GAN-based Massive MIMO Channel Model Trained on Measured Data

Florian Euchner, Janina Sanzi,
Marcus Henninger, Stephan ten Brink
Institute of Telecommunications, University of Stuttgart

27th International Workshop on Smart Antennas
March 19, 2024

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Prof. Dr. Ing. Stephan ten Brink

GAN-based channel models work, but are not useful (yet)[a]

[a]just my opinion

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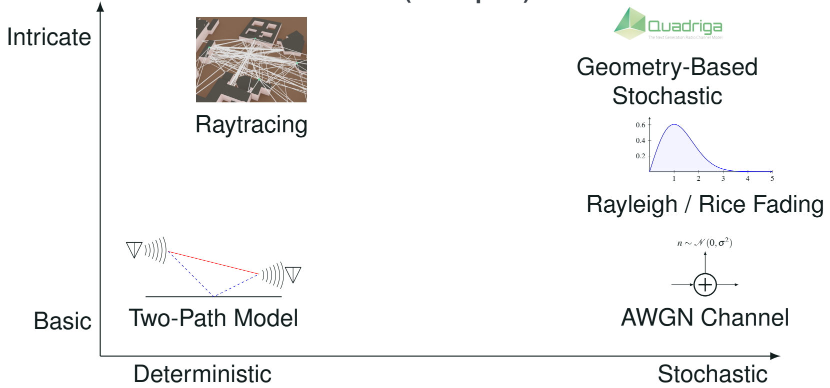
Outline

Agenda

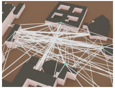
1. Channel Models
2. GAN-Based Channel Models
3. Evaluation on DICHASUS Dataset
4. Criticism, Summary and Outlook

Overview: Wireless Channel Models (Examples)

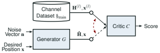


Overview: Wireless Channel Models (Examples)

Intricate



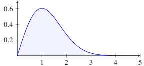
Raytracing



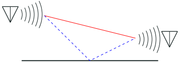
GAN-based Channel Model

Quadriga

Geometry-Based Stochastic

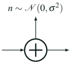


Rayleigh / Rice Fading



Basic

Two-Path Model



AWGN Channel

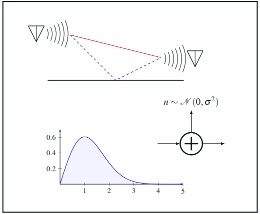
Deterministic

Stochastic

Why yet another channel model?

Measurement

Manual Analysis, Parameter Extraction, Geometric Modeling



Channel Model

- Existing channel models require **expert knowledge** for parametrization
- **Idea**: Automate generation of model from measurement data!

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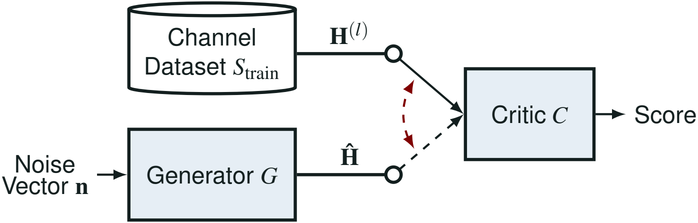
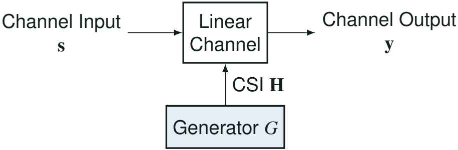
The GAN Game

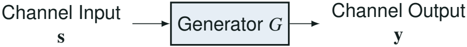


Here: Wasserstein GAN, Gradient Penalty

Prior Work / Literature



(a) Linear: Generator produces instantaneous CSI, e.g. [Yang et al., 2019, Xiao et al., 2022, Orekondy et al., 2022, Xie et al., 2023, Sengupta et al., 2023, Juhava, 2023]



(b) Nonlinear: Generator conditioned on input, e.g. [O'Shea et al., 2019, Dörner et al., 2020]

- Two types of GAN-based channel models in literature
- Here: Only *linear* type: Wireless channel is linear, do not learn what is known.

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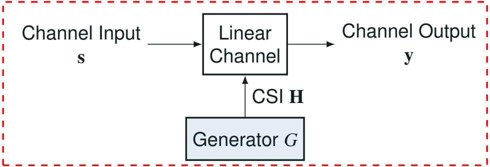

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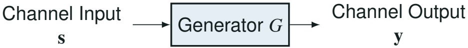

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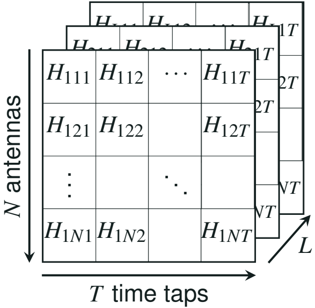
Contributions

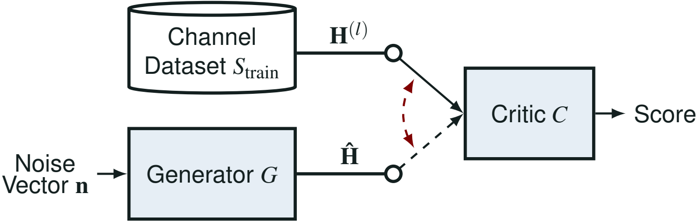
- GAN is trained / compared against on *real-world* measurement data for the first time
- Conditional GAN: Conditioning on position

Channel State Information Format



- Single UE, multi-antenna base station (BS)
- Channel impulse responses (CIRs) for each BS antenna
- Real / imaginary representation for neural network
- L datapoints (separate measurements)
- Later: $N = 32$, $T = 40$

Conditioning: From SIMO to massive MIMO



- Generator is given desired UE position $\mathbf{x}$, critic scores how realistic CSI is *for the given position*

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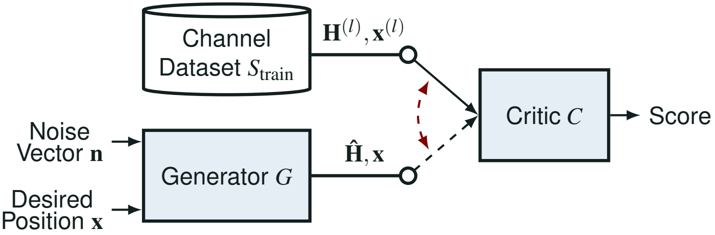

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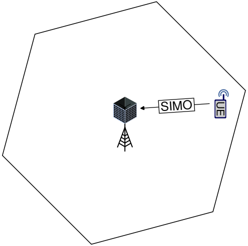

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- The GAN can be used as a massive MIMO channel model by generating multiple channel realizations at different locations (conditions)

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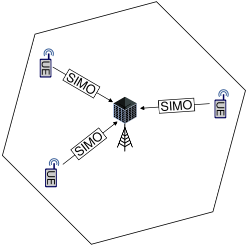

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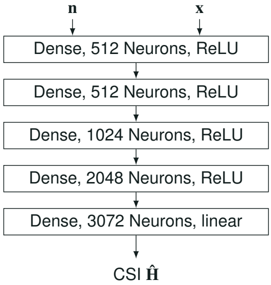
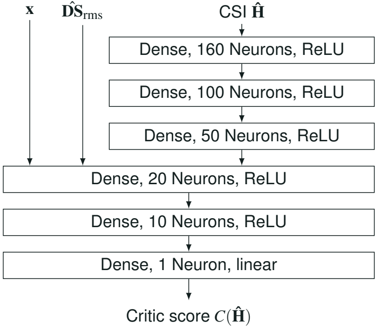
Generator / Critic Architecture





Nothing special here: “Just some dense layers”

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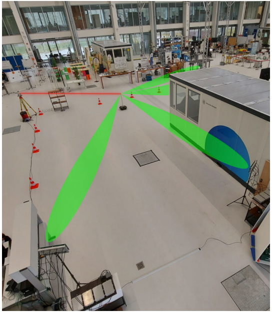
The Dataset: DICHASUS Channel Sounder

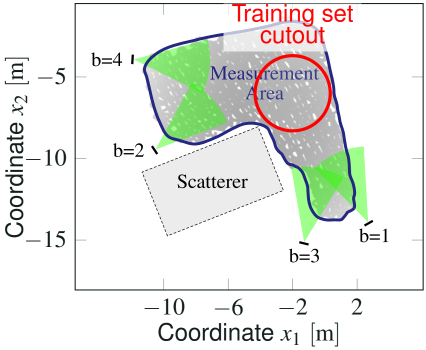


- Distributed massive MIMO channel sounder *DICHASUS*
- Phase-coherent, position-tagged CSI
- Datasets publicly available
- Single UE, multiple base station antennas

`https://dichasus.inue.uni-stuttgart.de`

The Dataset: ARENA2036 Factory Dataset

- $f_c = 1.272\,\mathrm{GHz}$ carrier frequency
- $B = 50\,\mathrm{MHz}$ bandwidth
- 4 antenna arrrays with 2×4 antennas each
- Training set $|S_{\mathrm{train}}| = 17857$ with "cutout"
- Test set $|S_{\mathrm{test}}| = 20973$



Purpose of a GAN-based channel model

- GAN as an *interpolator / extrapolator*
- GAN as a *random generator*
- Surprisingly, this question is hardly discussed in existing literature
- Evaluation criteria depend on the purpose!

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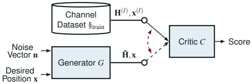

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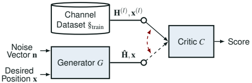

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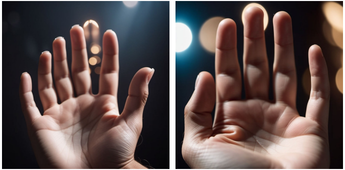

Source: Generated by stable diffusion

- Humans cannot interpret CSI directly
- We have to rely on derived statistics, for example:
  - Root mean square (RMS) delay spread (DS) (here)
  - Azimuth angle of arrival estimates, e.g. via MUSIC (here)
  - Received signal power

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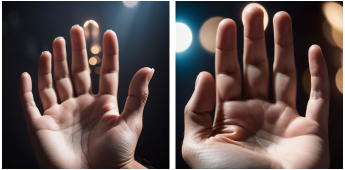

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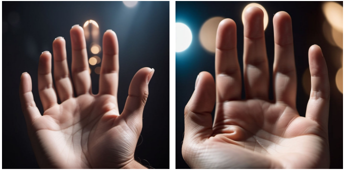

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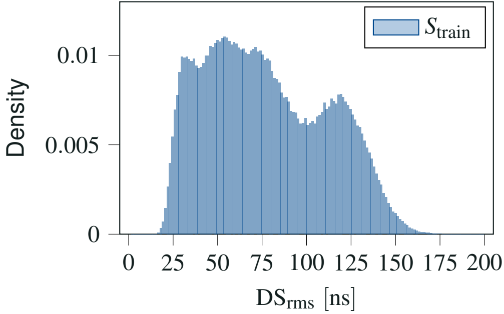
Stochastic Distribution Analysis: RMS DS



(RMS delay spread density, over all antennas in all arrays)

- 1[st] / 2[nd] order moment approximation insufficient
- GAN with variable input noise: Good random generator!
- GAN learns higher-order moments of distribution
- Linear interpolation works, too

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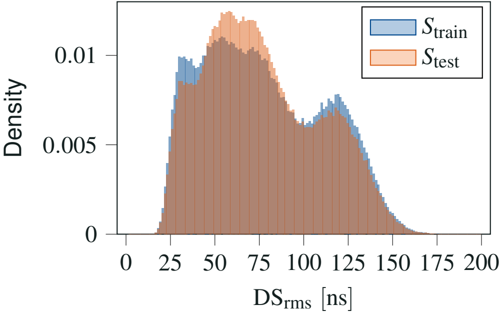

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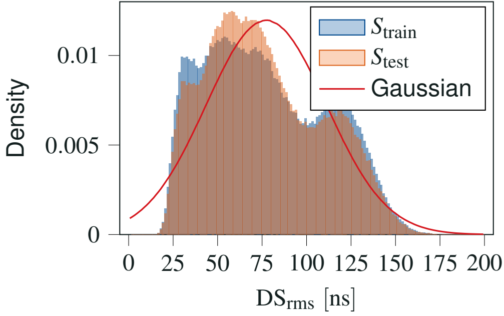

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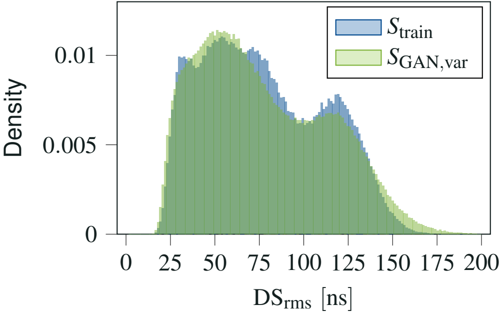

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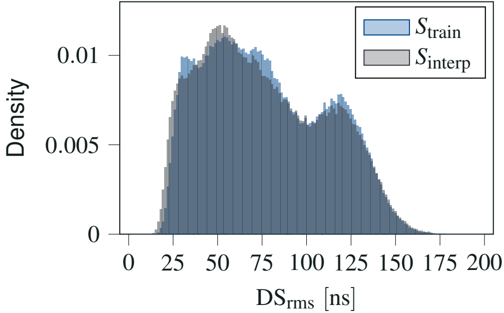

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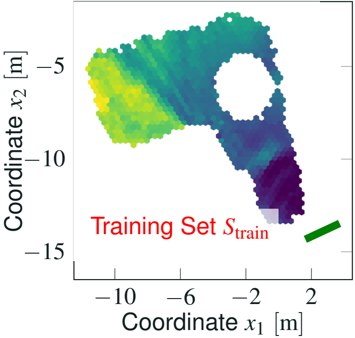
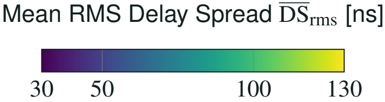
Spatial Distribution Analysis: RMS DS



- Mean RMS DS for all antennas in array $b = 1$, top view
- A GAN is **not** a good interpolator
- Linear interpolation beats GAN: Closer to reality



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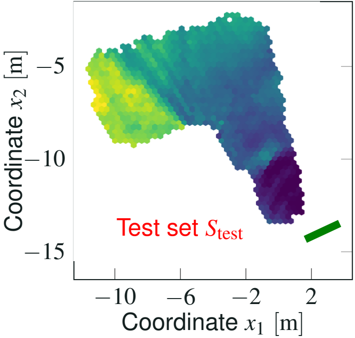

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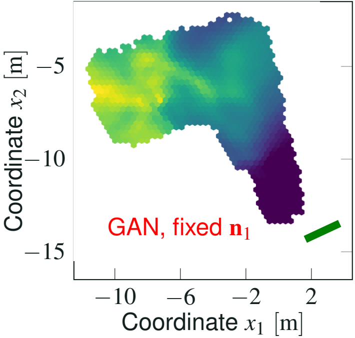

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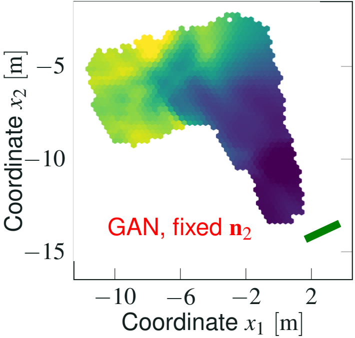

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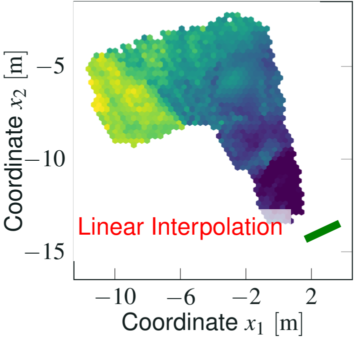

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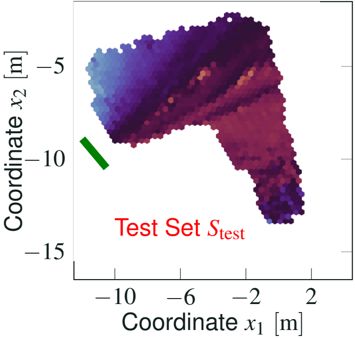
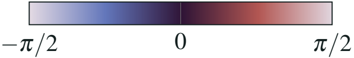
Spatial Distribution Analysis: Azimuth AoA



- AoA estimate (root-MUSIC) for antenna array $b = 2$, top view
- A GAN is **not** a good interpolator
- Bad spatial consistency
- Outperformed by linear interpolation



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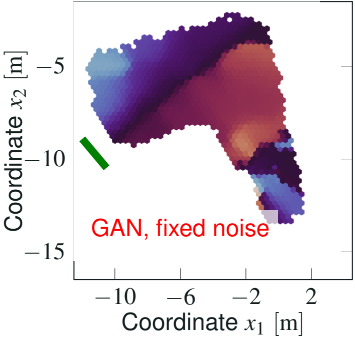

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Mean AoA Estimate $\hat{\alpha}^{(2)}$ [rad]

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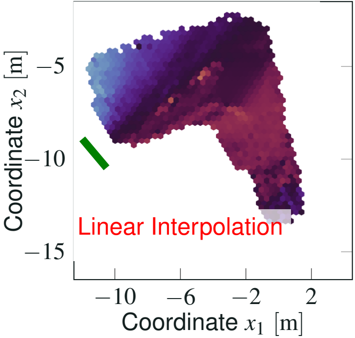

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1. No meaningful spatial consistency

- Spatial autocorrelation of statistics / large-scale statistics are merely a training artifact:
  - Consider locations $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$
  - Generator can produce CSI that is *plausible* for $\mathbf{x}^{(1)}$ and for $\mathbf{x}^{(2)}$
  - But: Taken together, CSI may be *implausible*!
- Architectural issue, different NN architecture could mitigate this

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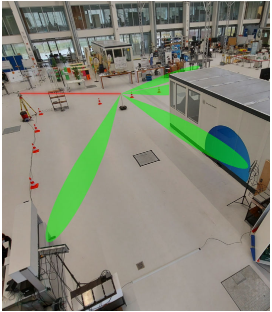
2. Lack of generalizability



Learned channel model is specific to:

- Environment
- Carrier frequency, bandwidth
- Antenna deployment
- ...

These parameters cannot be modified!

3. Lack of interpretability

Classical Channel Model

$$C = B \cdot \log_2\left(1 + \frac{E_s}{N_0}\right)$$

- Model parameters can be modified
- Influence of parameters can be understood

GAN-based Channel Model

- Fixed parameters
- It works, or it does not, hard to analyze

4. Availability of a dataset

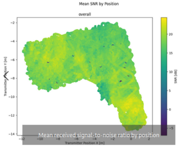
- For GAN training, dataset for particular environment needed
- Why not use the dataset itself instead of a channel model?
- Could apply data augmentation

50.000 MHz Signal Bandwidth	1024 OFDM Subcarriers	178314 Data Points	9347.6 s Total Duration
46.8 GB Total Download Size	32 Number of Antennas	Indoor Type of Environment	1.272000 GHz Carrier Frequency
Distributed Antenna Setup	3D Tachymeter Position-Tagged		

Experiment Setup


The Arena 2036 factory floor. The measurement area is on the left at the very back of the hall. Source: ARENA2036 e.V.

Data Analysis



Mean received signal-to-noise ratio by position

Conclusion

- GAN-based channel models work on **real data**
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- Need to answer some crucial questions and address issues:
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  - How to improve consistency, generalizability, interpretability?
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Source code:
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Thank you for your attention! Questions?

DICHASUS Channel Sounder

Source Code: GAN-based model

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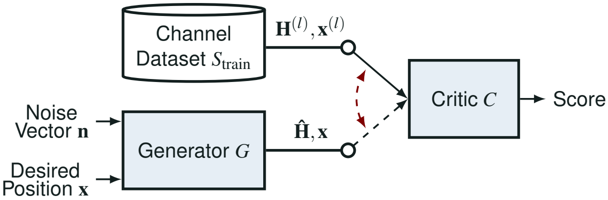
Evaluation Methods



Two evaluation options:

- Fixed noise (variable condition)
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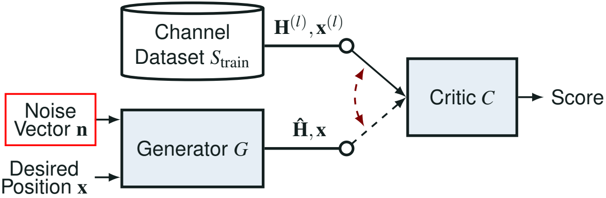

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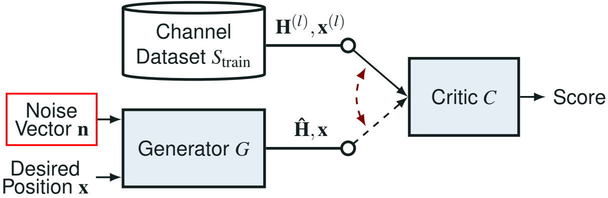

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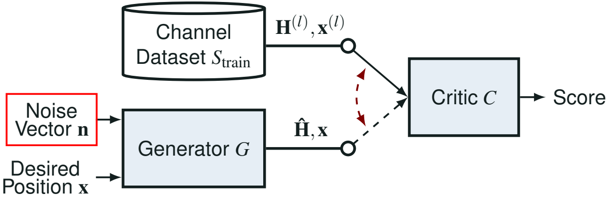

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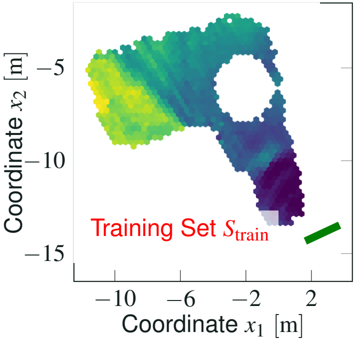
Spatial Distribution Analysis: RMS DS



- Mean RMS DS for all antennas in array $b = 1$, top view
- A GAN is **not** a good interpolator
- Averaged over all noise inputs, GAN output approximates true RMS DS at condition
- Linear interpolation beats GAN: Closer to reality

Mean RMS Delay Spread $\overline{\mathrm{DS}}_{\mathrm{rms}}$ [ns]

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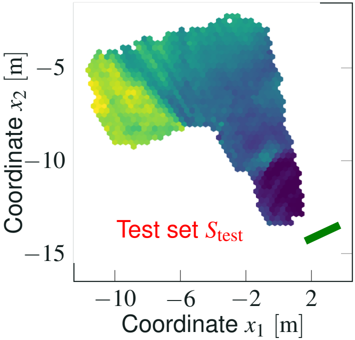

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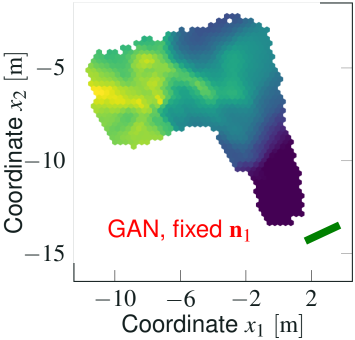

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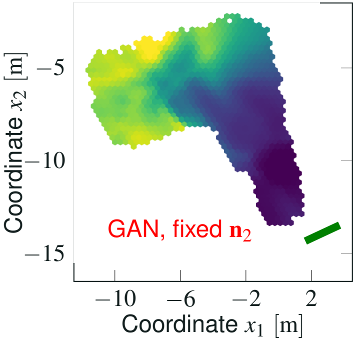

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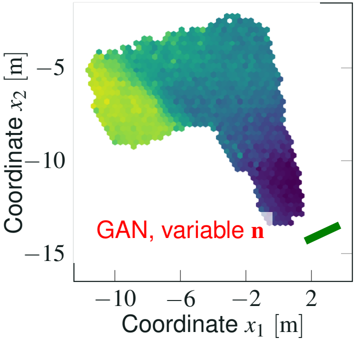

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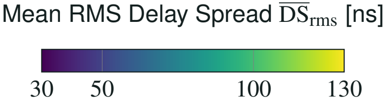

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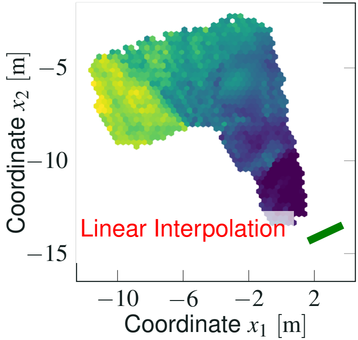

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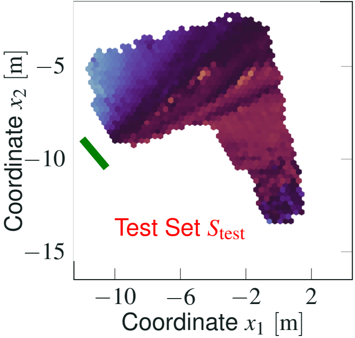

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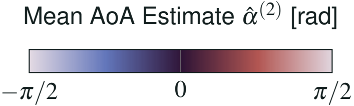

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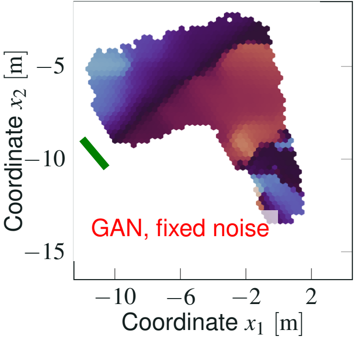

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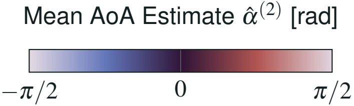

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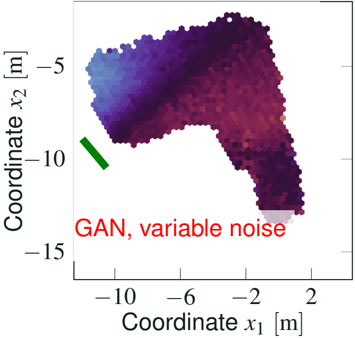

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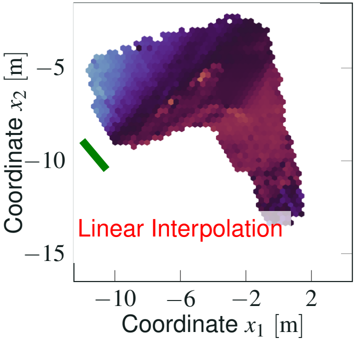

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