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There And Back Again: Learning to Simulate Radar Data for Real World Applications

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1524

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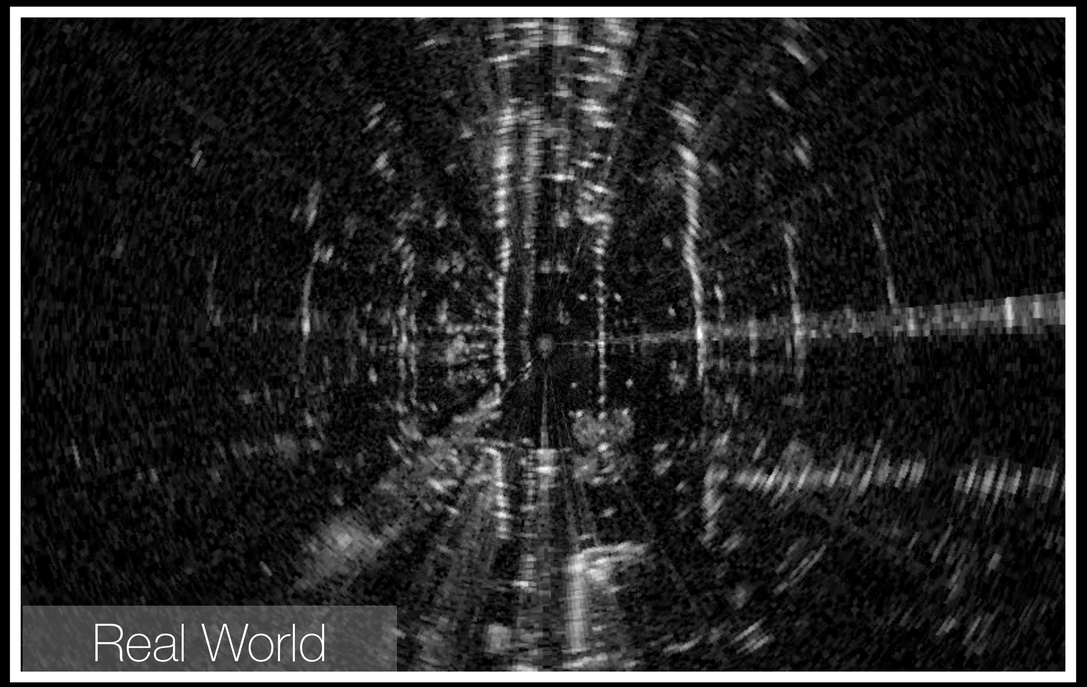
Introduction

Context

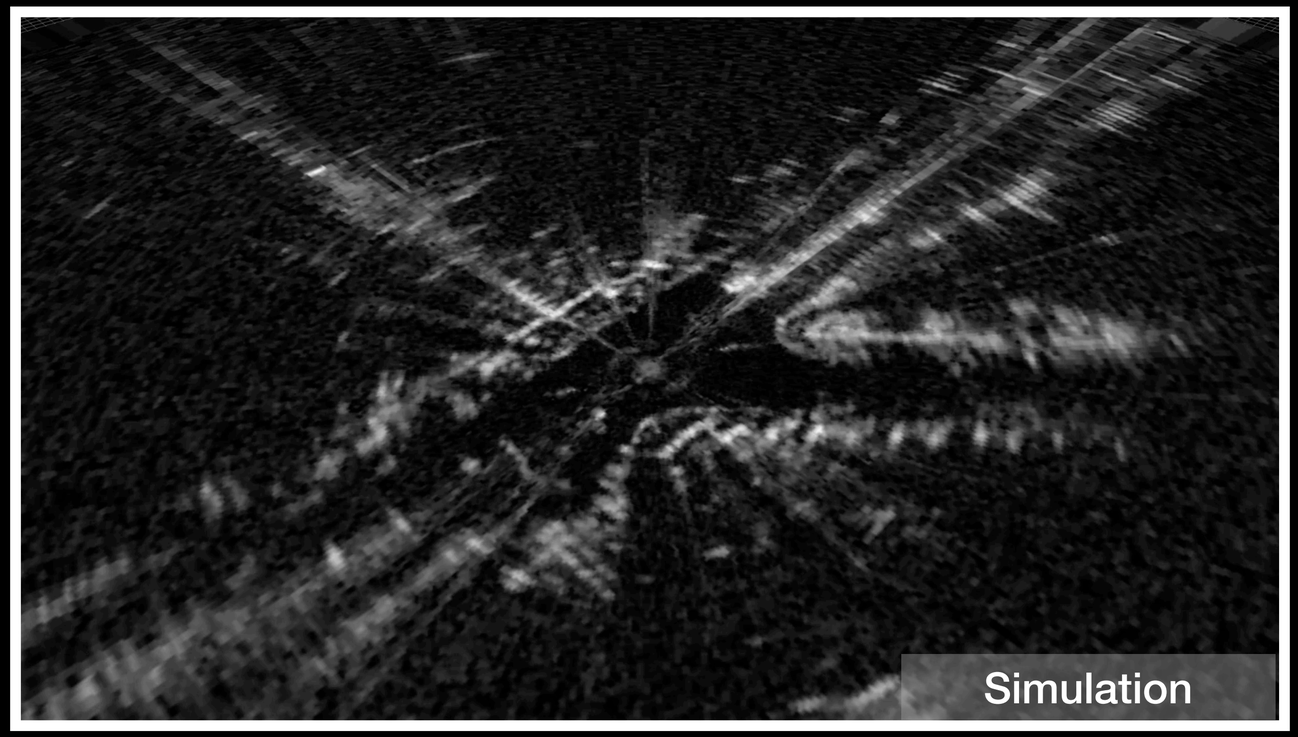
- Radar is a **promising** alternative to vision and lidar
- But notoriously challenging to work with as a result of challenging **noise artefacts**
- Data-driven approaches have made significant strides in using radar for a range of tasks in recent years
- But currently **limited by** size, quality and labelling of **datasets!**



Simulation has an **important** role to play…

Introduction

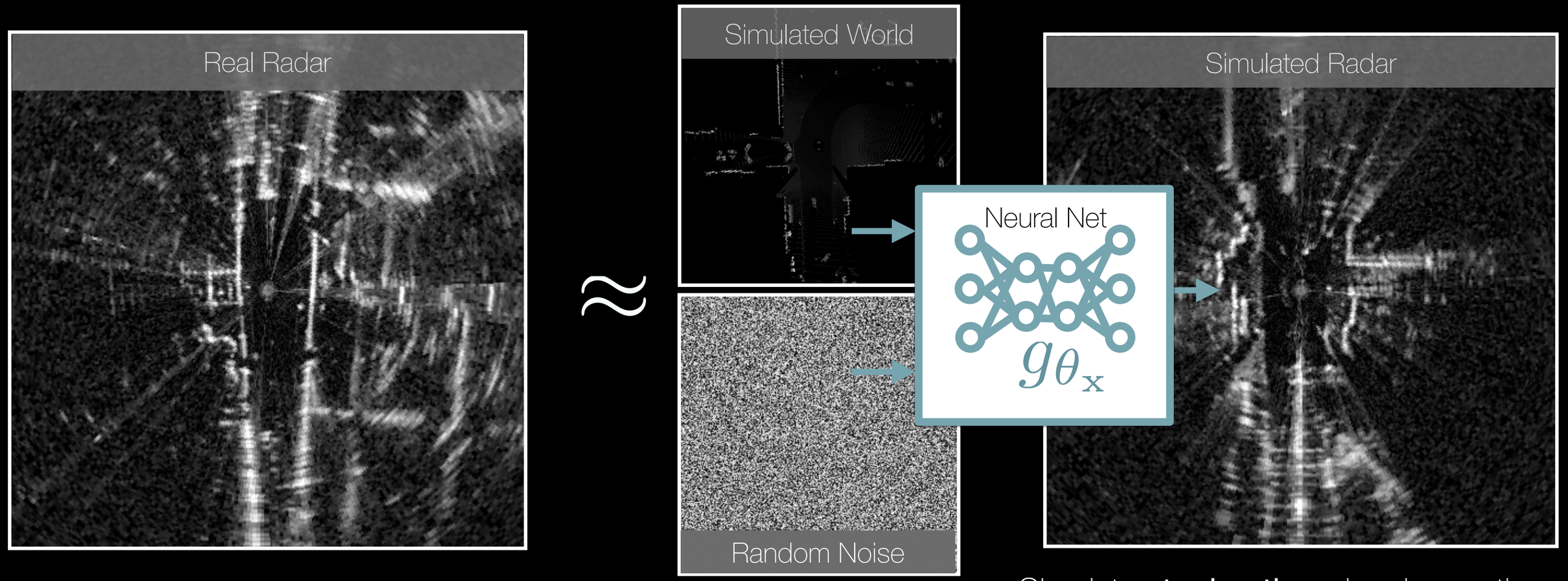
Our Aim



“Learn a radar sensor model, interfacing with an **existing** simulation environment, to train **new** models in simulation”

Our Approach

Stochastic Sensor Modelling with **Deep Implicit Model**



Real Radar is inherently **stochastic**

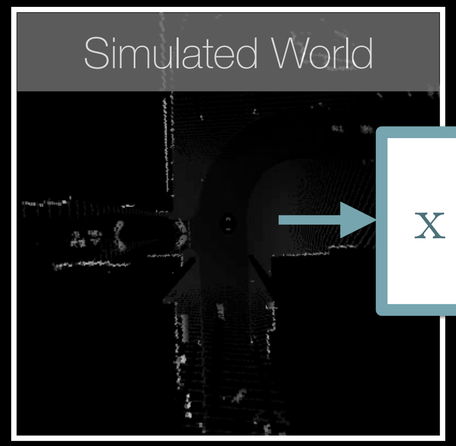
Simulate **stochastic** radar observations using deep implicit model

Our Approach

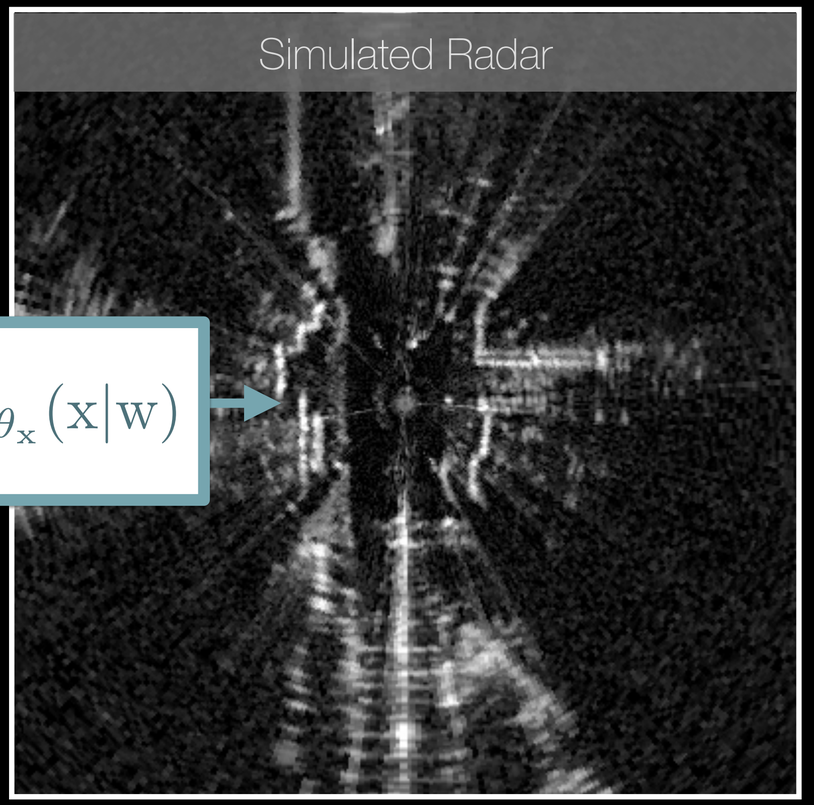
Stochastic Sensor Modelling with **Deep Implicit Model**

Implicitly capture **distribution** over radar observations

$\approx$



$$\mathrm{x} \sim p_{\theta_\mathrm{x}}(\mathrm{x}|\mathrm{w})$$



Real Radar is inherently **stochastic**

Our Approach

Training data generated **automatically** in **simulation** or in the **real world**

$$\mathbf{S} = \{\mathbf{w}_l\}_{l=1}^{L}$$

World state $\mathbf{W}$ characterised as an **elevation map** generated using **CARLA**

[D. Barnes, M. Gadd, P. Murcutt, P. Newman and I. Posner, "The Oxford Radar RobotCar Dataset: A Radar Extension to the Oxford RobotCar Dataset," *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2020, pp. 6433-6438, doi: 10.1109/ICRA40945.2020.9196884.]

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Simulated World State

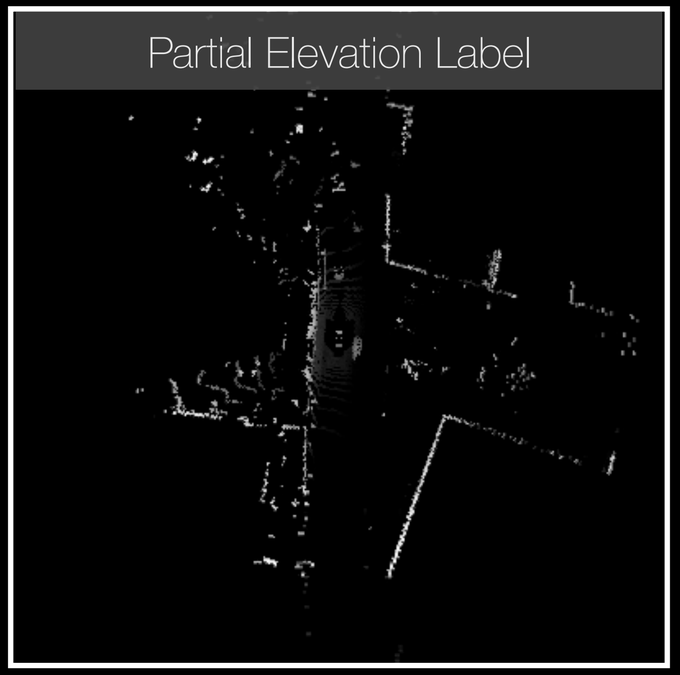
World state $\mathbf{W}$ characterised as an **elevation map** generated using **CARLA**

$$\mathbf{R} = \{(\mathbf{x}^*, \mathbf{m}^*)_n\}_{n=1}^{N}$$

Real Radar

Real radar observations $\mathbf{X}^*$ from **Radar Oxford 10k** dataset

Partial Elevation Label



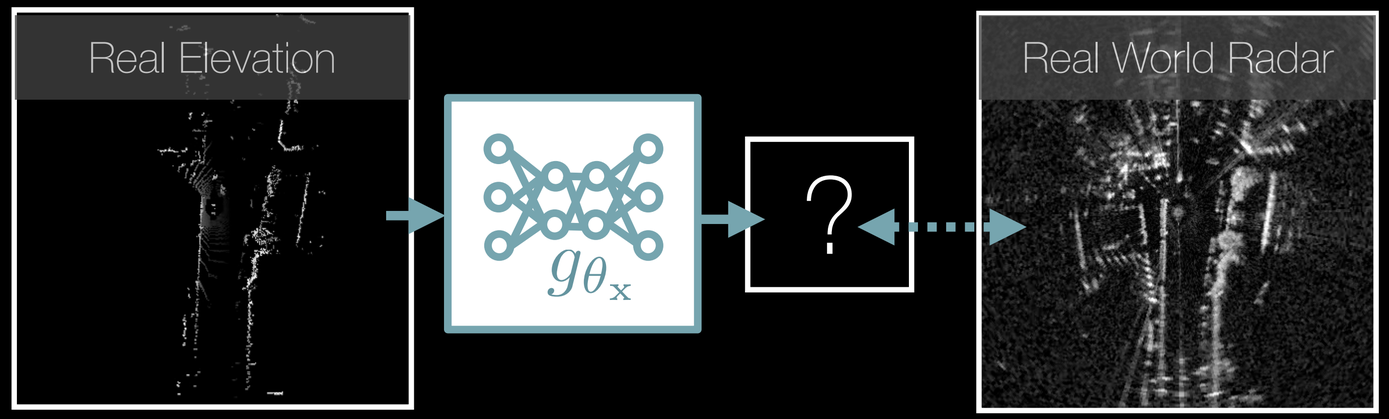
Partial elevation labels $\mathbf{m}^*$ **automatically** generated from lidar

[D. Barnes, M. Gadd, P. Murcutt, P. Newman and I. Posner, "The Oxford Radar RobotCar Dataset: A Radar Extension to the Oxford RobotCar Dataset," *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 2020, pp. 6433-6438, doi: 10.1109/ICRA40945.2020.9196884.]

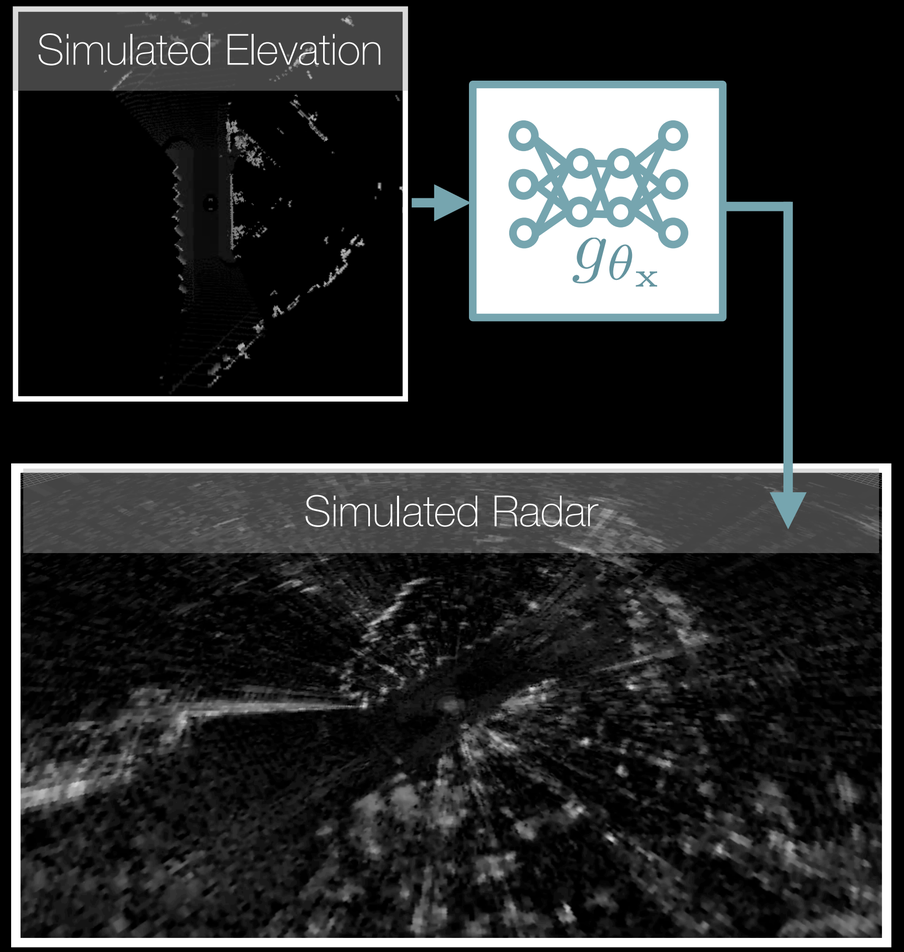
One Possible Approach?

Train model to simulate radar from **real** world elevation

(1) Train on **real** data $\mathbf{R} = \{(\mathbf{x}^*, \mathbf{m}^*)_n\}_{n=1}^{N}$



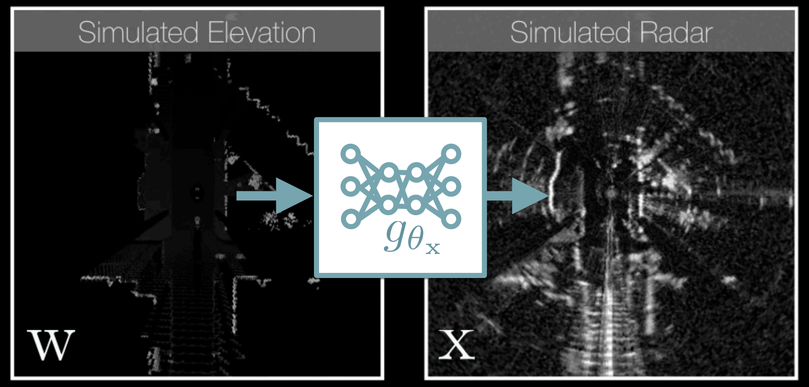
(2) Test on **simulated** data $\mathbf{S} = \{\mathbf{w}_l\}_{l=1}^{L}$



Models trained **only** on real elevation poorly generalise to simulated elevation states

Our Approach

Predict radar from **simulated states** using **adversarial** loss



Our Approach

Predict radar from **simulated states** using **adversarial** loss

Radar generated from
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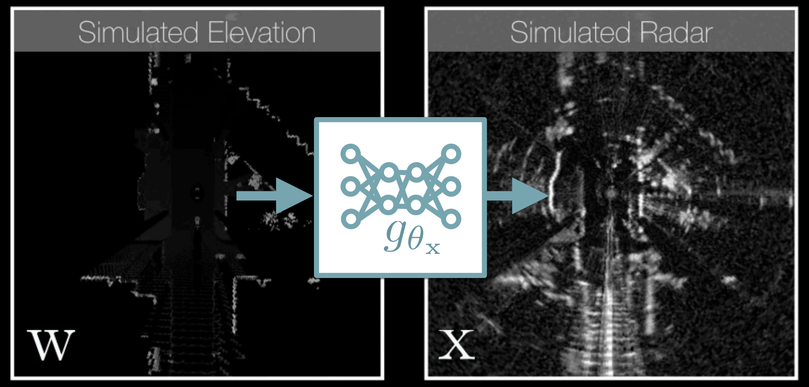

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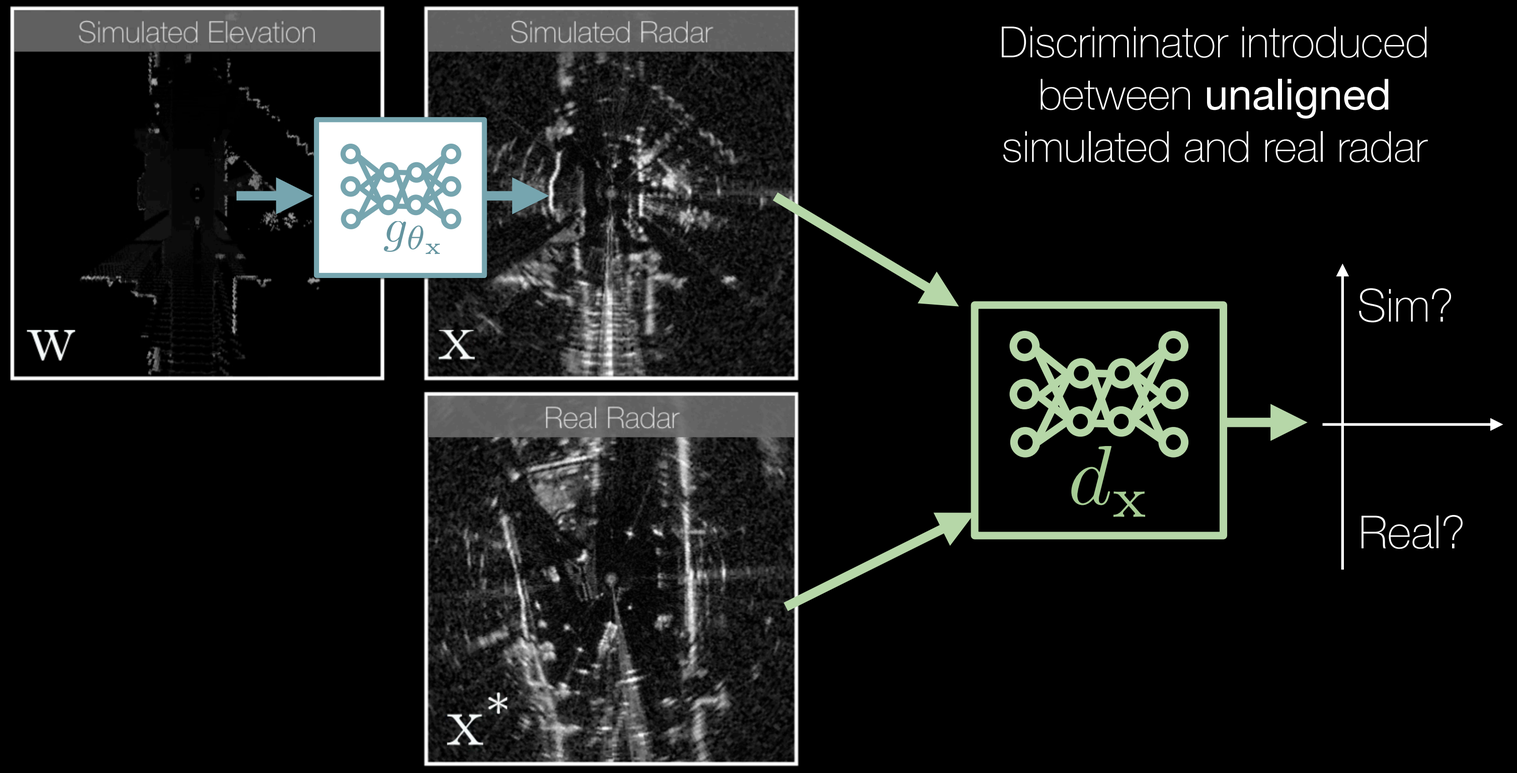
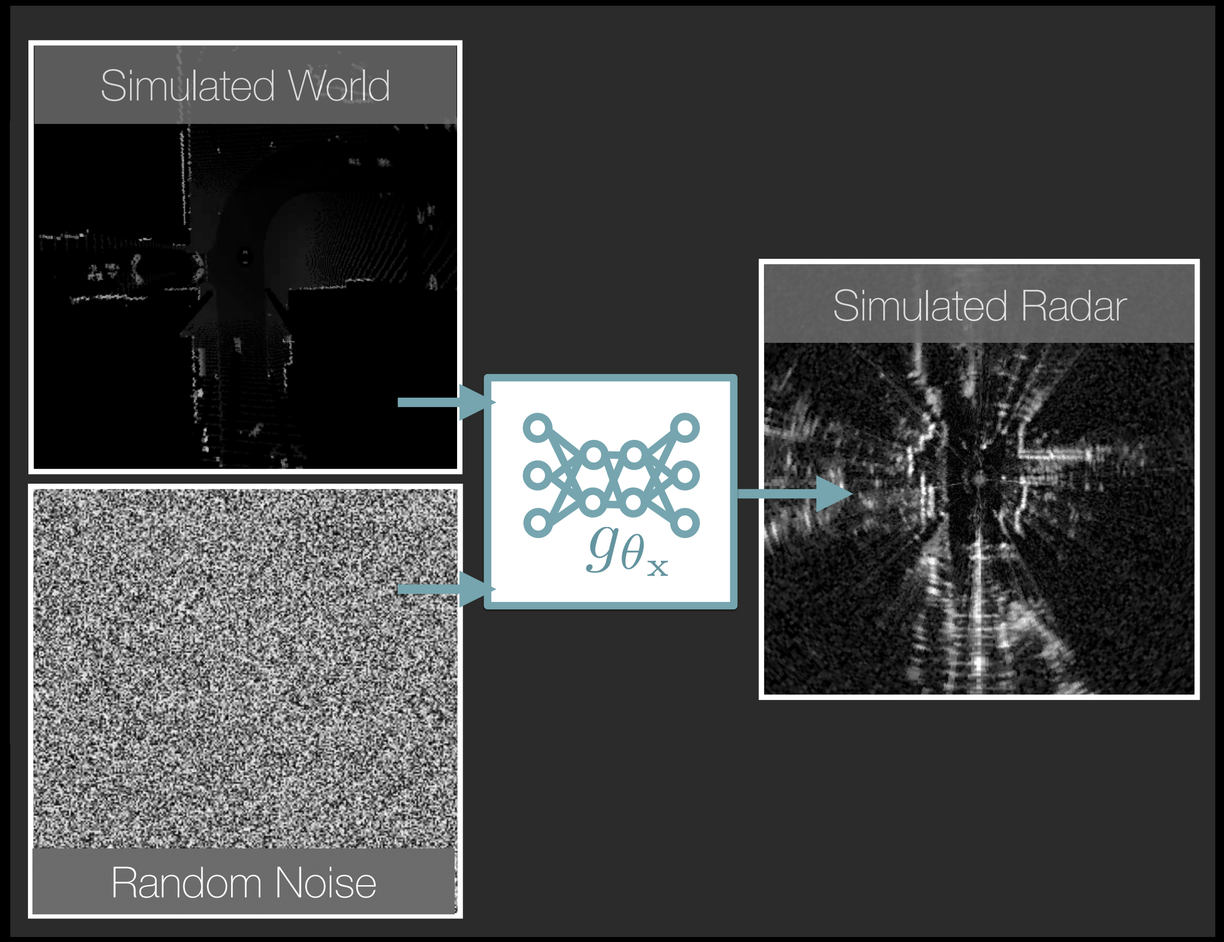
Radar generated from **simulated** elevation



Our Approach

Model both the **forward** and **backward** processes



Forward

Introduce new neural network predicting **elevation** from real **radar**

Backward

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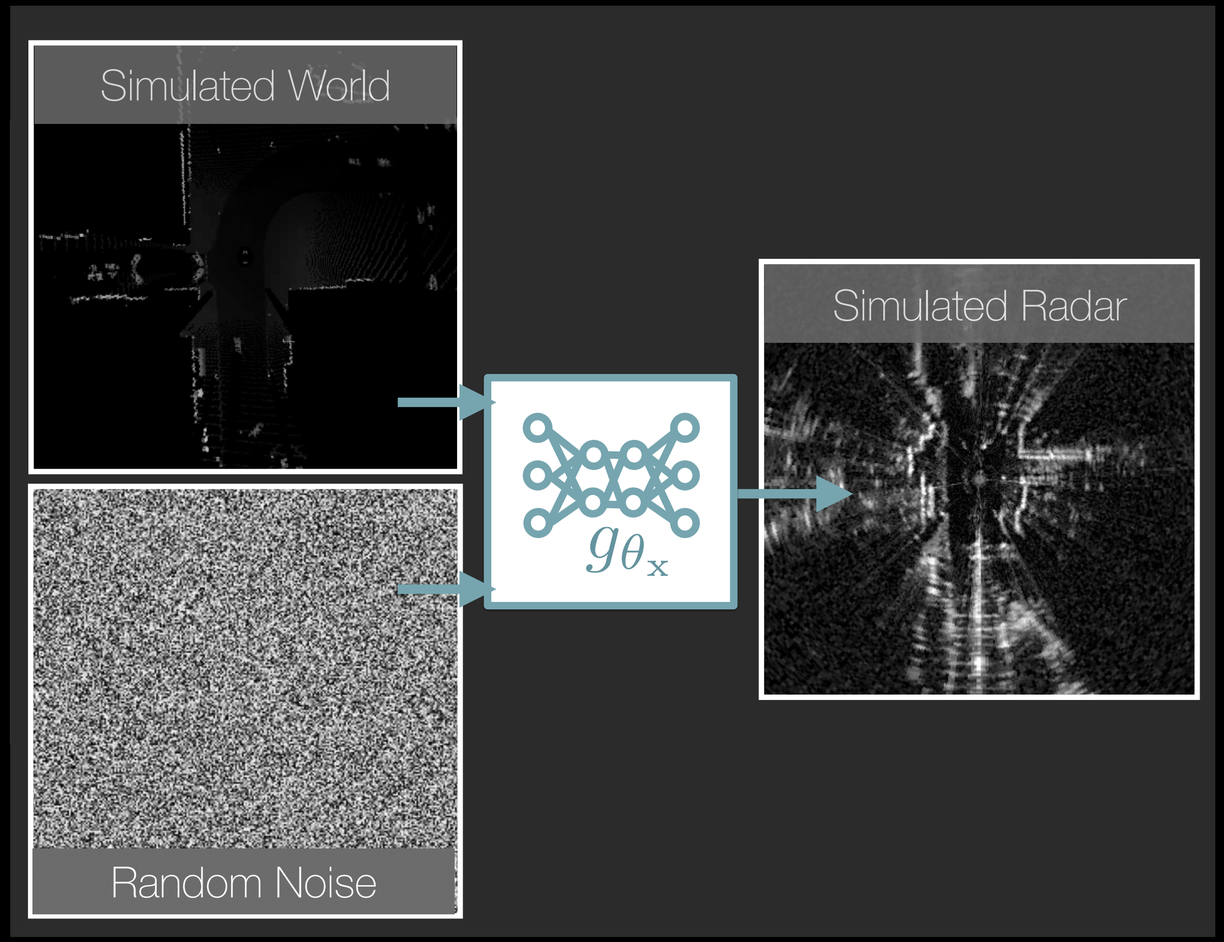

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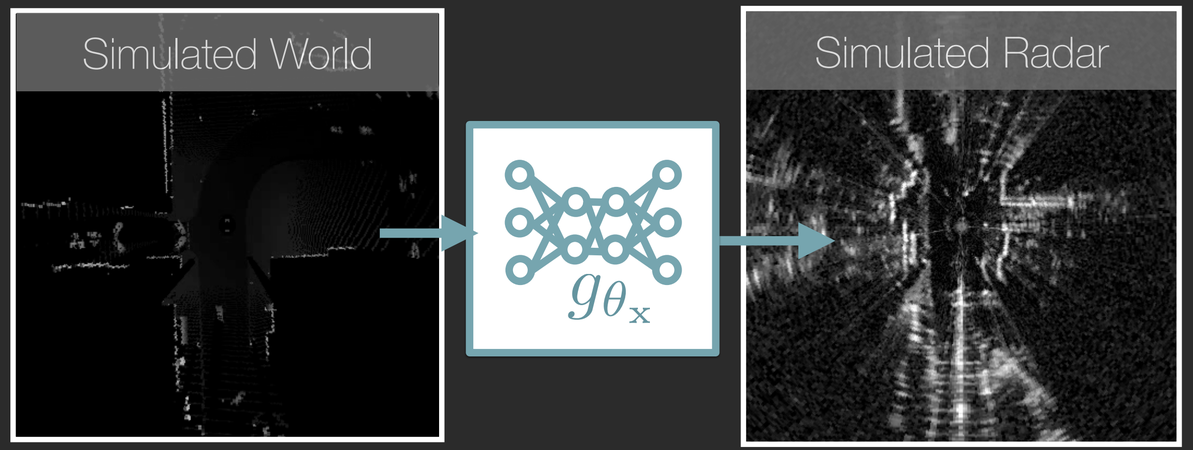
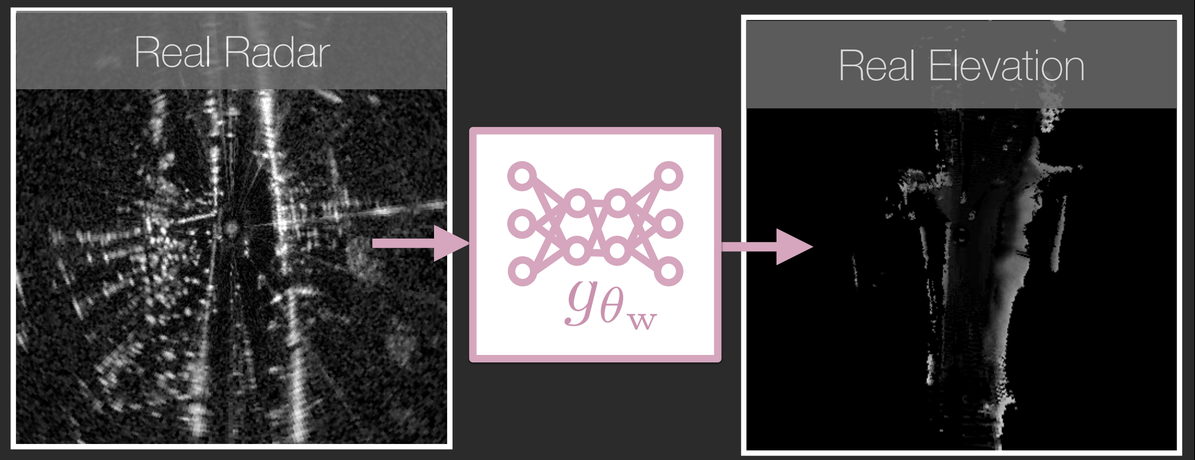
Forward: radar from simulated world state



Backward: elevation from real radar



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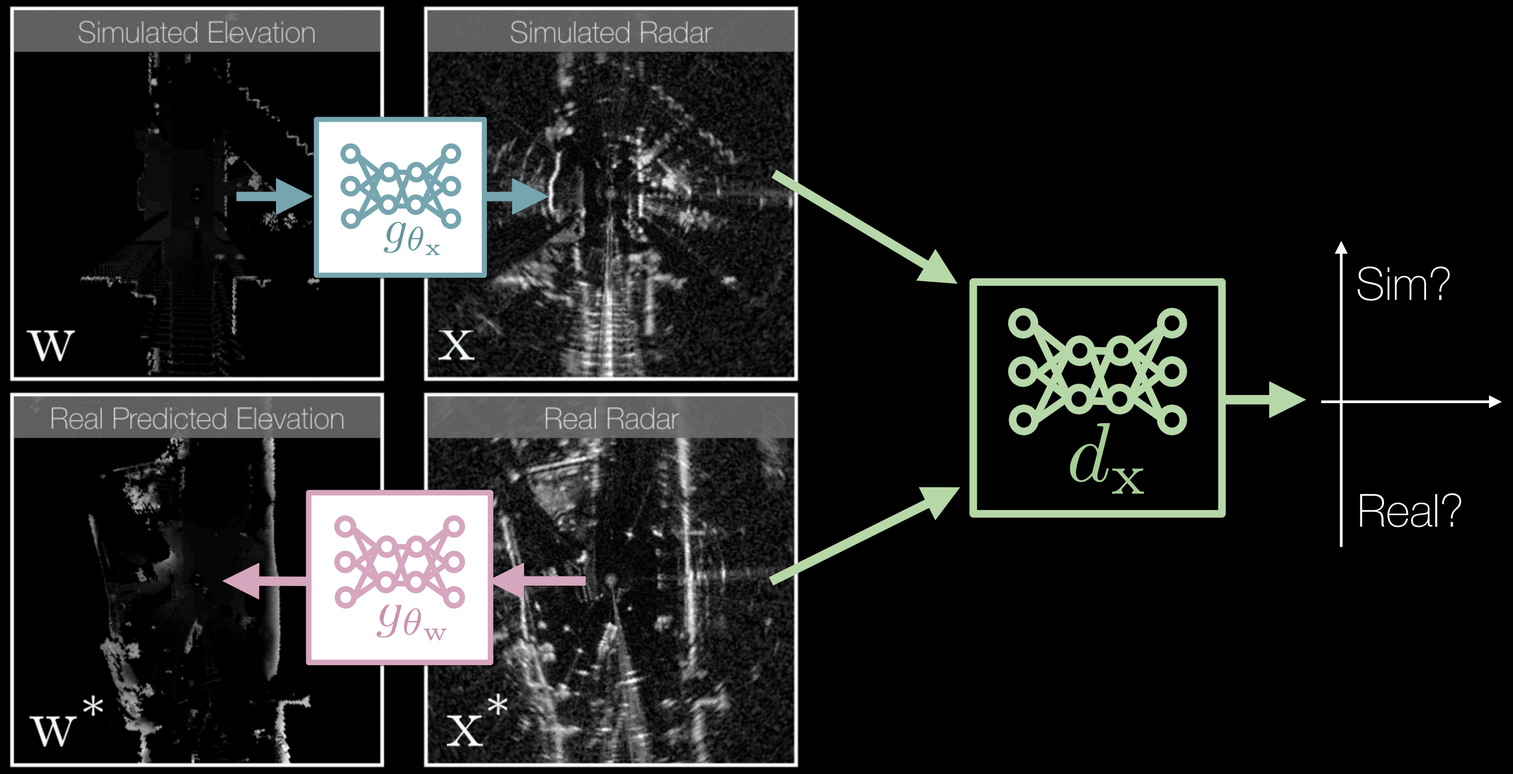

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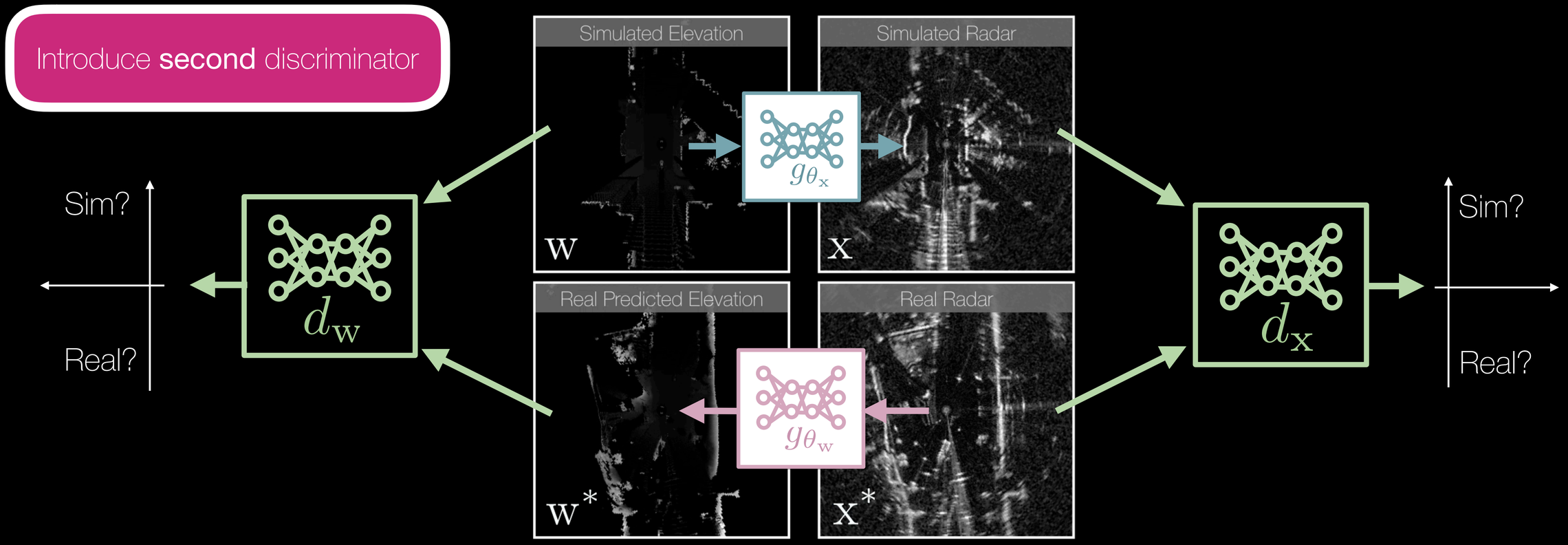
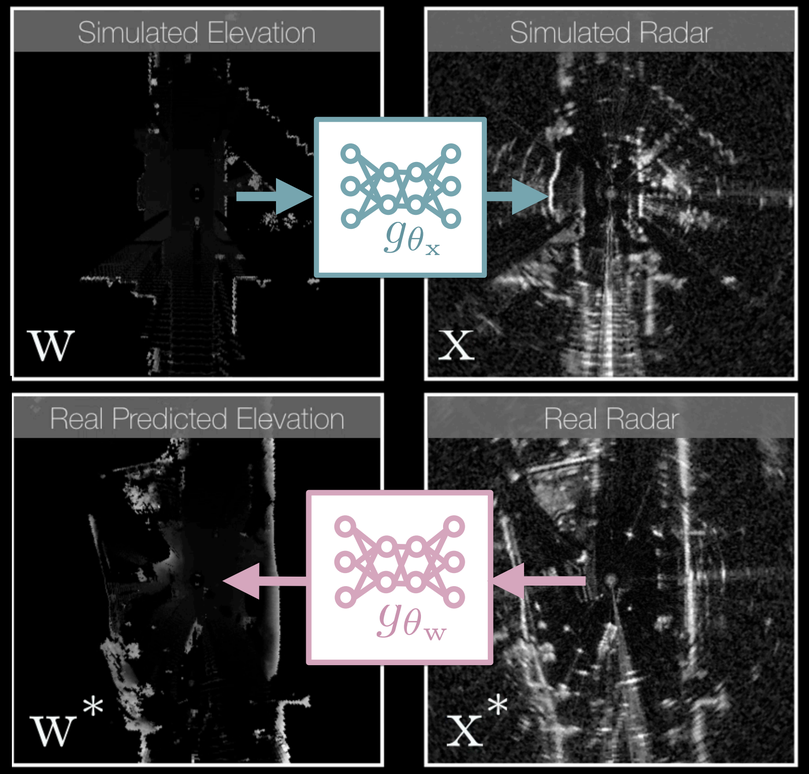


Our Approach

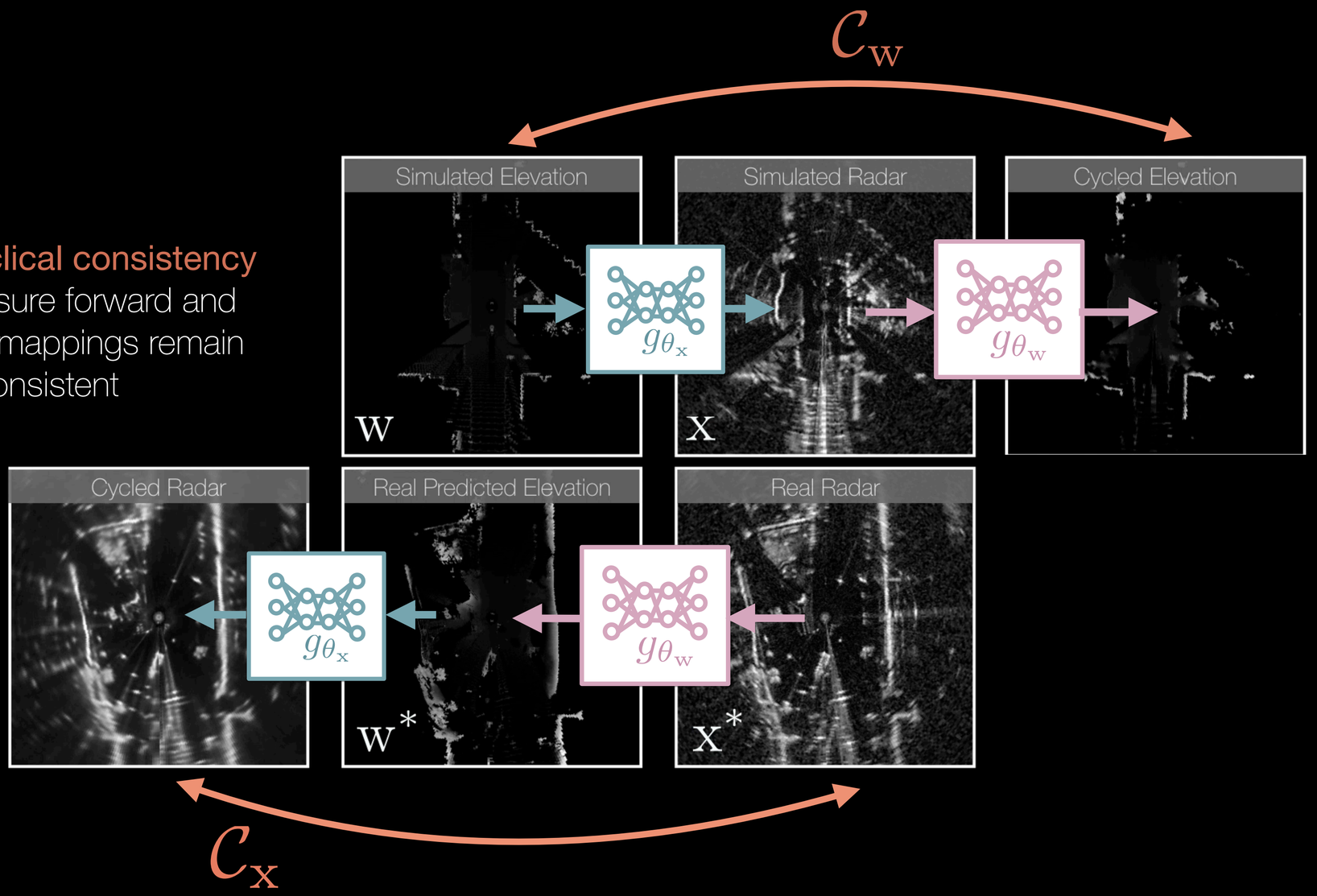
Further constrain training with **cyclical consistency** and **real world alignment**



Our Approach

Further constrain training with **cyclical consistency** and **real world alignment**

Use L1 **cyclical consistency** loss to ensure forward and backward mappings remain consistent



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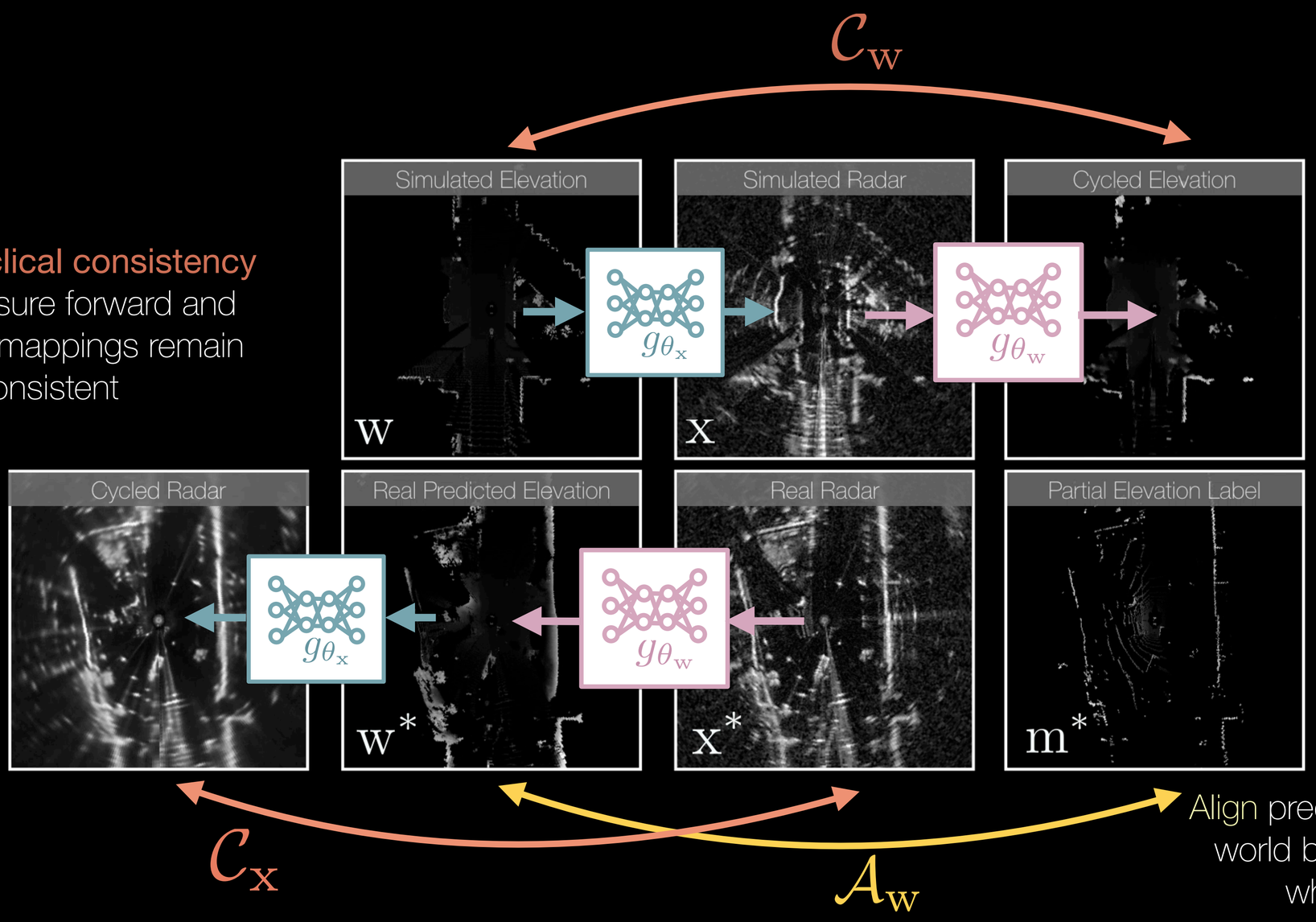
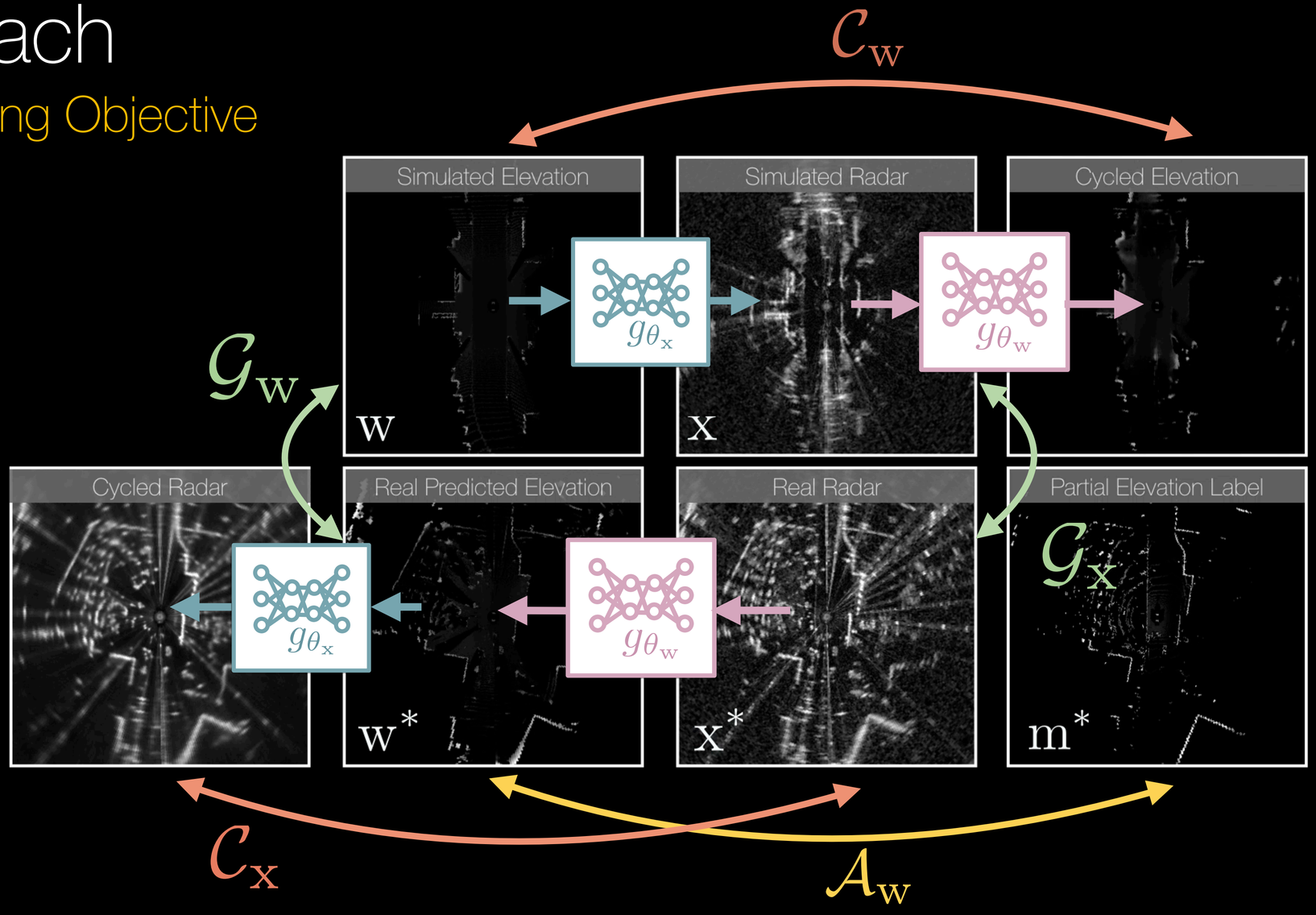


Align predicted elevation to real world backpropagating only where labels exist

Approach

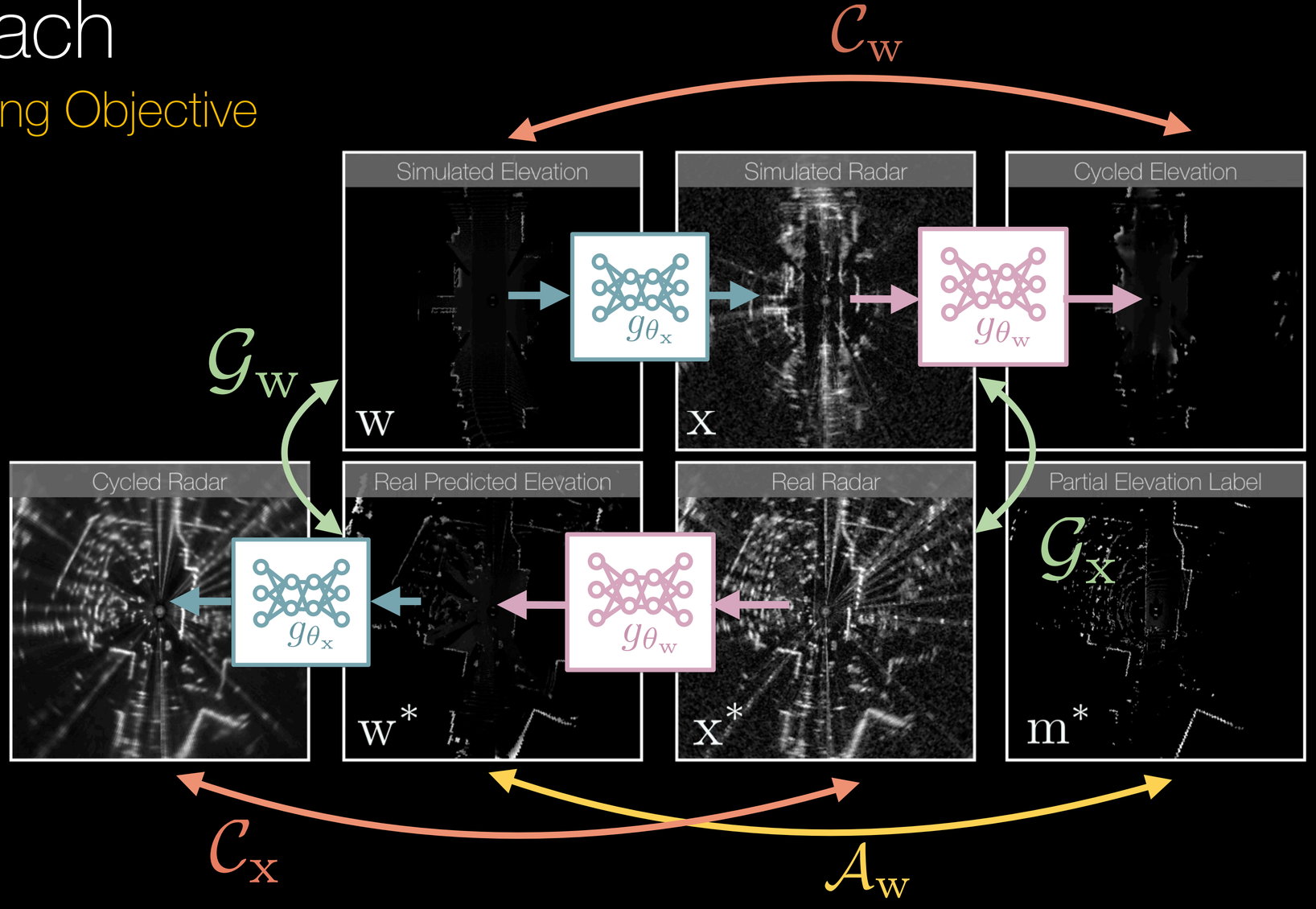
Final Training Objective



$$\mathcal{L}(\theta_{\mathrm{w}}, \theta_{\mathrm{x}}) = \mathcal{G}_{\mathrm{w}} + \mathcal{G}_{\mathrm{x}} + \mathcal{C}_{\mathrm{x}} + \mathcal{C}_{\mathrm{w}} + \mathcal{A}_{\mathrm{w}}$$

Approach

Final Training Objective



Train both networks **together**

$$\mathcal{L}(\theta_{\mathrm{w}}, \theta_{\mathrm{x}}) = \mathcal{G}_{\mathrm{w}} + \mathcal{G}_{\mathrm{x}} + \mathcal{C}_{\mathrm{x}} + \mathcal{C}_{\mathrm{w}} + \mathcal{A}_{\mathrm{w}}$$

Results

Radar Simulation Evaluation Setup

"Are we able to train **new** models in simulation?"

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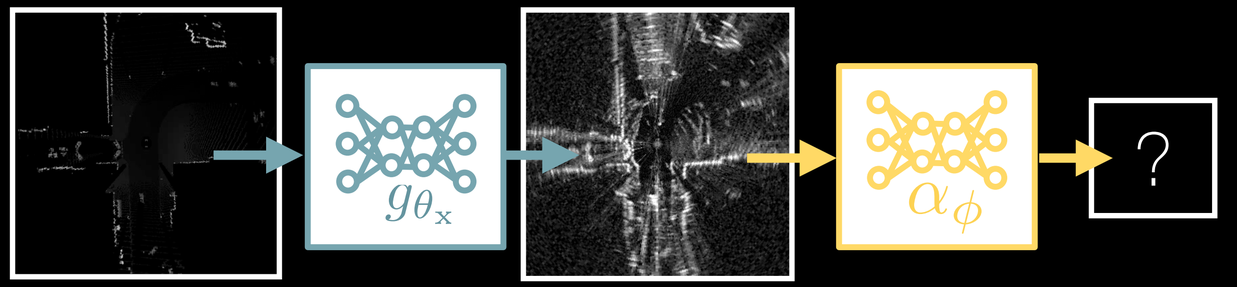
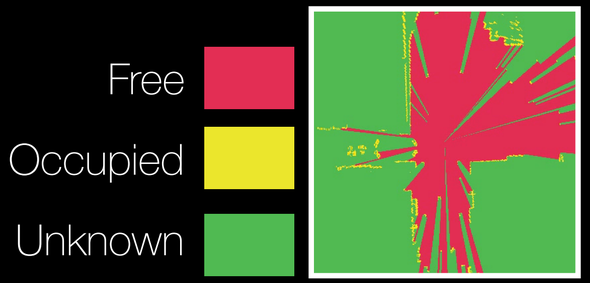
(1) **Train** segmentation model in **simulation**





Ground truth training labels from simulation

Results

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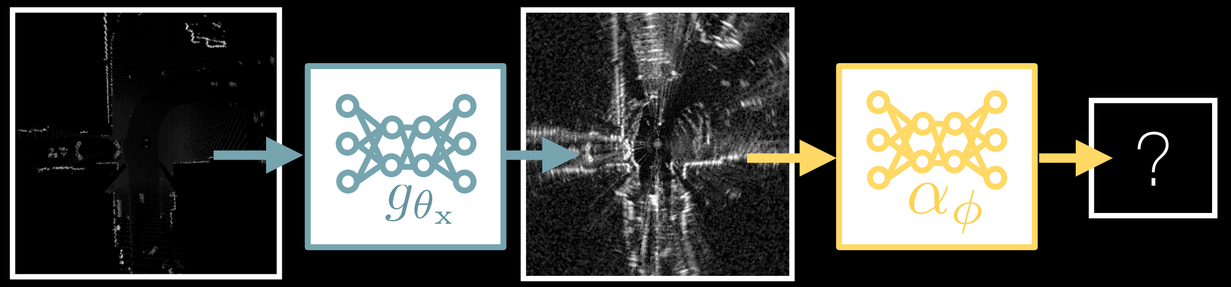
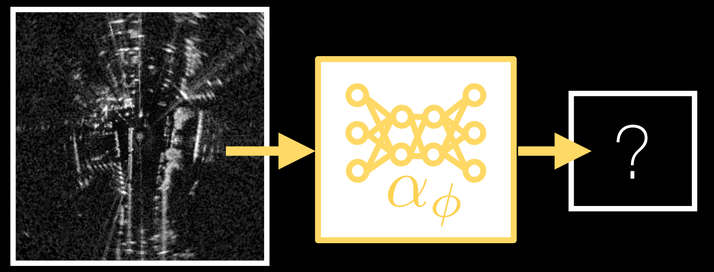


Ground truth training labels from simulation

(2) **Test** Model in **real world**



Real world ground truth

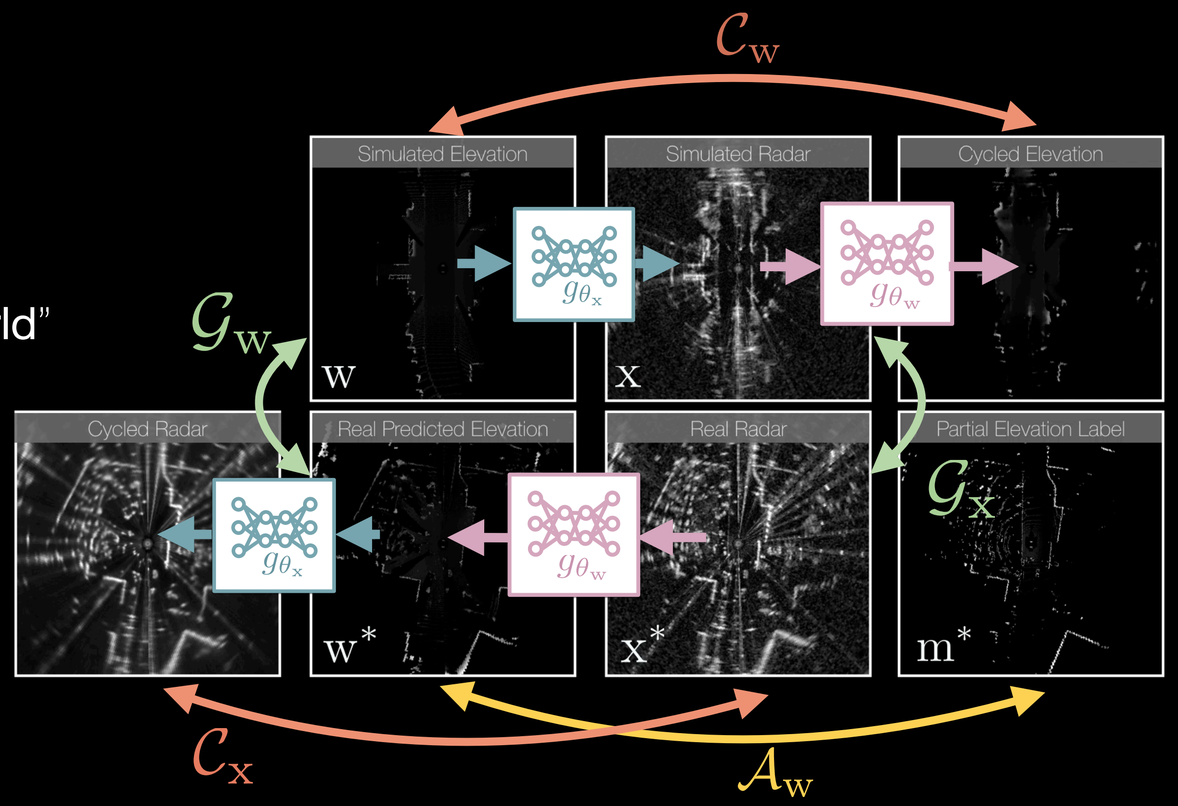
$$\mathcal{M}(\theta_x) = \frac{1}{2}\sum_c \left[\frac{\mathrm{TP}(c)}{\mathrm{FP}(c)+\mathrm{FN}(c)+\mathrm{TP}(c)}\right]$$

Mean Intersection Over Union Metric (mIoU) over free and occupied

Results

Radar Simulation

- Benchmark = “segmentation model trained in the **real world**”
- (a) and (b) trained only on real elevation inputs
- (c) trained only with GAN loss
- (d) trained with GAN loss + cycle constraints
- (e) trained with **full** training criterion

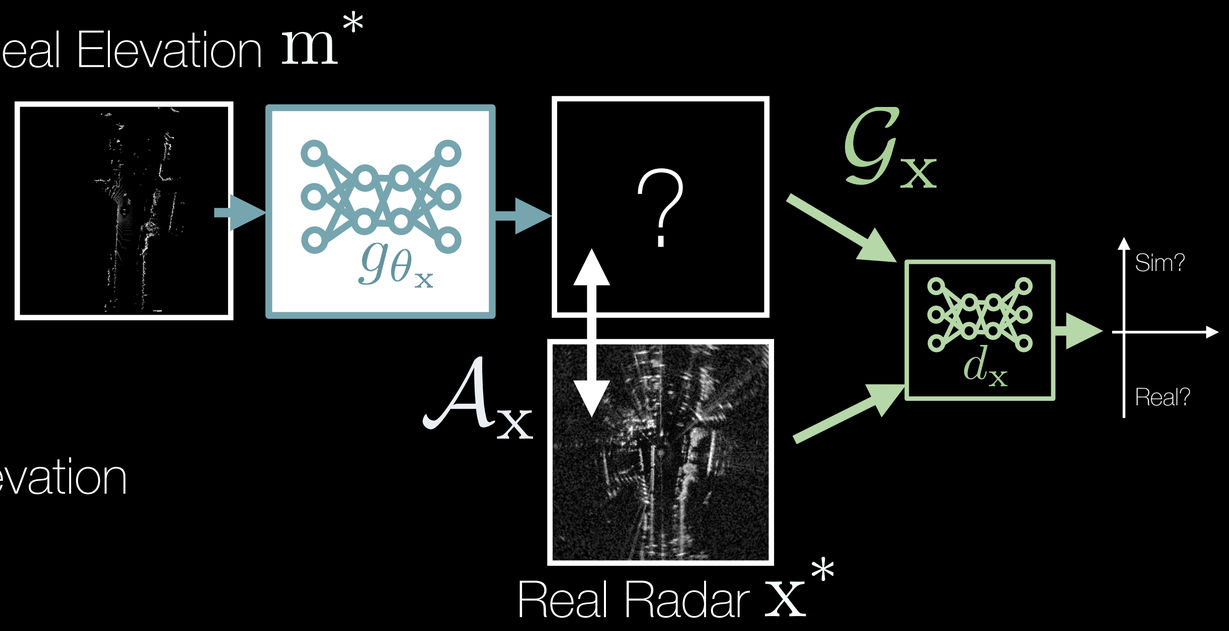


	trained on			training objective $\mathcal{A}_\mathrm{x}$	$\mathcal{A}_\mathrm{w}$	$\mathcal{G}_\mathrm{x}$	$\mathcal{G}_\mathrm{w}$	$\mathcal{C}_\mathrm{x}$	$\mathcal{C}_\mathrm{w}$	intersection over union free	occ	mean
benchmark												
real world	-	-	-	-	-	-	-	-	-	0.856	0.553	0.705
ours												
(a)	x*	m*	-	✓	-	-	-	-	-	0.396 (0.00)	0.275 (0.00)	0.335 (0.00)
(b)	x*	m*	-	✓	-	✓	-	-	-	0.558 (0.11)	0.221 (0.03)	0.389 (0.07)
(c)	x*	-	w	-	-	✓	-	-	-	0.385 (0.07)	0.148 (0.01)	0.266 (0.04)
(d)	x*	-	w	-	-	✓	✓	✓	✓	0.845 (0.02)	0.262 (0.02)	0.553 (0.02)
(e)	x*	m*	w	-	✓	✓	✓	✓	✓	**0.872** (0.01)	**0.455** (0.01)	**0.664** (0.01)

Results

Radar Simulation

- (a) and (b) simulators trained only on **real** data
  - (a) trained predicting radar from **real-world** elevation
  - (b) with **additional** GAN loss



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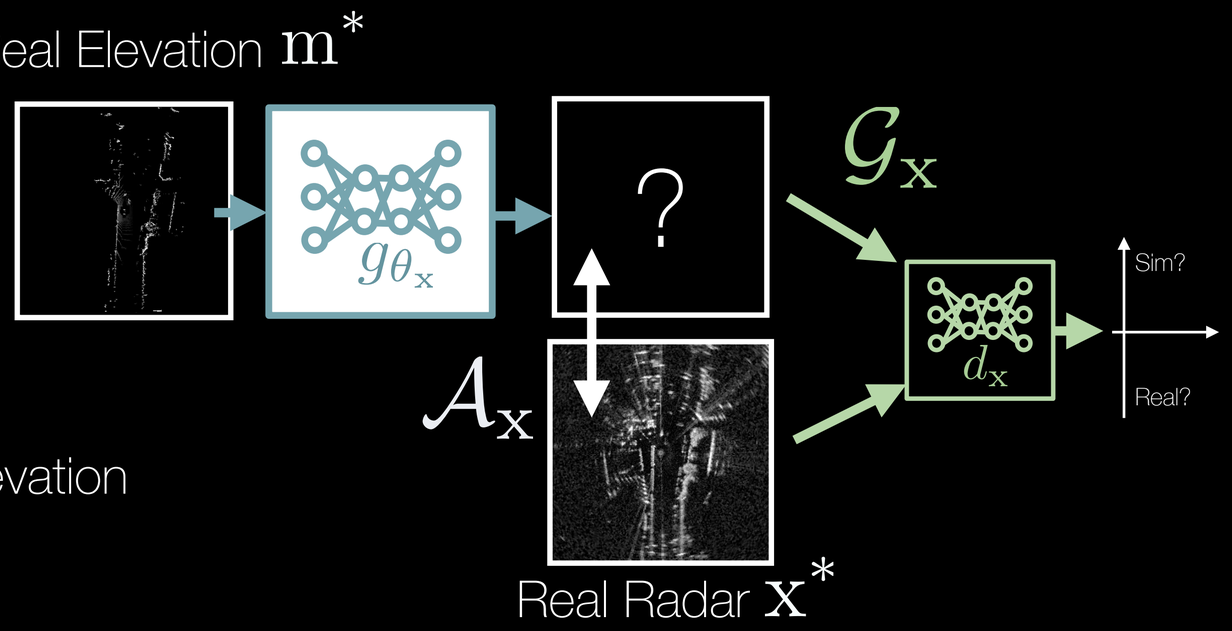
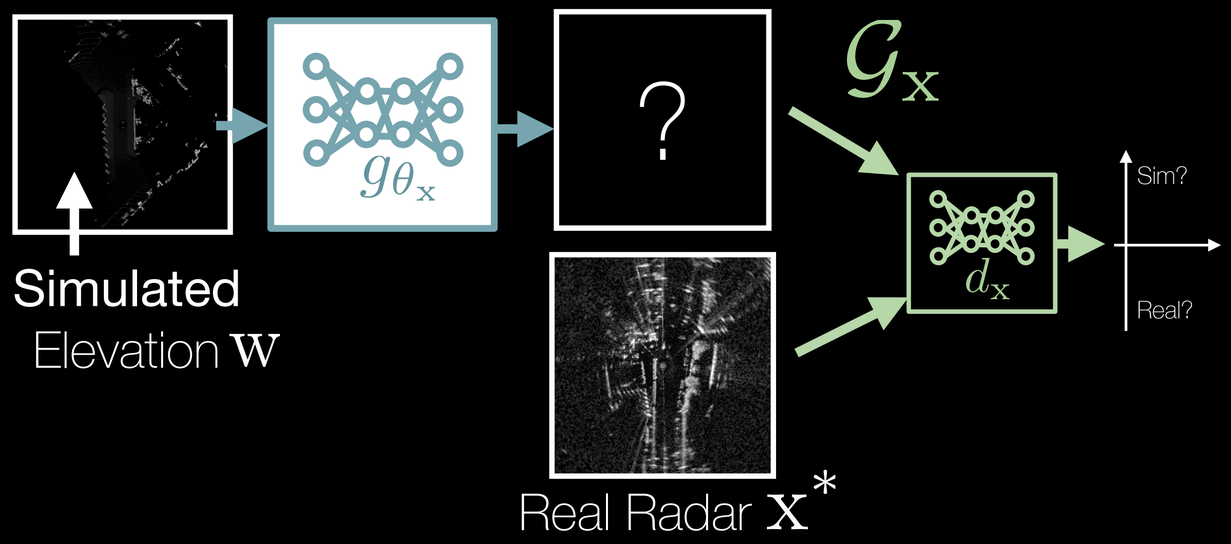


Performs poorly on simulated elevation maps

Results

Radar Simulation

- (c) trained to predict radar from **simulated** data using only **only** GAN loss



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Radar Simulation

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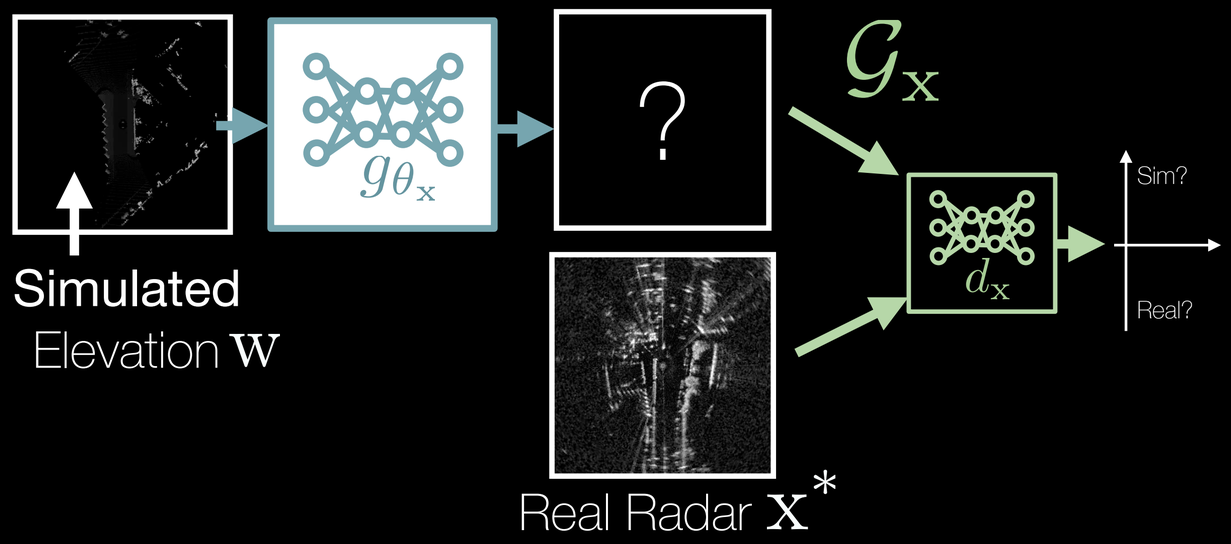

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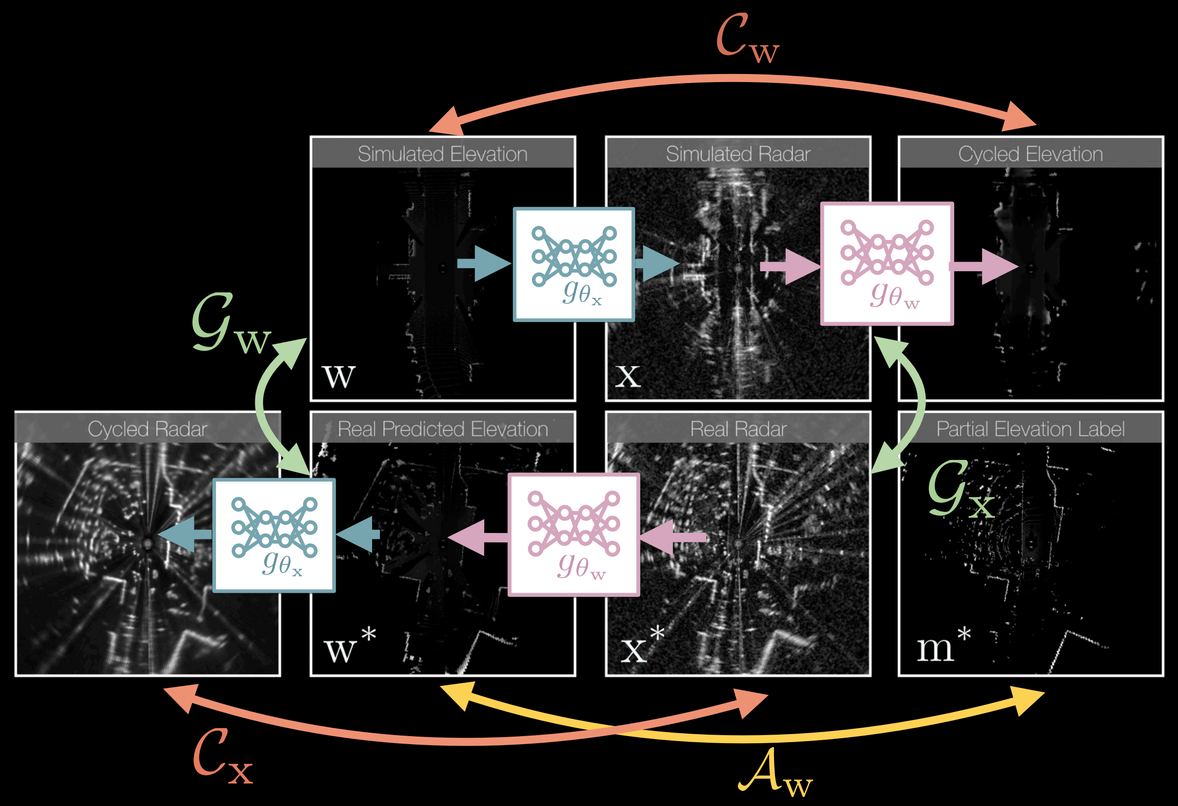
Radar Simulation

- (d) trained with GAN loss + cycle constraints
- (e) trained with **full** training criterion
  - Best performing model!
  - **Only** 5% percentage points off benchmark



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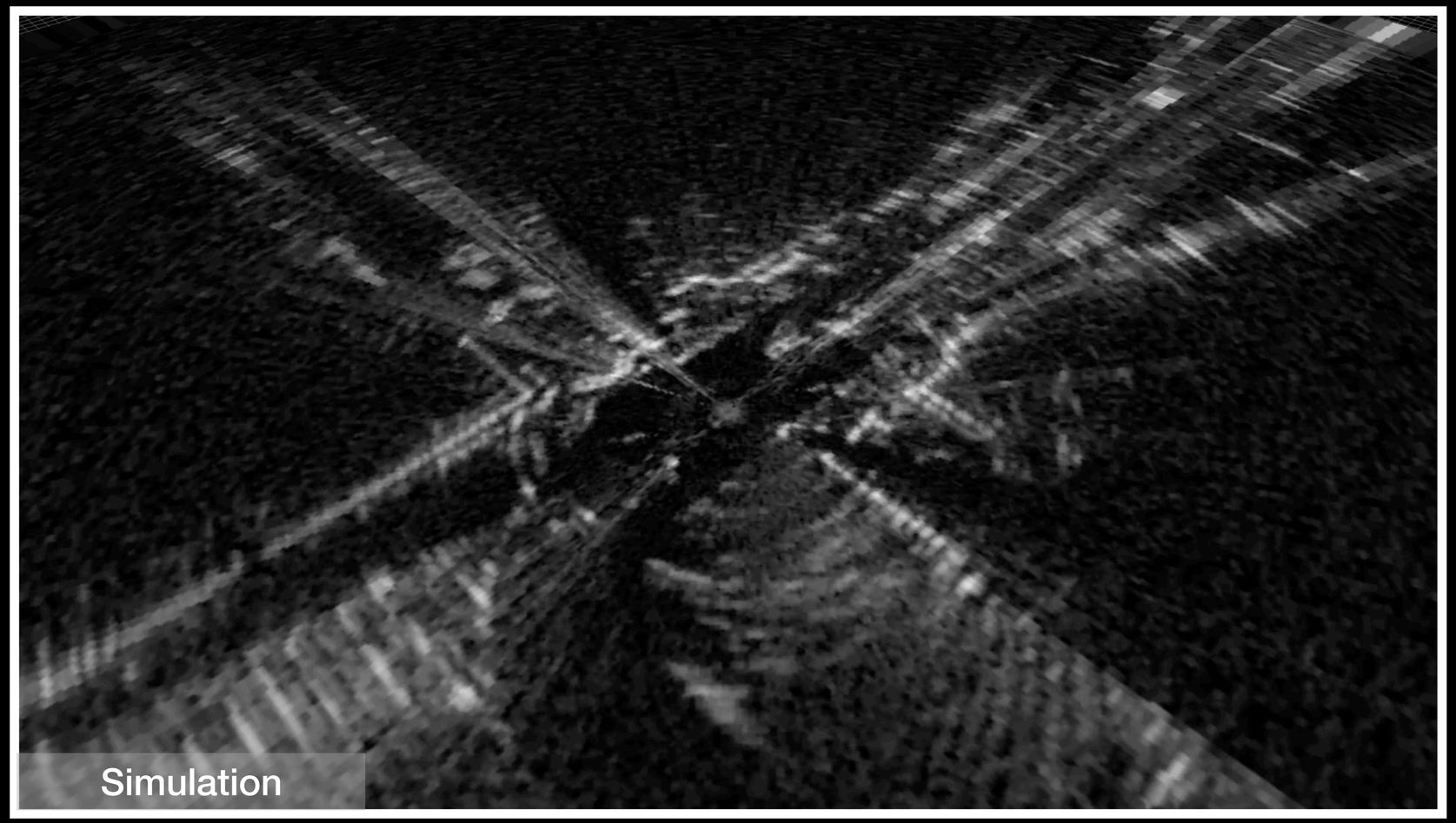
ours												
(a)	x*	m*	-	✓	-	-	-	-	-	0.396 (0.00)	0.275 (0.00)	0.335 (0.00)
(b)	x*	m*	-	✓	-	✓	-	-	-	0.558 (0.11)	0.221 (0.03)	0.389 (0.07)
(c)	x*	-	w	-	-	✓	-	-	-	0.385 (0.07)	0.148 (0.01)	0.266 (0.04)
(d)	x*	-	w	-	-	✓	✓	✓	✓	0.845 (0.02)	0.262 (0.02)	0.553 (0.02)
(e)	x*	m*	w	-	✓	✓	✓	✓	✓	**0.872** (0.01)	**0.455** (0.01)	**0.664** (0.01)

Results

Radar Simulation

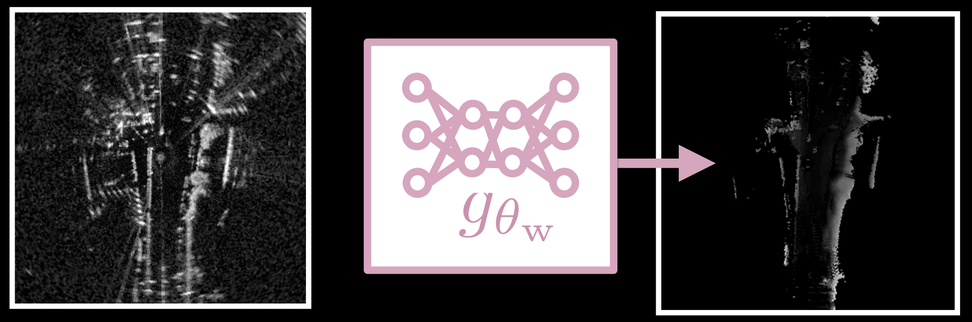


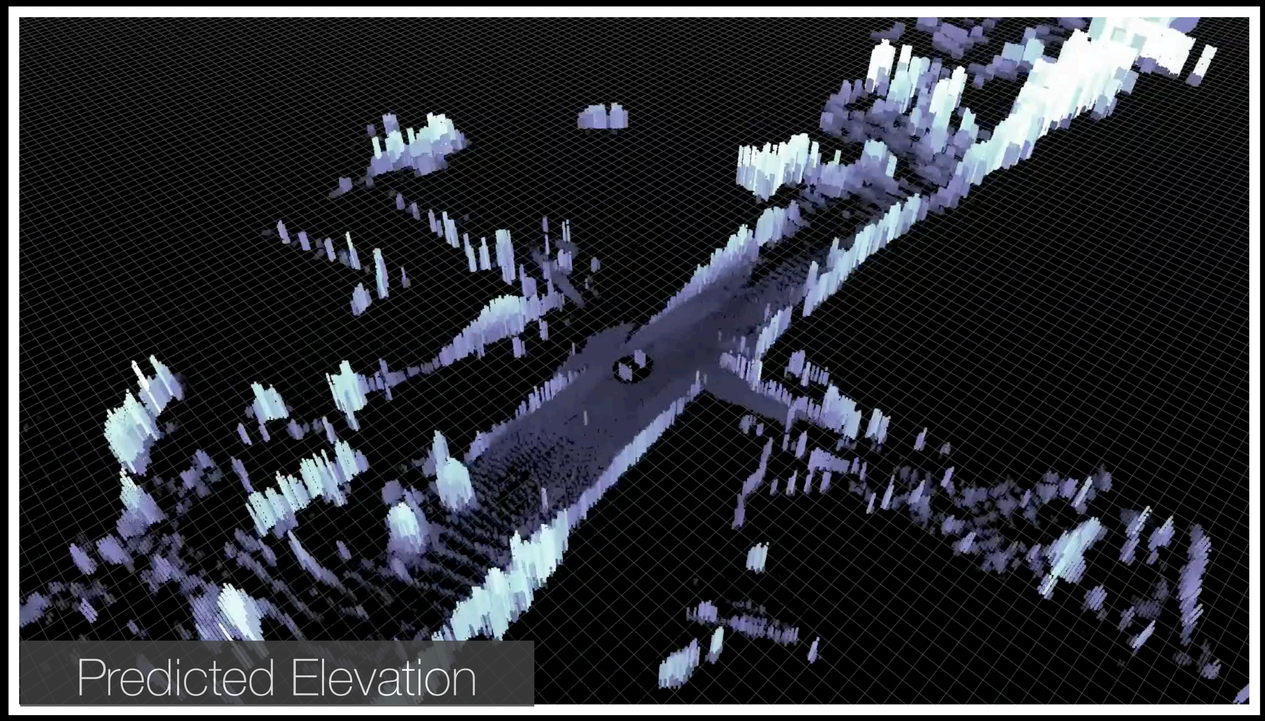
Successfully captures many of radars characteristic noise artefacts

Results

Backward Model

- Learnt as part of the same training setup
- Allows the elevation state to be inferred from real 2D radar data





Results

Backward Model Evaluation

- Evaluated against ground truth elevation labels using **Mean Absolute Error**
- **Benchmark** = **“**model trained directly regressing to partial elevation labels”
- **Ours**:
  - (a) trained with **just** cycle consistency
  - (b) trained with cycle consistency **and** alignment

					Mean Absolute Error (cm)		
	data	$\mathcal{A}_z$	$\mathcal{G}_w$	$\mathcal{C}_w$	free	occ	mean
Benchmark							
direct regression	R	✓	-	-	18.7	7.5	13.1
Ours							
(a)	R, S	-	✓	✓	3.9 (0.4)	74.2 (1.8)	39.0 (0.9)
(b)	R, S	✓	✓	✓	4.1 (0.6)	41.1 (5.7)	22.6 (2.6)

Results

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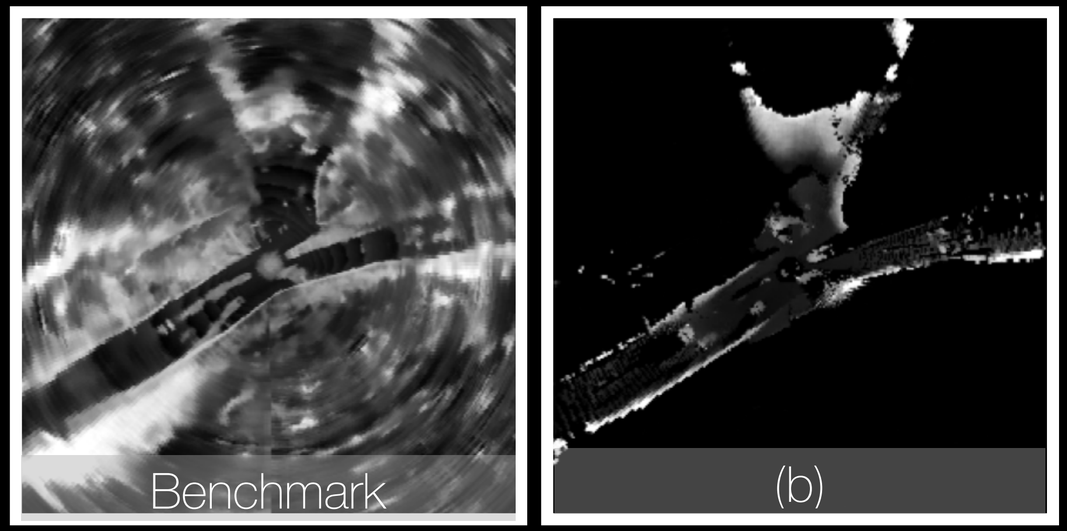
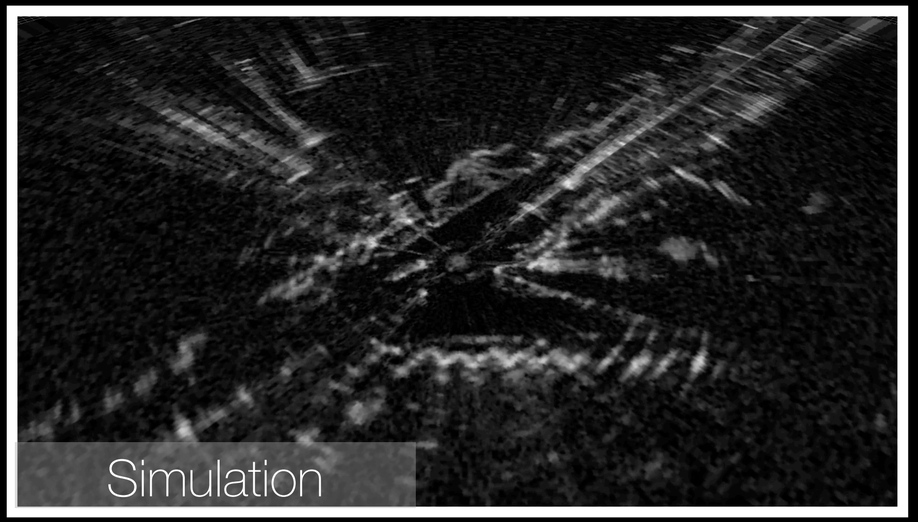


Only a few centimetres off benchmark whilst **generalising** to regions of space where elevation labels do not exist

Conclusion

- A **data-driven** approach to **stochastic** radar simulation **interfacing with commonly available** simulation environments
- Model the forward and backward processes **side-by-side**
    - Train on **simulated** inputs using adversarial losses, cyclical consistency and partial elevation labels
- Train **new** radar models in simulation (for the first time)
    - Only 4 percentage points off a segmentation model trained in the real world
- Backward model also infers the height state of the world to a **reasonable accuracy** (4-40cm) whilst remaining **regularised** where no elevation labels exist



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Thanks for listening!

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