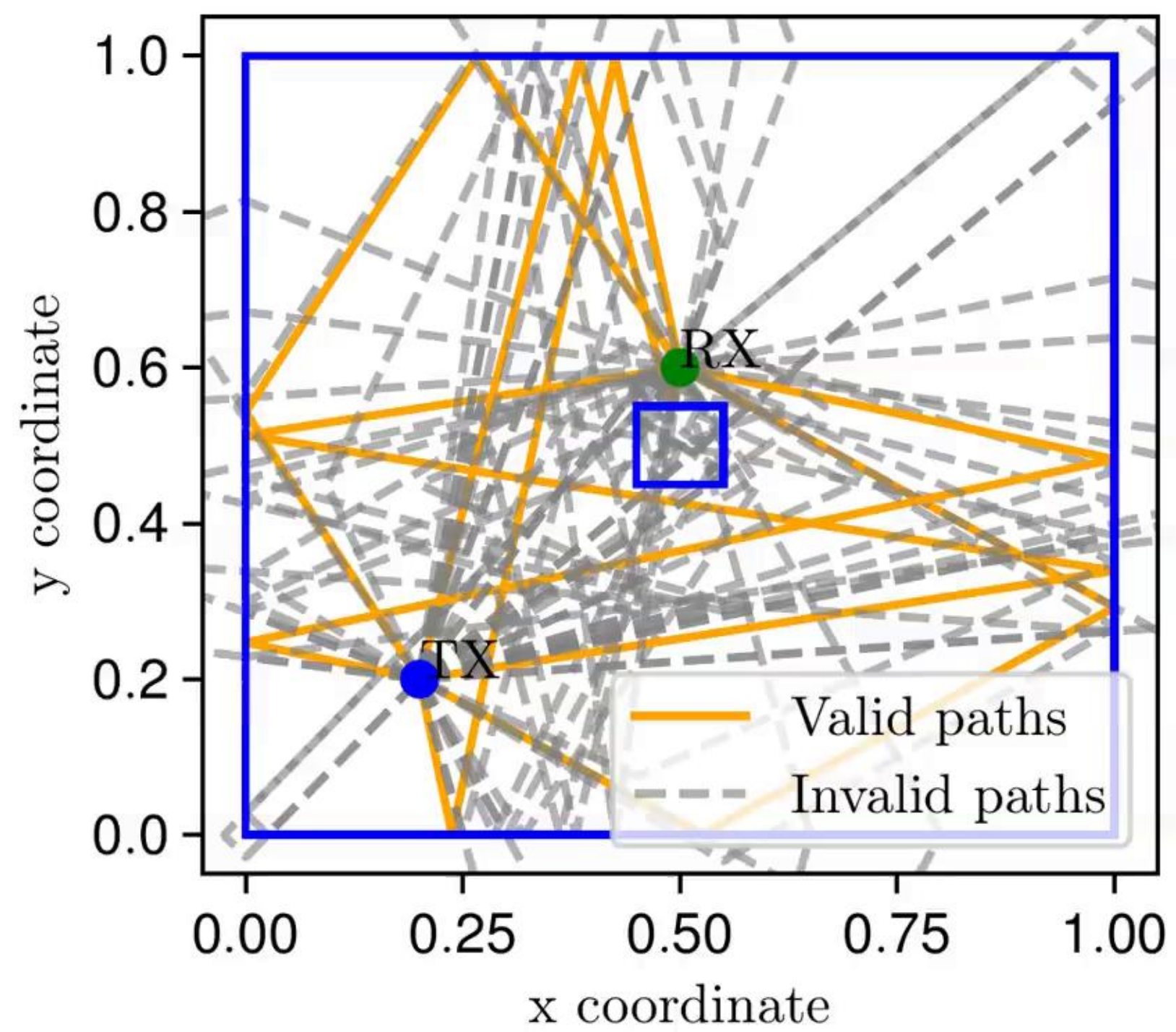


Generative Path Selection Technique for Efficient Ray Tracing Prediction (Invited)

Enrico Maria Vitucci - June 23-27, Bologna

Authors: Jérôme Eertmans, Nicola Di Cicco, Claude Oestges, Enrico Maria
Vitucci, Vittorio Degli-Esposti

	Point-to-Point (P2P) Ray Tracing (RT)	Ray Launching (RL)
Complexity	Exponential	Linear*
Accuracy	Excellent	Good*
Best for	P2P scenarios	Coverage map



Scene

Scene

TX

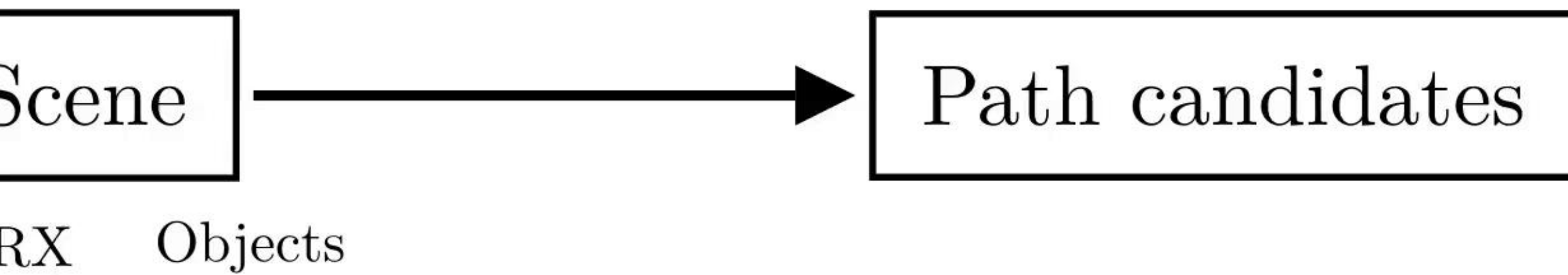
Scene

TX

RX

Scene

TX RX Objects



ates \longrightarrow paths for order N

ates

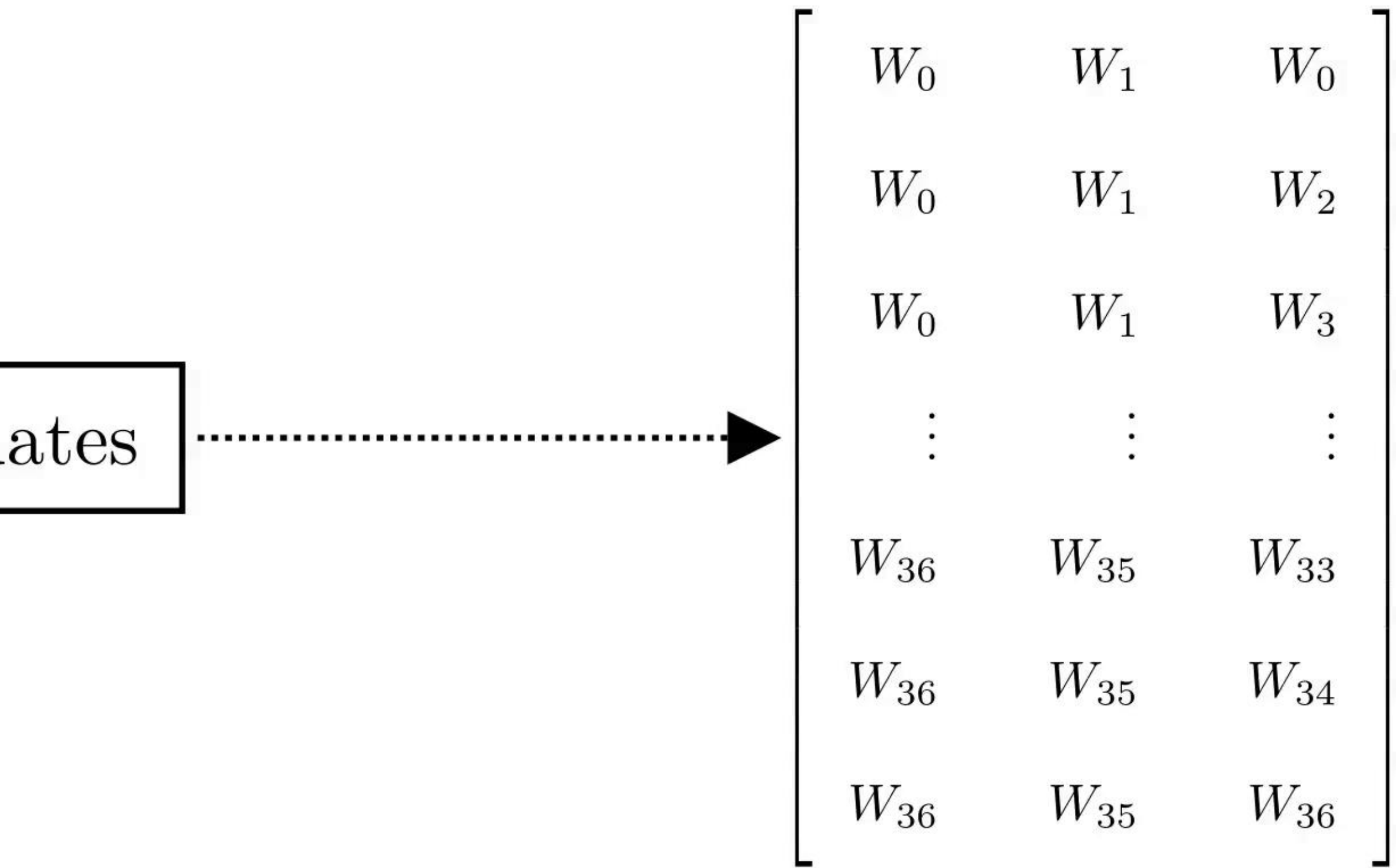


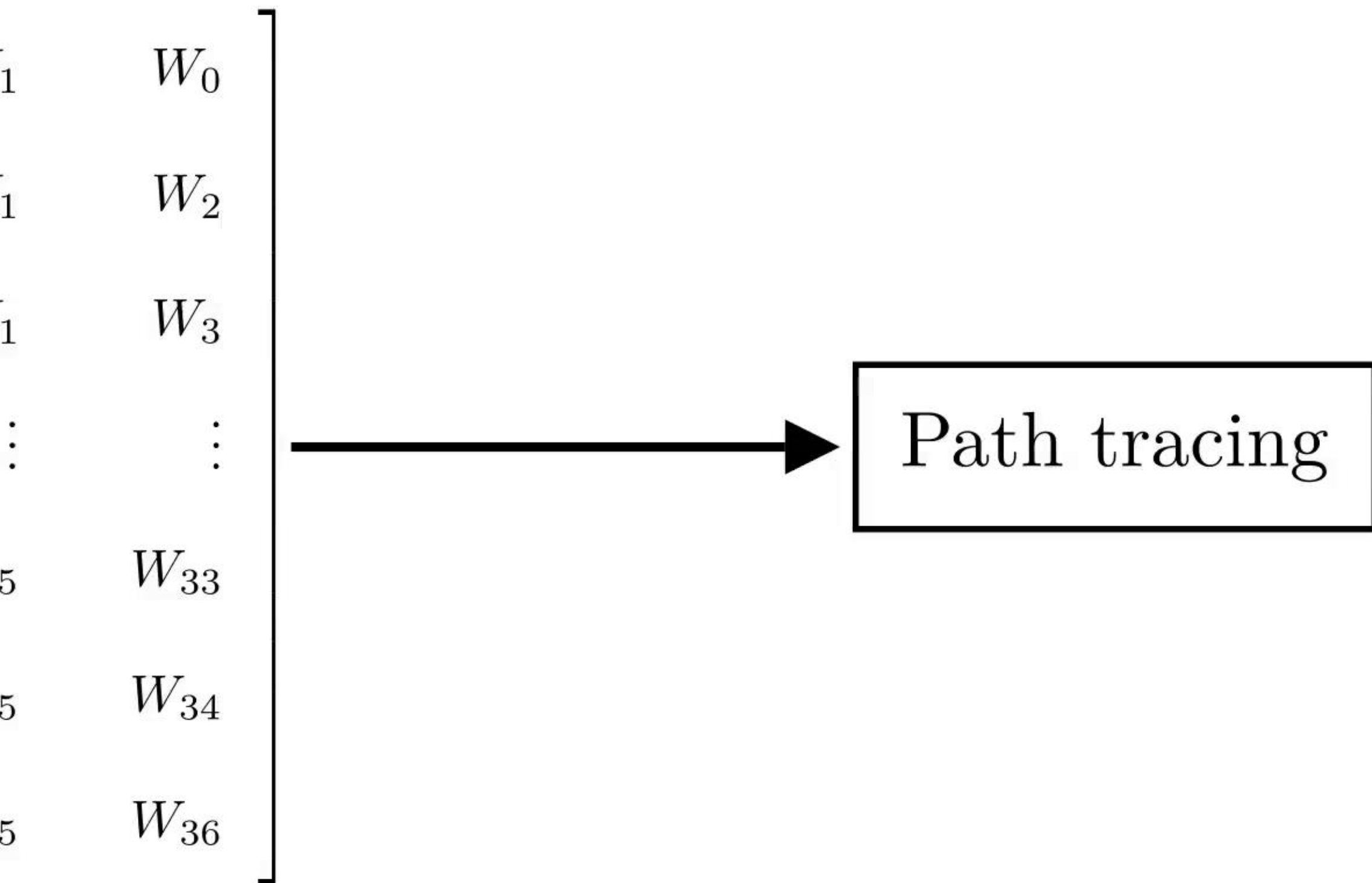
$$\begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ \vdots \\ W_{34} \\ W_{35} \\ W_{36} \end{bmatrix}$$

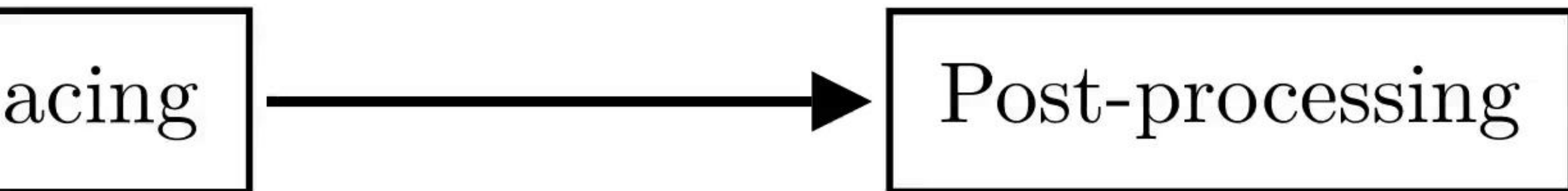
ates



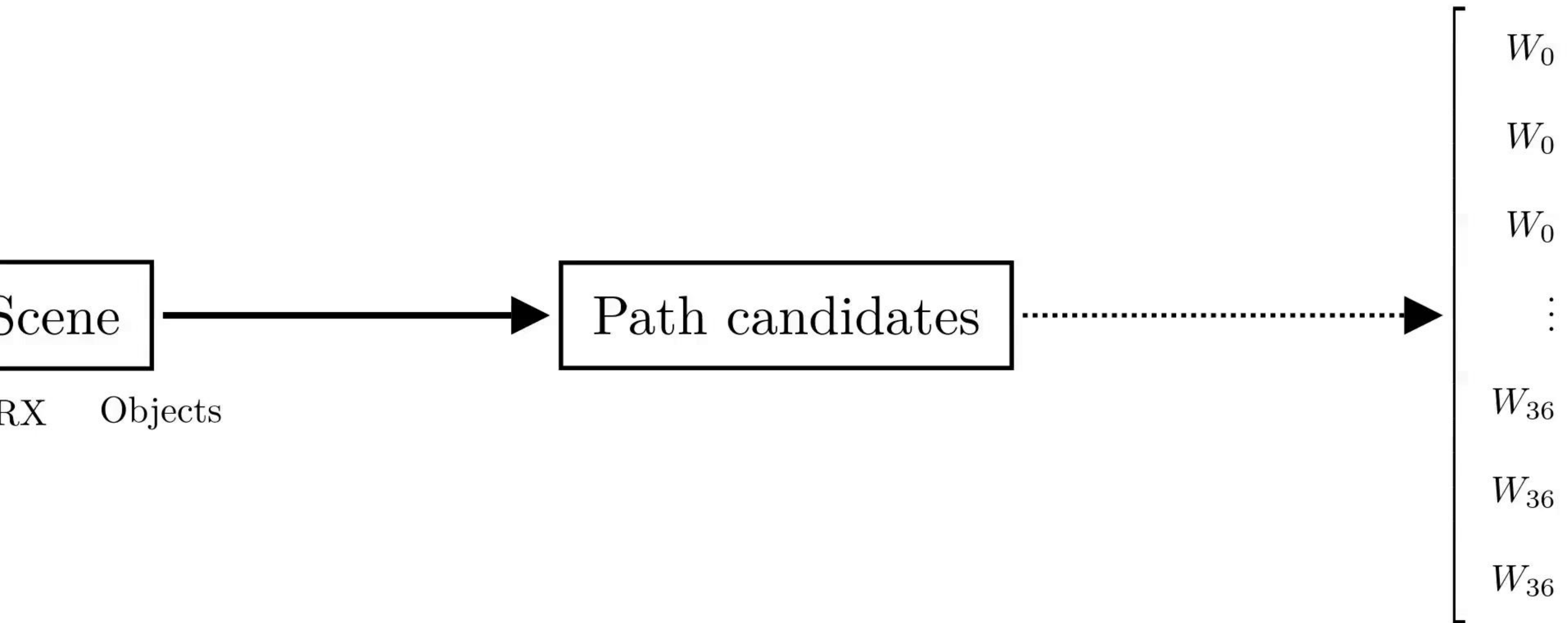
$$\begin{bmatrix} W_0 & W_1 \\ W_0 & W_2 \\ W_0 & W_3 \\ \vdots & \vdots \\ W_{36} & W_{33} \\ W_{36} & W_{34} \\ W_{36} & W_{35} \end{bmatrix}$$

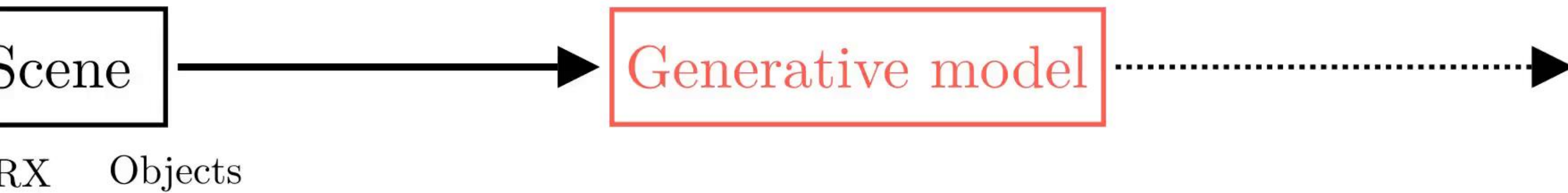


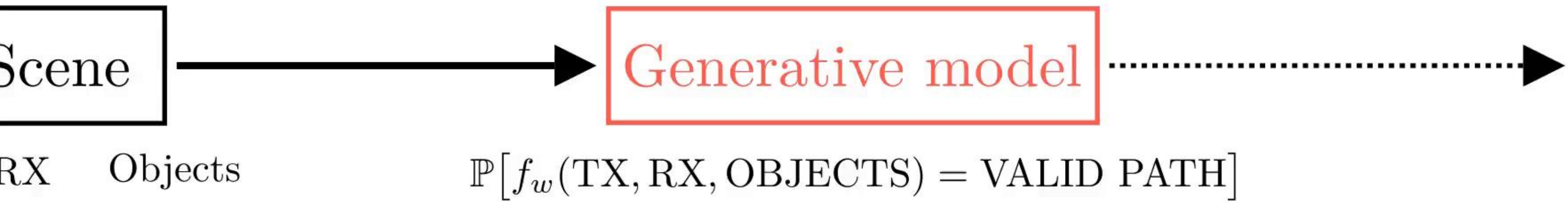


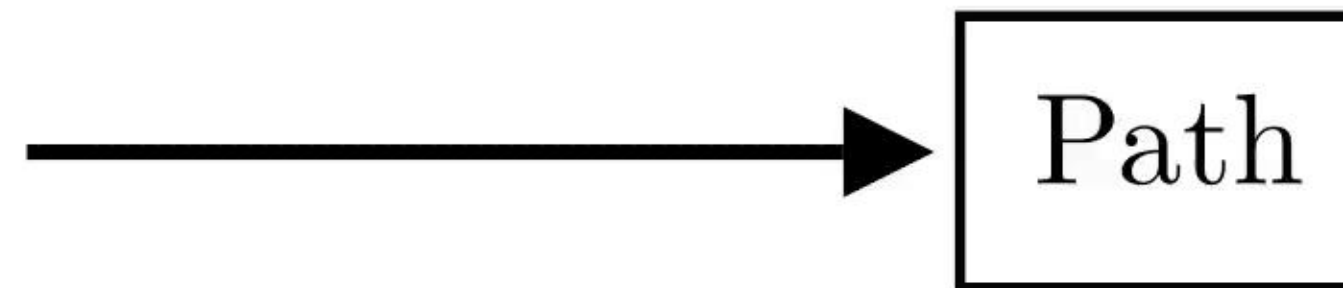
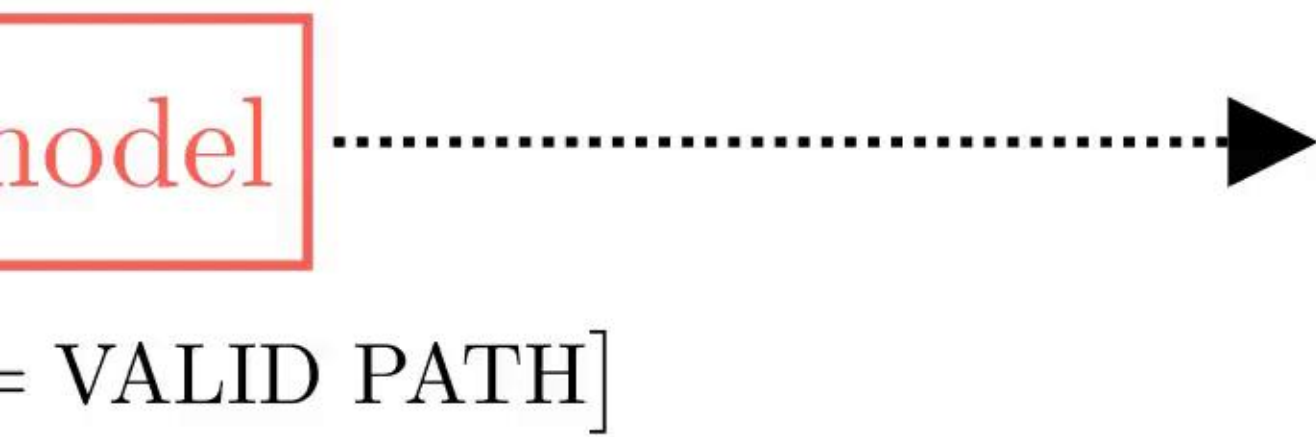


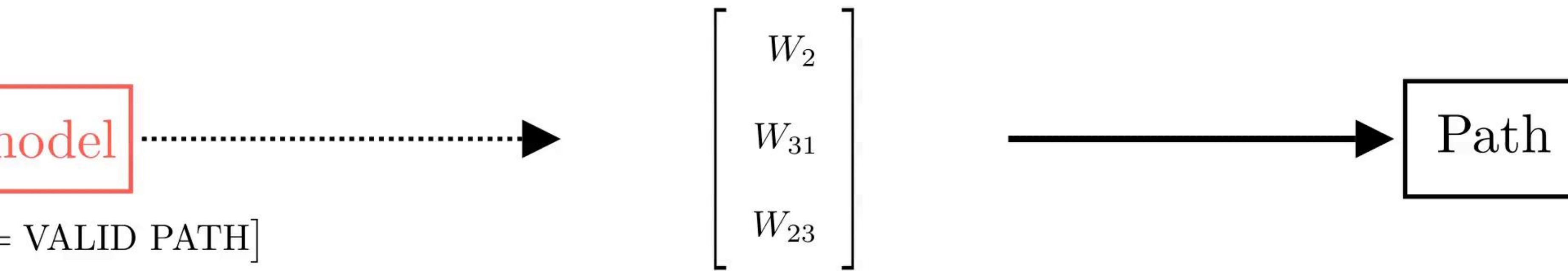


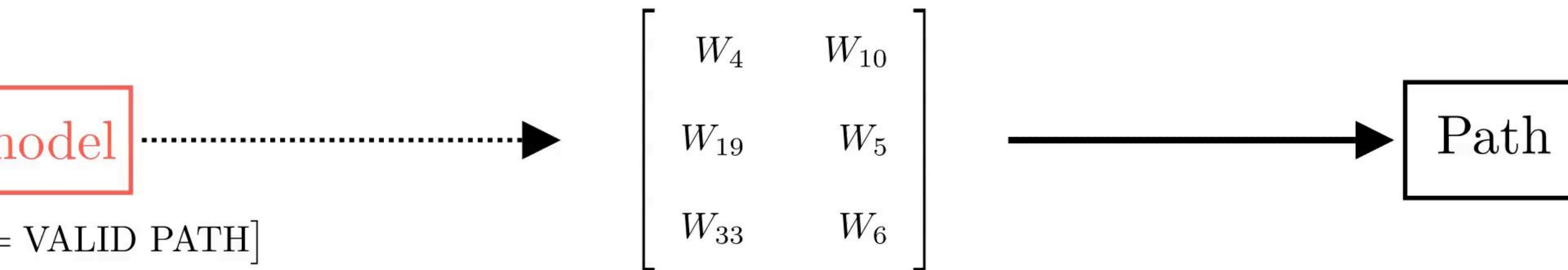


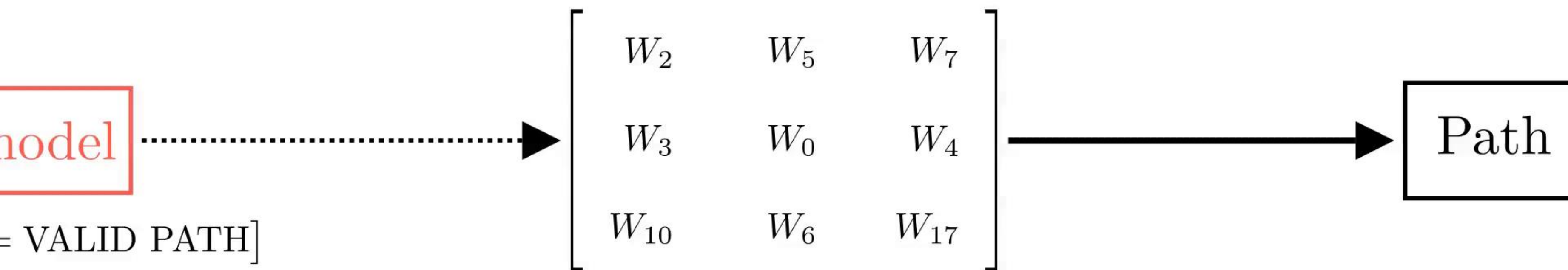












Model details:

1. Does not learn a specific scene
2. Arbitrary sized input scene
3. Reinforcement-based learning

What we train on:

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Accuracy: % of valid rays over the number of generated rays

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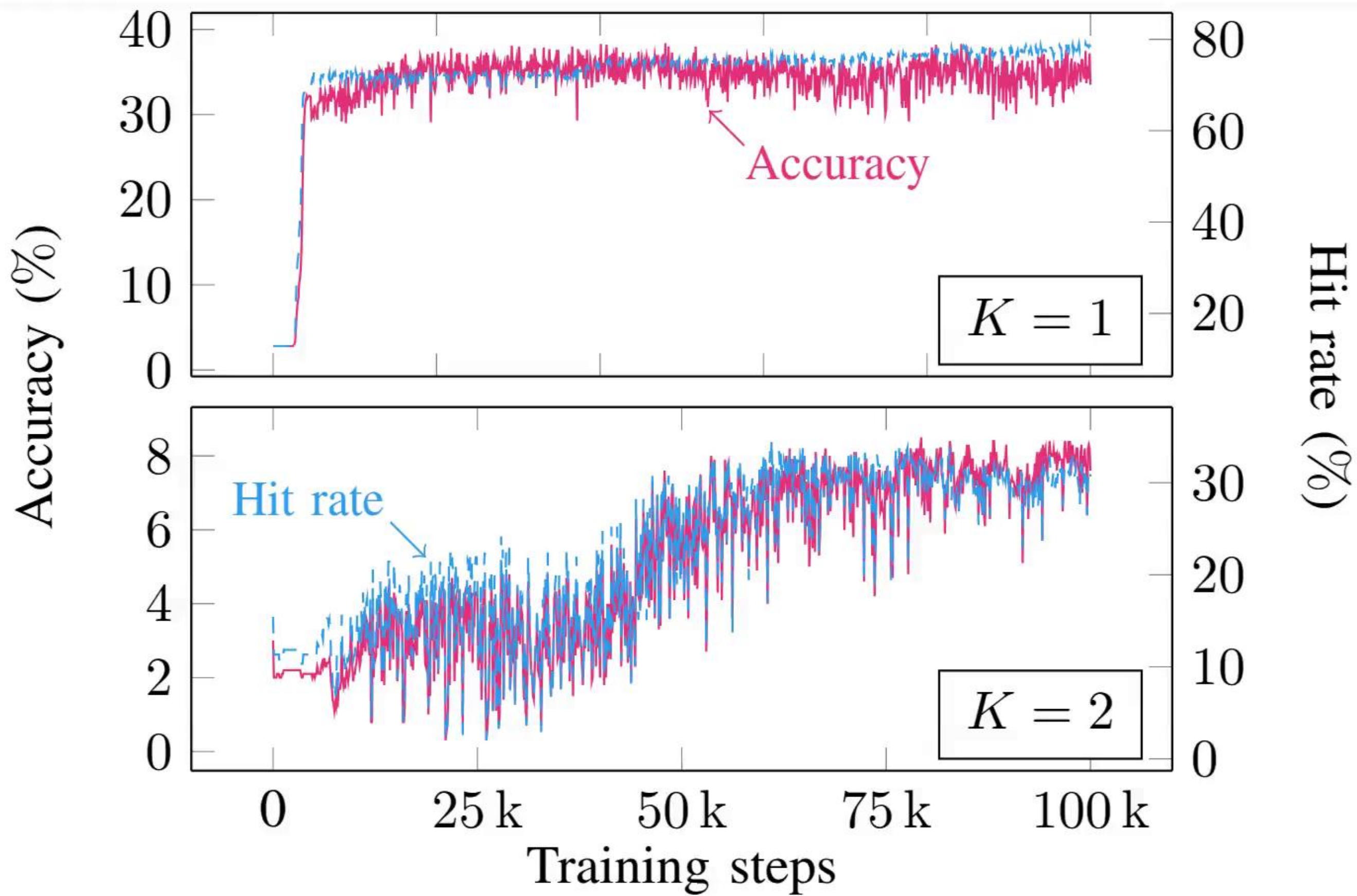
What we would like to maximize:

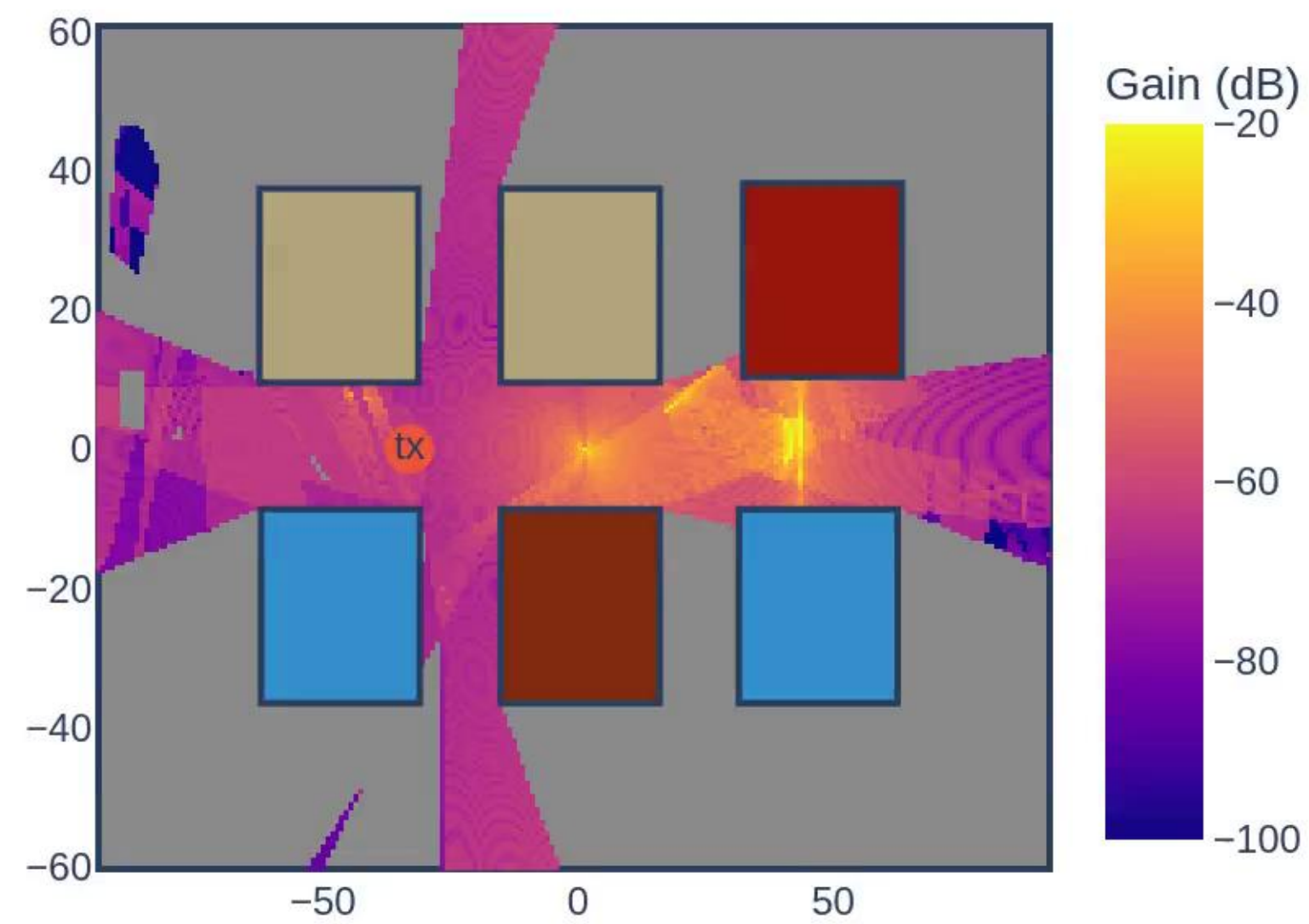
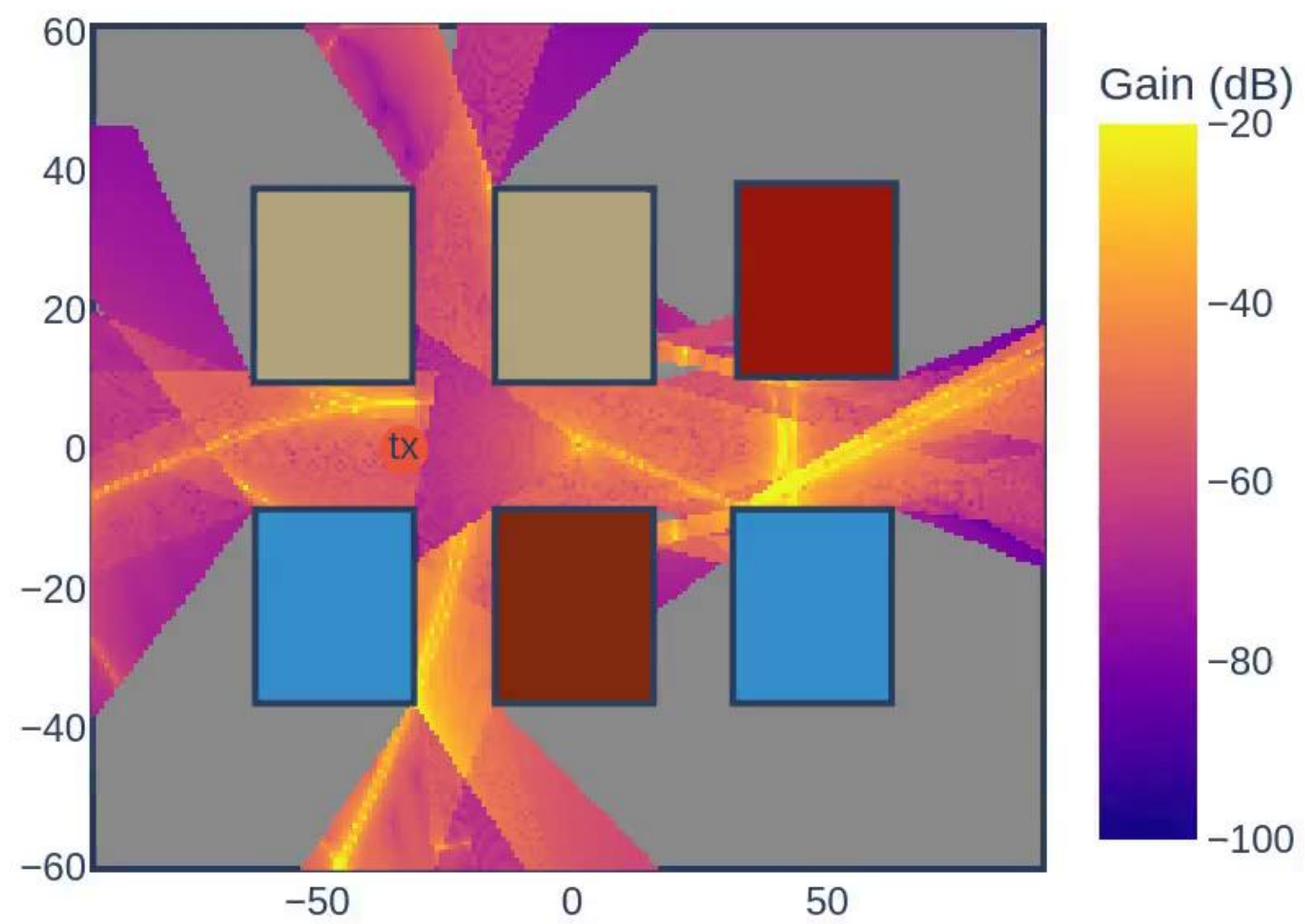
What we train on:

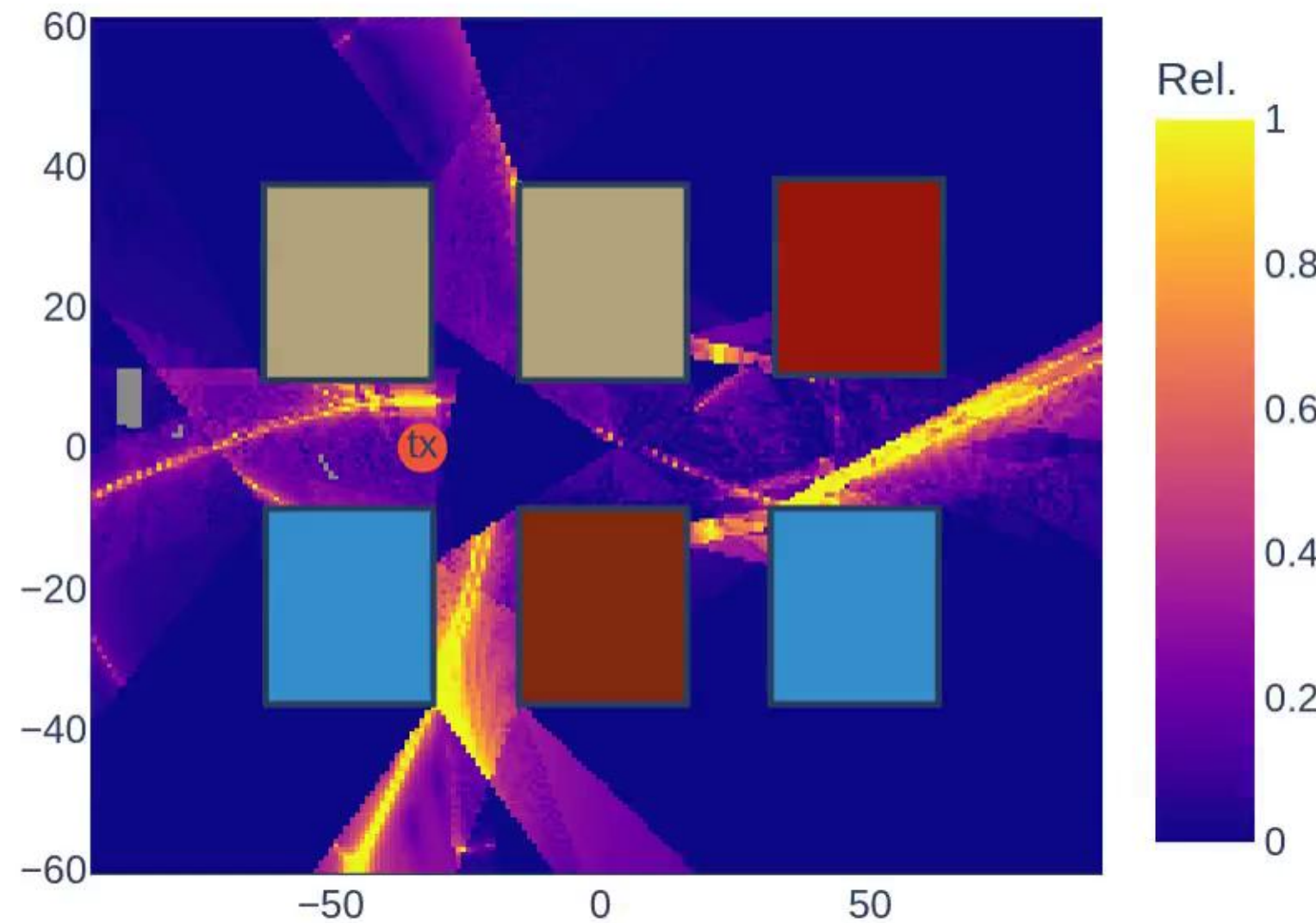
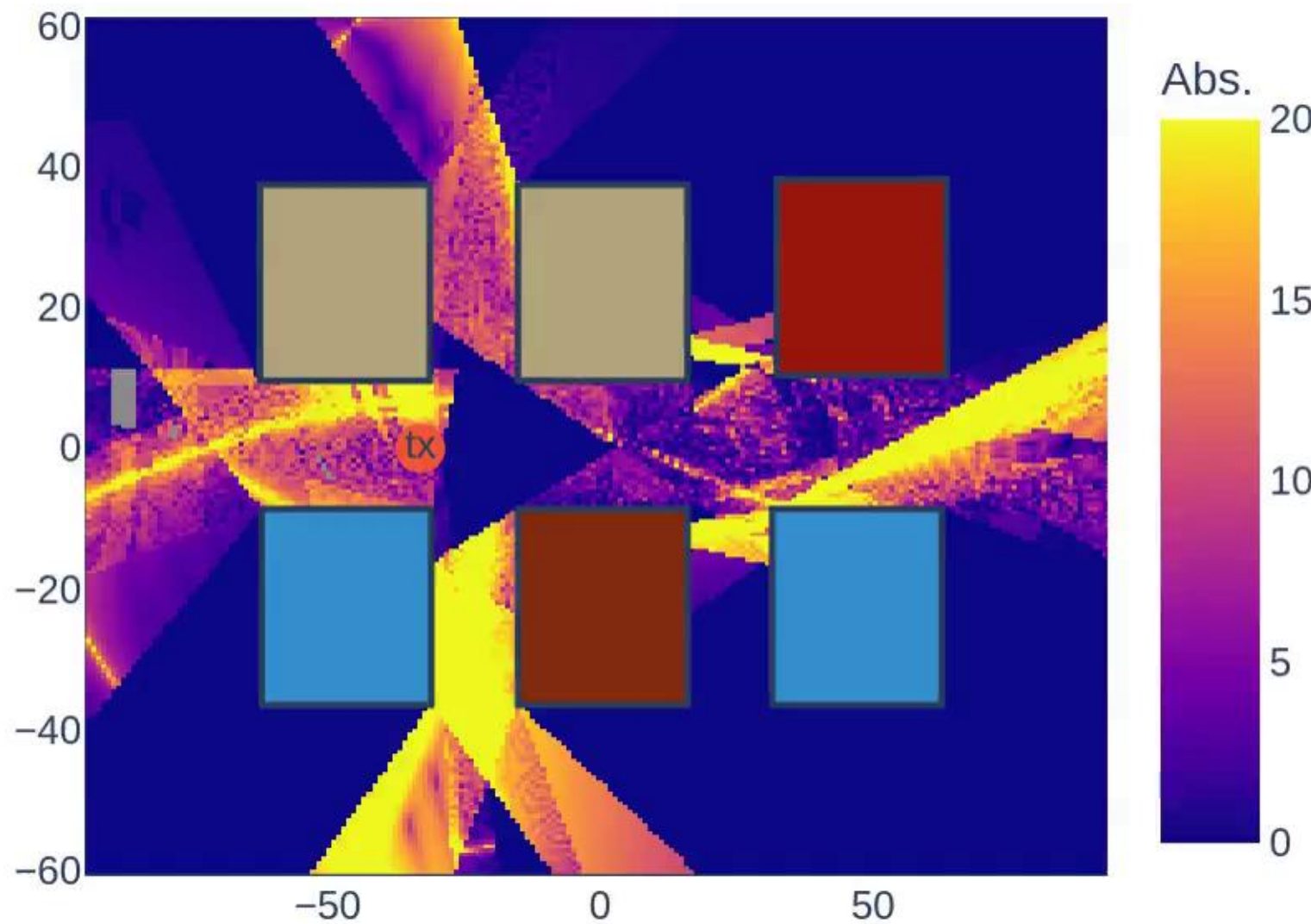
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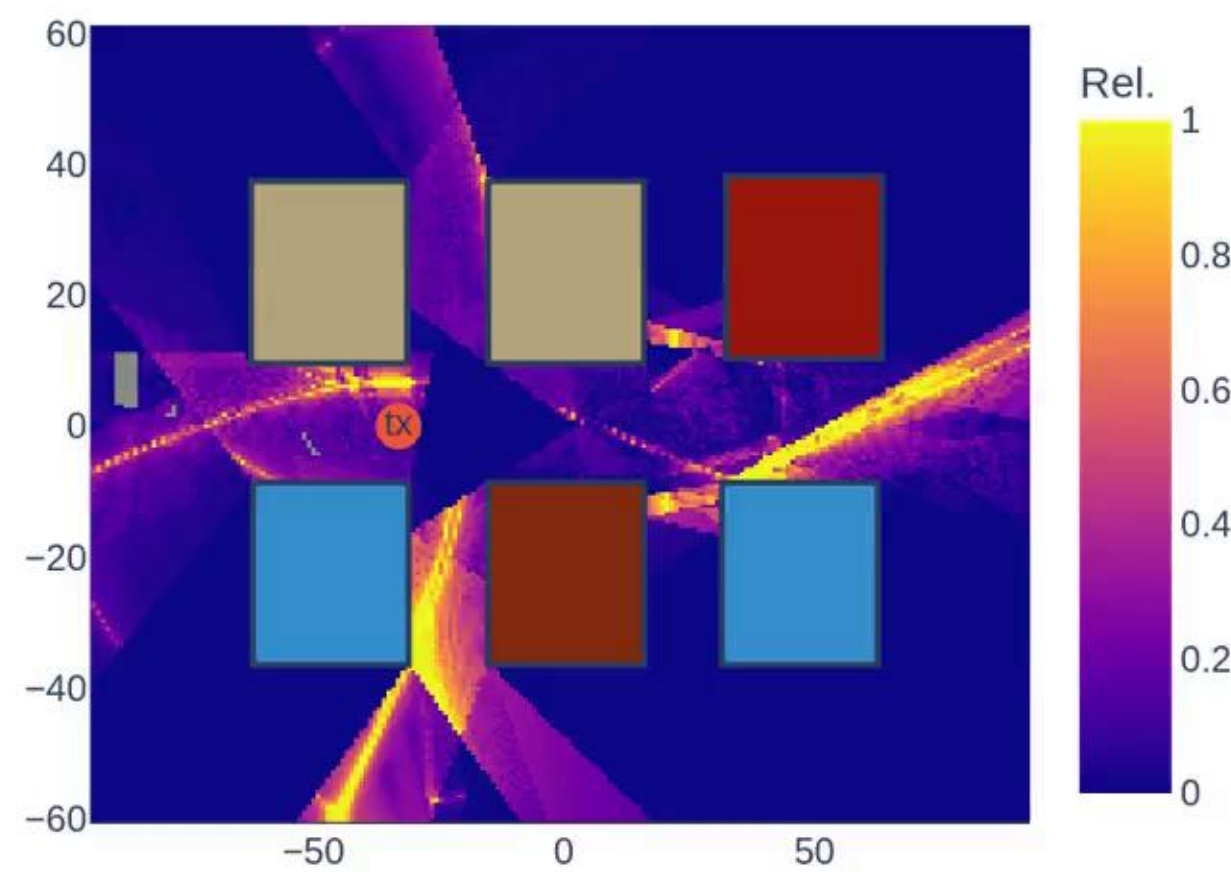
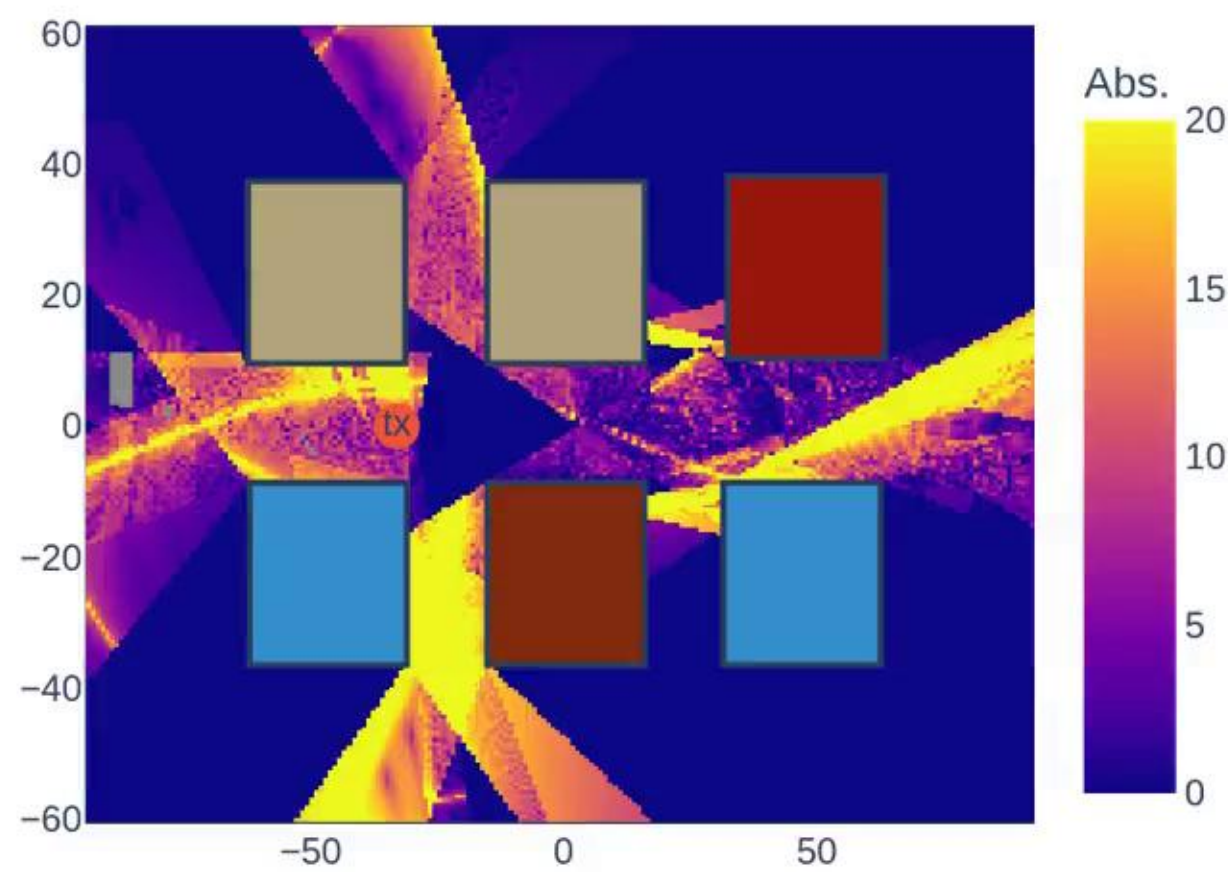
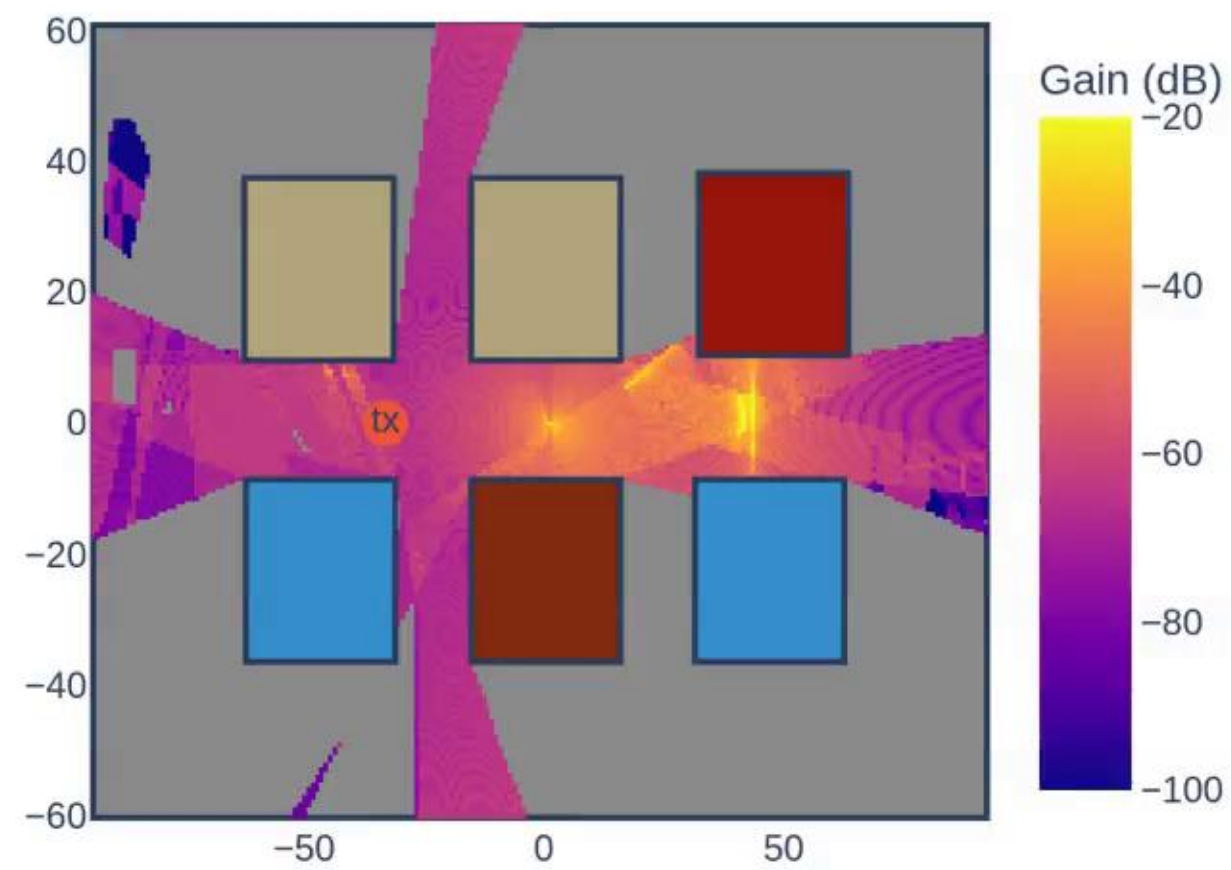
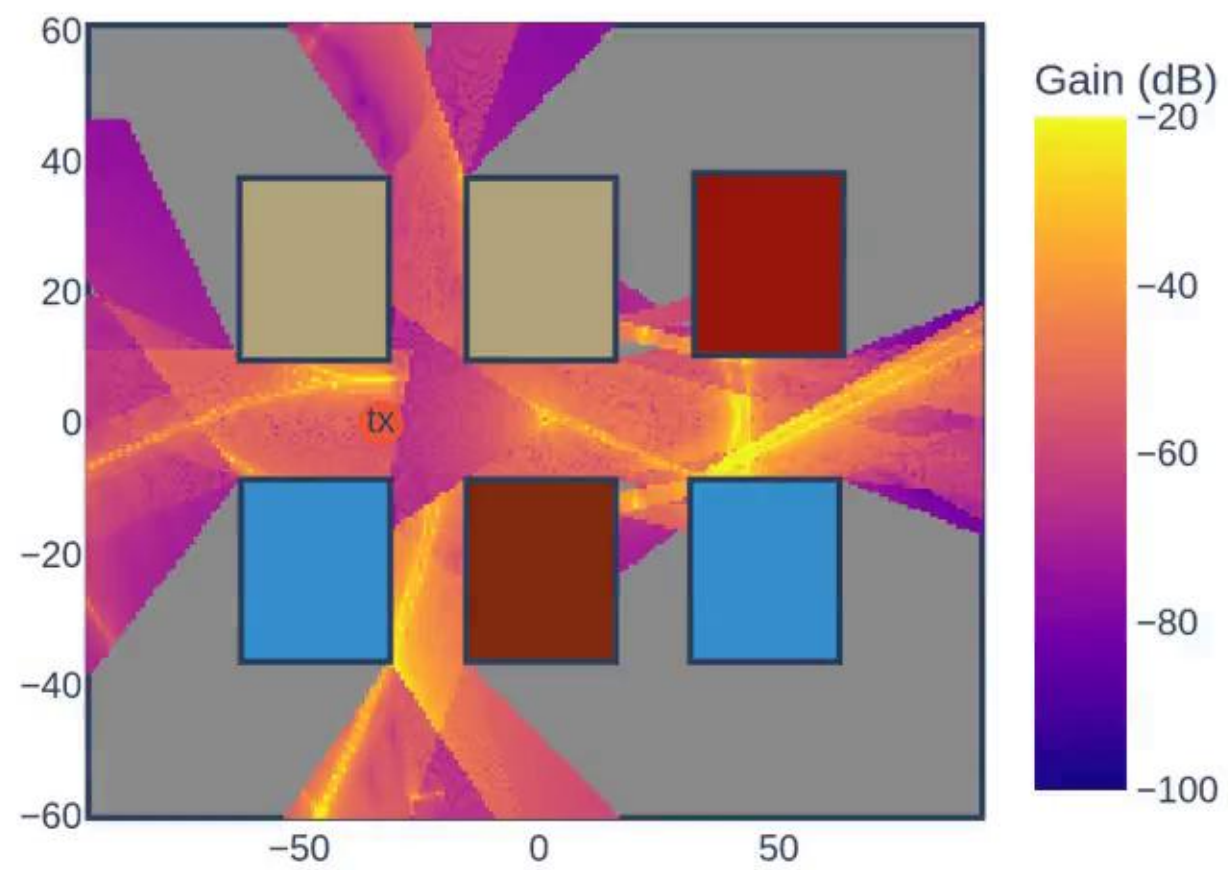
Hit rate: % of *different* valid rays found over the total number of existing valid rays







$$\delta P_{\text{dB}} = 10 |\log_{10} (P_{\text{GT}} + \epsilon) - \log_{10} (P_{\text{pred}} + \epsilon)| \quad \text{and} \quad \delta P_{\text{r,dB}} = \frac{|\log_{10} (P_{\text{GT}} + \epsilon) - \log_{10} (P_{\text{pred}} + \epsilon)|}{|\log_{10} (P_{\text{GT}} + \epsilon)|}$$



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- First application of our model to EM fields prediction
- Preliminary results show a not-so-good match between hit rate and good coverage map
- ML model cannot (yet) replace exhaustive RT
- EM coverage map analysis could help us improve the model

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- Train on more diverse and complex scenes
- Compare coverage maps generated with and without the model
- Evaluate actual computation gains
- Study non-sparse reward functions



Interactive tutorial



jeertmans/DiffeRT

Slides made with Manim Slides, free and open source tool.