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

Enrico Maria Vitucci - June 23-27, Bologna

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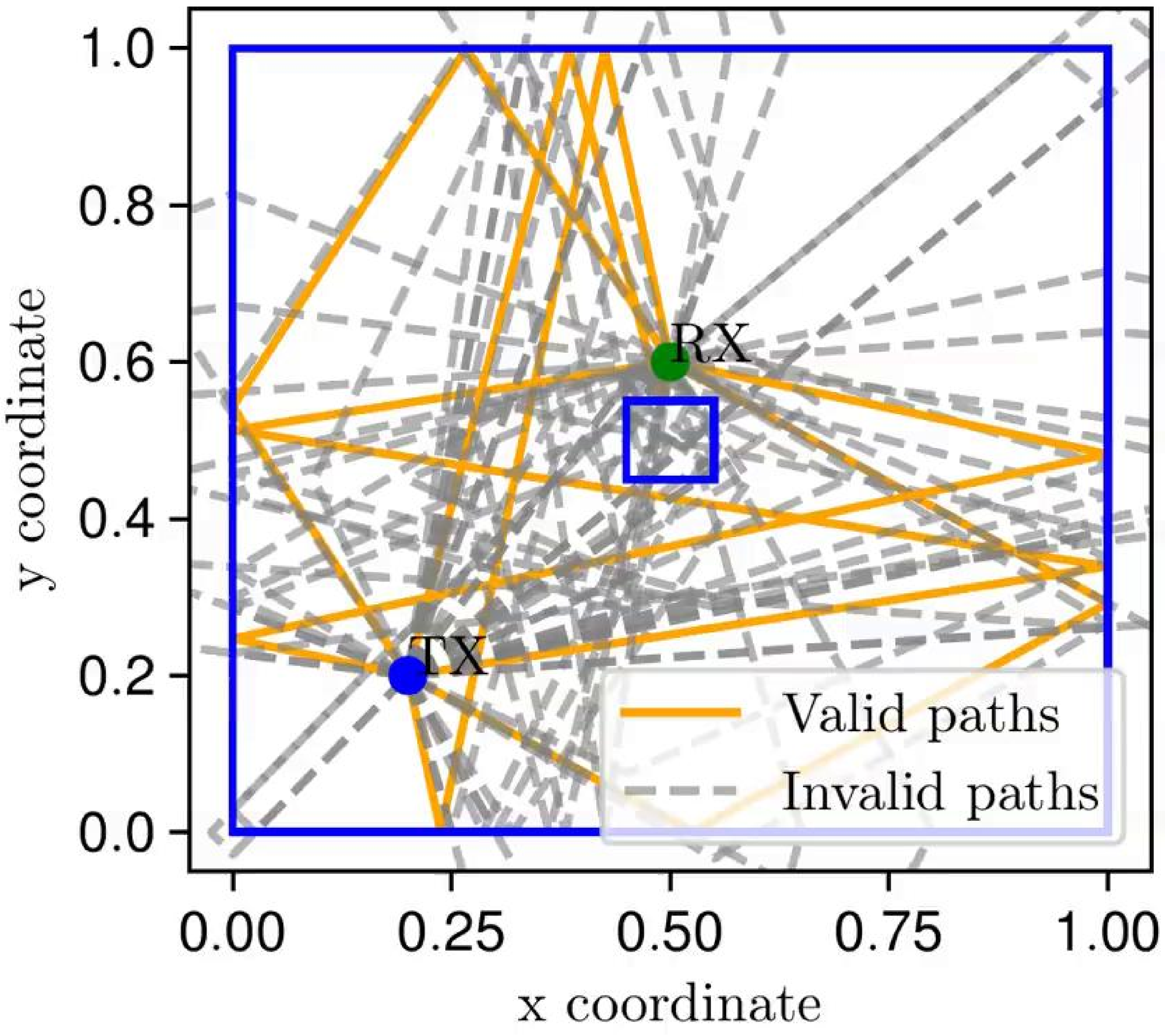
	Point-to-Point (P2P) Ray Tracing (RT)	**Ray Launching (RL)**
Complexity	Exponential	Linear*
Accuracy	Excellent	Good*
Best for	P2P scenarios	Coverage map

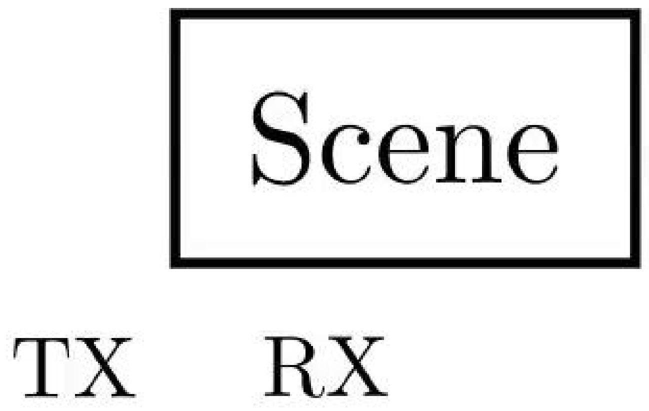


1.0
0.8
0.6
0.4
0.2
0.0
y coordinate
0.00
0.25
0.50
0.75
1.00
x coordinate
RX
TX
Valid paths
Invalid paths

$\boxed{\text{Scene}}$

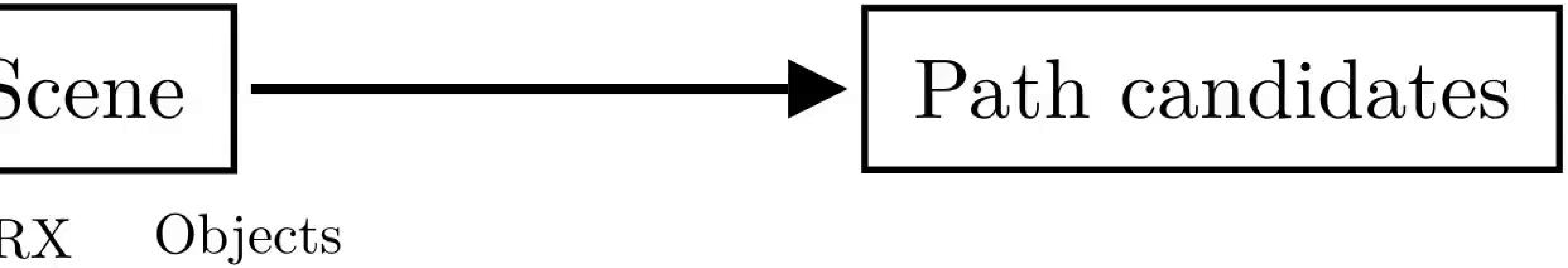
Scene

TX


Scene
TX
RX

Scene

TX RX Objects


Scene
Path candidates
RX
Objects

ates $\dashrightarrow$ paths for order N

ates

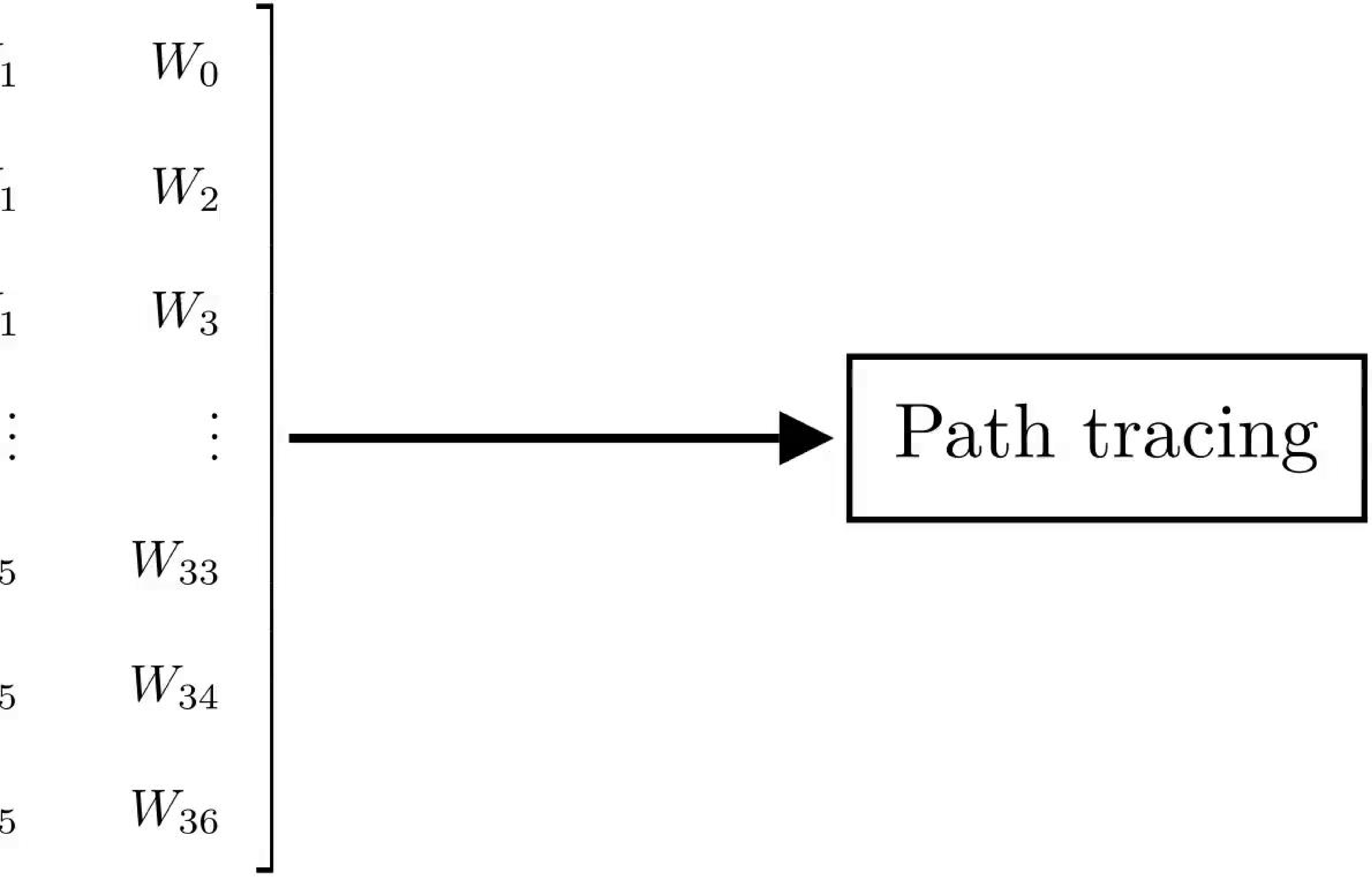
$$\begin{bmatrix} W_0 \\ W_1 \\ W_2 \\ \vdots \\ W_{34} \\ W_{35} \\ W_{36} \end{bmatrix}$$

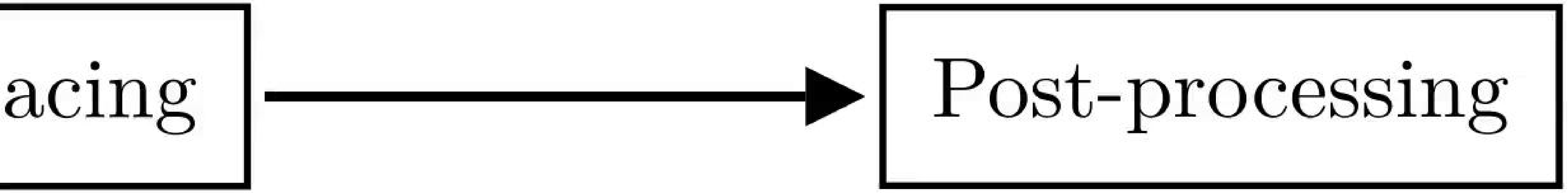
ates

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

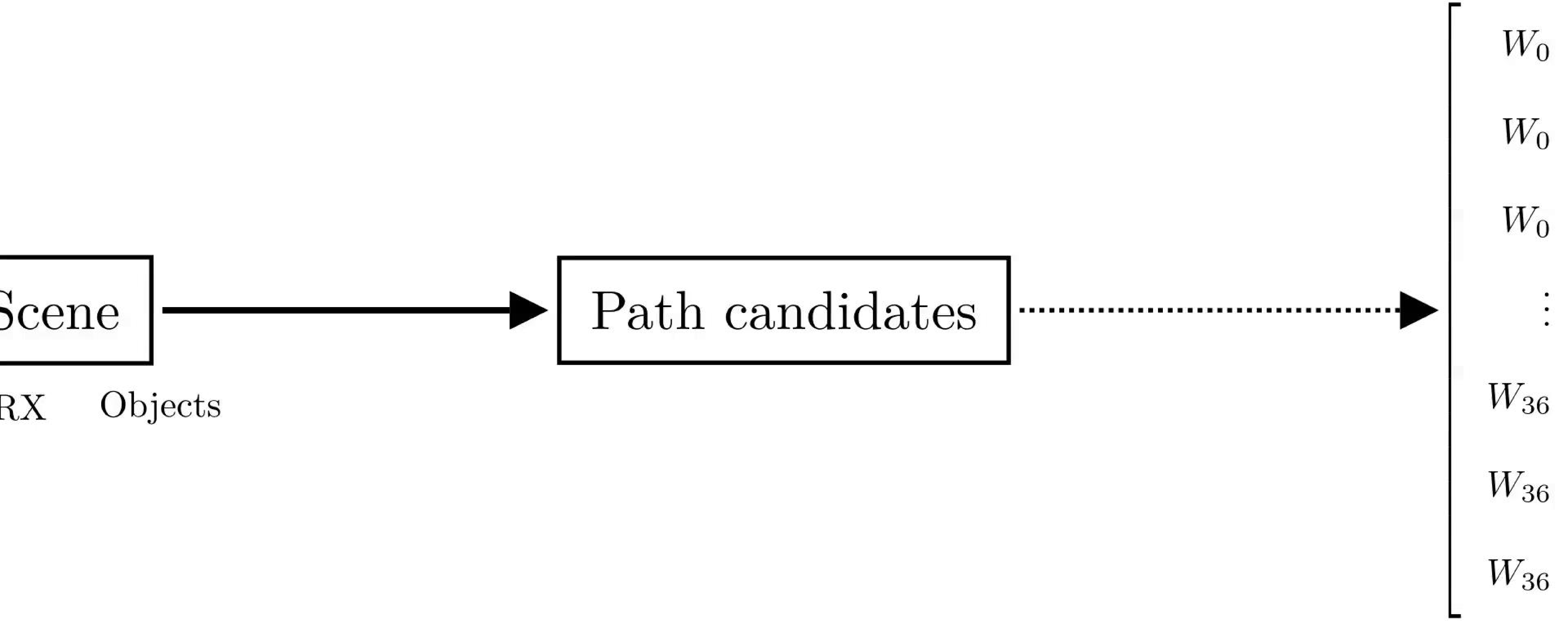
ates

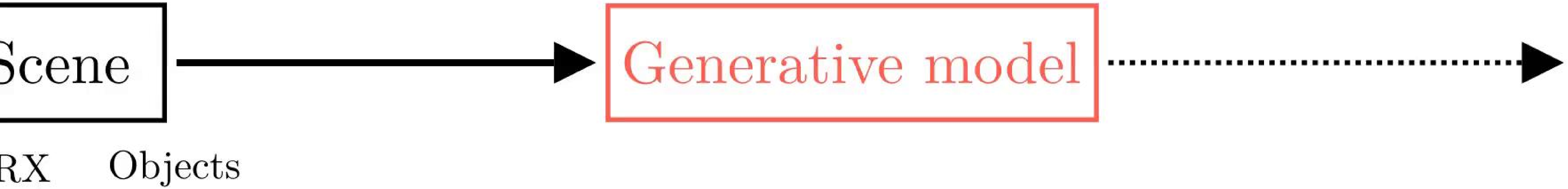
$$\begin{bmatrix} W_0 & W_1 & W_0 \\ W_0 & W_1 & W_2 \\ W_0 & W_1 & W_3 \\ \vdots & \vdots & \vdots \\ W_{36} & W_{35} & W_{33} \\ W_{36} & W_{35} & W_{34} \\ W_{36} & W_{35} & W_{36} \end{bmatrix}$$

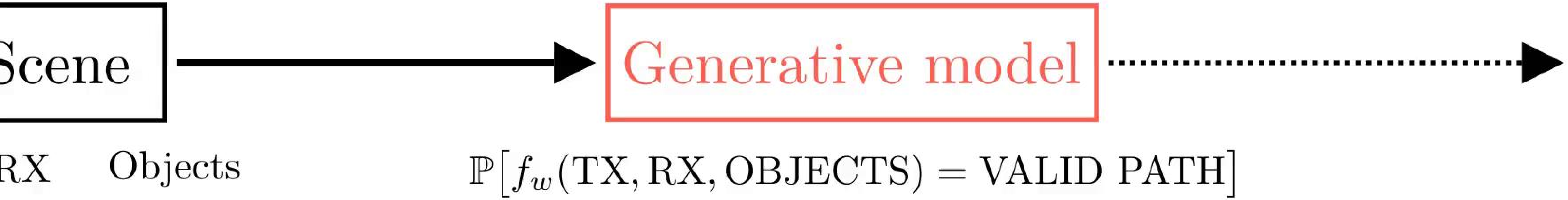

W_0
W_2
W_3
$\vdots$
W_{33}
W_{34}
W_{36}
Path tracing


acing
Post-processing


rocessing
EM fields


Scene
RX
Objects
Path candidates
W_0
W_0
W_0
$\vdots$
W_{36}
W_{36}
W_{36}


Scene
Generative model
RX
Objects


Scene
Generative model
RX
Objects
$\mathbb{P}\big[f_w(\mathrm{TX}, \mathrm{RX}, \mathrm{OBJECTS}) = \mathrm{VALID\ PATH}\big]$


nodel
Path
= VALID PATH]

model

= VALID PATH]

$$\begin{bmatrix} W_2 \\ W_{31} \\ W_{23} \end{bmatrix}$$

Path

nodel

= VALID PATH]

$$\begin{bmatrix} W_4 & W_{10} \\ W_{19} & W_5 \\ W_{33} & W_6 \end{bmatrix}$$

Path

nodel

= VALID PATH]

$$\begin{bmatrix} W_2 & W_5 & W_7 \\ W_3 & W_0 & W_4 \\ W_{10} & W_6 & W_{17} \end{bmatrix}$$

Path

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:

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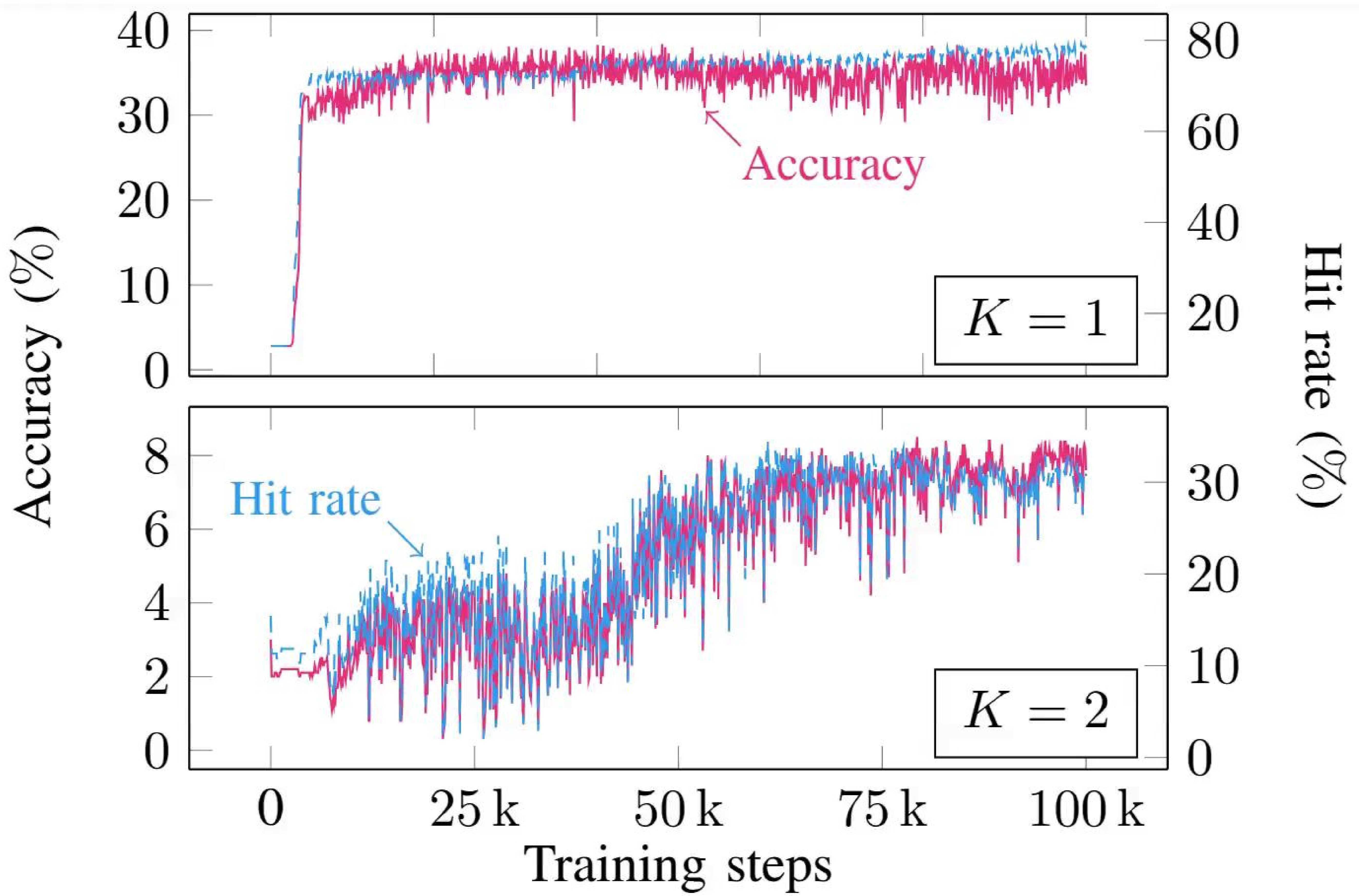
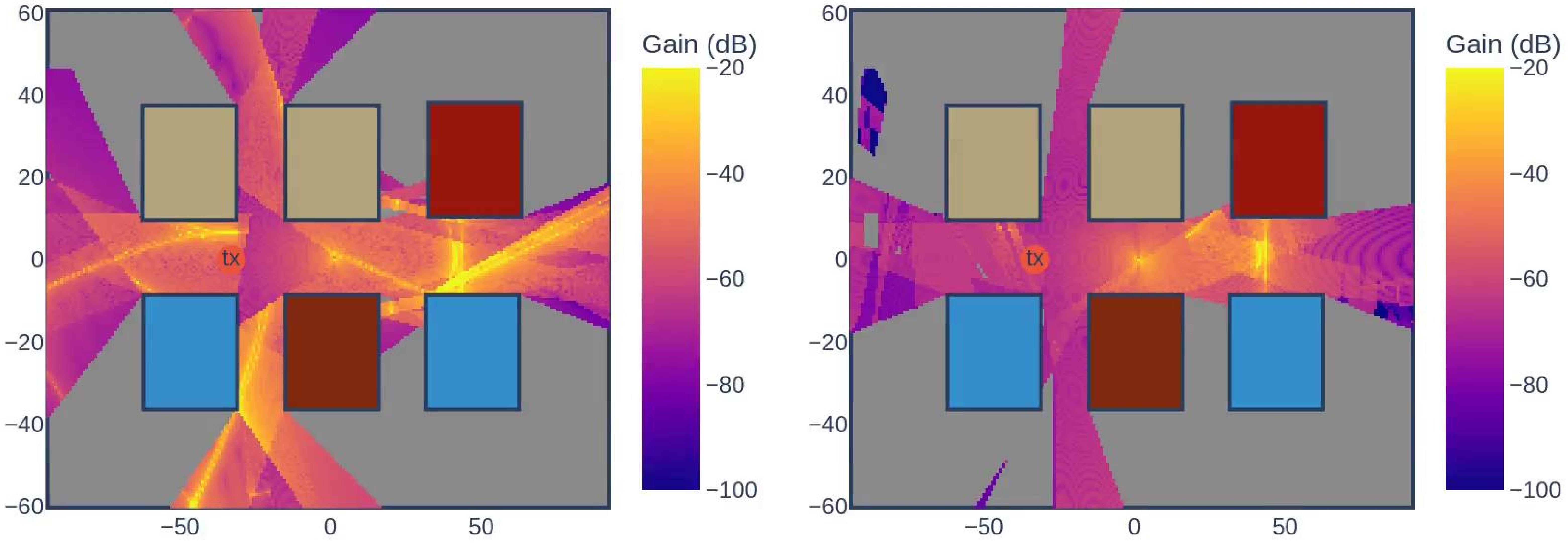
What we would like to maximize:

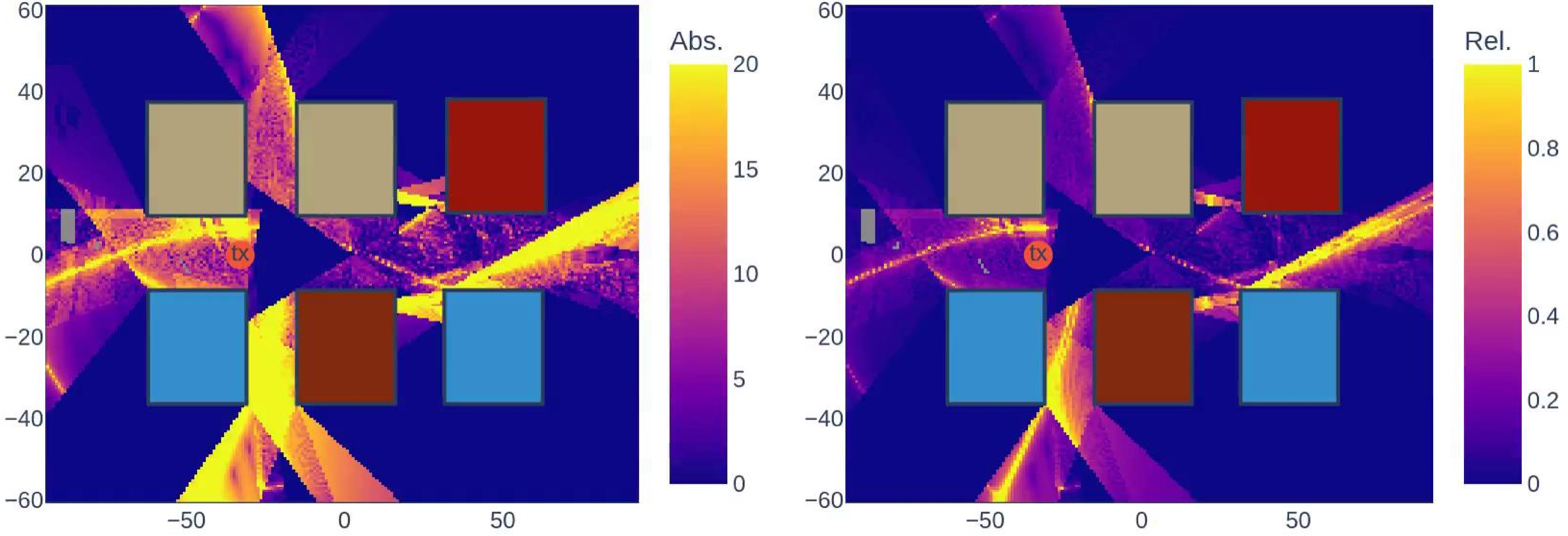
Hit rate: % of *different* valid rays found over the total number of existing valid rays



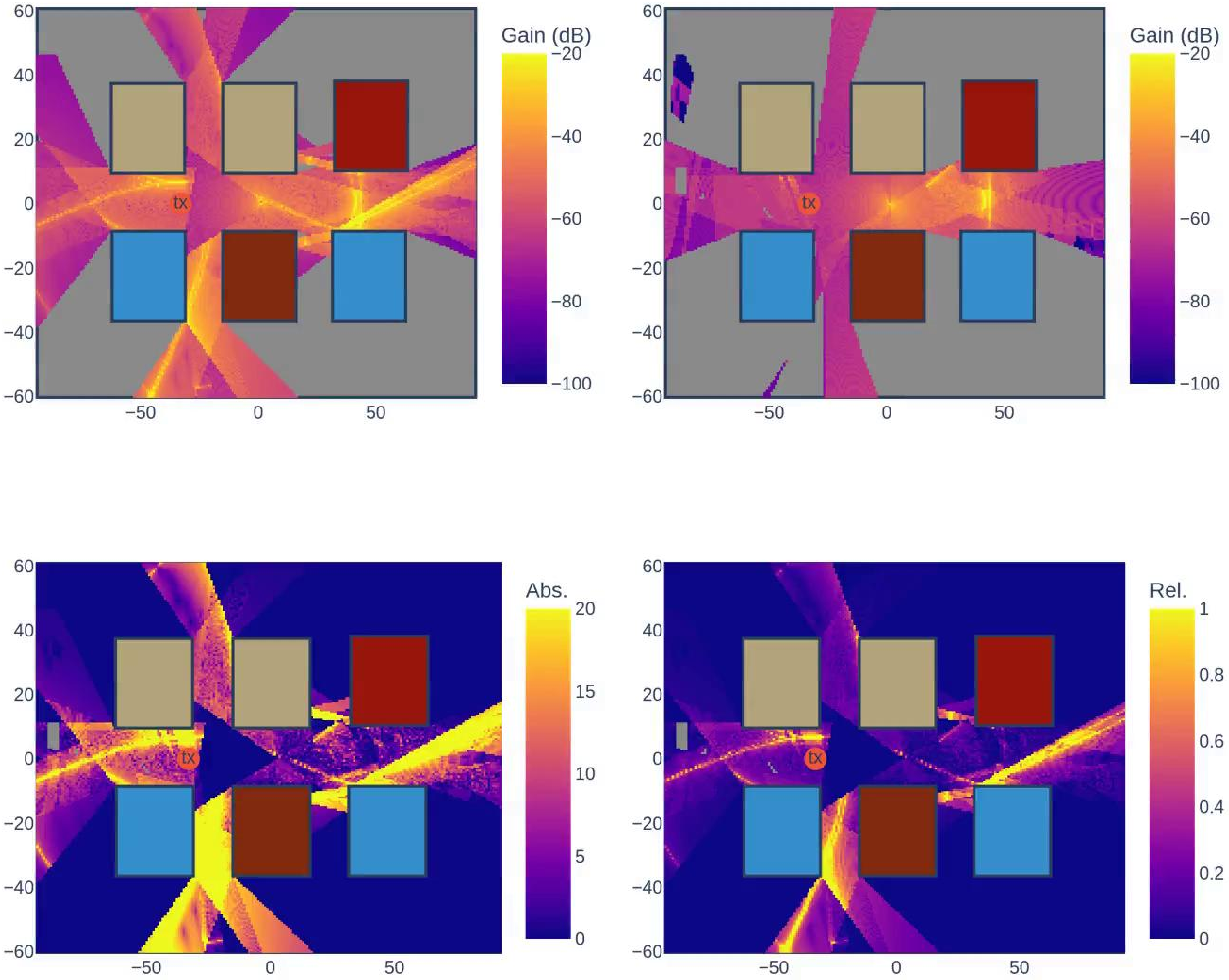
Accuracy
Hit rate
$K = 1$
$K = 2$
Accuracy (%)
Hit rate (%)
Training steps
0
25 k
50 k
75 k
100 k



Gain (dB)
−20
−40
−60
−80
−100
tx
60
40
20
0
−20
−40
−60
−50
0
50
Gain (dB)
−20
−40
−60
−80
−100
tx
60
40
20
0
−20
−40
−60
−50
0
50



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



Gain (dB)
Gain (dB)
Abs.
Rel.
tx

Summary:

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- 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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- 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.