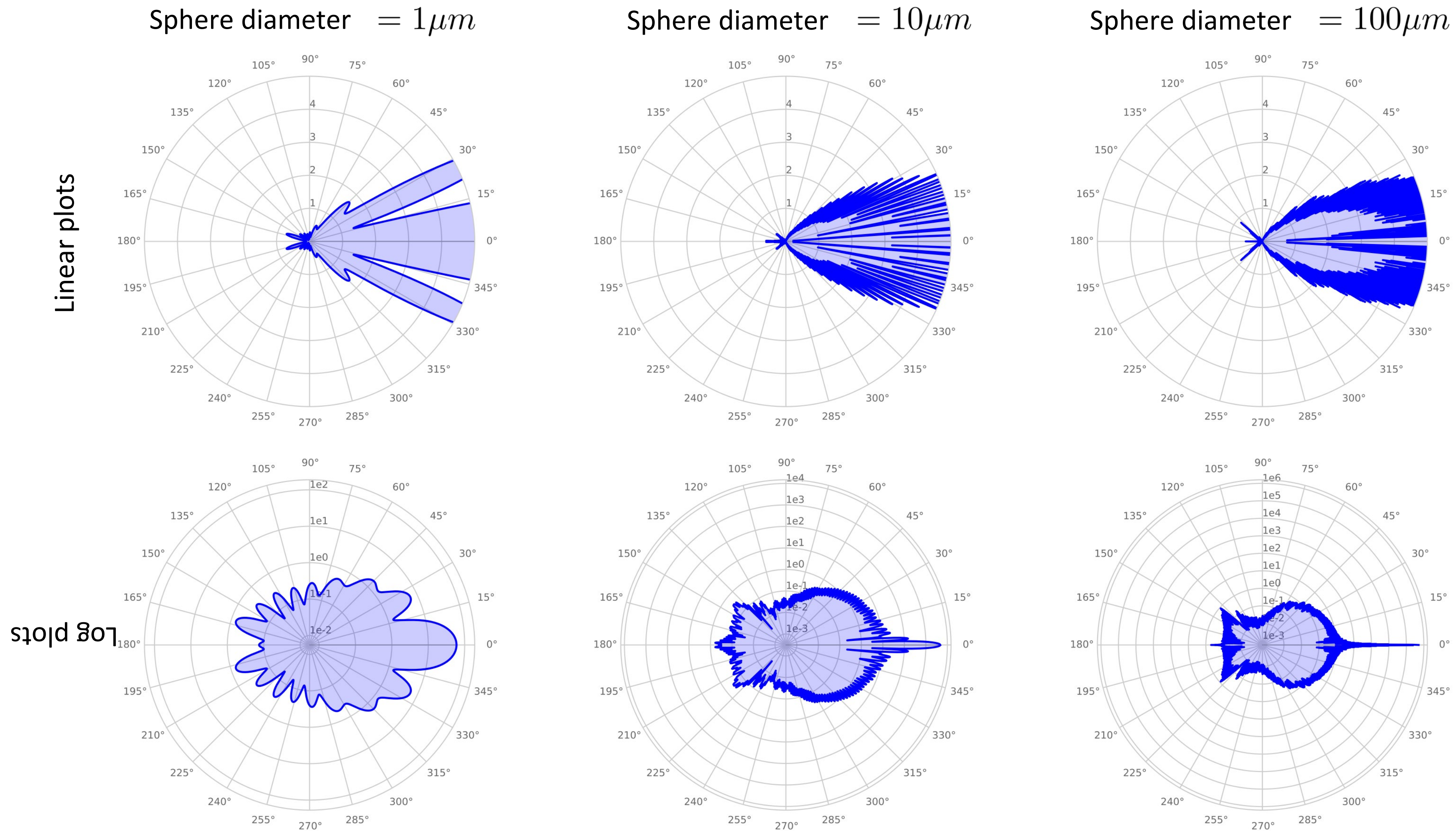
Explains many phenomena

Complicated:

- Solution is an infinite analytic series



# Lorenz-Mie Phase Function



Data obtained from <http://www.philiplaven.com/mieplot.htm>



# Rainbows

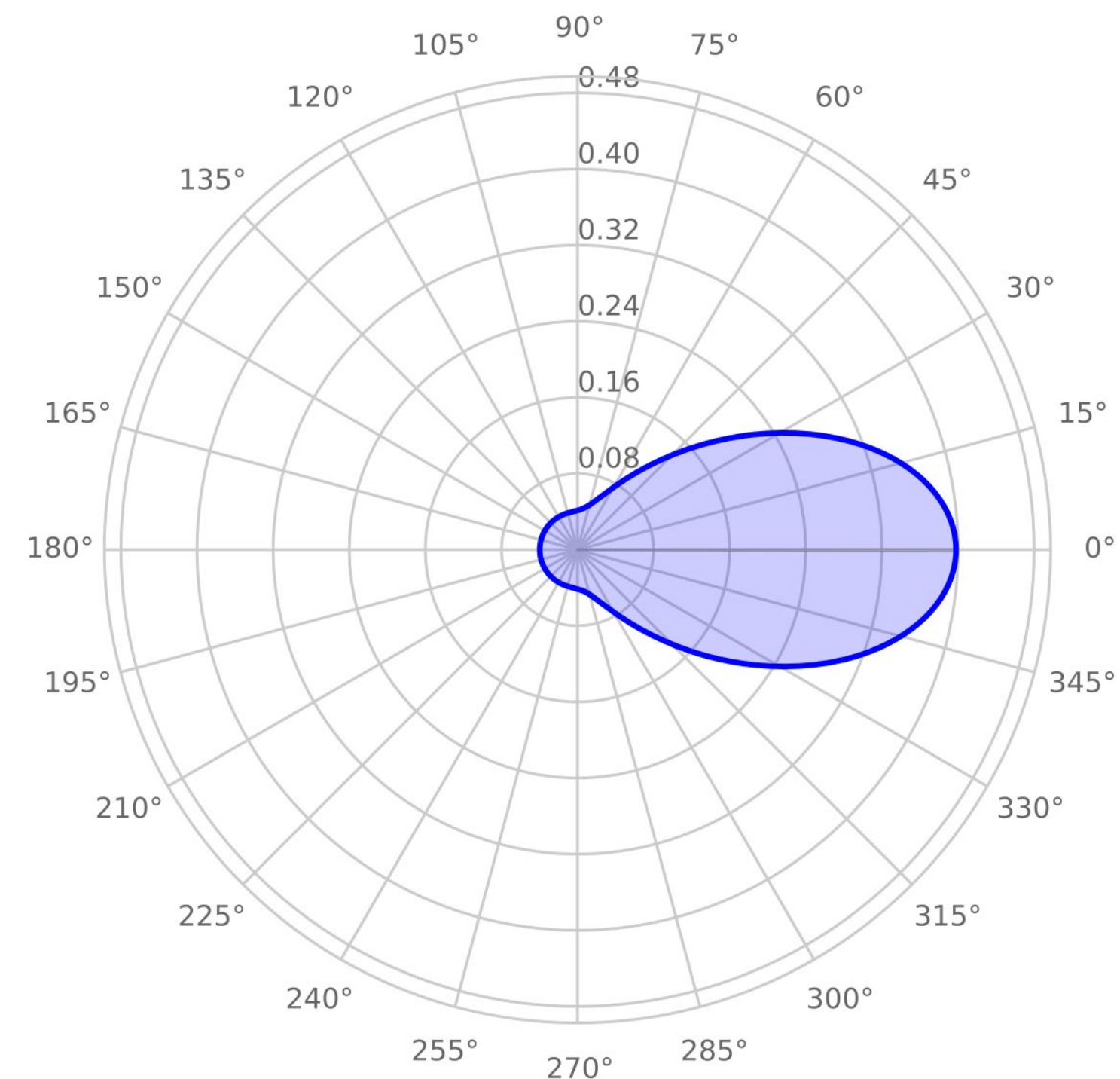
---



# Lorenz-Mie Approximations

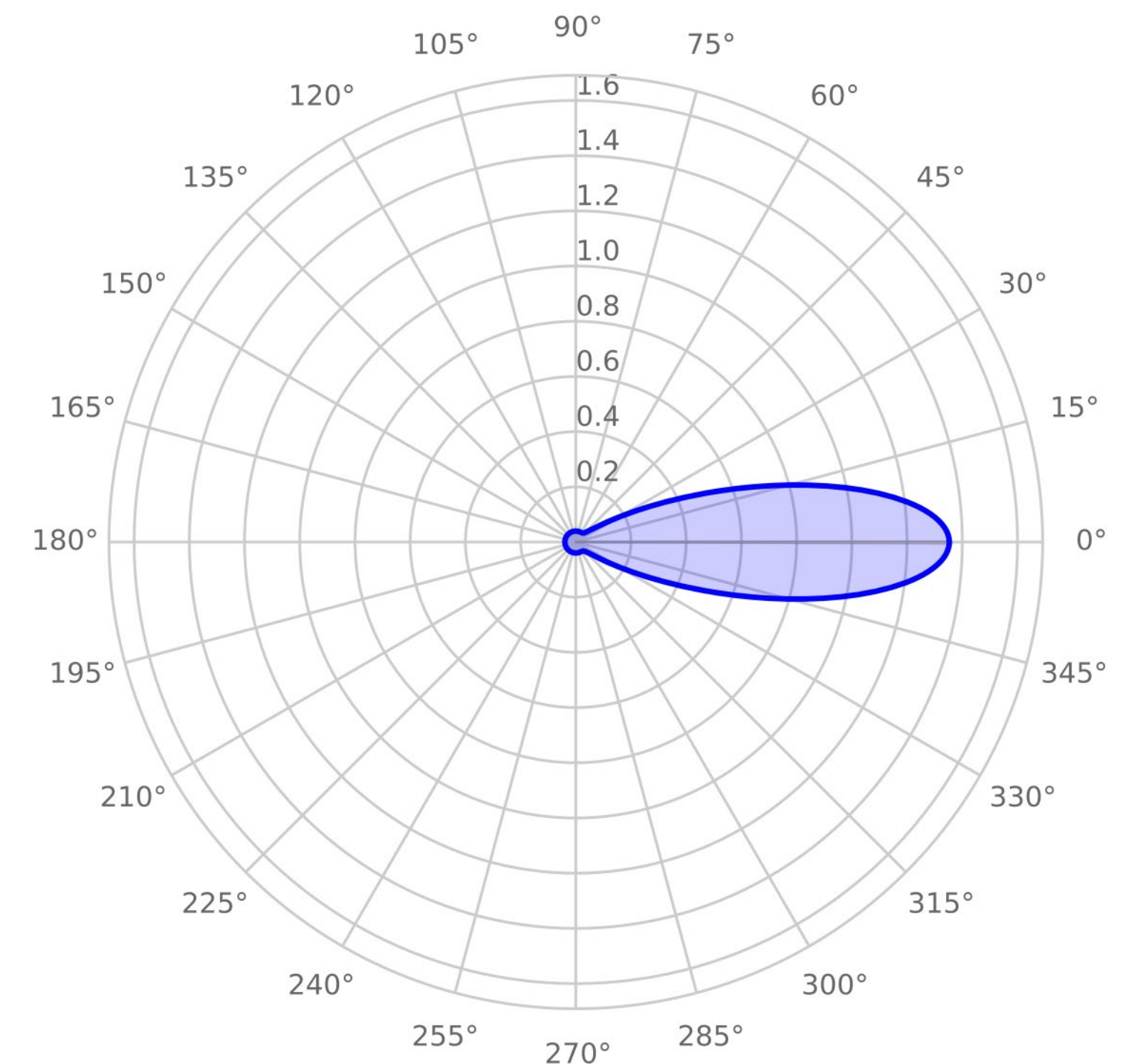
Hazy atmosphere

$$f_{p \text{ hazy}}(\theta) = \frac{1}{4\pi} \left( 5 + \left( \frac{1 + \cos \theta}{2} \right)^8 \right)$$



Murky atmosphere

$$f_{p \text{ murky}}(\theta) = \frac{1}{4\pi} \left( 17 + \left( \frac{1 + \cos \theta}{2} \right)^{32} \right)$$



# Lorenz-Mie Approximations

---

Hazy atmosphere

$$f_{p \text{ hazy}}(\theta) = \frac{1}{4\pi} \left( 5 + \left( \frac{1 + \cos \theta}{2} \right)^8 \right)$$

Murky atmosphere

$$f_{p \text{ murky}}(\theta) = \frac{1}{4\pi} \left( 17 + \left( \frac{1 + \cos \theta}{2} \right)^{32} \right)$$





# Rayleigh Scattering

---

Approximation of Lorenz-Mie for tiny scatterers that are typically smaller than  $1/10$ th the wavelength of visible light

Used for atmospheric scattering, gasses, transparent solids

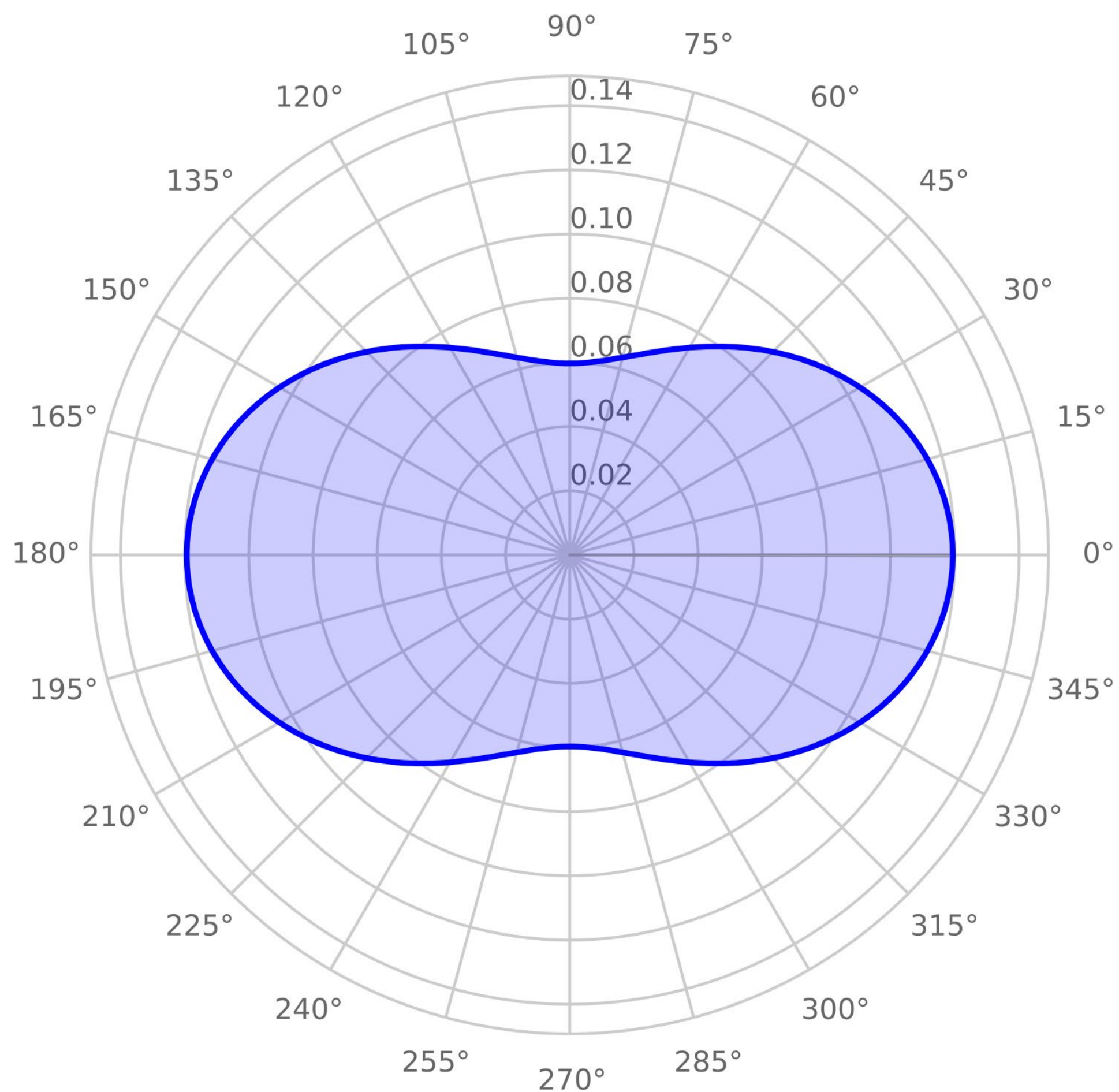
Highly wavelength dependent

# Rayleigh Phase Function

---

$$f_{p\text{Rayleigh}}(\theta) = \frac{3}{16\pi} (1 + \cos^2 \theta)$$

Scattering at right angles is half as likely as scattering forward or backward



# Rayleigh Scattering

---

Wavelength

Index of refraction

$$\sigma_{s\text{Rayleigh}}(\lambda, d, \eta, \rho) = \rho \frac{2\pi^5 d^6}{3\lambda^4} \left( \frac{\eta^2 - 1}{\eta^2 + 2} \right)^2$$

Density of scatterers

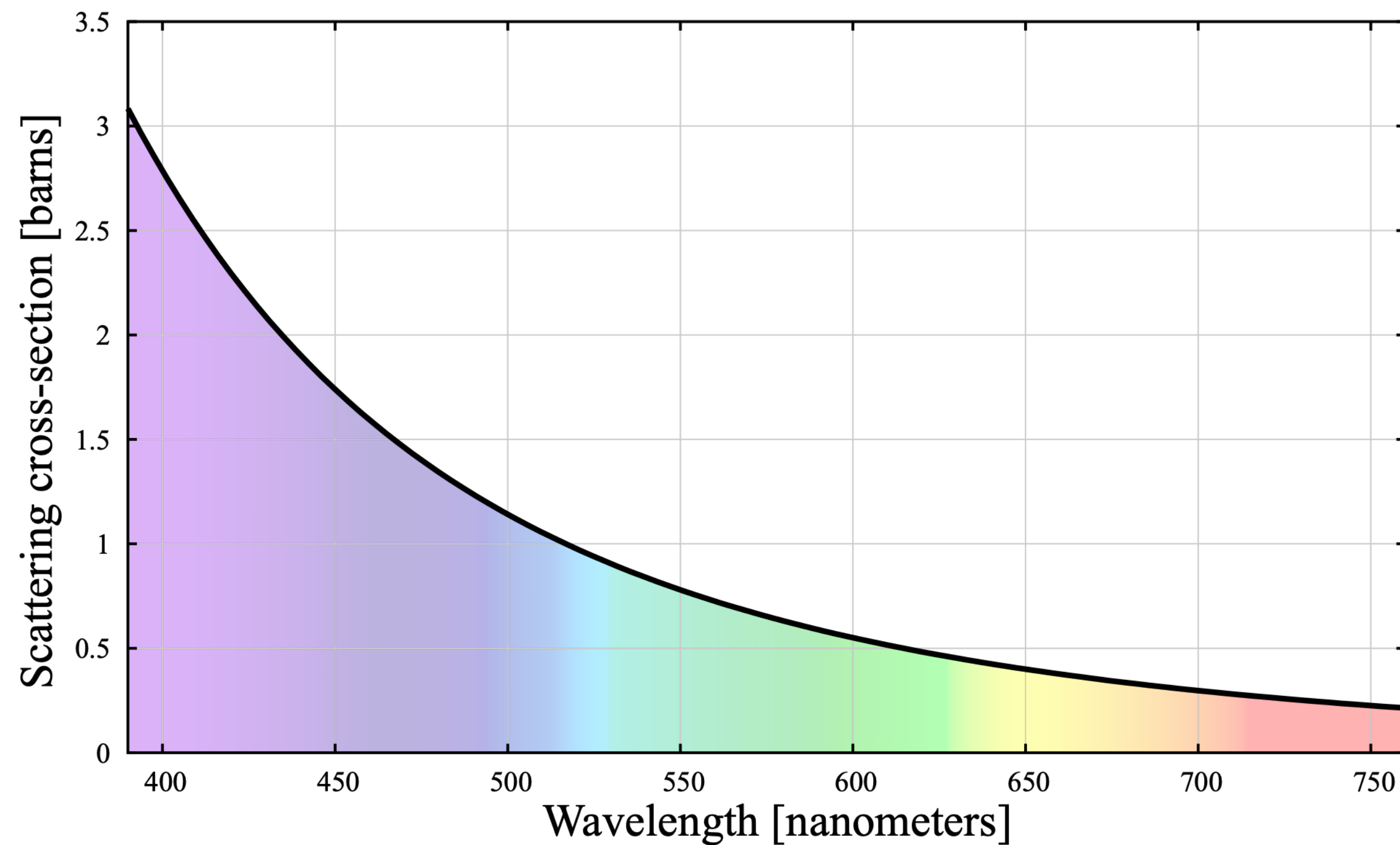
Diameter of scatterers



# Rayleigh Scattering

---

$$\sigma_{\text{sRayleigh}}(\lambda, d, \eta, \rho) = \rho \frac{2\pi^5 d^6}{3\lambda^4} \left( \frac{\eta^2 - 1}{\eta^2 + 2} \right)^2$$



# Examples

---



# Examples

---

Steam



Forward scattering

Smoke



Backward scattering



# Examples

---



Isotropic scattering

# Examples

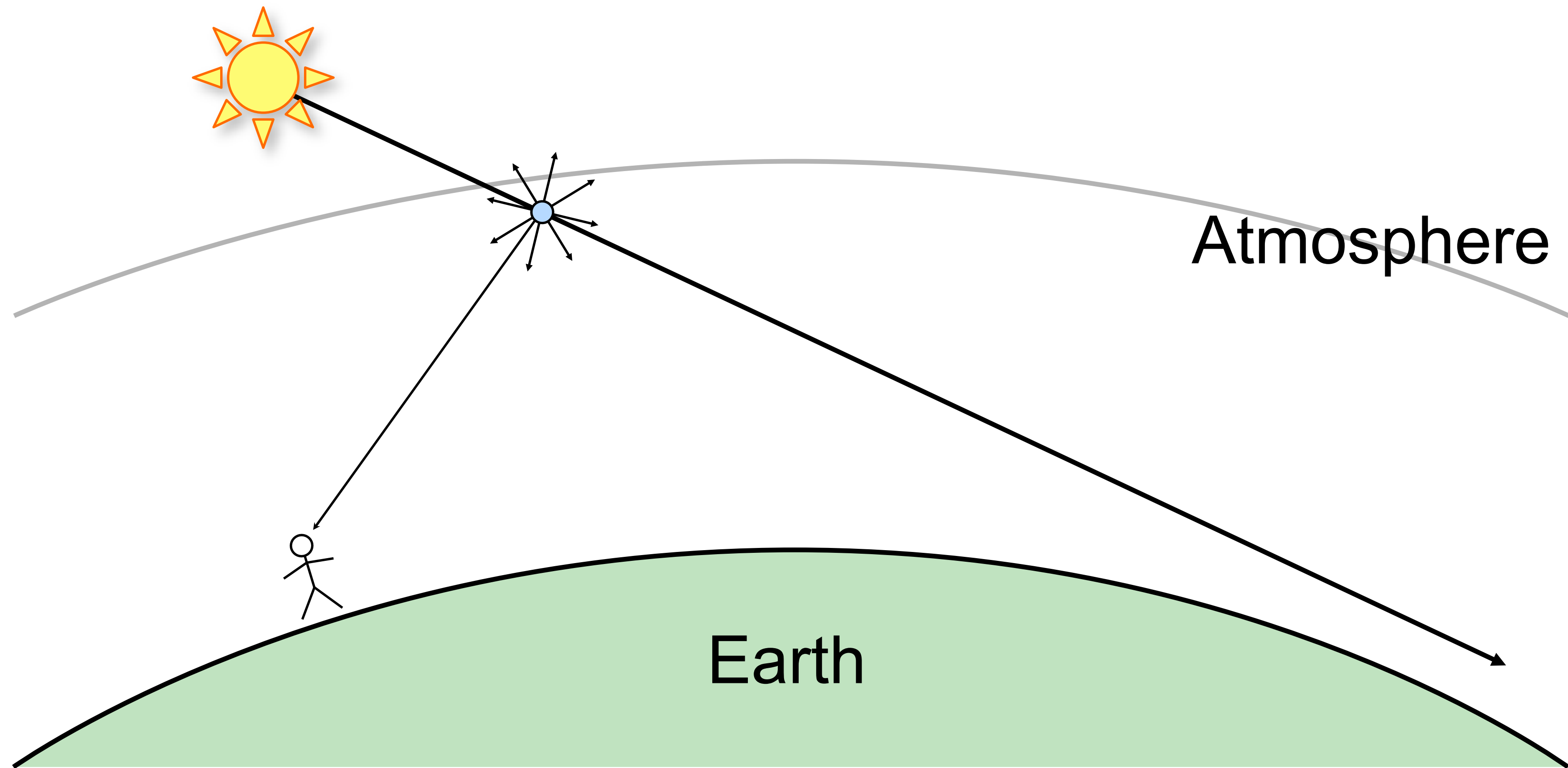
---



Forward scattering

# Why is the Sky Blue?

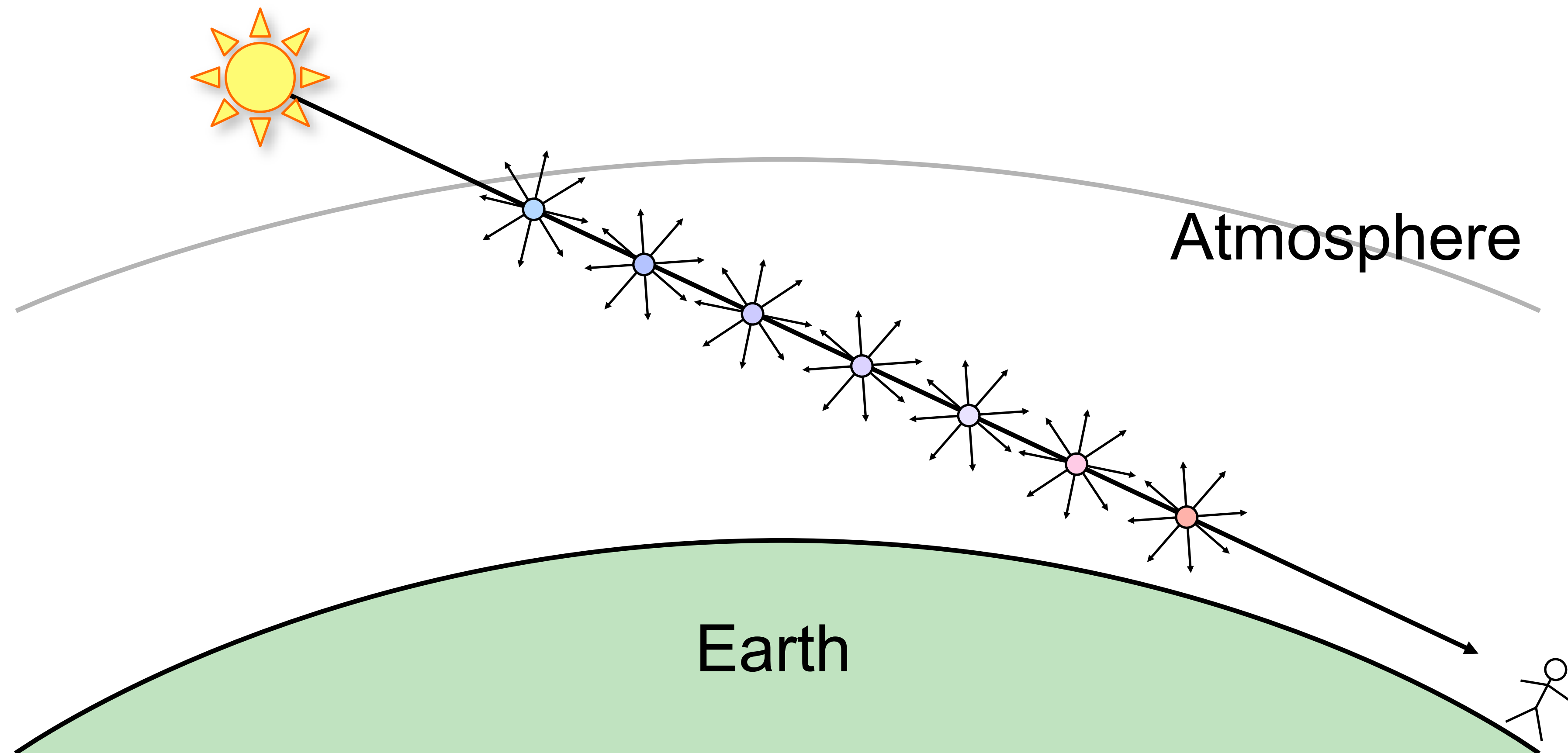
---





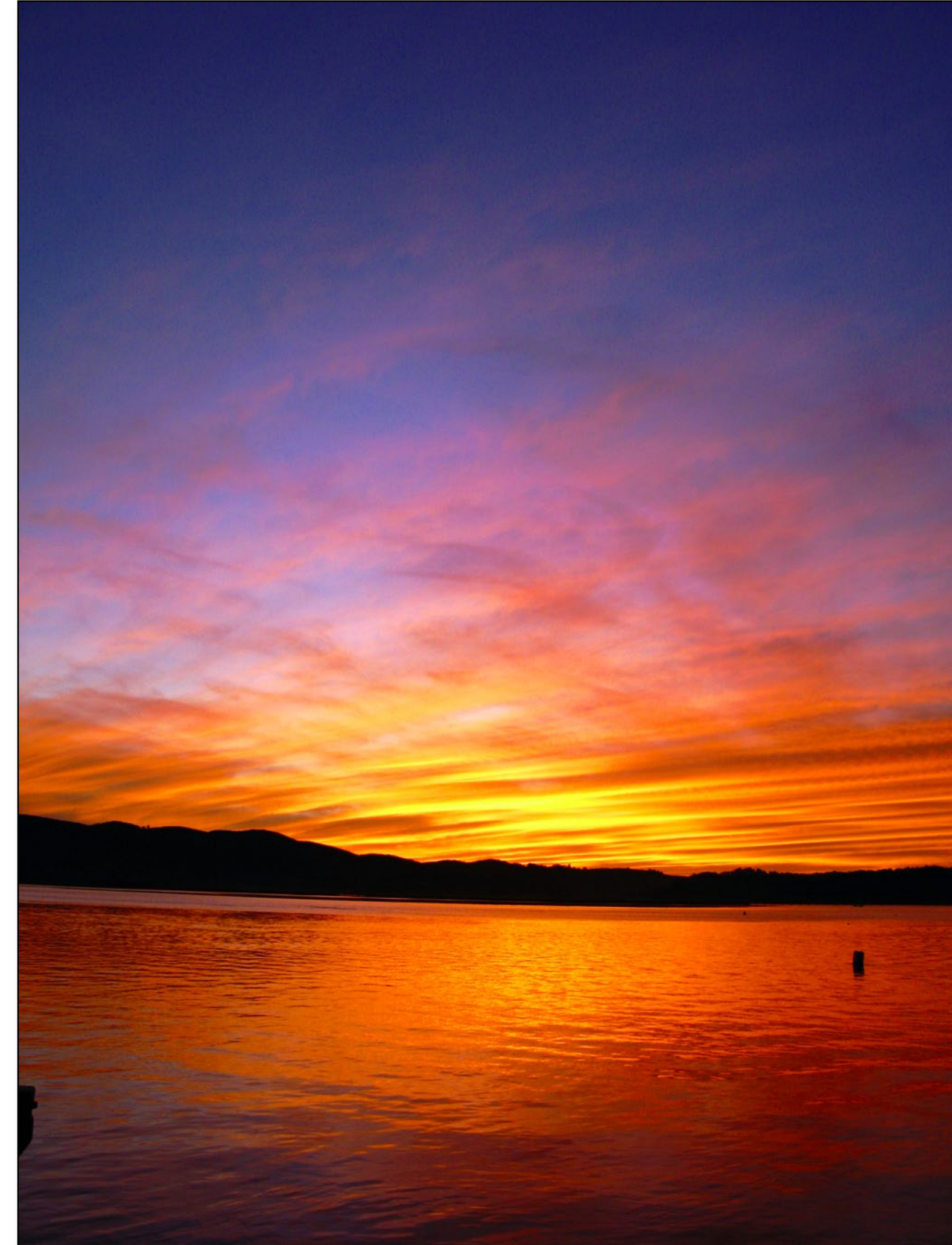
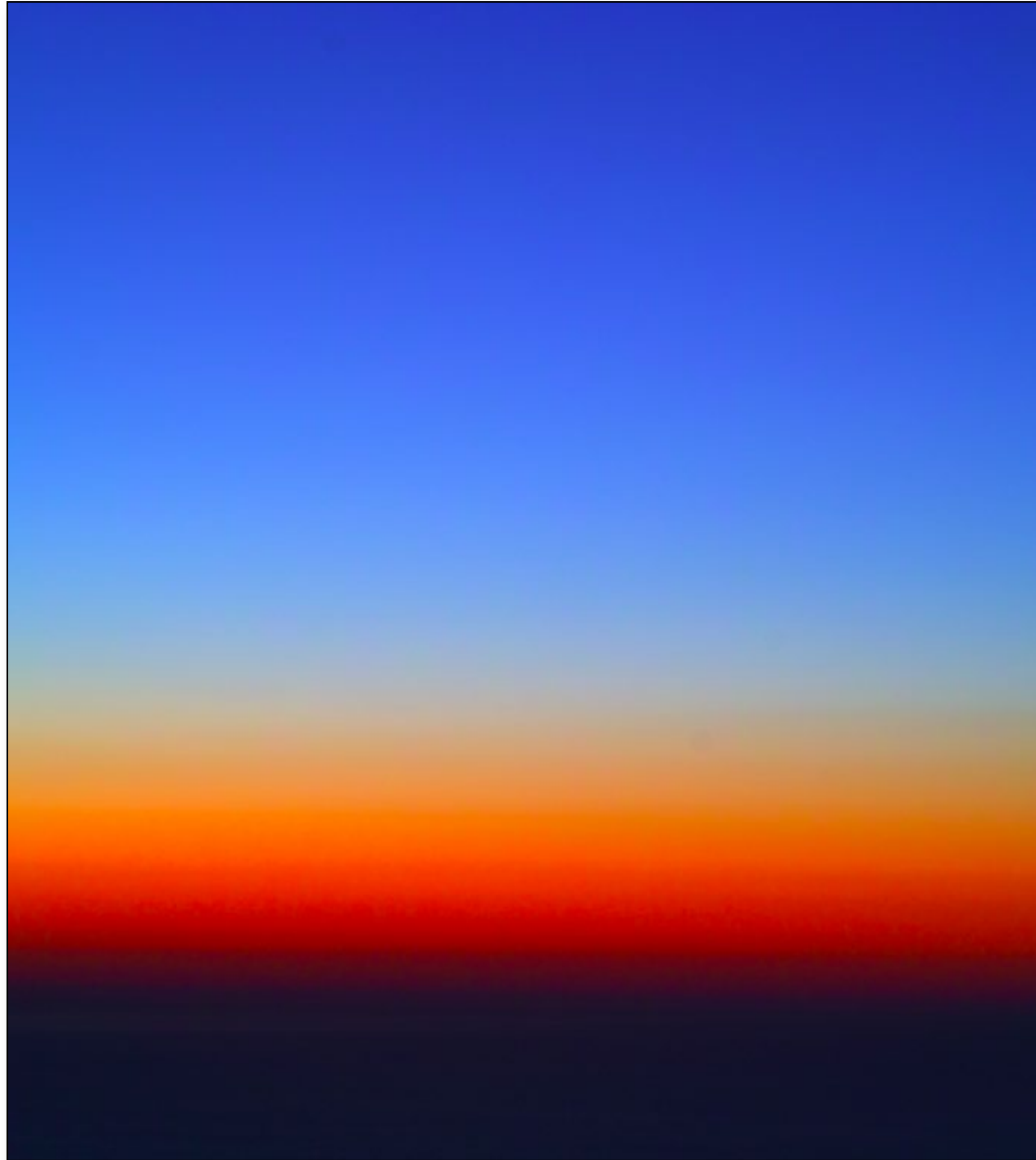
# Why is the Sunset Red?

---



# Rayleigh Scattering

---



# Media Properties (Recap)

---

Given:

- Absorption coefficient  $\sigma_a(\mathbf{x})$   $[\text{m}^{-1}]$
- Scattering coefficient  $\sigma_s(\mathbf{x})$   $[\text{m}^{-1}]$
- Phase function  $f_p(\mathbf{x}, \vec{\omega}', \vec{\omega})$   $[\text{sr}^{-1}]$

Derived:

- Extinction coefficient  $\sigma_t(\mathbf{x}) = \sigma_a(\mathbf{x}) + \sigma_s(\mathbf{x})$   $[\text{m}^{-1}]$
- Albedo  $\alpha(\mathbf{x}) = \sigma_s(\mathbf{x}) / \sigma_t(\mathbf{x})$  [none]
- Mean-free path  $1 / \sigma_t(\mathbf{x})$  [m]
- Transmittance  $T_r(\mathbf{x}, \mathbf{y}) = e^{-\int_0^{\|\mathbf{x}-\mathbf{y}\|} \sigma_t(t) dt}$  [none]



# Homogeneous Isotropic Medium

---

Given:

- Absorption coefficient	$\sigma_a$	$[\text{m}^{-1}]$
- Scattering coefficient	$\sigma_s$	$[\text{m}^{-1}]$
- Phase function	$\frac{1}{4\pi}$	$[\text{sr}^{-1}]$

Derived:

- Extinction coefficient	$\sigma_t = \sigma_a + \sigma_s$	$[\text{m}^{-1}]$
- Albedo	$\alpha = \sigma_s / \sigma_t$	[none]
- Mean-free path	$1 / \sigma_t$	[m]
- Transmittance	$T_r(\mathbf{x}, \mathbf{y}) = e^{-\sigma_t \ \mathbf{x} - \mathbf{y}\ }$	[none]

# What is this?

---



# Crepuscular Rays

---



source: [wikipedia](https://en.wikipedia.org/wiki/Crepuscular_rays)



# Anti-Crepuscular Rays

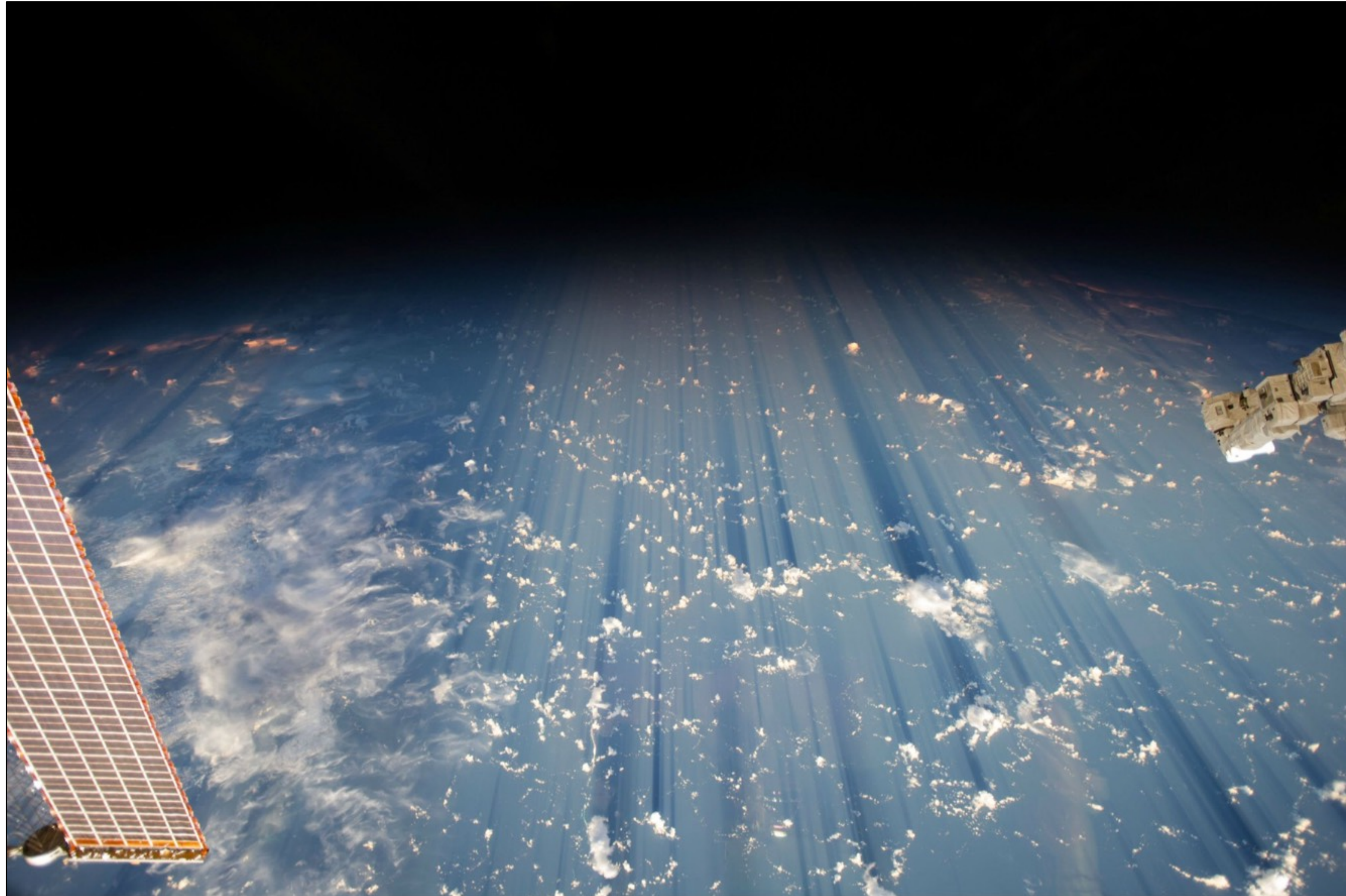
---





# Crepuscular rays from space

---



# Solving the Volume Rendering Equation



# Complexity Progression

---

homogeneous vs. heterogeneous

scattering

- none
- fake ambient
- single
- multiple

# Volume Rendering Equation

---

$$L(\mathbf{x}, \vec{\omega}) = \underbrace{T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})}_{\text{Attenuated background radiance}} + \underbrace{\int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt}_{\text{Accumulated emitted radiance}} + \underbrace{\int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) dt}_{\text{Accumulated in-scattered radiance}}$$

# Purely absorbing media

---

Attenuated background radiance

$$L(\mathbf{x}, \vec{\omega}) = T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})$$





# Fog

---



<http://anordinarymom.wordpress.com>

# Participating Media



$$L(\mathbf{x}, \vec{\omega}) = \int_0^s T_r(\mathbf{x} \leftrightarrow \mathbf{x}_t) \boxed{\sigma_s(\mathbf{x}_t)} L_i(\mathbf{x}_t, \vec{\omega}) dt + T_r(\mathbf{x} \leftrightarrow \mathbf{x}_s) L(\mathbf{x}_s, \vec{\omega})$$

$$L(\mathbf{x}, \vec{\omega}) = \boxed{\sigma_s} \int_0^s \boxed{T_r(\mathbf{x} \leftrightarrow \mathbf{x}_t)} L_i(\mathbf{x}_t, \vec{\omega}) dt + \boxed{T_r(\mathbf{x} \leftrightarrow \mathbf{x}_s)} L(\mathbf{x}_s, \vec{\omega})$$

$$L(\mathbf{x}, \vec{\omega}) = \sigma_s \int_0^s \boxed{e^{-t\sigma_t}} L_i(\mathbf{x}_t, \vec{\omega}) dt + \boxed{e^{-s\sigma_t}} L(\mathbf{x}_s, \vec{\omega})$$

# Fog

---



$$L(\mathbf{x}, \vec{\omega}) = \sigma_s \int_0^s e^{-t\sigma_t} L_i(\mathbf{x}_t, \vec{\omega}) dt + e^{-s\sigma_t} L(\mathbf{x}_s, \vec{\omega})$$



# Homogeneous Ambient Media

---

Assume in-scattered radiance is an ambient constant:

$$L(\mathbf{x}, \vec{\omega}) = \sigma_s \int_0^s e^{-t\sigma_t} L_i(\mathbf{x}_t, \vec{\omega}) dt + e^{-s\sigma_t} L(\mathbf{x}_s, \vec{\omega})$$

# Homogeneous Ambient Media

---

Assume in-scattered radiance is an ambient constant:

$$L(\mathbf{x}, \vec{\omega}) = \sigma_s \int_0^s e^{-t\sigma_t} L_i(\mathbf{x}_t, \vec{\omega}) dt + e^{-s\sigma_t} L(\mathbf{x}_s, \vec{\omega})$$

$$L(\mathbf{x}, \vec{\omega}) = \sigma_s \boxed{L_i} \boxed{\int_0^s e^{-t\sigma_t} dt} + e^{-s\sigma_t} L(\mathbf{x}_s, \vec{\omega})$$

$$L(\mathbf{x}, \vec{\omega}) = \sigma_s L_i \boxed{\frac{1 - e^{-s\sigma_t}}{\sigma_t}} + e^{-s\sigma_t} L(\mathbf{x}_s, \vec{\omega})$$

$$L(\mathbf{x}, \vec{\omega}) = \text{lerp} \left( \frac{\sigma_s}{\sigma_t} L_i, L(\mathbf{x}_s, \vec{\omega}), e^{-s\sigma_t} \right)$$

# OpenGL Fog

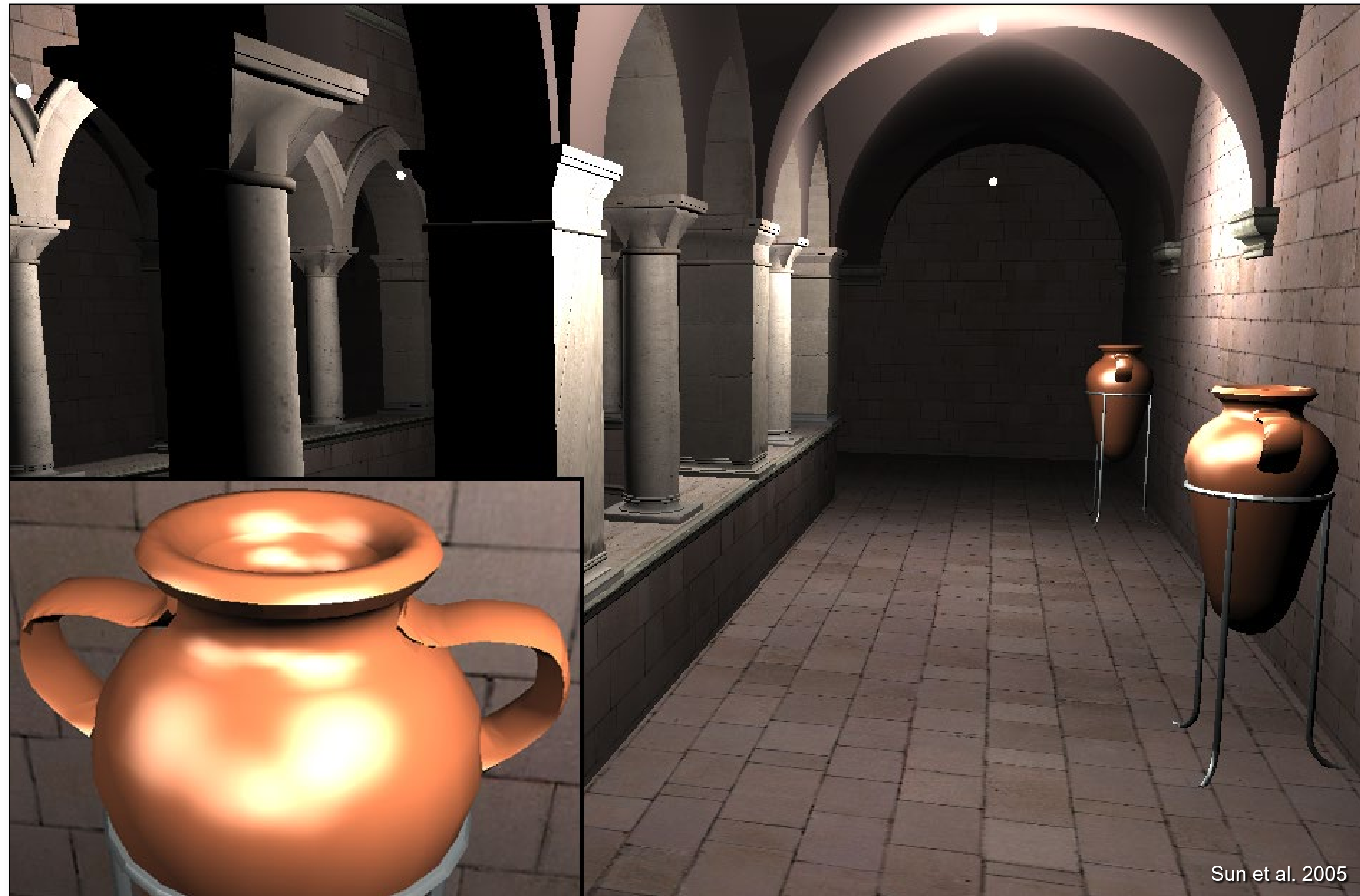
---





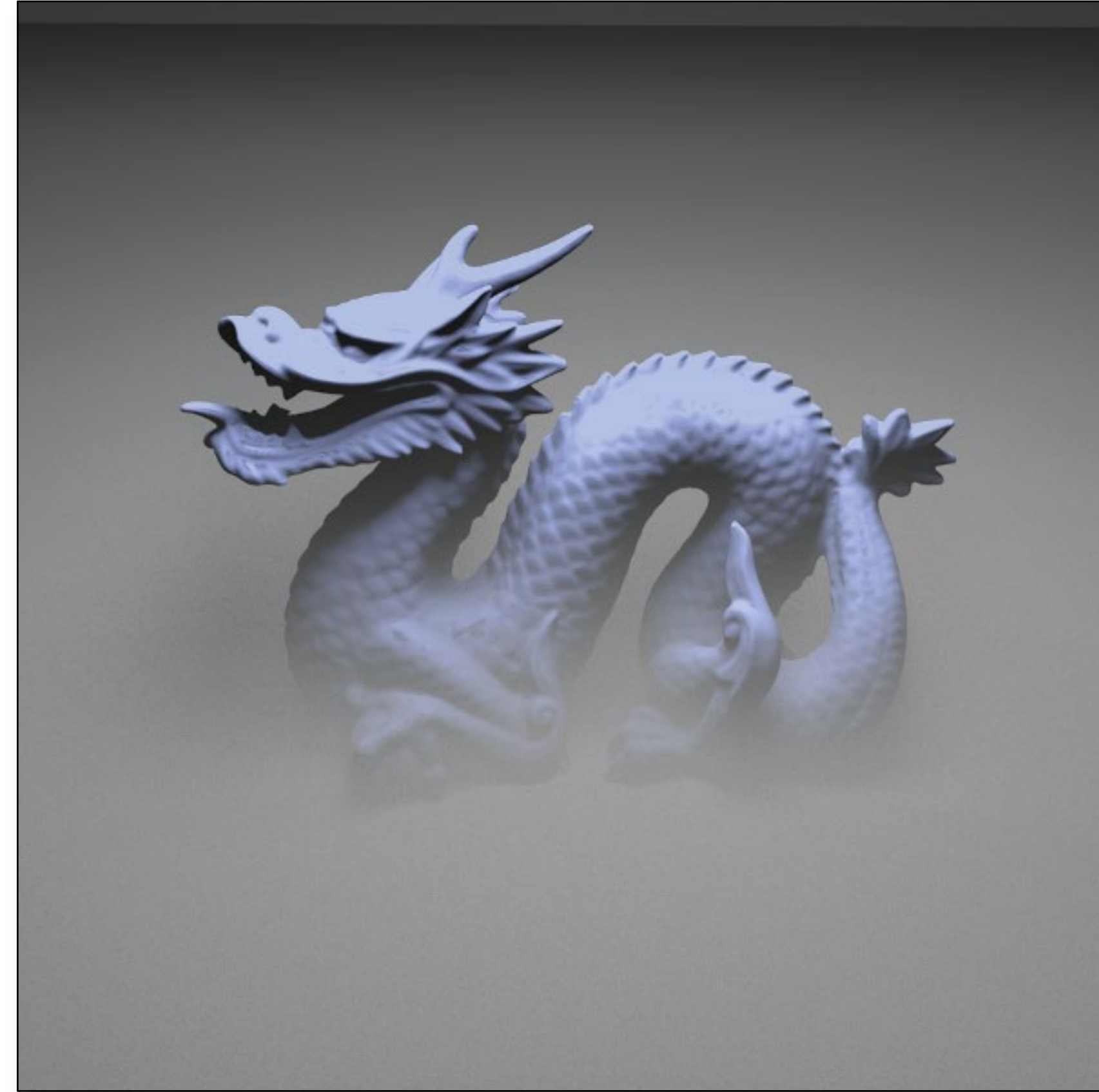
# OpenGL Clear Day

---



# Fog

---













# Volume Rendering Equation

---

$$\begin{aligned} L(\mathbf{x}, \vec{\omega}) = & T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega}) \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt \\ & + \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) dt \end{aligned}$$

↑ Accumulated in-scattered radiance



# In-scattered Radiance

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \boxed{L_s(\mathbf{x}_t, \vec{\omega})} dt$$

$$\boxed{L_s(\mathbf{x}_t, \vec{\omega})} = \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) \boxed{L_i(\mathbf{x}_t, \vec{\omega}')} d\vec{\omega}'$$

## Single scattering

- $L_i$  arrives directly from a light source (direct illum.)

i.e.:

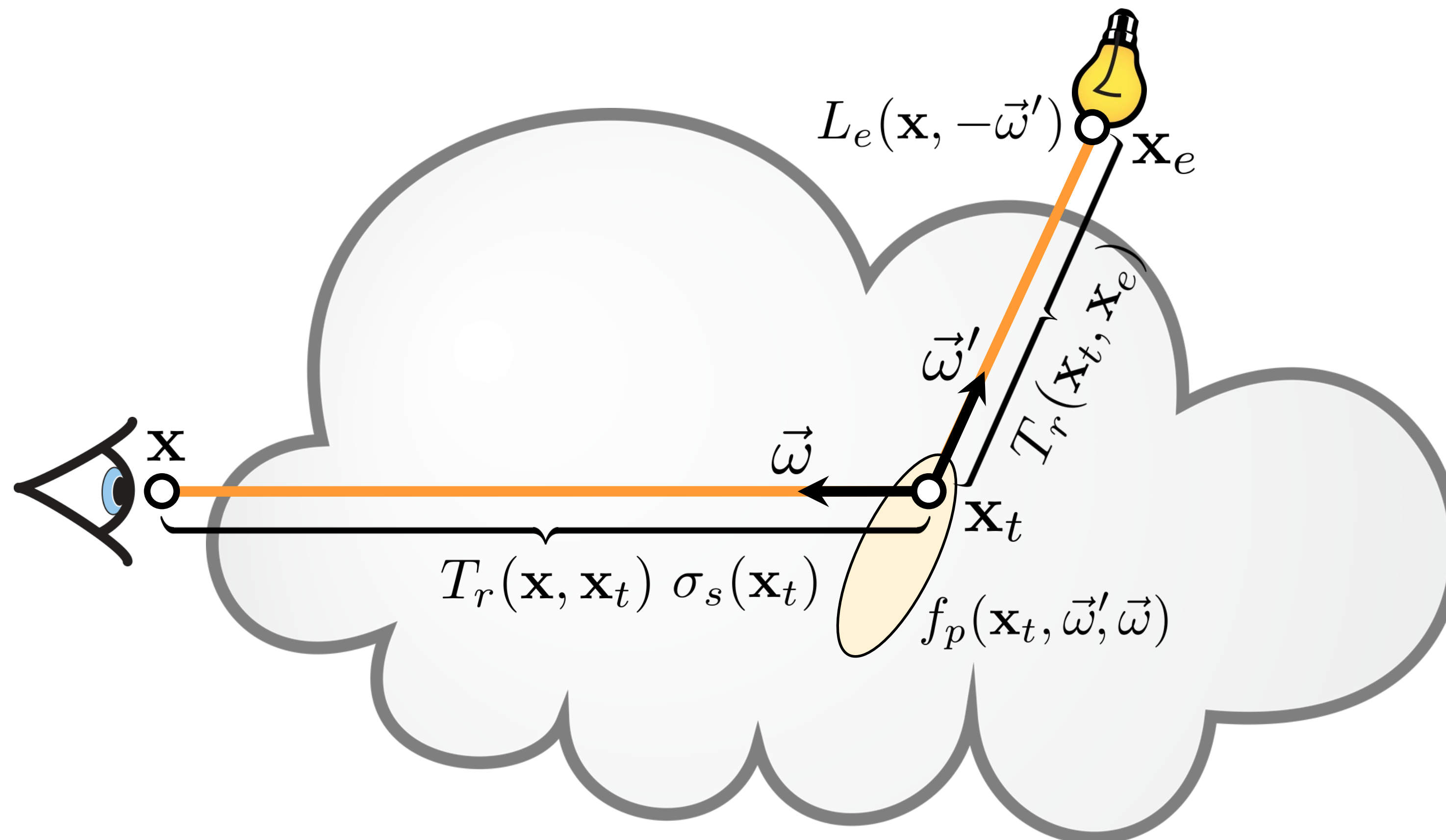
$$\boxed{L_i(\mathbf{x}, \vec{\omega})} = T_r(\mathbf{x}, r(\mathbf{x}, \vec{\omega})) L_e(r(\mathbf{x}, \vec{\omega}), -\vec{\omega})$$

## Multiple scattering

- $L_i$  arrives through multiple bounces (indirect illum.)

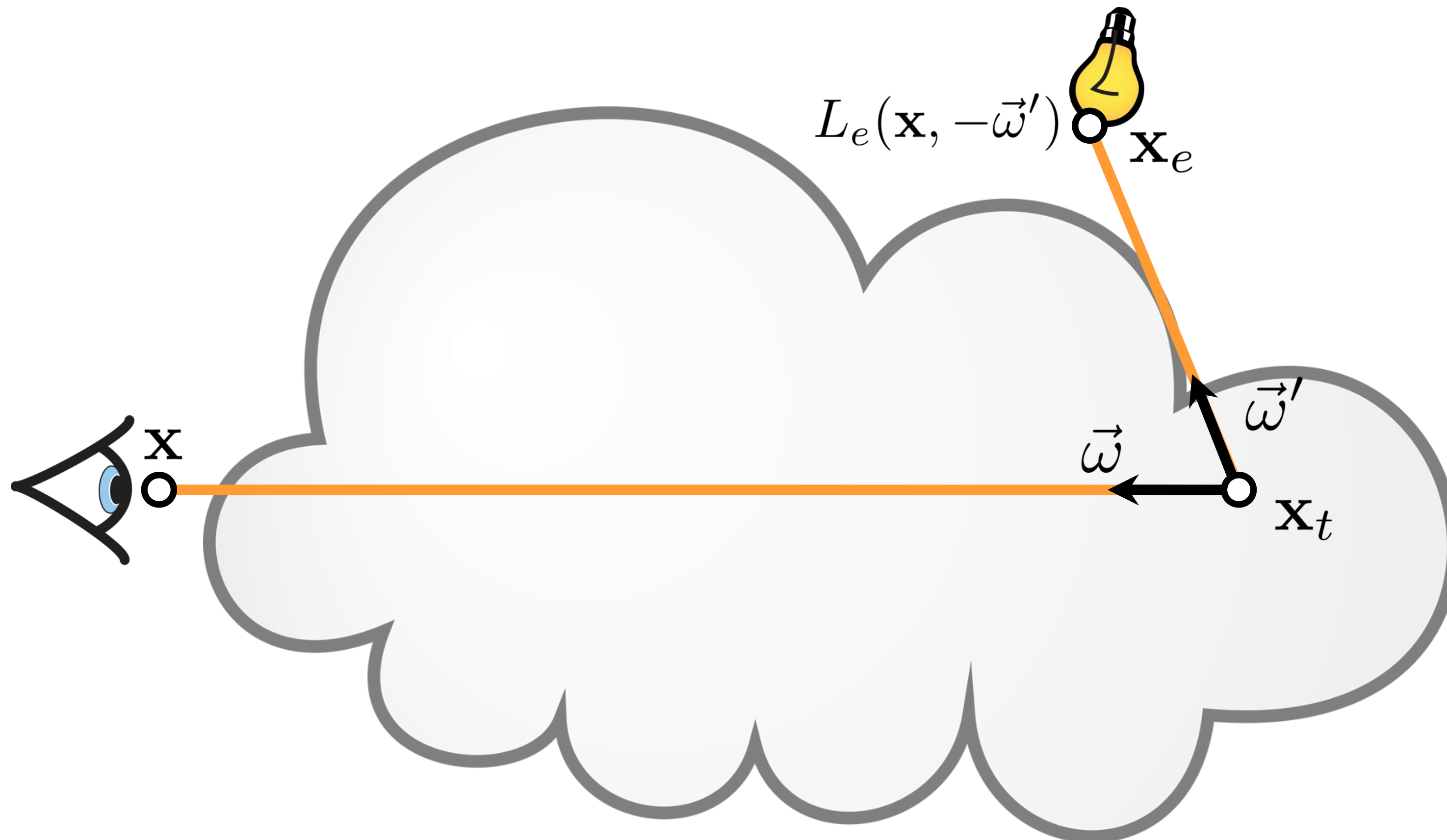
# Single Scattering

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$



# Single Scattering

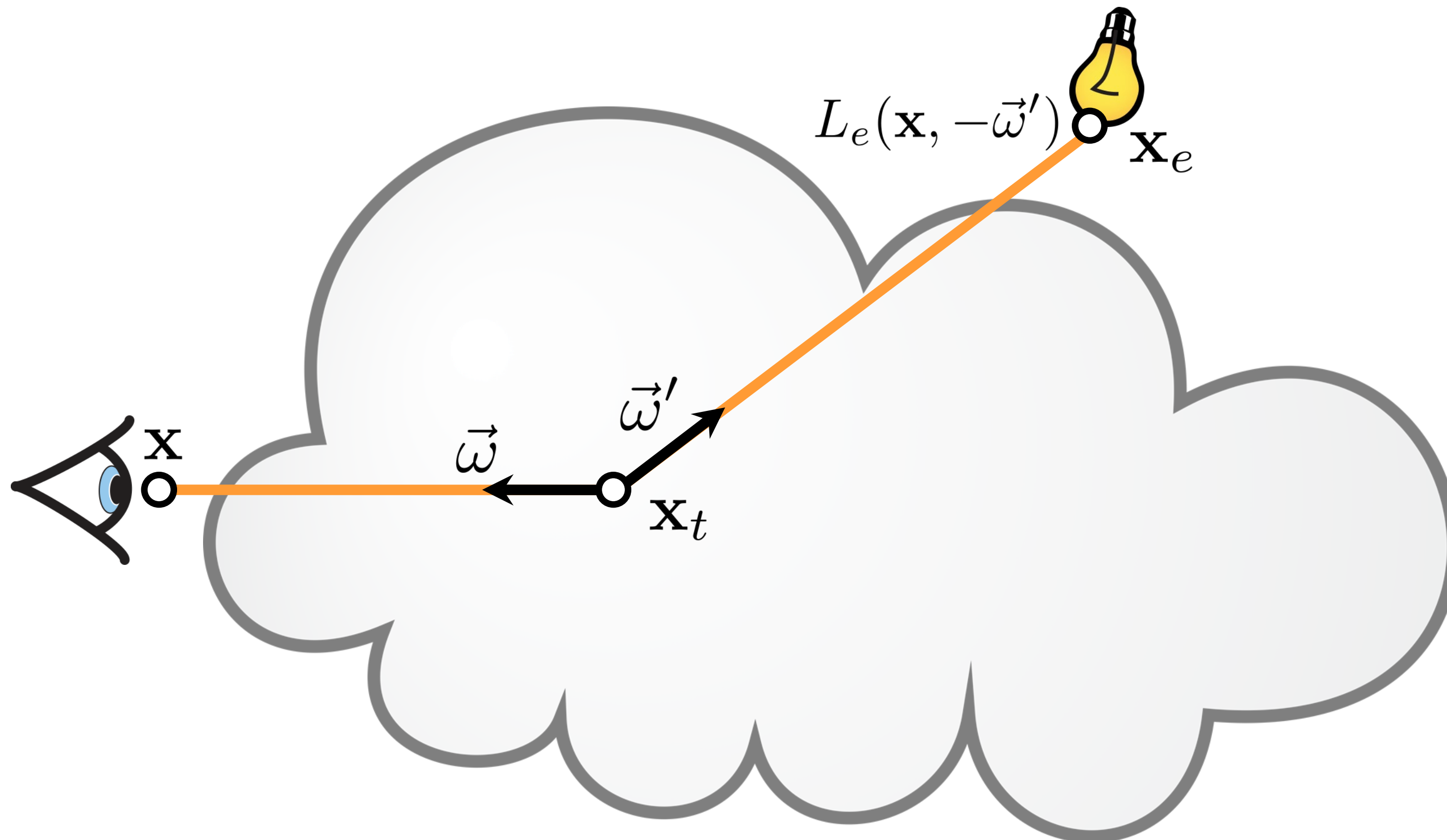
$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$





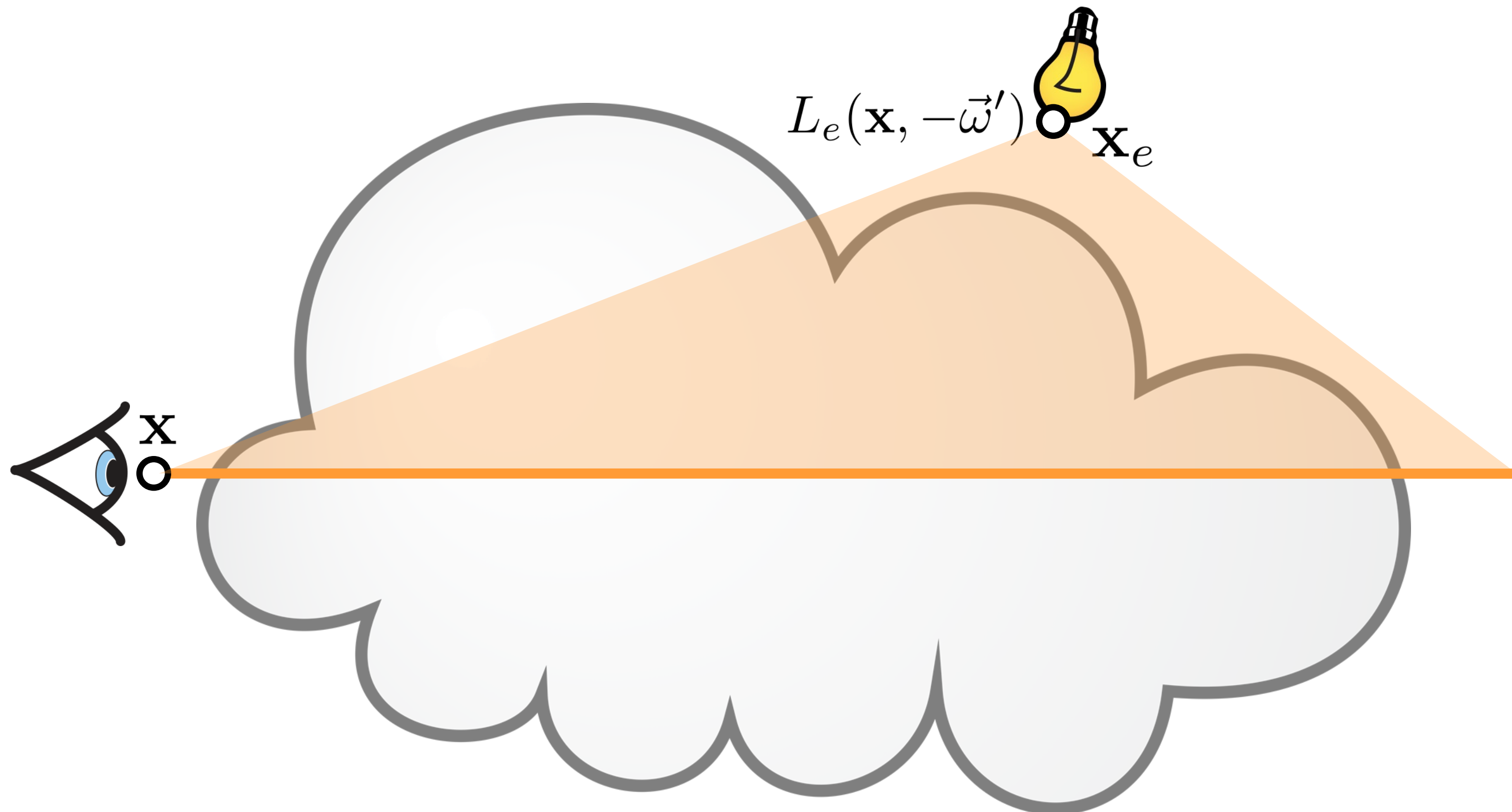
# Single Scattering

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$



# Single Scattering

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$



# Single Scattering

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$

(Semi-)analytic solutions:

- Sun et al. [2005]
- Pegoraro et al. [2009, 2010]

Numerical solutions:

- Ray-marching
- Equiangular sampling



# Analytic Single Scattering

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega}') d\vec{\omega}' dt$$

Assumptions:

- Homogeneous medium
- Point or spot light
- Relatively simple phase function
- No occlusion

$$L(\mathbf{x}, \vec{\omega}) = \frac{\Phi}{4\pi} \frac{1}{4\pi} \sigma_s \int_0^z e^{-\sigma_t \|\mathbf{x}, \mathbf{x}_t\|} \frac{e^{-\sigma_t \|\mathbf{x}_t, \mathbf{x}_p\|}}{\|\mathbf{x}_t, \mathbf{x}_p\|^2} dt$$

# OpenGL Fog



# Analytic Single Scattering

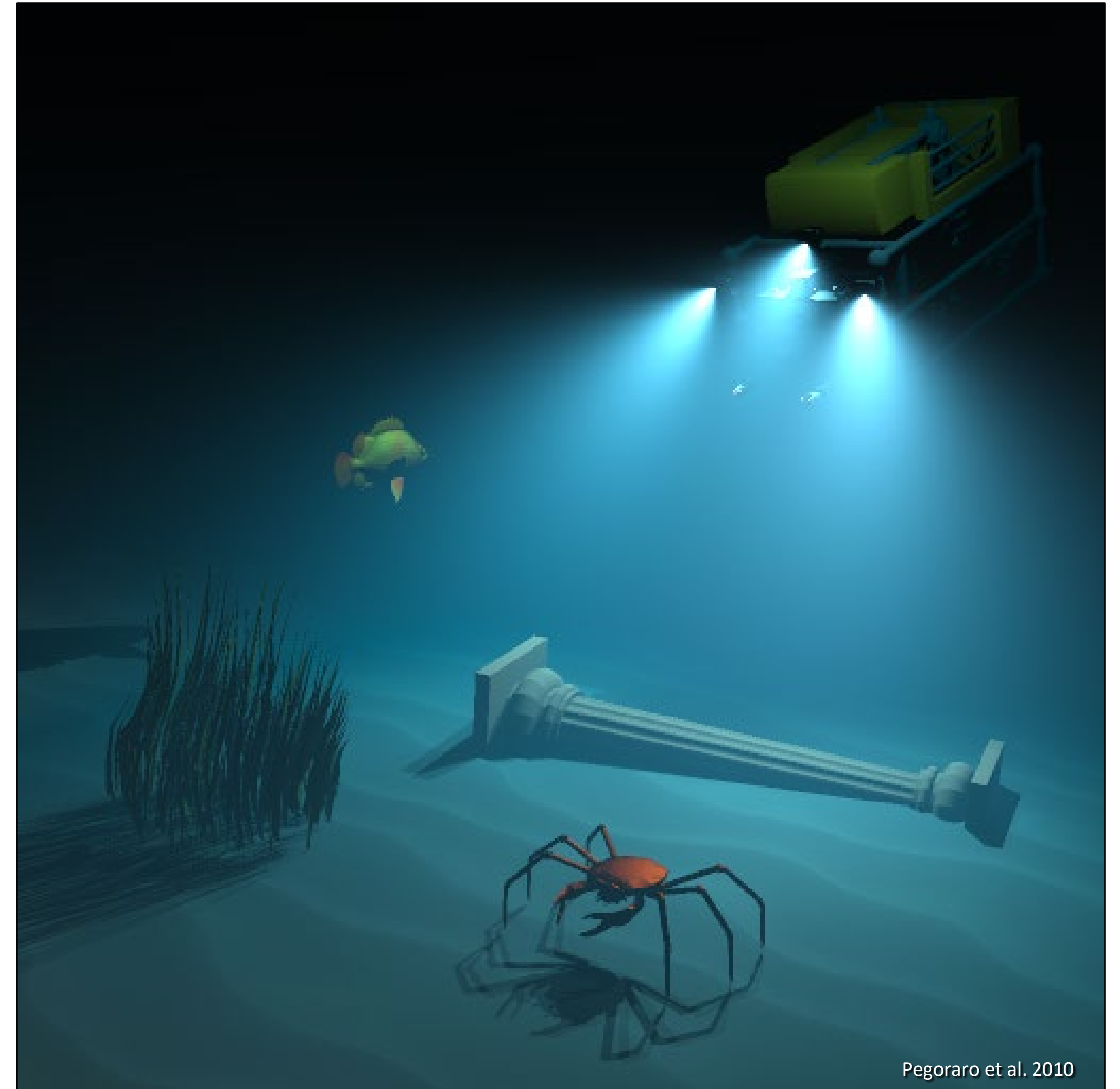
---



Sun et al. 2005



# Analytic Single Scattering







Andreas Levers







# Analytic Single Scattering

---

$$L_m(x_a, x_b, \vec{\omega}) = \frac{\kappa_s}{h} e^{\kappa_t(x_a - x_h)} 2 \sum_{n=0}^{N-1} c(n) \sum_{k=0}^{2n} d(n, k) \int_{v_a}^{v_b} \frac{e^{-Hv}}{(v^2 + 1)^{n+1}} v^k dv$$

$$\begin{aligned} \int \frac{e^{av}}{(v^2 + 1)^m} v^n dv &= \frac{1}{2^{m-1}} \sum_{l=0}^{m-1} \frac{1}{2^l} \binom{m-1+l}{m-1} \left( \sum_{k=0}^{\min\{m-1-l, n\}} \binom{n}{k} \left( \frac{a^{m-1-l-k}}{(m-1-l-k)!} E(a, v, m-n-l+k) \right. \right. \\ &\quad \left. \left. - e^{av} \sum_{j=1}^{m-1-l-k} \frac{(j-1)!}{(m-1-l-k)!} \frac{a^{m-1-l-k-j}}{(v^2 + 1)^j} \sum_{\substack{i=(m-n-l+k-j) \bmod 2 \\ i+=2}}^{\leq j} (-1)^{\frac{m-n-l+k-j+i}{2}} \binom{j}{i} v^i \right) \right. \\ &\quad \left. + \frac{e^{av}}{a} \sum_{k=0}^{\leq n-m+l} \binom{n}{k} \sum_{j=0}^{n-m+l-k} \frac{(n-m+l-k)!}{j!} \frac{1}{(-a)^{n-m+l-k-j}} \sum_{\substack{i=(-m+l+k-j) \bmod 2 \\ i+=2}}^{\leq j} (-1)^{\frac{-m+l+k-j+i}{2}} \binom{j}{i} v^i \right) \end{aligned}$$

No shadows, implementation nightmare, computationally intensive...

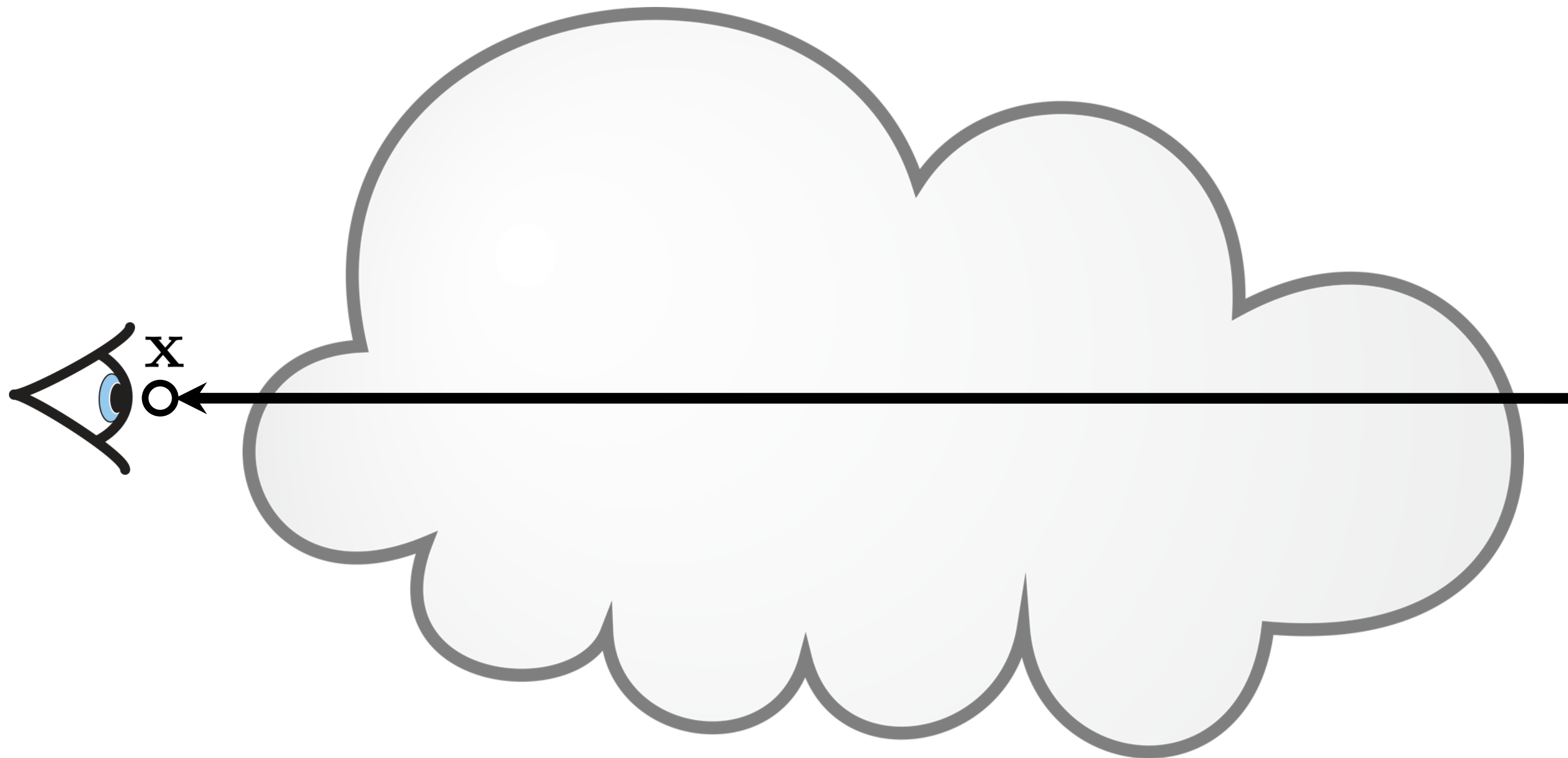
Let's try brute force!

# Ray-Marching

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) dt$$

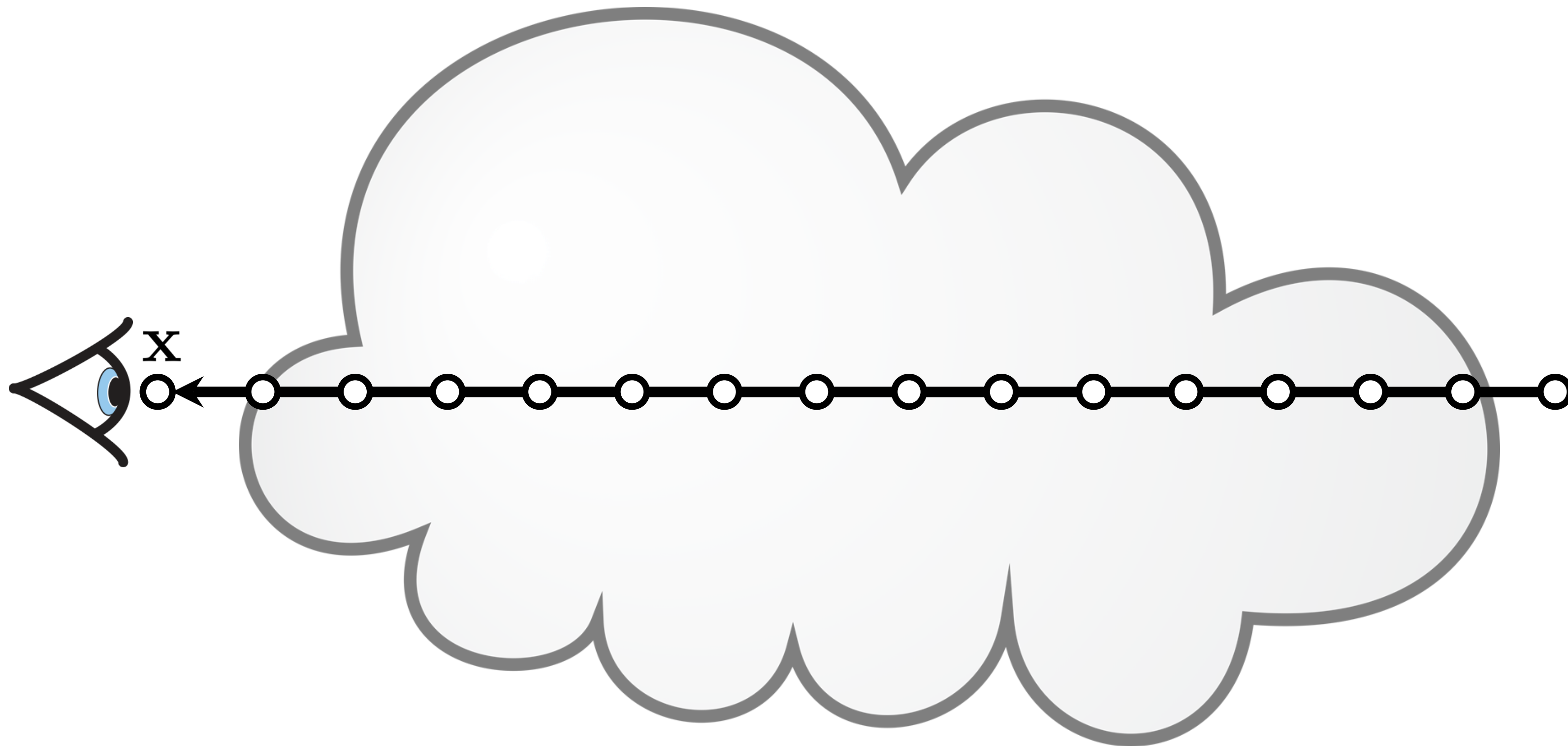
Approximate with Riemann sum



# Ray-Marching

---

$$L(\mathbf{x}, \vec{\omega}) \approx \sum_{i=1}^N T_r(\mathbf{x}, \mathbf{x}_{t,i}) \sigma_s(\mathbf{x}_{t,i}) L_s(\mathbf{x}_{t,i}, \vec{\omega}) \Delta t$$

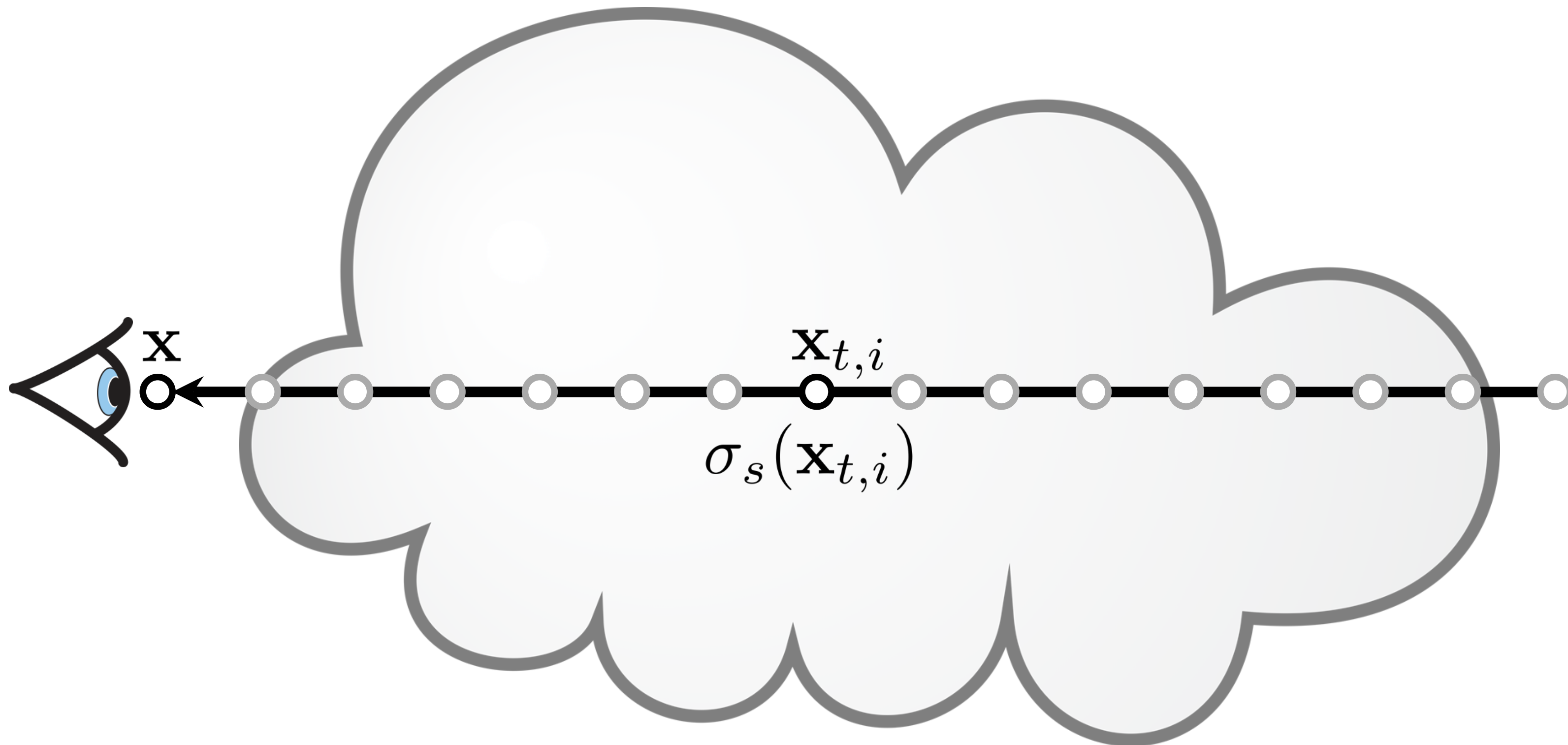




# Ray-Marching

---

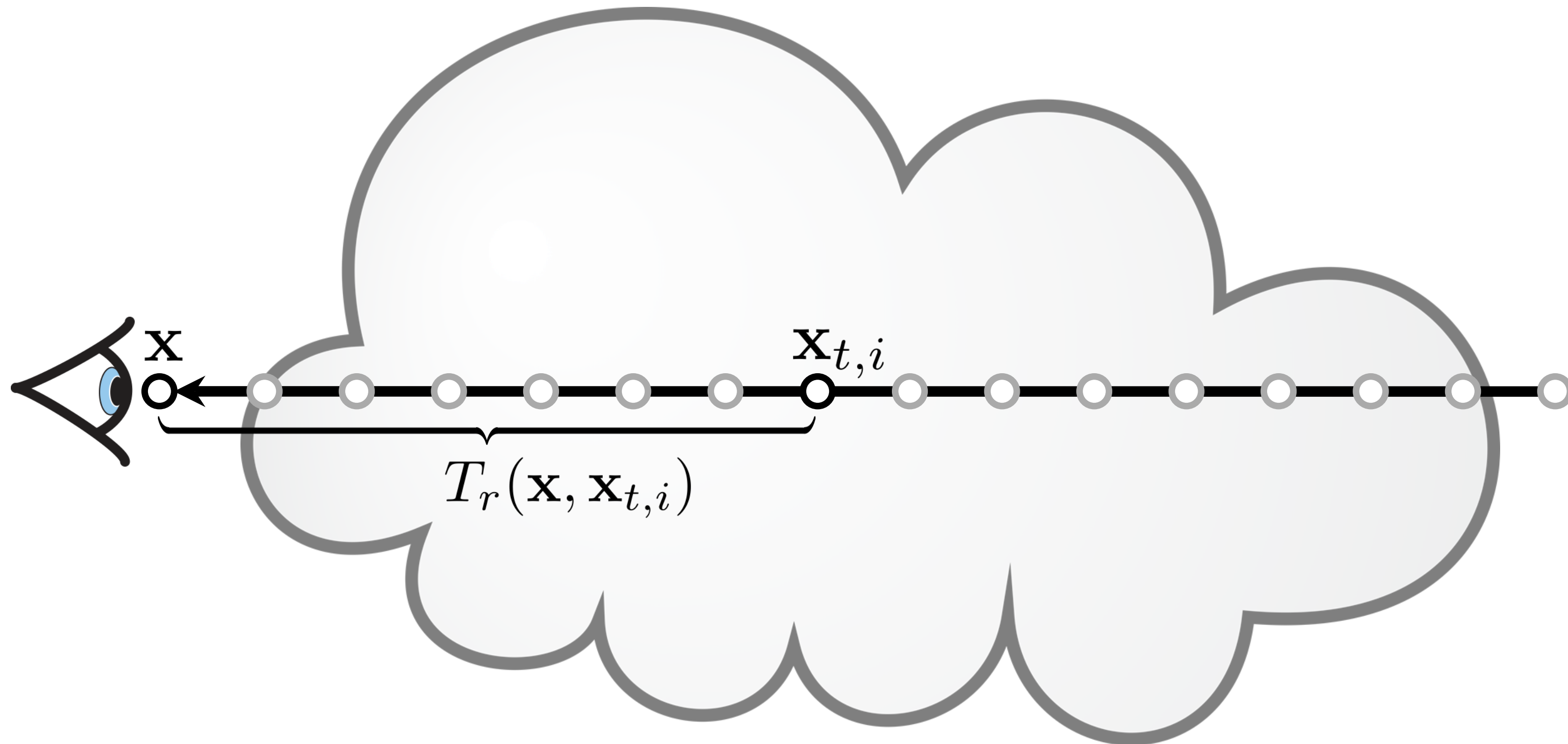
$$L(\mathbf{x}, \vec{\omega}) \approx \sum_{i=1}^N T_r(\mathbf{x}, \mathbf{x}_{t,i}) \boxed{\sigma_s(\mathbf{x}_{t,i})} L_s(\mathbf{x}_{t,i}, \vec{\omega}) \Delta t$$



# Ray-Marching

$$L(\mathbf{x}, \vec{\omega}) \approx \sum_{i=1}^N \boxed{T_r(\mathbf{x}, \mathbf{x}_{t,i})} \sigma_s(\mathbf{x}_{t,i}) L_s(\mathbf{x}_{t,i}, \vec{\omega}) \Delta t$$

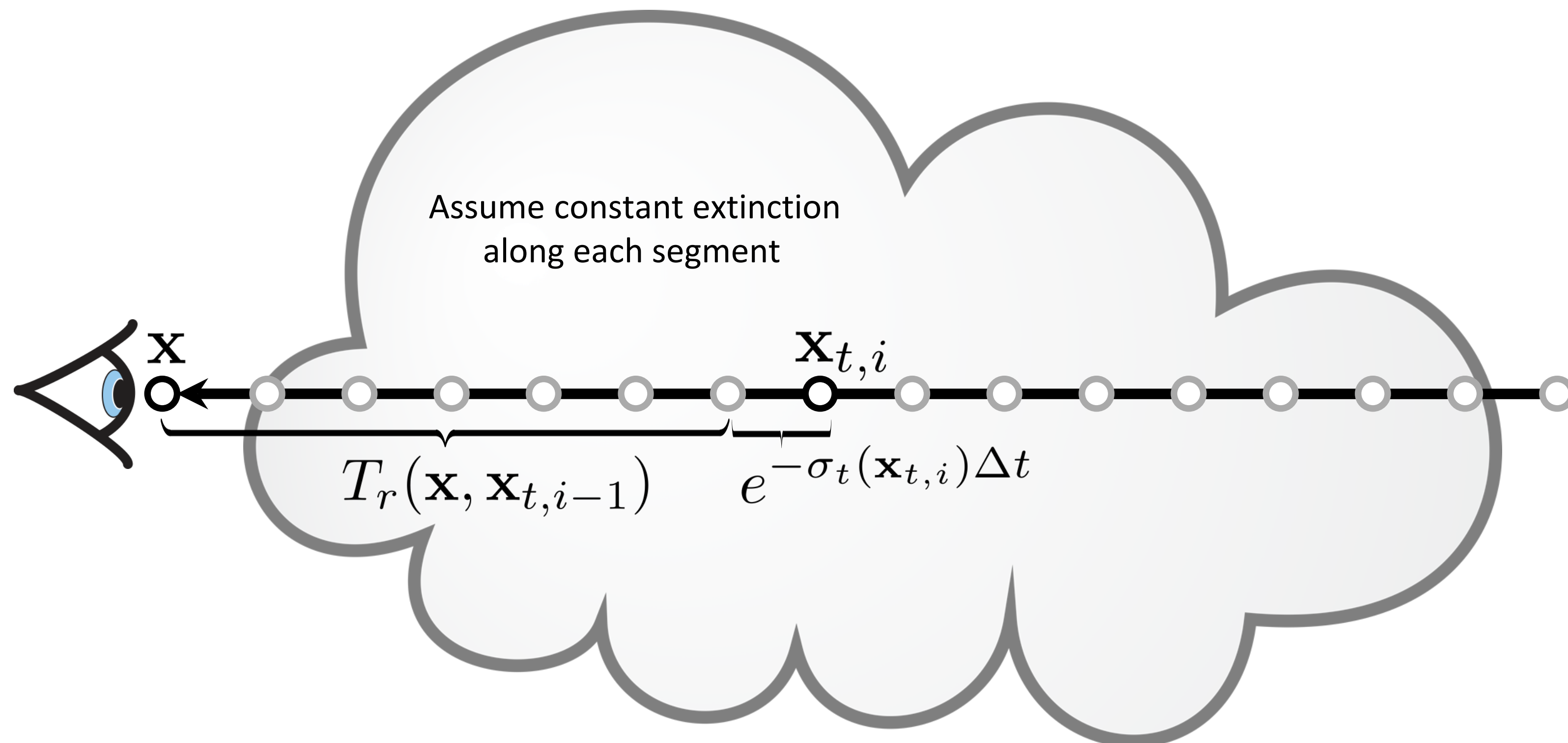
Homogeneous volume:  $T_r(\mathbf{x}, \mathbf{x}_{t,i}) = e^{-\sigma_t \|\mathbf{x}, \mathbf{x}_{t,i}\|}$



# Ray-Marching

$$L(\mathbf{x}, \vec{\omega}) \approx \sum_{i=1}^N \boxed{T_r(\mathbf{x}, \mathbf{x}_{t,i})} \sigma_s(\mathbf{x}_{t,i}) L_s(\mathbf{x}_{t,i}, \vec{\omega}) \Delta t$$

Heterogeneous volume:  $T_r(\mathbf{x}, \mathbf{x}_{t,i}) = T_r(\mathbf{x}, \mathbf{x}_{t,i-1}) e^{-\sigma_t(\mathbf{x}_{t,i}) \Delta t}$

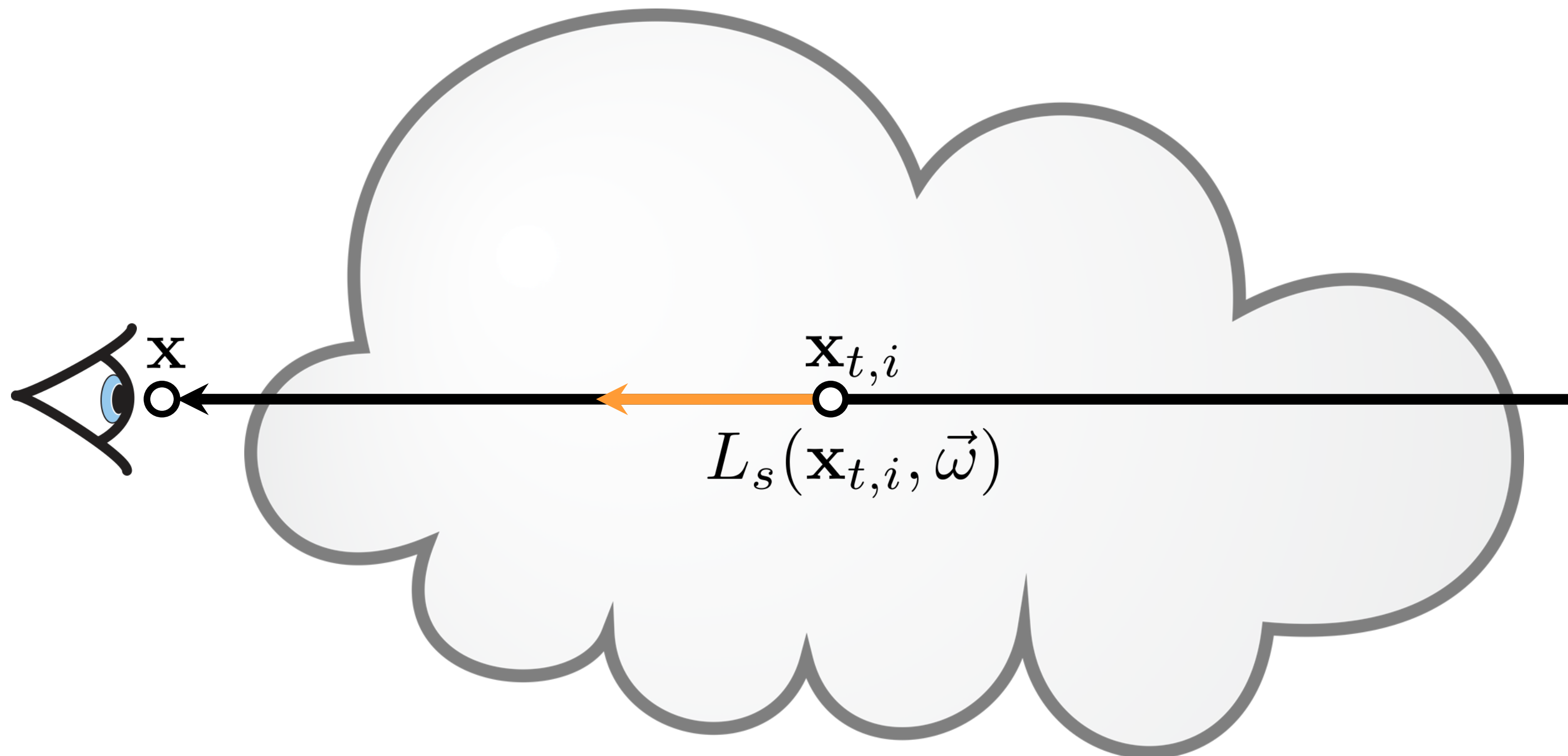




# Ray-Marching

---

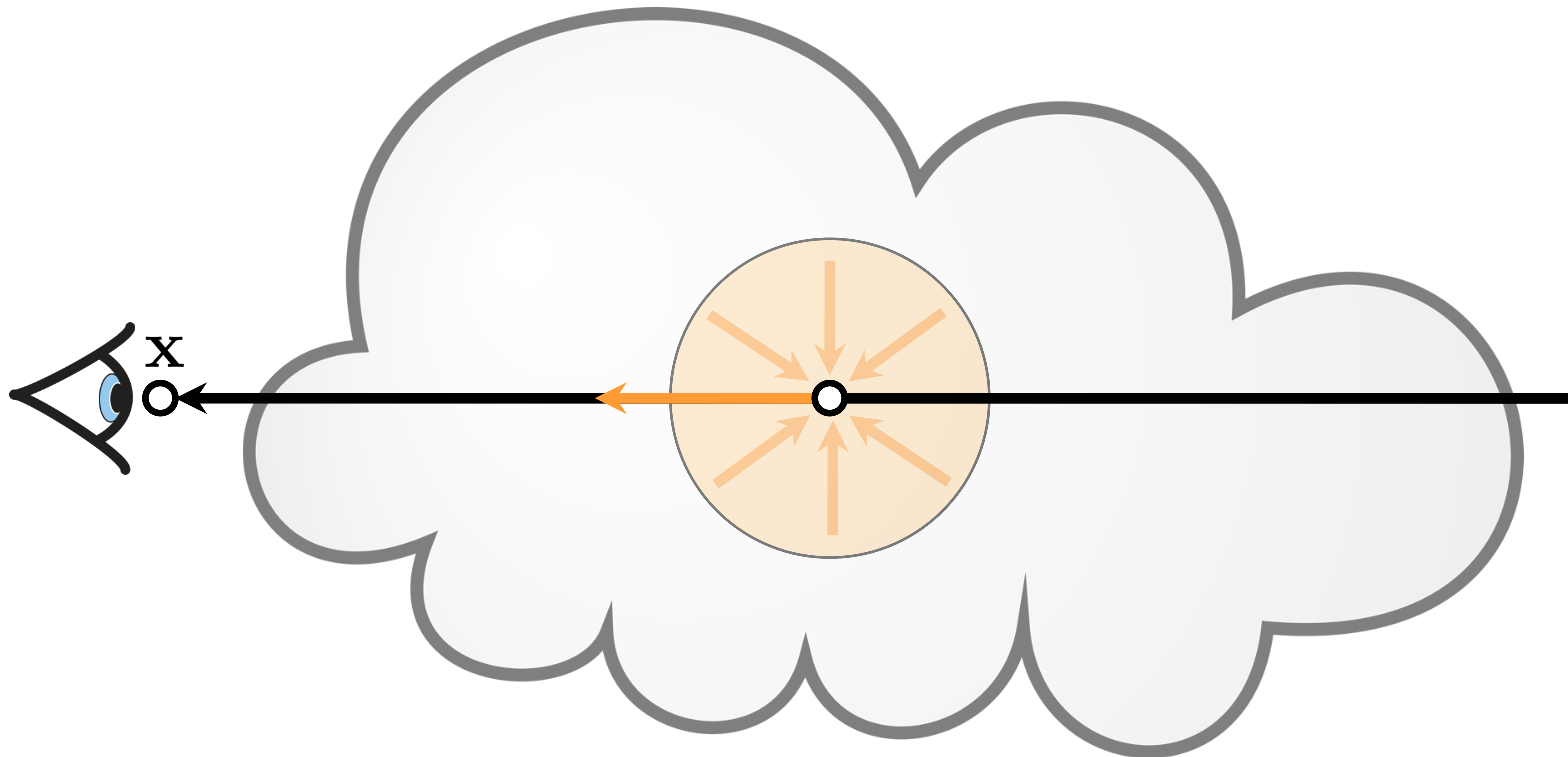
$$L(\mathbf{x}, \vec{\omega}) \approx \sum_{i=1}^N T_r(\mathbf{x}, \mathbf{x}_{t,i}) \sigma_s(\mathbf{x}_{t,i}) \boxed{L_s(\mathbf{x}_{t,i}, \vec{\omega})} \Delta t$$



# Ray-Marching

---

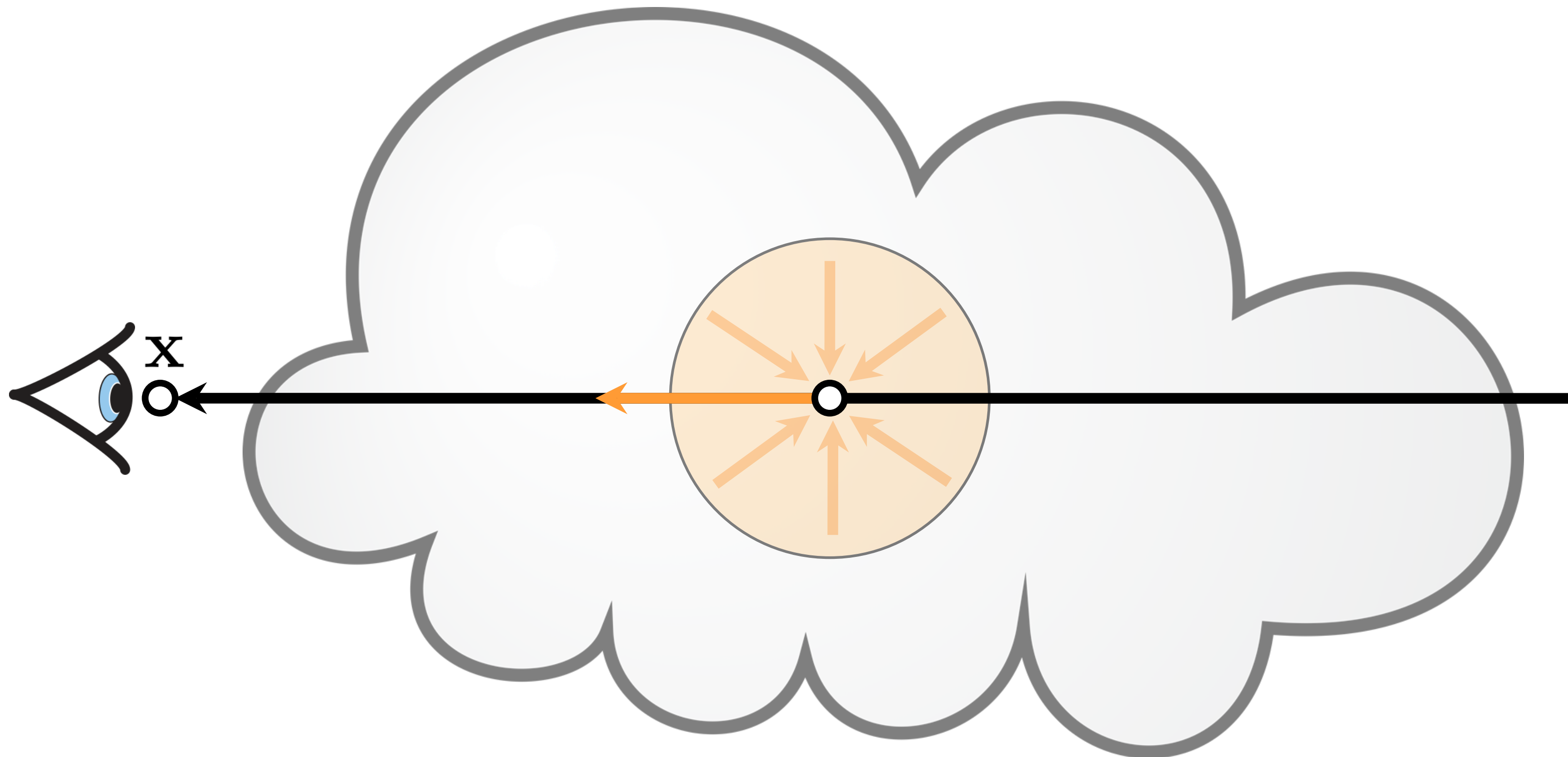
$$L_s(\mathbf{x}_t, \vec{\omega}) = \int_{S^2} f_p(\mathbf{x}_t, \vec{\omega}', \vec{\omega}) L_i(\mathbf{x}_t, \vec{\omega}') d\vec{\omega}'$$



# Ray-Marching

---

$$L_s(\mathbf{x}_t, \vec{\omega}) \approx \frac{1}{M} \sum_{j=0}^M \frac{f_p(\mathbf{x}_t, \vec{\omega}'_j, \vec{\omega}) \boxed{L_i(\mathbf{x}_t, \vec{\omega}'_j)}}{p(\vec{\omega}'_j)}$$

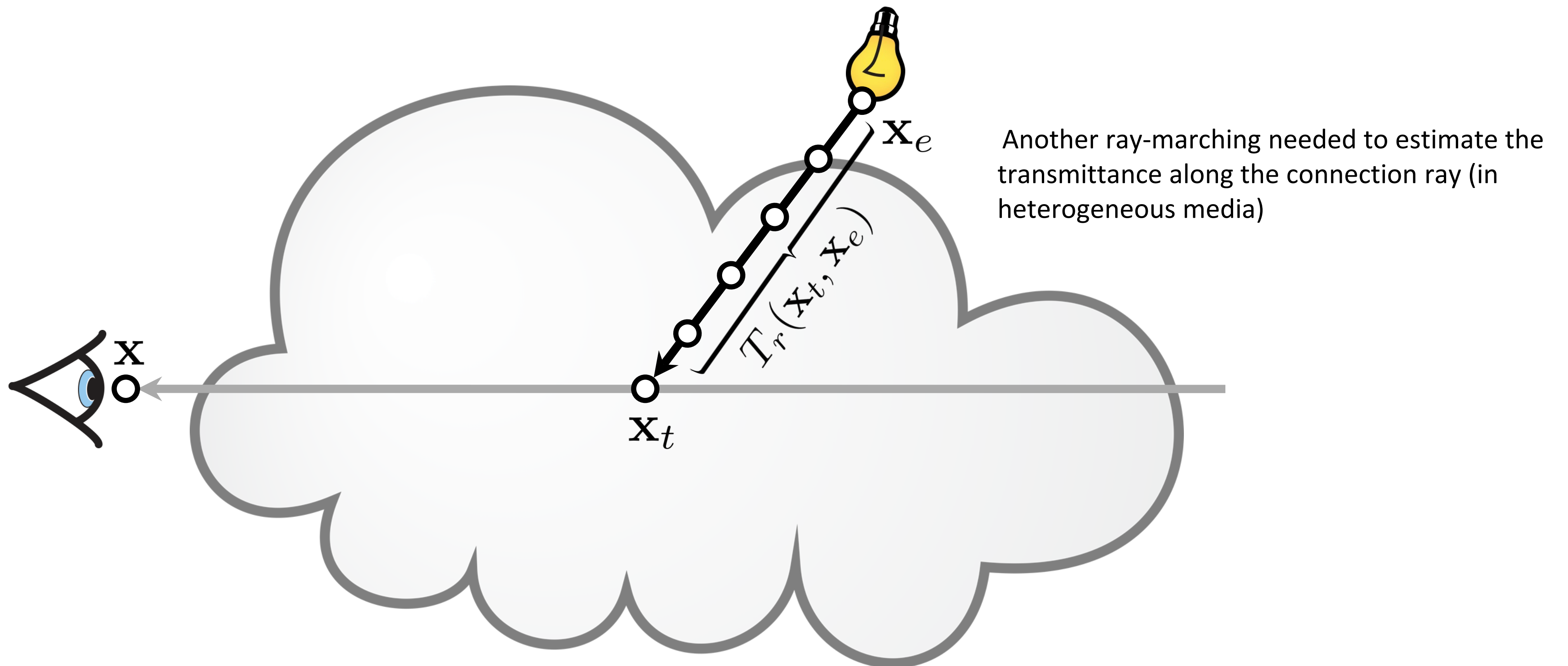




# Ray-Marching

Single scattering:

$$L_i(\mathbf{x}_t, \vec{\omega}) = T_r(\mathbf{x}_t, \mathbf{x}_e) L_e(\mathbf{x}_e, -\vec{\omega})$$

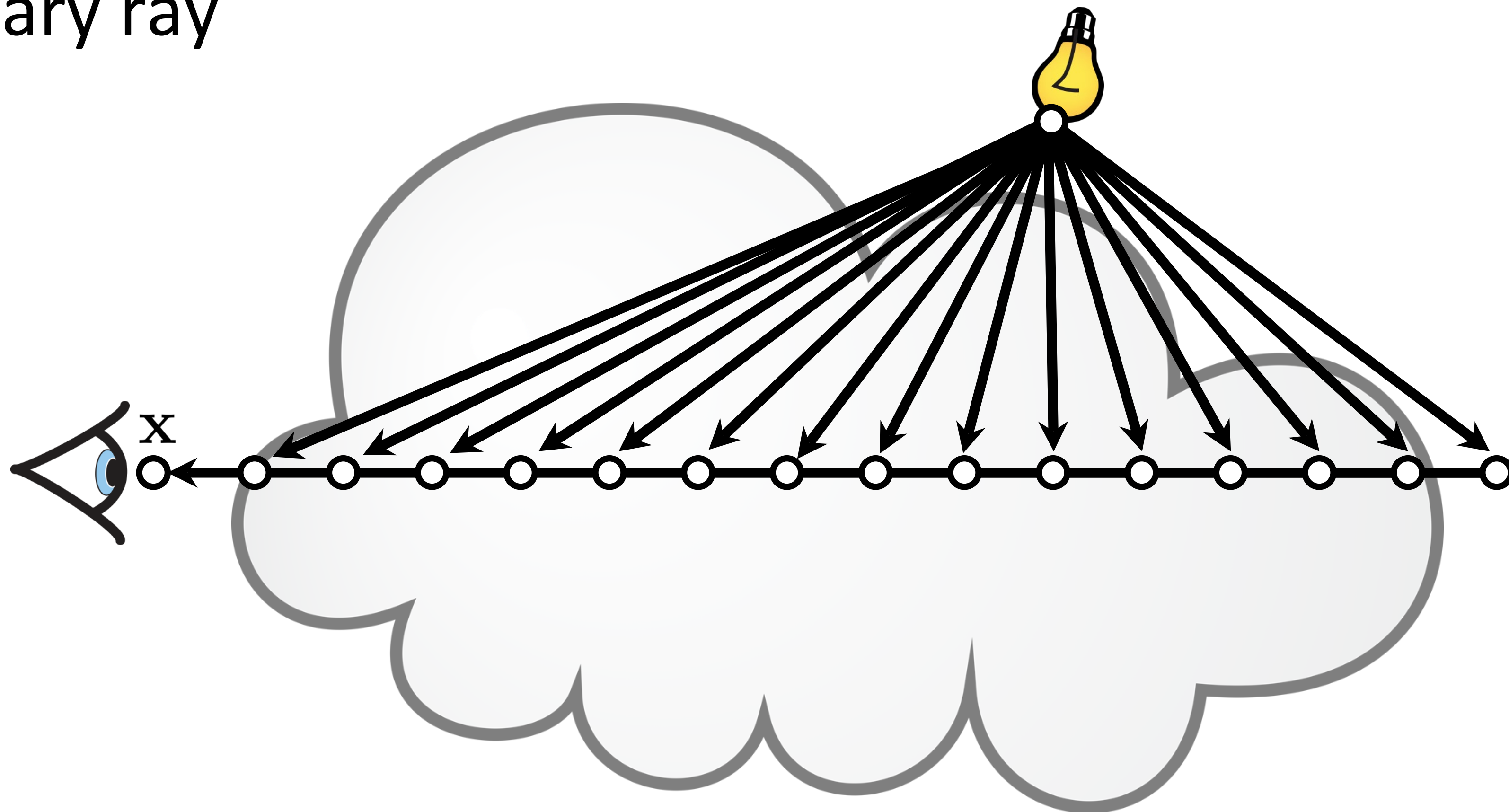


# Ray-Marching in Heterogeneous Media

---

Marching towards the light source

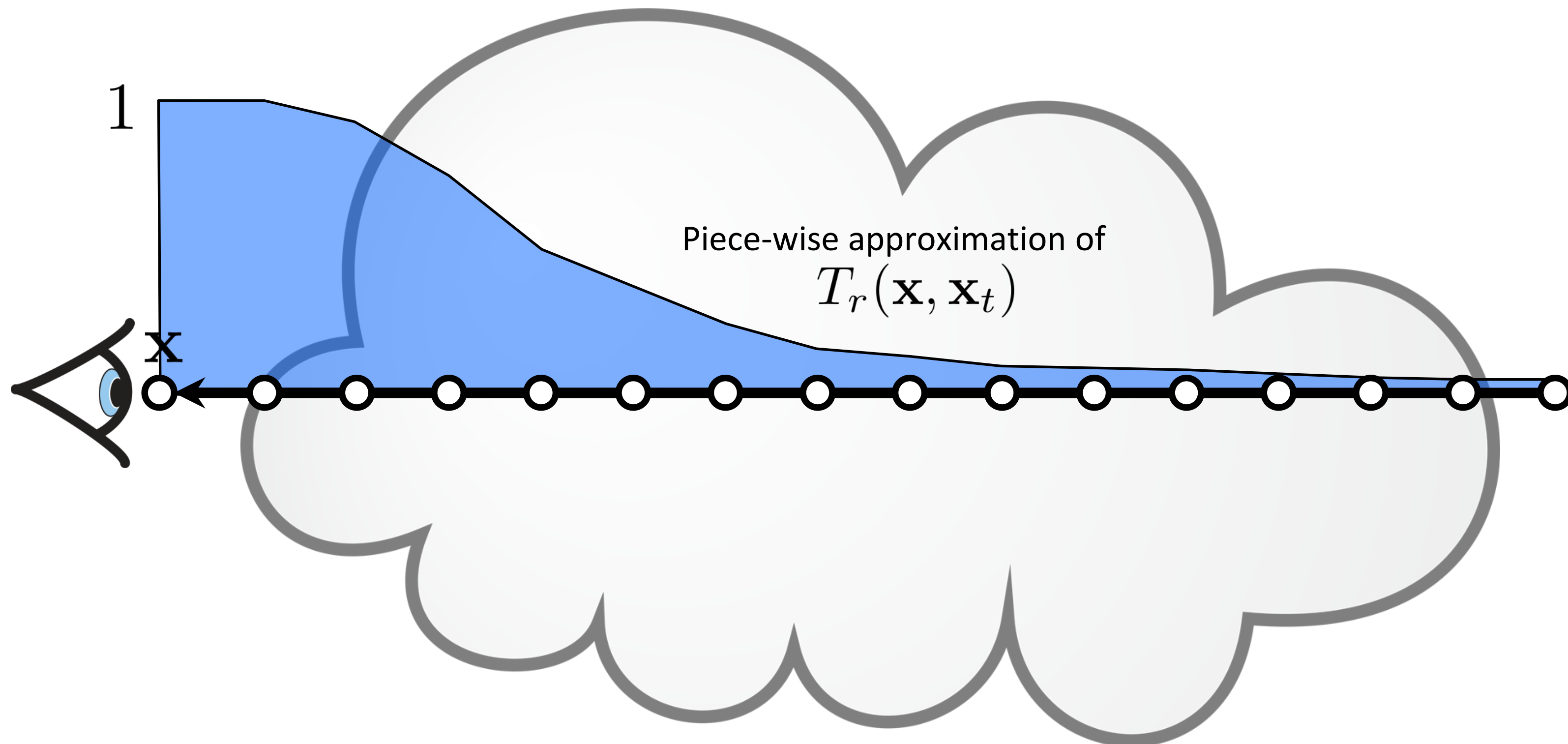
- Connections are expensive, many, and uniformly distributed along the primary ray



# Decoupled Transmittance and In-scattering

## 1. Ray-march and cache transmittance

- Choose step-size w.r.t. frequency content to accurately capture variations



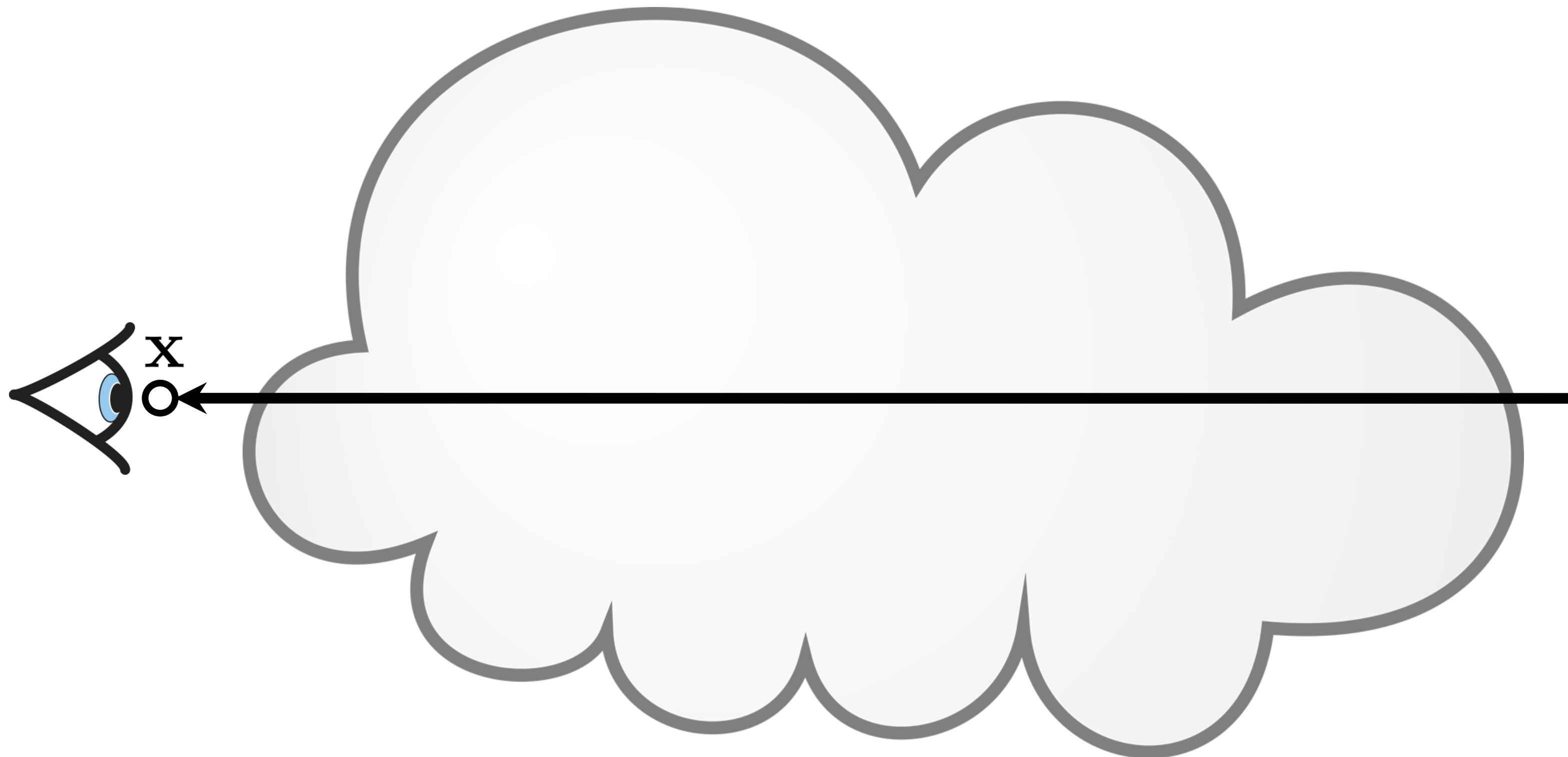


# Decoupled Transmittance and In-scattering

---

## 2. Estimate in-scattering using MC integration

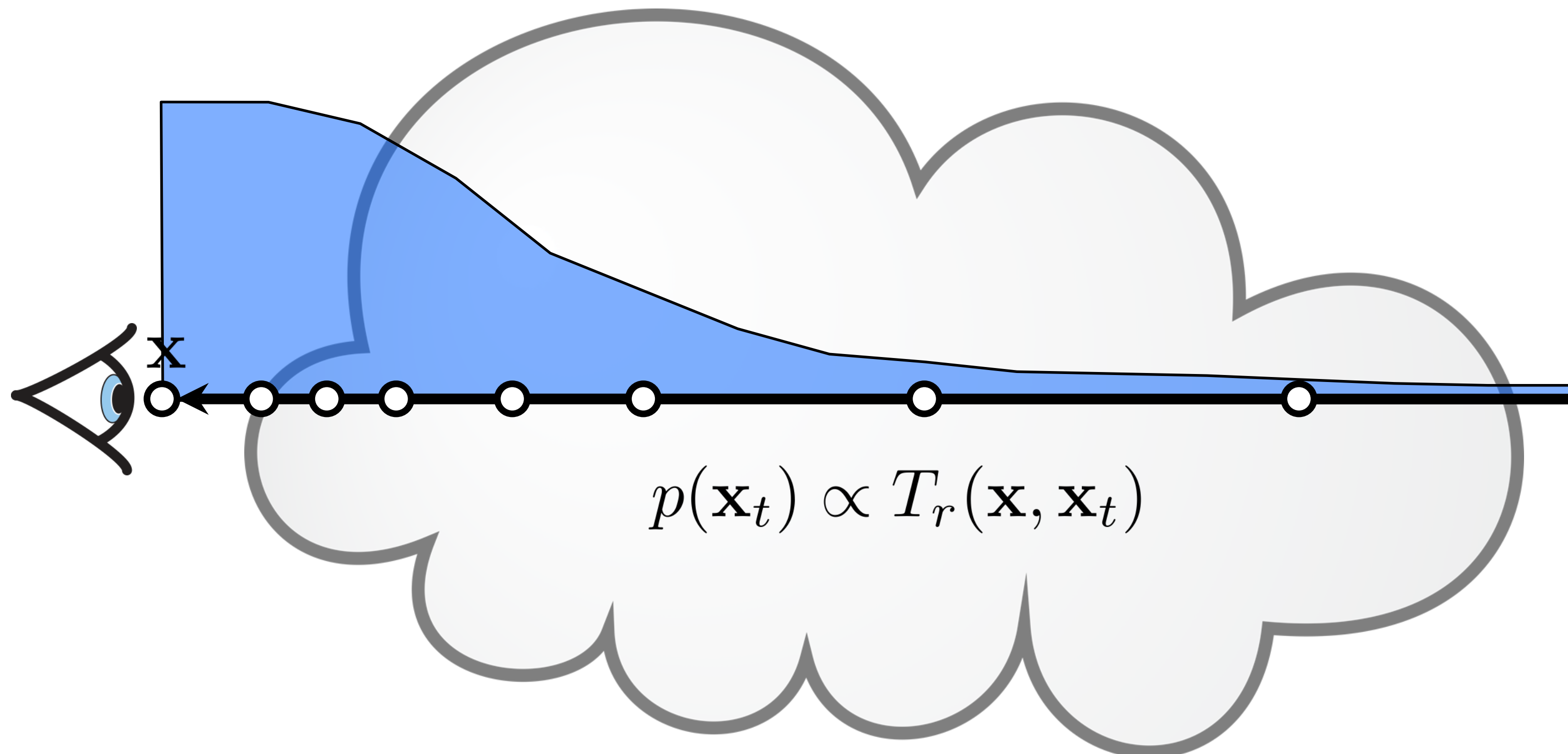
- Distribute samples  $\propto$  (part of) the integrand



# Decoupled Transmittance and In-scattering

## 2. Estimate in-scattering using MC integration

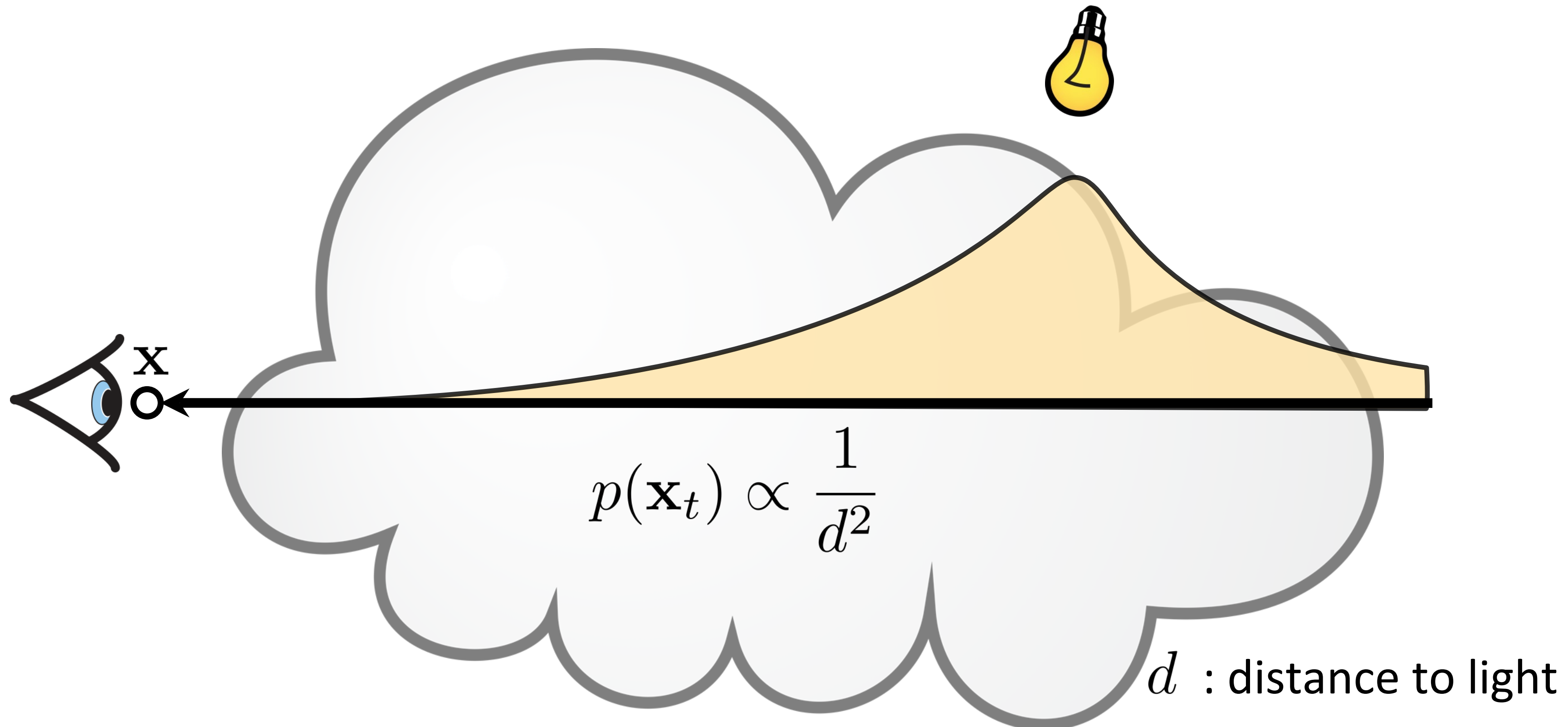
- Distribute samples  $\propto$  (part of) the integrand



# Decoupled Transmittance and In-scattering

## 2. Estimate in-scattering using MC integration

- Distribute samples  $\propto$  (part of) the integrand

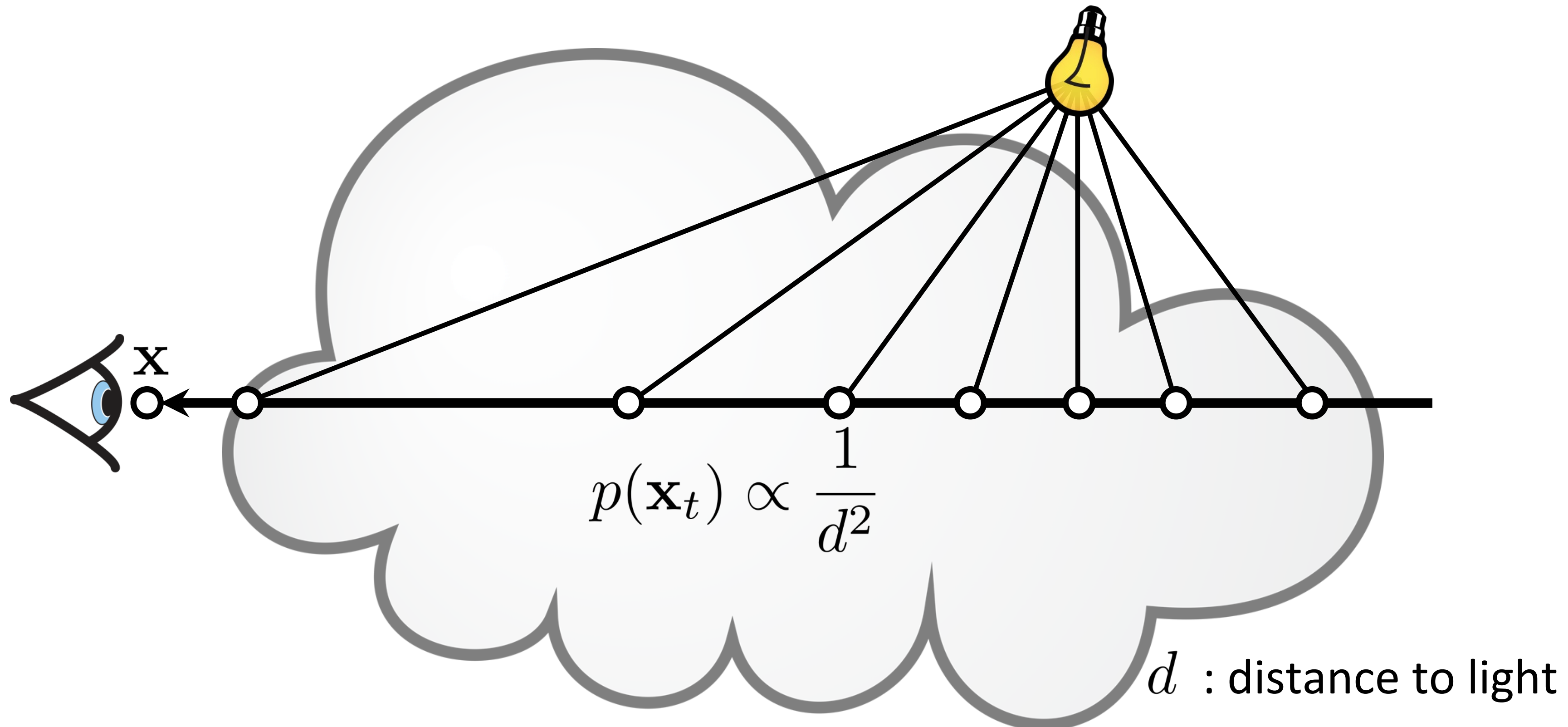




# Decoupled Transmittance and In-scattering

## 2. Estimate in-scattering using MC integration

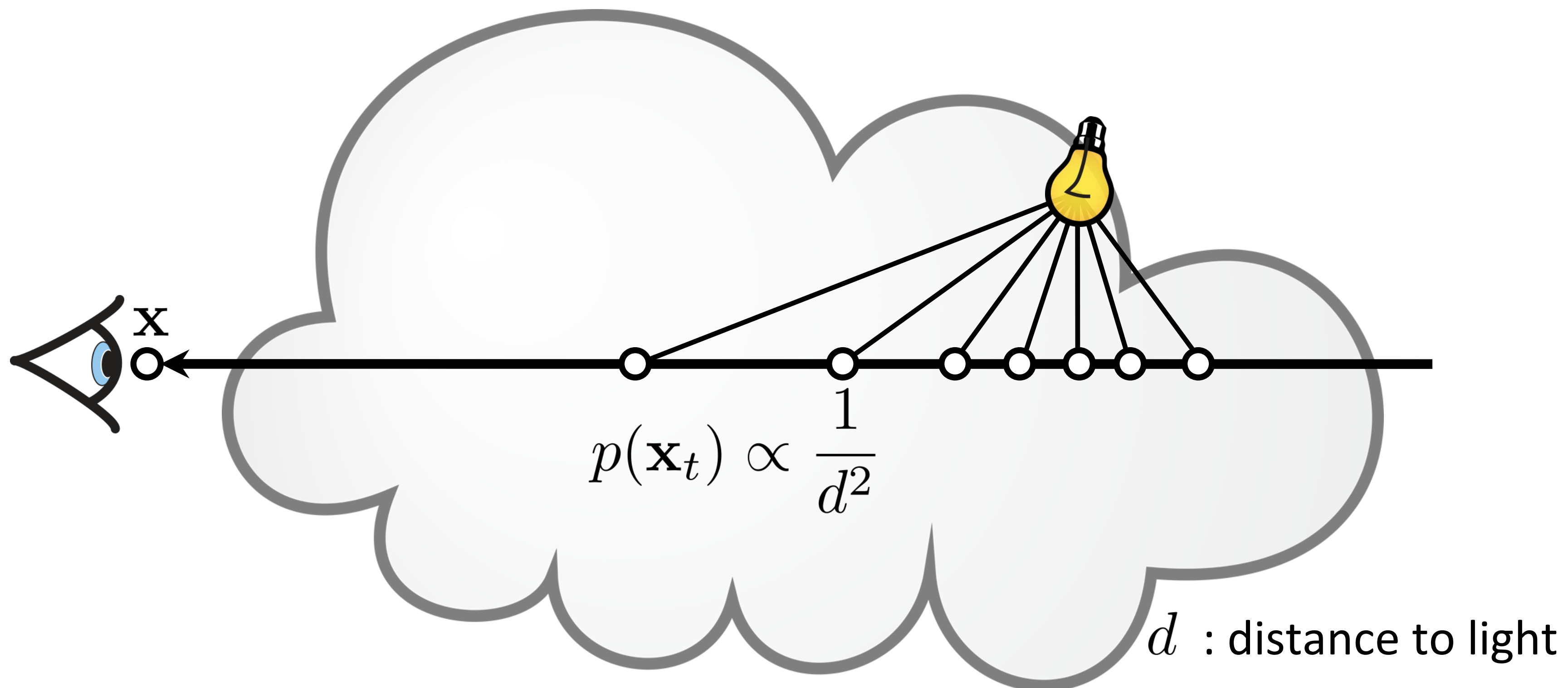
- Distribute samples  $\propto$  (part of) the integrand



# Decoupled Transmittance and In-scattering

## 2. Estimate in-scattering using MC integration

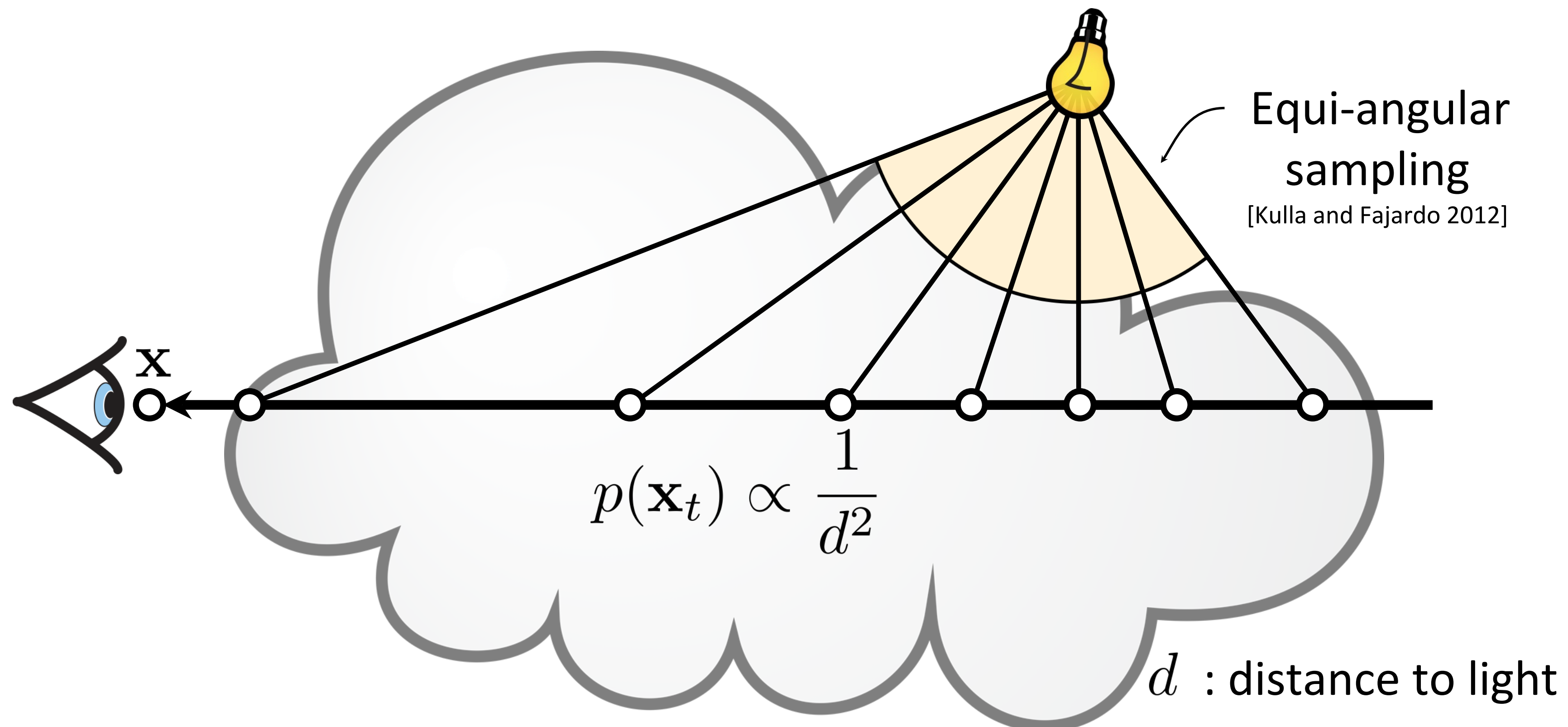
- Distribute samples  $\propto$  (part of) the integrand



# Decoupled Transmittance and In-scattering

## 2. Estimate in-scattering using MC integration

- Distribute samples  $\propto$  (part of) the integrand

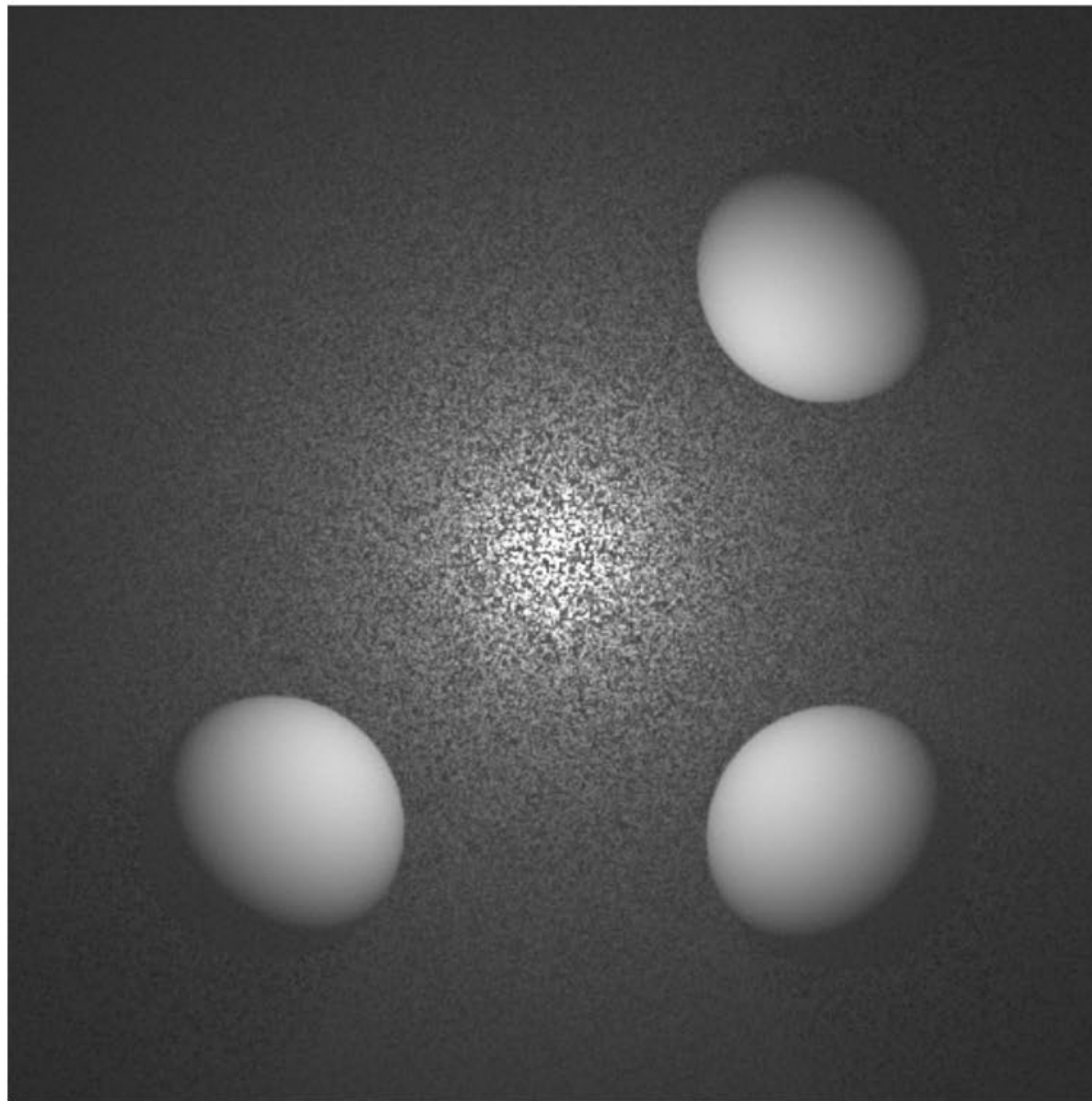




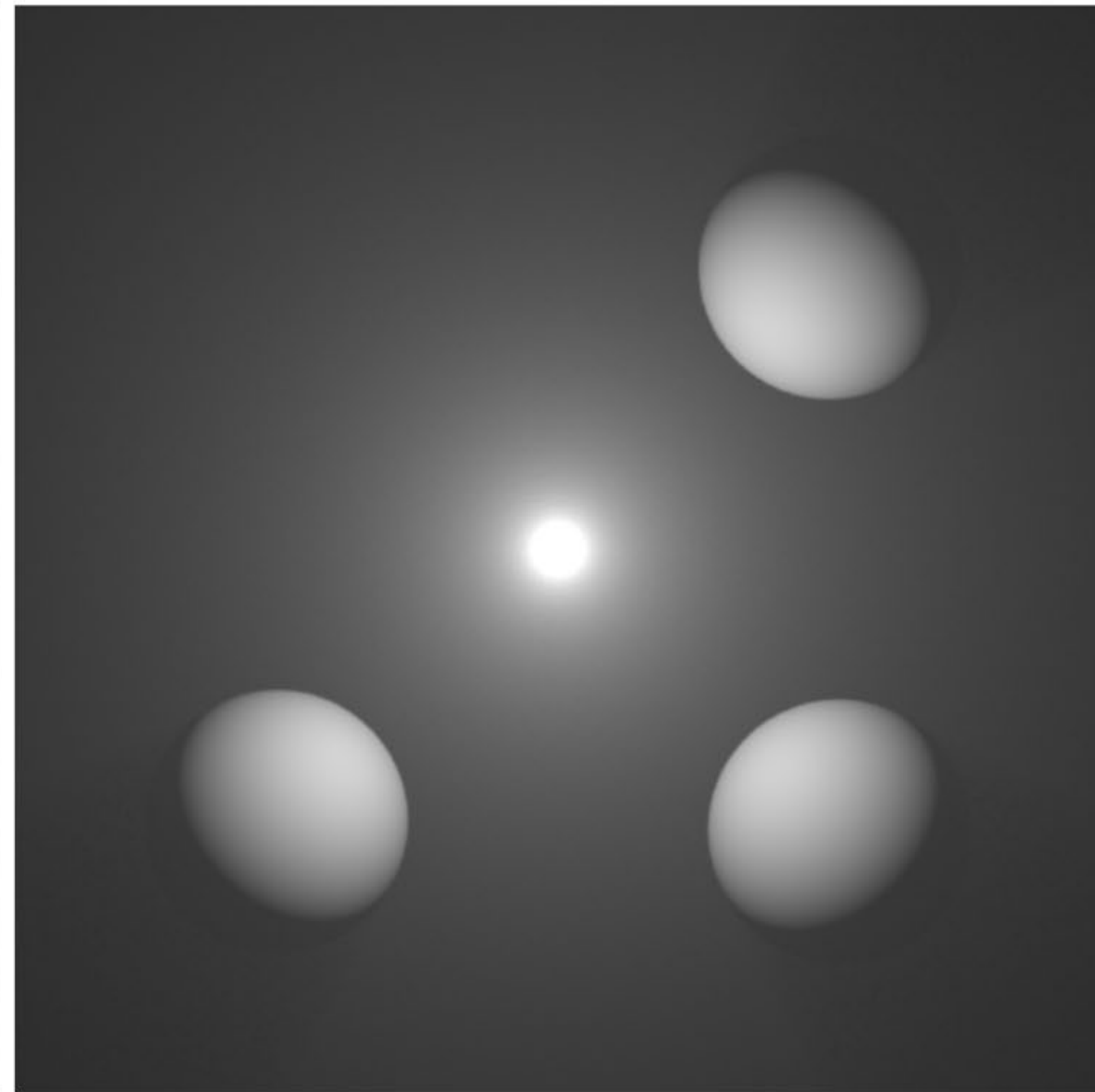
# Decoupled Transmittance and In-scattering

---

Ray-marching



Equiangular sampling

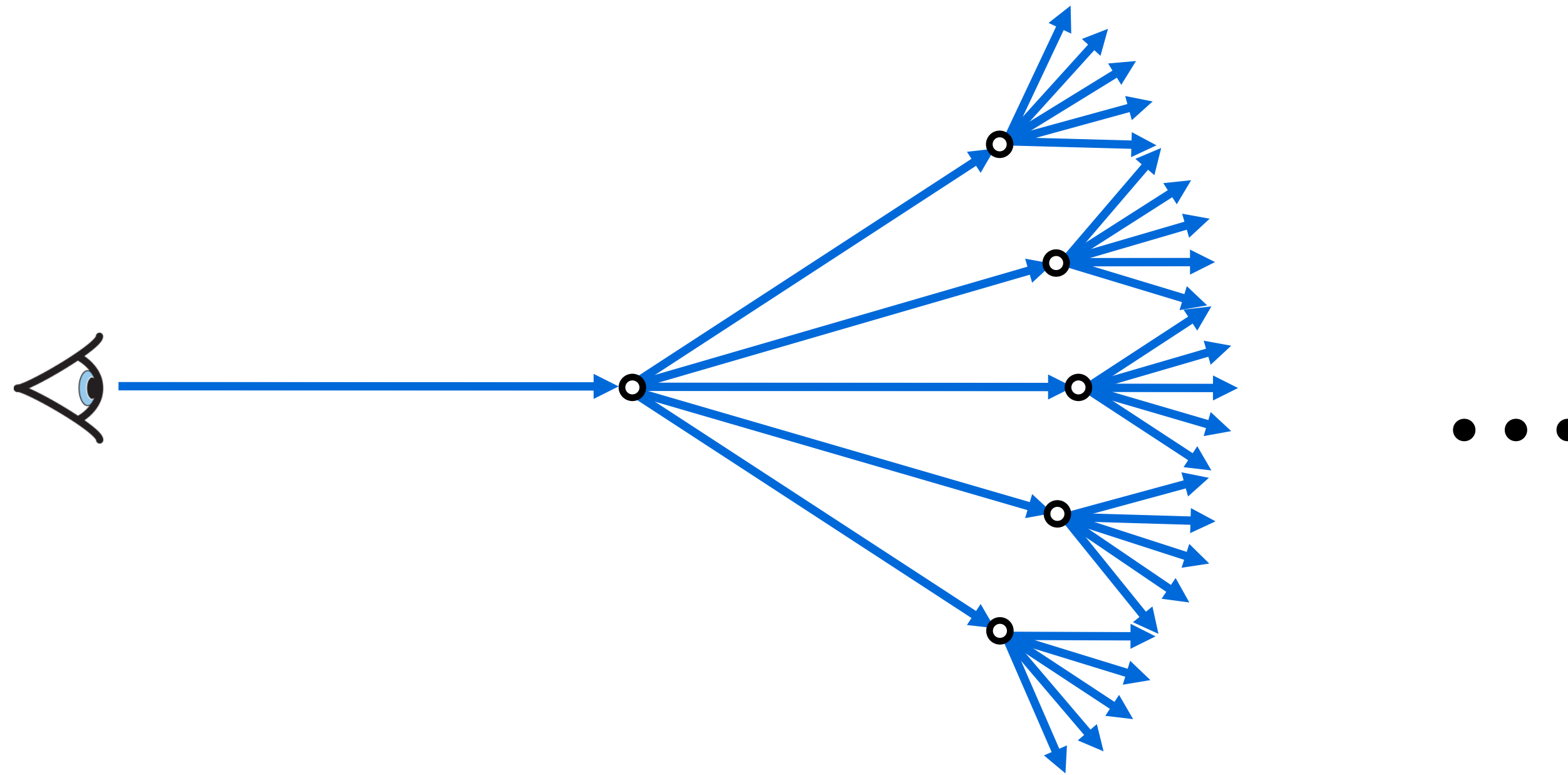


# Multiple Bounces

---

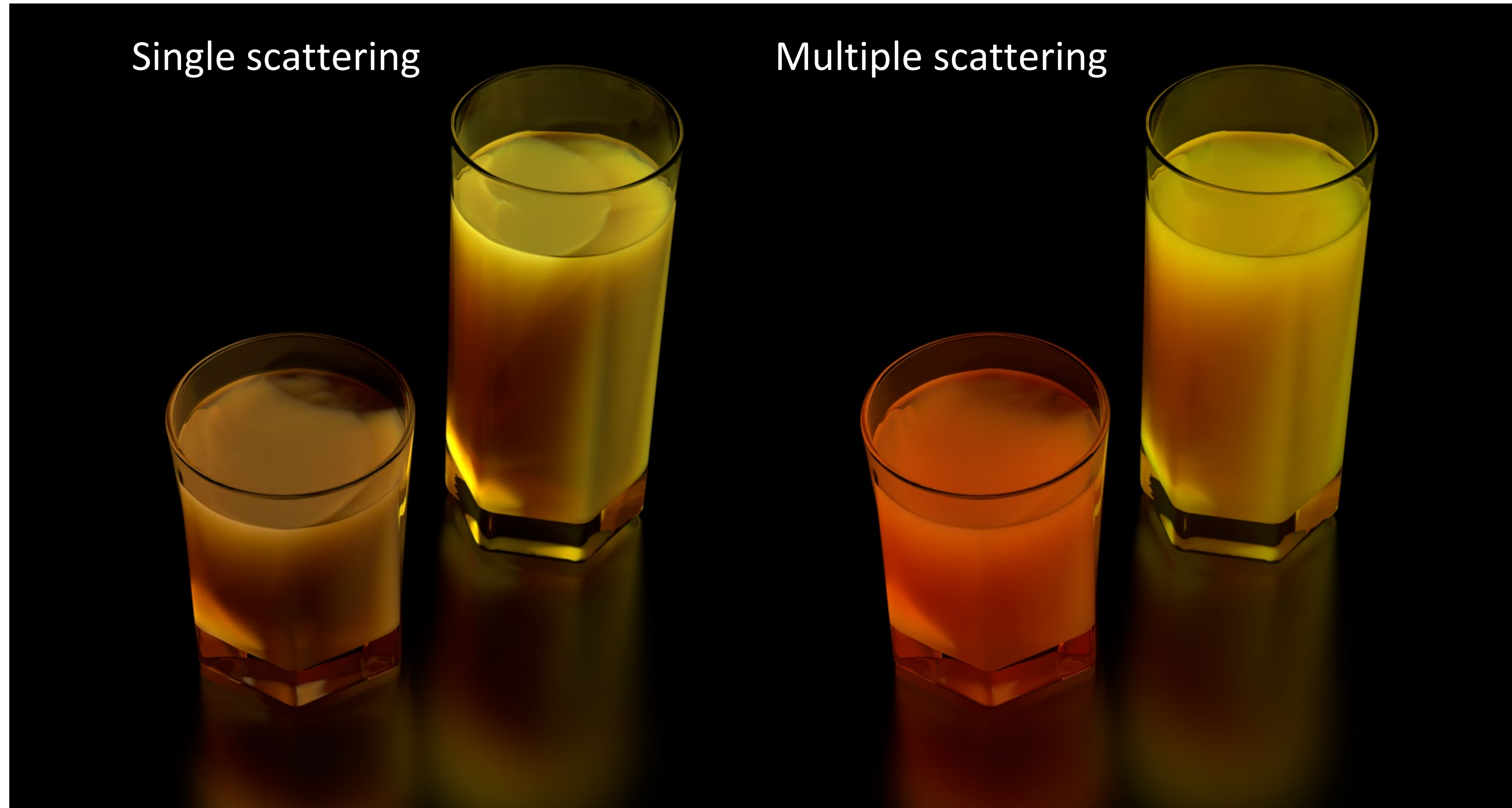
Same concept as in recursive Monte Carlo ray tracing, but taking into account volumetric scattering

Exponential growth:



# Visual Break

---





# Volumetric Path Tracing

# Volumetric Path Tracing

---

Motivation:

- Same as with standard path tracing: avoid the exponential growth

Paths can:

- Reflect/refract off surfaces
- Scatter inside a volume

# Volume Rendering Equation

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) dt$$

Accumulated emitted radiance

$$+ \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) dt$$
$$+ T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})$$

Accumulated in-scattered radiance

Attenuated background radiance



# Volume Rendering Equation

---

Accumulated emitted + in-scattered radiance

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) \right] dt$$

+

$$T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})$$

Attenuated background radiance

# Volume Rendering Equation

---

$$L(\mathbf{x}, \vec{\omega}) = \int_0^z T_r(\mathbf{x}, \mathbf{x}_t) \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) \right] dt \\ + T_r(\mathbf{x}, \mathbf{x}_z) L(\mathbf{x}_z, \vec{\omega})$$

# 1-Sample Monte Carlo Estimator

---

$$\begin{aligned}\langle L(\mathbf{x}, \vec{\omega}) \rangle &= \frac{T_r(\mathbf{x}, \mathbf{x}_t)}{p(t)} \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) L_s(\mathbf{x}_t, \vec{\omega}) \right] \\ &+ \frac{T_r(\mathbf{x}, \mathbf{x}_z)}{P(z)} L(\mathbf{x}_z, \vec{\omega})\end{aligned}$$

$p(t)$  - probability *density* of distance  $t$

$P(z)$  - *probability* of exceeding distance  $z$



# 1-Sample Monte Carlo Estimator

---

$$\begin{aligned}\langle L(\mathbf{x}, \vec{\omega}) \rangle &= \frac{T_r(\mathbf{x}, \mathbf{x}_t)}{p(t)} \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) \frac{f_p(\vec{\omega}, \vec{\omega}_i) L(\mathbf{x}_t, \vec{\omega}_i)}{p(\vec{\omega}_i)} \right] \\ &+ \frac{T_r(\mathbf{x}, \mathbf{x}_z)}{P(z)} L(\mathbf{x}_z, \vec{\omega})\end{aligned}$$

$p(t)$  - probability *density* of distance  $t$

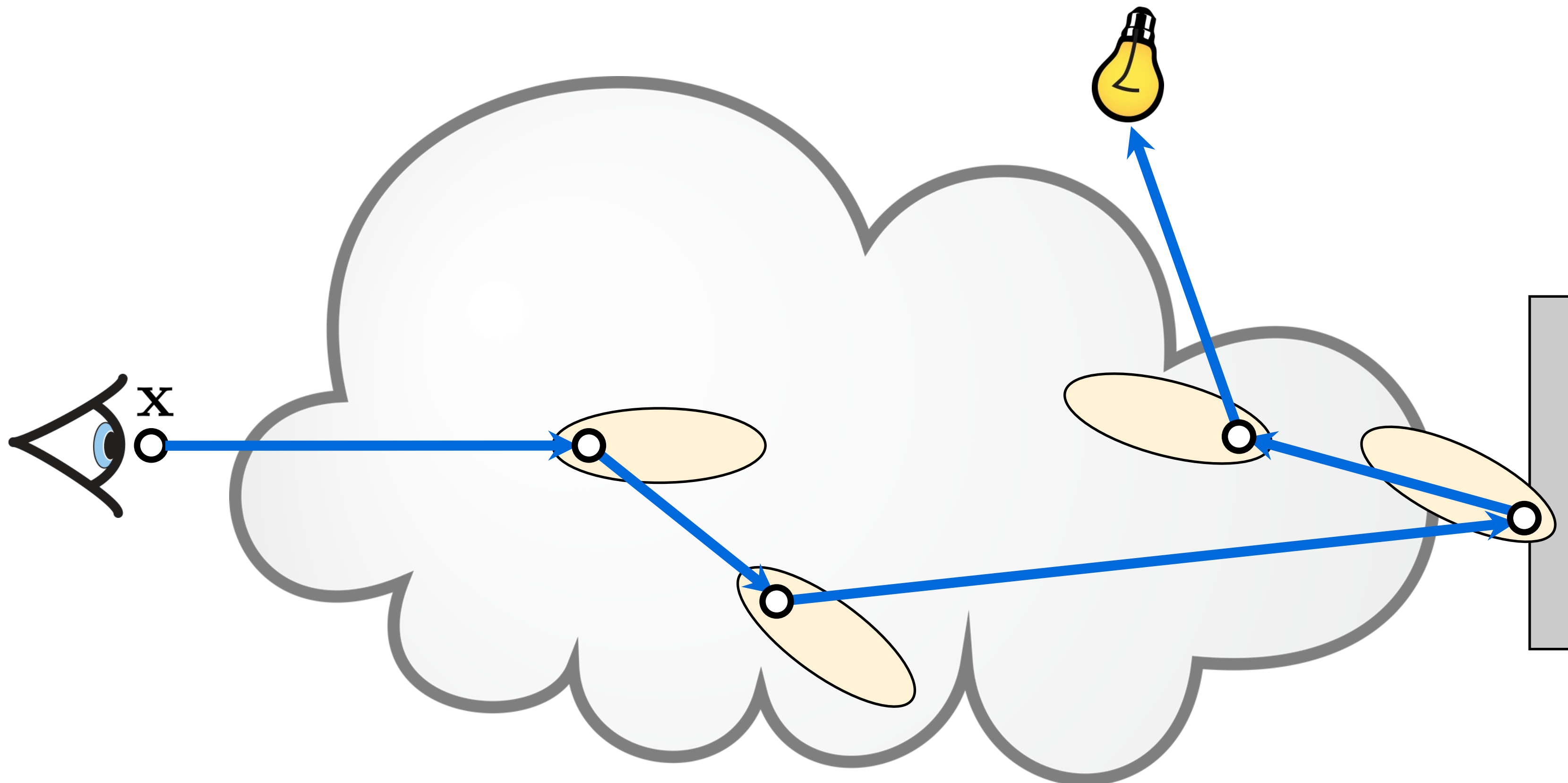
$P(z)$  - *probability* of exceeding distance  $z$

$p(\vec{\omega}_i)$  - probability *density* of direction  $\vec{\omega}_i$

# Volumetric Path Tracing

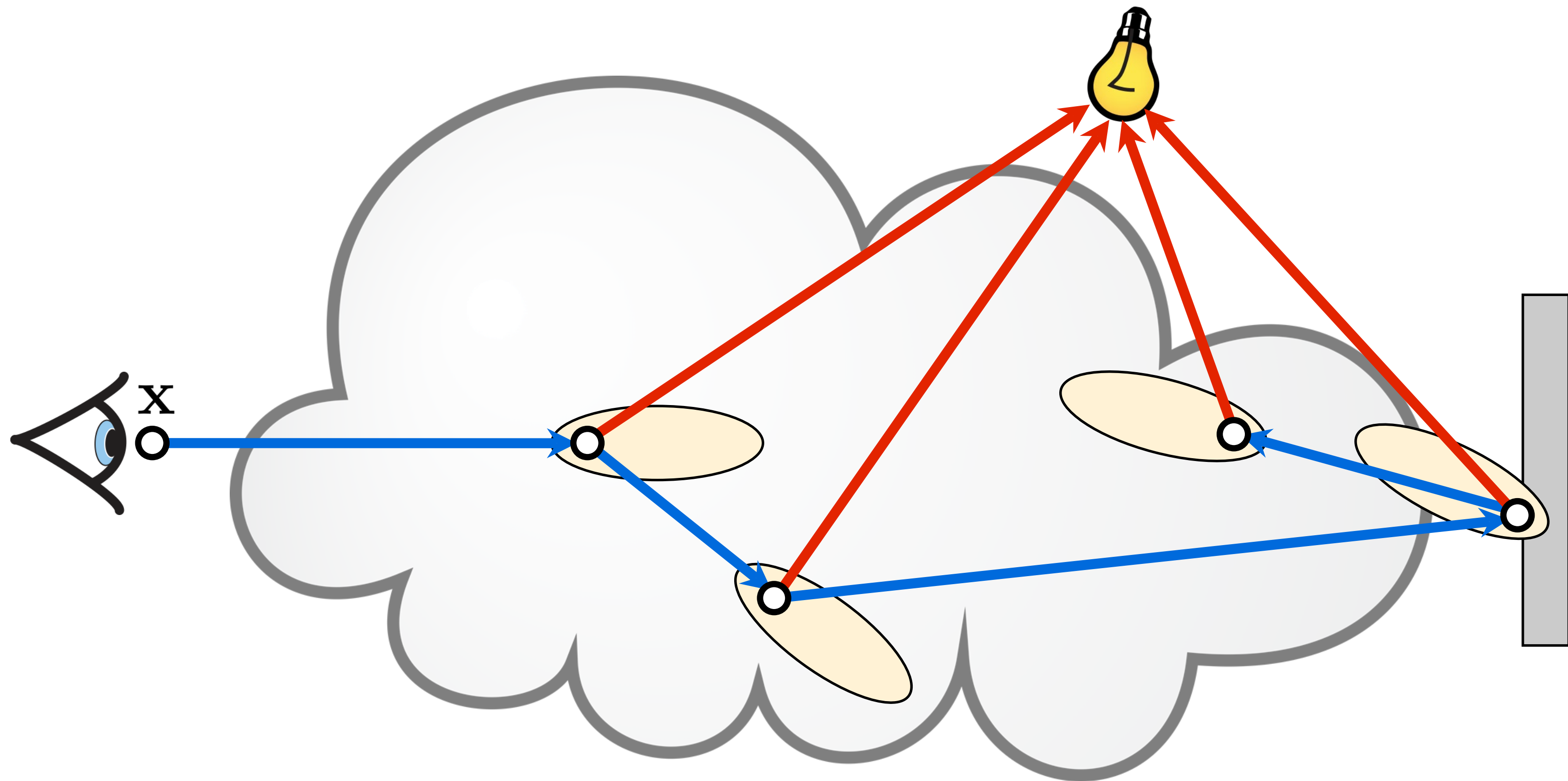
---

1. Sample distance to next interaction
2. Scatter in the volume or bounce off a surface



# Volumetric Path Tracing with NEE

---





# Sampling the Phase Function

---

Isotropic:

- Uniform sphere sampling

Henyey-Greenstein:

- Using the inversion method we can derive

$$\cos \theta = \frac{1}{2g} \left( 1 + g^2 - \left( \frac{1 - g^2}{1 - g + 2g\xi_1} \right)^2 \right)$$

- PDF is the value of the HG phase function  $\phi = 2\pi\xi_2$

# Free-path Sampling

---

Free-path (or free-flight distance):

- Distance to the next interaction within the medium
- Dense media (e.g. milk): short mean-free path
- Thin media (e.g. atmosphere): long mean-free path

Ideally, we want to sample proportional to (part of) integrand, e.g. transmittance:

$$\begin{aligned} p(\mathbf{x}_t | (\mathbf{x}, \vec{\omega})) &\propto T_r(\mathbf{x}, \mathbf{x}_t) \\ p(t) &\propto T_r(t) \end{aligned} \bigg)_{\text{simplified notation for brevity}}$$

# Free-path Sampling

---

Homogeneous media:  $T_r(t) = e^{-\sigma_t t}$

- PDF:  $p(t) \propto e^{-\sigma_t t}$

$$p(t) = \frac{e^{-\sigma_t t}}{\int_0^\infty e^{-\sigma_t s} ds} = \sigma_t e^{-\sigma_t t}$$

- CDF:  $P(t) = \int_0^t \sigma_t e^{-\sigma_t s} ds = 1 - e^{-\sigma_t t}$

- Inverted CDF:  $P^{-1}(\xi) = -\frac{\ln(1 - \xi)}{\sigma_t}$



# Free-path Sampling

---

Homogeneous media:  $T_r(t) = e^{-\sigma_t t}$

Recipe:

- Generate random number

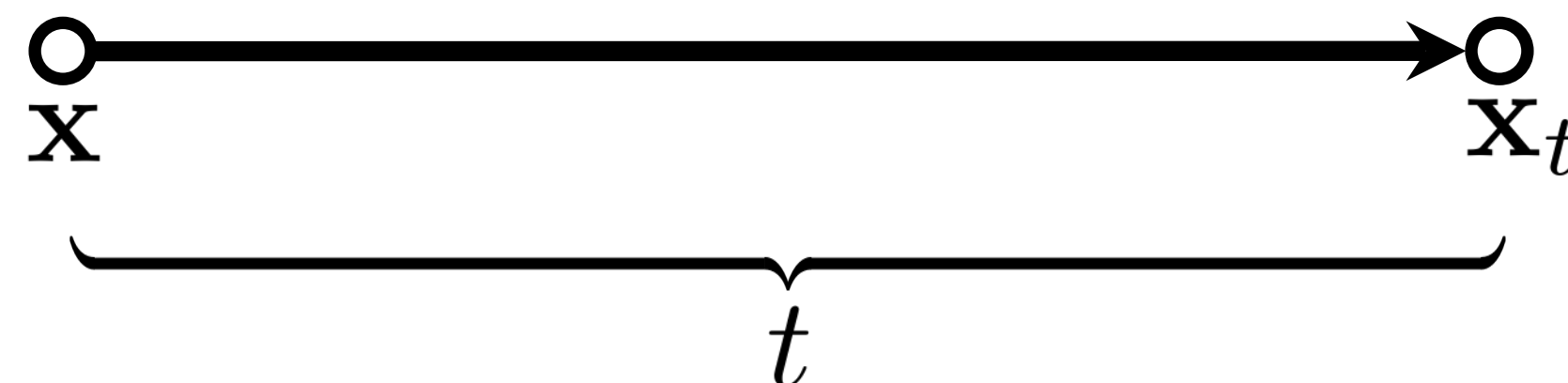
$\xi$

- Sample distance

$$t = -\frac{\ln(1 - \xi)}{\sigma_t}$$

- Compute PDF

$$p(t) = \sigma_t e^{-\sigma_t t}$$



# Free-path Sampling

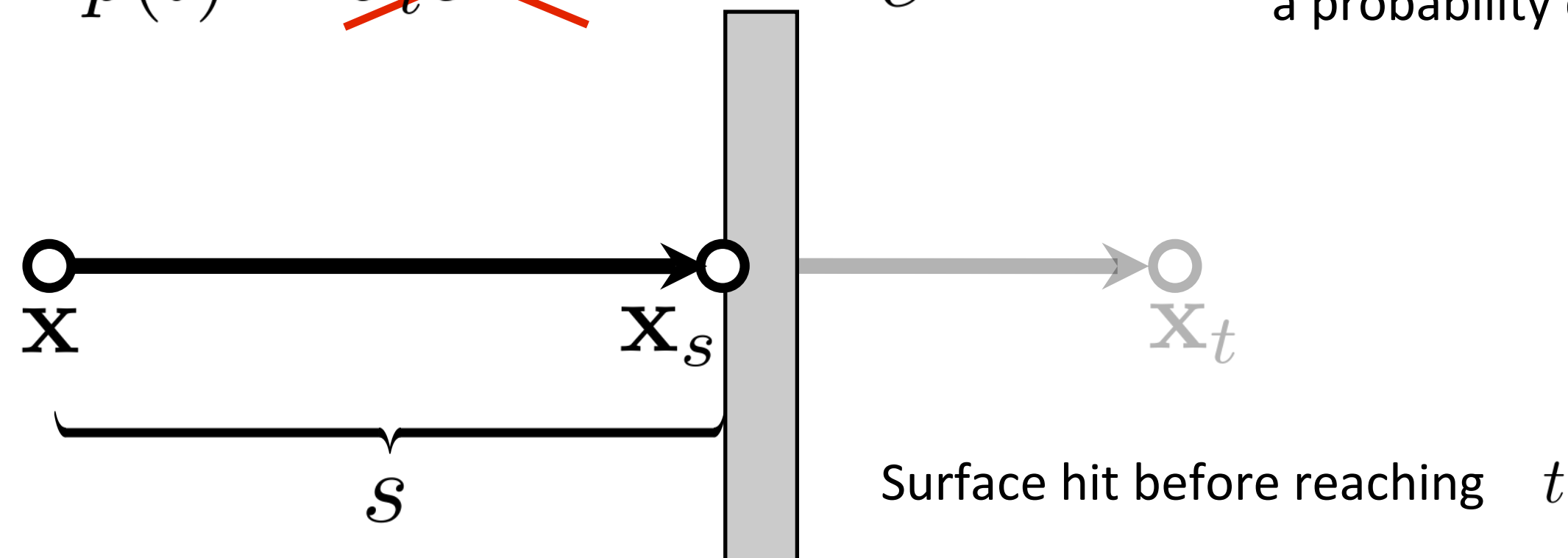
Homogeneous media:  $T_r(t) = e^{-\sigma_t t}$

Recipe:

- Generate random number  $\xi$
- Sample distance
- Compute PDF

$$~~t = -\frac{\ln(1 - \xi)}{\sigma_t} = s~~$$

$$~~p(t) = \sigma_t e^{-\sigma_t t}~~ = e^{-\sigma_t s} \quad \text{Note: This is now a probability, not a probability density!}$$



# Volumetric PT for Homogeneous Volumes

```
Color vPT(x,  $\omega$ )
    tmax = nearestSurface(x,  $\omega$ )
    t = -log(1 - randf()) /  $\sigma_t$     // Sample free path
    if t < tmax: // Volume interaction
        x += t *  $\omega$ 
        pdf_t =  $\sigma_t$  * exp(- $\sigma_t$  * t)
        ( $\omega'$ , pdf_ $\omega'$ ) = samplePF( $\omega$ )
        return Tr(t) / pdf_t * ( $\sigma_a$  *  $L_e(\mathbf{x}, \omega)$  +  $\sigma_s$  * PF( $\omega, \omega'$ ) * vPT(x,  $\omega'$ ) / pdf_ $\omega'$ )
    else: // Surface interaction
        x += tmax *  $\omega$ 
        Pr_tmax = exp(- $\sigma_t$  * tmax)
        ( $\omega'$ , pdf_ $\omega'$ ) = sampleBRDF(n,  $\omega$ )
        return Tr(tmax) / Pr_tmax * ( $L_e(\mathbf{x}, \omega)$  + BRDF( $\omega, \omega'$ ) * vPT(x,  $\omega'$ ) / pdf_ $\omega'$ )
```

$$\langle L(\mathbf{x}, \vec{\omega}) \rangle = \frac{T_r(\mathbf{x}, \mathbf{x}_t)}{p(t)} \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) \frac{f_p(\vec{\omega}, \vec{\omega}_i) L(\mathbf{x}_t, \vec{\omega}_i)}{p(\vec{\omega}_i)} \right] + \frac{T_r(\mathbf{x}, \mathbf{x}_z)}{P(z)} L(\mathbf{x}_z, \vec{\omega})$$



# Volumetric PT for Homogeneous Volumes

```
Color vPT(x,  $\omega$ )
    tmax = nearestSurface(x,  $\omega$ )
    t = -log(1 - randf()) /  $\sigma_t$     // Sample free path
    if t < tmax: // Volume interaction
        x += t *  $\omega$ 
        pdf_t =  $\sigma_t$  * exp(- $\sigma_t$  * t)
        ( $\omega'$ , pdf_ $\omega'$ ) = samplePF( $\omega$ )
        // Note: transmittance and PF cancel out with PDFs except for a constant factor 1/ $\sigma_t$ 
        return Tr(t) / pdf_t * ( $\sigma_a$  *  $L_e(\mathbf{x}, \omega)$  +  $\sigma_s$  * PF( $\omega, \omega'$ ) * vPT(x,  $\omega'$ ) / pdf_ $\omega'$ )
    else: // Surface interaction
        x += tmax *  $\omega$ 
        Pr_tmax = exp(- $\sigma_t$  * tmax)
        ( $\omega'$ , pdf_ $\omega'$ ) = sampleBRDF(n,  $\omega$ )
        // Note: transmittance and prob of sampling the distance cancel out
        return Tr(tmax) / Pr_tmax * ( $L_e(\mathbf{x}, \omega)$  + BRDF( $\omega, \omega'$ ) * vPT(x,  $\omega'$ ) / pdf_ $\omega'$ )
```

$$\langle L(\mathbf{x}, \vec{\omega}) \rangle = \frac{T_r(\mathbf{x}, \mathbf{x}_t)}{p(t)} \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) \frac{f_p(\vec{\omega}, \vec{\omega}_i) L(\mathbf{x}_t, \vec{\omega}_i)}{p(\vec{\omega}_i)} \right] + \frac{T_r(\mathbf{x}, \mathbf{x}_z)}{P(z)} L(\mathbf{x}_z, \vec{\omega})$$

# Volumetric PT for Homogeneous Volumes

```
Color vPT(x,  $\omega$ )
tmax = nearestSurface(x,  $\omega$ )
t = -log(1 - randf()) /  $\sigma_t$     // Sample free path
if t < tmax: // Volume interaction
    x += t *  $\omega$ 
    pdf_t =  $\sigma_t$  * exp(- $\sigma_t$  * t)
    ( $\omega'$ , pdf_ $\omega'$ ) = samplePF( $\omega$ )
    // Note: transmittance and PF cancel out with PDFs except for a constant factor 1/ $\sigma_t$ 
    return  $\sigma_a/\sigma_t$  *  $L_e(\mathbf{x}, \omega)$  +  $\sigma_s/\sigma_t$  * vPT(x,  $\omega'$ )
else: // Surface interaction
    x += tmax *  $\omega$ 
    Pr_tmax = exp(- $\sigma_t$  * tmax)
    ( $\omega'$ , pdf_ $\omega'$ ) = sampleBRDF(n,  $\omega$ )
    // Note: transmittance and prob of sampling the distance cancel out
    return  $L_e(\mathbf{x}, \omega)$  + BRDF( $\omega$ ,  $\omega'$ ) * vPT(x,  $\omega'$ ) / pdf_ $\omega'$ 
```

$$\langle L(\mathbf{x}, \vec{\omega}) \rangle = \frac{T_r(\mathbf{x}, \mathbf{x}_t)}{p(t)} \left[ \sigma_a(\mathbf{x}_t) L_e(\mathbf{x}_t, \vec{\omega}) + \sigma_s(\mathbf{x}_t) \frac{f_p(\vec{\omega}, \vec{\omega}_i) L(\mathbf{x}_t, \vec{\omega}_i)}{p(\vec{\omega}_i)} \right] + \frac{T_r(\mathbf{x}, \mathbf{x}_z)}{P(z)} L(\mathbf{x}_z, \vec{\omega})$$

# What about heterogeneous media?

---



# Free-path Sampling

---

Heterogeneous media:  $T_r(t) = e^{\int_0^t -\sigma_t(s)ds}$

- Closed-form solutions exist only for simple media
  - e.g. linearly or exponentially varying extinction
- Other solutions:
  - Regular tracking (3D DDA)
  - Ray marching
  - Delta tracking

# Free-path Sampling

---

How to sample the flight distance to the next interaction?

Random variable representing flight distance

$$T(t) = e^{-\int_0^t \sigma_t(s) ds} = \begin{matrix} P(X > t) \\ P(X \leq t) = F(t) \end{matrix}$$

CDF

Partition of unity

The diagram shows the equation  $T(t) = e^{-\int_0^t \sigma_t(s) ds} = \begin{matrix} P(X > t) \\ P(X \leq t) = F(t) \end{matrix}$ . A blue arrow points from the text 'Random variable representing flight distance' to the variable  $X$  in the probability expressions. Another blue arrow points from the text 'CDF' to the expression  $F(t)$ . A third blue arrow points from the text 'Partition of unity' to the entire boxed expression. The text 'Recipe for generating samples' is located below the equation, with a blue arrow pointing from it to the  $F(t)$  term in the equation  $F(t) = 1 - T(t)$ .

$$F(t) = 1 - T(t)$$

Recipe for generating samples

# Free-path Sampling

---

Cumulative distribution function (**CDF**)

$$F(t) = 1 - T(t) = 1 - e^{-\tau(t)}$$

Probability density function (**PDF**)

$$p(t) = \frac{dF(t)}{dt} = \frac{d}{dt} \left( 1 - e^{-\tau(t)} \right) = \sigma_t(t) e^{-\tau(t)}$$

Inverted cumulative distr. function (**CDF<sup>-1</sup>**)

$$\xi = 1 - e^{-\tau(t)}$$

↑ Solve for t

$$\int_0^t \sigma_t(s) ds = -\ln(1 - \xi)$$

**Approaches for finding t:**

- 1) ANALYTIC (closed-form CDF<sup>-1</sup>)**
- 2) SEMI-ANALYTIC (regular tracking)**
- 3) APPROXIMATE (ray marching)**



# Regular Tracking (Semi-Analytic)

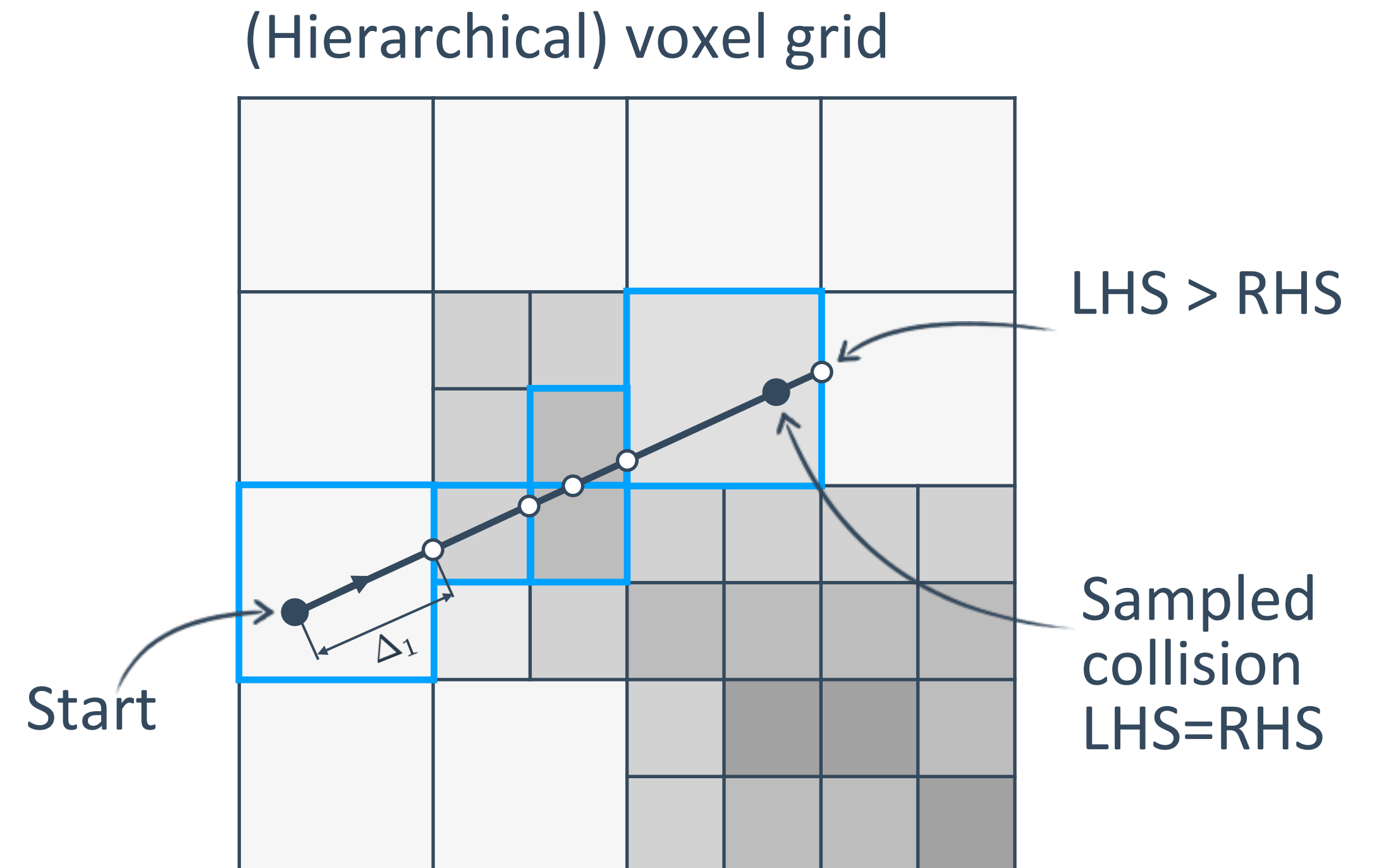
For piecewise-simple (e.g. piecewise-constant), summation replaces integration

$$\int_0^t \sigma_t(s) ds = -\ln(1 - \xi)$$

$$\sum_{i=1}^k \sigma_{t,i} \Delta_i = -\ln(1 - \xi)$$

Regular tracking:

- 1) Draw a random number  $\xi$
- 2) While LHS < RHS  
move to the next intersection
- 3) Find the exact location  
in the last segment analytically



# Ray Marching

Find the collision distance approximately

$$\int_0^t \sigma_t(s) ds = -\ln(1 - \xi)$$

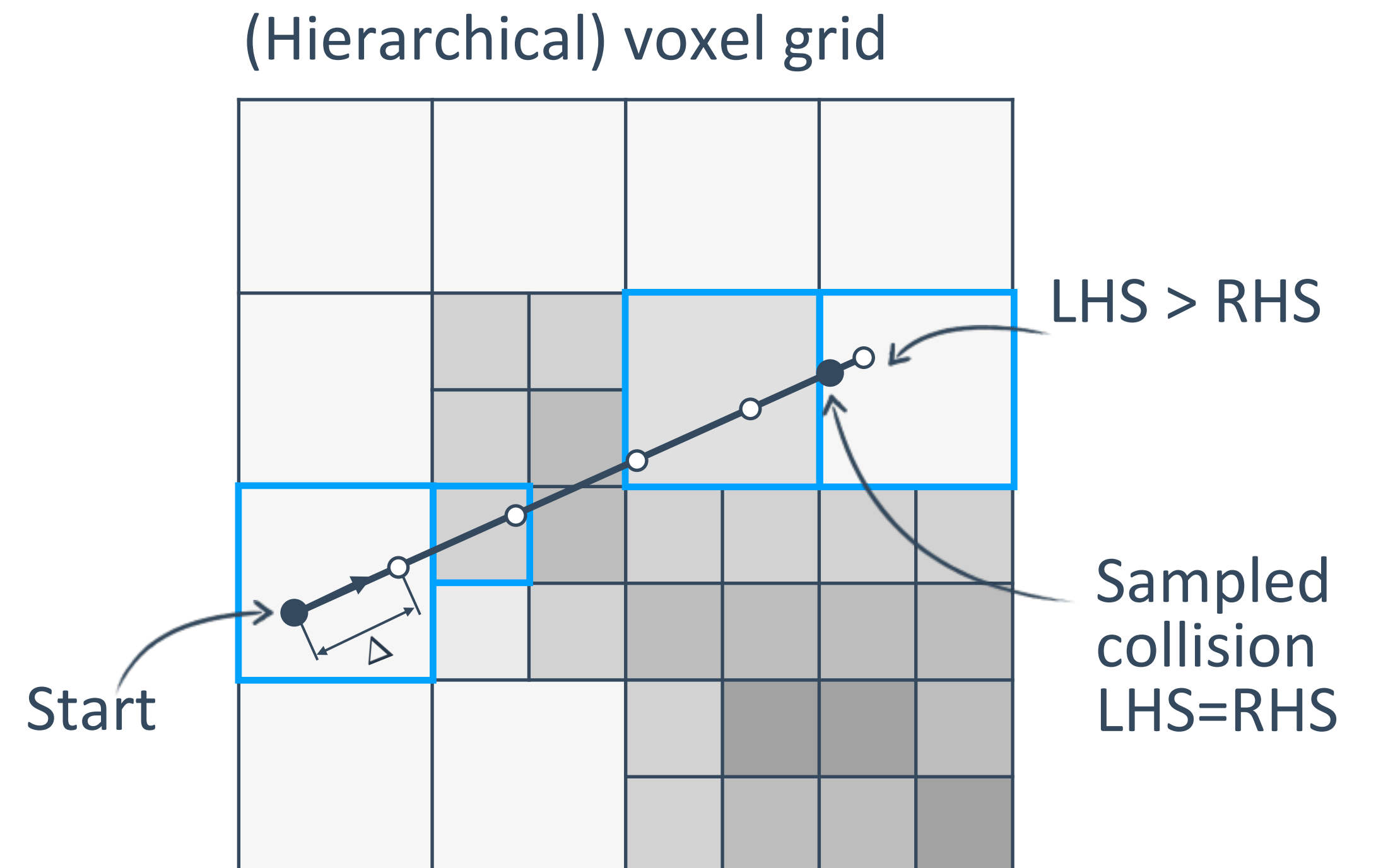
⚡

$$\sum_{i=1}^k \sigma_{t,i} \Delta = -\ln(1 - \xi)$$

Constant step

Ray marching:

- 1) Draw a random number  $\xi$
- 2) While LHS < RHS  
make a (fixed-size) step
- 3) Find the exact location  
in the last segment analytically



# Ray Marching

Find the collision distance approximately

$$\int_0^t \sigma_t(s) ds = -\ln(1 - \xi)$$

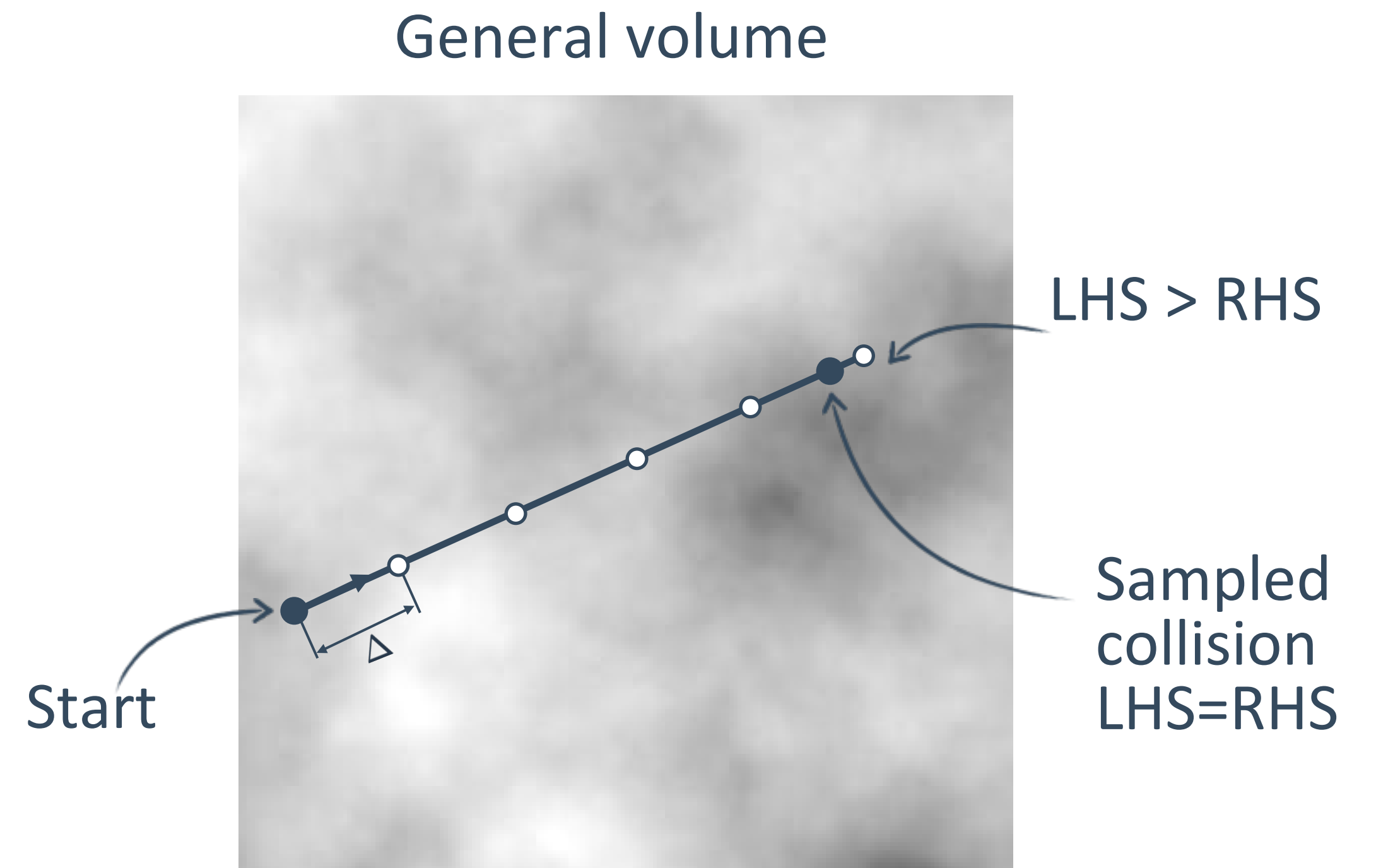
⧻

$$\sum_{i=1}^k \sigma_{t,i} \Delta = -\ln(1 - \xi)$$

Constant step

Ray marching:

- 1) Draw a random number  $\xi$
- 2) While LHS < RHS  
make a (fixed-size) step
- 3) Find the exact location  
in the last segment analytically



# Ray Marching

Find the collision distance approximately

$$\int_0^t \sigma_t(s) ds = -\ln(1 - \xi)$$

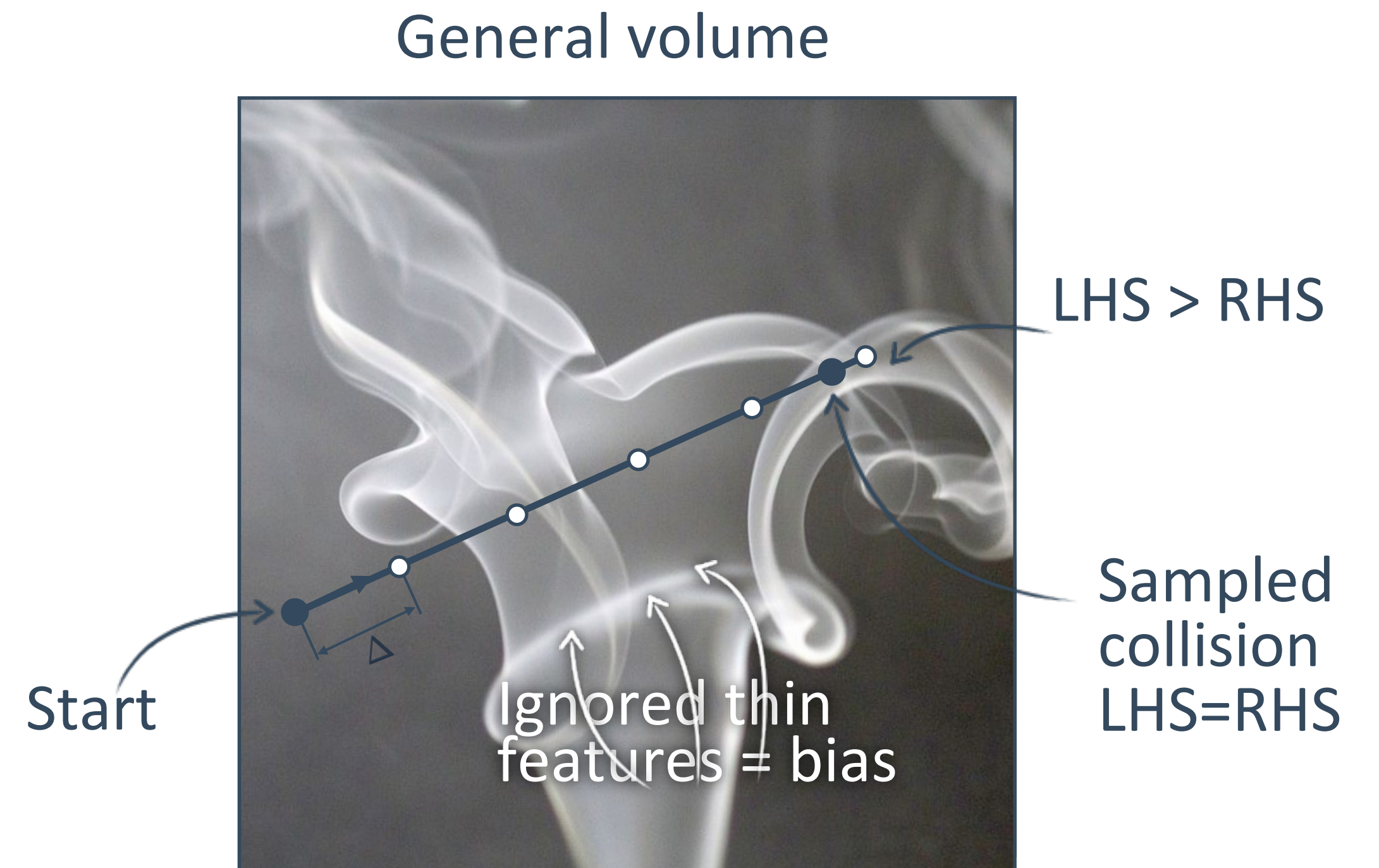
⚡

$$\sum_{i=1}^k \sigma_{t,i} \Delta = -\ln(1 - \xi)$$

Constant step

Ray marching:

- 1) Draw a random number  $\xi$
- 2) While LHS < RHS  
make a (fixed-size) step
- 3) Find the exact location  
in the last segment analytically





# Free-path Sampling

---

---

## ANALYTIC CDF<sup>-1</sup>

- ▶ Efficient & simple, limited to few volumes
- ▶ Simple volumes (e.g. homogeneous)
- ▶ Unbiased

## REGULAR TRACKING

- ▶ Iterative, inefficient if free paths cross many boundaries
- ▶ Piecewise-simple volumes
- ▶ Unbiased

## RAY MARCHING

- ▶ Iterative, inaccurate (or inefficient) for media with high frequencies
- ▶ Any volume
- ▶ Biased

**Common approach: sample optical thickness, find corresponding distance**

# Delta Tracking

(a.k.a. Woodcock tracking, pseudo scattering, hole tracking, null-collision method,...)

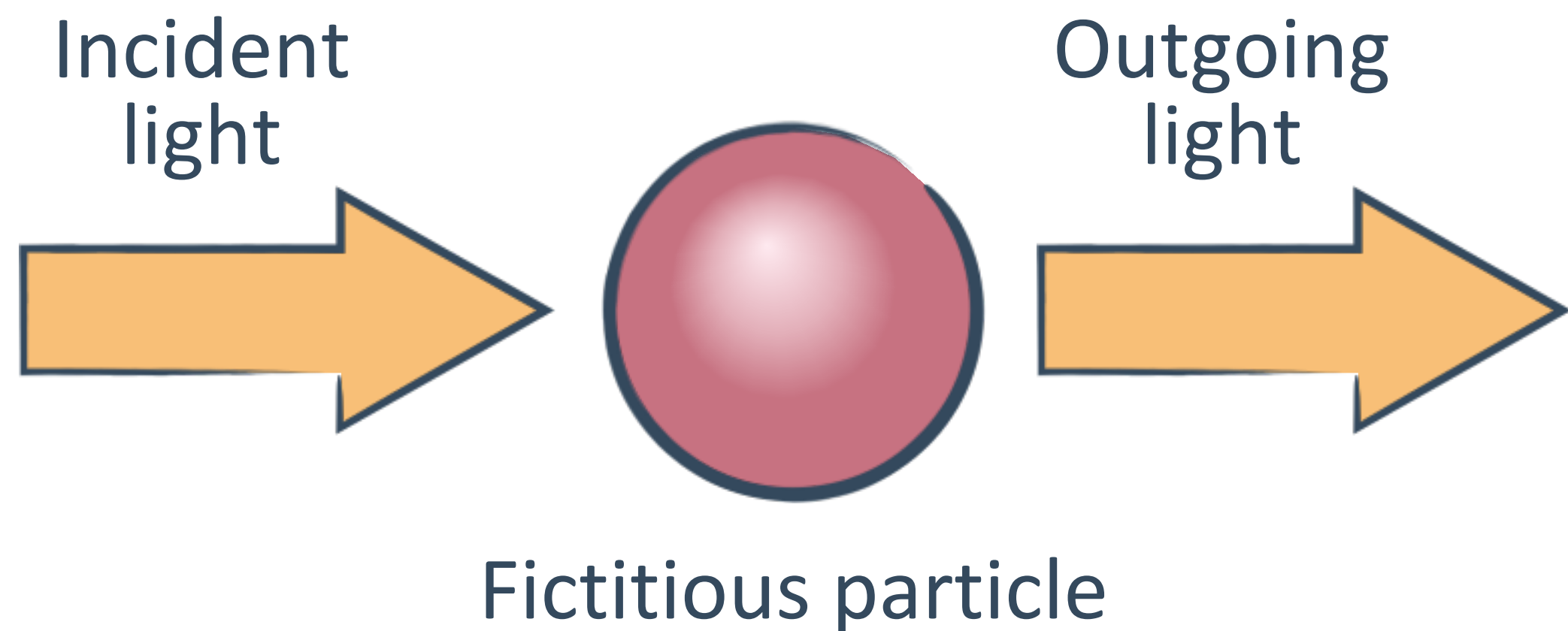
# Delta tracking idea

---

Add **FICTITIOUS MATTER** to homogenize medium

- albedo:  $\alpha(\mathbf{x}) = 1$

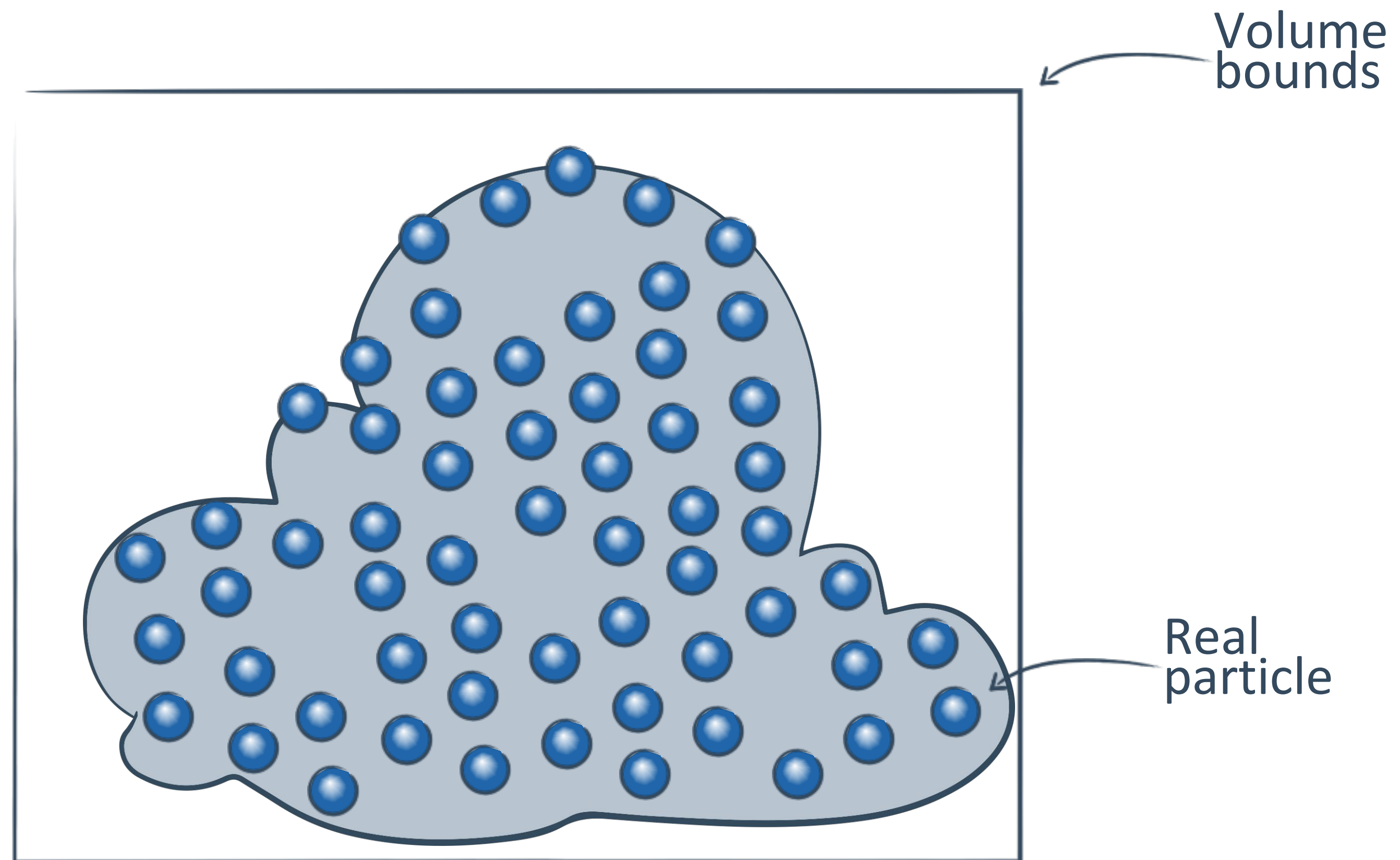
- phase function:  $f_p(\vec{\omega}, \vec{\omega}') = \delta(\vec{\omega} - \vec{\omega}')$



Presence of fictitious matter  
does not impact light transport

# Homogenization

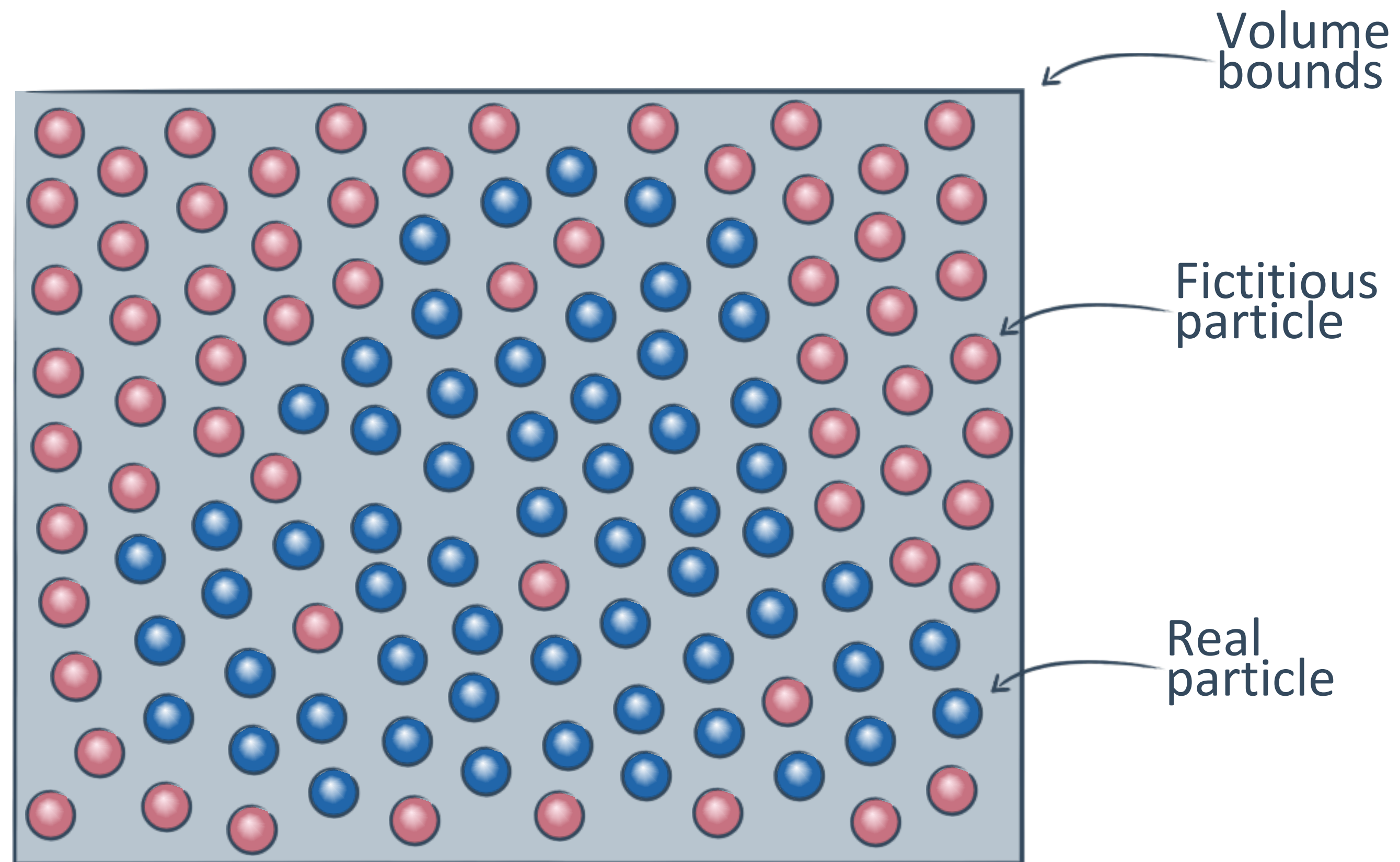
---





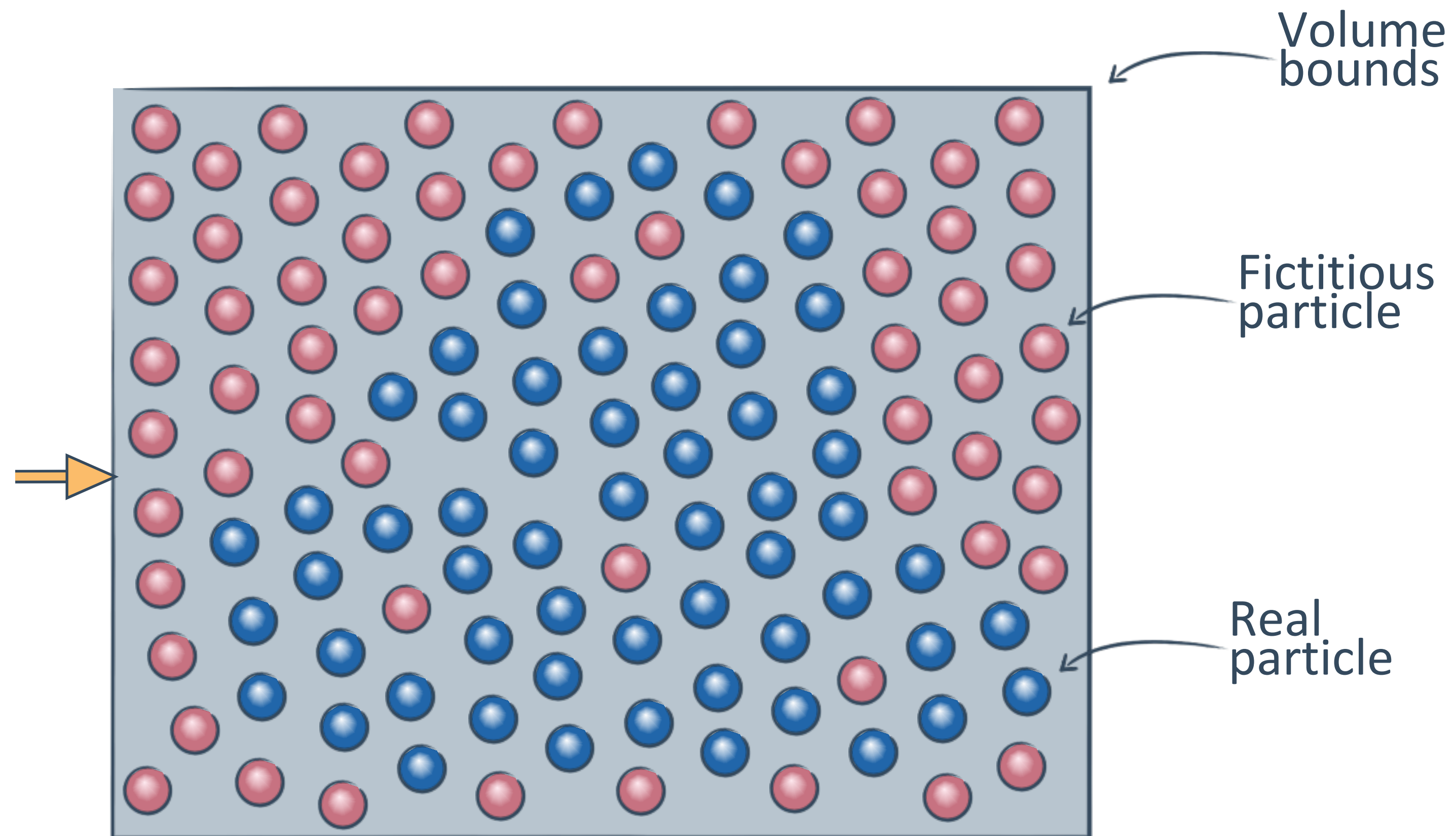
# Homogenization

---



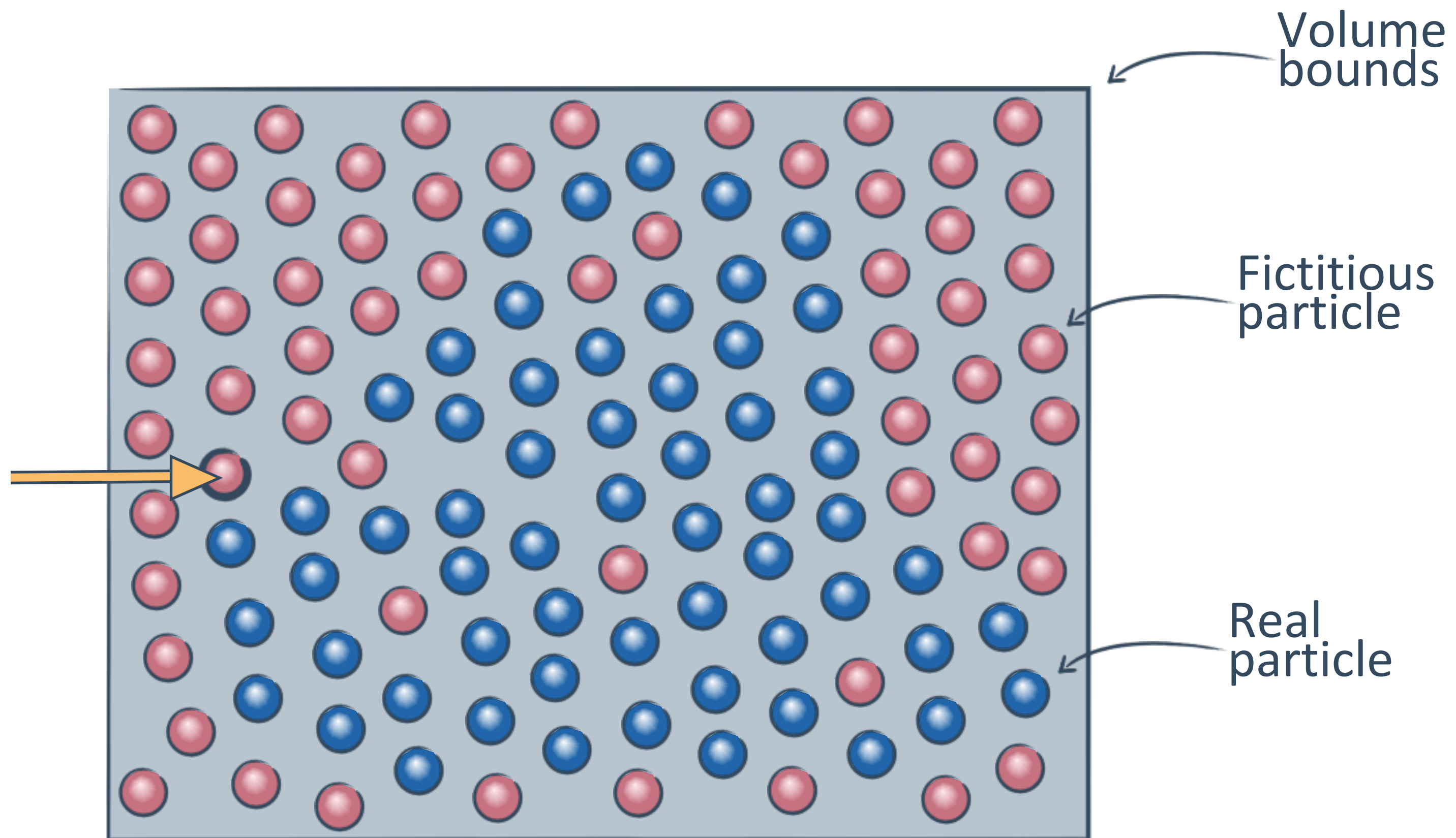
# Homogenization

---



# Homogenization

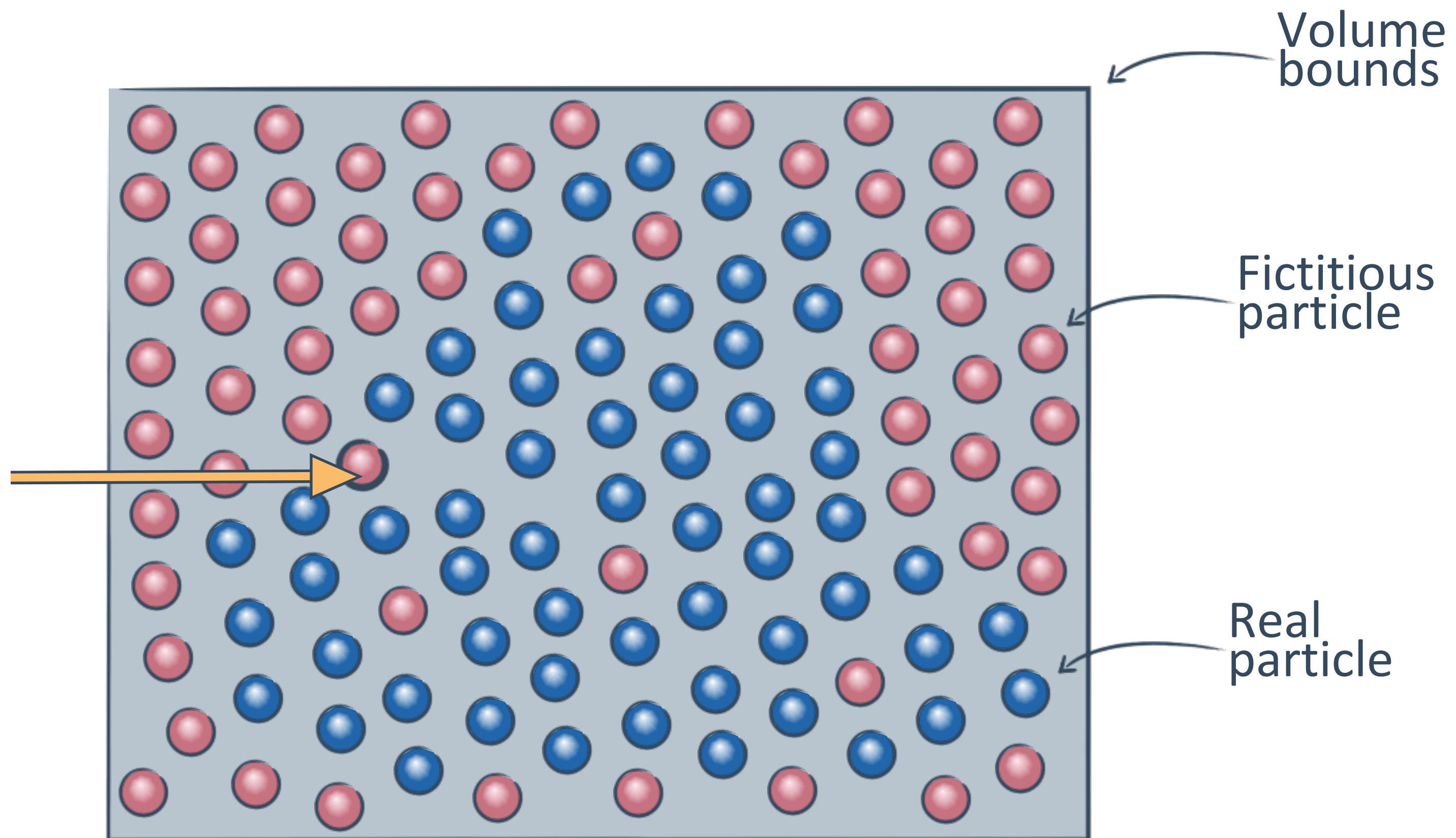
---





# Homogenization

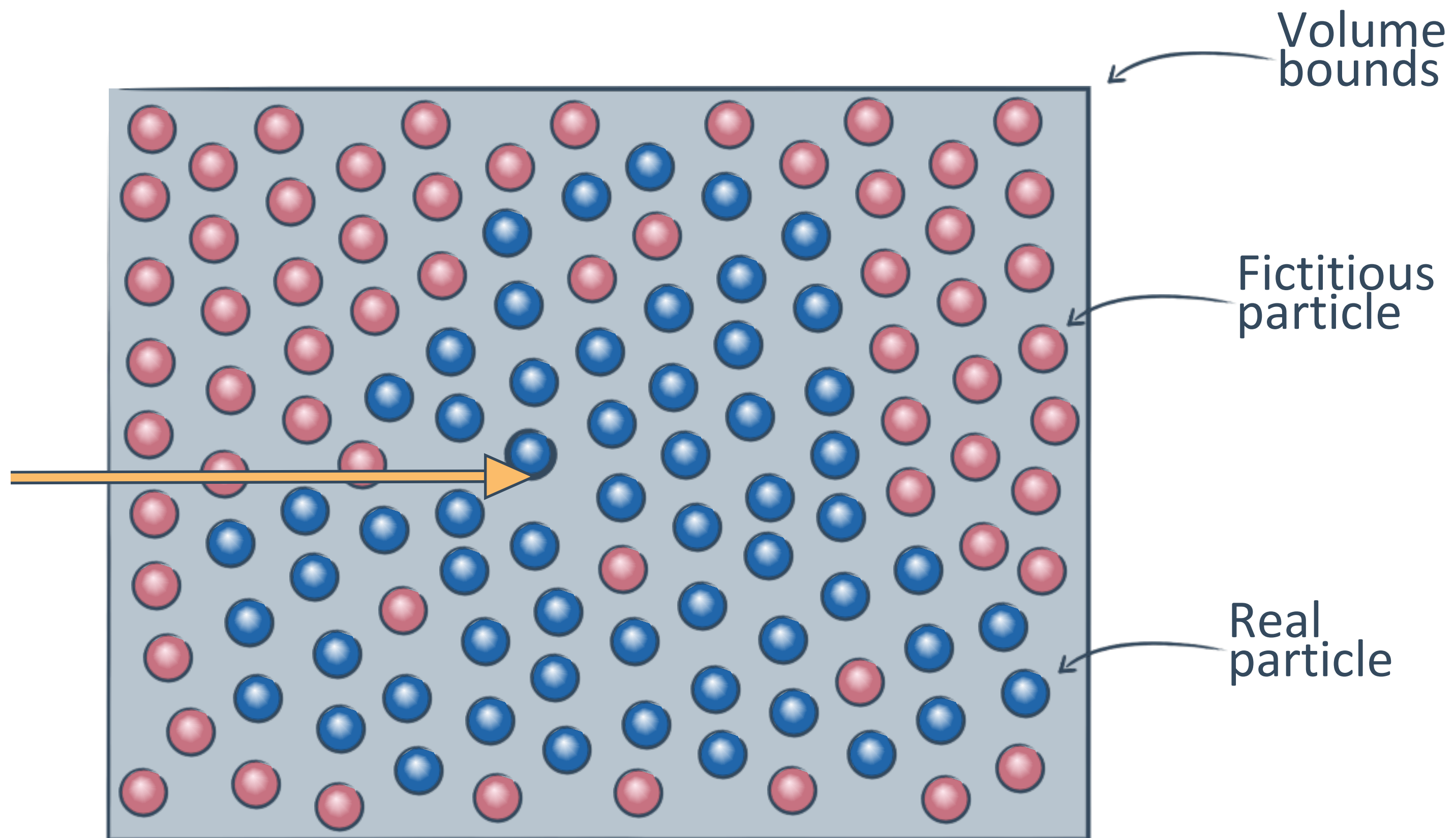
---





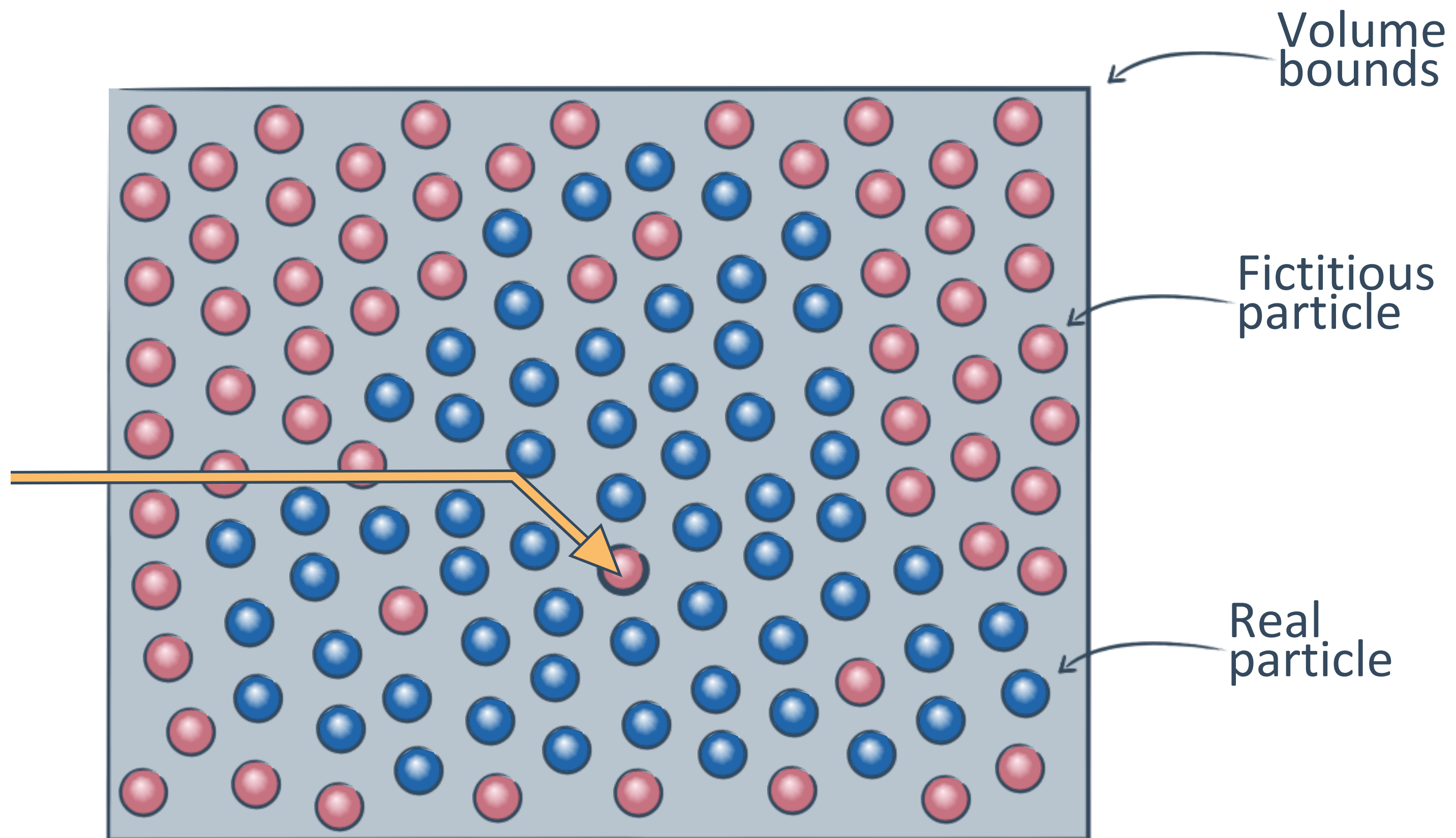
# Homogenization

---



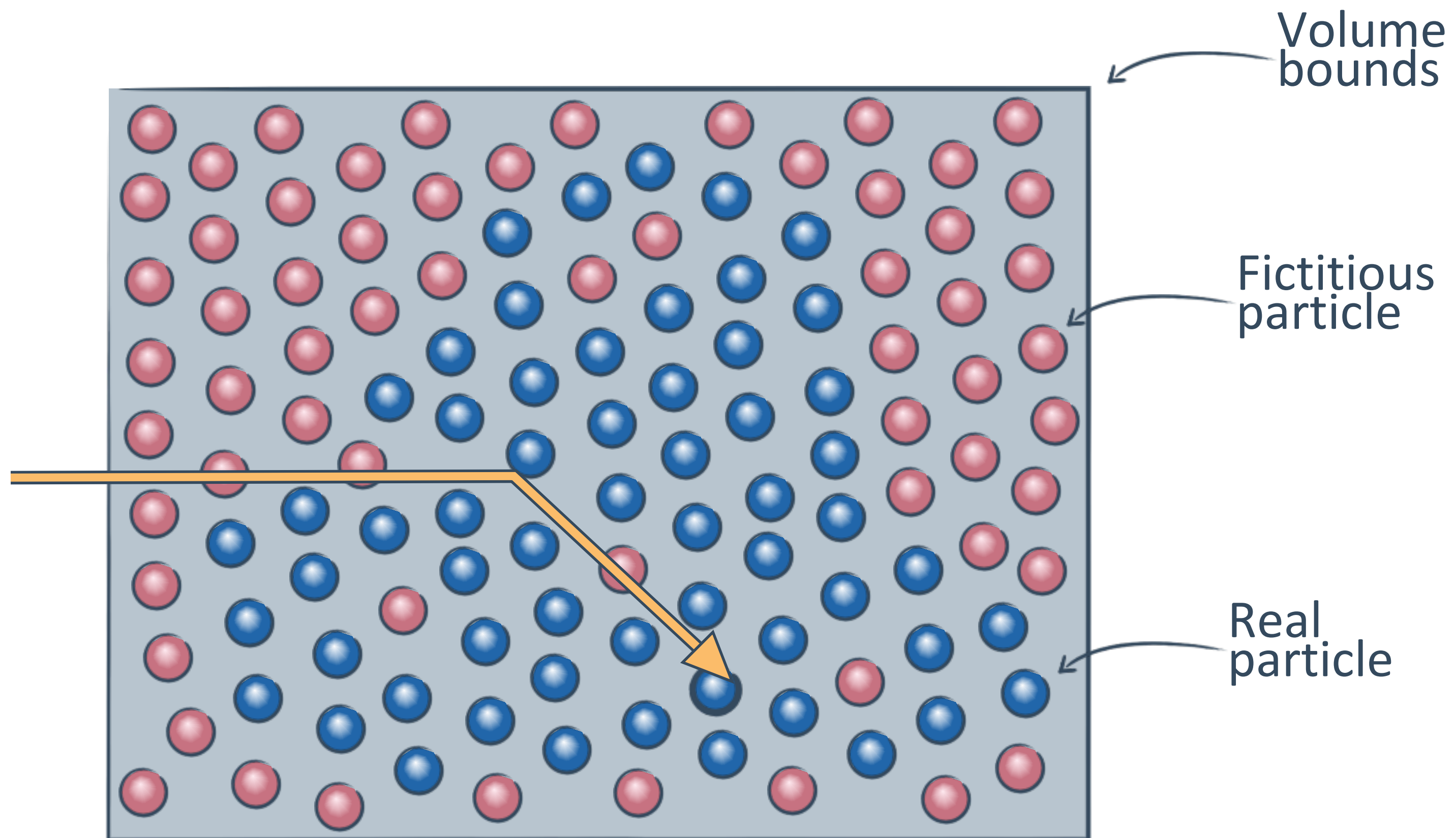
# Homogenization

---



# Homogenization

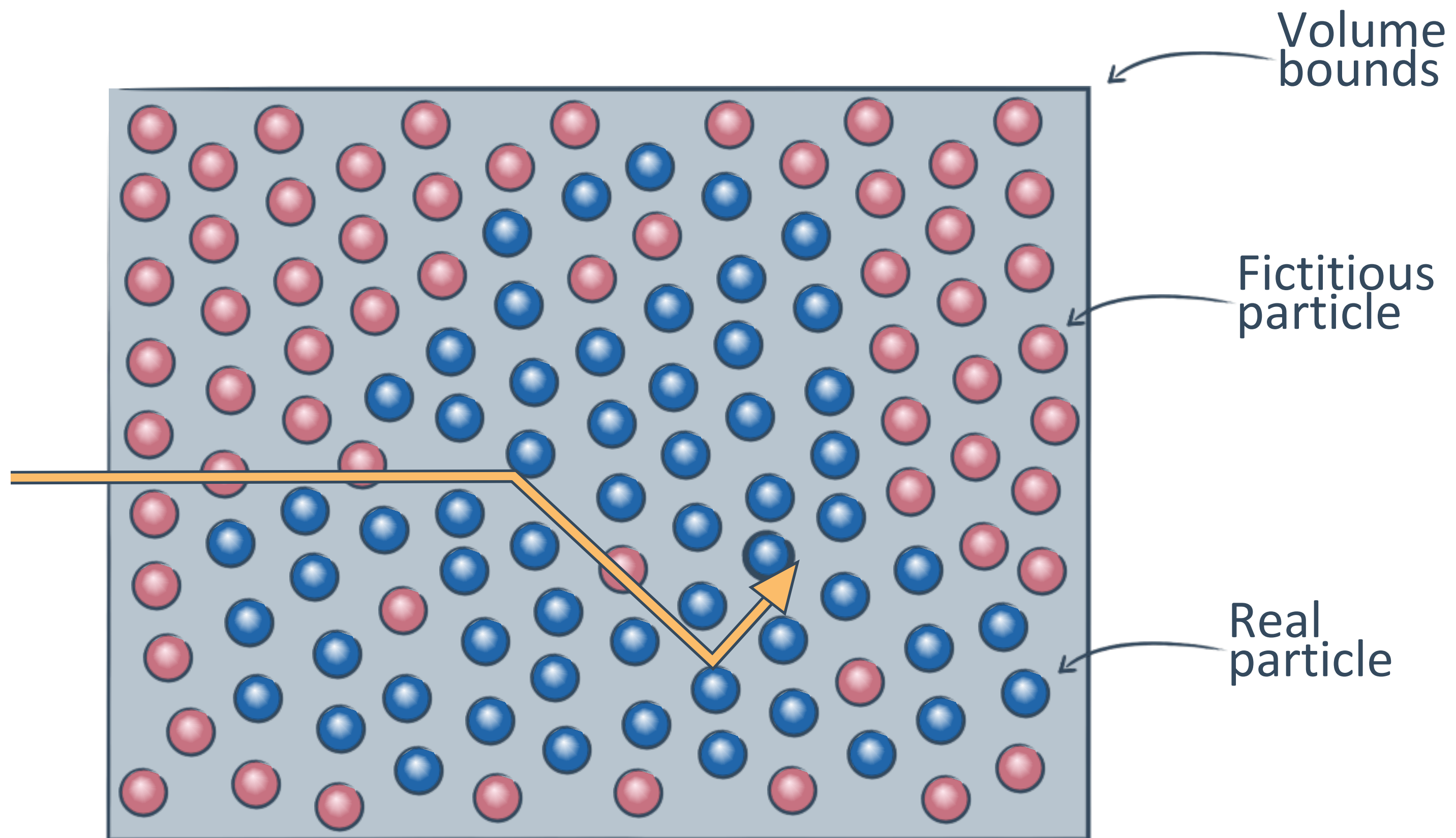
---





# Homogenization

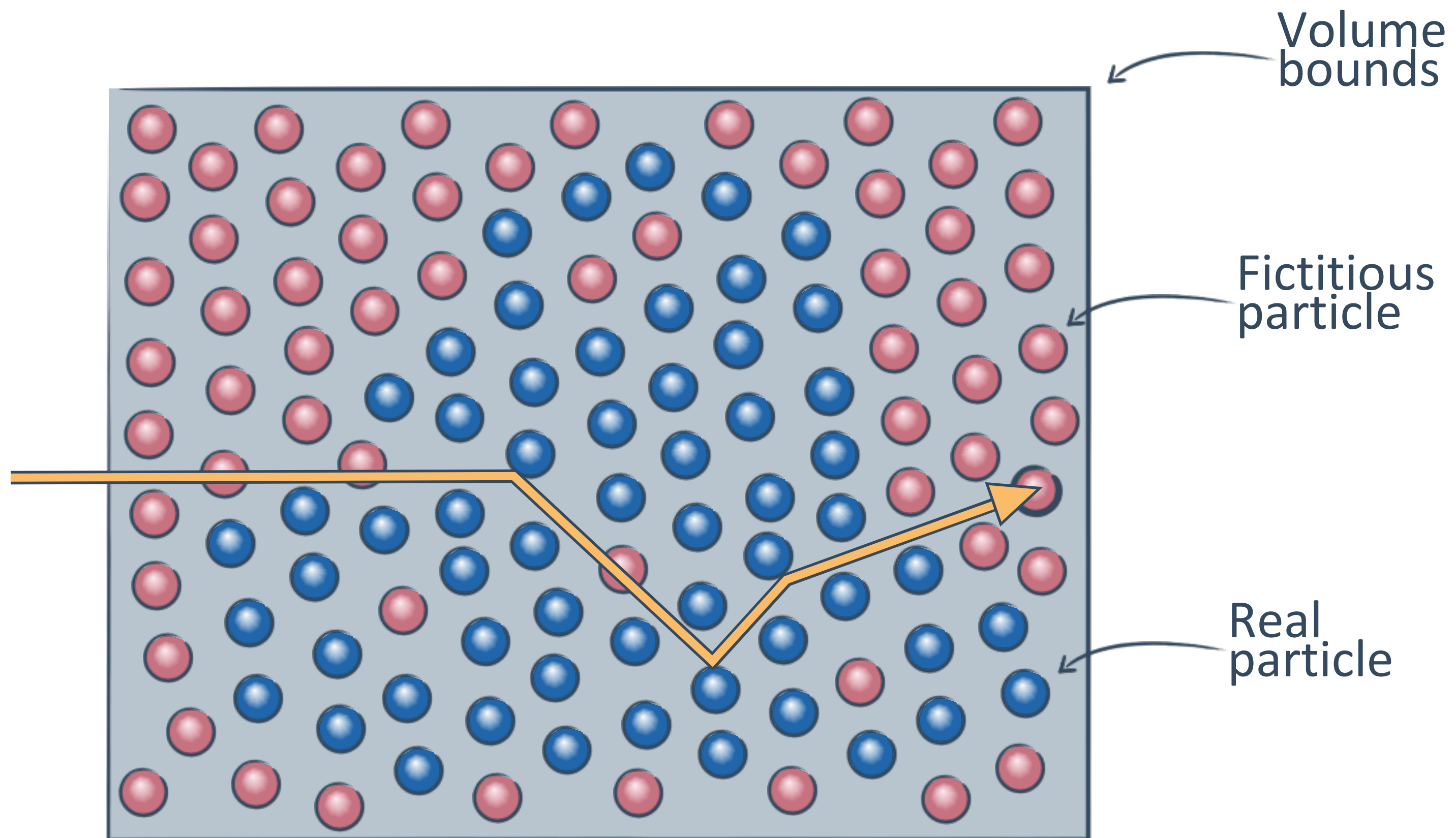
---





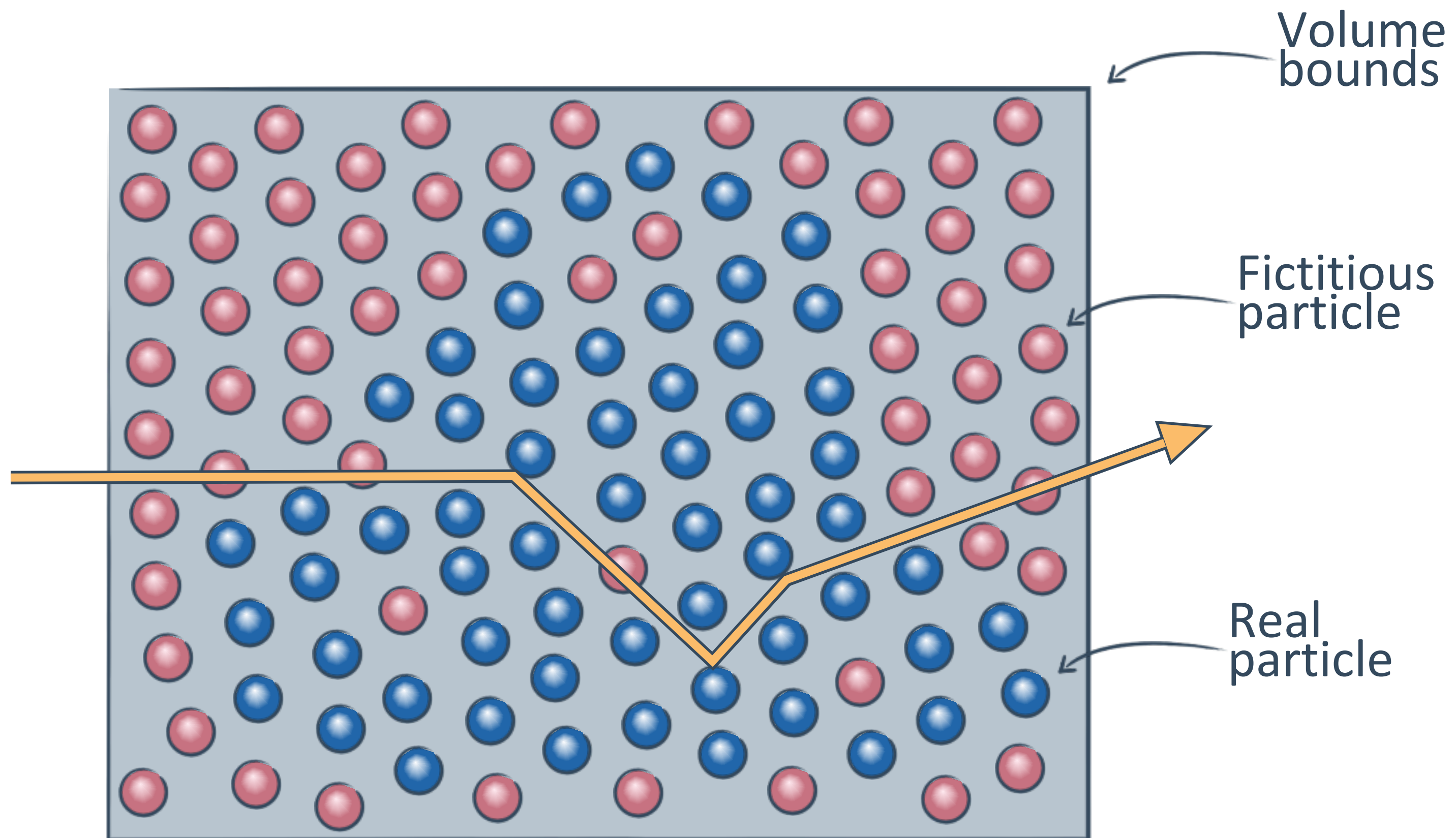
# Homogenization

---



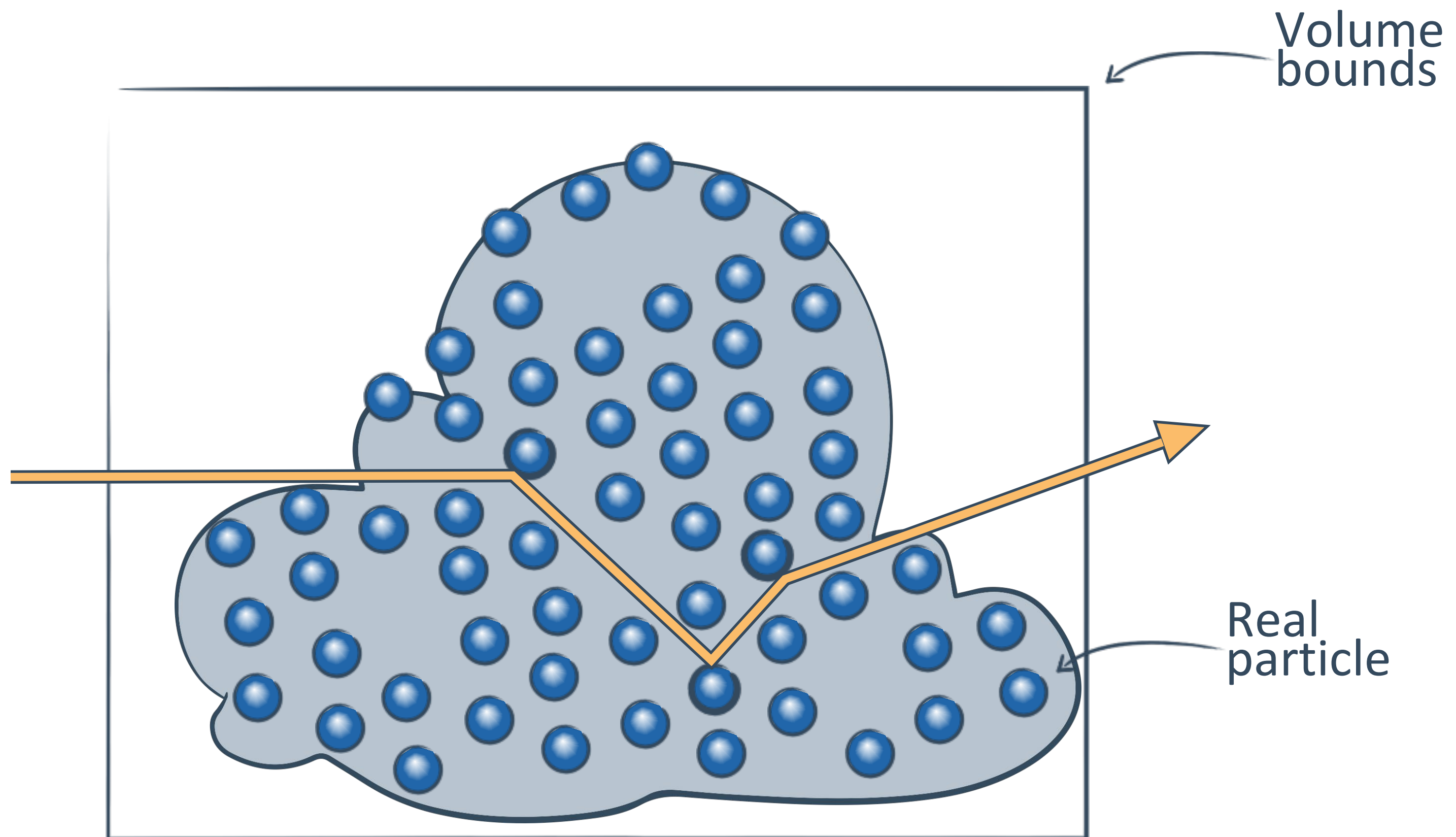
# Homogenization

---



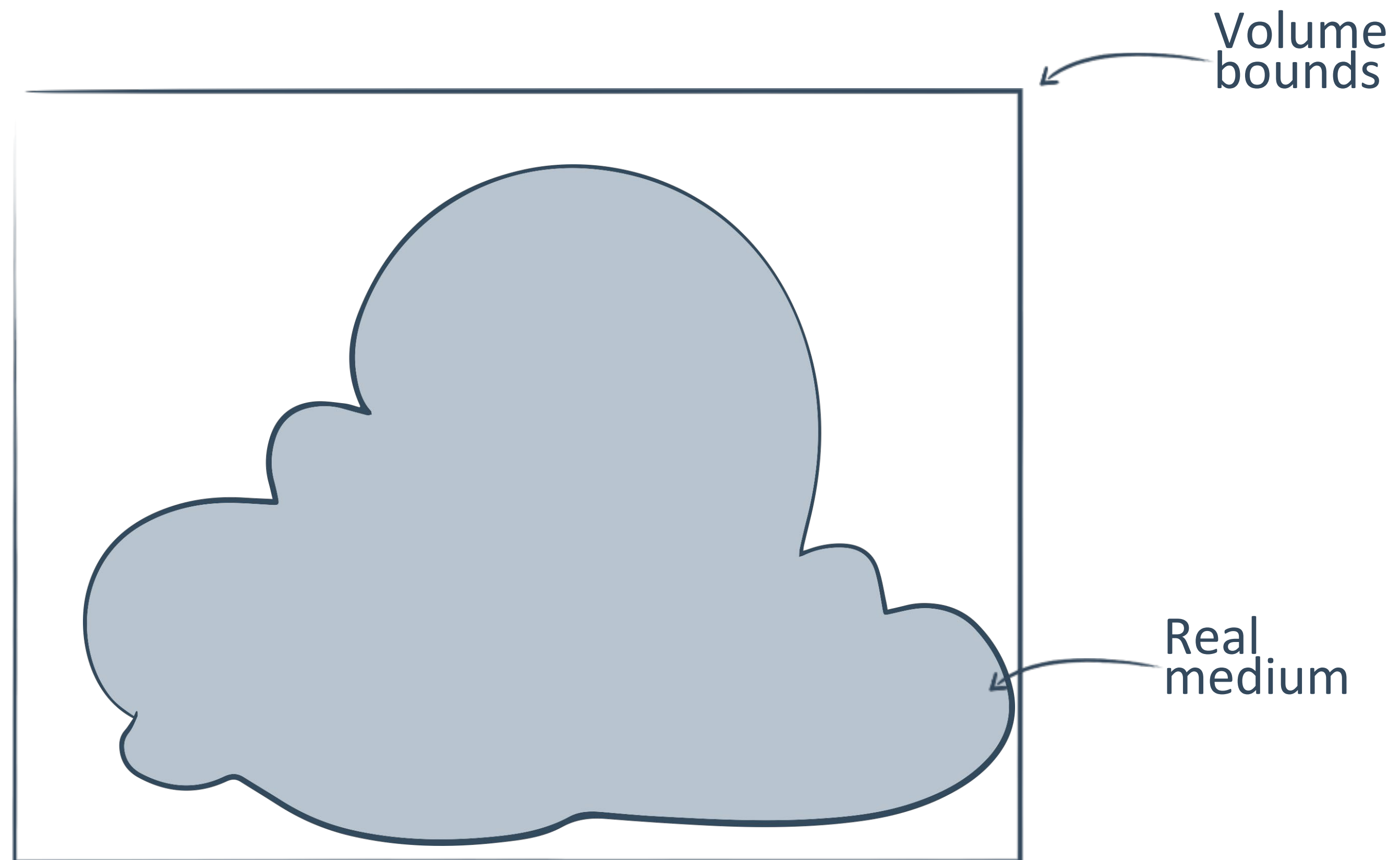
# Homogenization

---



# Stochastic Sampling

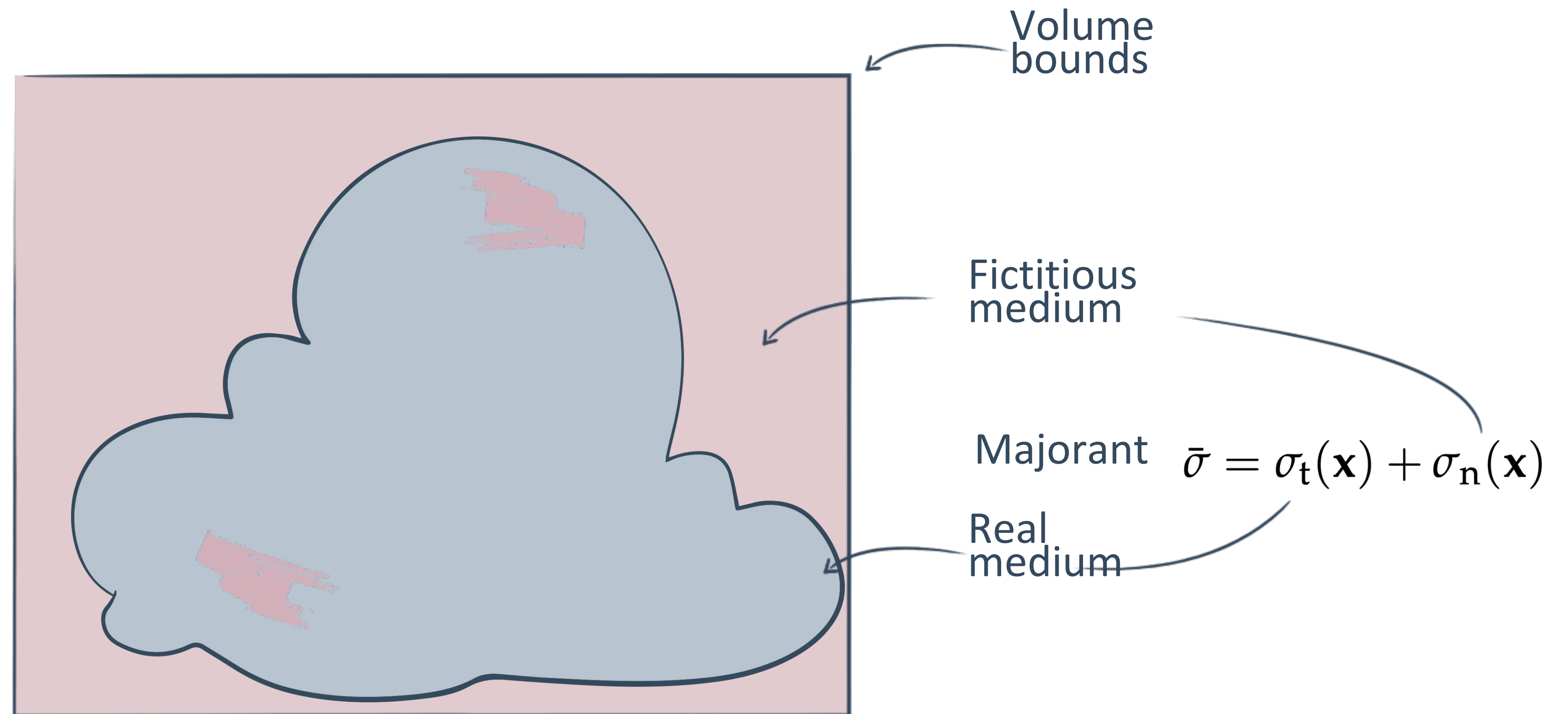
---



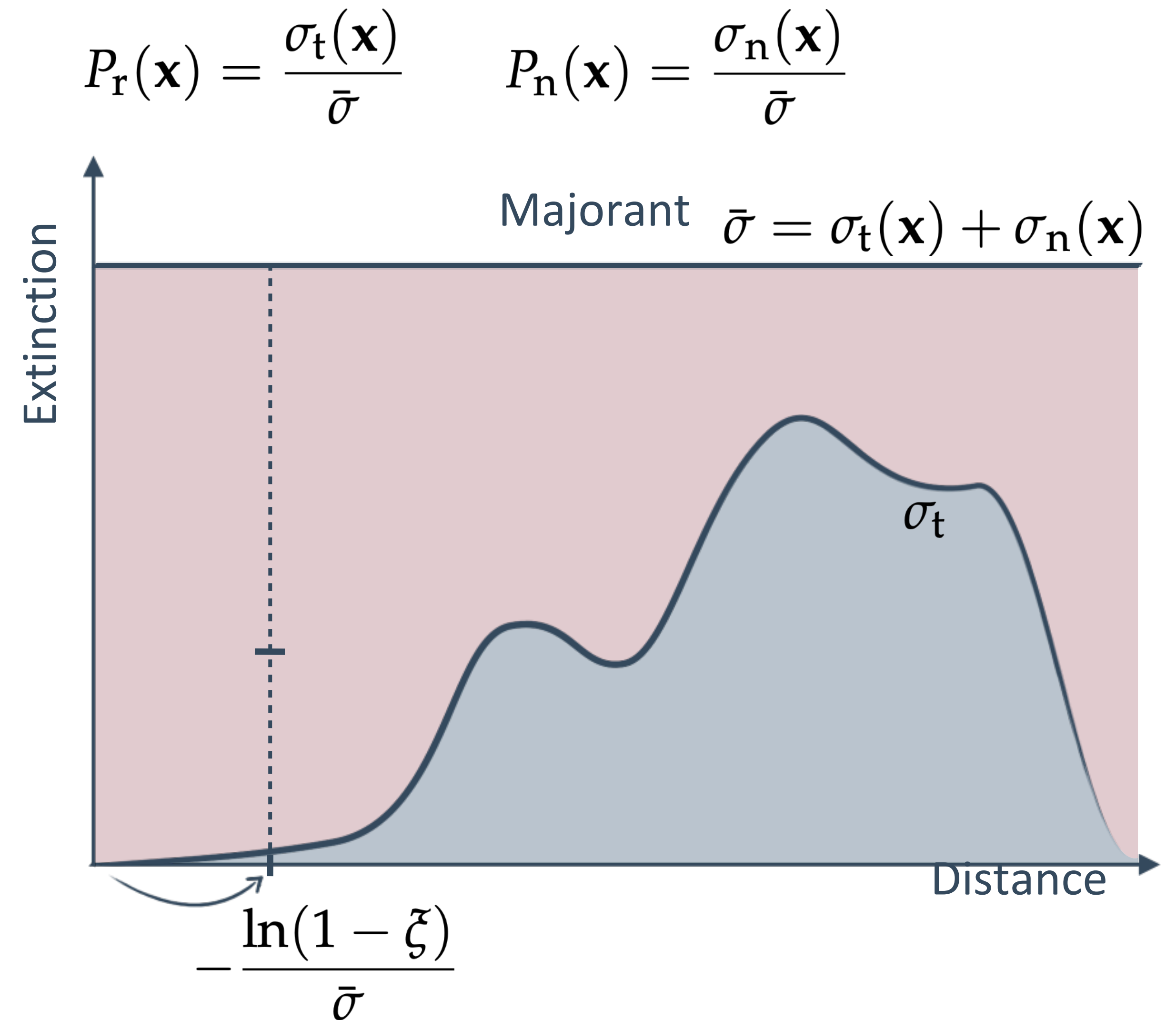
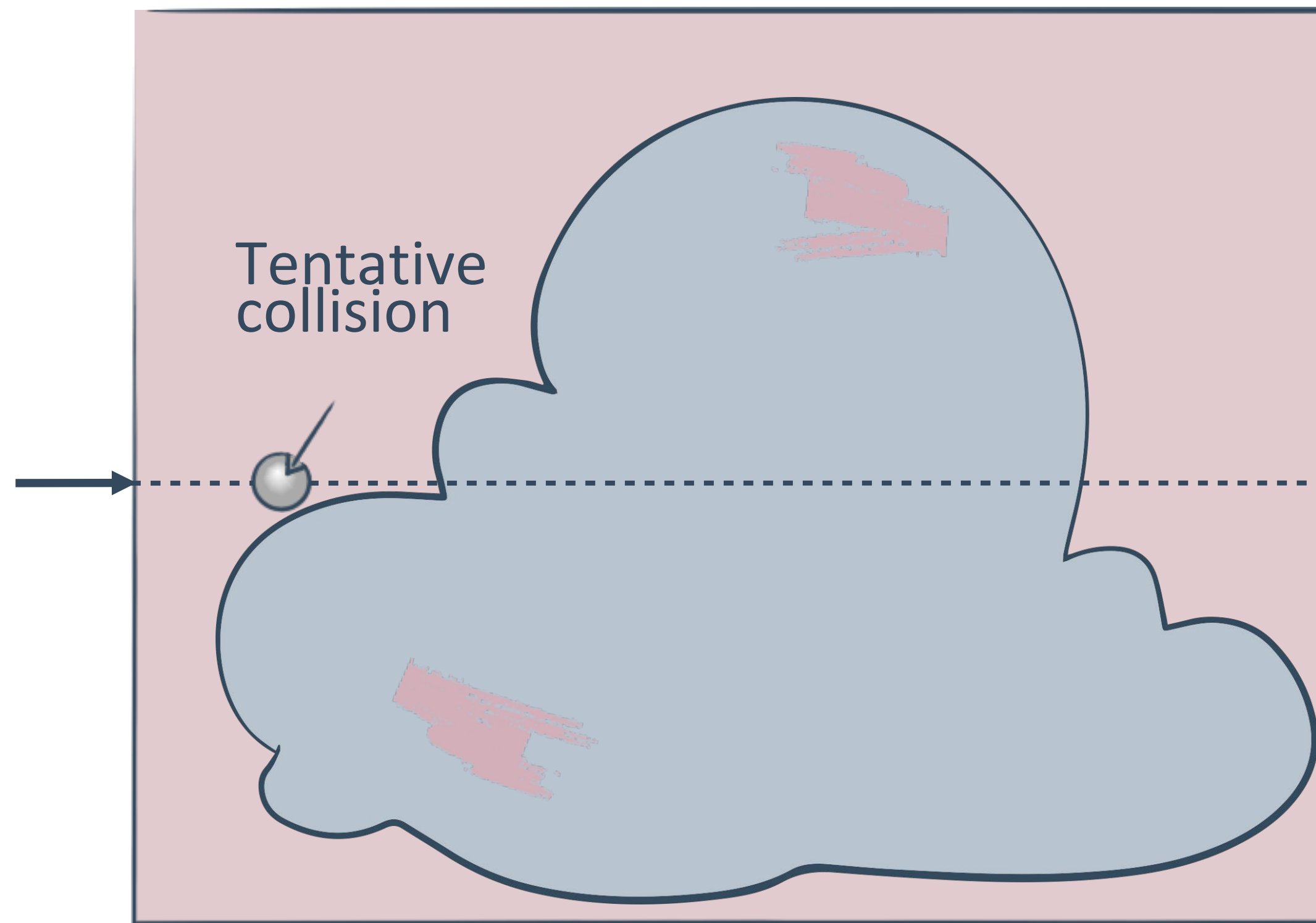


# Stochastic Sampling

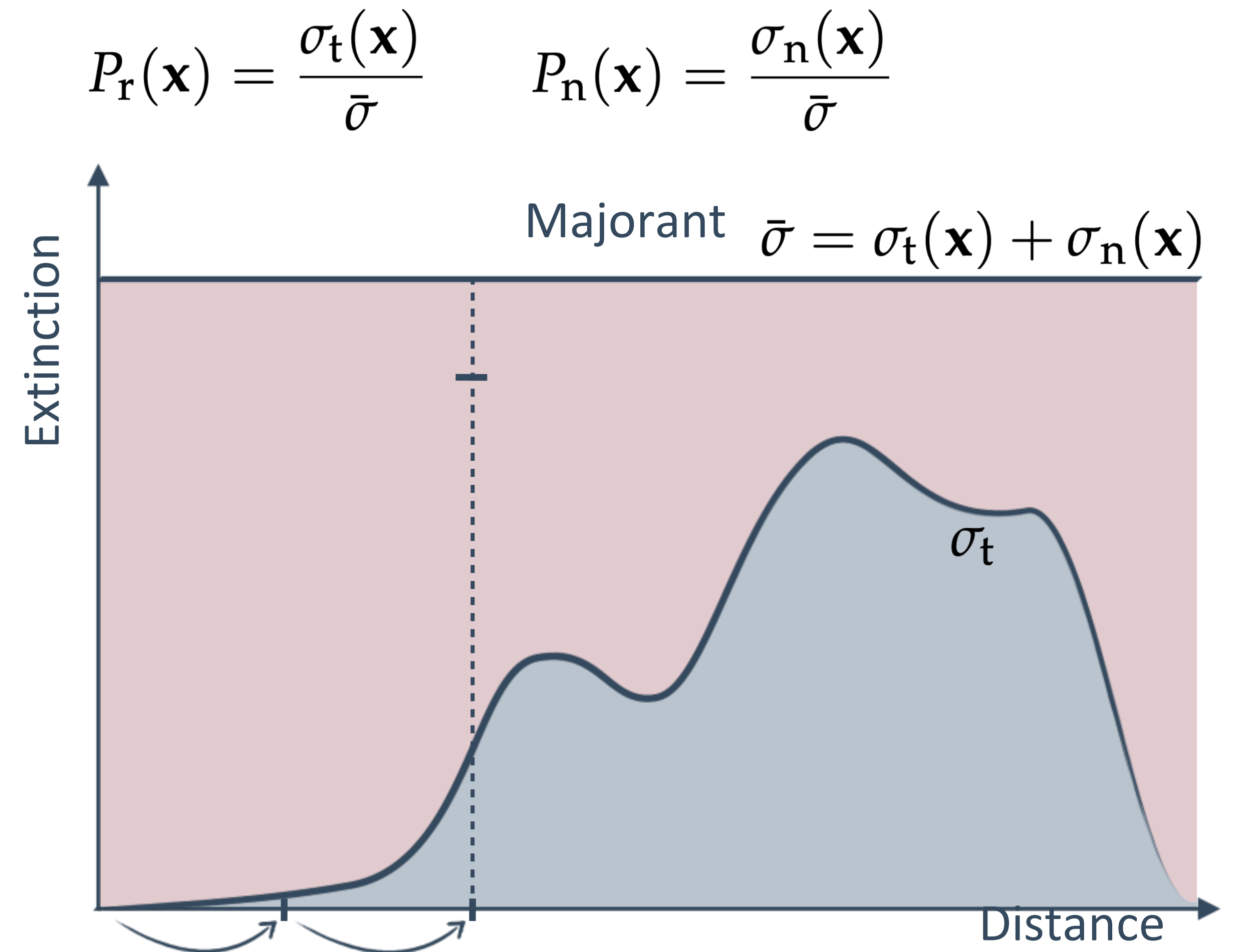
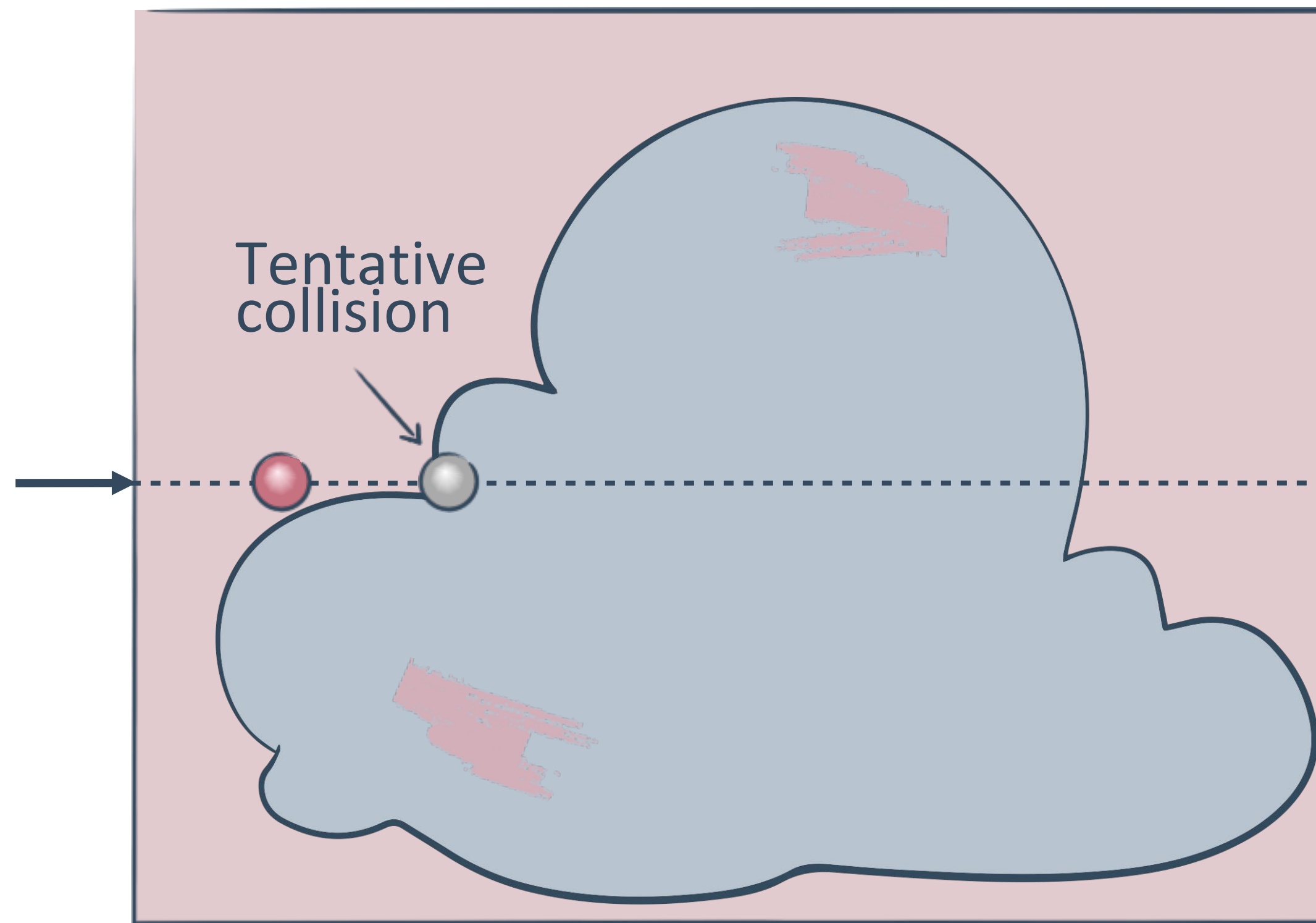
---



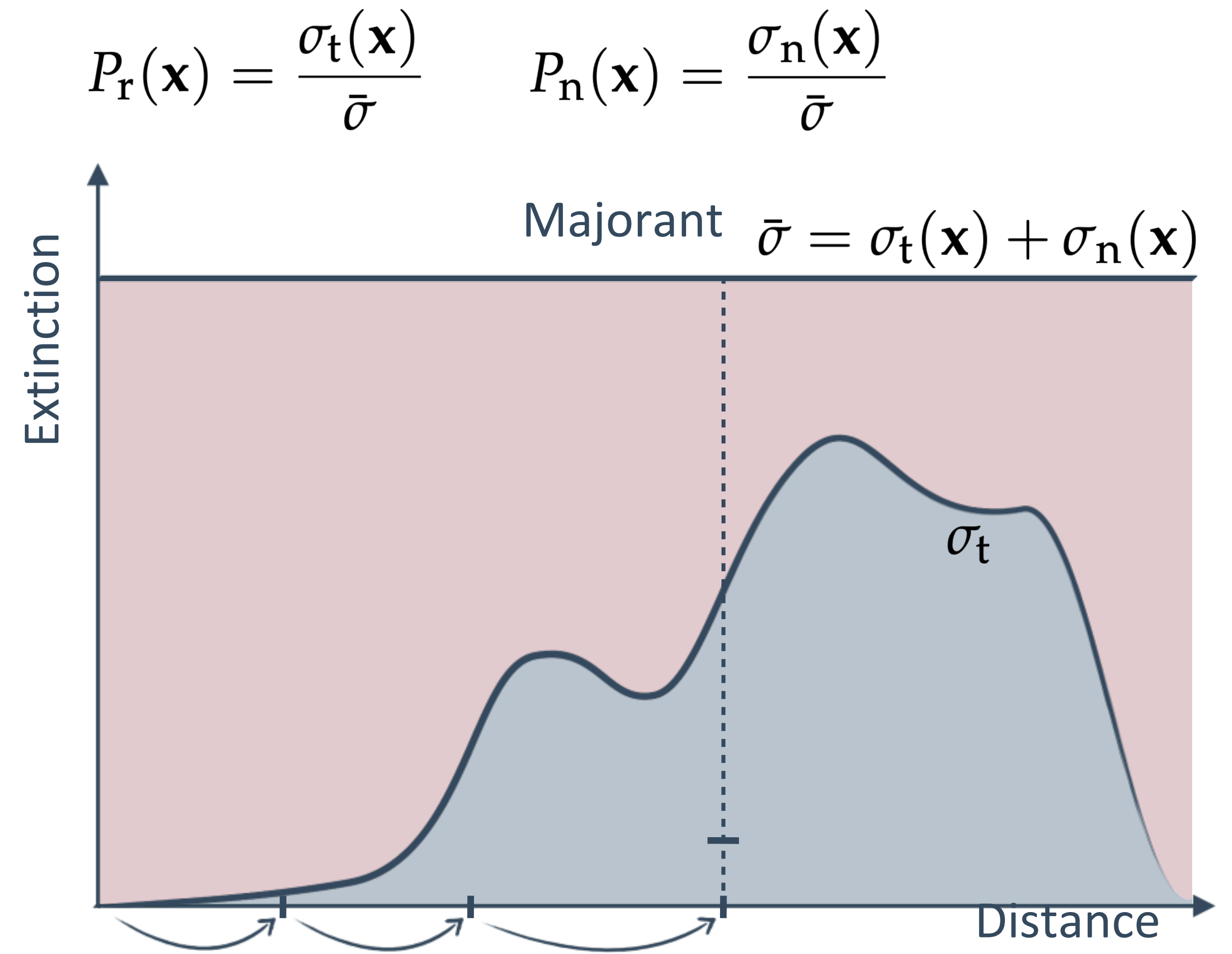
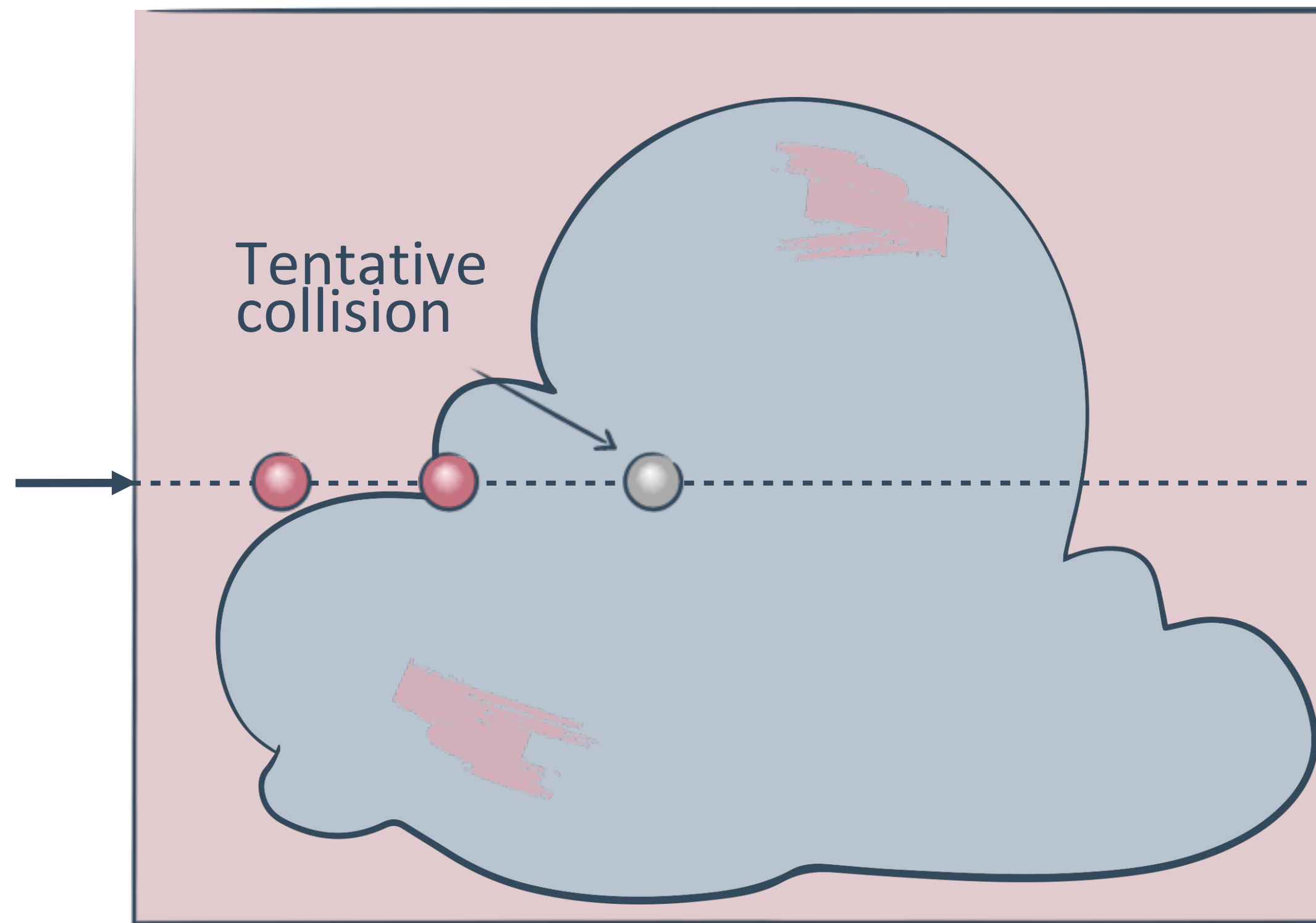
# Stochastic Sampling



# Stochastic Sampling

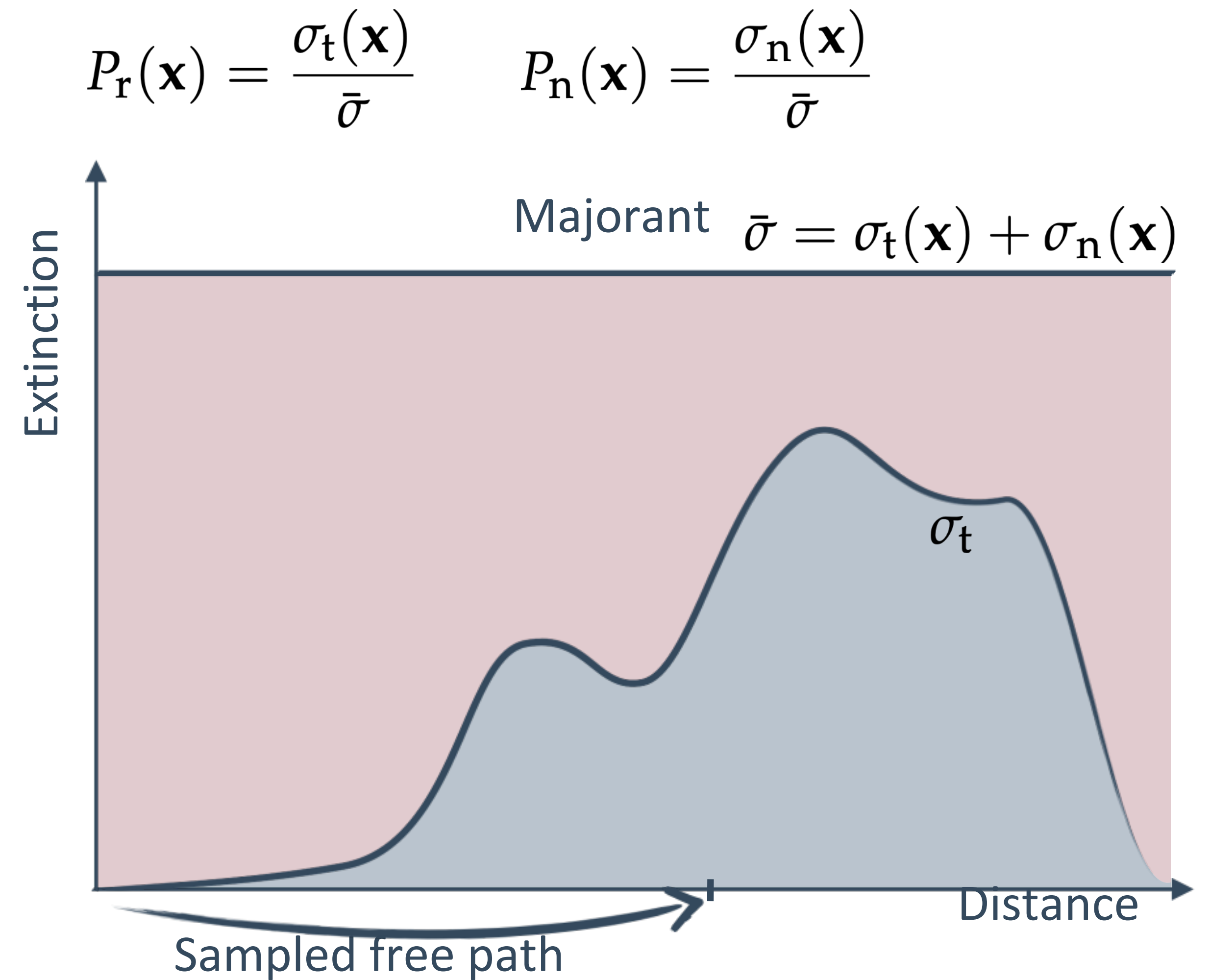
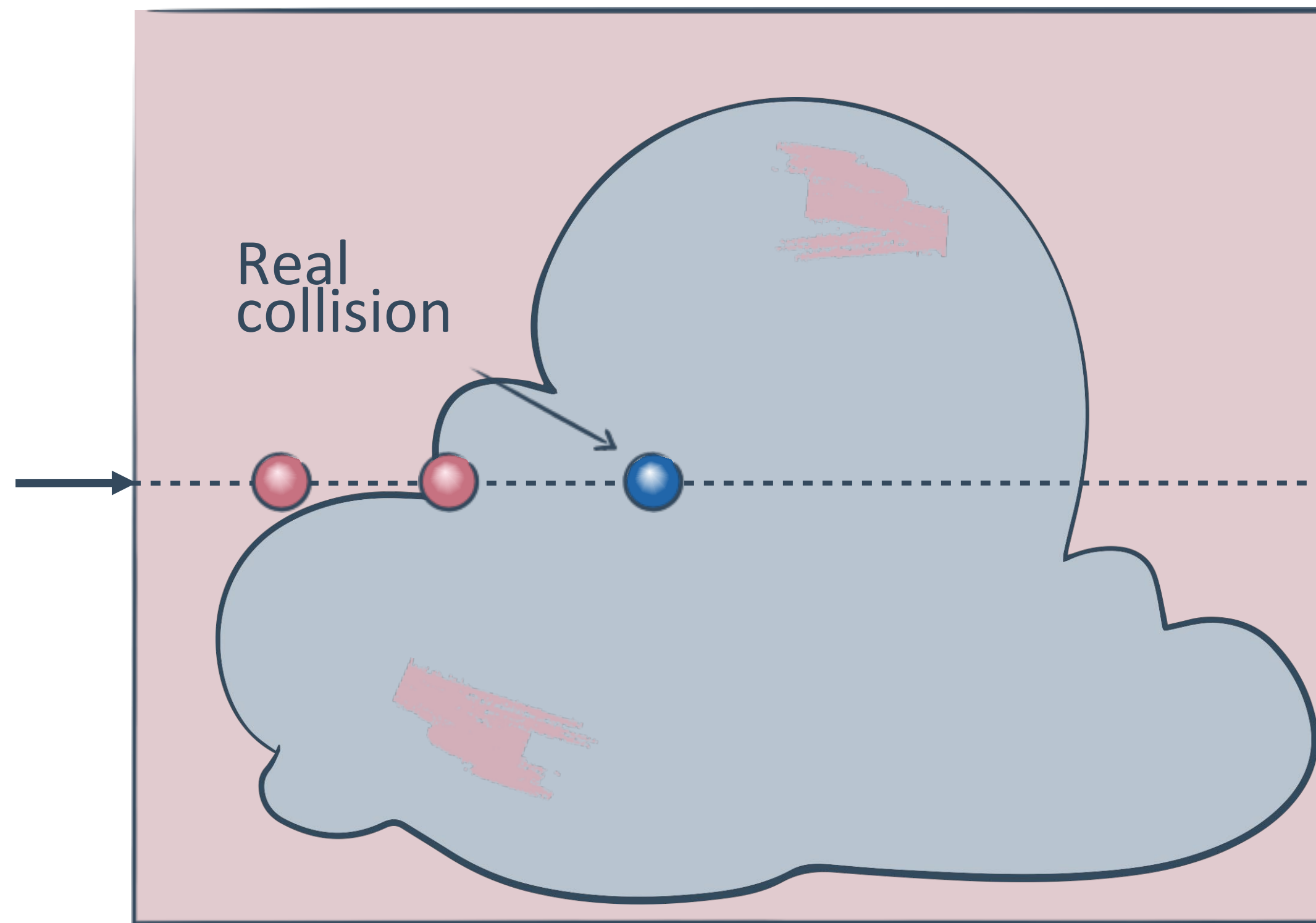


# Stochastic Sampling

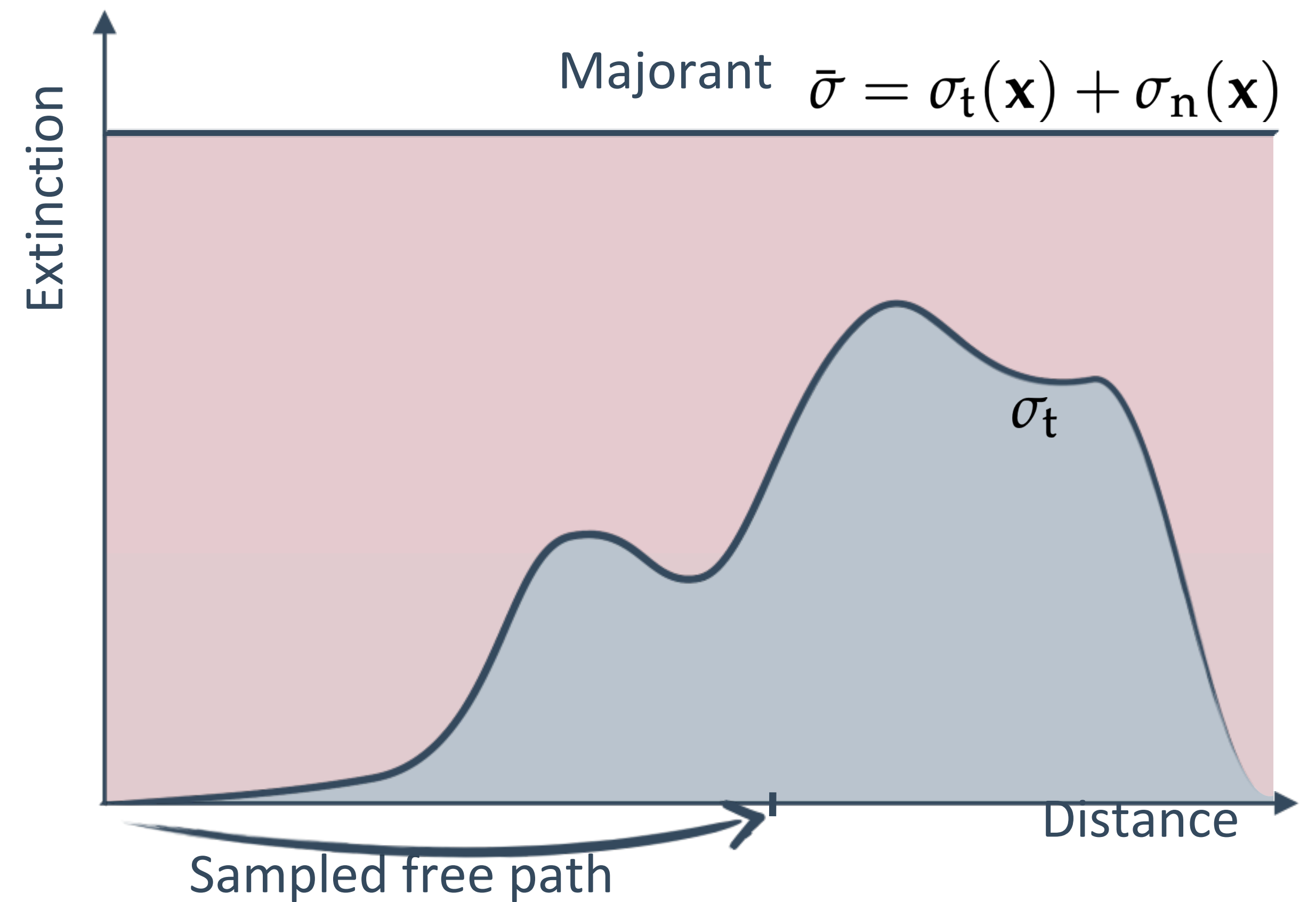




# Stochastic Sampling

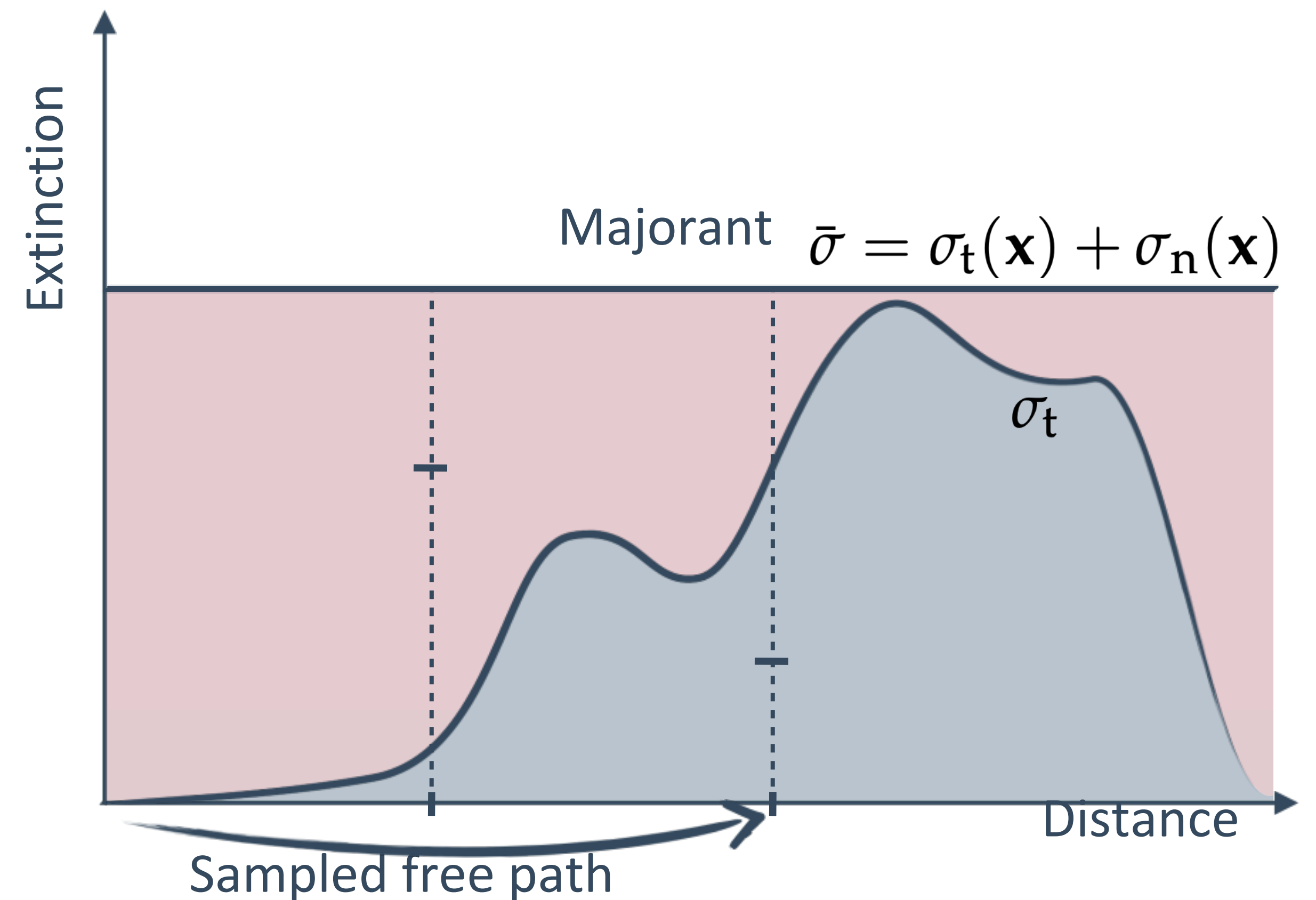


# Impact of Majorant



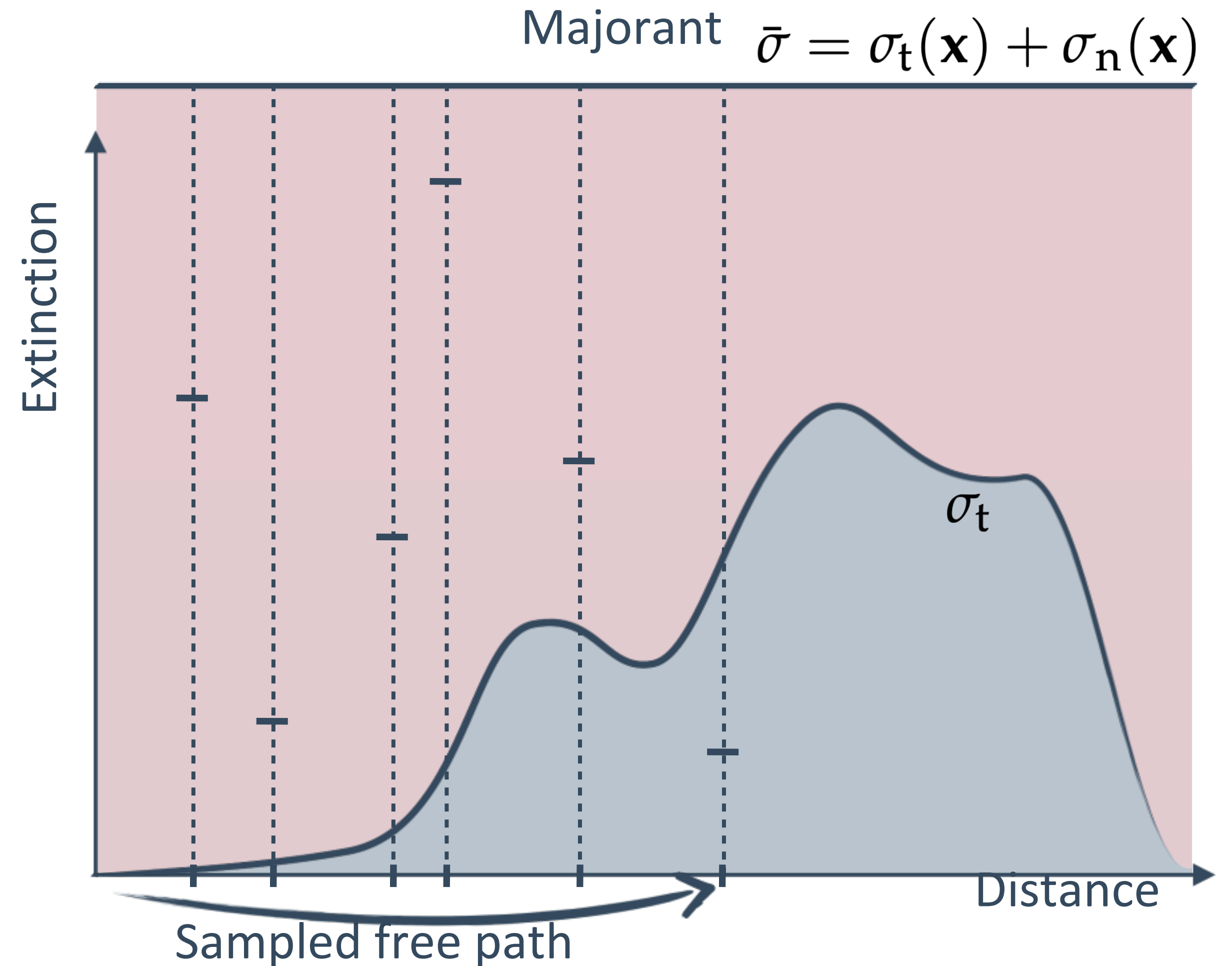
# Impact of Majorant

Tight majorant = GOOD  
(few rejected collisions)



# Impact of Majorant

Loose majorant = BAD  
(many expensive rejected collisions)





# Delta Tracking

---

```
void preprocess()
```

```
majorant = findMaximumExtinction()
```

```
void sampleFreePath(x,  $\omega$ )
```

```
t = 0
```

```
do:
```

```
// Sample distance to next tentative collision
```

```
t += -ln(1 - randf()) / majorant
```

```
// Compute probability of a real collision
```

```
Pr = getExtinction(x + t* $\omega$ ) / majorant
```

```
while Pr < randf()
```

```
return t
```

# Delta Tracking Summary

## Unbiased, see [Coleman 68] for a proof

### Mathematical Verification of a Certain Monte Carlo Sampling Technique and Applications of the Technique to Radiation Transport Problems

W. A. Coleman

Oak Ridge National Laboratory, Oak Ridge, Tennessee 37830

Received September 27, 1967

Revised November 10, 1967

The first section of this paper is a mathematical construction of a certain Monte Carlo procedure for sampling from the distribution

$$F(X) = \int_0^X \Sigma(x) \exp \left[ - \int_0^x \Sigma[v] dv \right] dx, \quad 0 \leq X.$$

The construction begins by defining a particular random variable  $\lambda$ . The distribution function of  $\lambda$  is developed and found to be identical to  $F(X)$ . The definition of  $\lambda$  describes the sampling procedure. Depending on the behavior of  $\Sigma(x)$ , it may be more efficient to sample from  $F(X)$  by obtaining realizations of  $\lambda$  than by the more conventional procedure described in the paper.

Section II is a discussion of applications of the technique to problems in radiation transport where  $F(X)$  is frequently encountered as the distribution function for nuclear collisions. The first application is in charged particle transport where  $\Sigma(x)$  is essentially a continuous function of  $x$ . An application in complex geometries where  $\Sigma(x)$  is a step function, and changes values numerous times over a mean path, is also cited. Finally, it is pointed out that the technique has been used to improve the efficiency of estimating certain quantities, such as the number of absorptions in a material.

#### INTRODUCTION

In certain Monte Carlo problems it is necessary to obtain realizations (sample values) of a random variable having a distribution function<sup>a</sup> given by

$$F(X) = \int_0^X \Sigma(x) \exp \left[ - \int_0^x \Sigma(v) dv \right] dx, \quad 0 \leq X, \quad (1)$$

where  $\Sigma(x)$  is any real valued function having the properties:

- $0 \leq \Sigma(x)$  for  $0 \leq x$ .
- $\lim_{y \rightarrow \infty} \int_0^y \Sigma(x) dx = \infty$ .
- $\Sigma(x)$  is bounded; there is an  $M > 0$  with  $0 \leq \Sigma(x) \leq M$  for all  $x$ .

<sup>a</sup>If  $F(X)$  is a distribution function it is nondecreasing,  $F(-\infty) = 0$ , and  $F(\infty) = 1$ . Many authors refer to such functions as cumulative distribution functions.

Restriction (a) ensures that  $F(x)$  is a nondecreasing function of  $x$ , while (b) ensures that  $F(\infty) = 1$ .

One scheme for obtaining realizations of a random variable having the distribution  $F(X)$  is as follows. Consider the random variable  $\eta$  which has distribution

$$F_{\eta}(Y) = \int_0^Y e^{-v} dv, \quad 0 \leq Y.$$

For each value of  $\eta$  define

$$\theta = \phi^{-1}(\eta),$$

where

$$\eta = \phi(\theta) = \int_0^{\theta} \Sigma(u) du.$$

The random variable  $\theta$  has the distribution  $F(X)$  given in Eq. (1). To obtain a realization of  $\theta$  one might first sample from  $F_{\eta}(Y)$ , realizing  $\eta$ . Then

$$\theta_1 = \phi^{-1}(\eta_1). \quad (2)$$

Sampling from  $F_{\eta}(Y)$  is common practice in Monte Carlo calculations. However, the solution of Eq. (2) for  $\theta_1$ , given  $\eta_1$ , may be rather laborious.

In practice it is often easier to obtain realizations from Eq. (1) by another procedure. This procedure is described in Sec. I in terms of the definition of a certain random variable  $\lambda$ , whose distribution is identical to that given in Eq. (1). In most applications it is fairly easy to argue that  $\lambda$  must be distributed according to Eq. (1) for physical reasons. The development in Sec. I is intended to provide a mathematical perspective for understanding existing applications and to encourage recognition of new applications. Section II is a summary of three current applications.

#### I. DEVELOPING THE DISTRIBUTION FUNCTION FOR $\lambda$

The purpose of this section is to construct the distribution function of a random variable  $\lambda$  whose values are the termination points of a certain random walk to be described presently. The construction is based on the following hypotheses:

A. Let  $\Sigma(x)$  be as described in conjunction with the distribution in Eq. (1).

B. Let  $\{\xi_1, \xi_2, \dots, \xi_n, \dots\}$  denote an infinite sequence of totally independent random variables having a common distribution function,

$$P(\xi_i \leq X) = F_{\xi}(X) = \int_0^X M e^{-Mx} dx,$$

$$0 \leq X; \quad i = 1, 2, \dots$$

where  $M$  is a fixed upper bound of  $\Sigma(x)$ .

C. Define  $\sigma(x) \equiv \Sigma(x)/M$  and  $\alpha(x) = 1 - \sigma(x)$ , where  $0 \leq x$ , to simplify notation.

D. Let  $\{\rho_1, \rho_2, \dots, \rho_n, \dots\}$  denote an infinite sequence of totally independent random variables having a common uniform distribution function,

$$P(\rho_i \leq R) = F_{\rho}(R) = R, \quad 0 \leq R \leq 1;$$

$$i = 1, 2, \dots.$$

E. Let  $\{\zeta_1, \zeta_2, \dots, \zeta_n, \dots\}$  denote the infinite sequence of random variables which are the cumulative sums of the  $\xi_i$ :

$$\zeta_i = \sum_{j=1}^i \xi_j = \zeta_{i-1} + \xi_i, \quad i = 1, 2, \dots,$$

$$\zeta_0 = \xi_0 = 0.$$

F. Denote the minimum value of  $n$  for which

$$\rho_n \leq \sigma(\zeta_n), \quad n = 1, 2, \dots,$$

by  $N$ .

G. Let  $\lambda$  denote the random variable  $\zeta_N$ . The values of  $\lambda$  are defined as those values of the  $\zeta_n$  for which  $n$  takes on the value  $N$ .

The hypotheses A through G form a constructive definition of  $\lambda$ . They describe explicitly the procedure for obtaining realizations of  $\lambda$ . Let  $x_i, r_i, z_i$ , and  $L$  denote realizations of  $\xi_i, \rho_i, \zeta_i$ , and  $\lambda$ , respectively. Using this notation, the procedure is as follows:

- Assign  $i$  the value 1,  $z_0$  the value 0.
- Generate  $x_i$  and  $r_i$ .
- Calculate  $z_i = z_{i-1} + x_i$ .
- If  $r_i \leq \sigma(z_i)$ , stop and assign  $L$  the value  $z_i$ ; otherwise increment  $i$  by 1 and proceed to step 2.

For brevity in all of the discussion that follows, the procedure outlined above will be referred to as the  $\lambda$  procedure. The distribution function for  $\lambda$  will now be constructed using the hypotheses A through G.

Denote the event for which  $N = 1$  and  $\lambda \leq Z$  by

$$E_1 = \{\rho_1 \leq \sigma(\zeta_1), \zeta_1 \leq Z\},$$

where  $Z$  is an arbitrary fixed value in the range of  $\lambda$ . Similarly denote the event for which  $N = 2$  and  $\lambda \leq Z$  by

$$E_2 = \{\rho_1 > \sigma(\zeta_1), \rho_2 \leq \sigma(\zeta_2), \zeta_2 \leq Z\}.$$

This notation is extended to describe the events for general  $N > 1$  and  $\lambda \leq Z$ :

$$E_n = \{\rho_1 > \sigma(\zeta_1), \rho_2 > \sigma(\zeta_2), \dots, \rho_{n-1} > \sigma(\zeta_{n-1}), \rho_n \leq \sigma(\zeta_n), \zeta_n \leq Z\}.$$

The event  $\{\lambda \leq Z\}$  can occur in any of the mutually exclusive ways  $E_1, E_2, \dots, E_n, \dots$ . Hence, the distribution function for  $\lambda$  may be written as

$$P[\lambda \leq Z] = F_{\lambda}(Z) = \sum_{n=1}^{\infty} P(E_n). \quad (3)$$

Each of the joint probabilities  $P(E_n)$ ,  $n = 1, 2, \dots$ , may be expressed in terms of the random walk increments  $\xi_i$ ,  $i = 1, 2, \dots$ :

$$P(E_1) = P[\rho_1 \leq \sigma(\xi_1), \xi_1 \leq Z]$$

$$\vdots$$

$$\vdots$$

$$P(E_n) = P\left[\rho_1 > \sigma(\xi_1), \dots, \rho_{n-1} > \sigma\left\{\sum_{i=1}^{n-1} \xi_i\right\}, \rho_n \leq \sigma\left\{\sum_{i=1}^n \xi_i\right\}, \xi_n \leq Z - \sum_{i=1}^{n-1} \xi_i\right],$$

$$\vdots$$

$$\vdots$$

$$\vdots$$

The probability that  $\rho_1 \leq \sigma(\xi_1)$  and  $\xi_1 \leq Z$  may be expressed as the integral of the conditional probability that  $\rho_1 \leq \sigma(\xi_1)$  given  $\xi_1 = x_1$  with respect to the marginal distribution<sup>1</sup>  $F_{\xi}(x_1)$ :

$$P(E_1) = \int_0^Z P[\rho_1 \leq \sigma(\xi_1) | \xi_1 = x_1] dF_{\xi}(x_1) = \int_0^Z \sigma(x_1) M e^{-Mx_1} dx_1. \quad (4)$$

Similarly,

$$P(E_n) = \int_0^Z \int_0^{Z-x_1} \dots \int_0^{Z-\sum_{i=1}^{n-1} x_i} P\left[\rho_1 > \sigma(\xi_1), \dots, \rho_{n-1} > \sigma\left\{\sum_{i=1}^{n-1} \xi_i\right\}, \rho_n \leq \sigma\left\{\sum_{i=1}^n \xi_i\right\} | \xi_1 = x_1, \dots, \xi_n = x_n\right] dF_{\xi_1} \dots dF_{\xi_n}(x_1, \dots, x_n).$$

$$\vdots$$

$F_{\xi_1, \dots, \xi_n}(x_1, \dots, x_n)$  denotes the joint distribution function of the variables  $\xi_1, \dots, \xi_n$ . The integral limits in Eq. (5) are determined by first noting that  $0 < \xi_i$ , and, hence  $\xi_{i-1} < \xi_i$ ,  $i = 1, 2, \dots$ . For the event  $E_n$  to occur, it is necessary that  $\zeta_n < Z$ , which implies  $\zeta_1 < \dots < \zeta_n < Z$ . In terms of  $\xi_i$ , it is necessary that  $\xi_i < Z - \sum_{j=1}^{i-1} \xi_j$  for  $i = 2, 3, \dots, n$ .

Since  $\rho_2, \rho_3, \dots, \rho_n$  are totally independent, the integrand in Eq. (5) is equal to

$$P[\rho_1 > \sigma(\xi_1) | \xi_1 = x_1] \dots P[\rho_{n-1} > \sigma\left\{\sum_{i=1}^{n-1} \xi_i\right\} | \xi_1 = x_1, \dots, \xi_{n-1} = x_{n-1}] \times P\left[\rho_n \leq \sigma\left\{\sum_{i=1}^n \xi_i\right\} | \xi_1 = x_1, \dots, \xi_n = x_n\right].$$

Also  $\xi_1, \dots, \xi_n$  are totally independent and have a common distribution function, so that

$$F_{\xi_1, \dots, \xi_n}(x_1, \dots, x_n) = F_{\xi_1}(x_1) \dots F_{\xi_n}(x_n) = F_{\xi}(x_1) \dots F_{\xi}(x_n).$$

Substituting these relations into Eq. (5) gives

$$P(E_n) = \int_0^Z \int_0^{Z-x_1} \dots \int_0^{Z-\sum_{i=1}^{n-1} x_i} P[\rho_1 > \sigma(\xi_1) | \xi_1 = x_1] \dots P[\rho_{n-1} > \sigma\left\{\sum_{i=1}^{n-1} \xi_i\right\} | \xi_1 = x_1, \dots, \xi_{n-1} = x_{n-1}] \times P\left[\rho_n \leq \sigma\left\{\sum_{i=1}^n \xi_i\right\} | \xi_1 = x_1, \dots, \xi_n = x_n\right] dF_{\xi}(x_1) \dots dF_{\xi}(x_n) \\ = \int_0^Z \int_0^{Z-x_1} \dots \int_0^{Z-\sum_{i=1}^{n-1} x_i} [1 - \sigma(x_1)] \dots \left[1 - \sigma\left\{\sum_{i=1}^{n-1} x_i\right\}\right] \sigma\left\{\sum_{i=1}^n x_i\right\} M e^{-Mx_1} \dots M e^{-Mx_n} dx_1 \dots dx_n.$$

It is convenient to proceed with the probabilities expressed in terms of the variables  $\zeta_1, \dots, \zeta_n$ . The transformations from  $\xi_1, \dots, \xi_n$  are direct. Introducing  $\alpha(x)$  for brevity, the expressions for  $P(E_1)$  and  $P(E_n)$ ,  $n \geq 2$ , become

$$P(E_1) = \int_0^Z \sigma(z_1) M e^{-Mz_1} dz_1,$$

and

$$P(E_n) = \int_0^Z dz_n M^n \sigma(z_n) e^{-Mz_n} \int_0^{z_n} dz_{n-1} \alpha(z_{n-1}) \int_0^{z_{n-1}} dz_{n-2} \dots \int_0^{z_2} dz_1 \alpha(z_1) \\ = \int_0^Z dz_1 \sigma(z_1) M^n e^{-Mz_1} \int_0^{z_1} dz_2 \alpha(z_2) \int_0^{z_2} \dots \int_0^{z_{n-1}} dz_n \alpha(z_n). \quad (6)$$

<sup>1</sup>See for example, WILLIAM FELLER, *An Introduction to Probability Theory and its Applications*, Vol. II, p. 154 ff (1966).

It will now be proved that

$$\int_0^{z_1} dz_2 \alpha(z_2) \int_0^{z_2} \dots \int_0^{z_{n-1}} dz_n \alpha(z_n) = \frac{\left[ \int_0^{z_1} \alpha(v) dv \right]^{n-1}}{(n-1)!}, \quad 2 \leq n. \quad (7)$$

Equation (7) is true for  $n = 2$  by inspection. For  $n = 3$ ,

$$\int_0^{z_1} dz_2 \alpha(z_2) \int_0^{z_2} dz_3 \alpha(z_3) = \int_0^{z_1} dz_2 \frac{d}{dz_2} \frac{\left[ \int_0^{z_2} \alpha(z) dz \right]^2}{2} = \frac{\left[ \int_0^{z_1} \alpha(z) dz \right]^2}{2!}.$$

Assuming Eq. (7) to be true for arbitrary  $n$ , it can be shown to hold for  $n + 1$  by multiplying Eq. (7) by  $\alpha(z_1)$  and integrating from 0 to  $z$ .

$$\int_0^z dz_1 \alpha(z_1) \int_0^{z_1} dz_2 \dots \int_0^{z_{n-1}} dz_n \alpha(z_n) = \int_0^z dz_1 \alpha(z_1) \frac{\left[ \int_0^{z_1} \alpha(v) dv \right]^{n-1}}{(n-1)!} \\ \times \int_0^z dz_1 \frac{d}{dz_1} \frac{\left[ \int_0^{z_1} \alpha(v) dv \right]^n}{n!} = \frac{\left[ \int_0^z \alpha(v) dv \right]^n}{n!}.$$

It follows that Eq. (7) holds for arbitrary  $n \geq 2$ .

Substituting the identity [Eq. (7)] into Eq. (6) gives

$$P(E_n) = \int_0^Z dz_1 \sigma(z_1) M^n e^{-Mz_1} \frac{\left[ \int_0^{z_1} \alpha(v) dv \right]^{n-1}}{(n-1)!}, \quad 2 \leq n.$$

Equation (3) becomes

$$P(\lambda \leq Z) = \sum_{n=1}^{\infty} P(E_n) = P(E_1) + \sum_{n=2}^{\infty} \int_0^Z dz_1 \sigma(z_1) M^n e^{-Mz_1} \frac{\left[ \int_0^{z_1} \alpha(v) dv \right]^{n-1}}{(n-1)!} \\ = \sum_{n=0}^{\infty} \int_0^Z dz_1 \sigma(z_1) M e^{-Mz_1} \frac{\left[ M \int_0^{z_1} \alpha(v) dv \right]^n}{n!} \\ = \int_0^Z dz_1 \sigma(z_1) M e^{-Mz_1} \exp \left[ M \int_0^{z_1} \alpha(v) dv \right] = \int_0^Z dz_1 M \sigma(z_1) \exp \left[ - \int_0^{z_1} M \sigma(v) dv \right] \\ = \int_0^Z \Sigma(z) \exp \left[ - \int_0^z \Sigma(v) dv \right] dz.$$

Hence  $\lambda$  has the distribution function given in Eq. (1).

#### II. APPLICATIONS OF THE TECHNIQUE TO RADIATION TRANSPORT PROBLEMS

The  $\lambda$  procedure described in Sec. I is useful as a Monte Carlo technique in solving certain transport problems. This section is a summary of three situations in which the  $\lambda$  procedure has been utilized. In each case  $\Sigma(z)$  is a nuclear cross section and  $z$  is a relative position variable to be determined. The value of  $\Sigma(z)$  determines the relative frequency of nuclear collisions per unit of particle track length.

##### High-Energy Charged Particle Transport

The macroscopic cross section for a particle of type  $p$  undergoing a nonelastic collision with a stationary nucleus of type  $N$  depends upon  $p, N$ ,

and the kinetic energy  $E$  of the incident particle. The kinetic energy of a charged particle varies between nuclear events due to interactions with electrons. For the more massive charged particles, such as protons and alphas, the kinetic energy is usually assumed to be a continuous, decreasing function of position. Consider a material composed uniformly of one nuclear species  $N$ . Assume the kinetic energy  $E_0$  of a particular type of particle  $p$  at a position  $z_0 = 0$  is known. The kinetic energy  $E$  of  $p$  at an arbitrary point  $z > z_0$  is a function of  $z$ .

$$E = f_{p,N,E_0}(z).$$

Each of the variables  $p, N$ , and  $E_0$  has been fixed. Denote the macroscopic nonelastic cross section, under these conditions, by  $\Sigma_1(z)$ . The distance



# Delta Tracking Summary

---

Unbiased, see [Coleman 68] for a proof

Majorant extinction

- defines the combined homogeneous volume
- must bound the real extinction
- loose majorants lead to many fictitious collisions