Poster ID: THU-PM-002

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CVPR
VANCOUVER, CANADA

RobustNerf: Ignoring Distractors with Robust Losses

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Google Brain
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VECTOR INSTITUTE
SFU SIMON FRASER UNIVERSITY

NeRF is amazing at **3D multi view reconstruction from 2D images**

Inputs photos

NeRF is amazing at **3D rendering from 2D images**

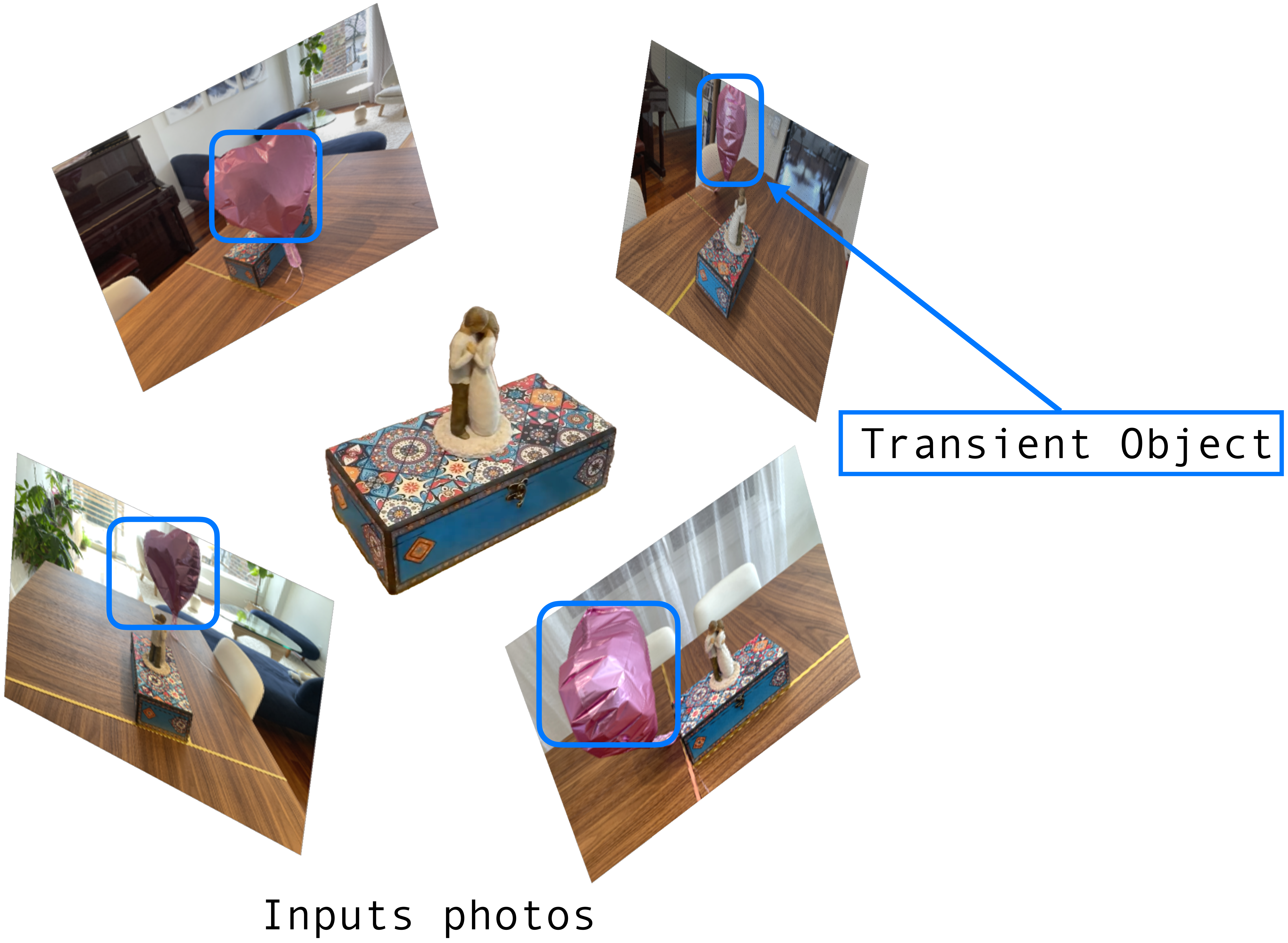
Inputs photos

MipNerf360

NeRF struggles with **photometric inconsistencies**

Inputs photos

NeRF struggles with **photometric inconsistencies**



NeRF struggles with **photometric inconsistencies**

Inputs photos

MipNerf360:Charbonnier Loss

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MipNerf360:Charbonnier Loss

Cloudy

NeRF struggles with **photometric inconsistencies**

Inputs photos

MipNerf360:Charbonnier Loss

Cloudy Floater

NeRF struggles with **photometric inconsistencies**

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RobustNeRF

Clean & Clear

RobustNerf successfully removes artifacts!

Photometric inconsistencies are Outliers in a robust optimization task.

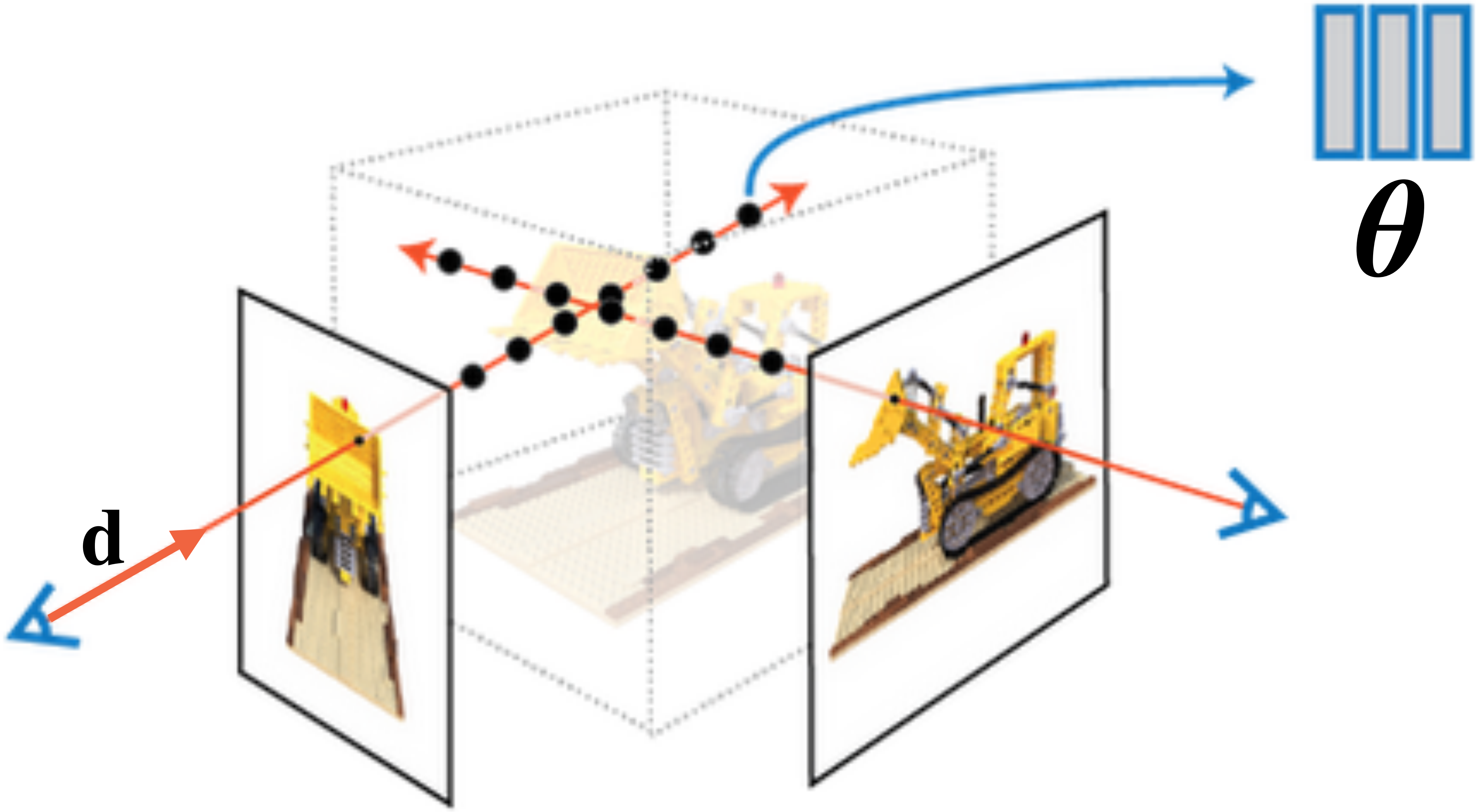
MipNeRF360

RobustNeRF

Poster ID: THU-PM-002 link: https://robustnerf.github.io

Photometric Consistency

- NeRF: optimizes the model parameters $\boldsymbol{\theta}$ by:
  - Assuming all pictures taken are of exactly the same scene
  - It is ideal for gaussian noise



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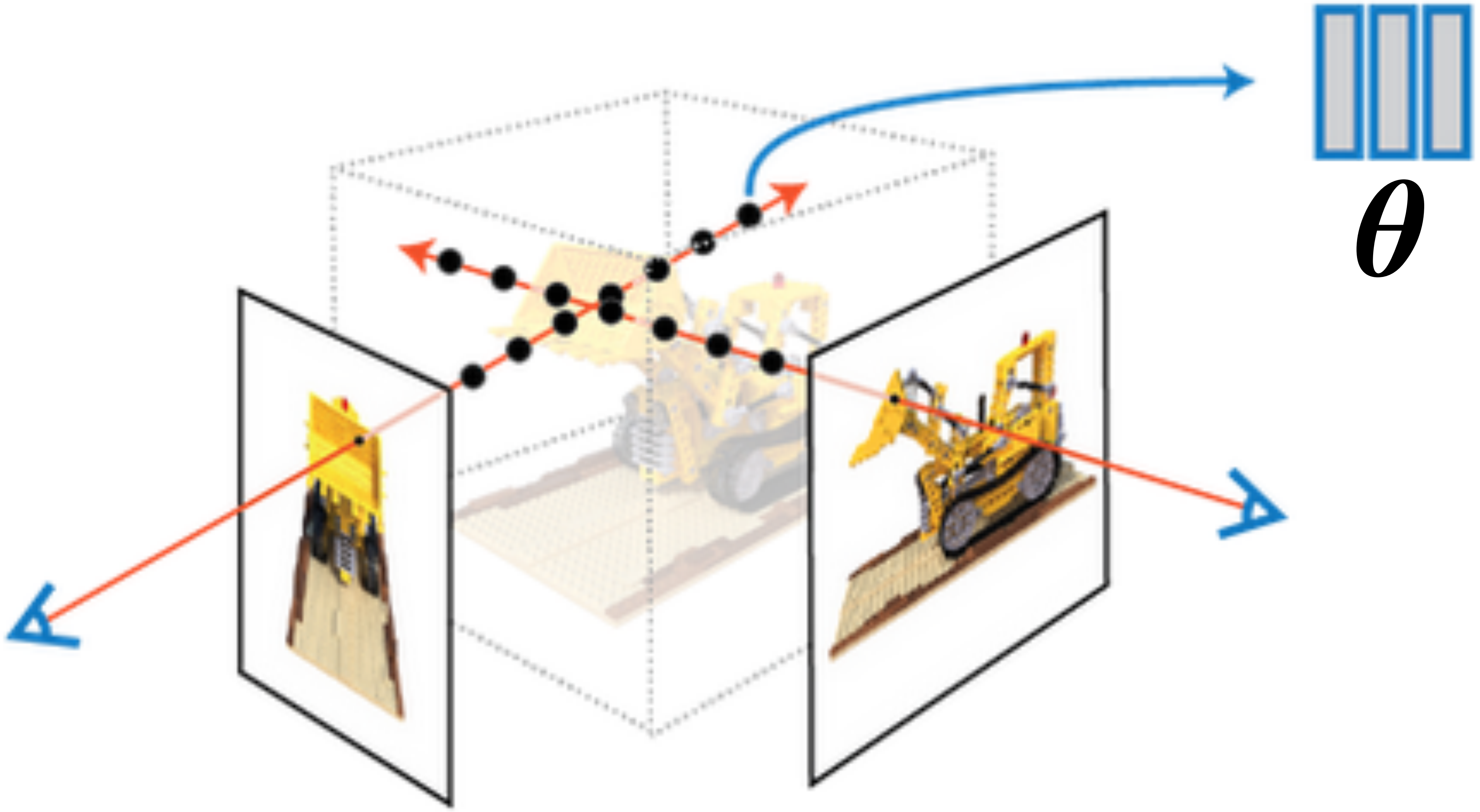

$$\mathcal{L}_{\text{rgb}}^{\mathbf{r},i}(\boldsymbol{\theta}) = ||\mathbf{C}(\mathbf{r};\boldsymbol{\theta}) - \mathbf{C}_i(\mathbf{r})||_2^2$$

photometric consistency

Robust Estimation

- automatically identify non-consistent information
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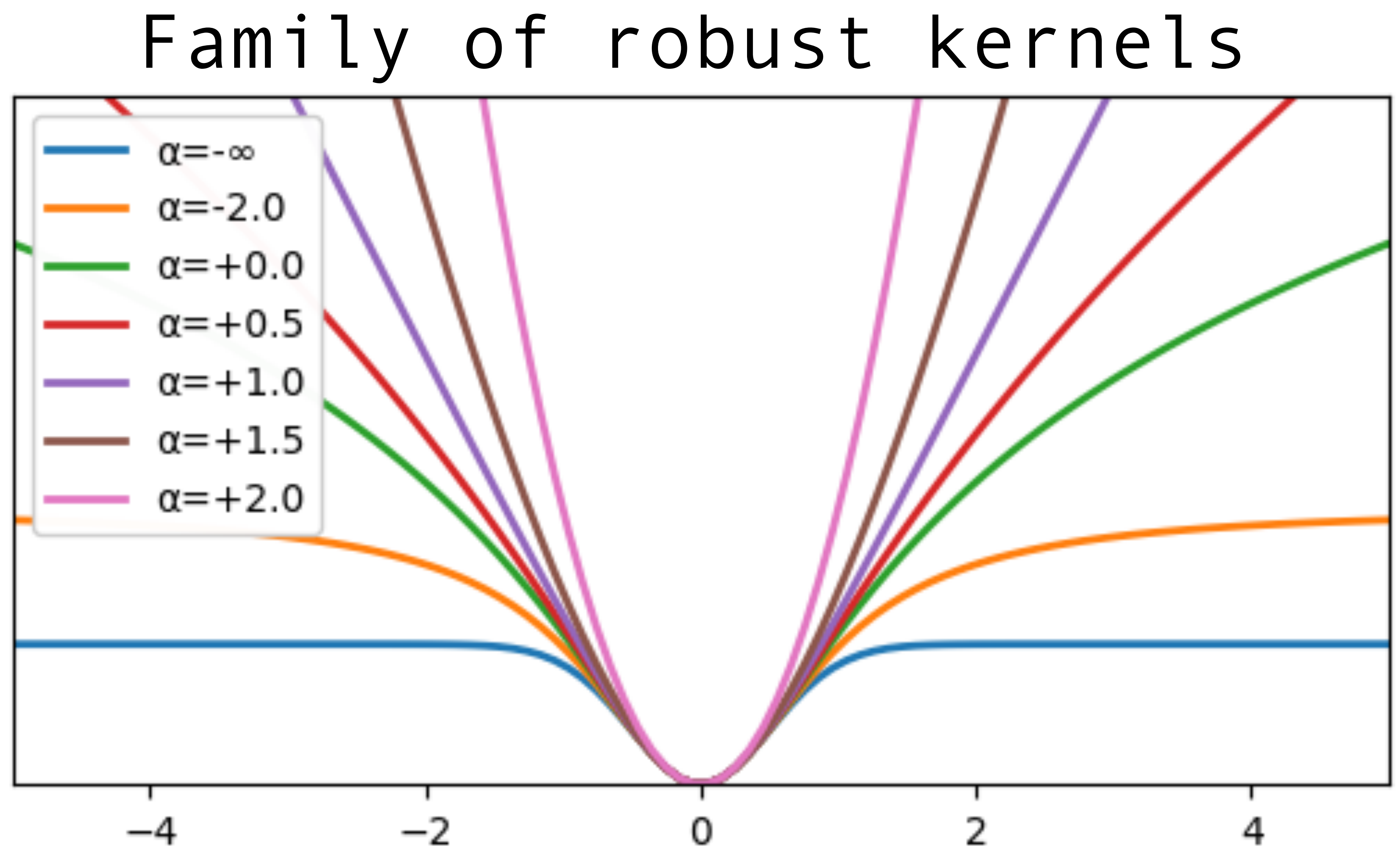

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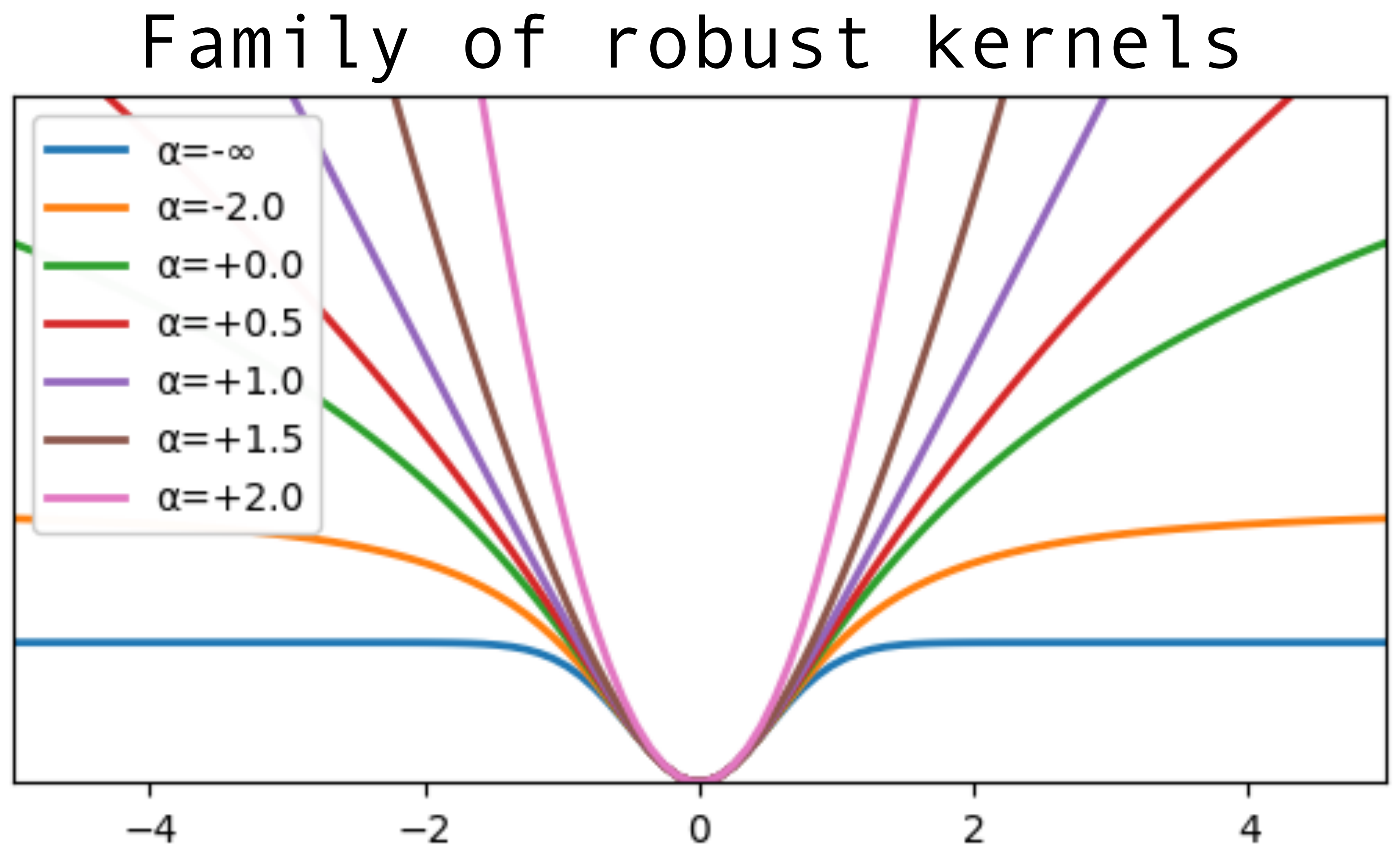

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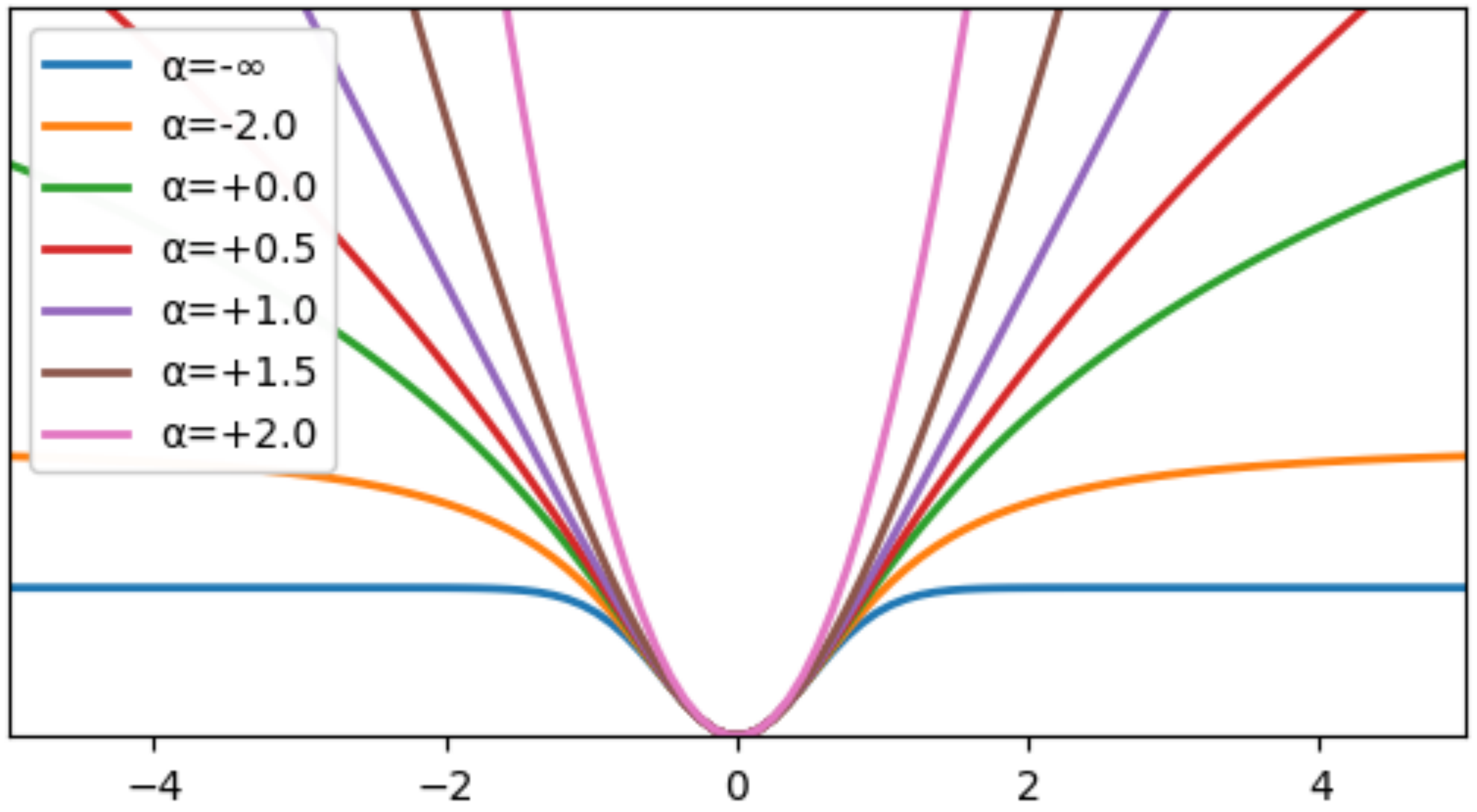
Family of robust kernels



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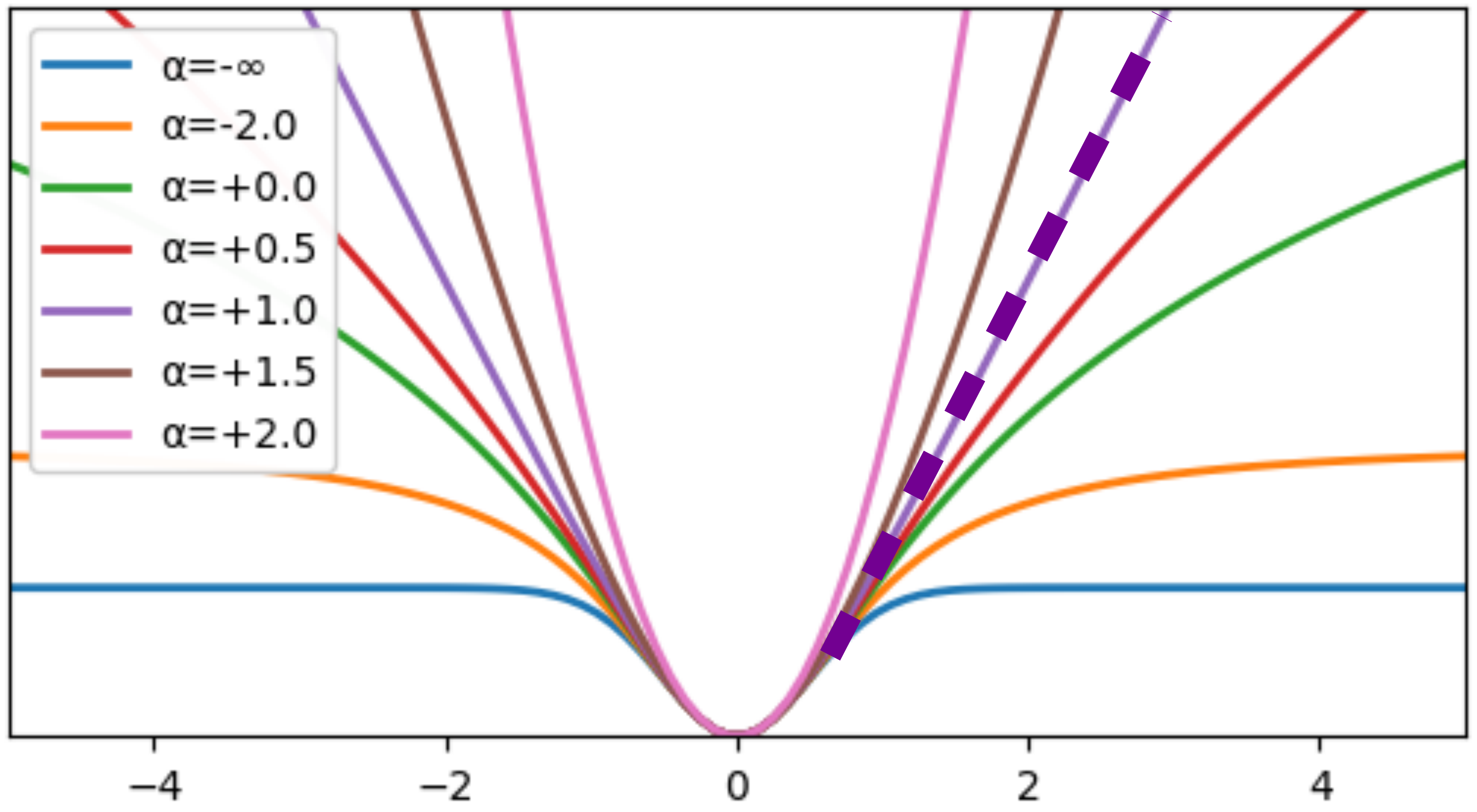
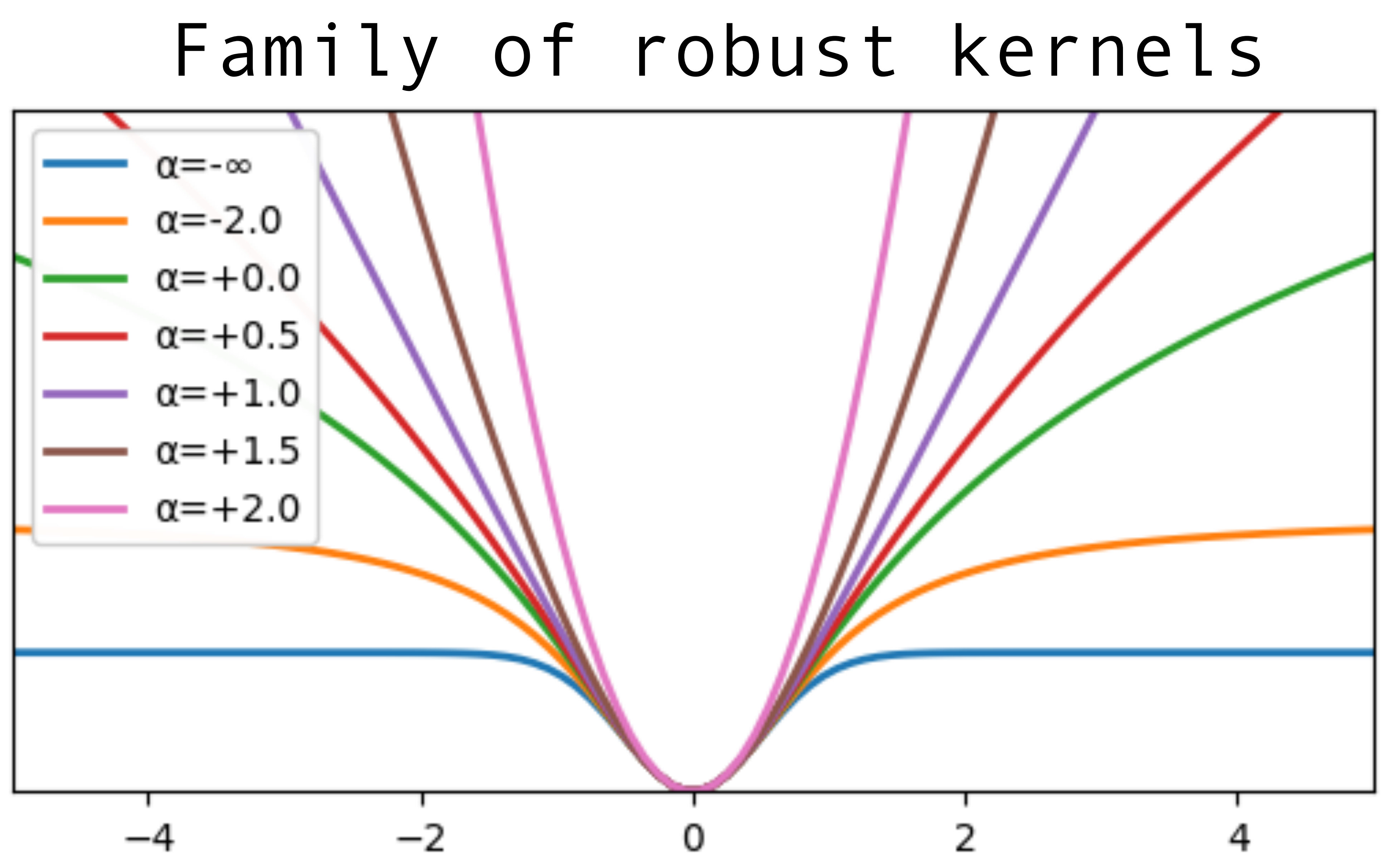


MipNerf360: Charbonnier Loss

Does it work?



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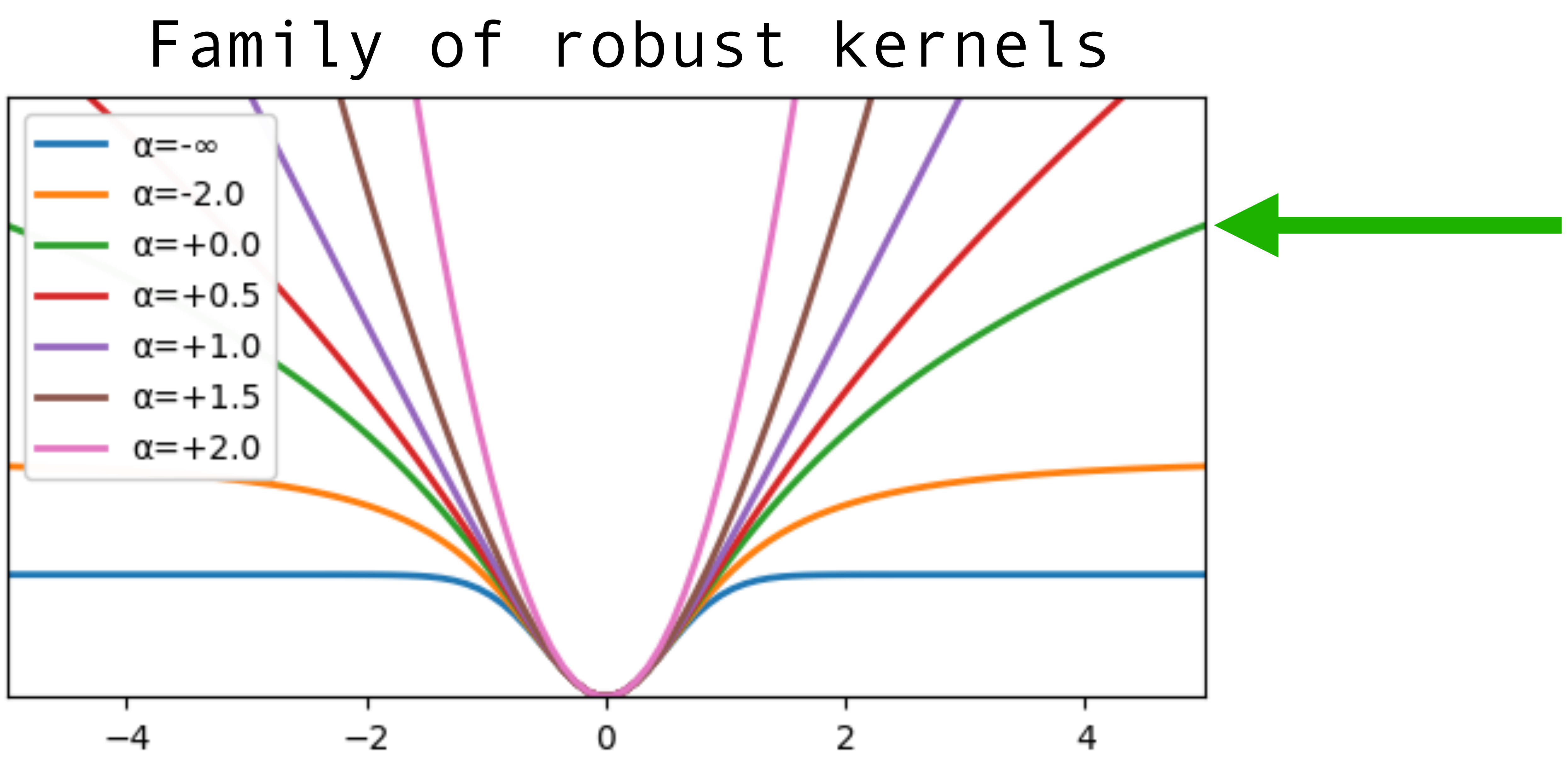

details preserved, but floaters

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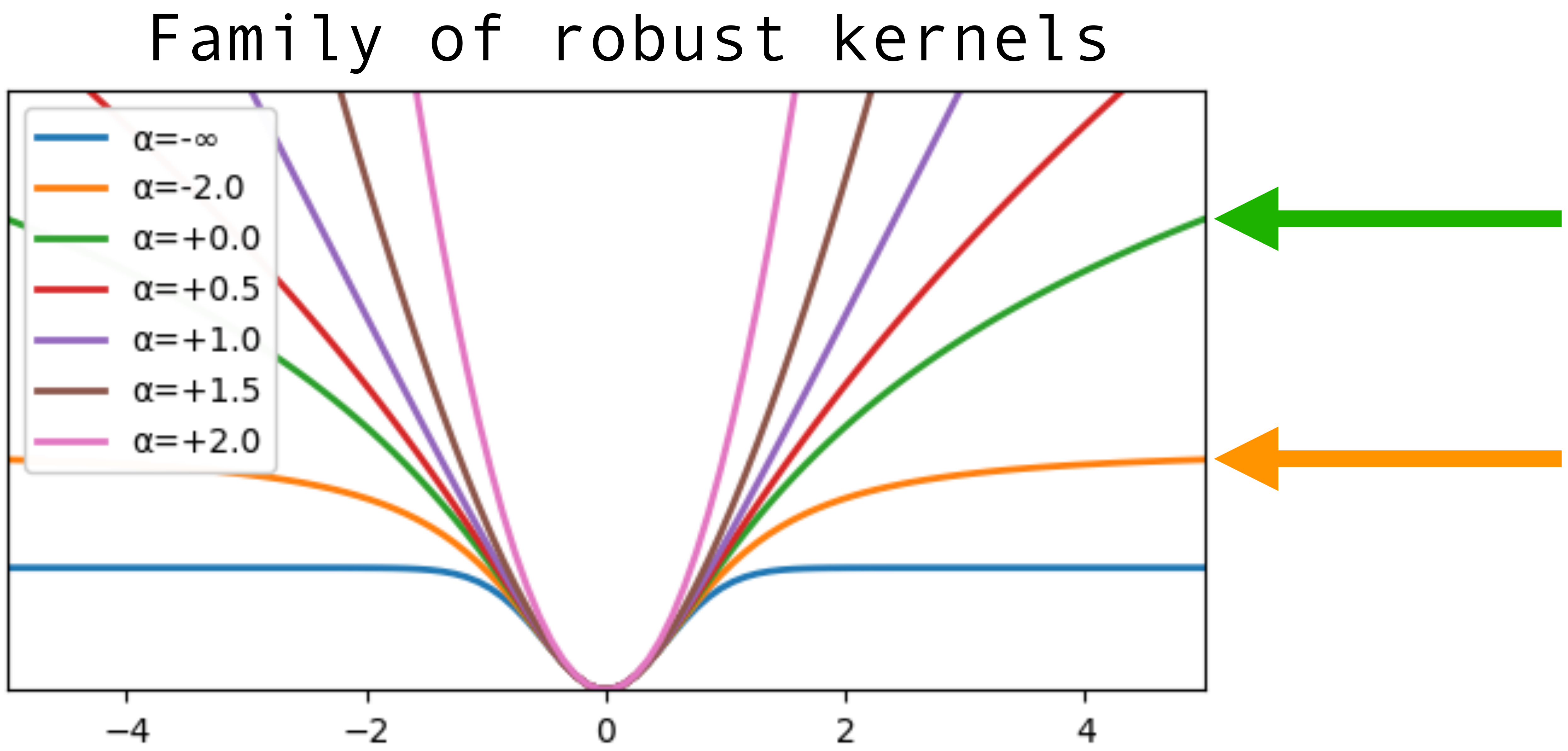
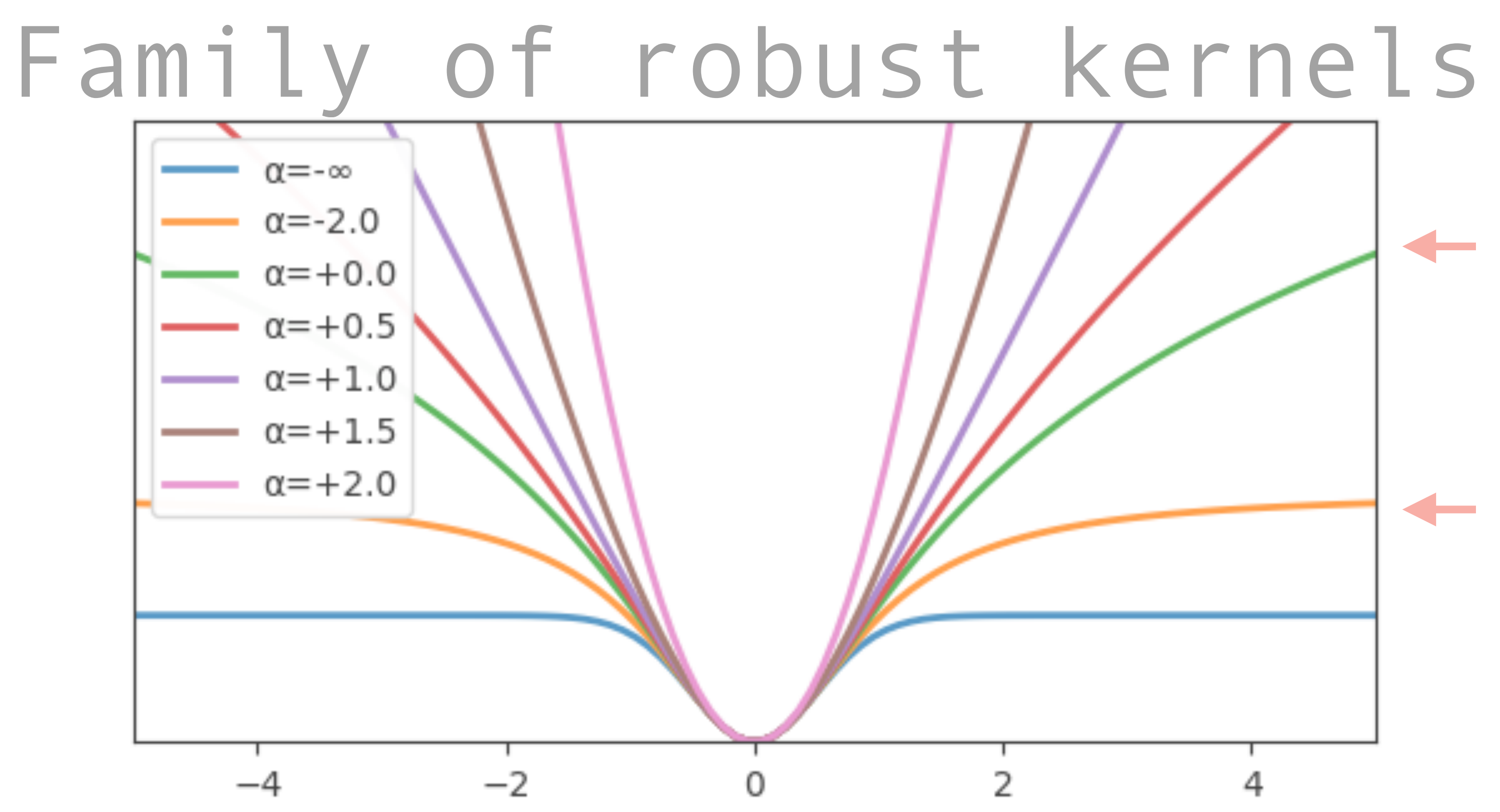
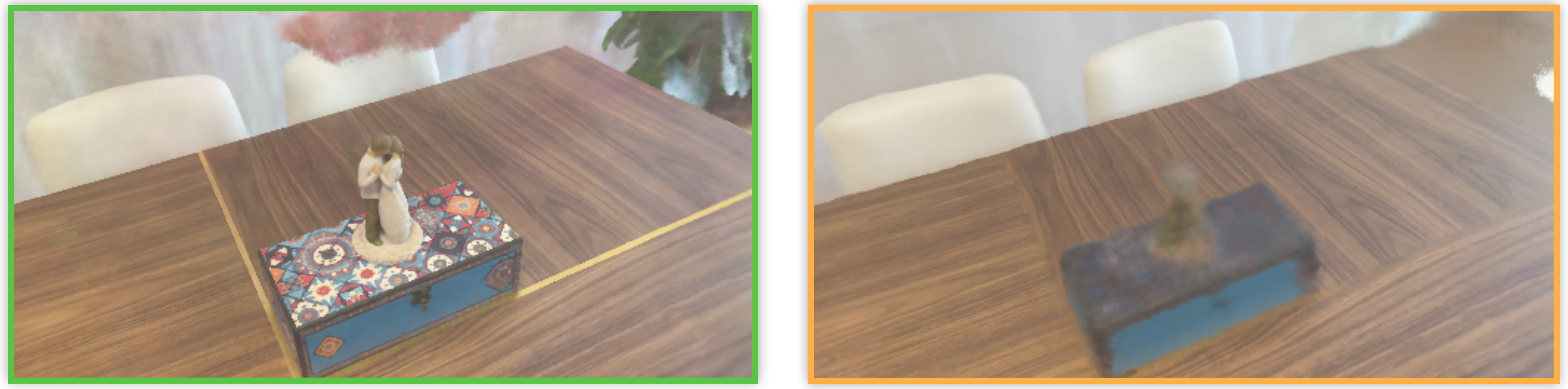


details preserved, but floaters

floaters gone, but details not preserved

Are outlier pixels independant in transient objects?





Good at **independent** noise

VS

Bad at **structured** noise

Robust Optimization w/ IRLS

- IRLS: Iteratively Re-Weighted Least Squares
  - weights are spatially consistent
  - weights are in {0, 1}   (hard weights)

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v.s.

$$\mathcal{L}^{\mathbf{r},i}_{\text{robust}}(\boldsymbol{\theta}) = \omega(\boldsymbol{\epsilon}^{(t-1)}(\mathbf{r})) \cdot ||\mathbf{C}(\mathbf{r};\boldsymbol{\theta}) - \mathbf{C}_i(\mathbf{r})||_2^2$$

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Residuals at the previous iteration

Trimmed / Diffused Least Squares

$$\tilde{\omega}(\mathbf{r}) = \epsilon(\mathbf{r}) \leq \mathcal{T}_\epsilon \ , \quad \mathcal{T}_\epsilon = \mathrm{Median}_{\mathbf{r}}\{\epsilon(\mathbf{r})\} \ .$$

threshold the residuals

residuals – $\epsilon(\mathbf{r})$

inliers – $\tilde{\omega}(\mathbf{r})$

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$$\mathcal{W}(\mathbf{r}) = (\tilde{\omega}(\mathbf{r}) \circledast \mathcal{B}_{3\times3}) \geq \mathcal{T}_\circledast \ , \quad \mathcal{T}_\circledast = 0.5 \ .$$

diffuse the classification

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diffusion – $\tilde{\omega}(\mathbf{r}) \circledast \mathcal{B}_{3\times3}$

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$$\omega(\mathcal{R}_8(\mathbf{r})) = \mathbb{E}_{\mathbf{s}\sim\mathcal{R}_{16}(\mathbf{r})}\left[\mathcal{W}(\mathbf{s})\right] \geq \mathcal{T}_\mathcal{R} \,, \quad \mathcal{T}_\mathcal{R} = 0.6 \,.$$

threshold again

residuals – $\epsilon(\mathbf{r})$ | inliers – $\tilde{\omega}(\mathbf{r})$ | diffusion – $\tilde{\omega}(\mathbf{r}) \circledast \mathcal{B}_{3\times 3}$ | (IRLS) weights – $\mathcal{W}(\mathbf{r})$

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(IRLS) weights – $\mathcal{W}(\mathbf{r})$

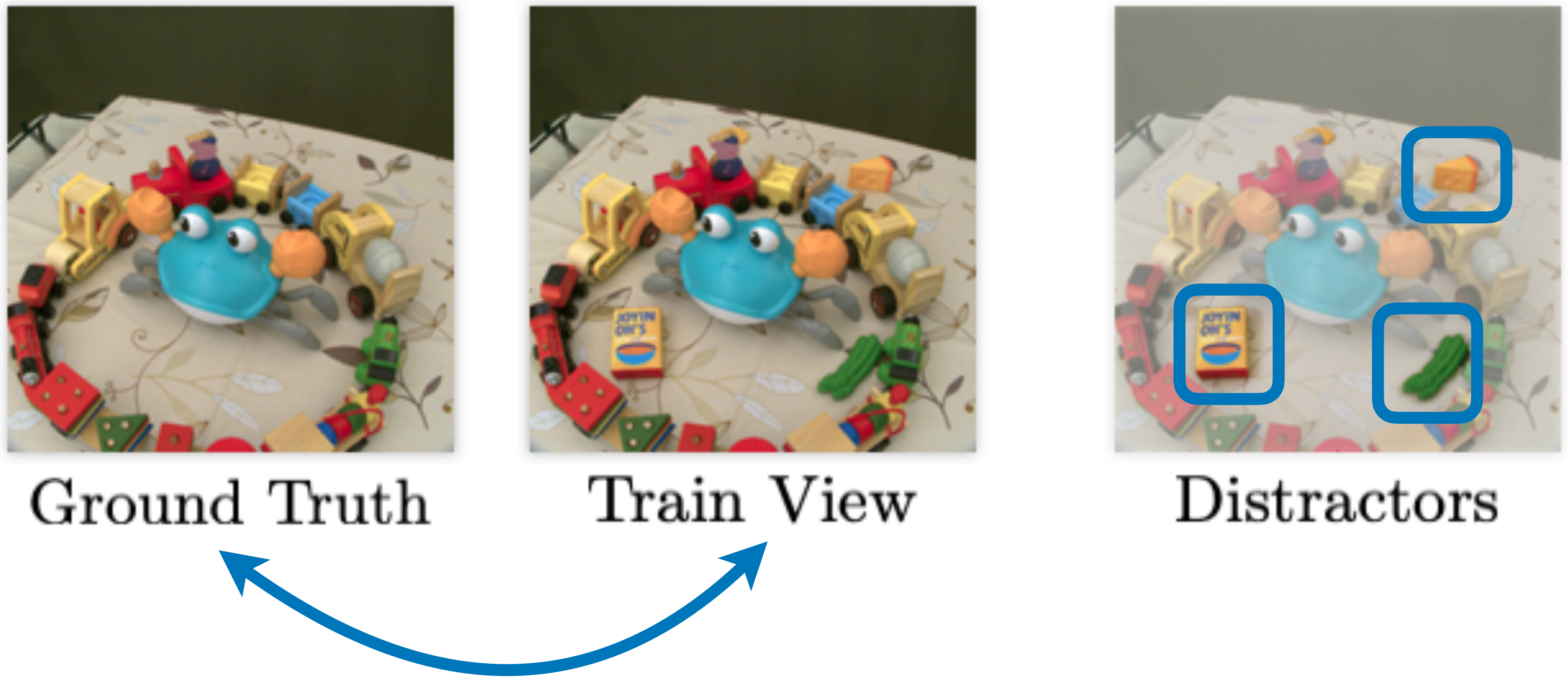
Training Progress w/ IRLS

Ground Truth

Train View

Distractors

Training Progress w/ IRLS



Training Progress w/ IRLS

Distractors

.5% 2% 12% 100% (t/T)

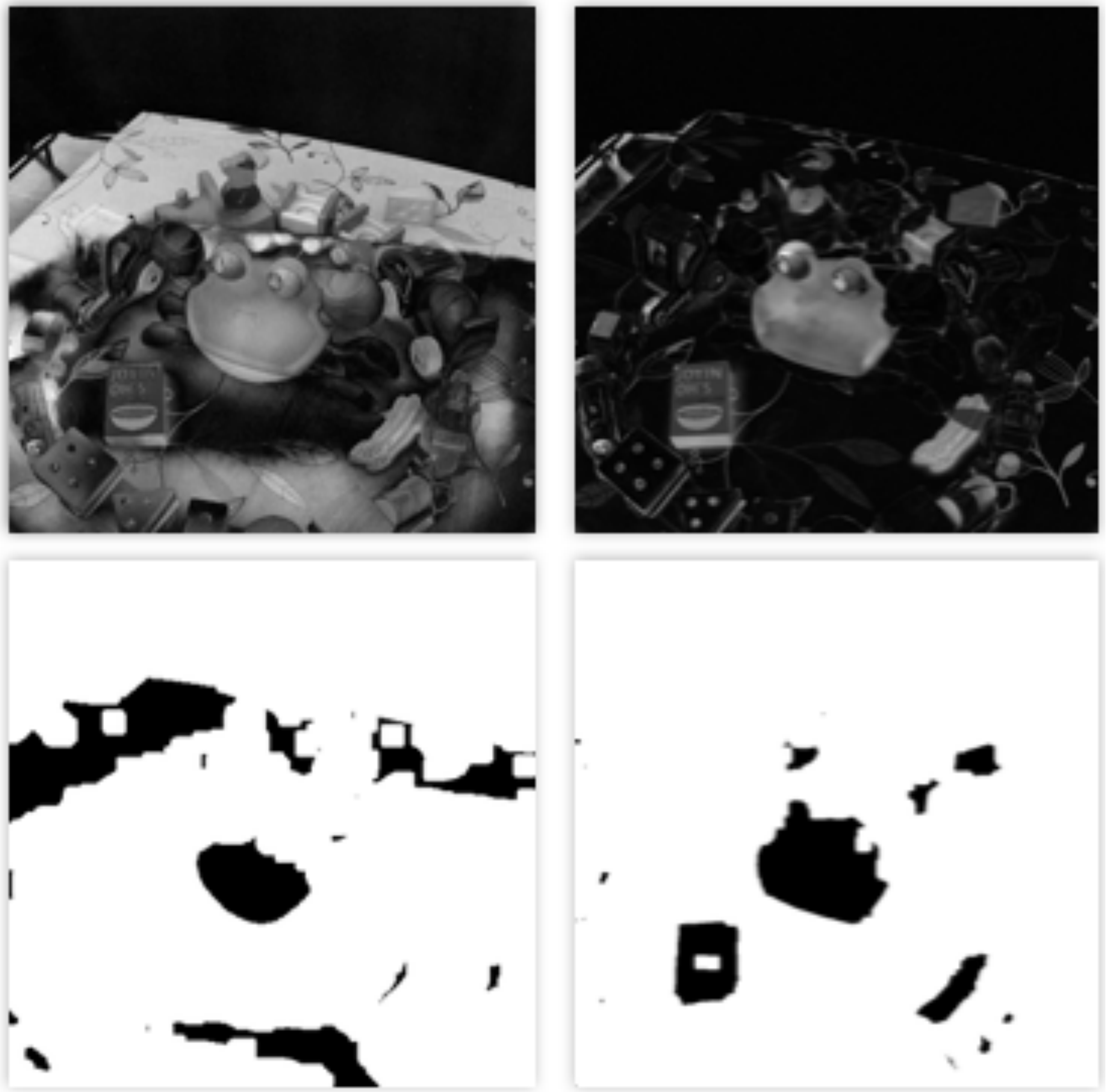
residuals
$\epsilon(\mathbf{r})$

weights
$\mathcal{W}(\mathbf{r})$

Training Progress w/ IRLS

Distractors

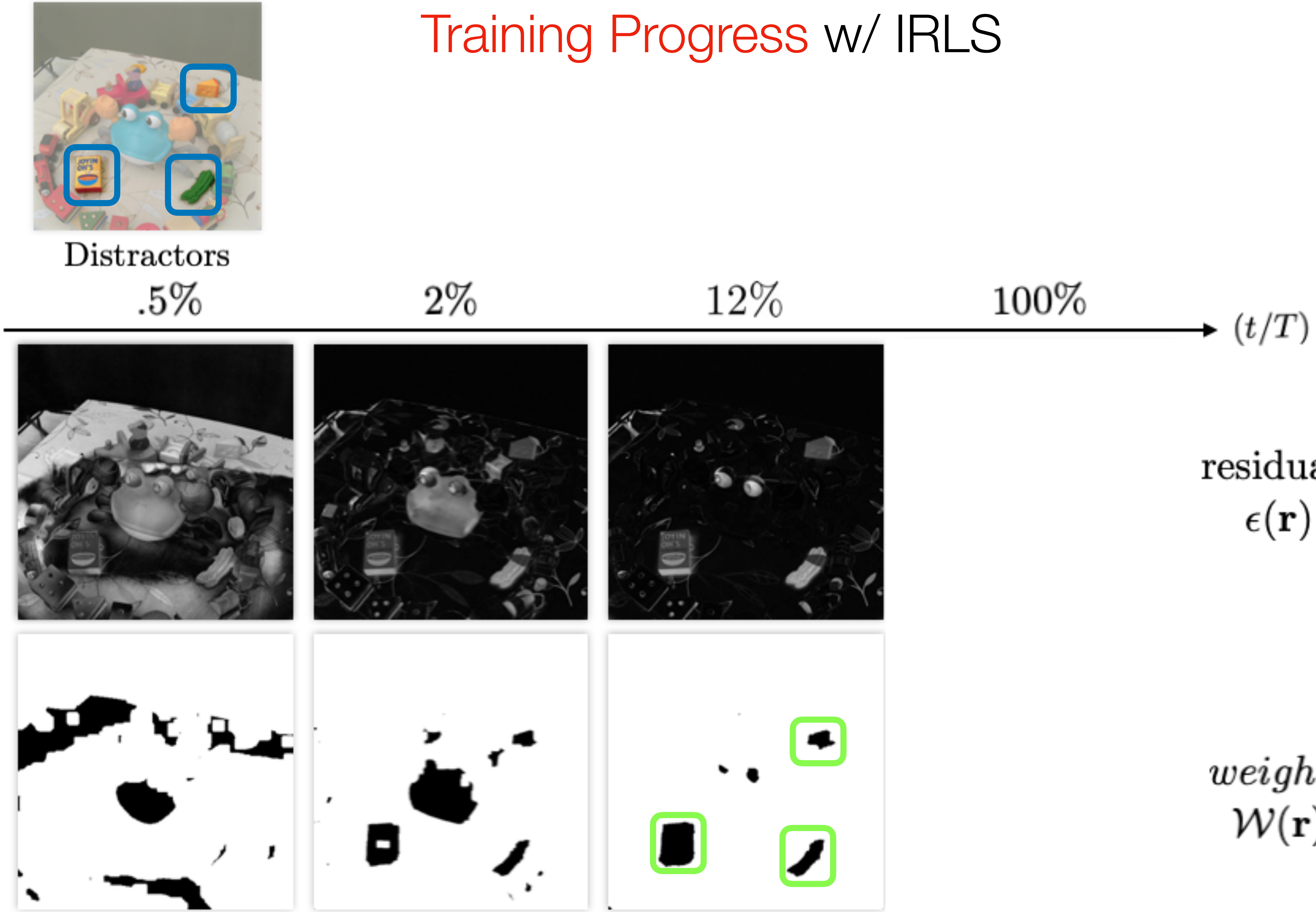
.5% 2% 12% 100% → (t/T)



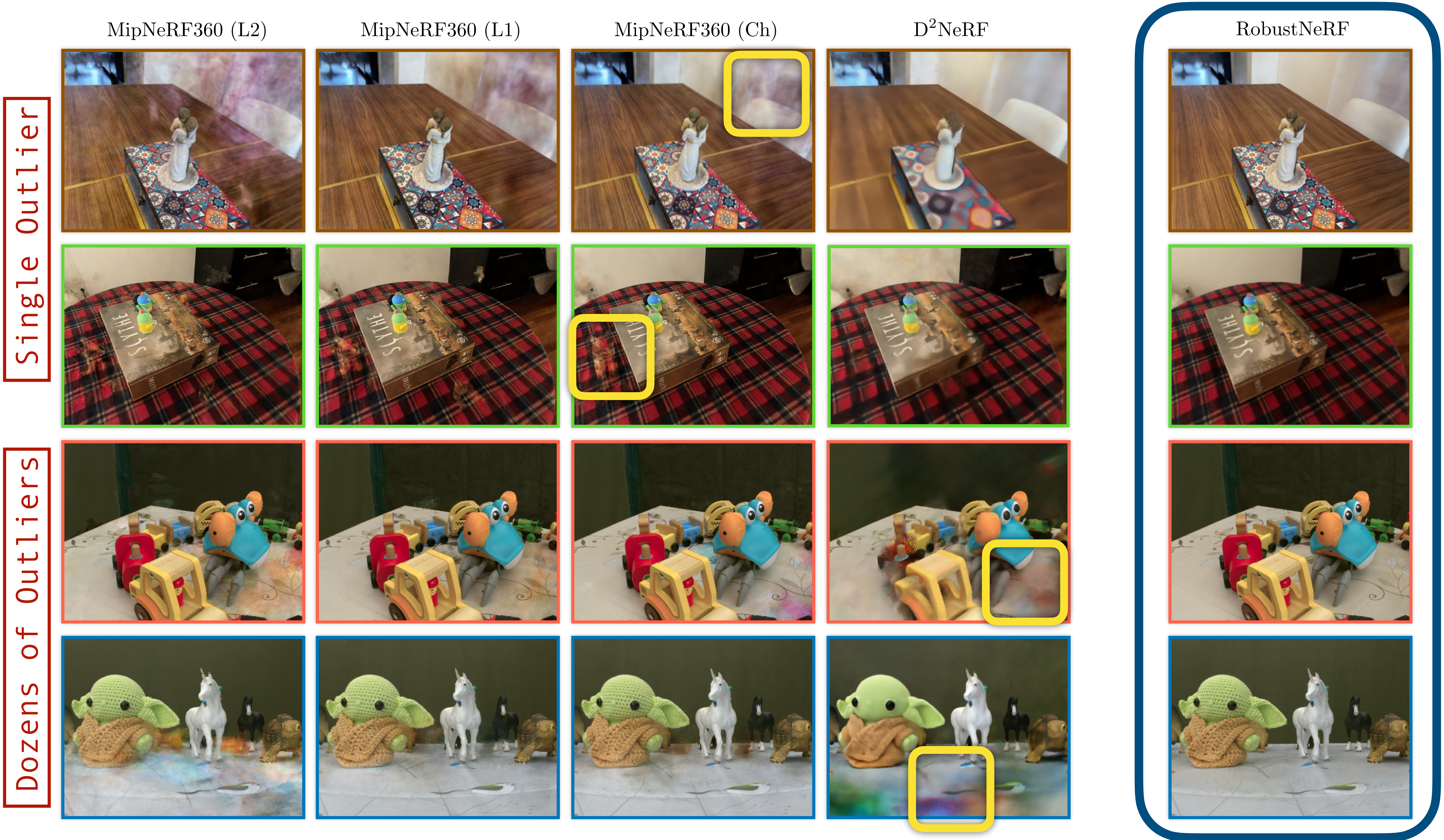
residuals $\epsilon(\mathbf{r})$

weights $\mathcal{W}(\mathbf{r})$

Training Progress w/ IRLS




MipNeRF360 (L2)
MipNeRF360 (L1)
MipNeRF360 (Ch)
D2NeRF
RobustNeRF
Single Outlier
Dozens of Outliers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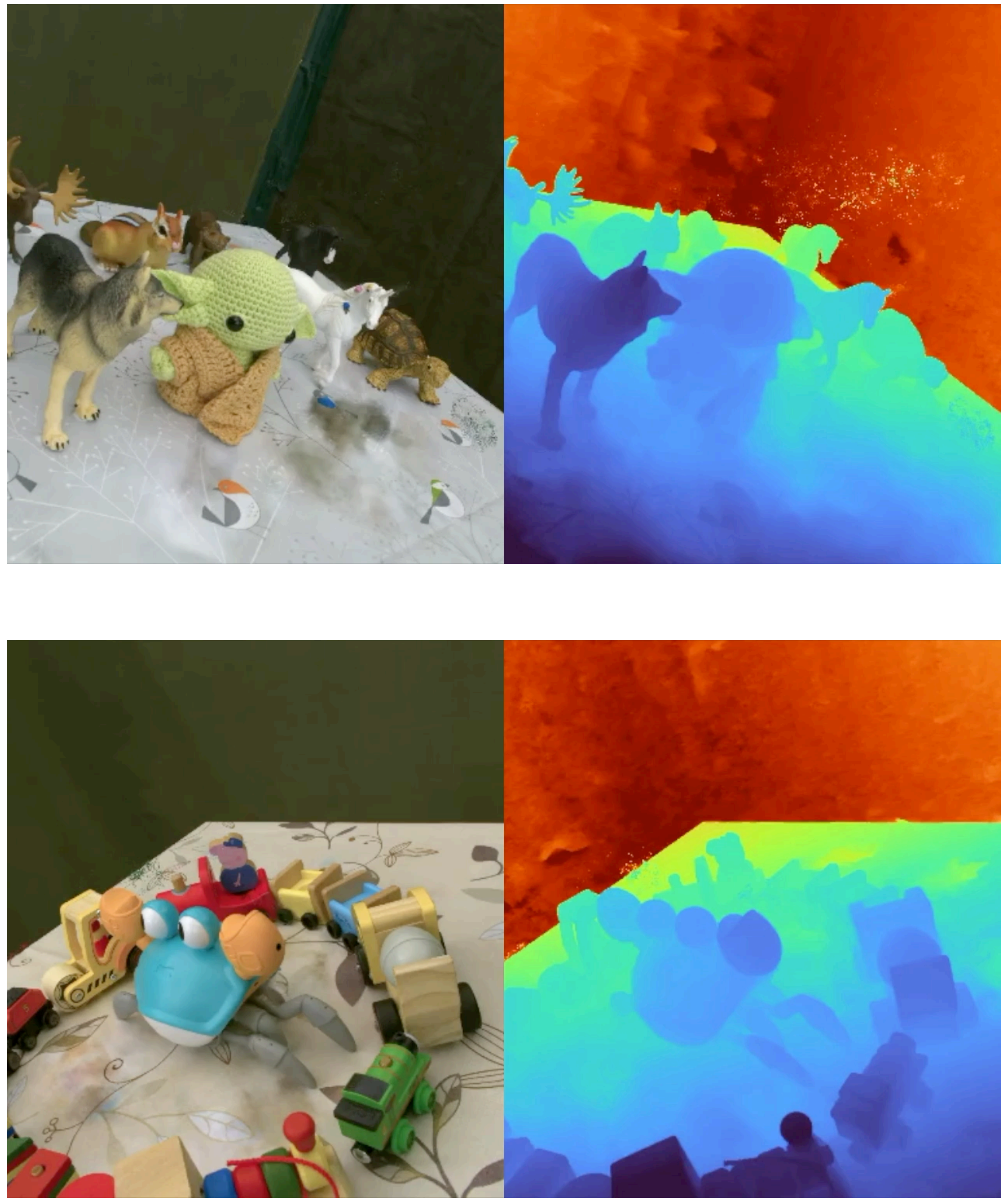
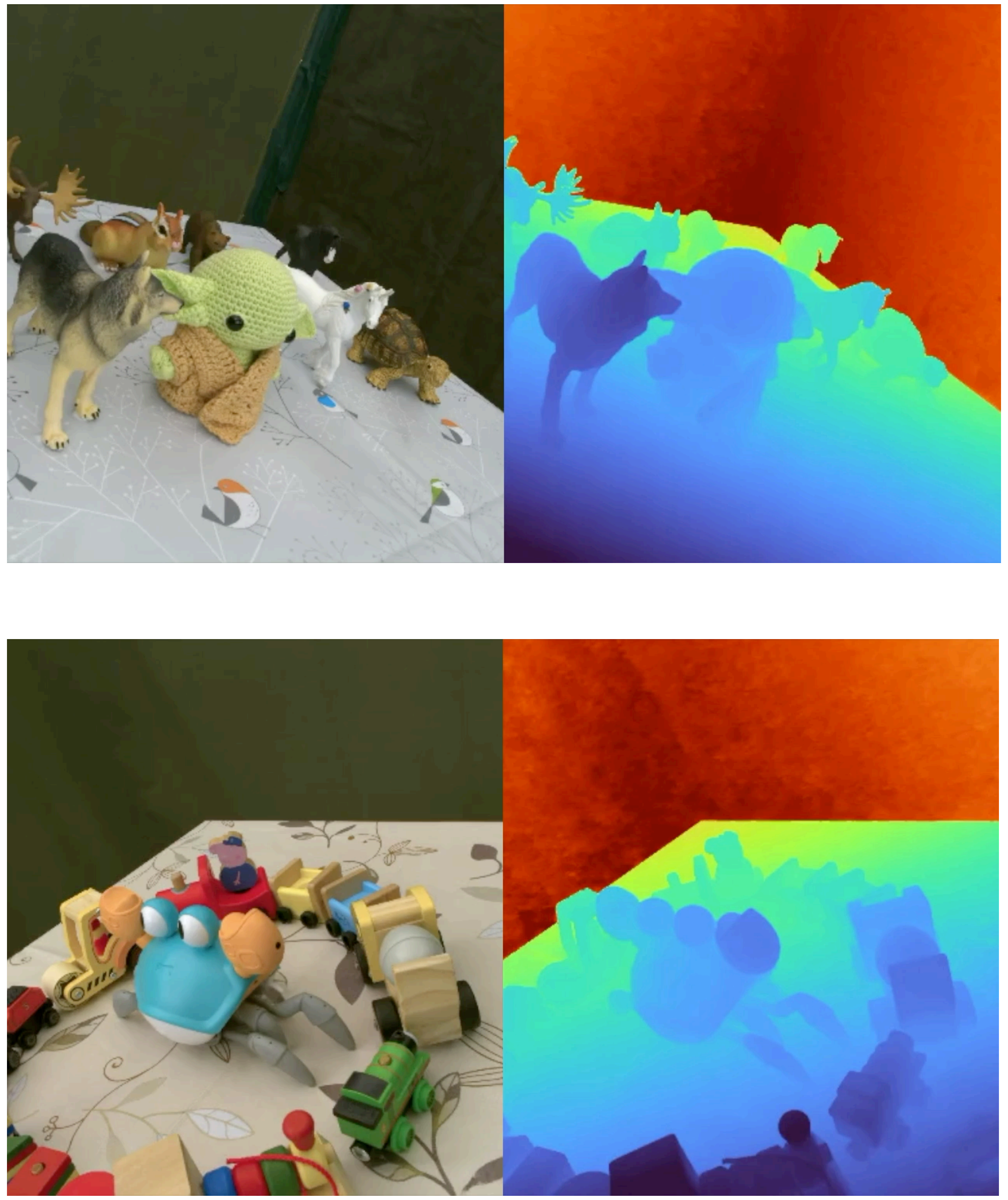
Comparison with MipNeRF360



MipNeRF360



RobustNeRF

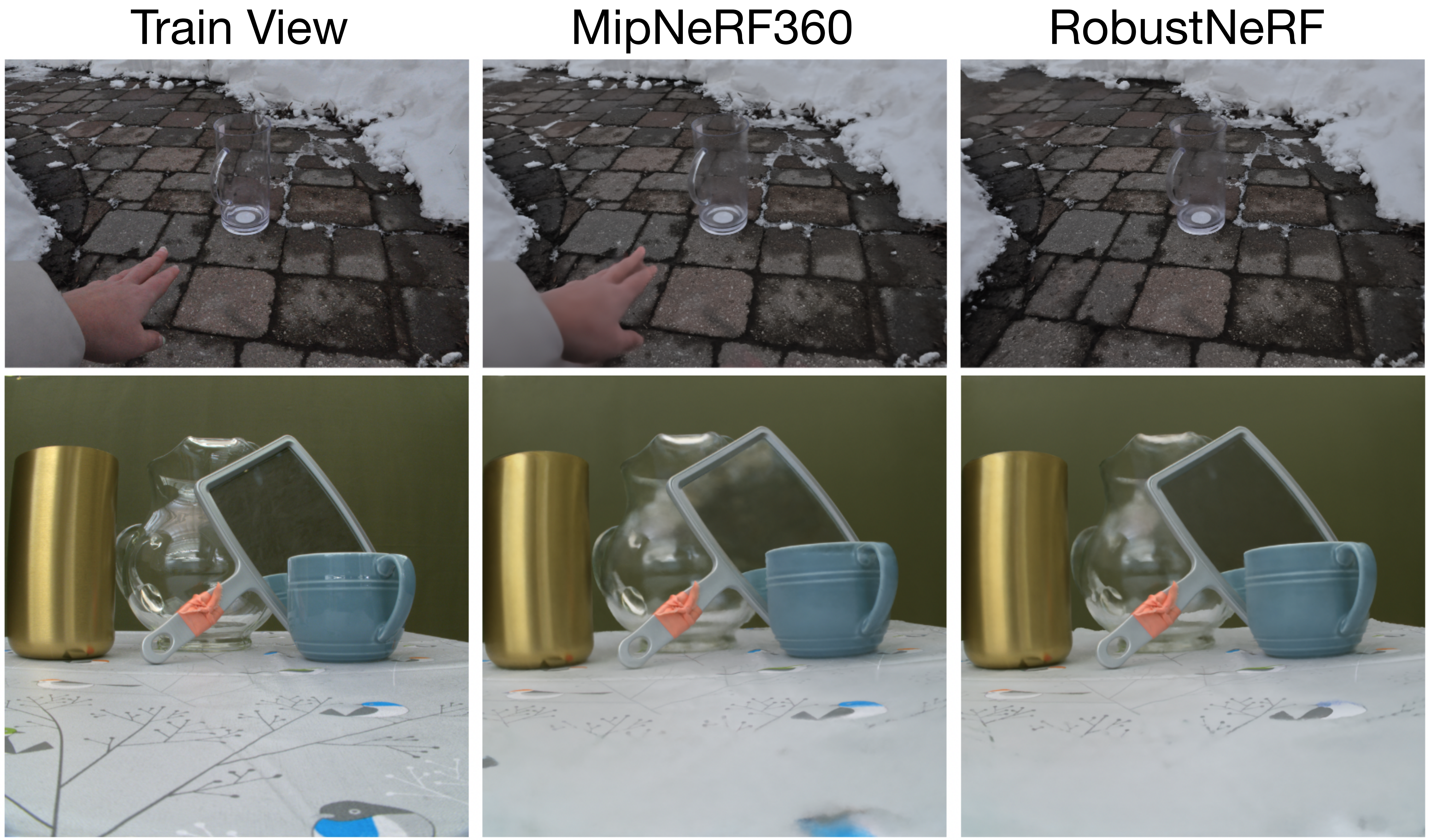
Viewdependent Scene Challenge

Train View

MipNeRF360

RobustNeRF

Viewdependent Scene Challenge



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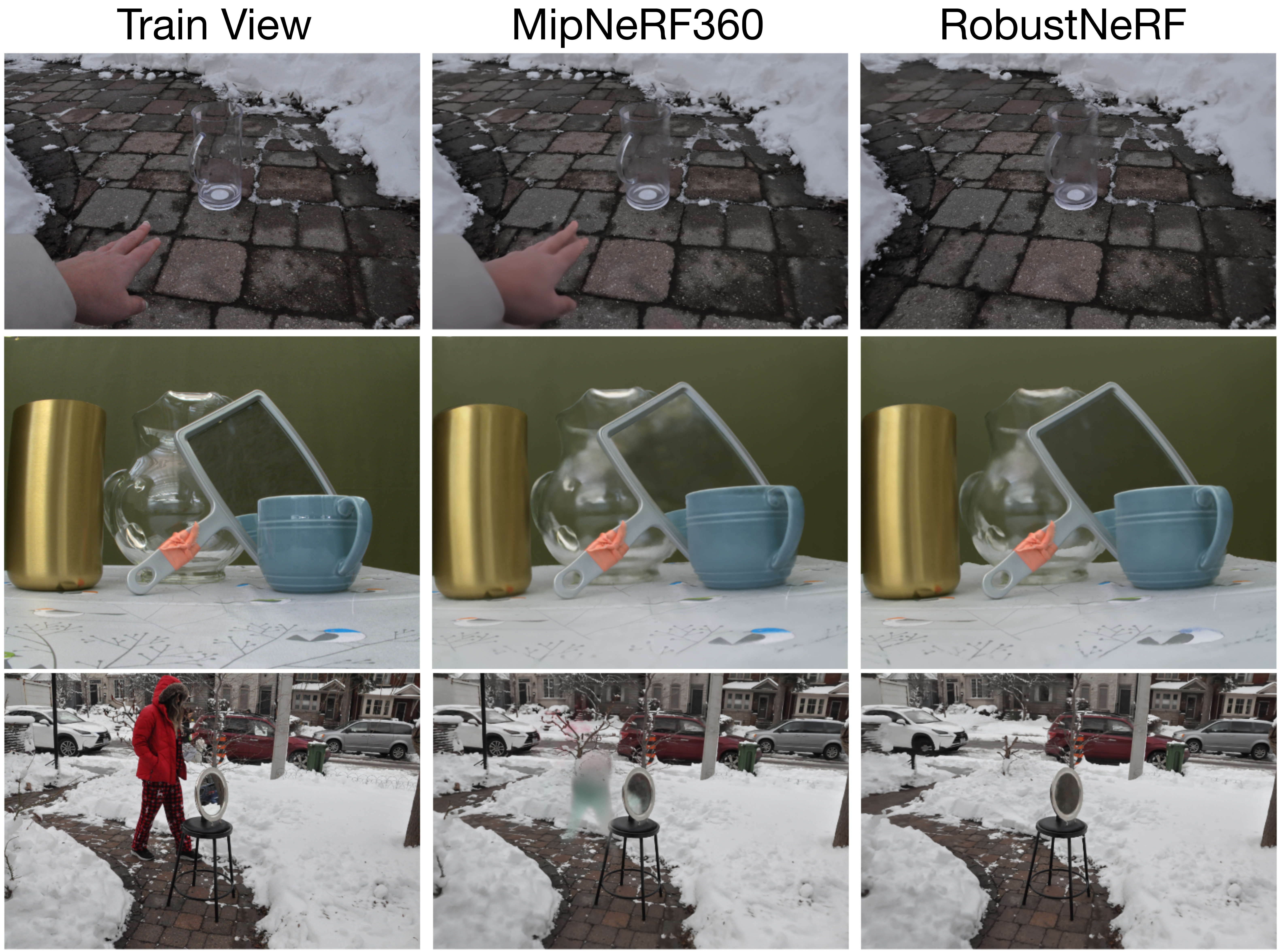
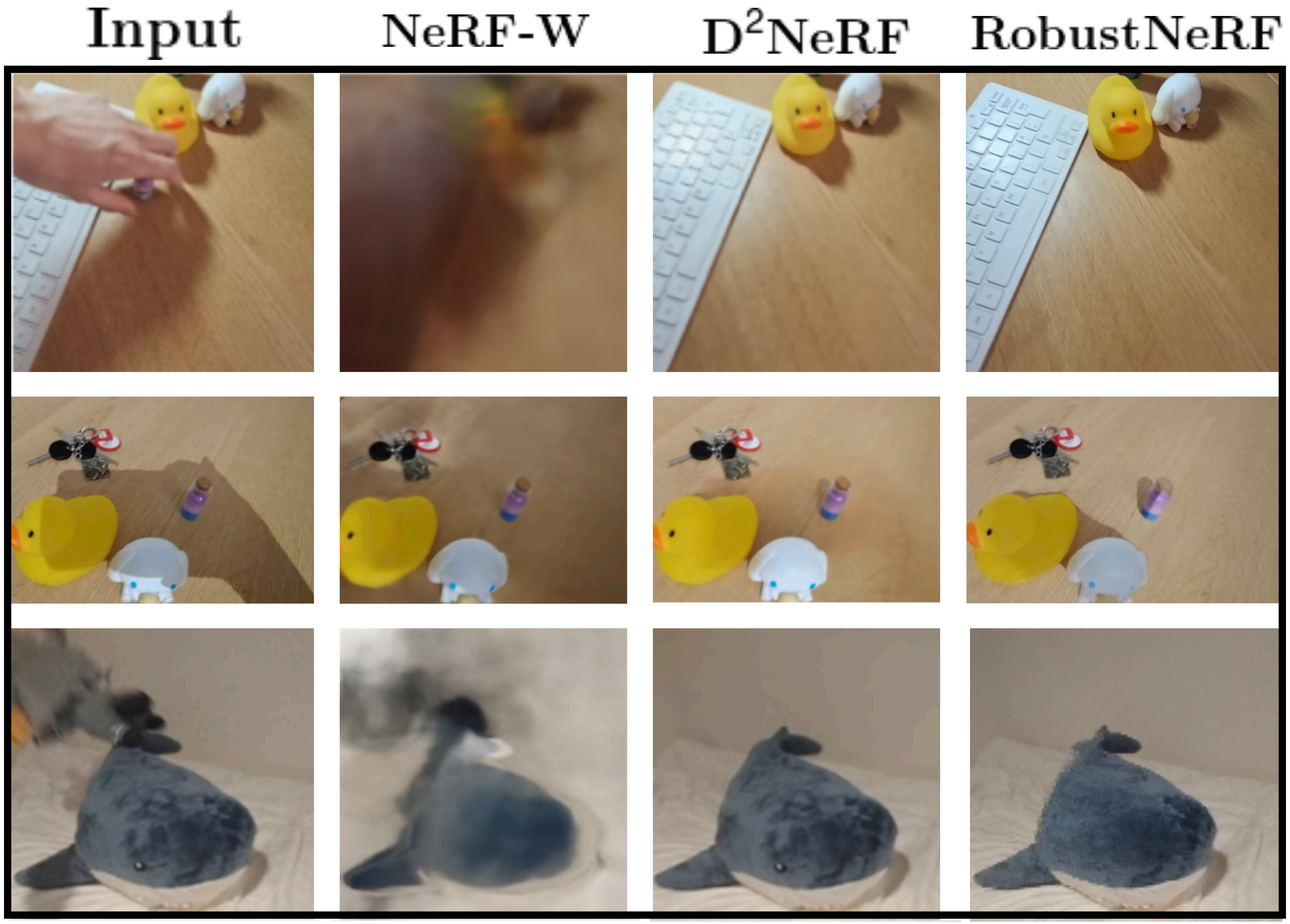
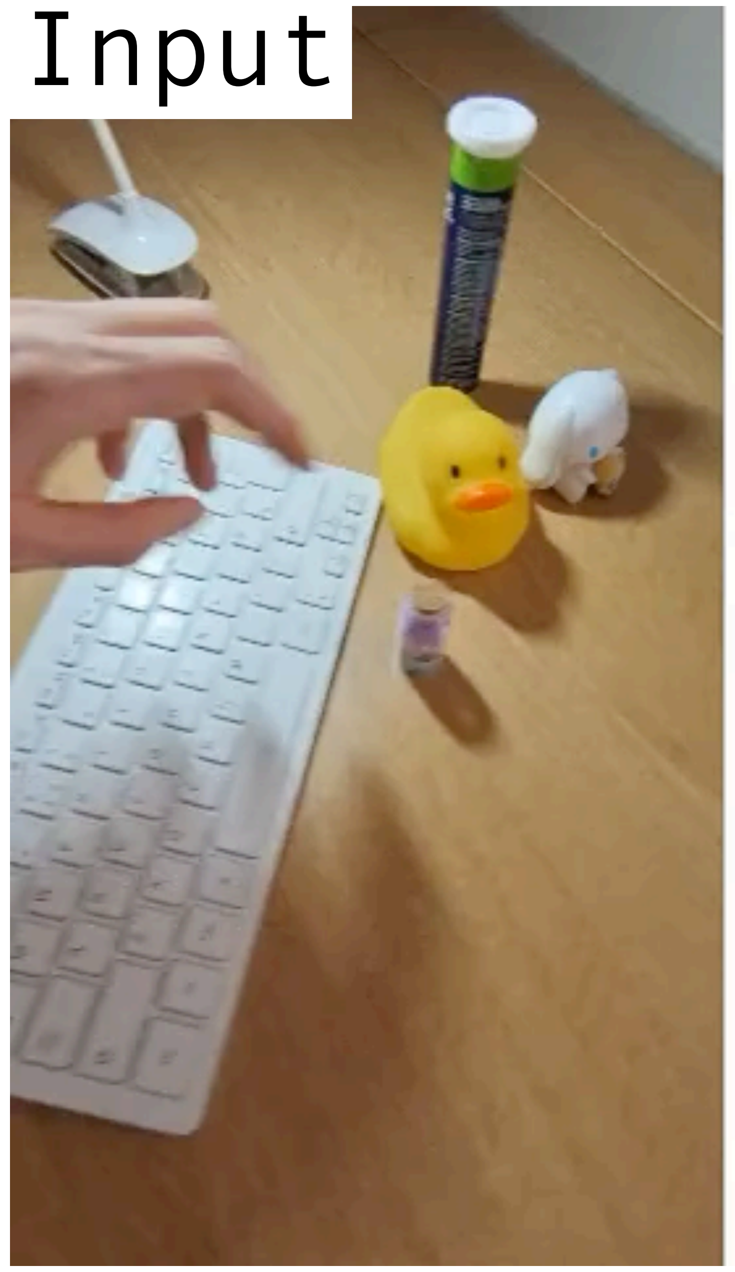


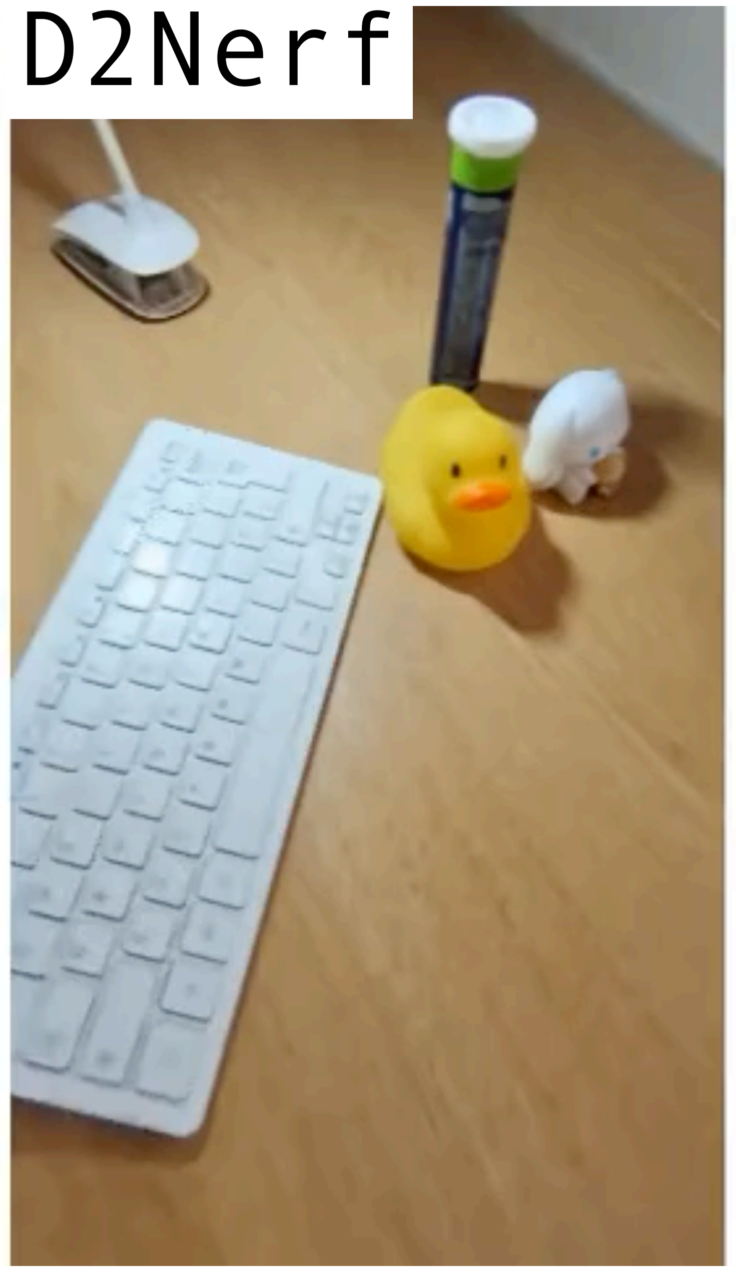
Transient Shadow Challenge

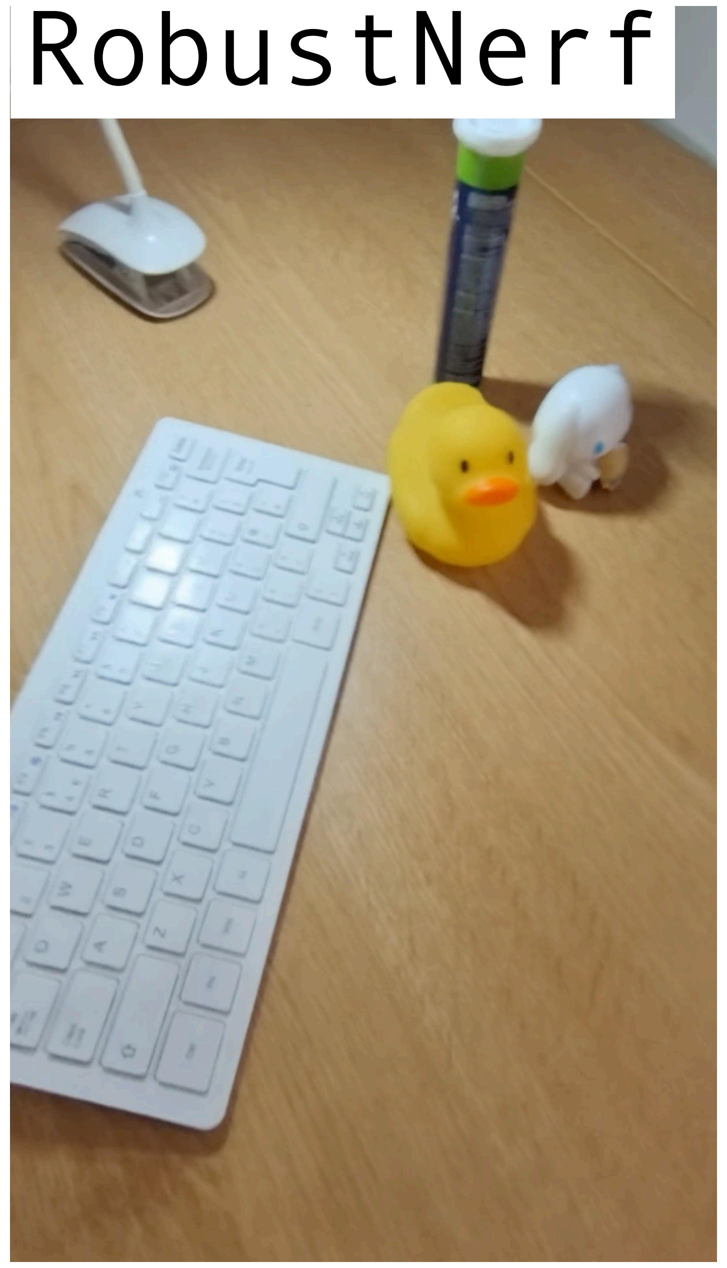


Wu, Tianhao, et al. "D $^ 2$ NeRF: Self-Supervised Decoupling of Dynamic and Static Objects from a Monocular Video." *arXiv preprint arXiv:2205.15838* (2022).

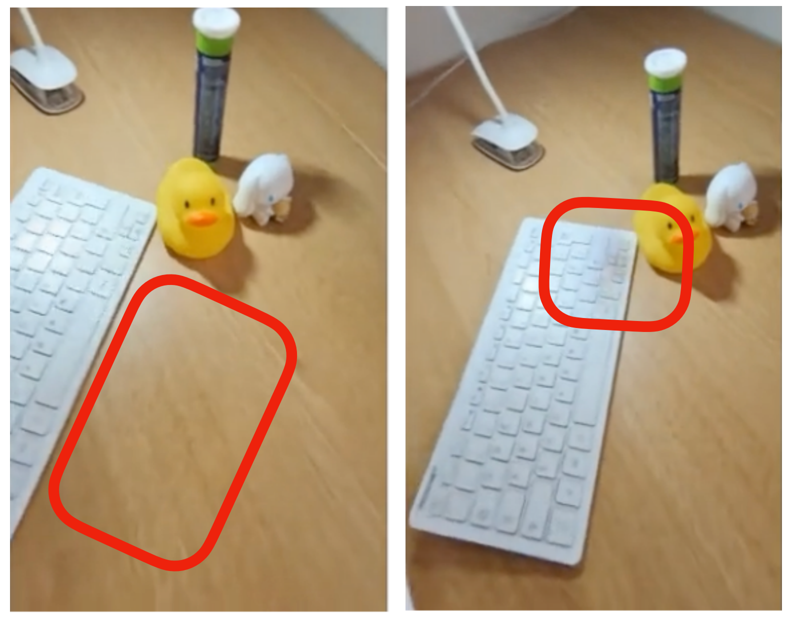
Side by Side Video on ”D2NeRF Pick”







1`` 6``



shadow

Floater

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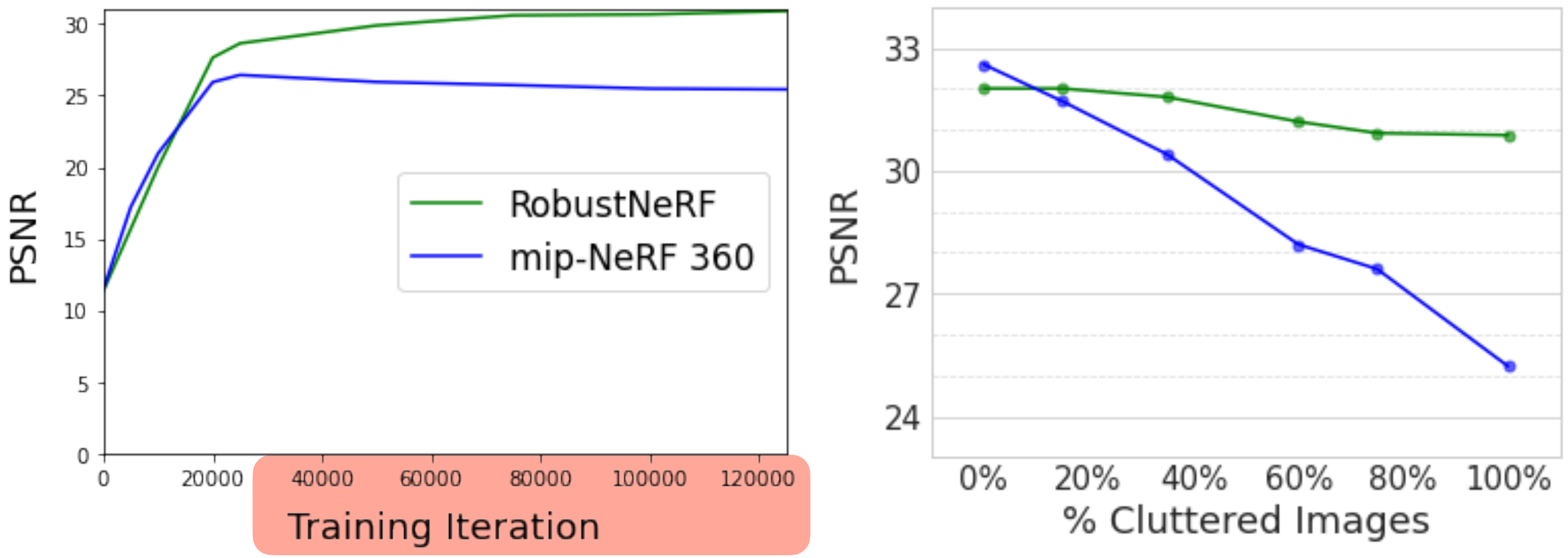
Limitations



Statistical inefficiency

Scenes take longer to reach peak accuracy. Clean scenes suffer a bit.

Cause: robust loss always considers a (fixed) portion of data as outliers

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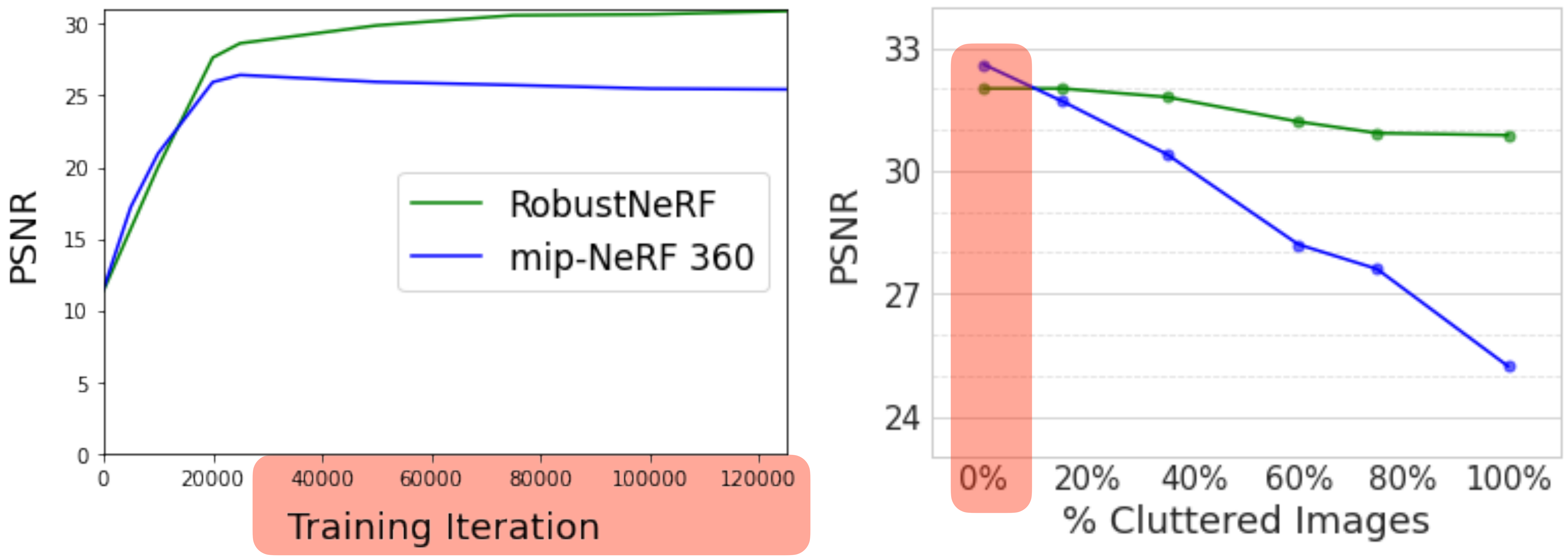

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Limitations

Lots of transients will confuse Colmap.

No Colmap No Camera No NeRF.

Transients in the mirror -> The mirrored surface is replaced with blanks.

RobustNeRF

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