NeRF^2: Neural Radio-Frequency Radiance Fields

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(paper review)

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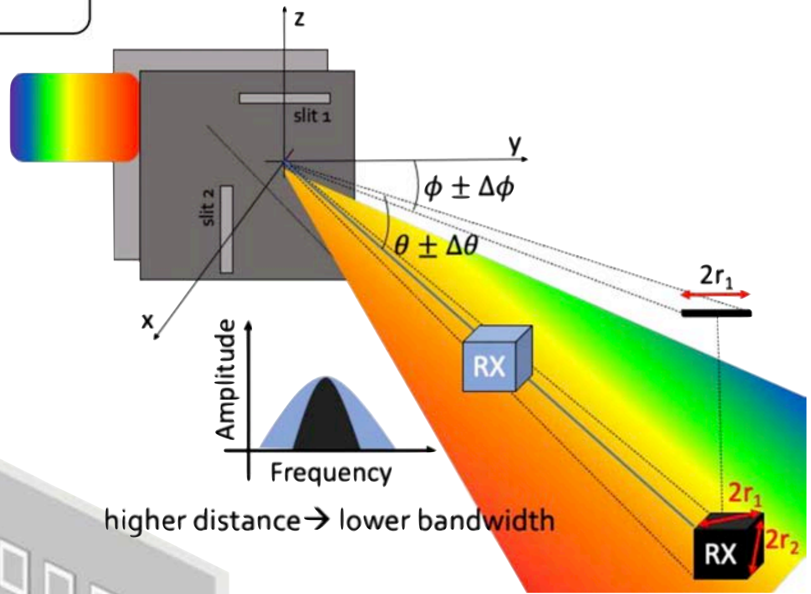
Modeling Radio Frequency (RF) Propagation

- Uplink channel modeling/prediction using downlink info

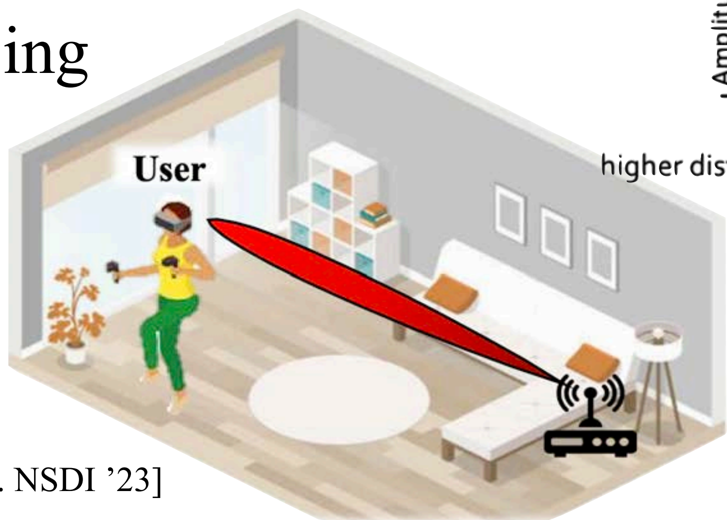
Channel at Band 1 → Paths along which signal is received → Channel at Band 2

[Vasisht, et al. SIGCOMM ’16]

- Indoor localization and sensing
- 5G beamforming

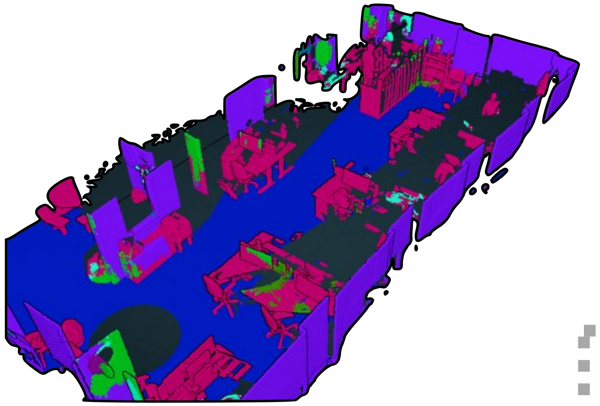


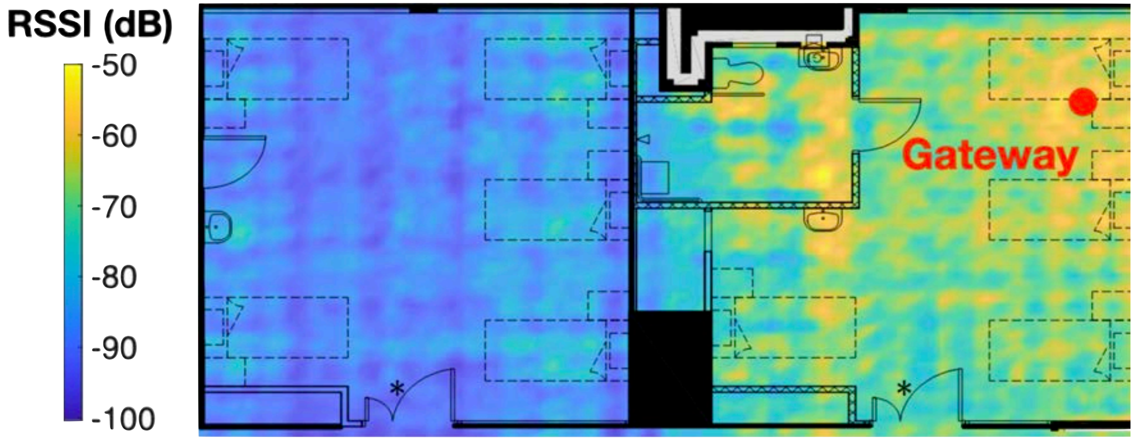
[Kludze, et al. MobiCom ’22]



[Cho, et al. NSDI ’23]

Conventional Methods



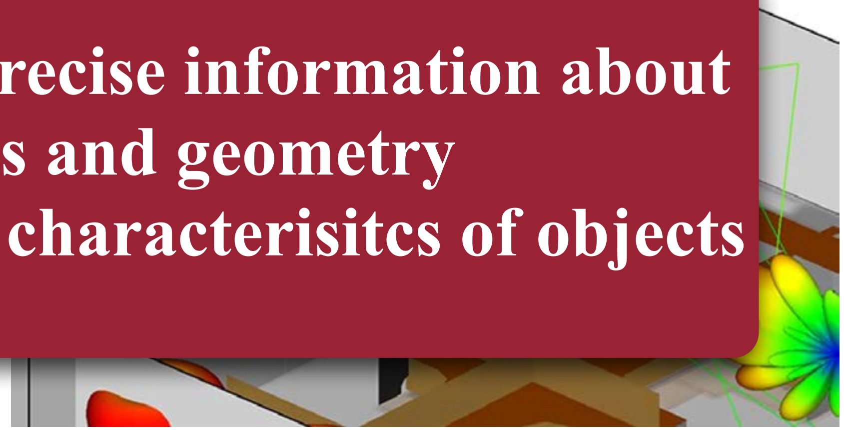


TX position

Ray config

Statistical/generative models

Electromagnetic (EM) ray tracing

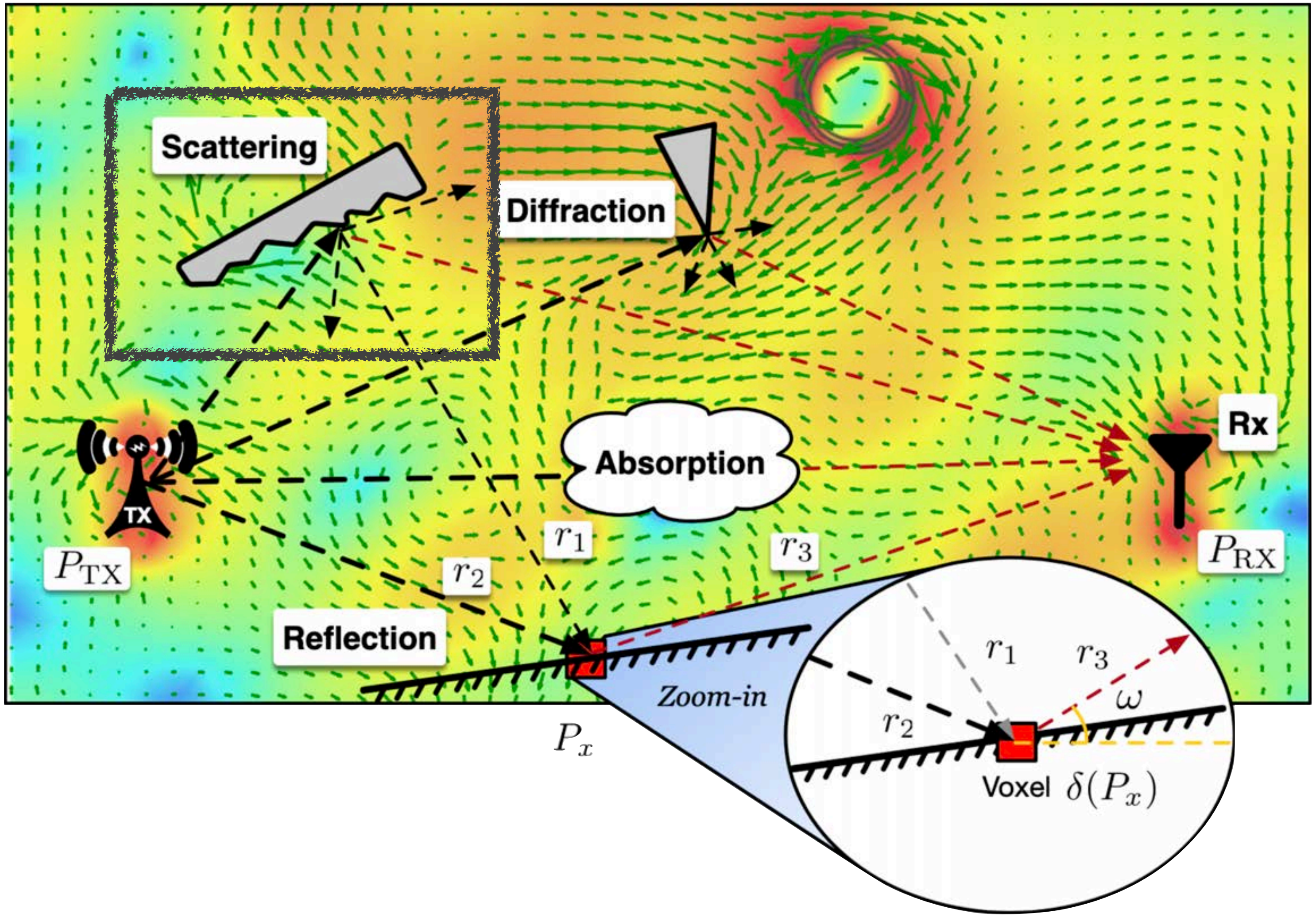


[Image source: Remcom]

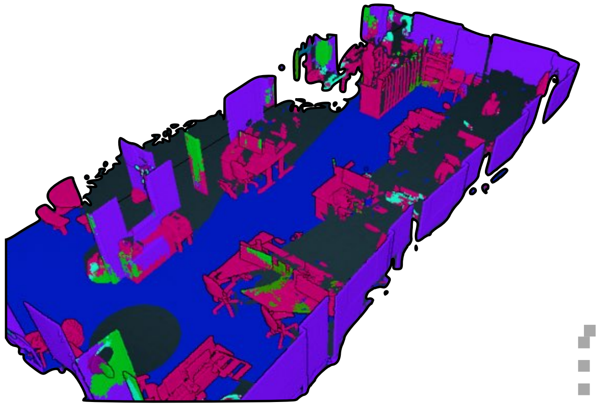
Requires precise information about

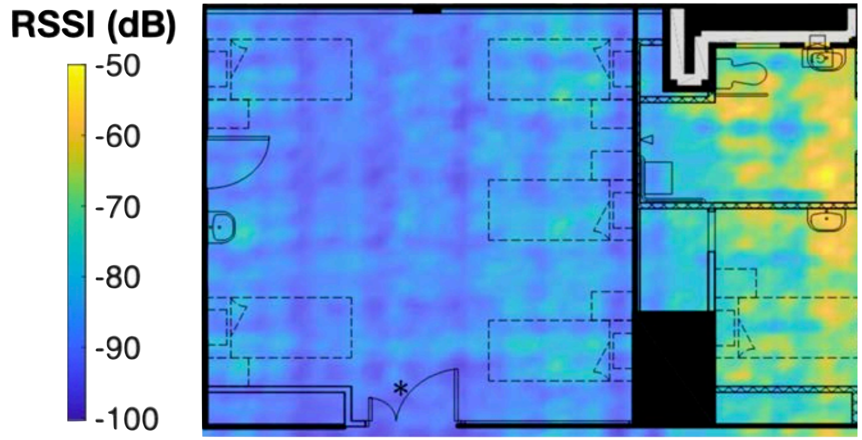
- Materials and geometry
- Physical characterisitcs of objects

Complexity of RF Radiance Field



Proposed Approach





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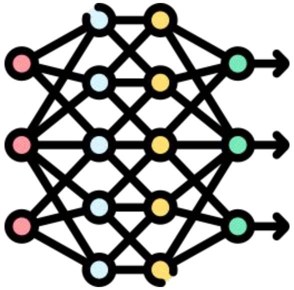
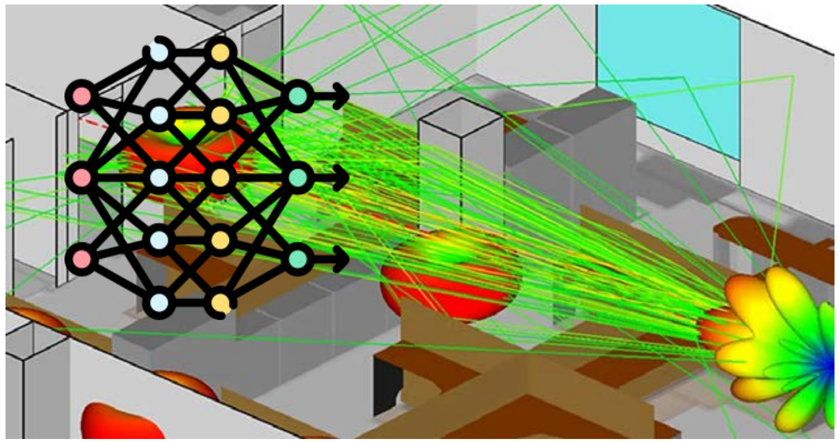
Statistical/generative models



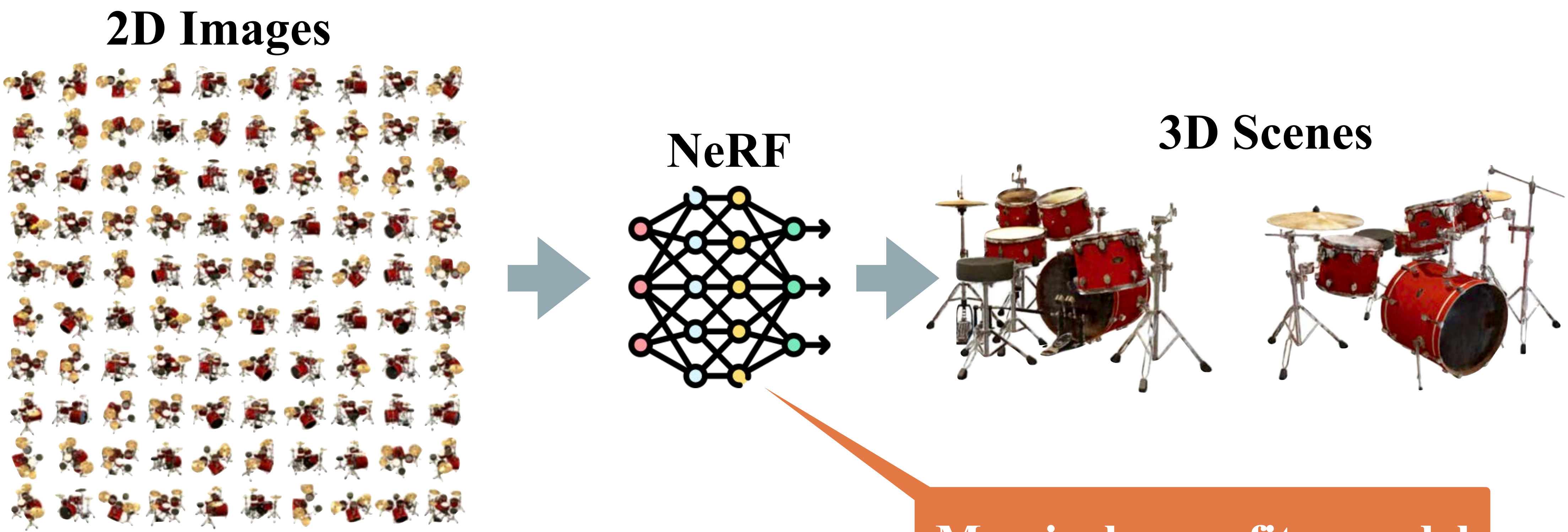
OR

Electromagnetic (EM) ray tracing



[Image source: Remcom]

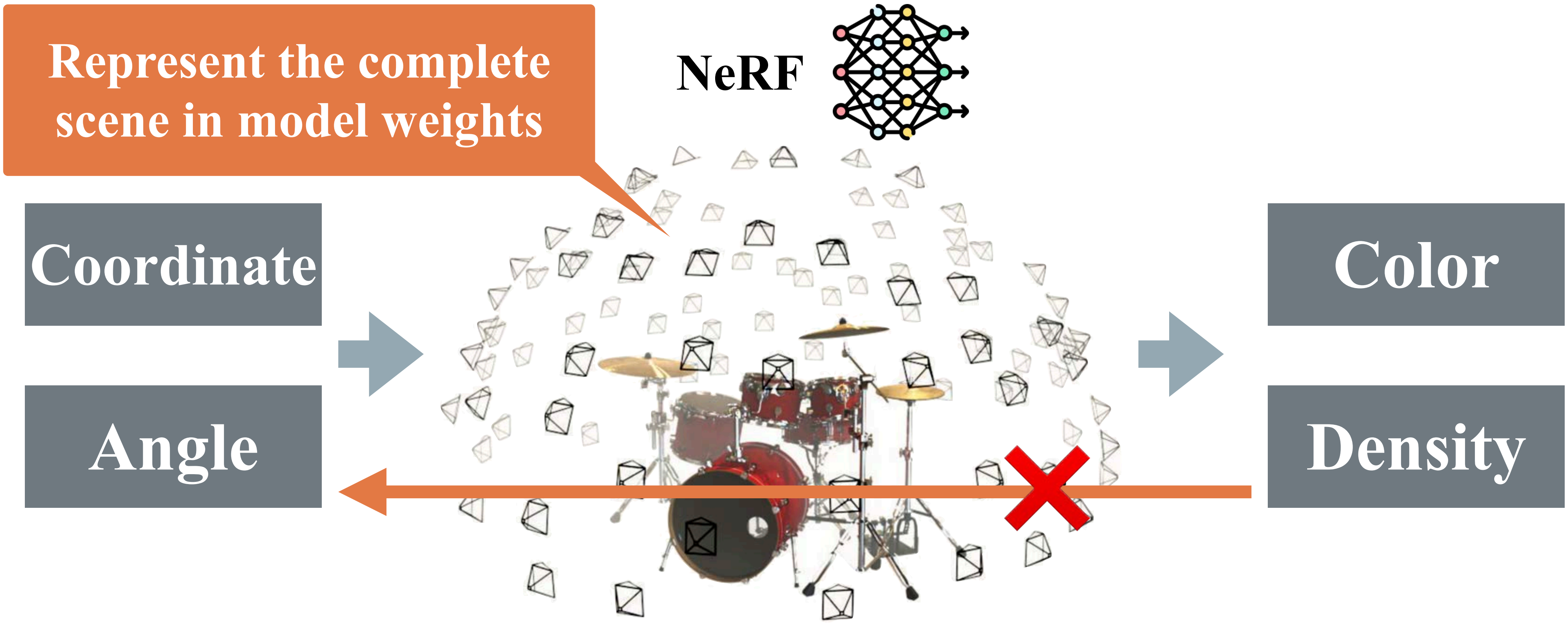
NeRF: Representing Scenes as Neural Radiance Fields



Massively overfit a model for a specific scene

[Mildenhall et al. ECCV ’20]

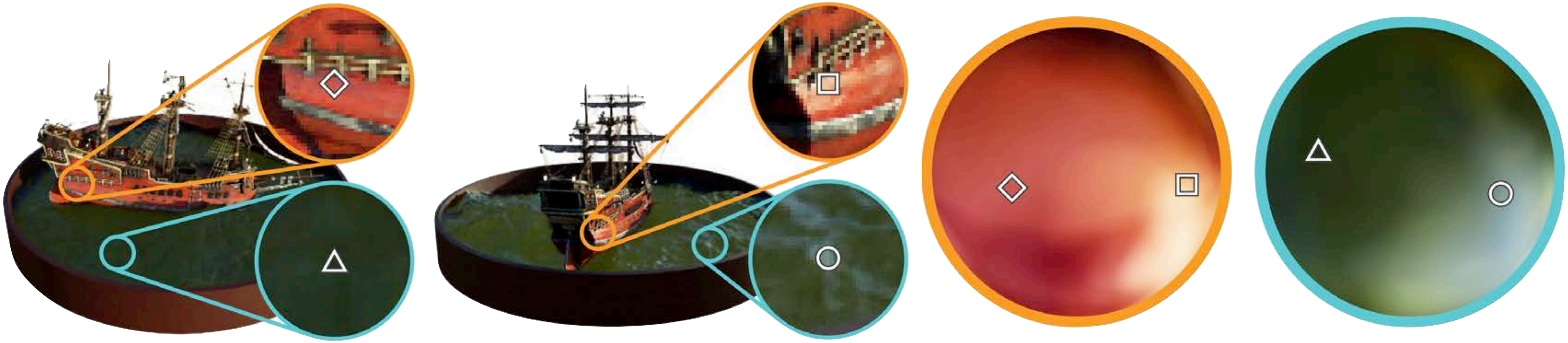
NeRF: Representing Scenes as Neural Radiance Fields



[Mildenhall et al. ECCV ’20]

View-dependent Color Density

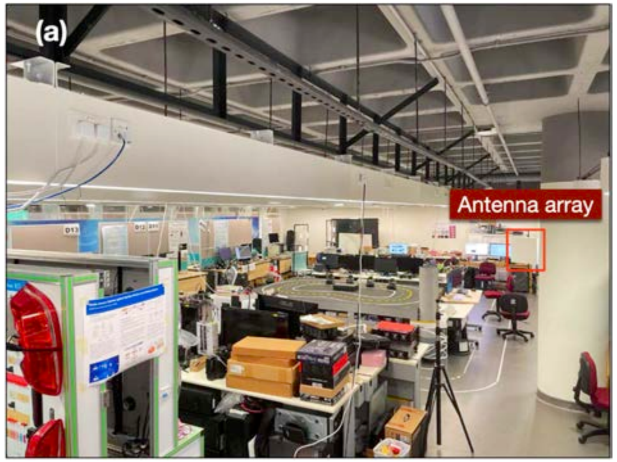
Neural radiance field—NeRF:

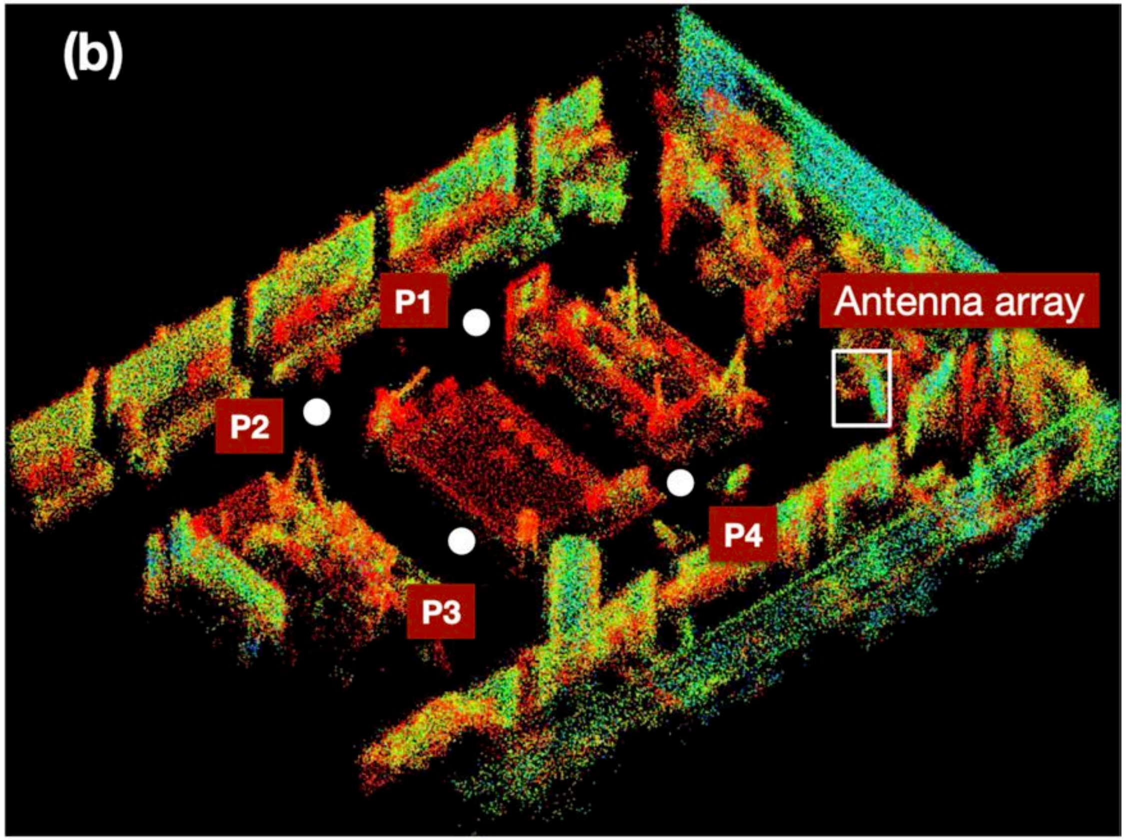


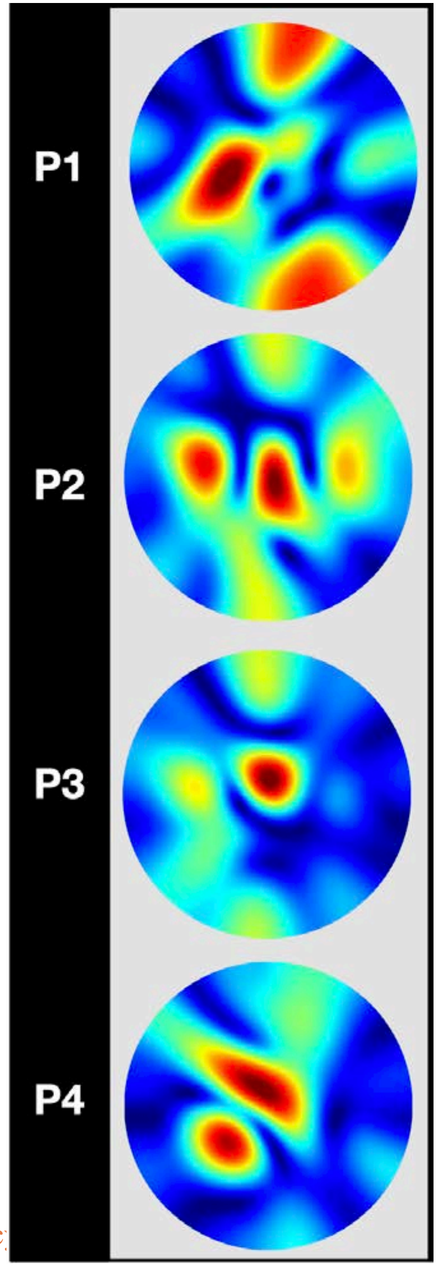
(a) View 1 (b) View 2 (c) Radiance Distributions

[Mildenhall et al. ECCV ’20]

"View"-dependent Spatial Spectrums

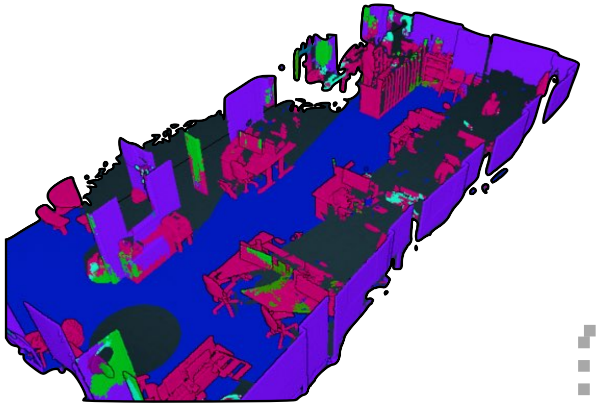






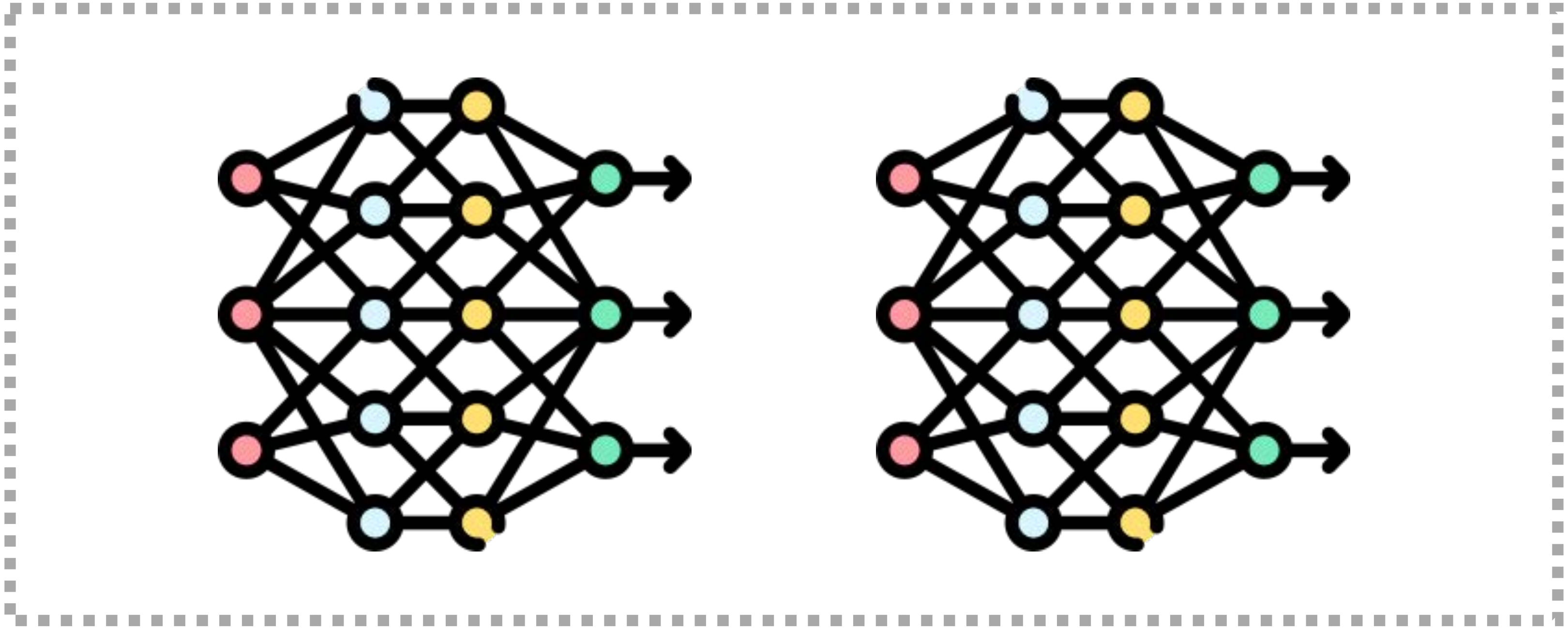
NeRF^2 Design

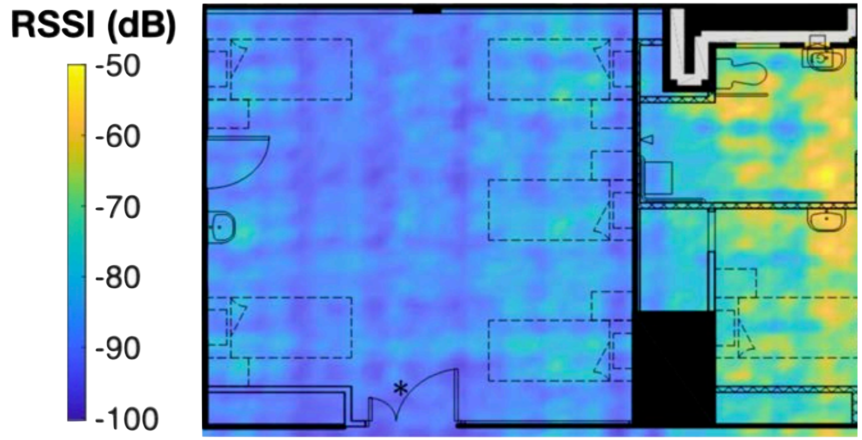
Proposed Approach



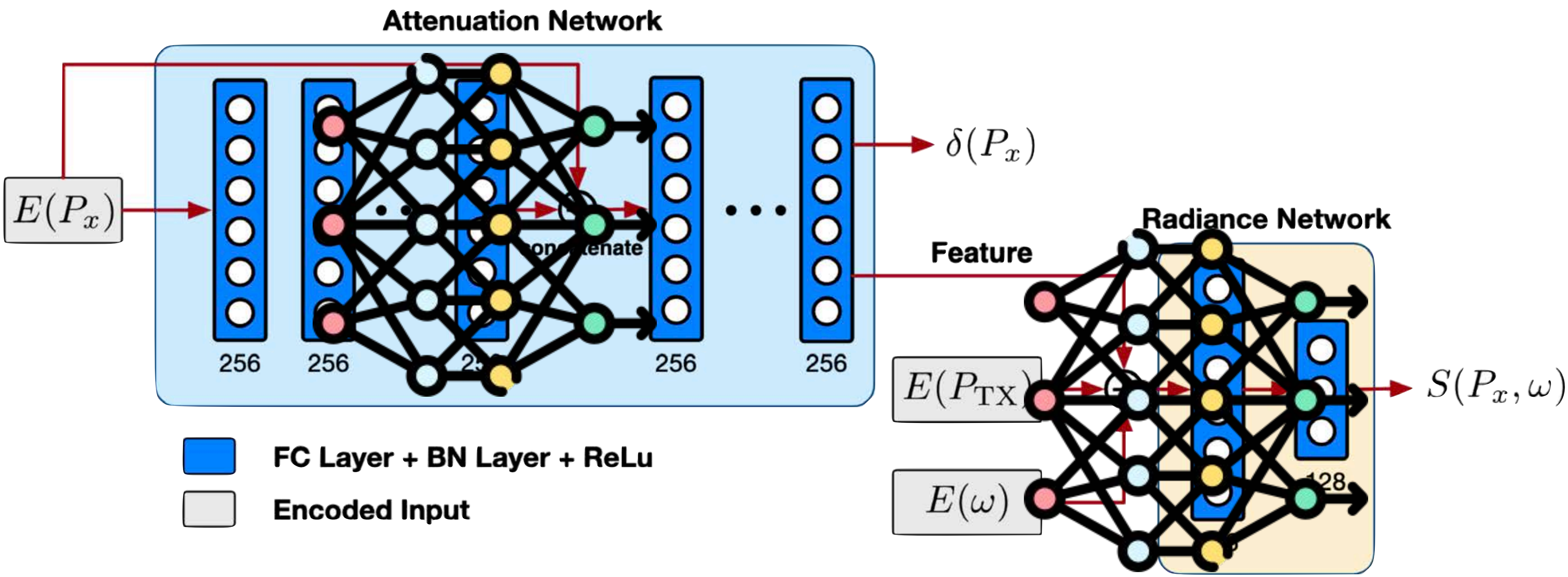
TX position

Ray config

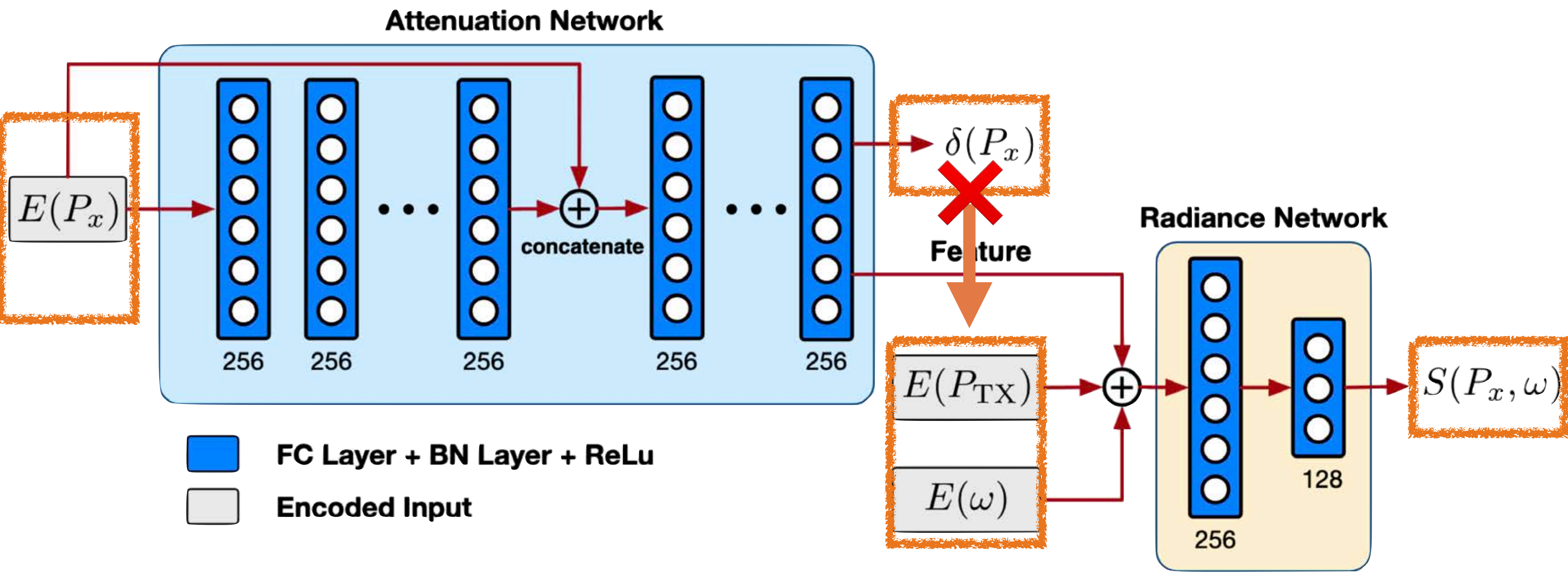




Neural Radiance Network for RF Propagation



Neural Radiance Network for RF Propagation

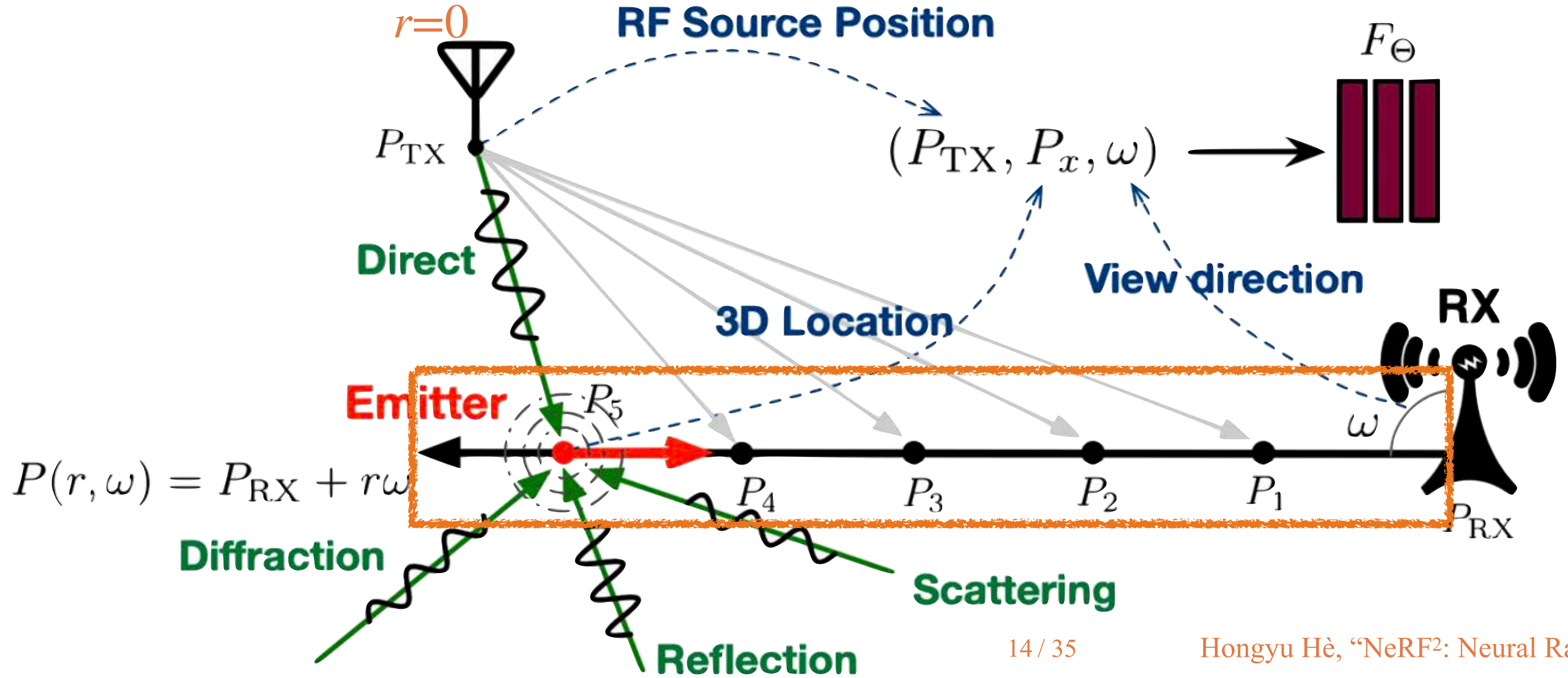


$$\mathbf{F}_\Theta : (P_x, P_{\mathrm{TX}}, \omega) \rightarrow \big(\delta(P_x), S(P_x, \omega)\big)$$

EM Ray Tracing (Using F_Θ)

- RX receives $R = H_{\mathrm{TX}\to\mathrm{RX}} \cdot S = \boxed{(a}_{\mathrm{TX}\to\mathrm{RX}}\boxed{e^{J\theta_{TX\to RX}})} \cdot \boxed{S}$ (Friis eq.)
- Accumulated power from voxels $P_i(r, \omega)$ along the ray to $P_{\mathrm{RX}}(0,\omega)$:

$$R(\omega) = \sum_{r=0}^{D} H_{P(r,\omega)\to P_{RX}} \cdot S(P(r,\omega), \boxed{-\ \omega})$$



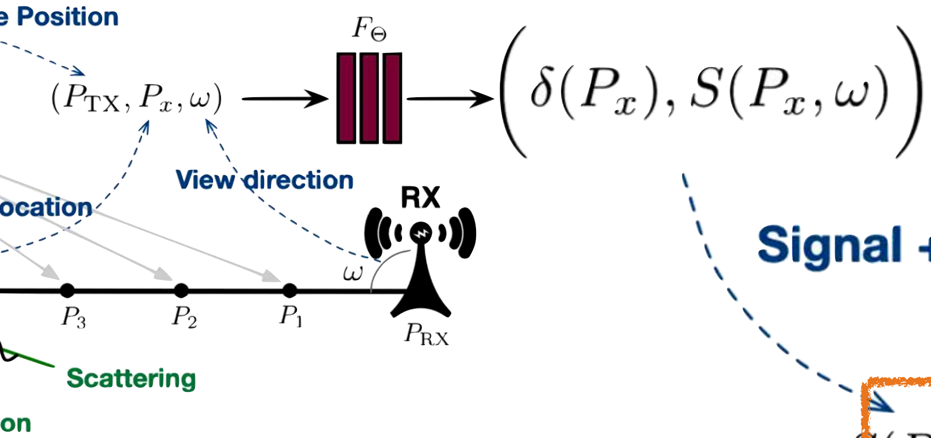
EM Ray Tracing (Using F_Θ)

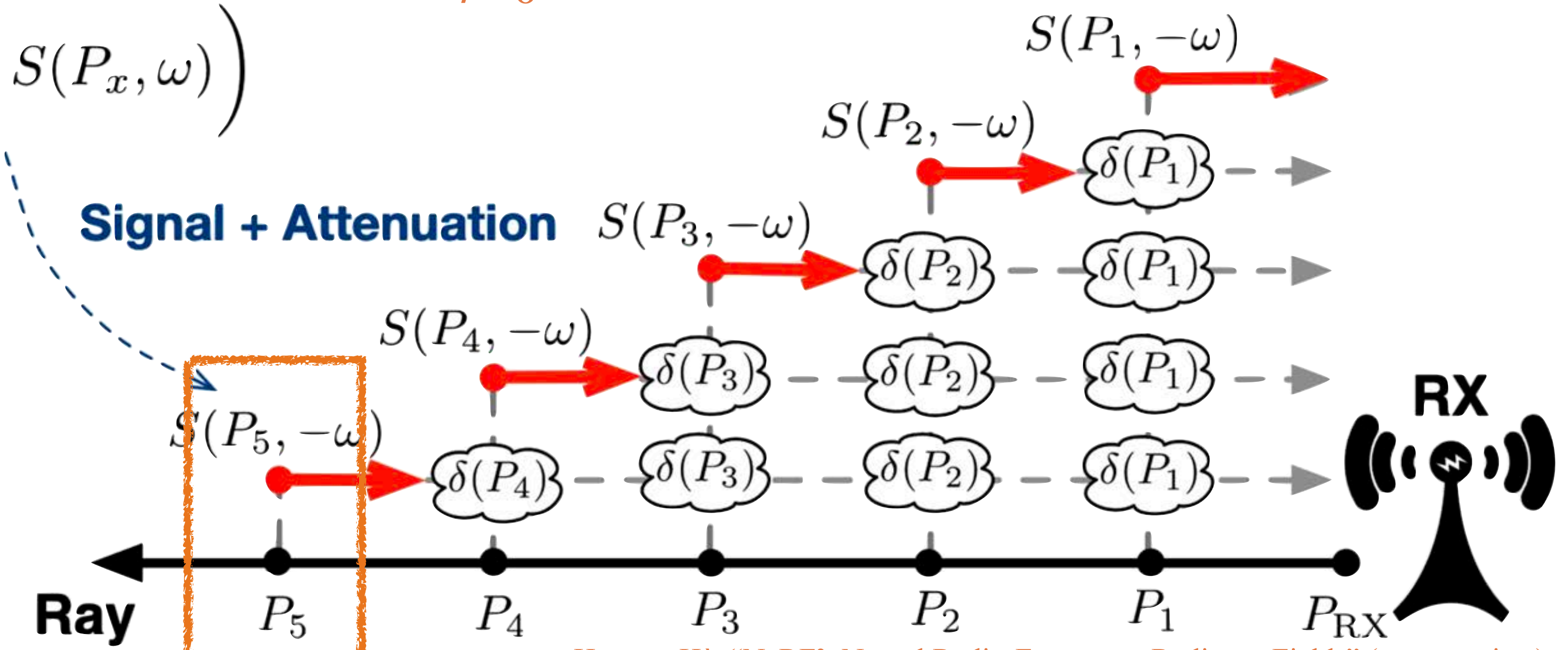
$$R(\omega) = \sum_{r=0}^{D} \boxed{H_{P(r,\omega)\rightarrow P_{RX}}} \cdot S(P(r,\omega), -\omega)$$

$\mathcal{O}(N^2)$

Individual Attenuation $H_{P(r,\omega)\rightarrow P_{RX}} = \prod_{r=0}^{r} \Delta a_{P(r,\omega)} \cdot e^{\mathrm{J}\Delta\theta_{P(r,\omega)}}$

$\boxed{\delta\left(P(r,\omega)\right)}$





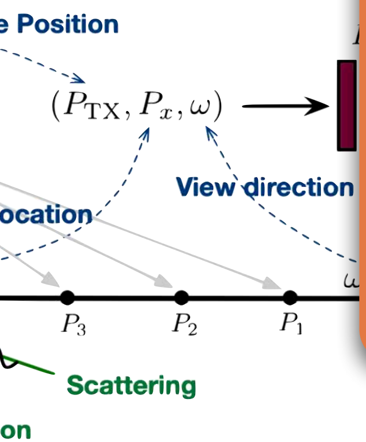
EM Ray Tracing (Using F_Θ)

$$R(\omega) = \sum_{r=0}^{D} \boxed{H_{P(r,\omega)\to P_{RX}}} \cdot S(P(r,\omega), -\omega)$$

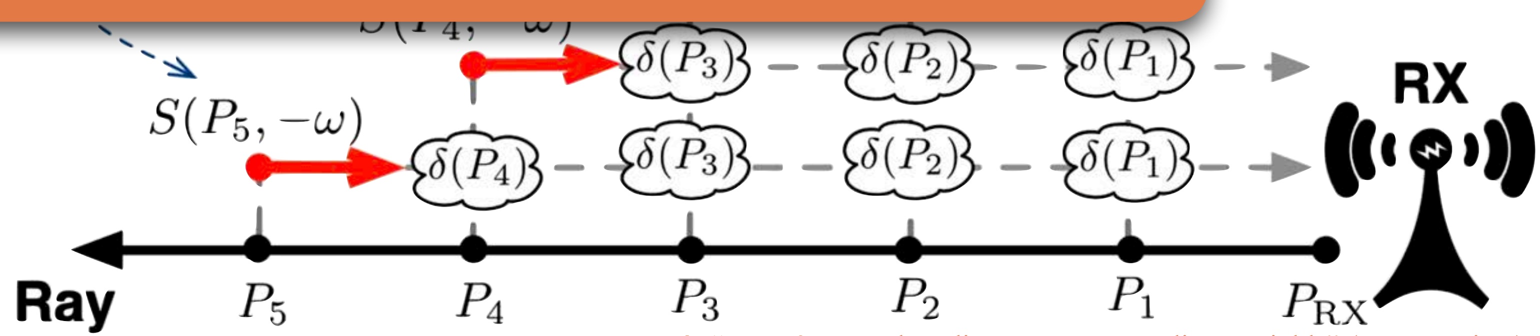
$\mathcal{O}(N^2)$

$\boxed{\delta\left(P(r,\omega)\right)}$

Individual Attenuation H $= \prod^{r} \Delta a \cdots e^{J\Delta\theta_{P(r,\omega)}}$



NeRF²
≈ Physical model parameterized by ML models
(“Physics-informed ML methods”)



Two Antenna-specific Training Methods

- Single/omnidirectional RX antenna (gain G_{RX})
  - No directionality $\Rightarrow$ Combines single from all directions Ω
  - $R = \sum_{\omega}^{\Omega} \sqrt{G_{\mathrm{RX}}(\omega)} \cdot R(\omega)$, trained with L2 loss
- Phased RX antenna array $A_{K \times K}$

Power along ω: $\Psi(\omega) = \frac{1}{K^2 - 1} \left| \sum_{i=1}^{K} \sum_{j=1}^{K} \boxed{w_{i,j}(\omega)} \cdot e^{\mathbf{J}\Delta\theta_{i,j}} \right|$

Two Antenna-specific Training Methods

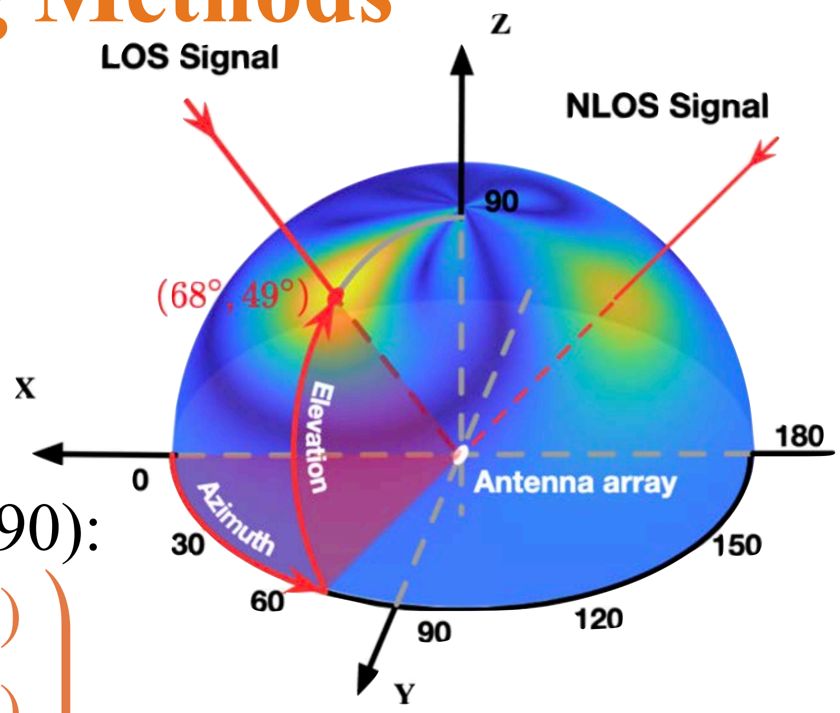
$$\Psi(\omega) = \frac{1}{K^2 - 1} \left| \sum_{i=1}^{K} \sum_{j=1}^{K} w_{i,j}(\omega) \cdot e^{\mathbf{J}\Delta\theta_{i,j}} \right|$$

Direction $\omega = (\text{Azimuth } \alpha, \text{Elevation } \beta)$

Special Spectrum (one degree resolution 360×90):

$$\Psi = \begin{pmatrix} \Psi(0^\circ,0^\circ) & \Psi(1^\circ,0^\circ) & \cdots & \Psi(360^\circ,0^\circ) \\ \Psi(0^\circ,1^\circ) & \Psi(1^\circ,1^\circ) & \cdots & \Psi(360^\circ,1^\circ) \\ \vdots & \vdots & \ddots & \vdots \\ \Psi(0^\circ,90^\circ) & \Psi(1^\circ,90^\circ) & \cdots & \Psi(360^\circ,90^\circ) \end{pmatrix}$$

Also L2 loss: $\mathscr{L} = \sum_{\omega \in \Omega} |\Psi(\omega) - \Psi'(\omega)|^2$



"Turbo-Learning"

Motivation: Volume and quality of data are important for deep learning

⇒ Training with synthetic data generated by $NeRF^2$

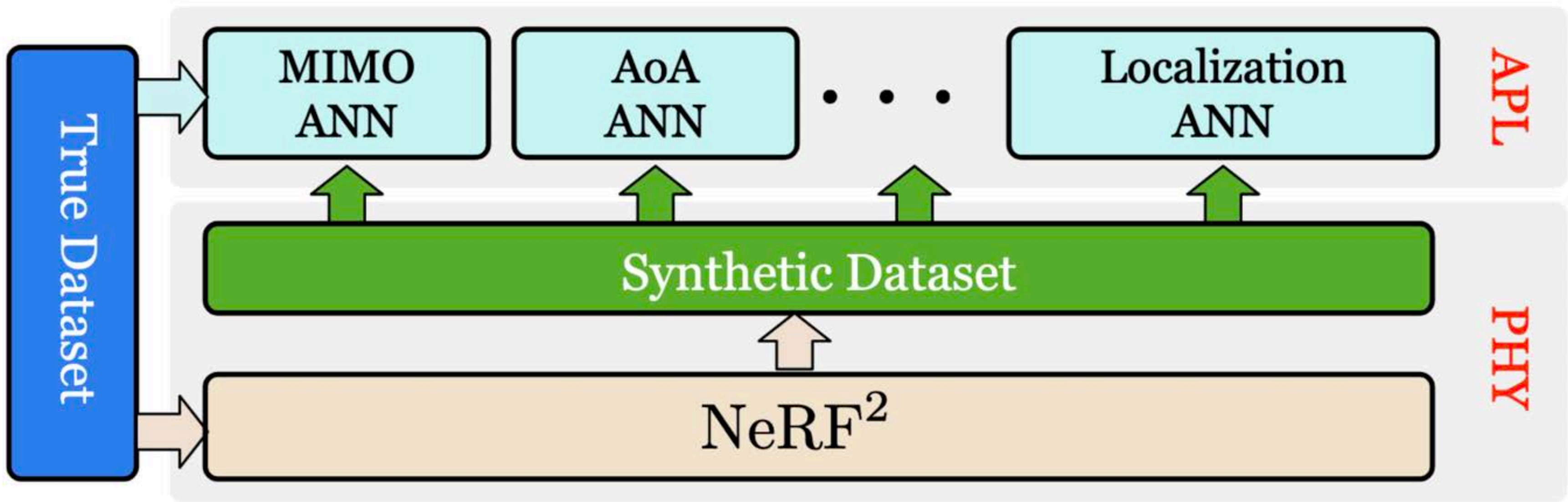


Fig. 6: Illustration of turbo-learning

“Turbo-Learning”

Motivation: Volume and quality of data are important for deep learning

⇒ Training with synthetic data generated by NeRF²

Large amounts of synthetic data

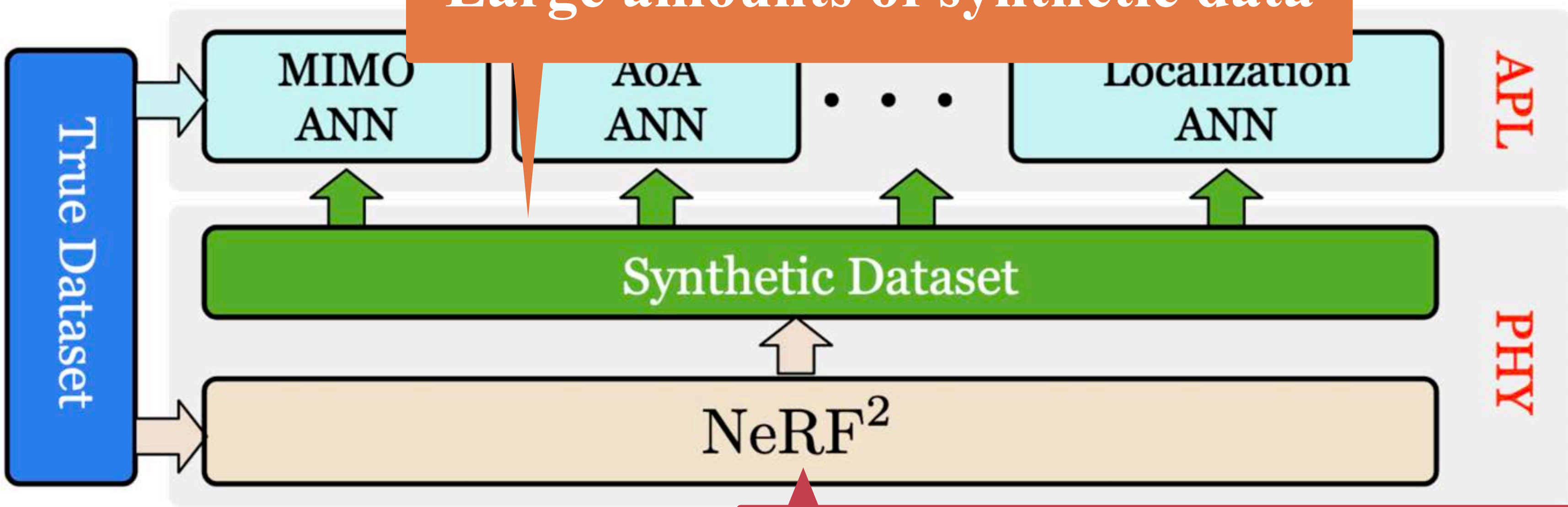


Fig. 6: Illustrati

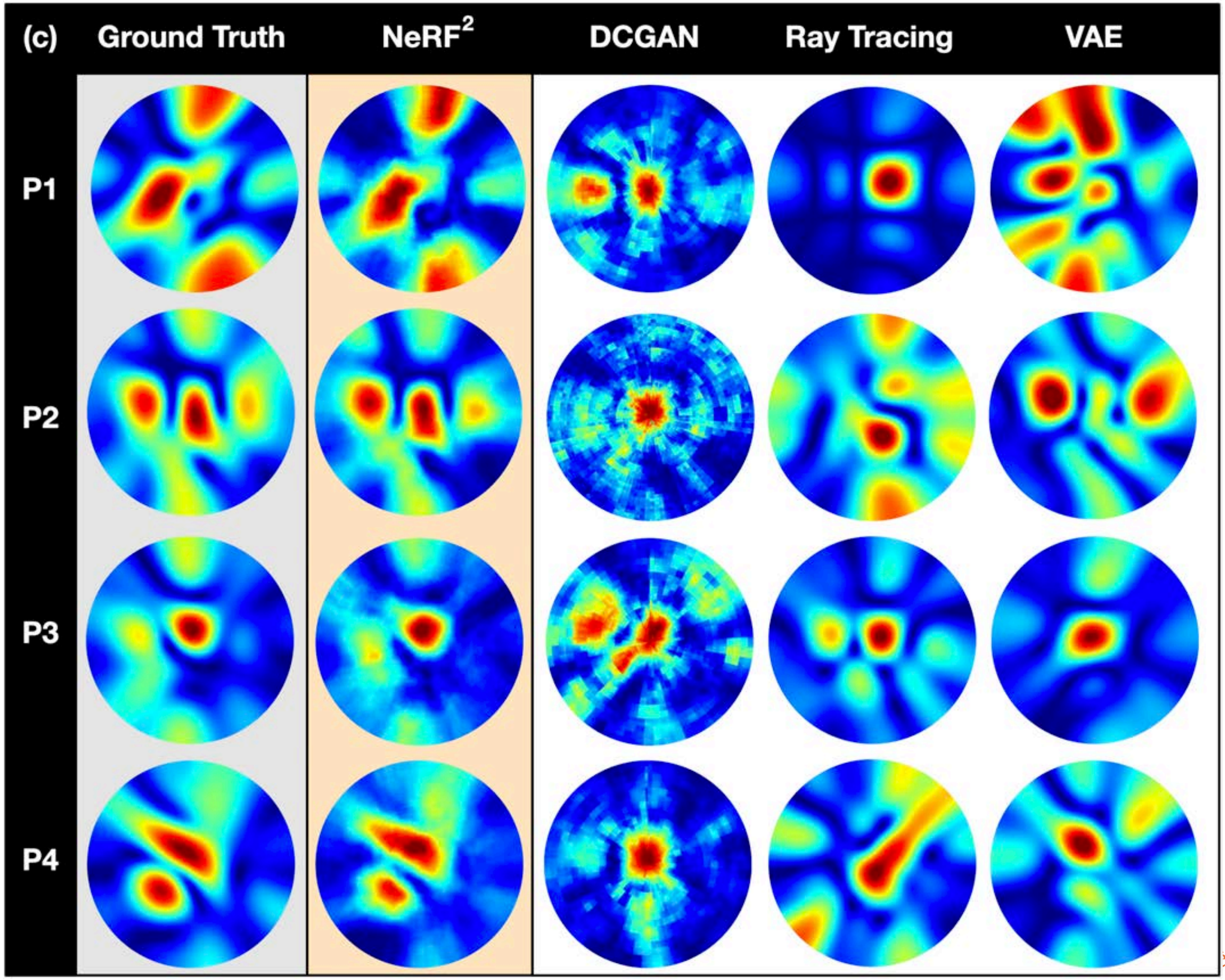
Needs to collect data for each scene!
(thousands of positions)

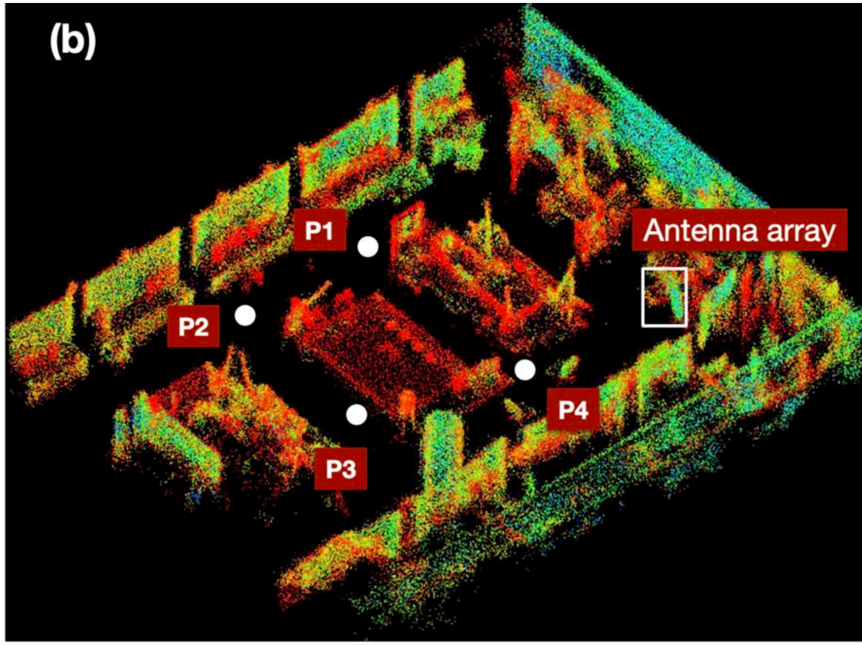
Evaluation

Spectrum Synthesis

1. Ground truth: $\Psi(\omega) = \frac{1}{K^2 - 1} \left| \sum_{i=1}^{K} \sum_{j=1}^{K} w_{i,j}(\omega) \cdot e^{\mathbf{J}\Delta\theta_{i,j}} \right|$
2. Pure Ray Tracing (Matlab)
3. Deep Convolutional Generative Adversarial Network (DCGAN)
   (TX's location → spectrum as an image)
4. Variational Autoencoder (VAE)
   (spectrum images → spectrum images)

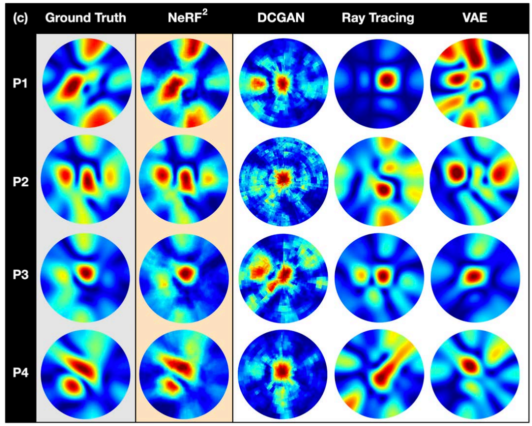
Spectrum Synthesis





Spectrum Synthesis

SSIM: structural similarity index measure



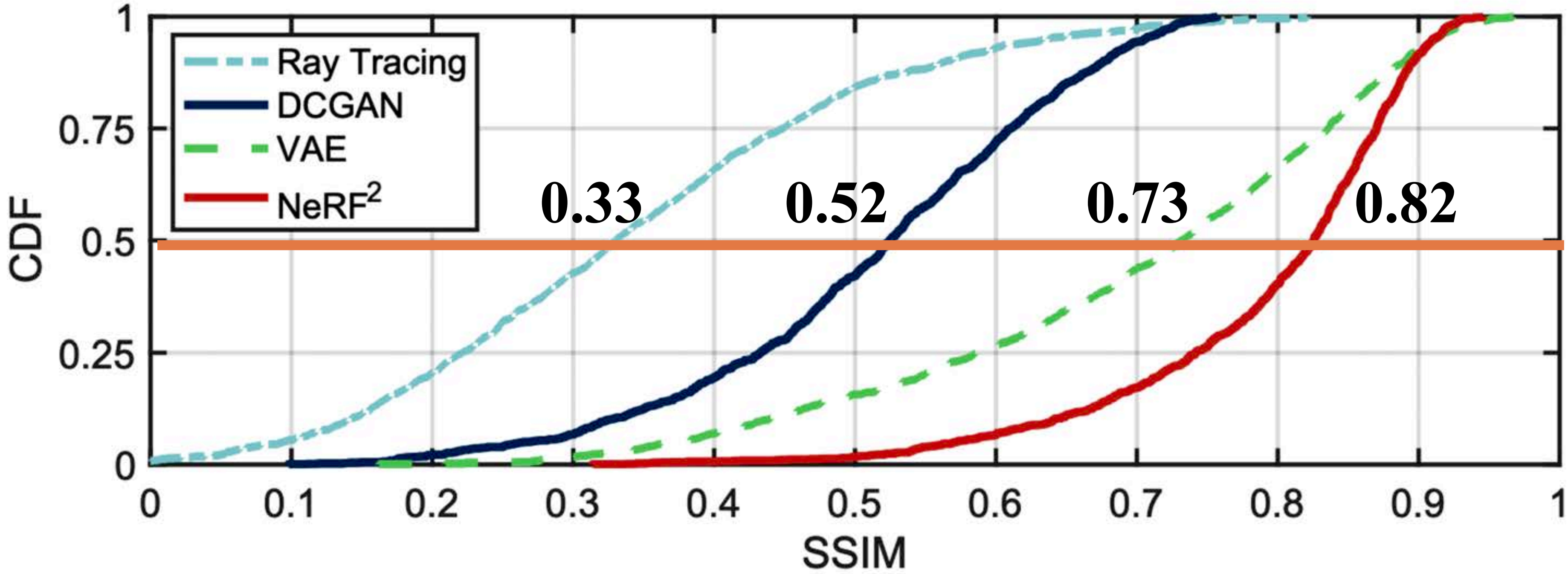
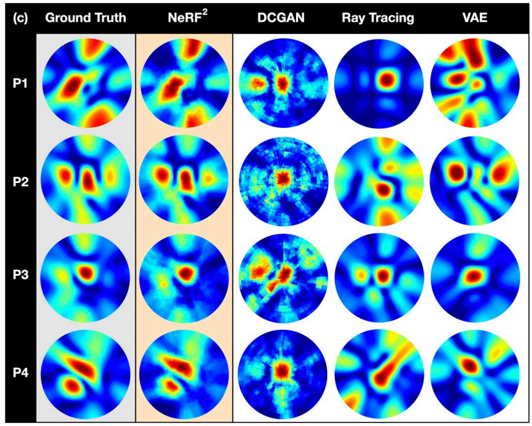
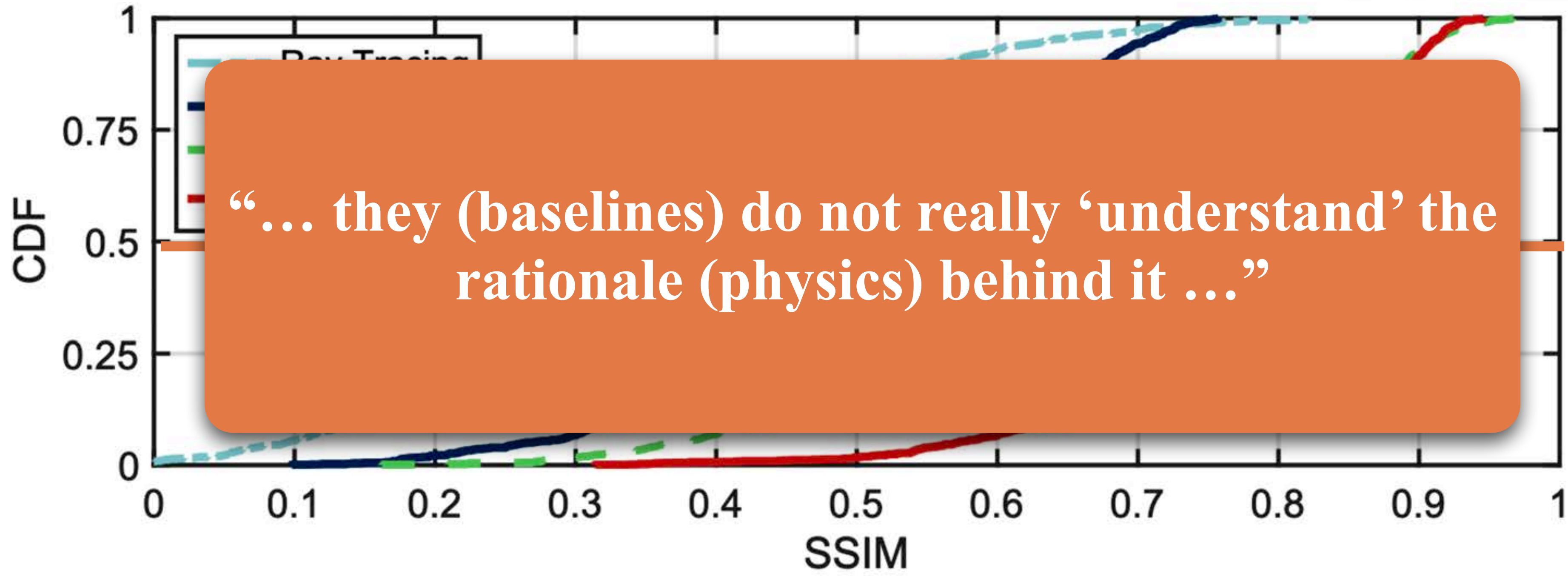


Fig. 8: SSIM Comparison

Spectrum Synthesis

SSIM: structural similarity index measure





"… they (baselines) do not really 'understand' the rationale (physics) behind it …"

Fig. 8: SSIM Comparison

Spectrum Synthesis

1. Ground truth: $\Psi(\omega) = \frac{1}{K^2 - 1} \left| \sum_{i=1}^{K} \sum_{j=1}^{K} w_{i,j}(\omega) \cdot e^{\mathbf{J}\Delta\theta_{i,j}} \right|$
2. Pure Ray Tracing (Matlab)
3. Deep Convolutional Generative Adversarial Network (DCGAN)
   ($\boxed{\text{TX's location}} \rightarrow$ spectrum as an image)
4. Variational Autoencoder (VAE)
   ($\boxed{\text{spectrum images}} \rightarrow$ spectrum images)

No physics related info provided!

Use of NeRF² Generated Data

Task: Predicting angles of arrive (AoAs) given spatial spectrum images

Model: Angular artificial neural networks (AANNs)

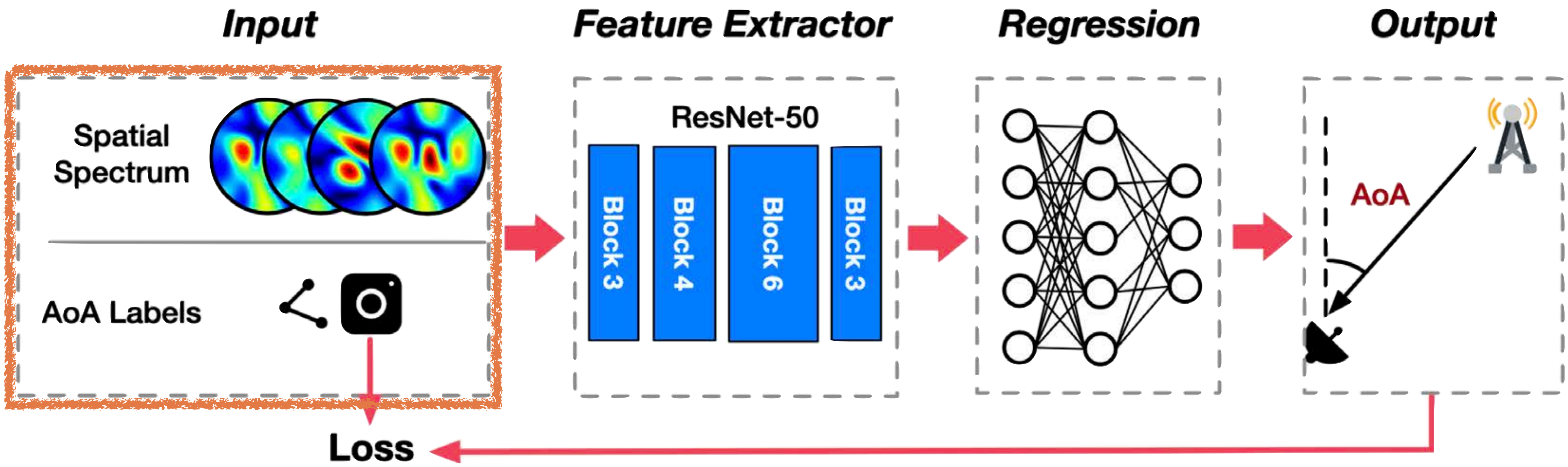


Fig. 10: Architecture of Angular Artificial Neural Network

Field Study: 5G MIMO

Task: Estimation of massive MIMO channel for the Frequency Domain Duplex (FDD) systems for beamforming

- Uplink frequency ≠ Downlink frequency
- Uplink path == Downlink path (path sharing)
- Uplink CSI → Downlink CSI

Uplink CSI in place of the TX (client) location

NeRF formulation

$\mathbf{F}_\Theta : (\mathrm{CSI}_{\mathrm{uplink}}, P_x, \omega) \rightarrow \left(\delta_x, S_x\right)$

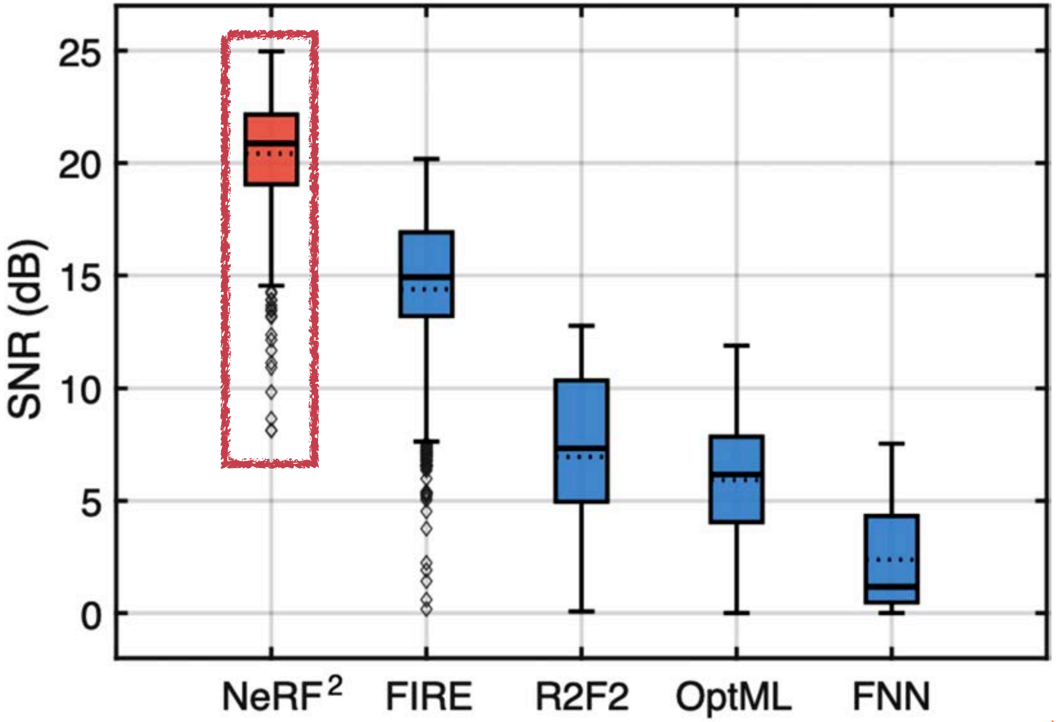
Baselines

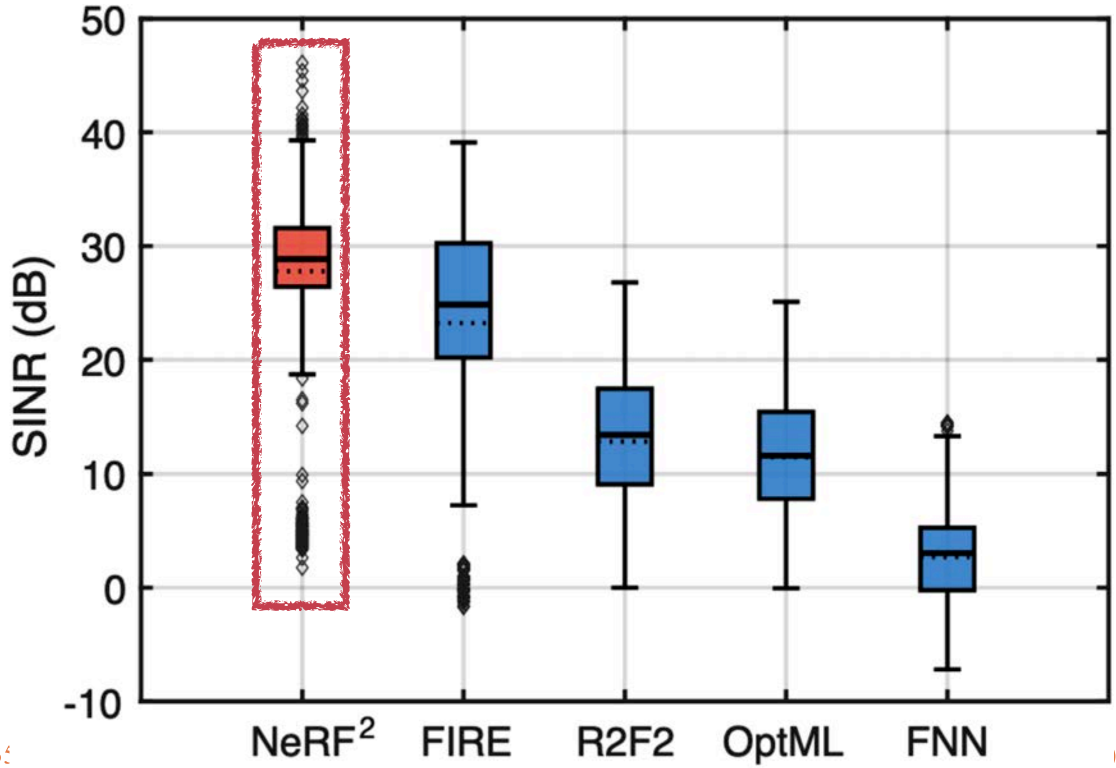
FIRE [MobiCom ’21], R2F2 [SICOMM ’16], OptML [MobiCom ’19], and FNN [ICC ’19]

Field Study: 5G MIMO

Metrics

- CSI prediction: Signal to noise ratio SNR = S/N
- MU-MIMO: Signal to interference and noise ratio SINR = $S/(N+I)$





My Review

Strengths

S1. Novel idea: Physics informed ML model

S2. Spectrum "as a service" with great performance

Weaknesses

W1. No direct evaluation on attenuation δ prediction

W2. Scaling to outdoor environments with dynamic objects

W3. Long training time

Future Ideas

Generalizability across scenes

Backup slides …

Use of NeRF² Generated Data (larger scale)

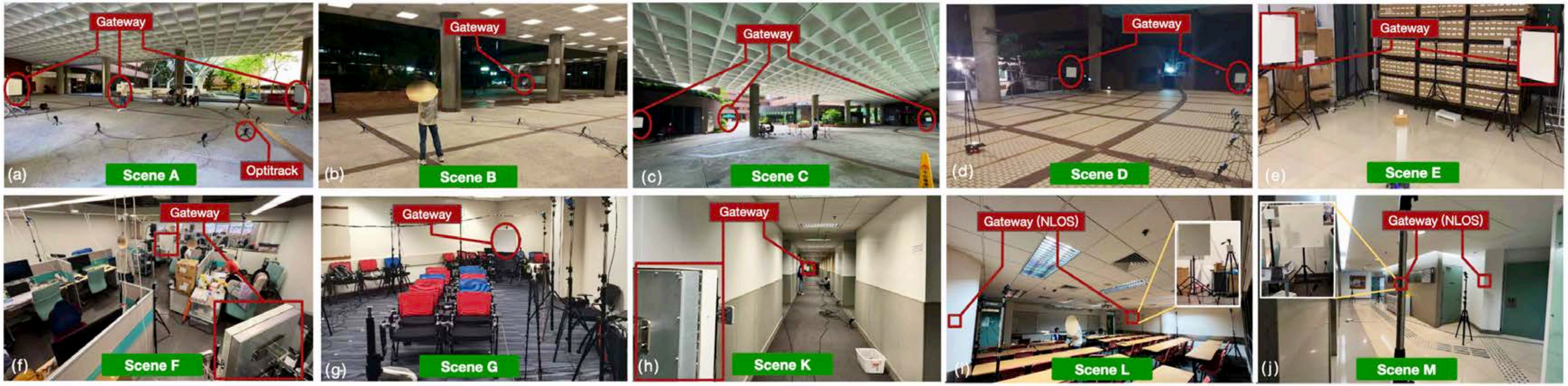


Fig. 9: Illustration of example scenes. (a)-(d) shows the semi-indoor environment, which is large-sized and semi-closed halls. (e)-(j) show the full-indoor environment.

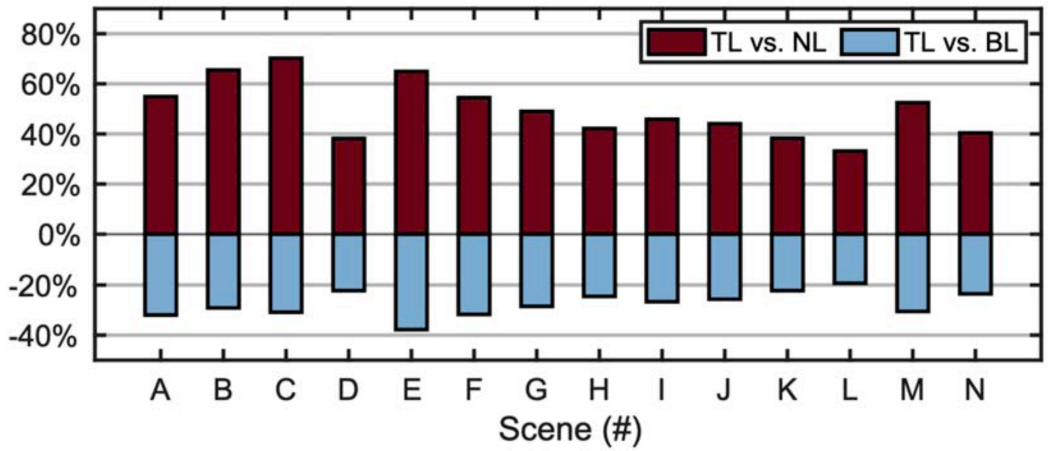
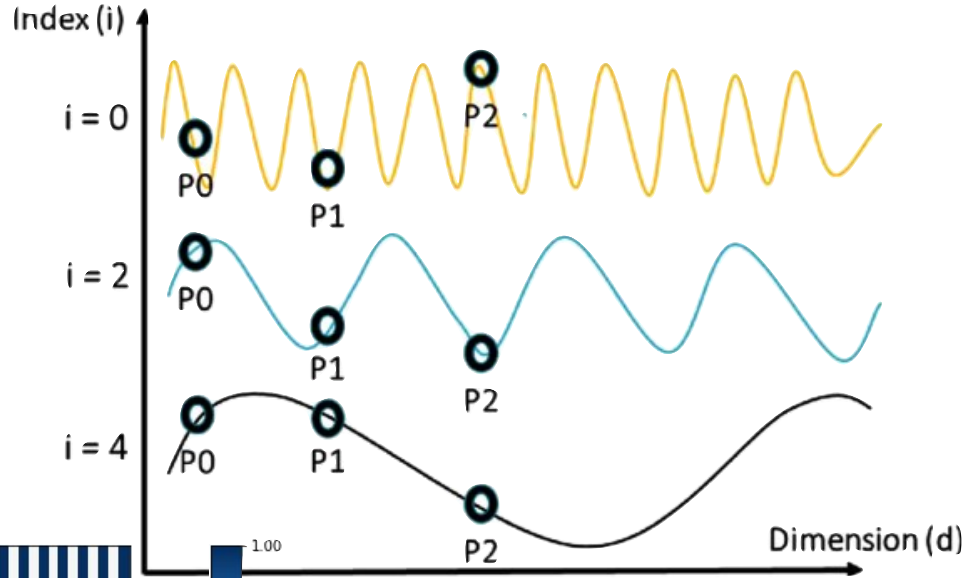
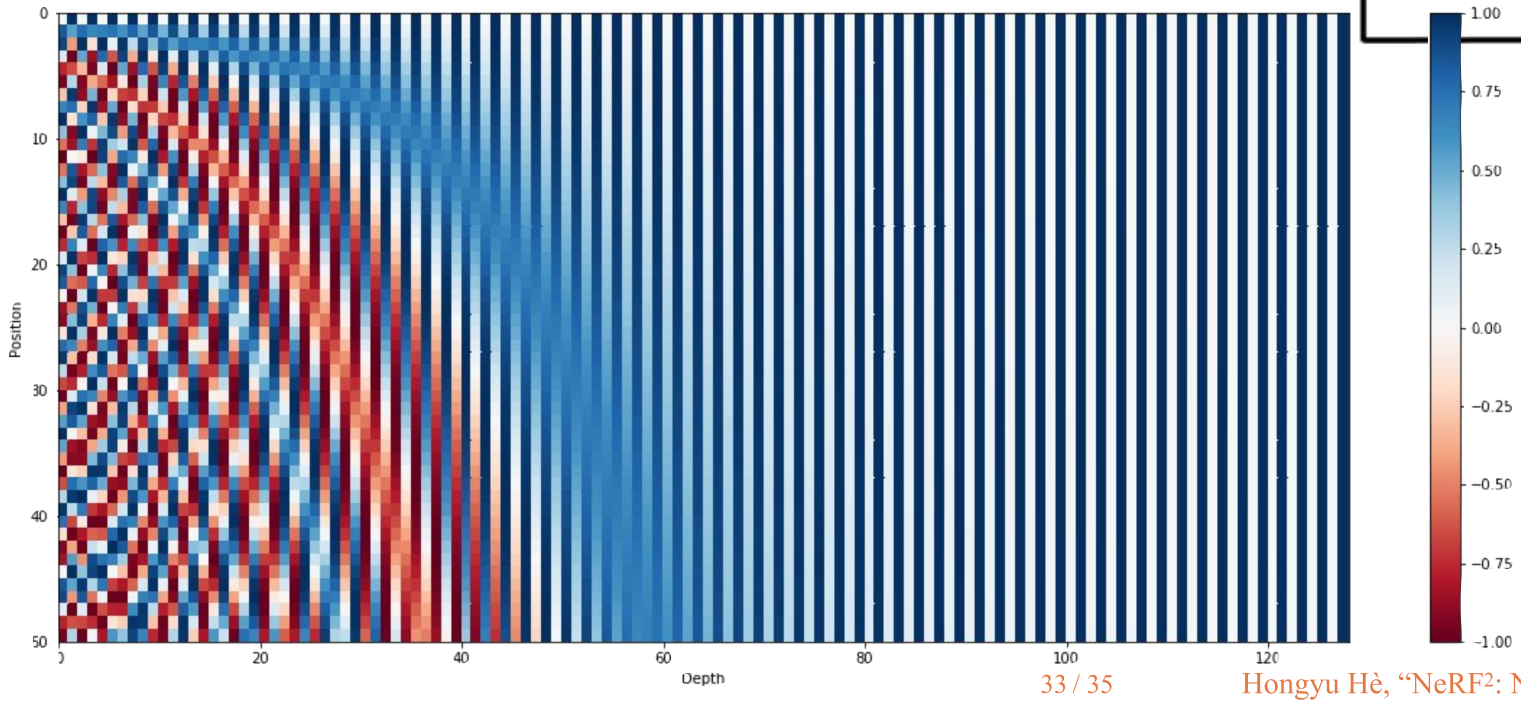


Fig. 11: AoA Accuracy vs. Scenes

Positional Encoding





Class Discussion