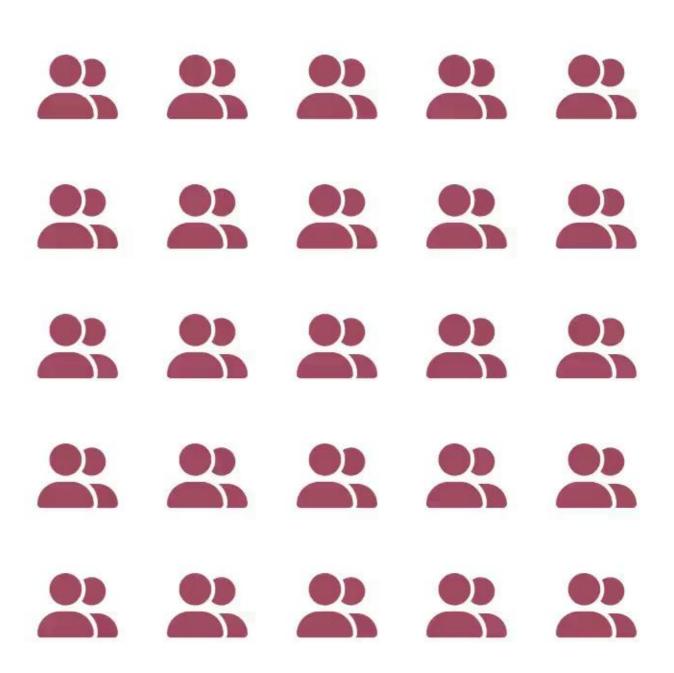
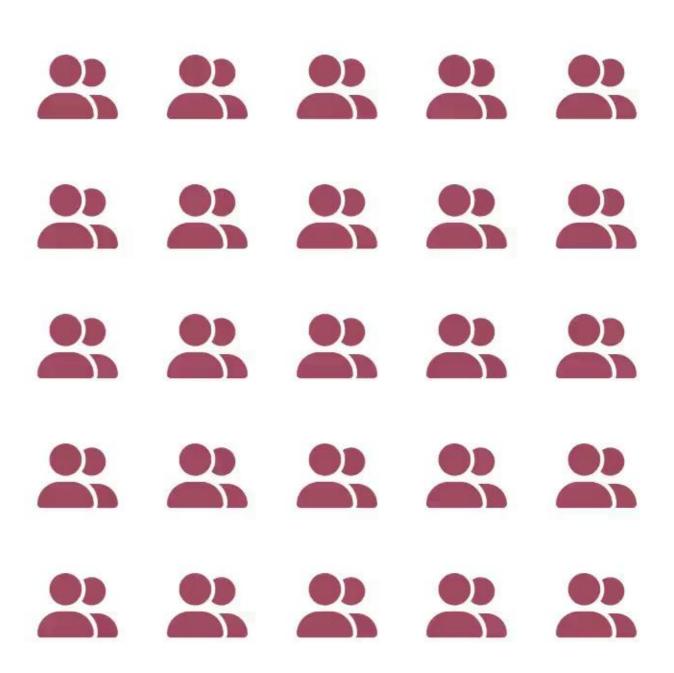
#### Differentiable Ray Tracing for Telecommunications

Jérome Eertmans - December 7th 2023

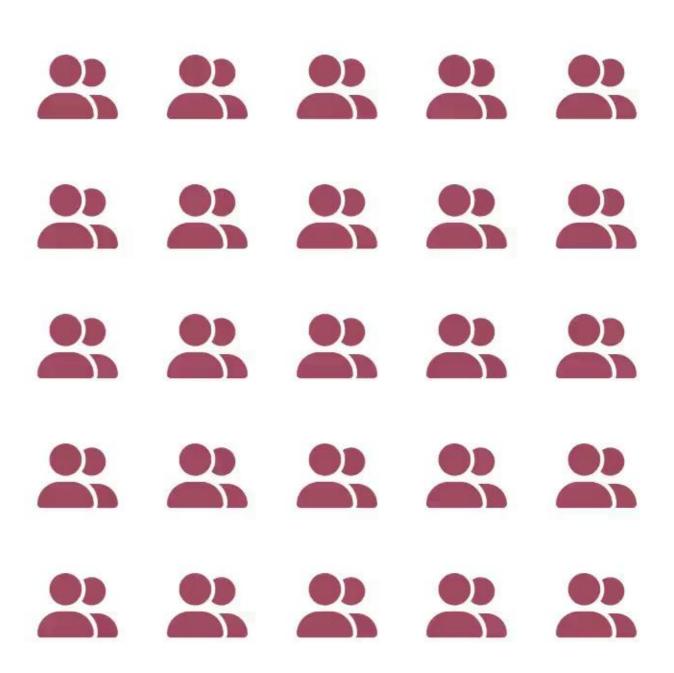


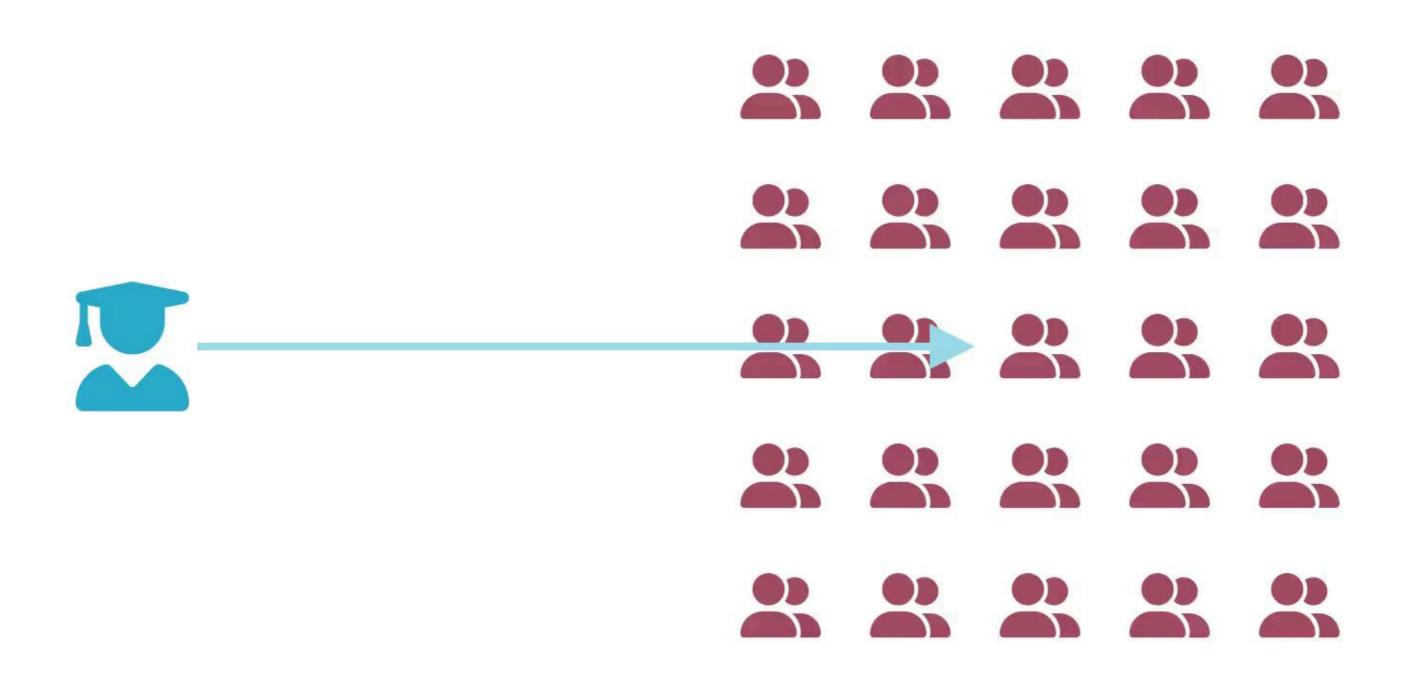


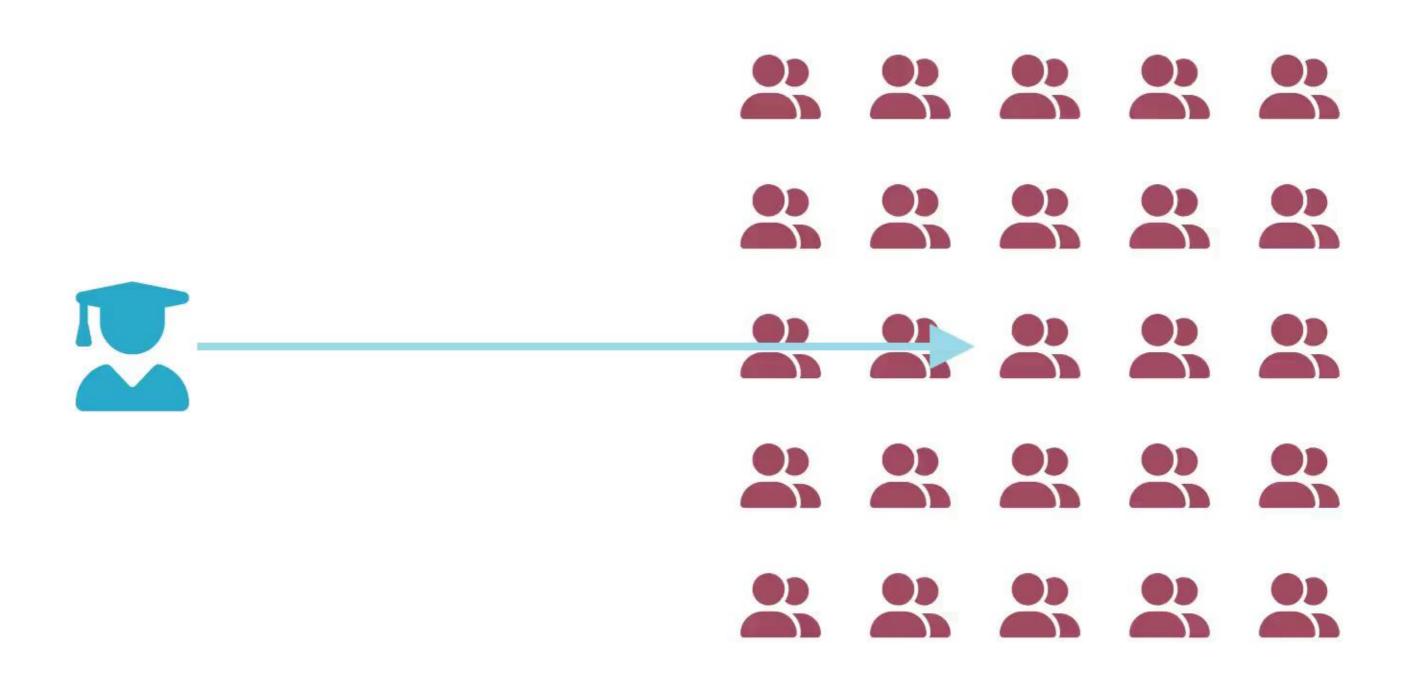


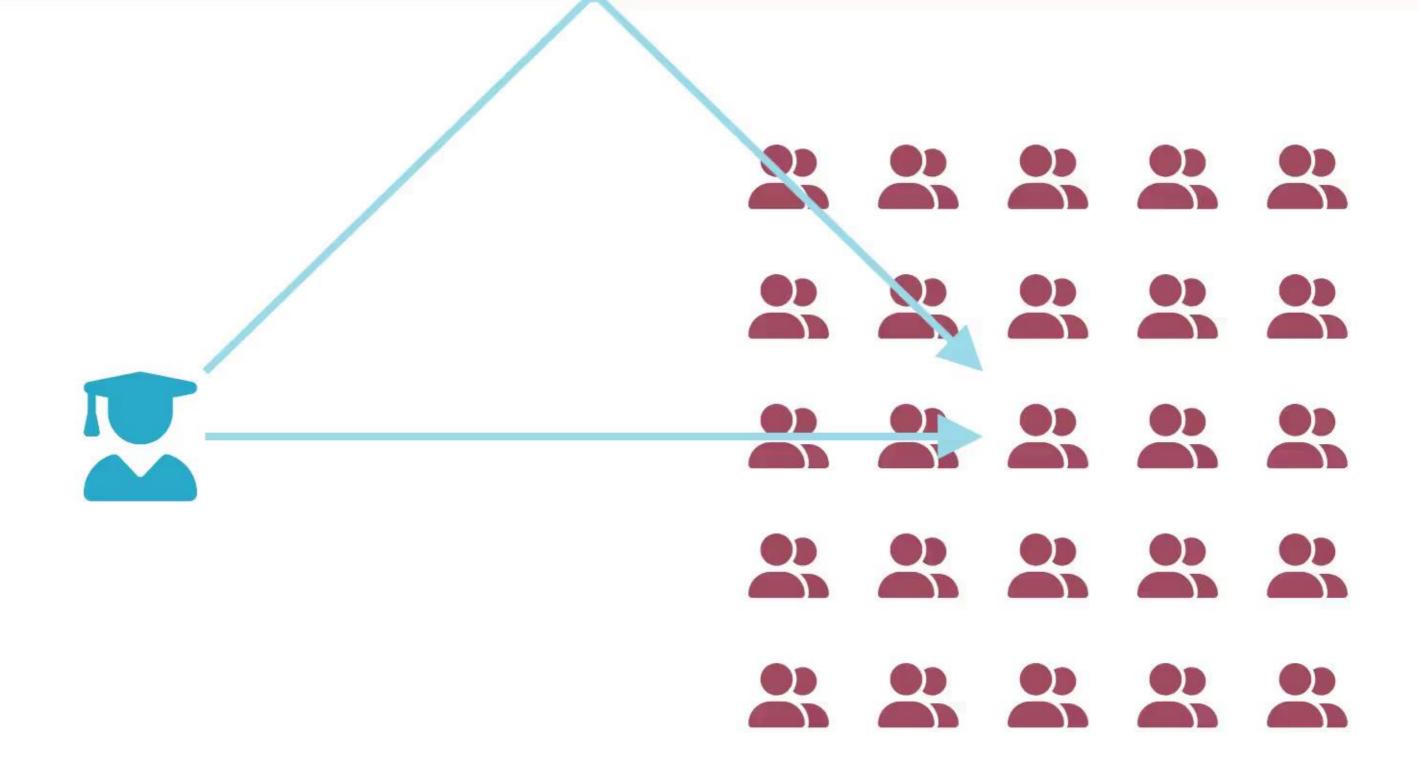


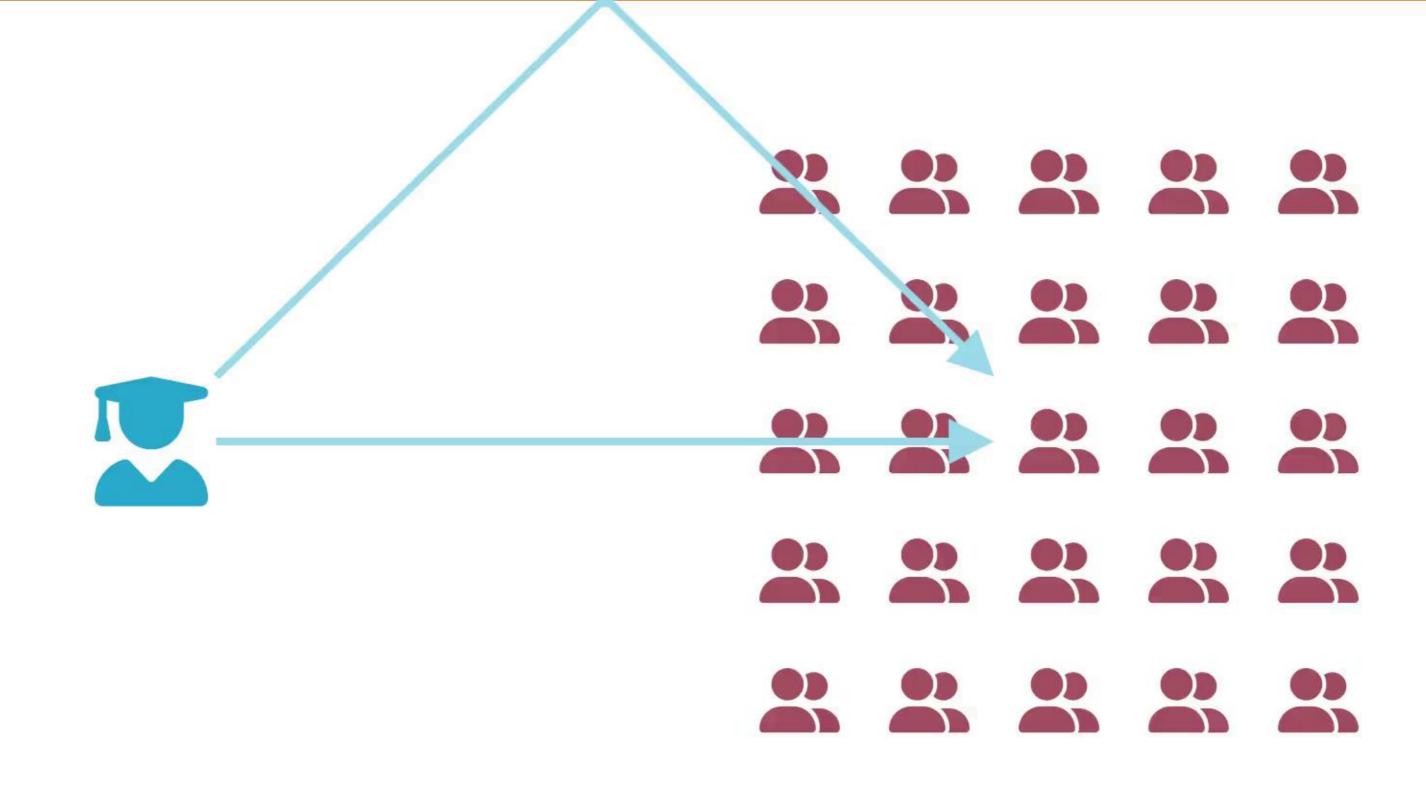


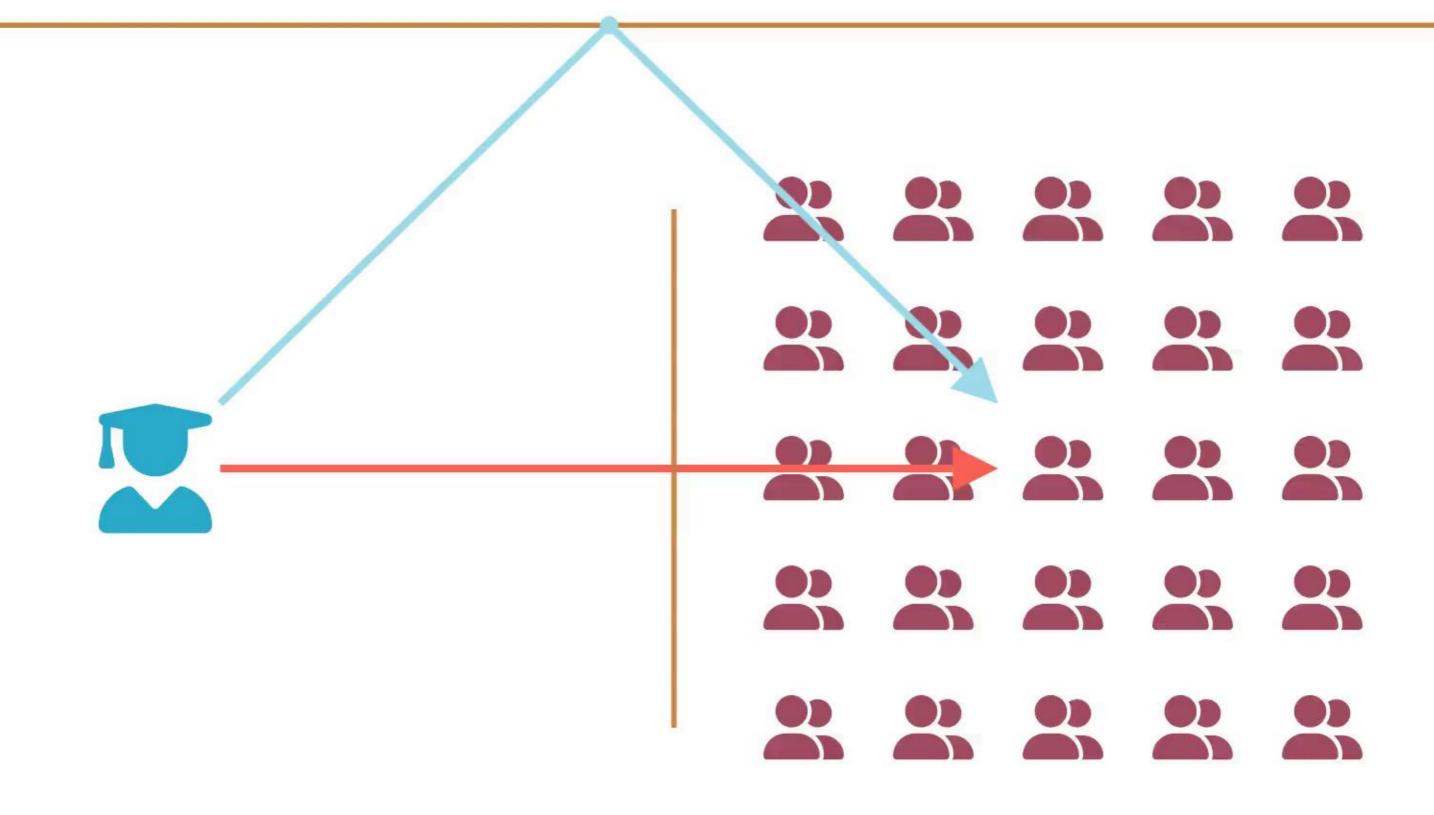


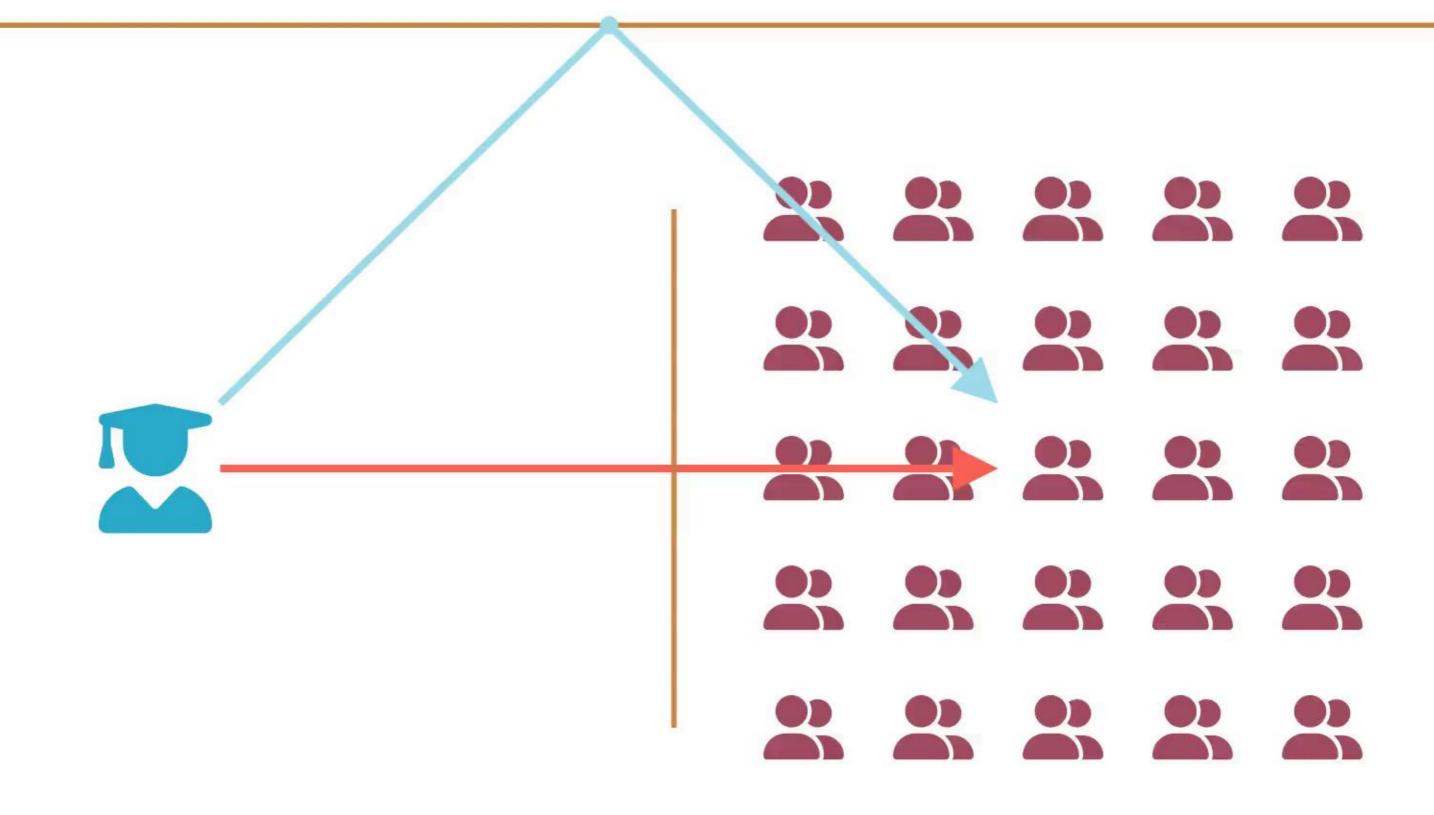


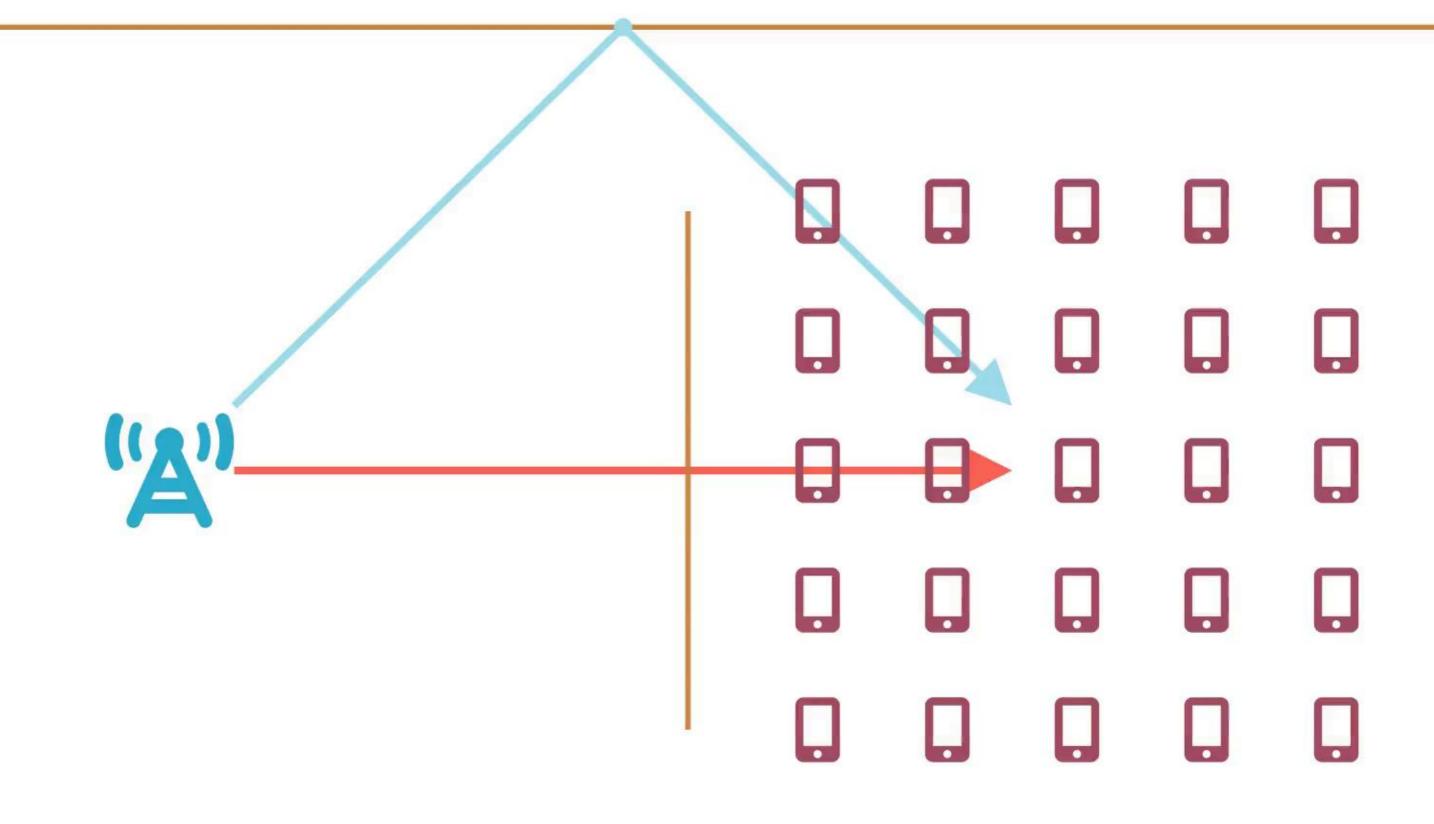


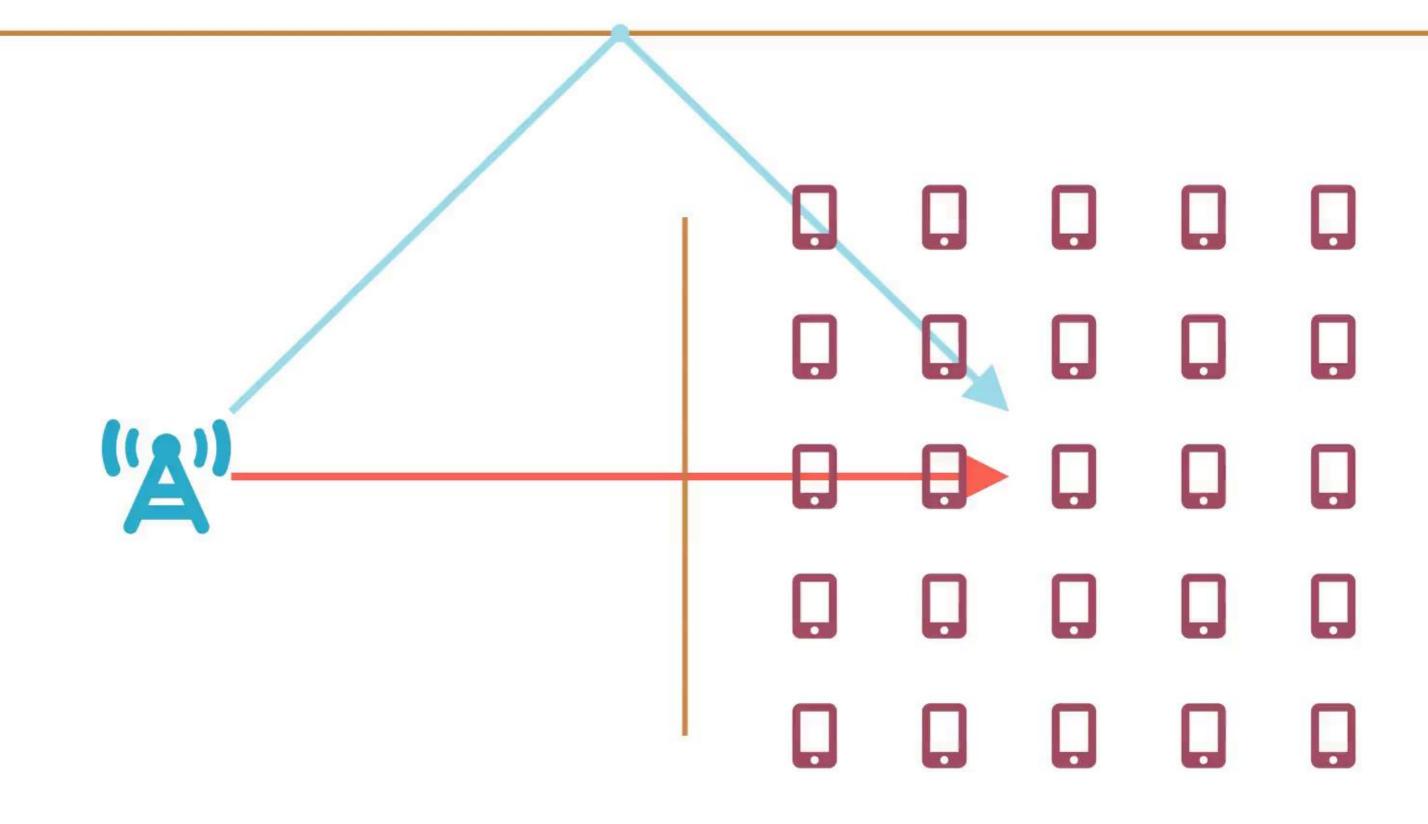












We just did Ray Tracing (RT)!

### Contents

- 1. Ray Tracing and EM Fundamentals;
- 2. Motivations for Differentiable Ray Tracing;
- 3. How to trace paths;
- 4. Differentiable Ray Tracing;
- 5. Status of Work;
- 6. and Conclusion.

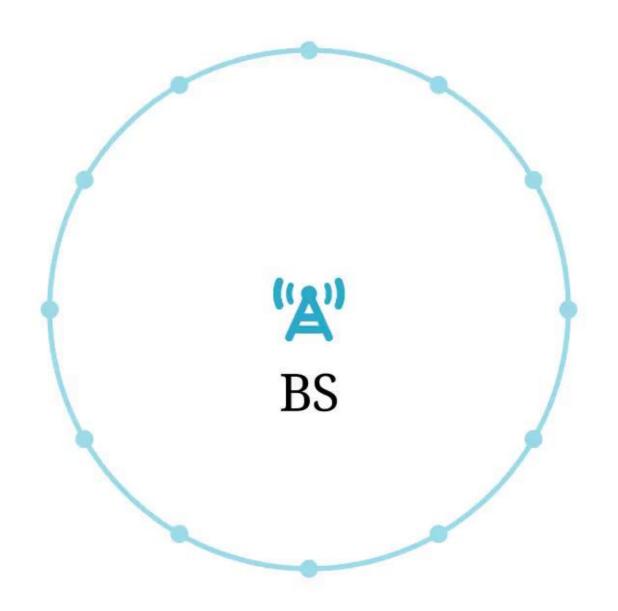
- Core idea;
- Architecture and Challenges;
- Applications;
- Alternative methods.

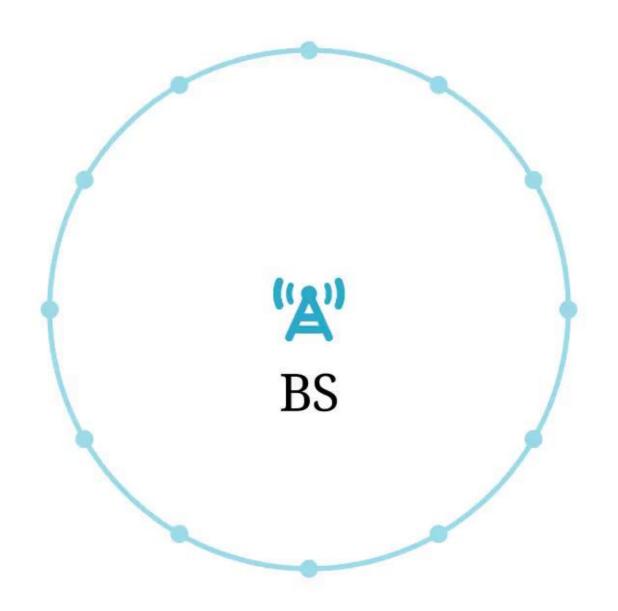


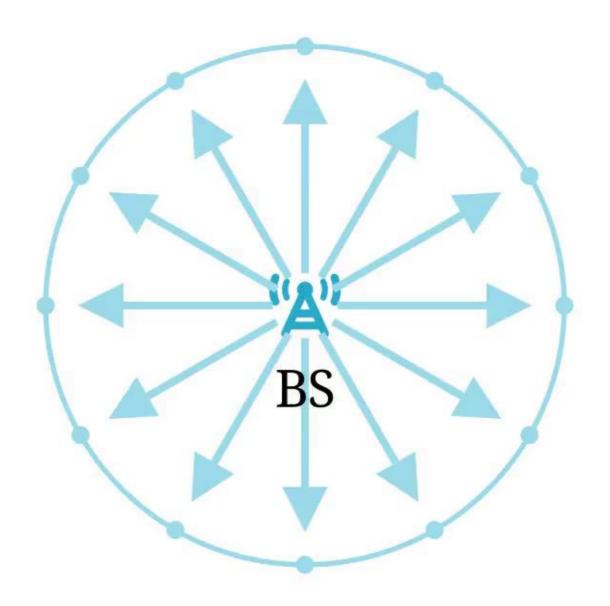
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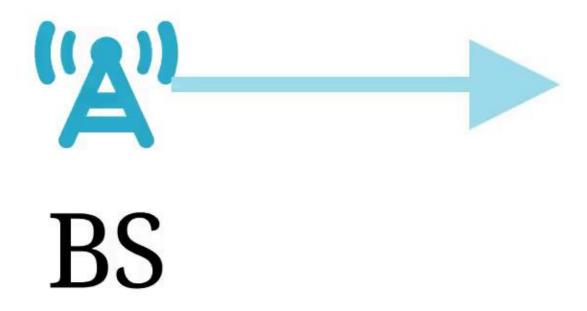


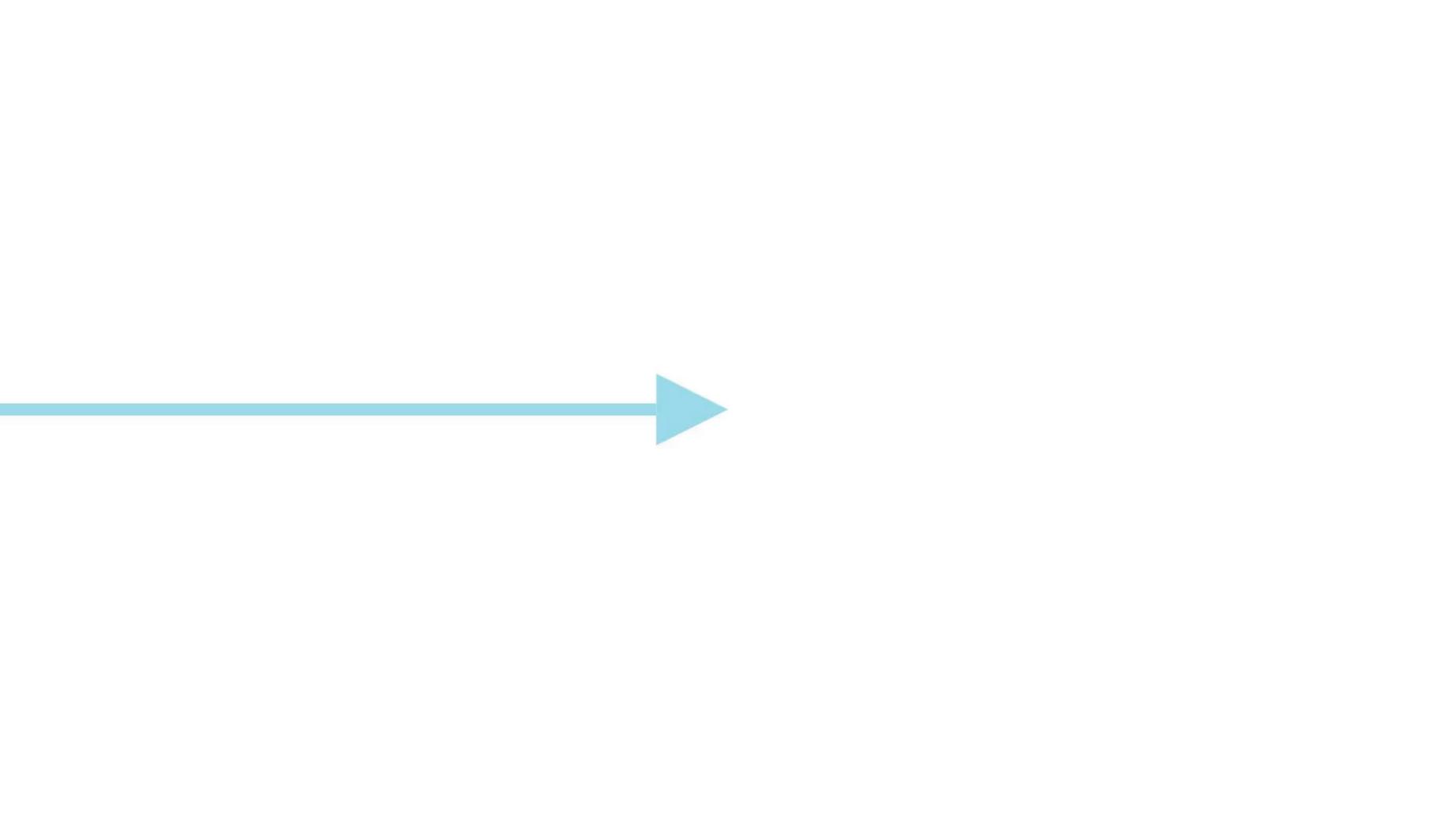
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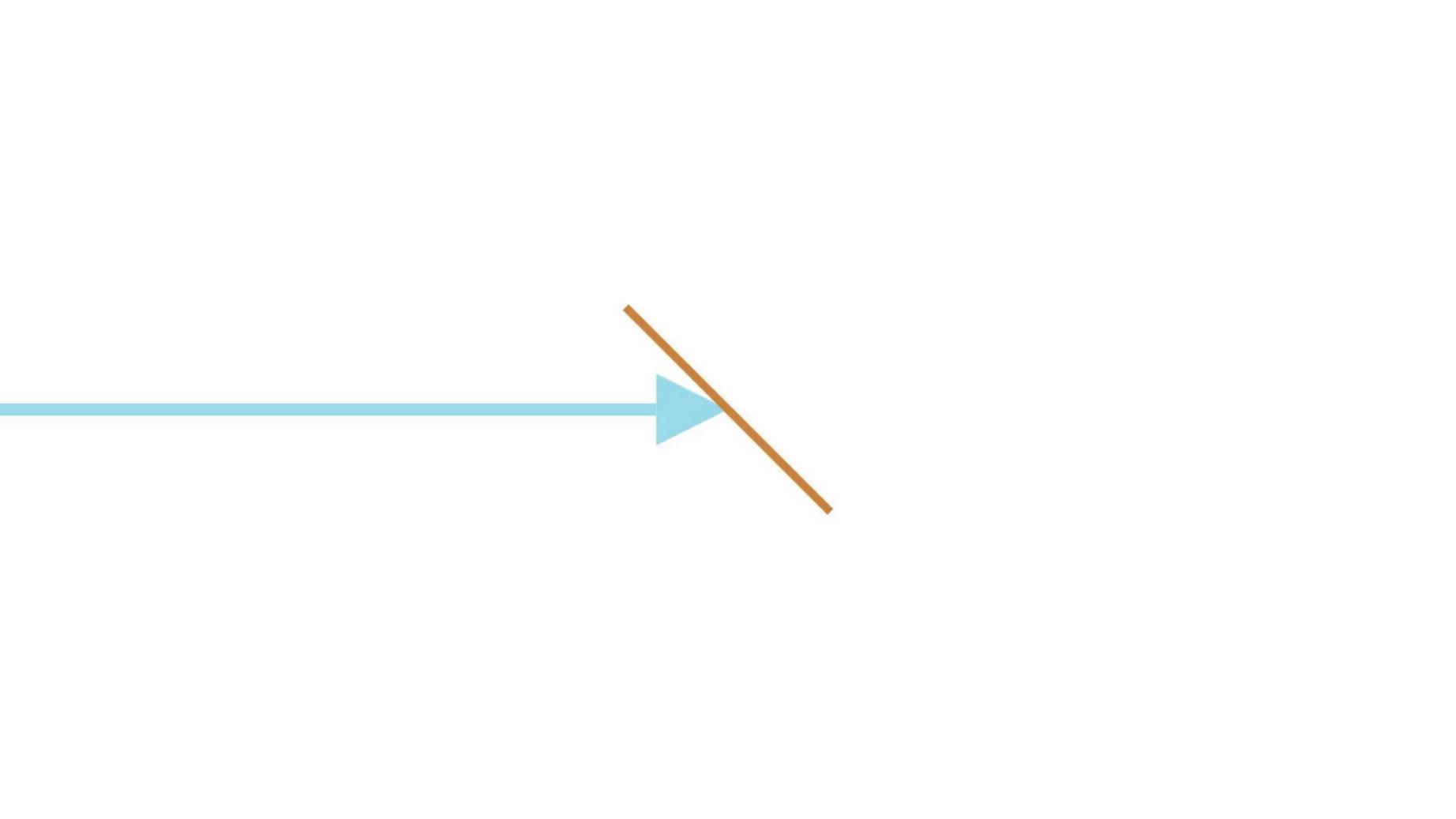




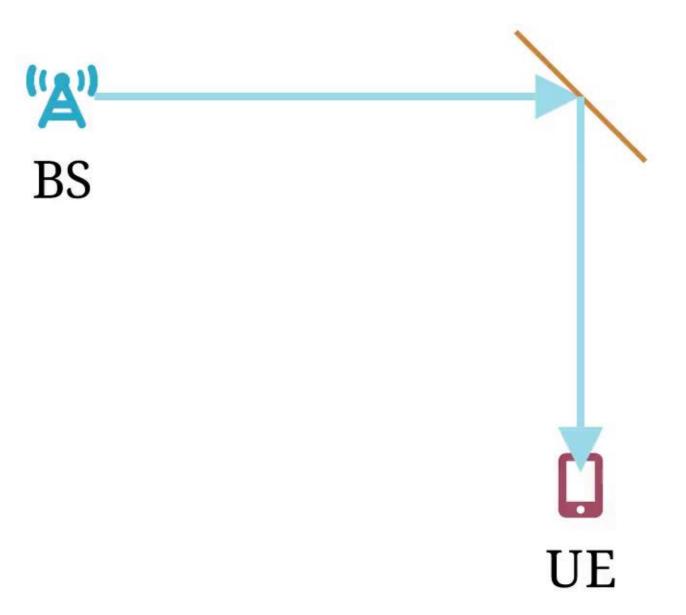


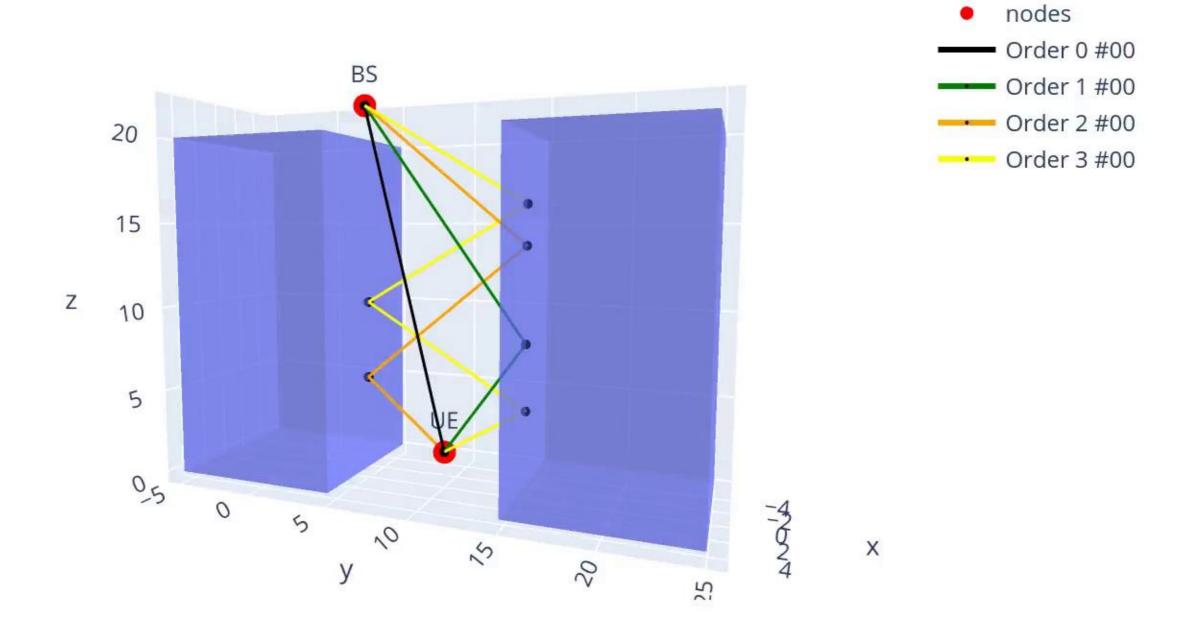












#### Electrical and Magnetic fields

$$\vec{E} \; (V \, \text{m}^{-1}) \; \& \; \vec{B} \; (T)$$

#### Electrical and Magnetic fields

$$\vec{E} (V m^{-1}) \& \vec{B} (T)$$

$$\vec{E}(x, y, z) = \sum_{P \in \mathcal{S}} \bar{C}(P) \cdot \vec{E}(P_1),$$

#### Electrical and Magnetic fields

$$\vec{E} \text{ (V m}^{-1}) \& \vec{B} \text{ (T)}$$

$$\vec{E}(x, y, z) = \sum_{\mathcal{P} \in \mathcal{S}} \bar{C}(\mathcal{P}) \cdot \vec{E}(\mathcal{P}_1),$$
where  $\bar{C}(\mathcal{P}) = \prod_{i \in \mathcal{I}} \bar{D}_i \cdot \alpha_i \cdot e^{-j\phi_i}.$ 

Input scene

Input scene

Preprocessing

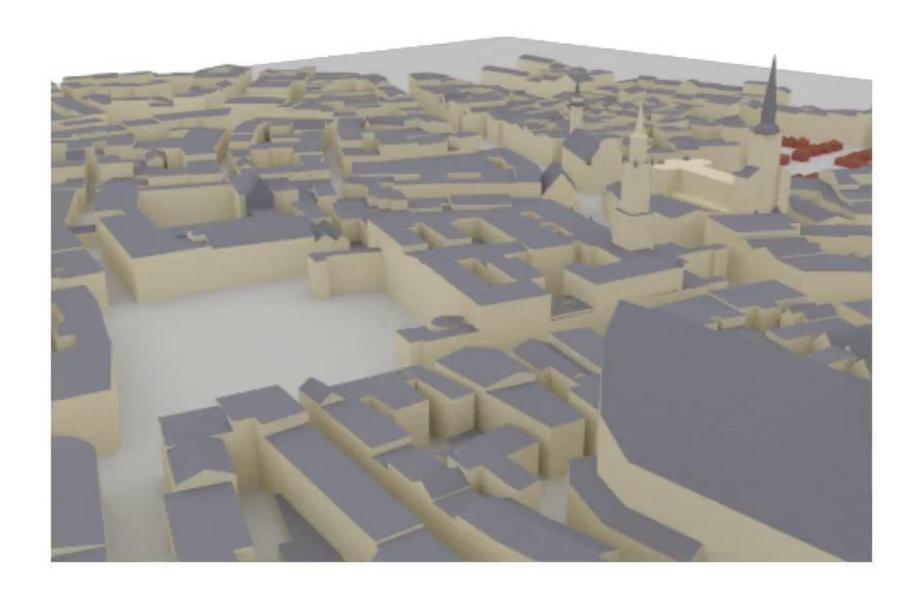
Input scene

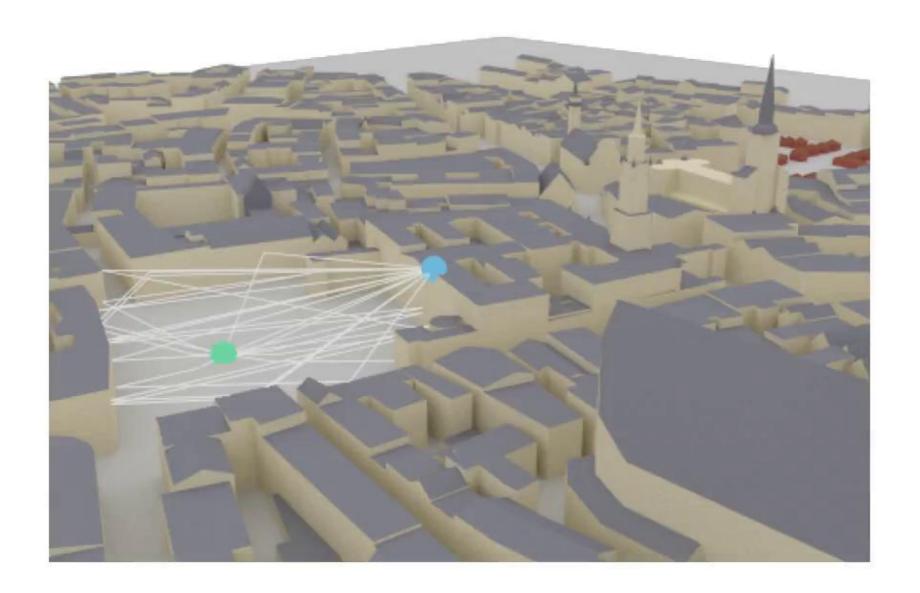
Preprocessing

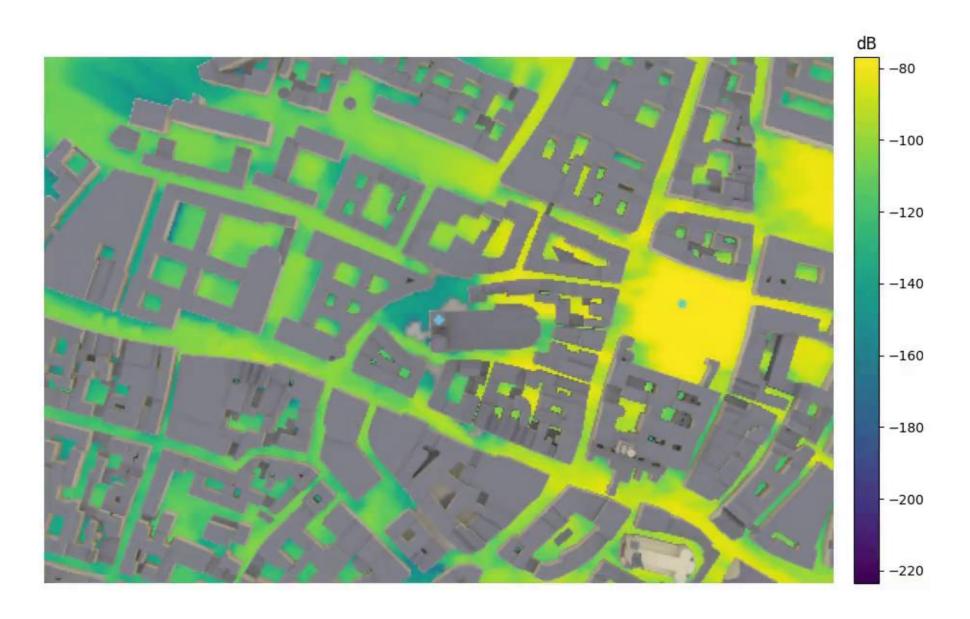
Tracing paths

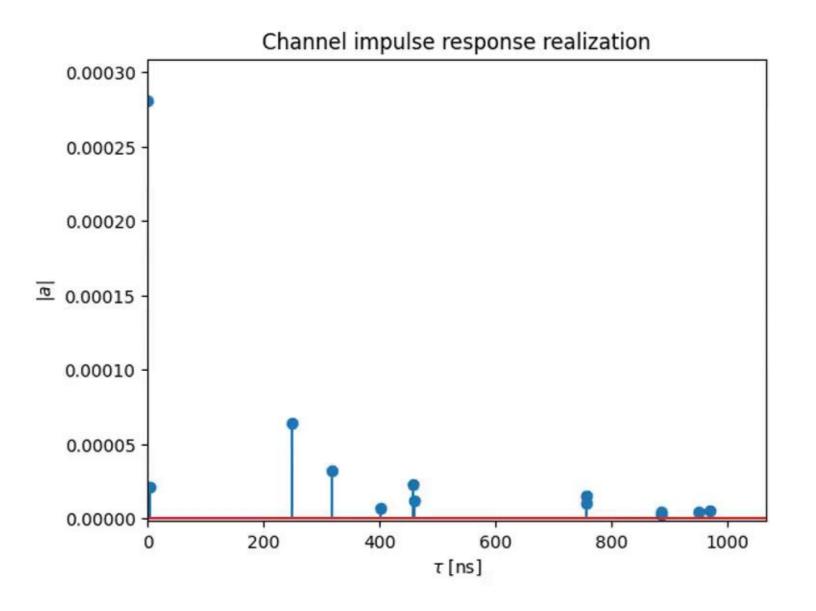
Input scene Preprocessing Tracing paths Postprocessing

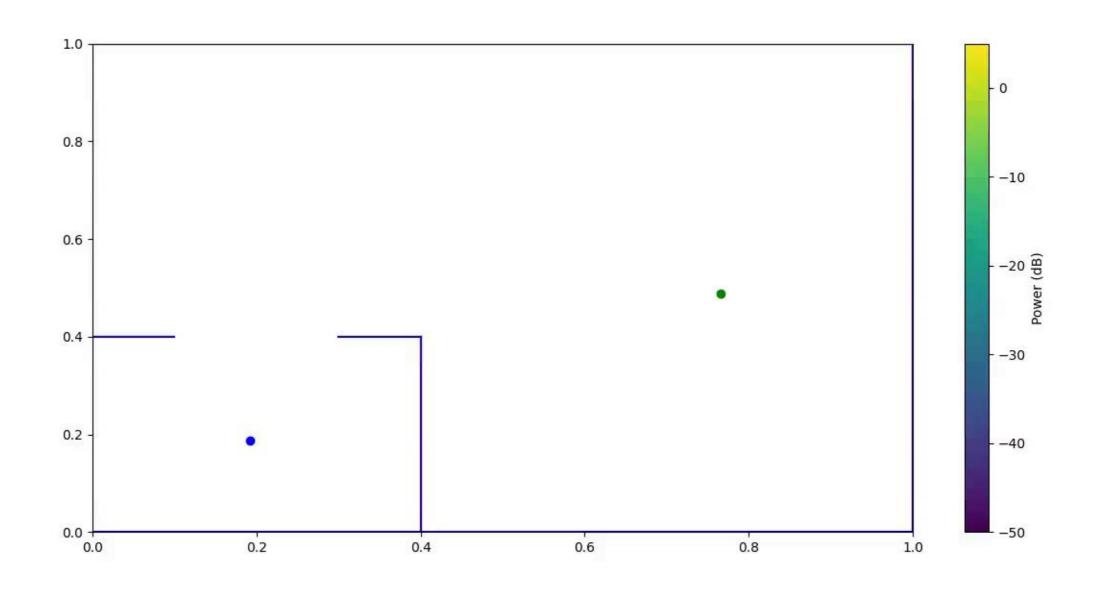
Input scene Preprocessing Tracing paths Postprocessing EM fields

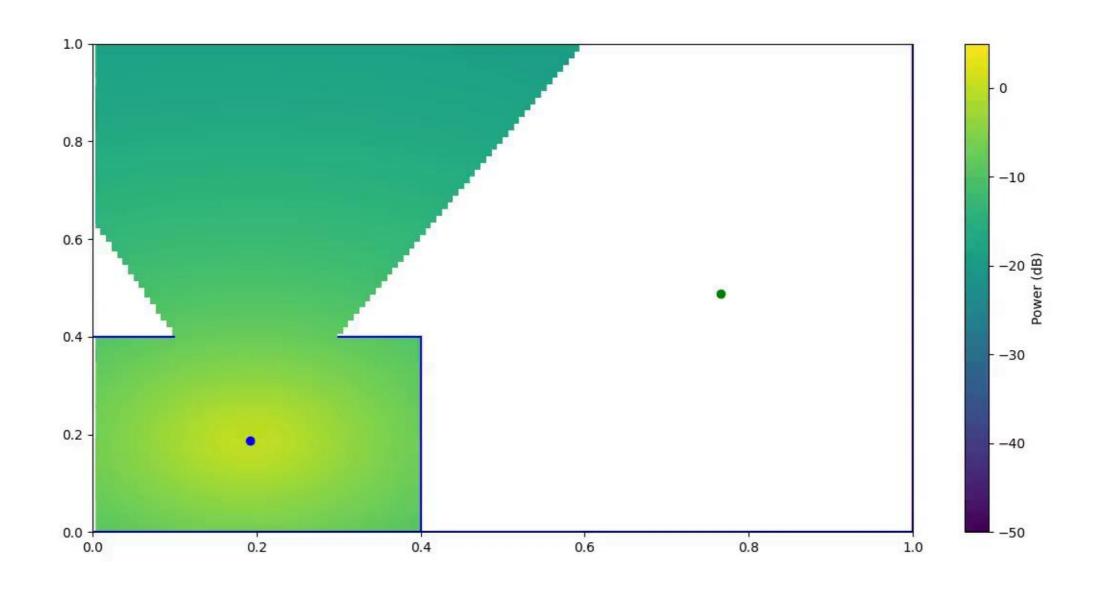


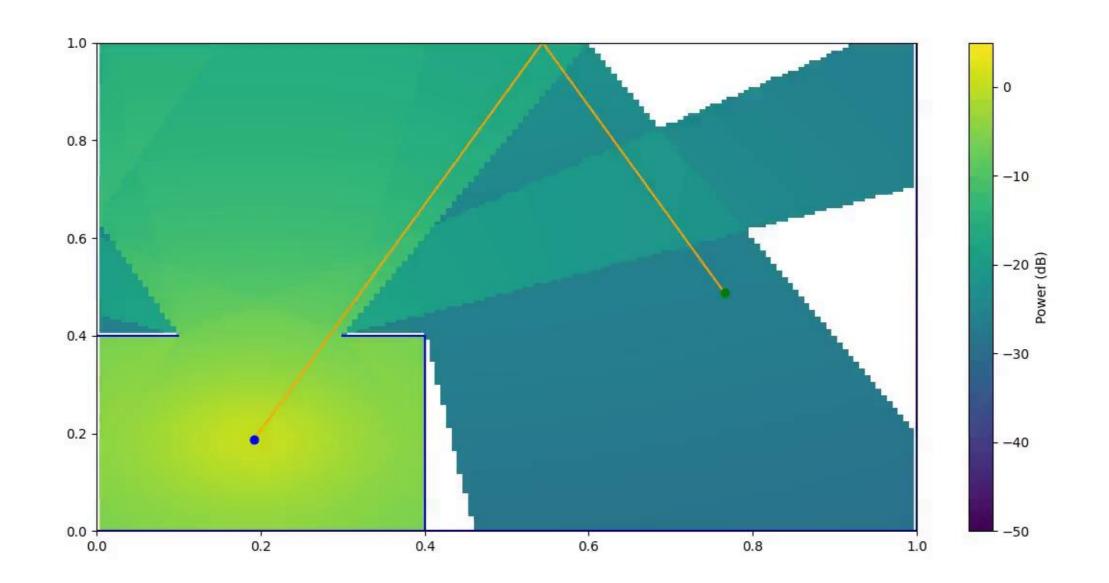


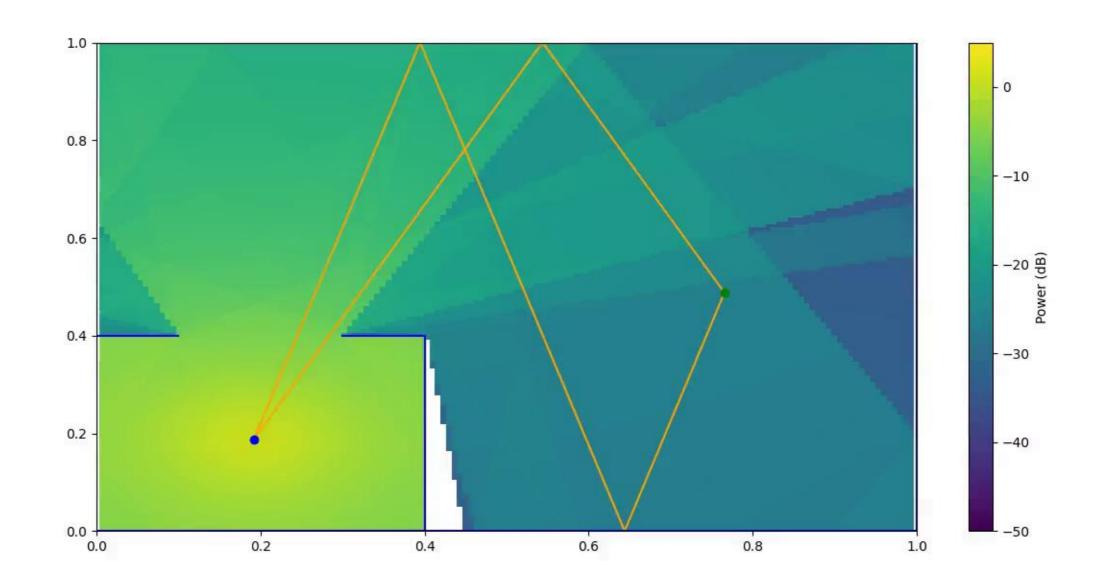


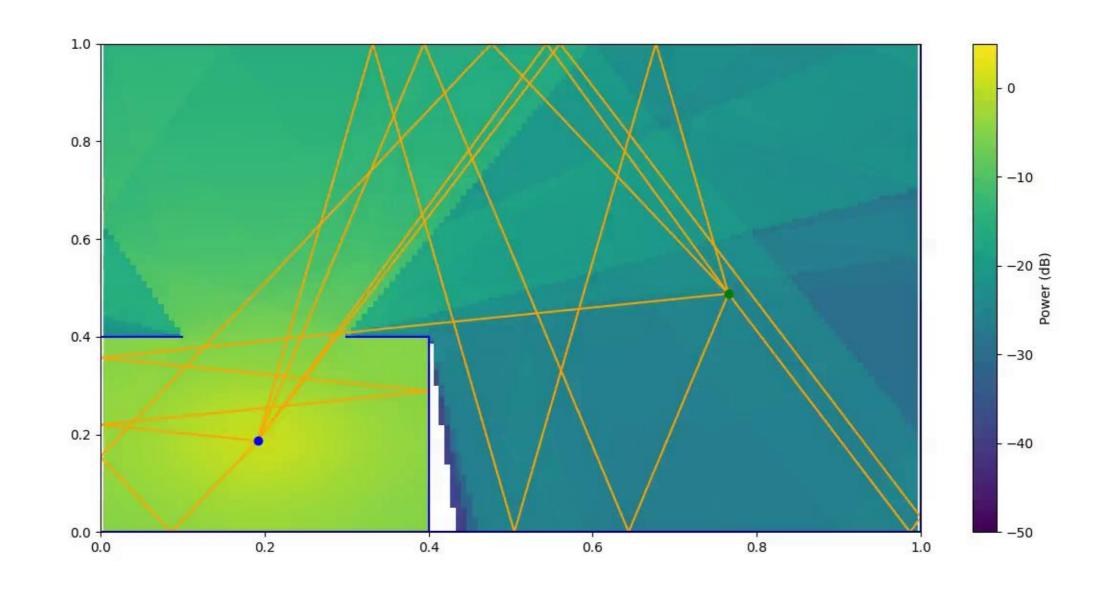


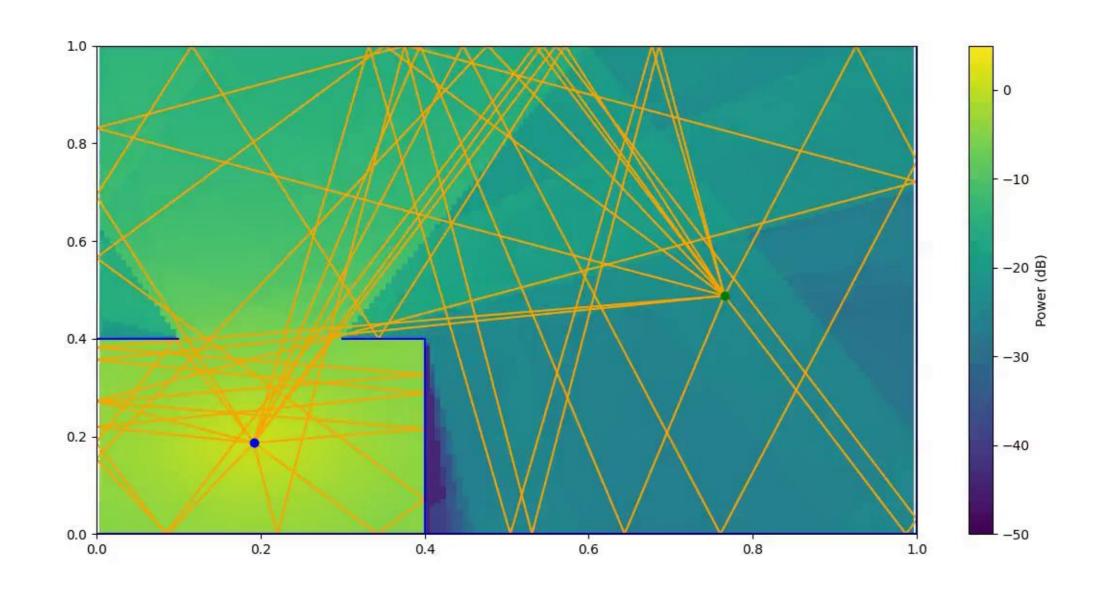


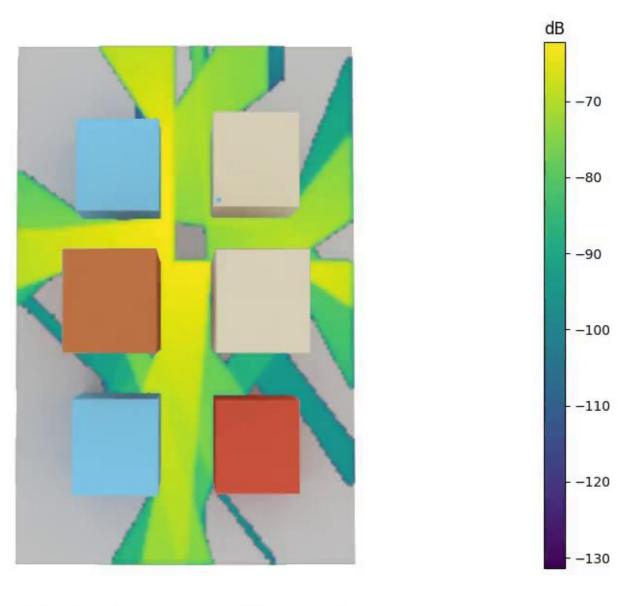






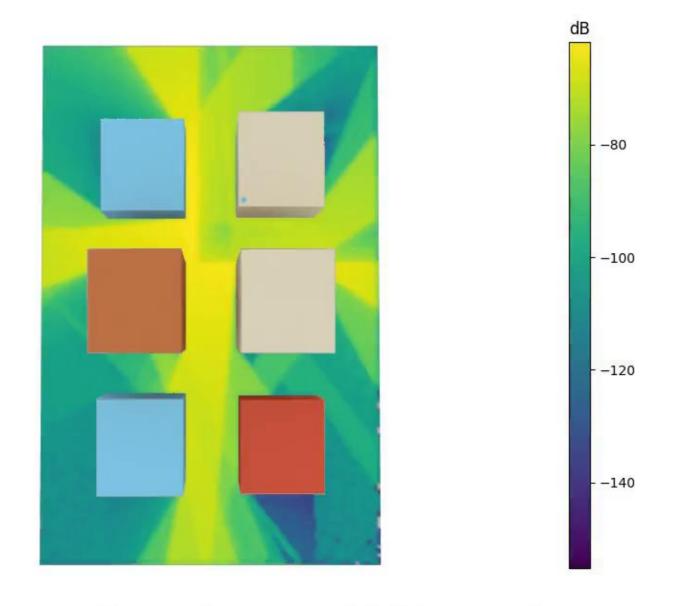






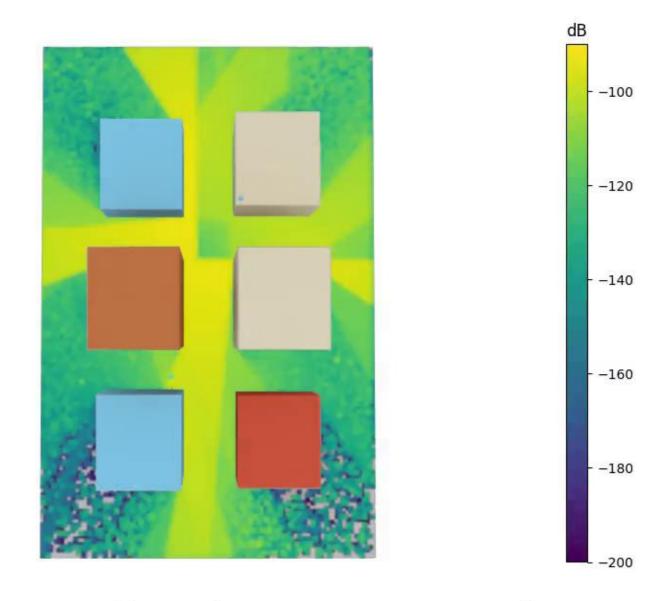
LOS + reflection

Challenge: coverage vs order and types.



LOS + reflection + diffraction

Challenge: coverage vs order and types.



LOS + reflection + scattering

Challenge: coverage vs order and types.

#### Main RT applications:

- radio channel modeling;
- sound and light prop. in video games;
- inverse rendering in graphics;
- lenses design and manufacturing.

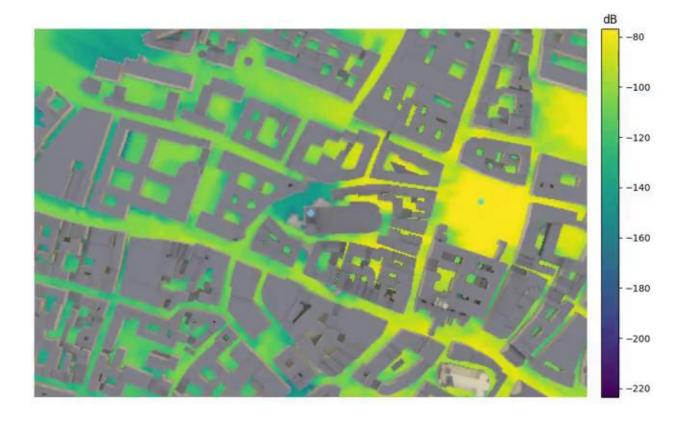
Most used channel modeling methods:

- $\sim$  RT;
- → empirical models;

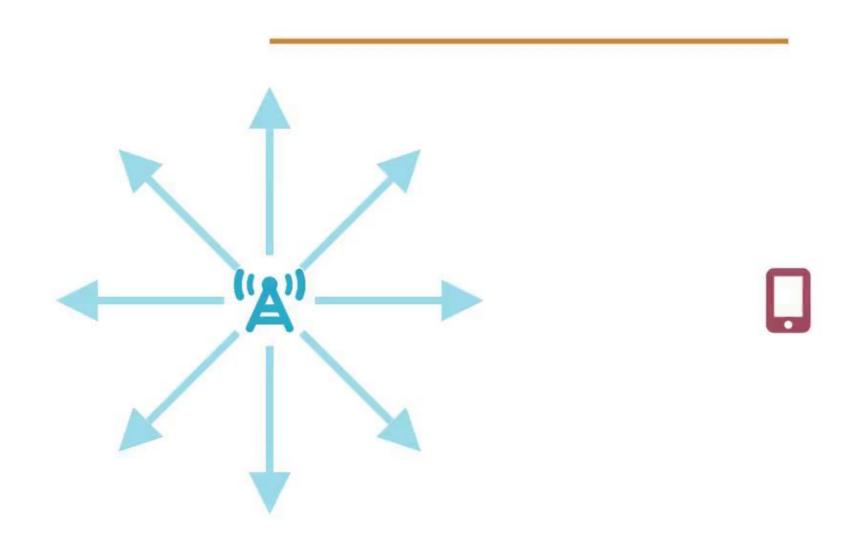
#### Motivations

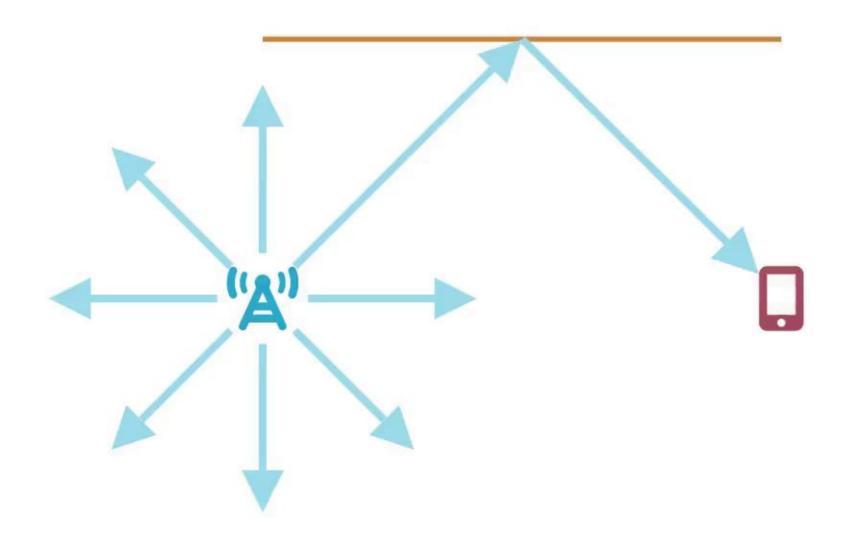
Why Differentiable Ray Tracing?

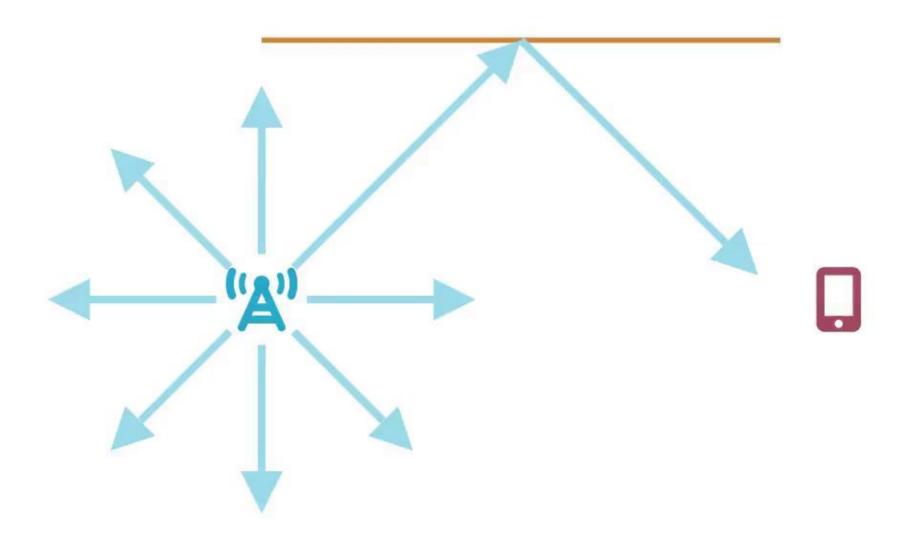
- but scenarios are becoming dynamic;
- → Differentiability should be a goal!

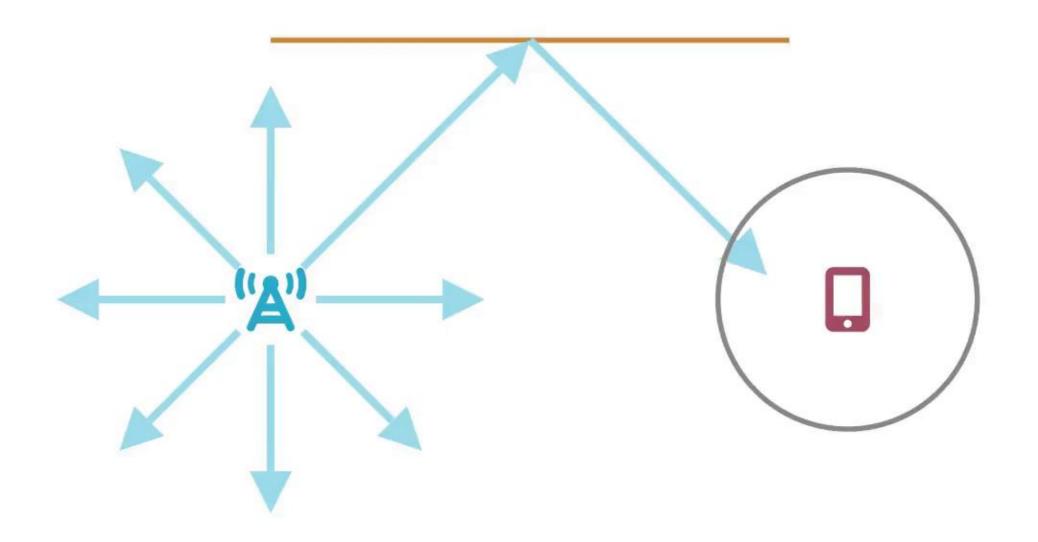


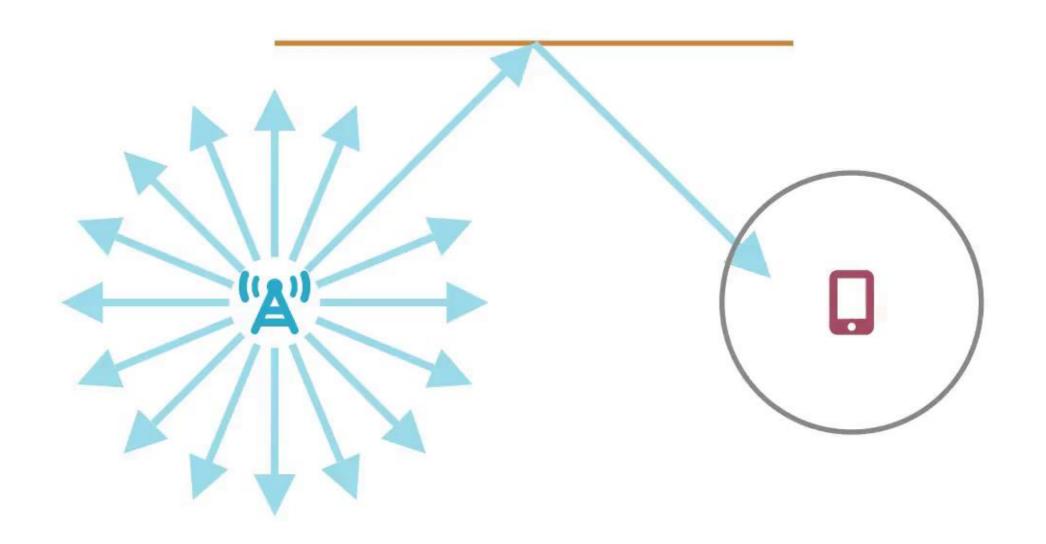
- Ray Launching vs Ray Tracing;
- Image Method and similar;
- Min-Path-Tracing;
- Arbitrary geometries.













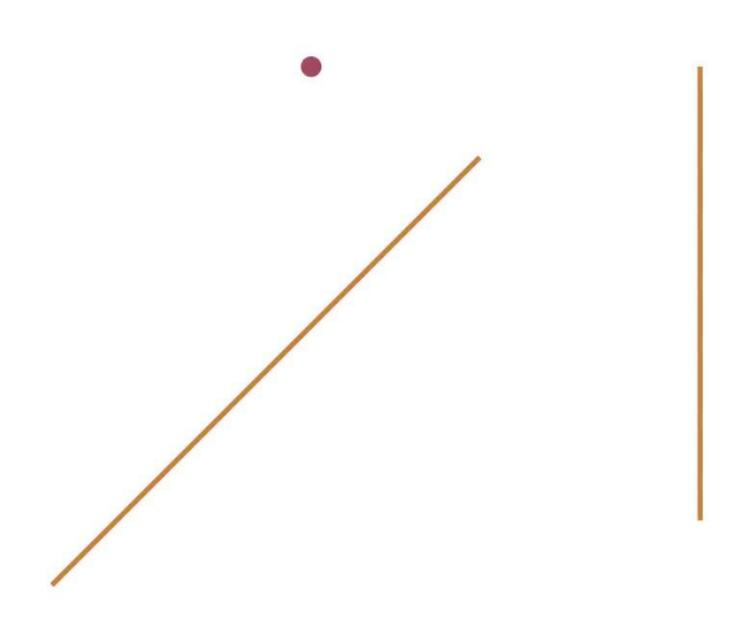


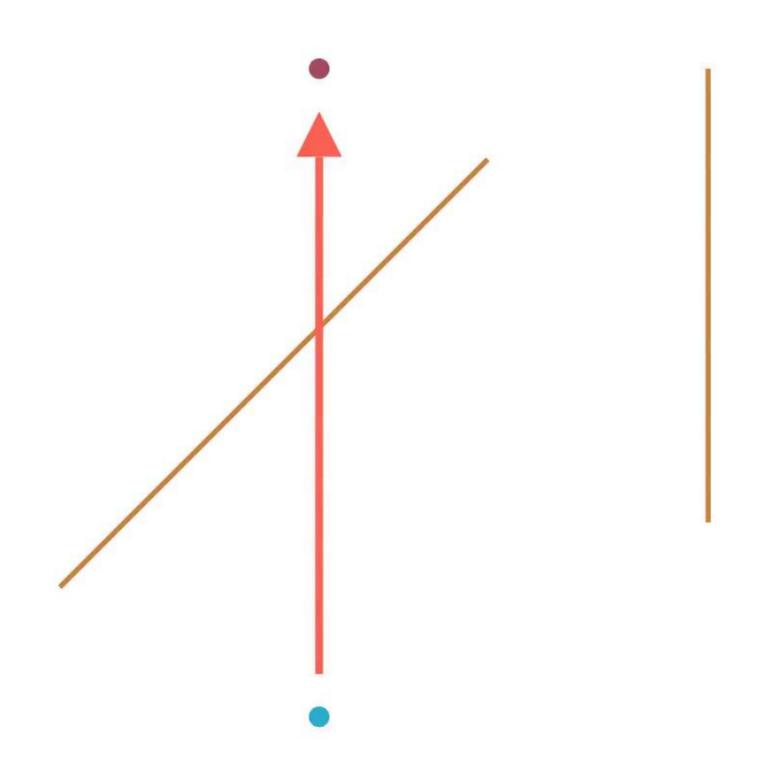
Not very efficient for "point-to-point" RT

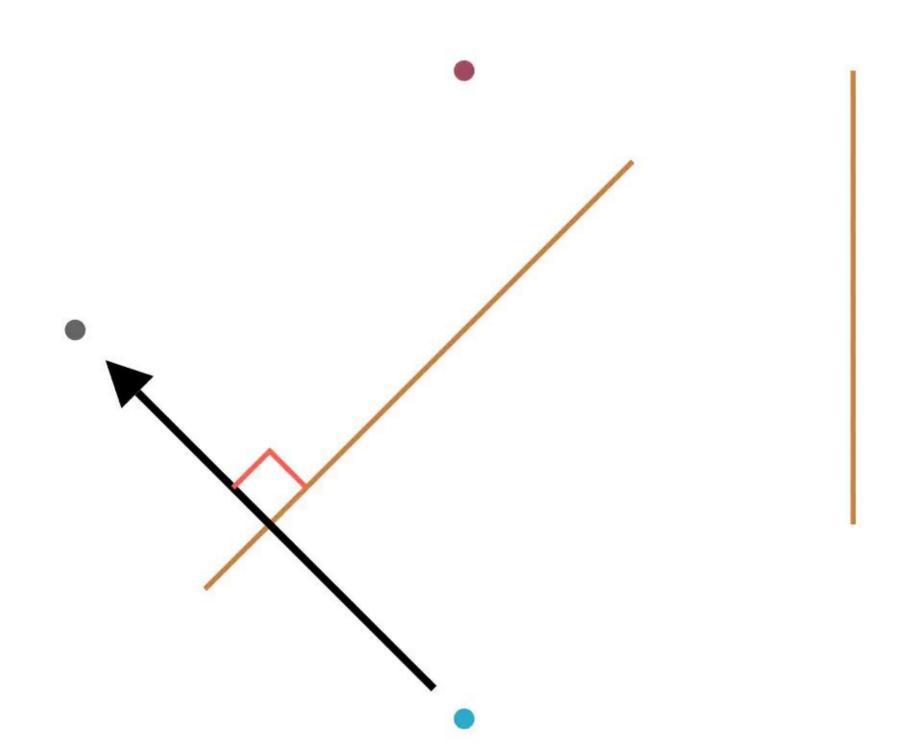


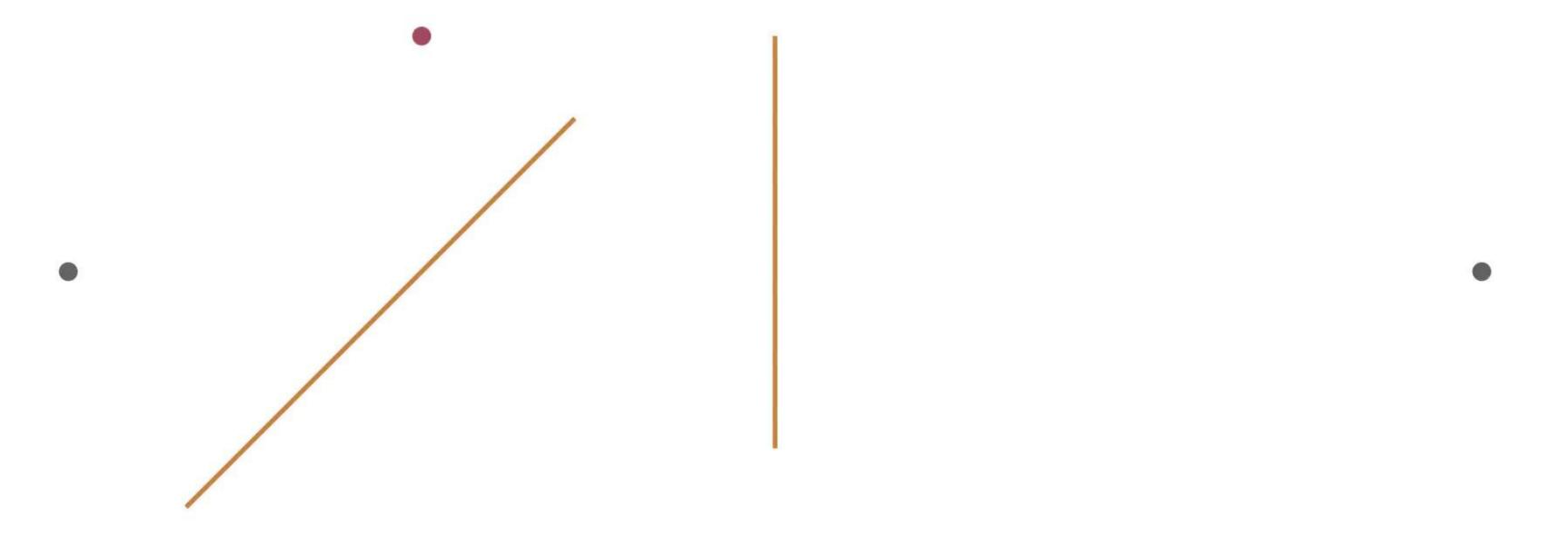


Not very efficient for "point-to-point" RT How to exactly find paths?

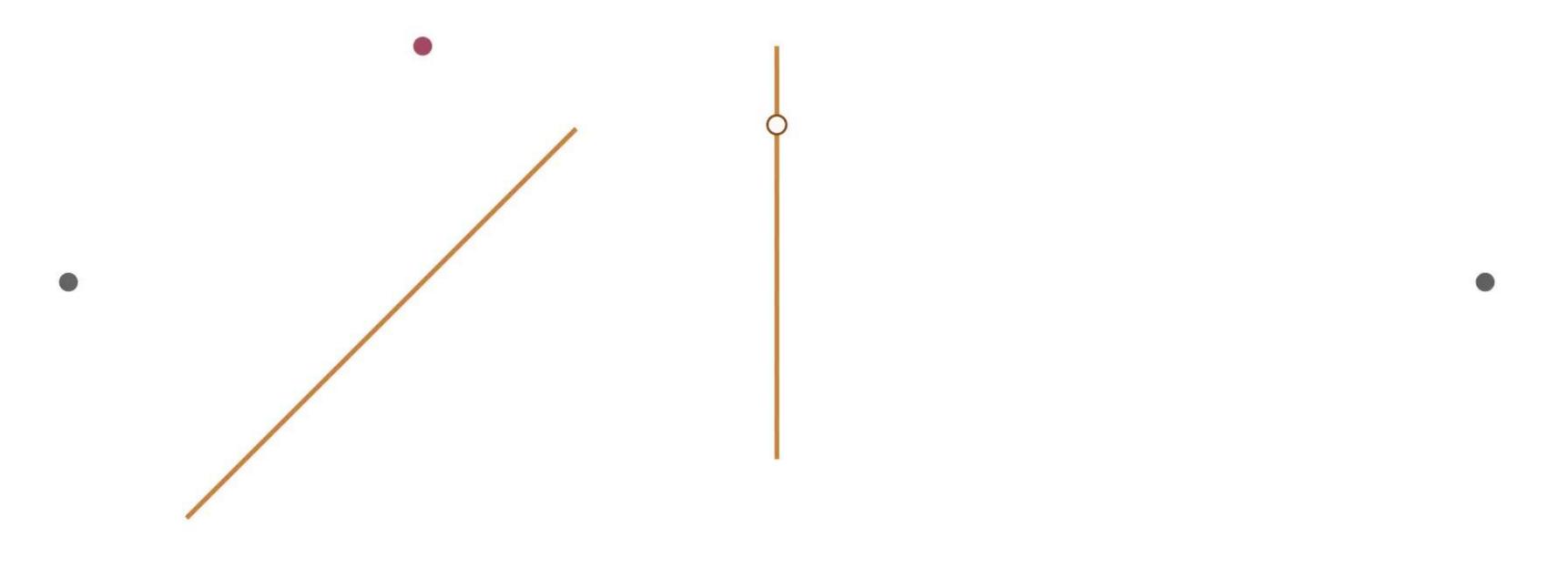




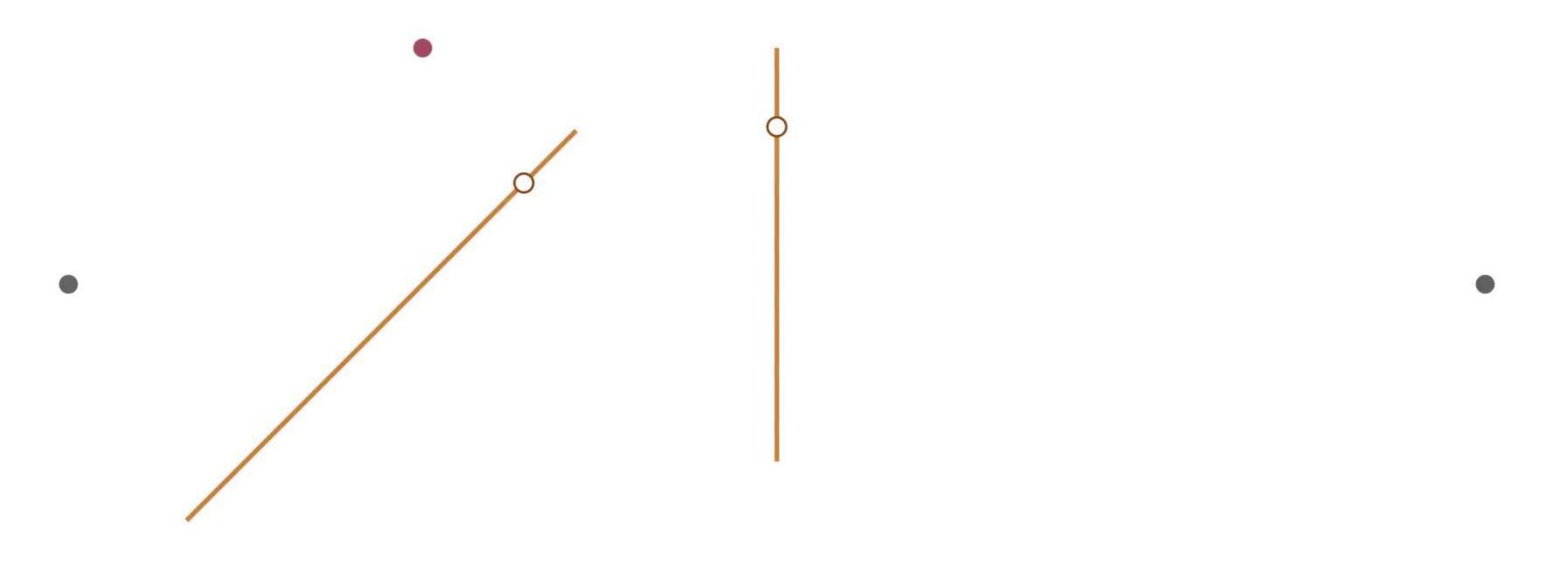




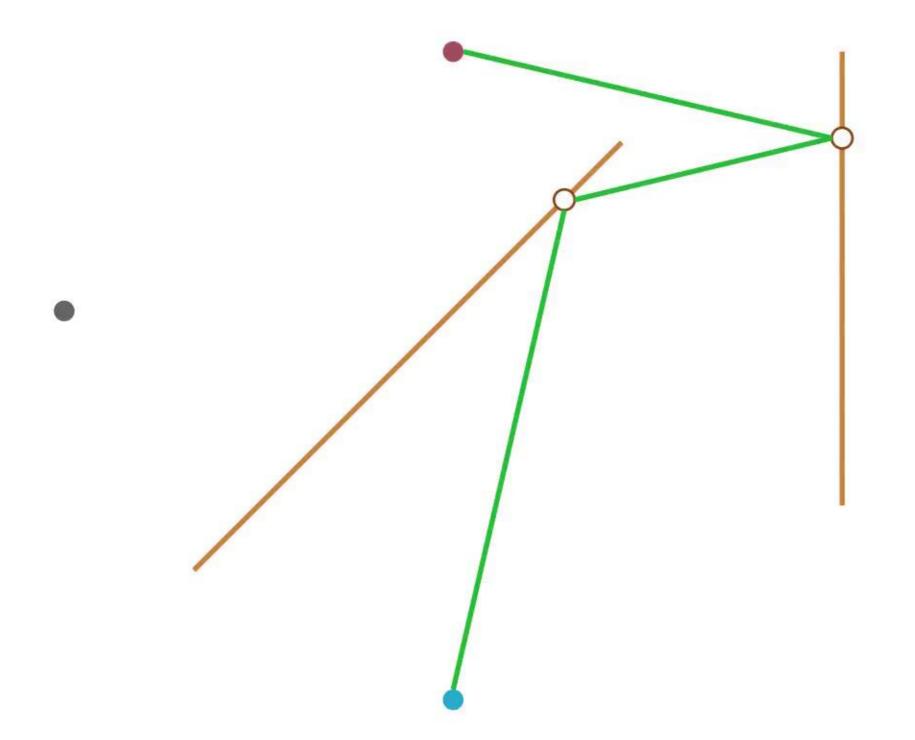
17



17

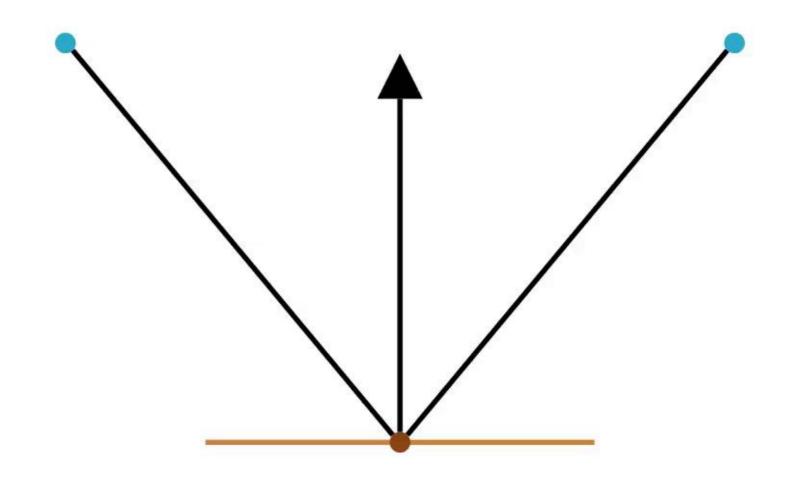


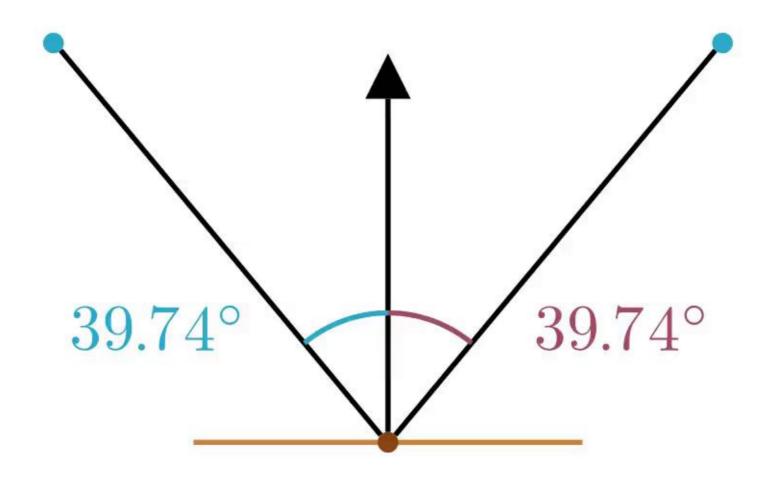
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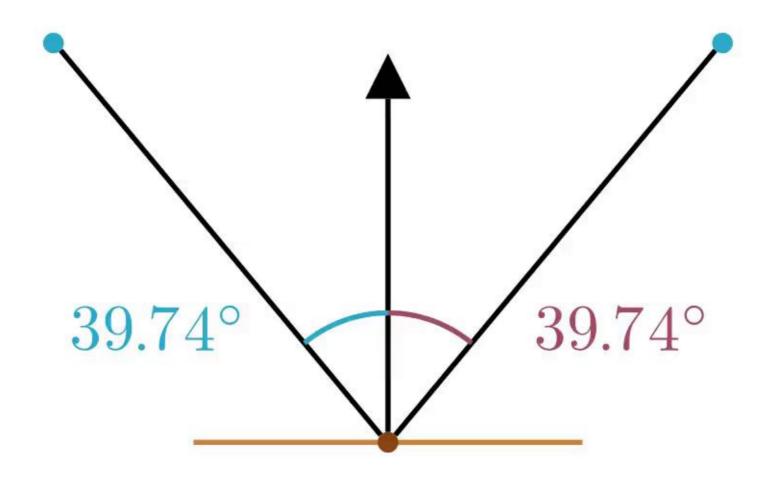


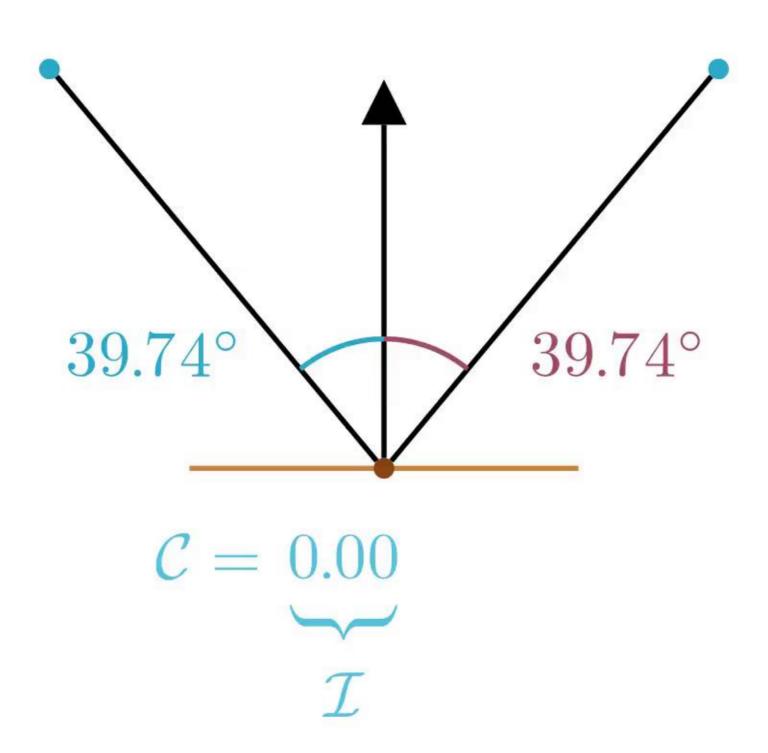
	Ray Launching	Ray Tracing
Complexity	$\mathcal{O}(N_R)$	$\mathcal{O}(N^o)$
Paths missed	Unknown	None
Scalability	Good	Bad
Accuracy	Good	Excellent

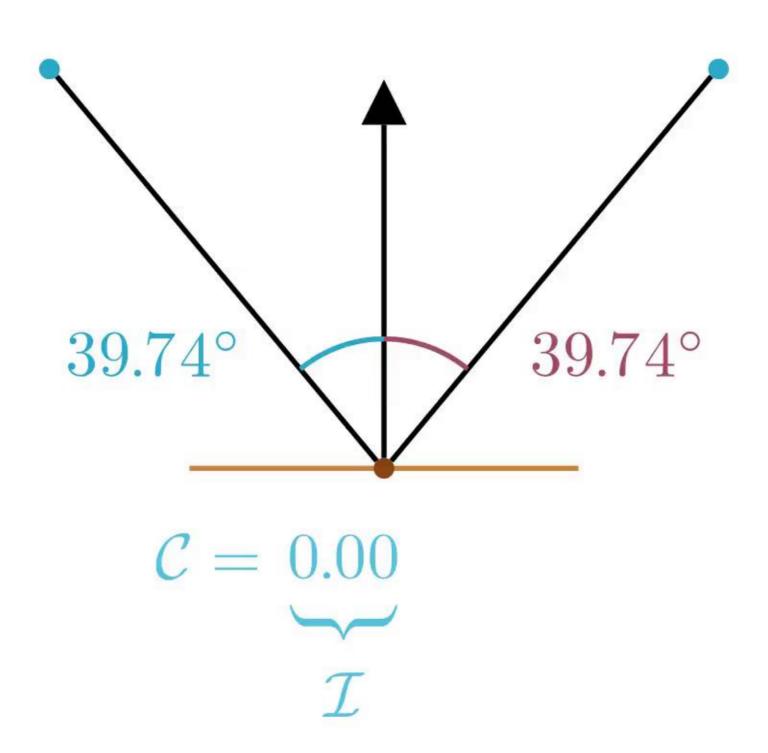
What if we want to simulate something else than reflection on planar surfaces?

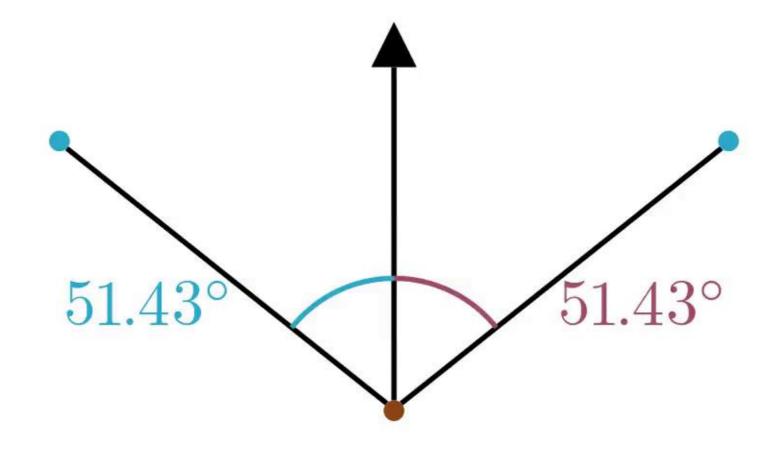




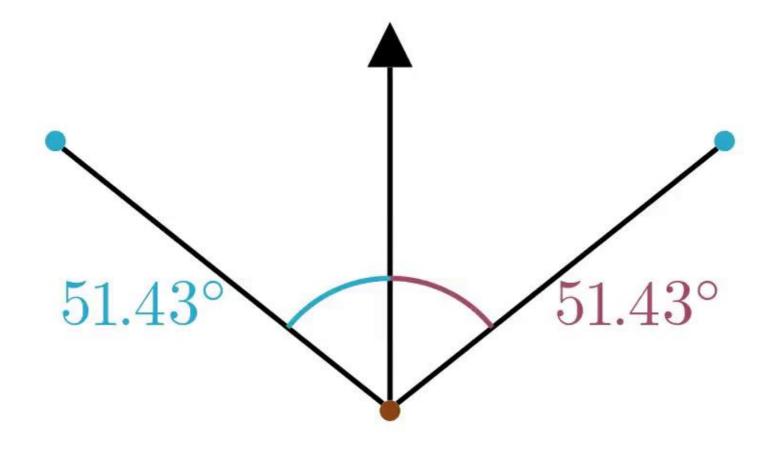








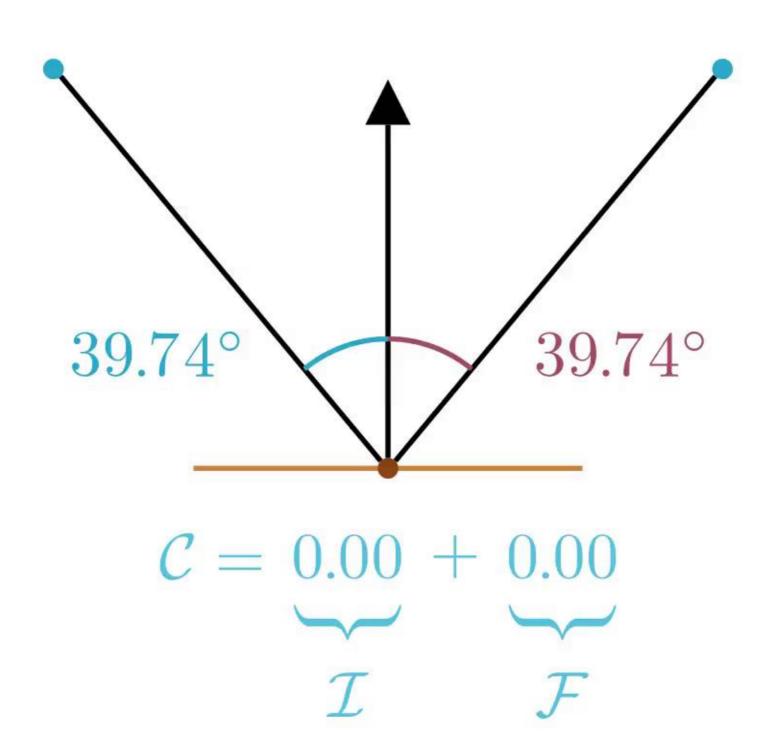
$$C = 0.00$$
 $\tau$ 



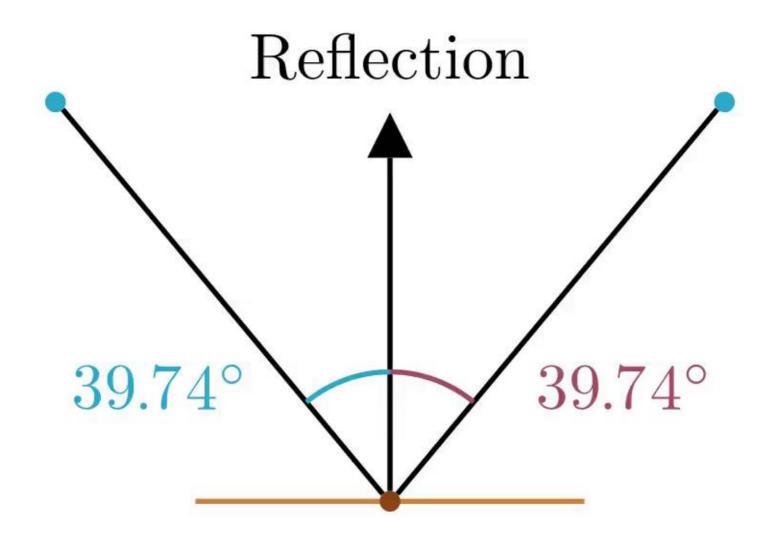
$$C = 0.00 + 1.00$$

$$\mathcal{I}$$

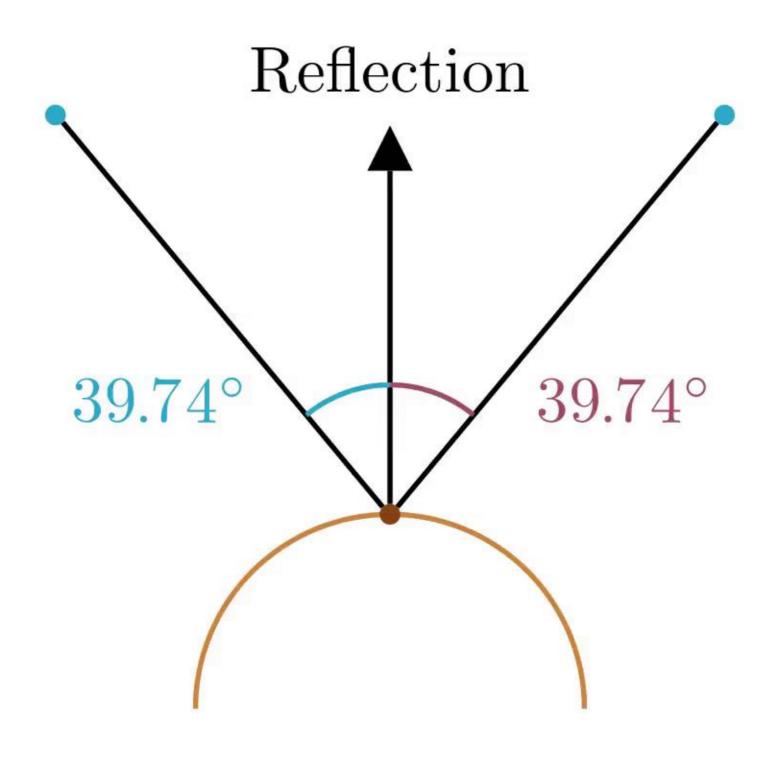
$$\mathcal{F}$$



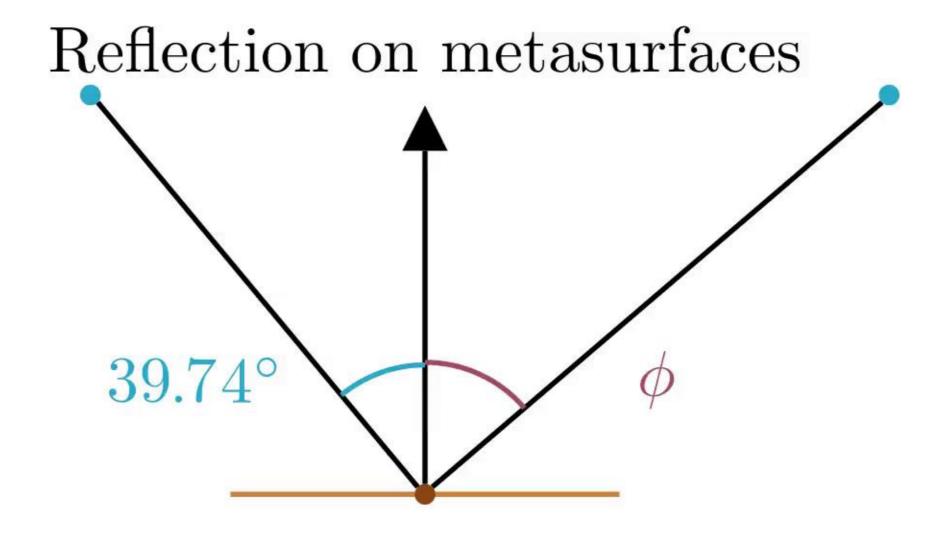
$$\mathcal{I} \sim \hat{\boldsymbol{r}} = \hat{\boldsymbol{\imath}} - 2\langle \hat{\boldsymbol{\imath}}, \hat{\boldsymbol{n}} \rangle \hat{\boldsymbol{n}}$$



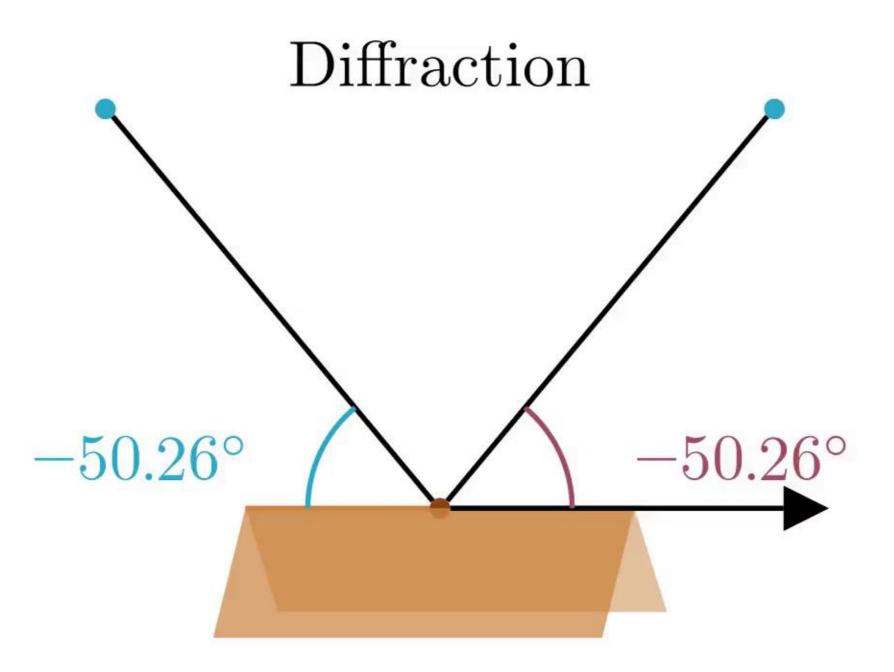
$$\mathcal{I} \sim \hat{\boldsymbol{r}} = \hat{\boldsymbol{\imath}} - 2\langle \hat{\boldsymbol{\imath}}, \hat{\boldsymbol{n}} \rangle \hat{\boldsymbol{n}}$$



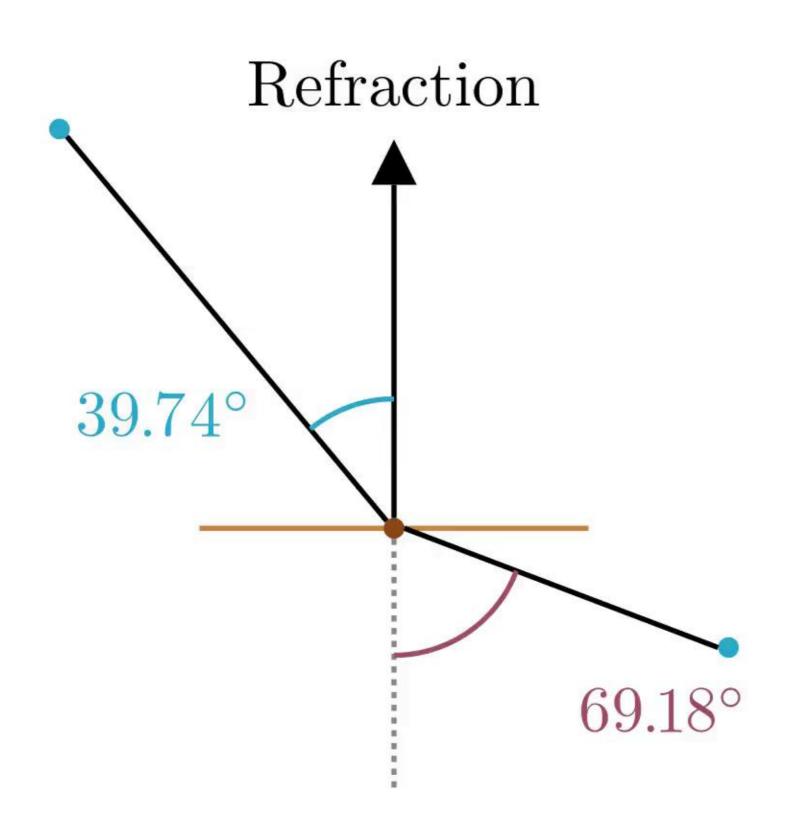
 $\mathcal{I} \sim \boldsymbol{r} = f(\hat{\boldsymbol{n}}, \phi)$ 



$$\mathcal{I} \sim rac{\langle m{i}, \hat{m{e}}
angle}{\|m{i}\|} = rac{\langle m{d}, \hat{m{e}}
angle}{\|m{d}\|}$$



$$\mathcal{I} \sim v_1 \sin(\theta_2) = v_2 \sin(\theta_1)$$



$$\min_{\boldsymbol{\mathcal{X}} \in \mathbb{R}^{n_t}} ^{\text{minize}} \; \mathcal{C}(\boldsymbol{\mathcal{X}}) := \|\mathcal{I}(\boldsymbol{\mathcal{X}})\|^2 + \|\mathcal{F}(\boldsymbol{\mathcal{X}})\|^2$$

$$\min_{\boldsymbol{\mathcal{X}} \in \mathbb{R}^{n_t}} ^{\text{minize}} \; \mathcal{C}(\boldsymbol{\mathcal{X}}) := \|\mathcal{I}(\boldsymbol{\mathcal{X}})\|^2 + \|\mathcal{F}(\boldsymbol{\mathcal{X}})\|^2$$

$$\min_{\boldsymbol{\mathcal{X}} \in \mathbb{R}^{n_t}} ^{\text{minize}} \; \mathcal{C}(\boldsymbol{\mathcal{X}}) := \|\mathcal{I}(\boldsymbol{\mathcal{X}})\|^2 + \|\mathcal{F}(\boldsymbol{\mathcal{X}})\|^2$$

$$\mathcal{C}(\mathcal{X}) = 0$$

$$\min_{\boldsymbol{\mathcal{X}} \in \mathbb{R}^{n_t}} ^{\text{minize}} \; \mathcal{C}(\boldsymbol{\mathcal{X}}) := \|\mathcal{I}(\boldsymbol{\mathcal{X}})\|^2 + \|\mathcal{F}(\boldsymbol{\mathcal{X}})\|^2$$

$$C(\mathcal{X}) \leq \epsilon$$

If we know a mapping s.t.  $(x_k, y_k) \leftrightarrow t_k$ 

$$\underset{\boldsymbol{\mathcal{X}} \in \mathbb{R}^{n_t}}{\operatorname{minimize}} \ \mathcal{C}(\boldsymbol{\mathcal{X}}) := \|\mathcal{I}(\boldsymbol{\mathcal{X}})\|^2 + \|\mathcal{F}(\boldsymbol{\mathcal{X}})\|^2$$

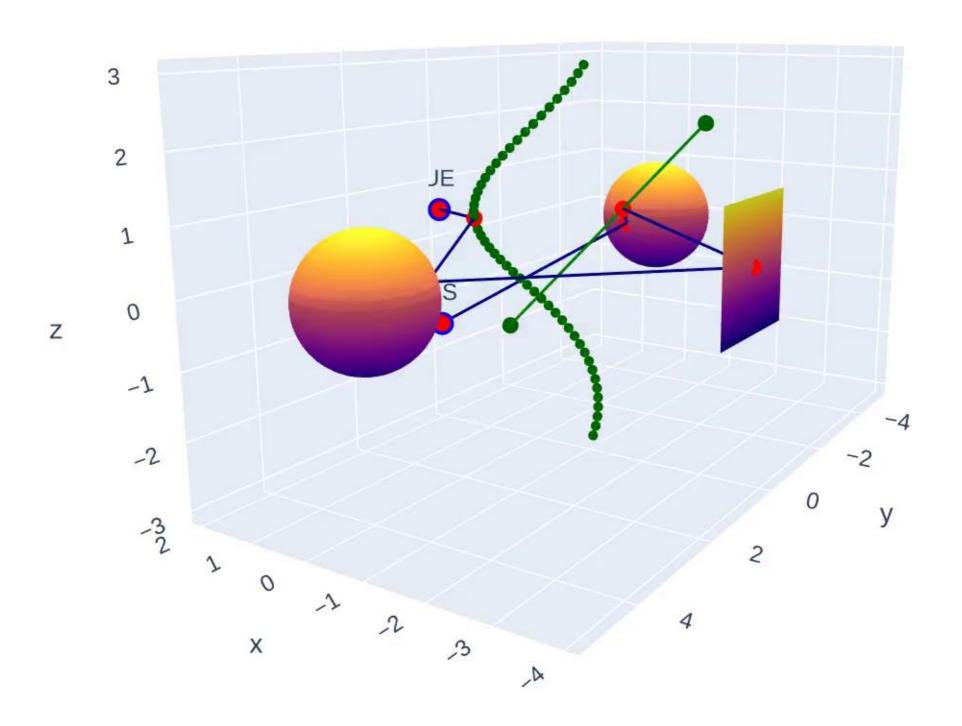
$$C(\mathcal{X}) \leq \epsilon$$

If we know a mapping s.t.  $(x_k, y_k) \leftrightarrow t_k$ 

$$\min_{\boldsymbol{\mathcal{T}} \in \mathbb{R}^{n_r} } \text{ize } \mathcal{C}(\boldsymbol{\mathcal{X}}(\boldsymbol{\mathcal{T}})) := \|\mathcal{I}(\boldsymbol{\mathcal{X}}(\boldsymbol{\mathcal{T}}))\|^2$$

where  $n_r$  is the total number of (2d) reflections

$$\mathcal{C}(\mathcal{X}(\mathcal{T})) \leq \epsilon$$



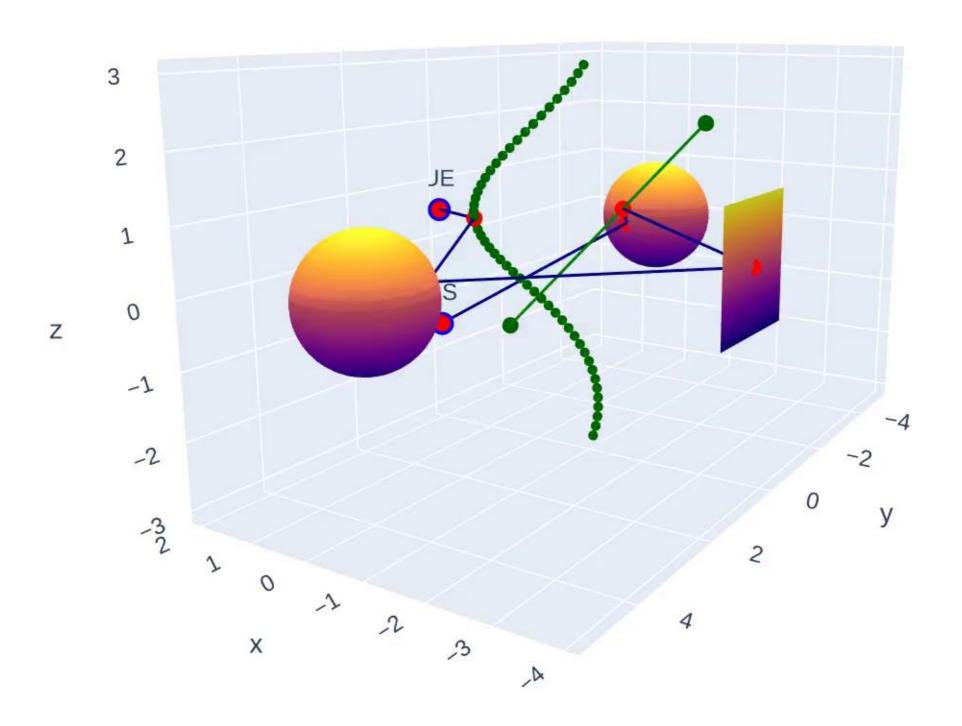
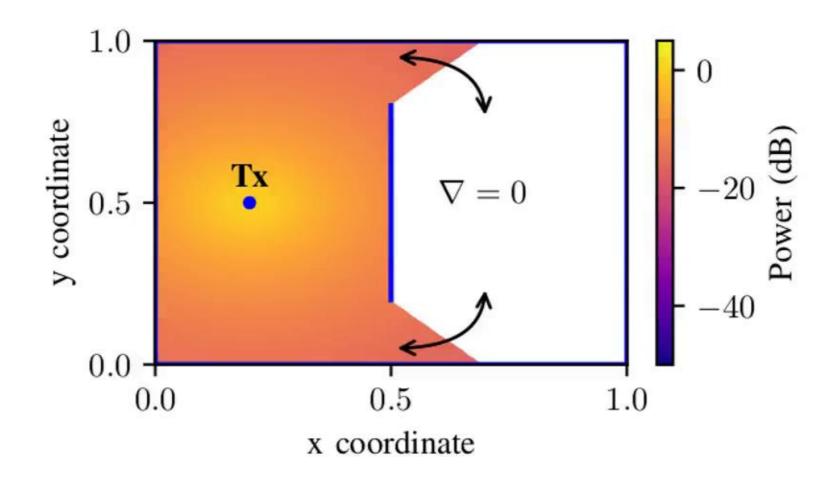


	Image	FPT	MPT
Complexity	$\mathcal{O}(n)$	$\mathcal{O}(n \cdot n_{\mathrm{iter}})$	$\mathcal{O}(n \cdot n_{ ext{iter}})$
Objects	Planes	All	Any*
Types	LOS+R	All	All+Custom
Convexity	N/A	Convex on planar	Non convex
Convergence check	N/A or MPT	None or MPT	self

- How to compute derivatives;
- Zero-gradient and discontinuity issues;
- Smoothing technique;
- Optimization example.

How to compute derivatives?

- using finite-differences;



$$\theta(x) = \begin{cases} 1, & \text{if } x > 0, \\ 0, & \text{otherwise,} \end{cases}$$

$$\lim_{\alpha \to \infty} s(x; \alpha) = \theta(x)$$

[C1]  $\lim_{x\to-\infty} s(x;\alpha) = 0$  and  $\lim_{x\to+\infty} s(x;\alpha) = 1$ ;

[C2]  $s(\cdot; \alpha)$  is monotonically increasing;

[C3]  $s(0; \alpha) = \frac{1}{2};$ 

[C4] and  $s(x; \alpha) - s(0; \alpha) = s(0; \alpha) - s(-x; \alpha)$ .

$$s(x;\alpha) = s(\alpha x). \tag{1}$$

The sigmoid is defined with a real-valued exponential

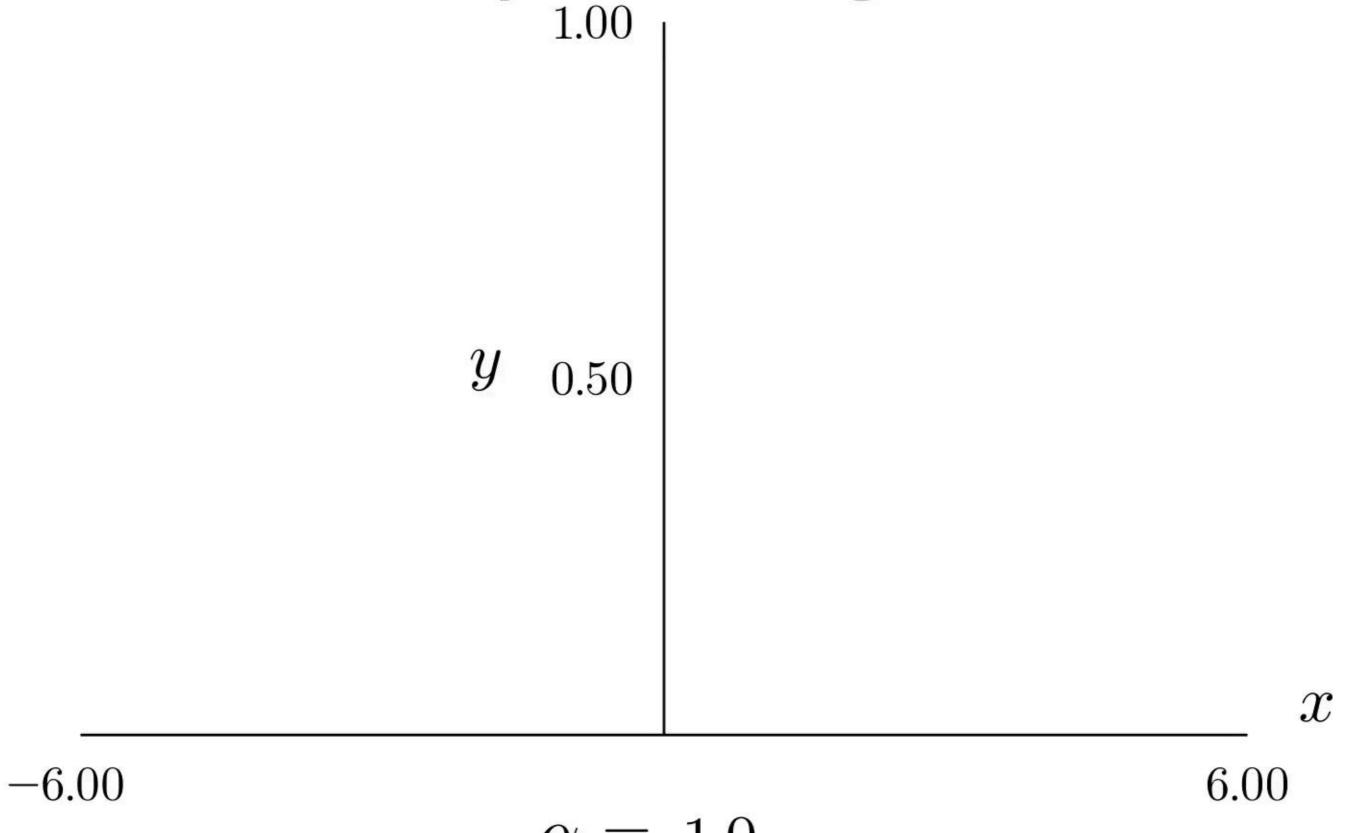
$$sigmoid(x; \alpha) = \frac{1}{1 + e^{-\alpha x}},$$
(2)

and the hard sigmoid is the piecewise linear function defined by

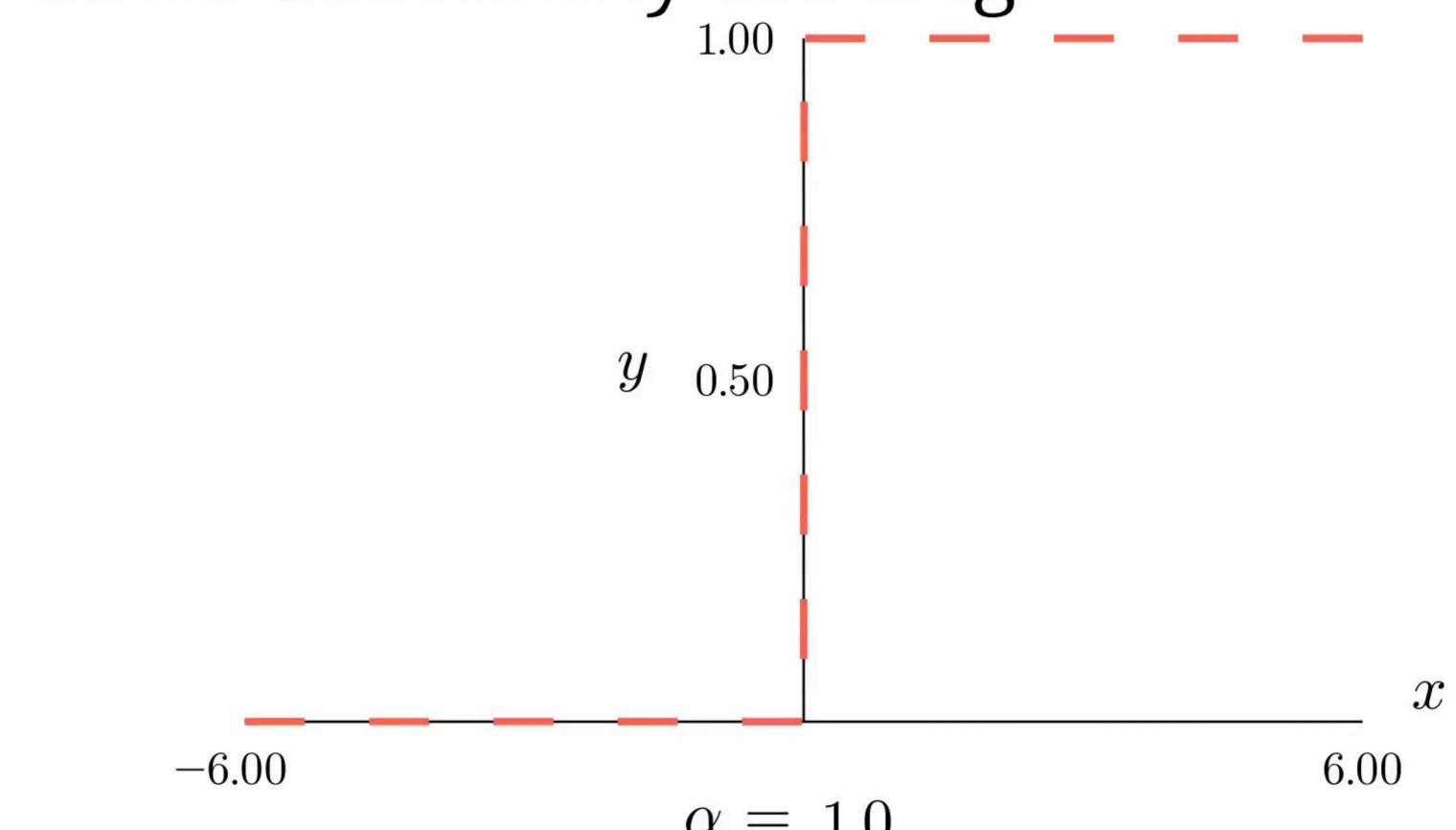
hard sigmoid
$$(x; \alpha) = \frac{\text{relu6}(\alpha x + 3)}{6},$$
 (3)

where

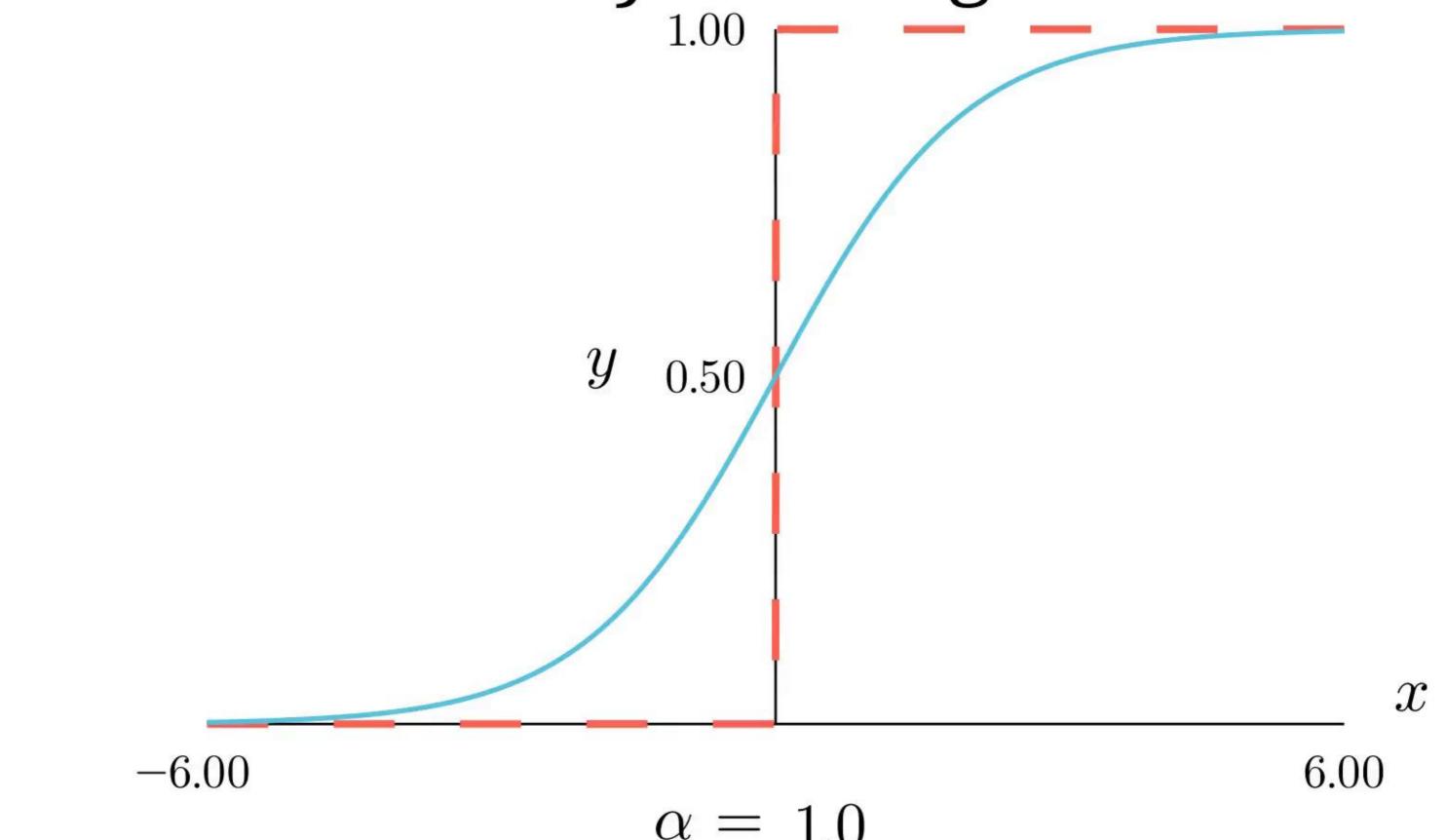
$$relu6(x) = \min(\max(0, x), 6). \tag{4}$$

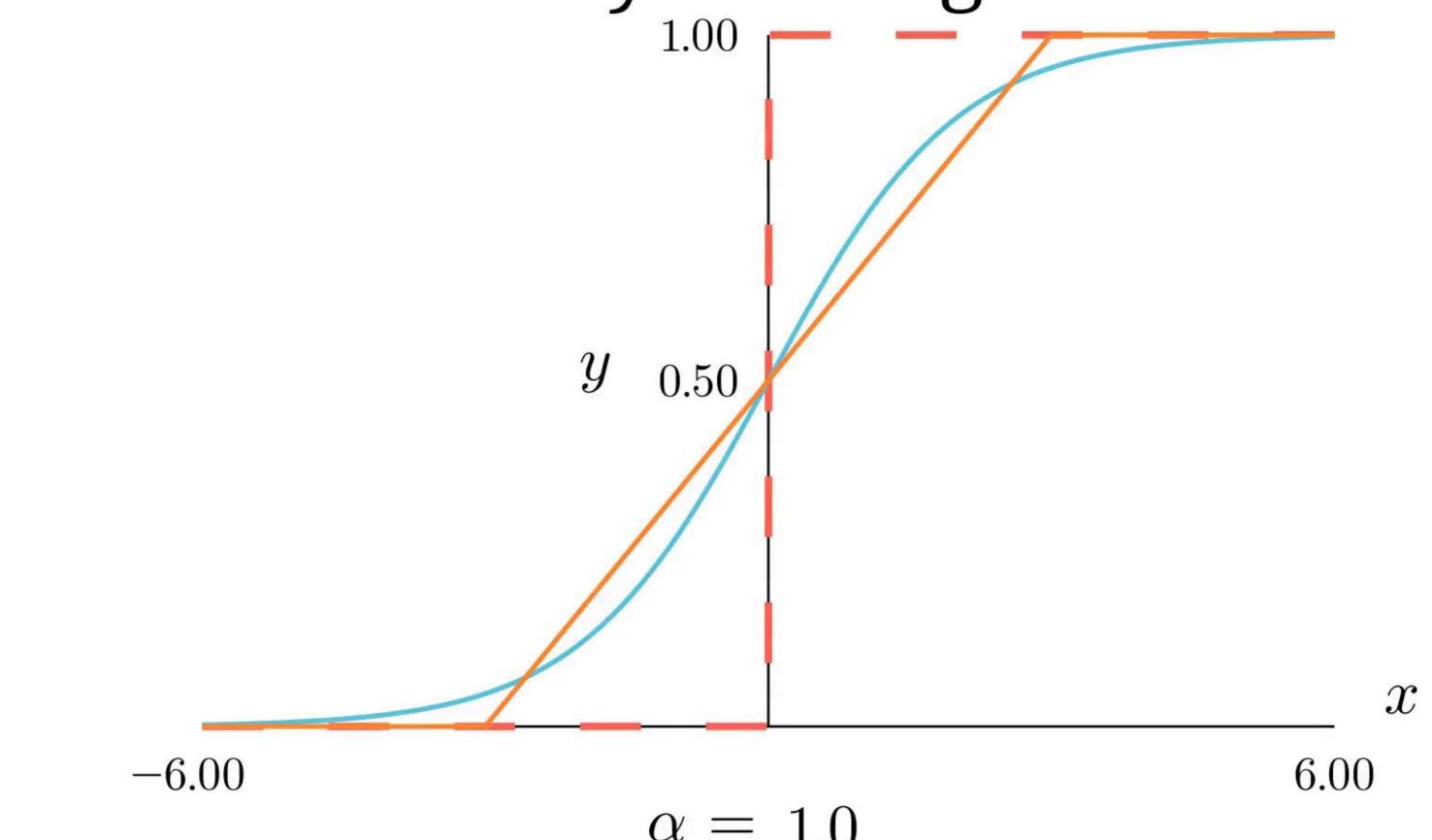


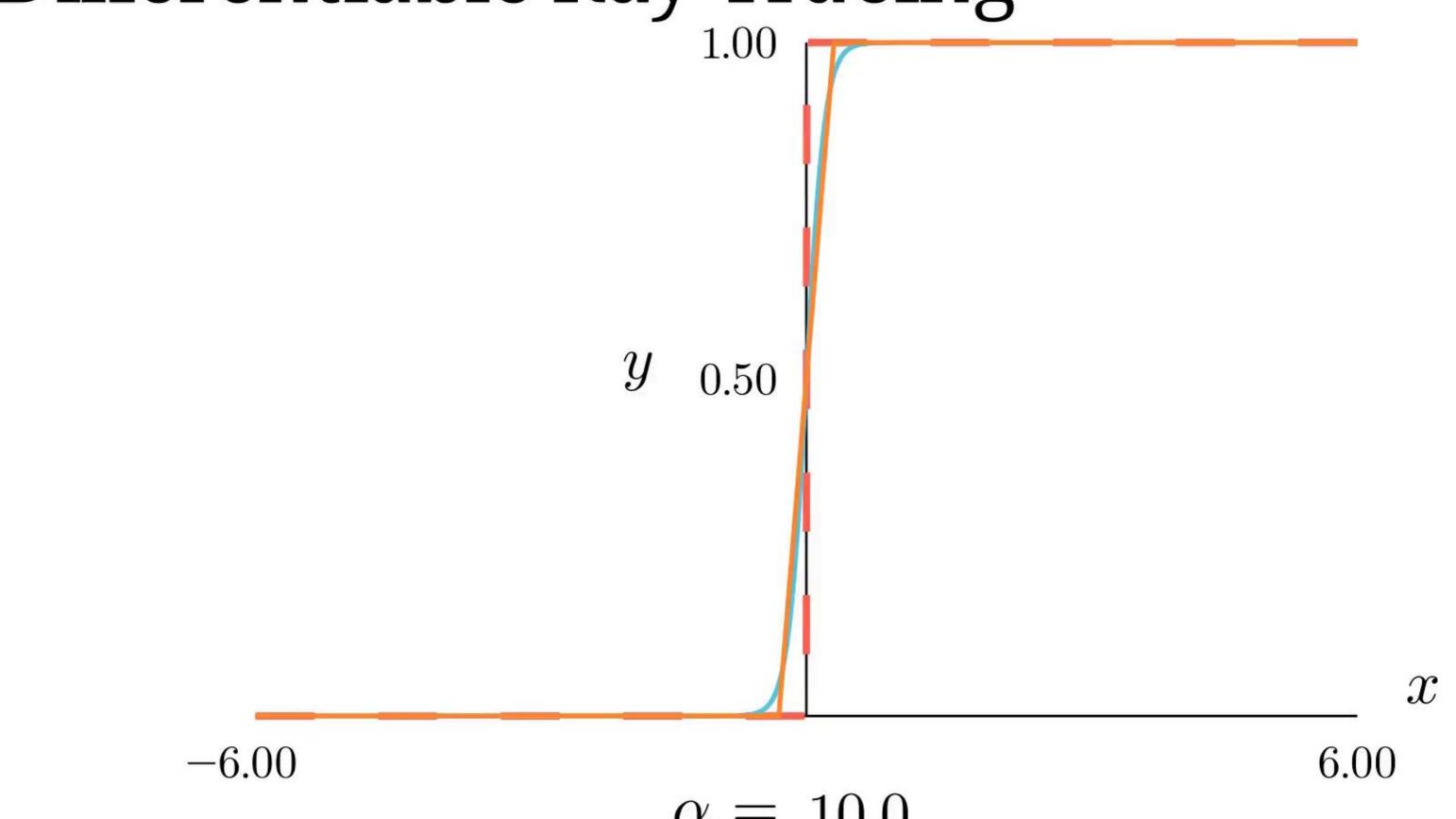
29



29

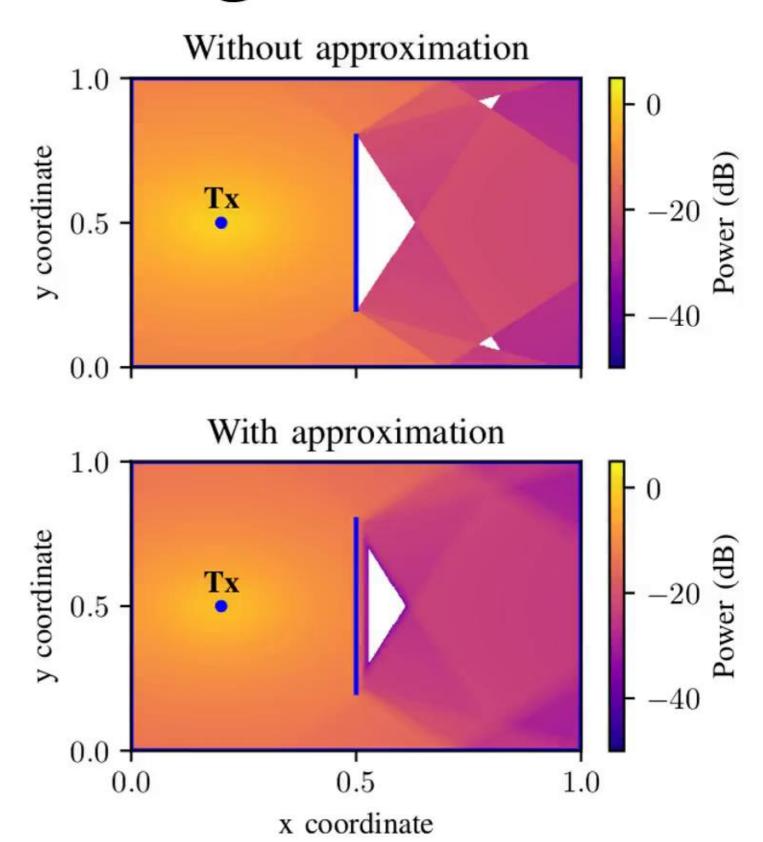


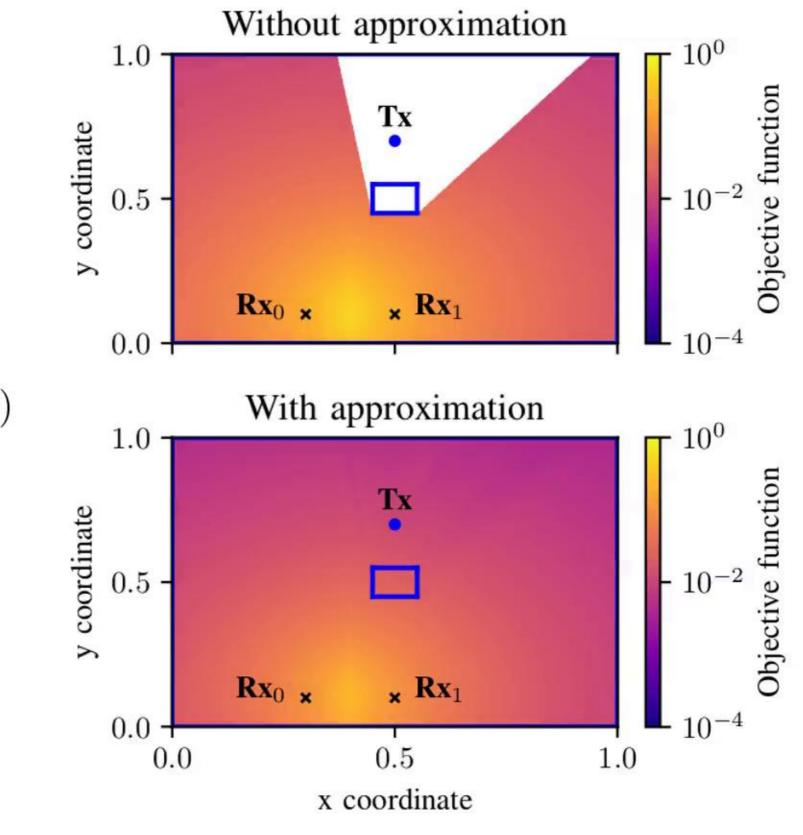




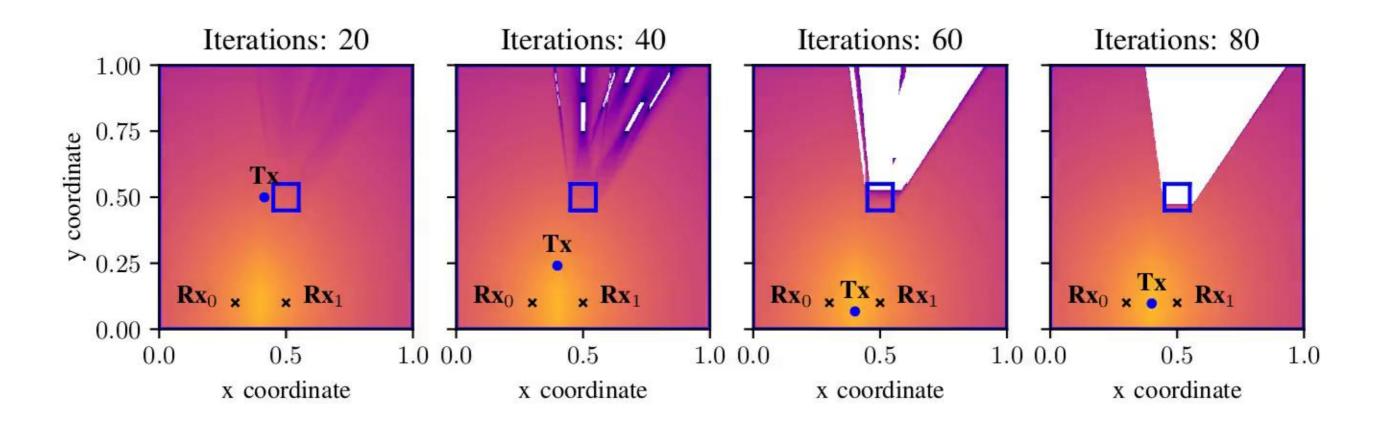
29

$$\vec{E}(x,y) = \sum_{\mathcal{P} \in \mathcal{S}} V(\mathcal{P}) (\bar{C}(\mathcal{P}) \cdot \vec{E}(\mathcal{P}_1))$$





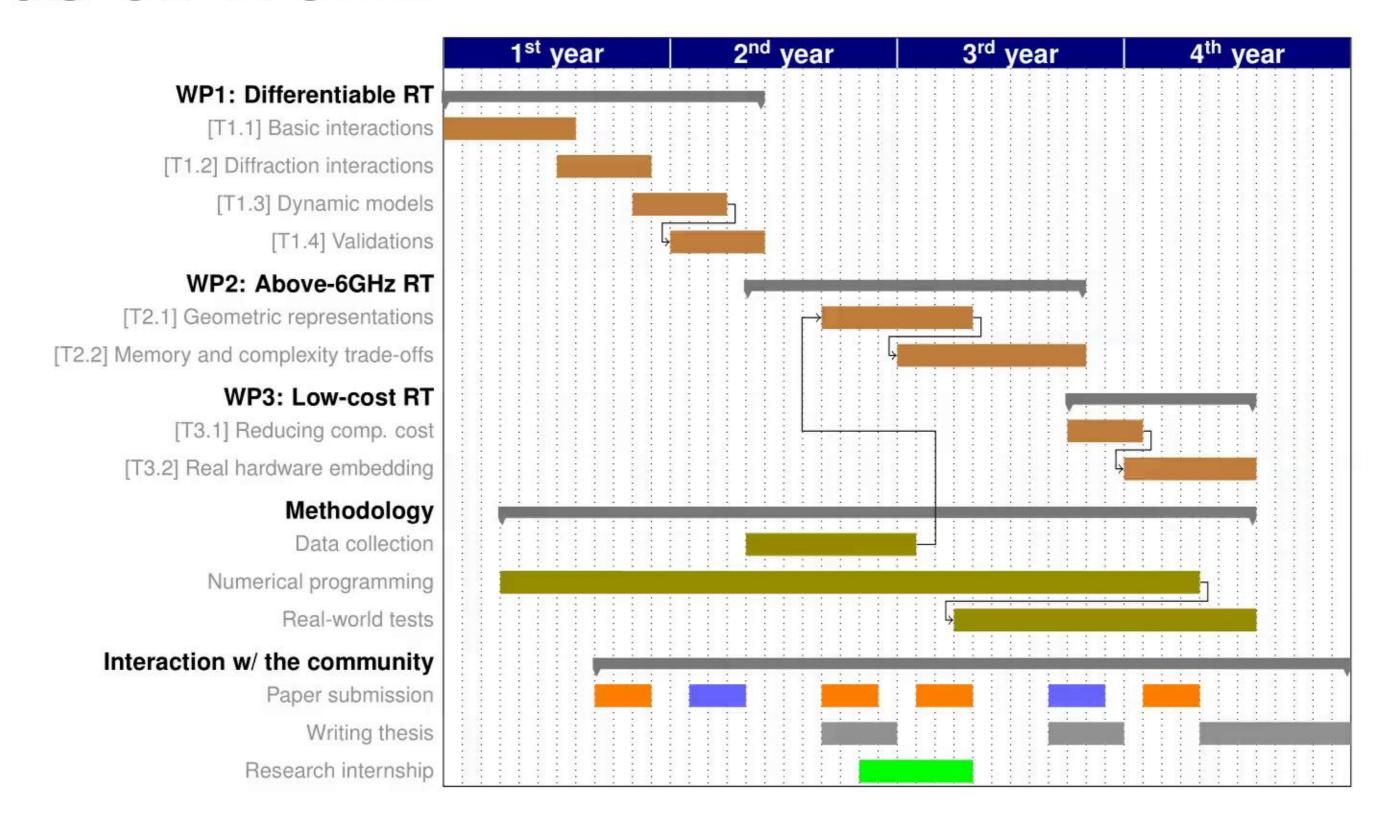


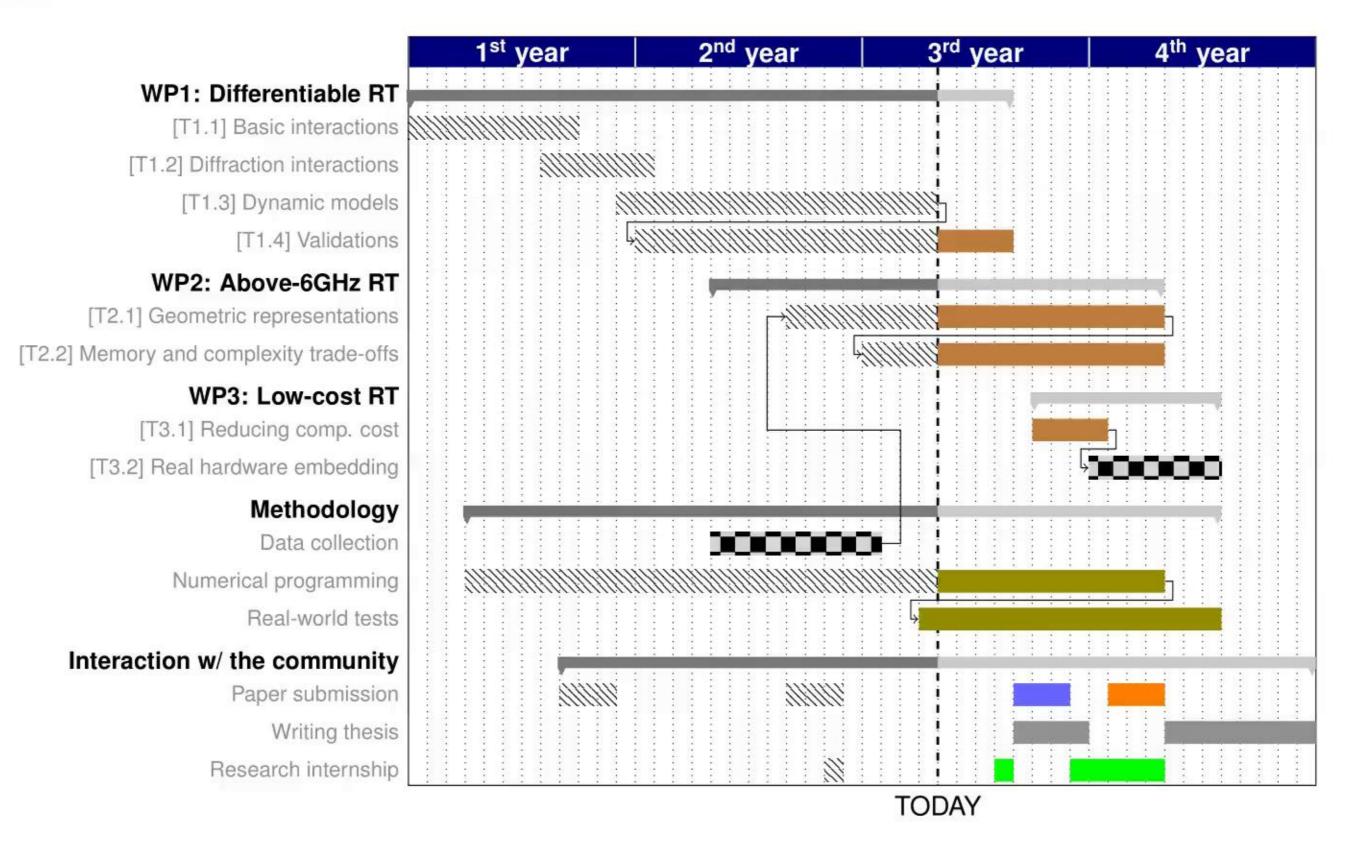


#### Goals:

⊳ (G1): Enable RT dynamic scalability;

⊳ (G2): Novel geometrical environment representations.





#### Achievements:

- Created general-purpose path tracing method;
- □ Introduced smoothing techniques in radio-propa. RT;

#### Future work:

- → Perform quantitative comp. of RL vs RT;
- Study compat. of MPT w/ good RIS models;
- Learning how to trace paths with ML (deep sets).

#### Collaborations:

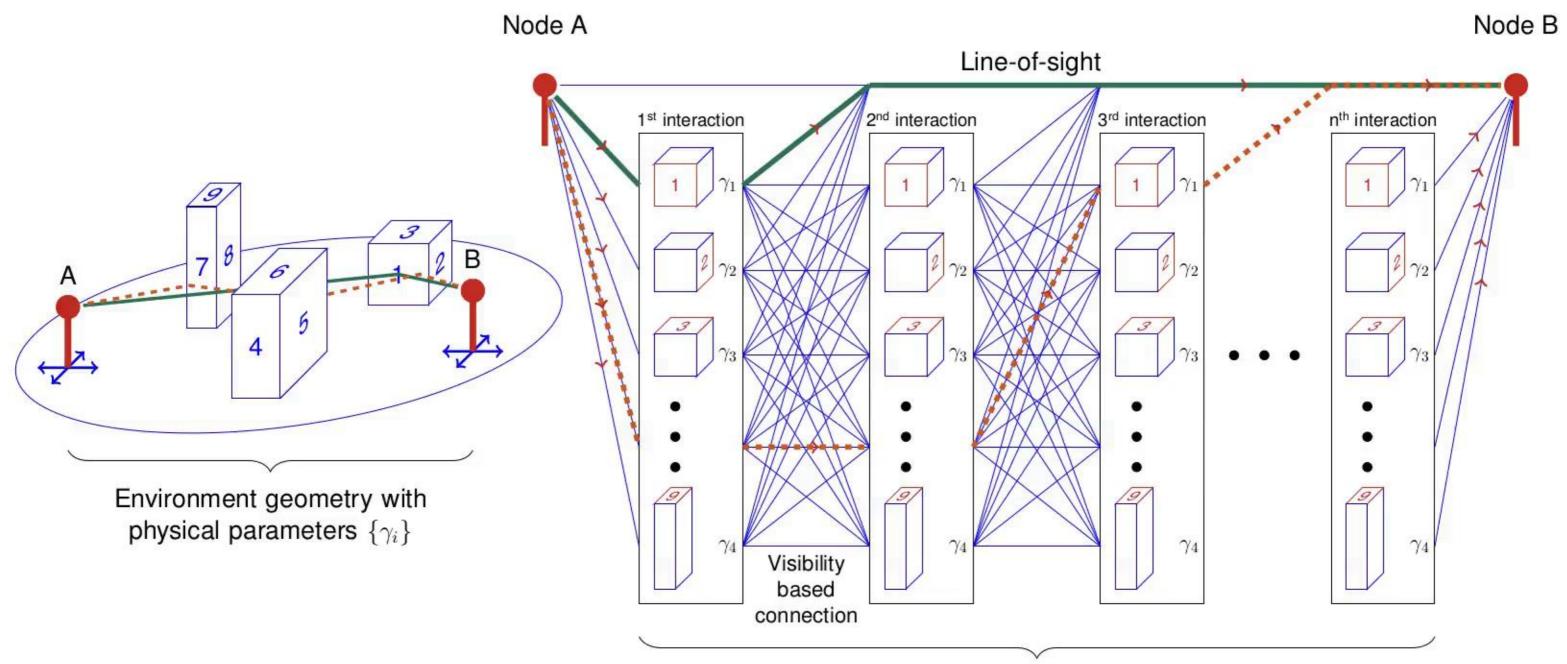
- □ UniSiegen, Mohammed Saleh (Pr. Andreas Kolb) 07/2023;
- → Huawei, Allan W. M. 03/2023-?;
- ~ Nvidia, Sionna, Jakob Hoydis -?

#### Conclusion

#### Conclusion

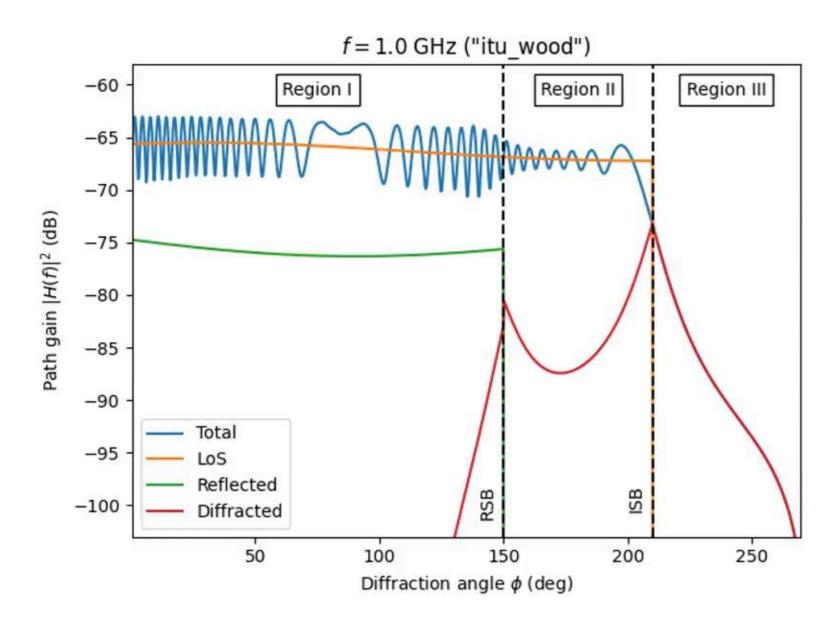
Questions time!

#### ML-like structure

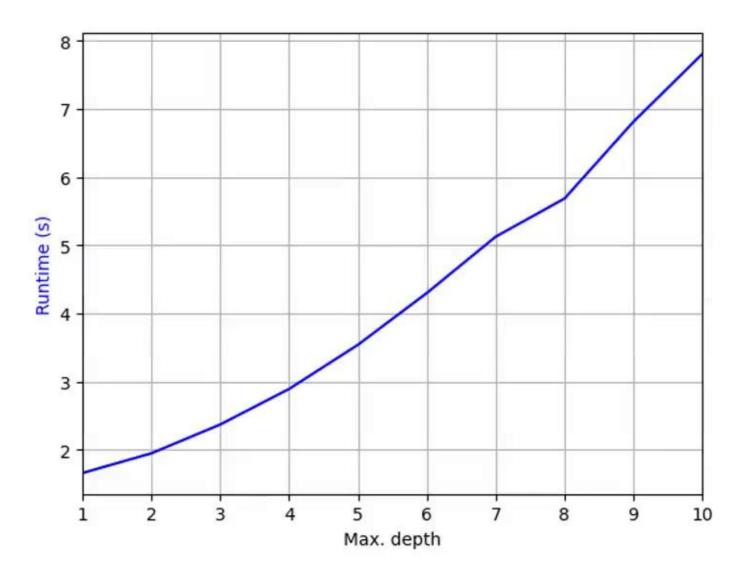


Number of layers = number of considered interactions

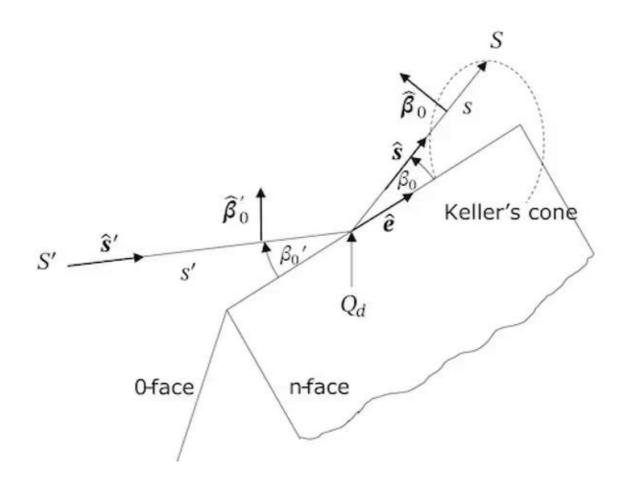
# Diffraction regions



#### RT runtime



#### Keller cone



# Edge diffraction

