WixUp: A Generic Data Augmentation Framework for Wireless Human Tracking

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Background

Intro to wireless human tracking

Background
- *Intro to wireless human tracking*

Wireless sensing (mmWave, sound, WiFi)

- ubiquitous
- under-cm resolution
- less privacy issue
- non-line-of-sight

Background
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Problems of using data-driven, learning-based algorithms:

- **Insufficient training data**
  - Efforts for data collection from physical world
- **Poor model generalizability:**
  - Explosion in search space. e.g. 3D human tracking

Background
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Remedy = Data augmentation:

- In CV, NLP...
- In wireless:
  - using **generative model** to generate pseudo data for certain tasks, data formats, etc.
  - by slightly shifting, rotating, or adding noise in the feature maps and the ground truth (**closed-form**)
  - lack of **benchmarking**

Can we build a generic data augmentation for wireless signals?

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  - lack of benchmarking

Can we build a generic data augmentation for wireless signals?

- Tailored for unique characteristics of wireless signals
- Work for different (datasets) tasks, data formats, models, modalities, etc.

Background
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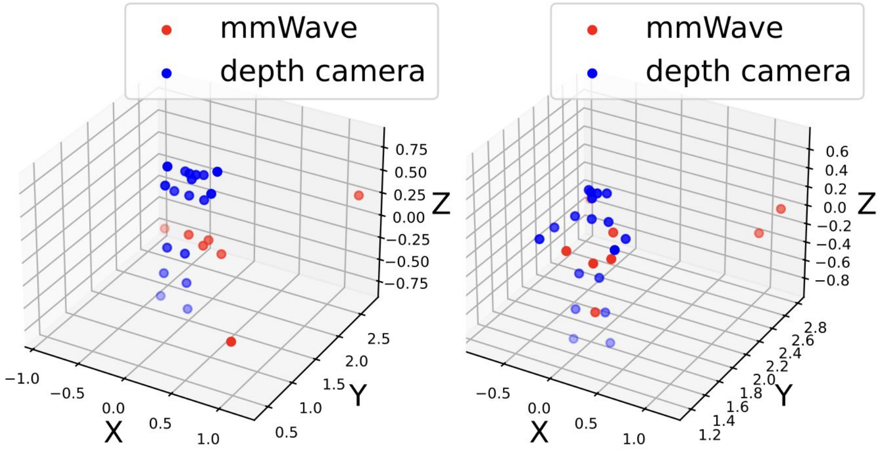
Challenges:

The sparsity issue in wireless point clouds in public datasets

Datasets availability and discrepancy

- No raw signal available
- Lossy point clouds only



We propose **WixUp**

Goal:

A generic data augmentation framework tailored for unique characteristics of wireless signal

.

Tested for:

- 3 **Tasks**: Pose Estimation, Action Recognition, User ID
- 3 **Models architectures:** DGCNN, PointTransformer, LSTM+CNN
- 2 **Data Formats**: Raw signals, Point Clouds
- 2 **Modalities**: mmWave, Acoustics

We propose **WixUp**

Overview:
- A **mixing-based** local augmentation
- A custom **Gaussian mixture** and probability-based transformation
- In-depth augmentation at the dense **range profile** level.

Usage:
- Improving accuracy for supervised learning
- **Unsupervised domain adaptation** via self-training (training without ground truth labels)

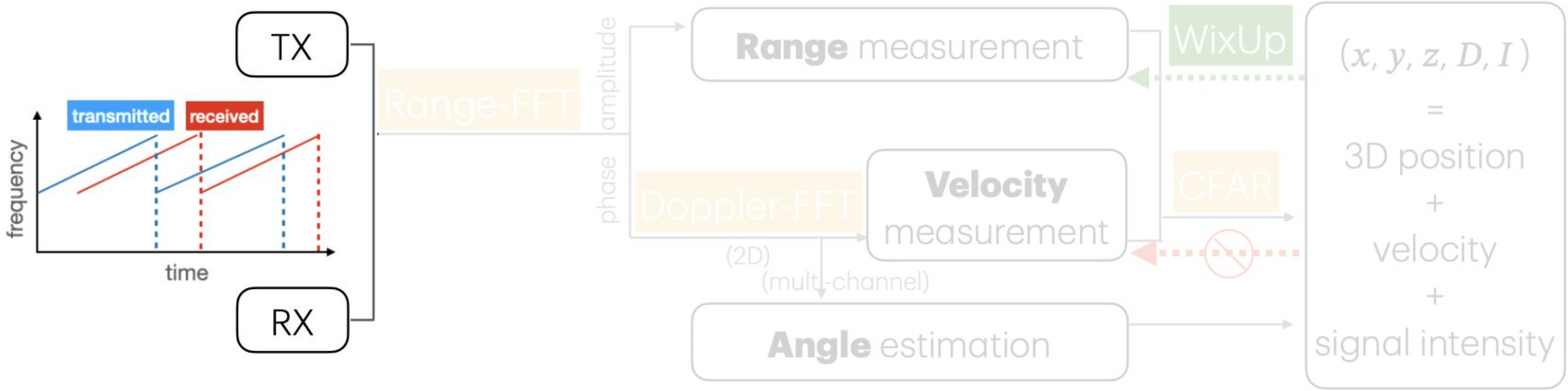
02

Method

A generic data augmentation framework

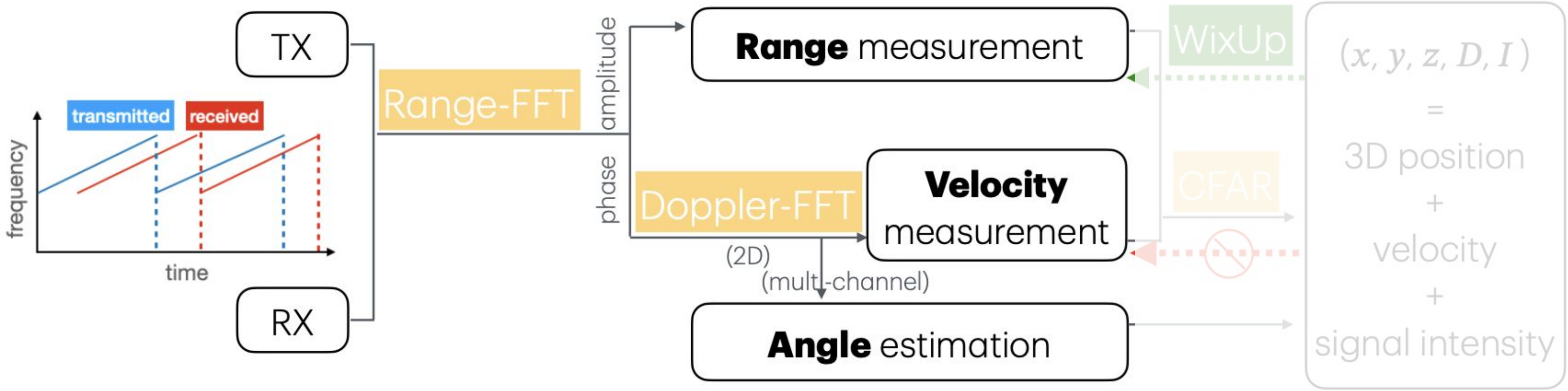
Method

- The common data processing pipeline for wireless perception.



Method

- The common data processing pipeline for wireless perception.



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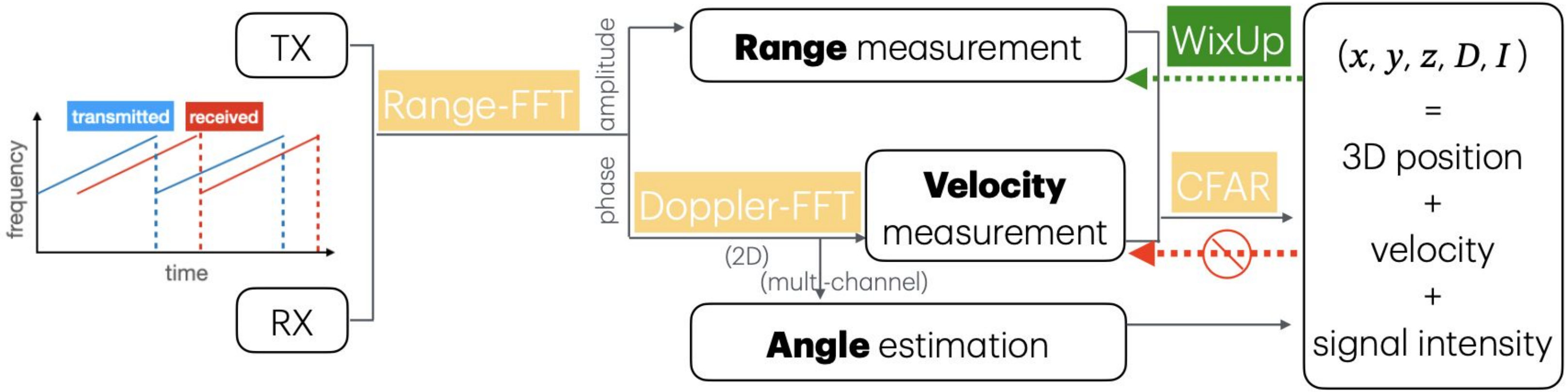

Method

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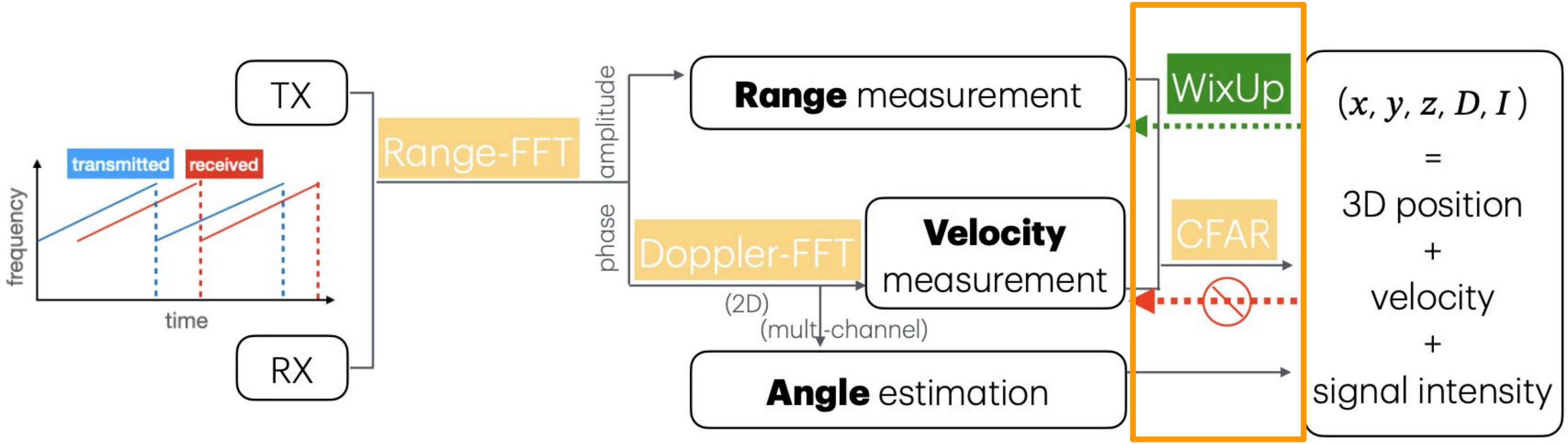
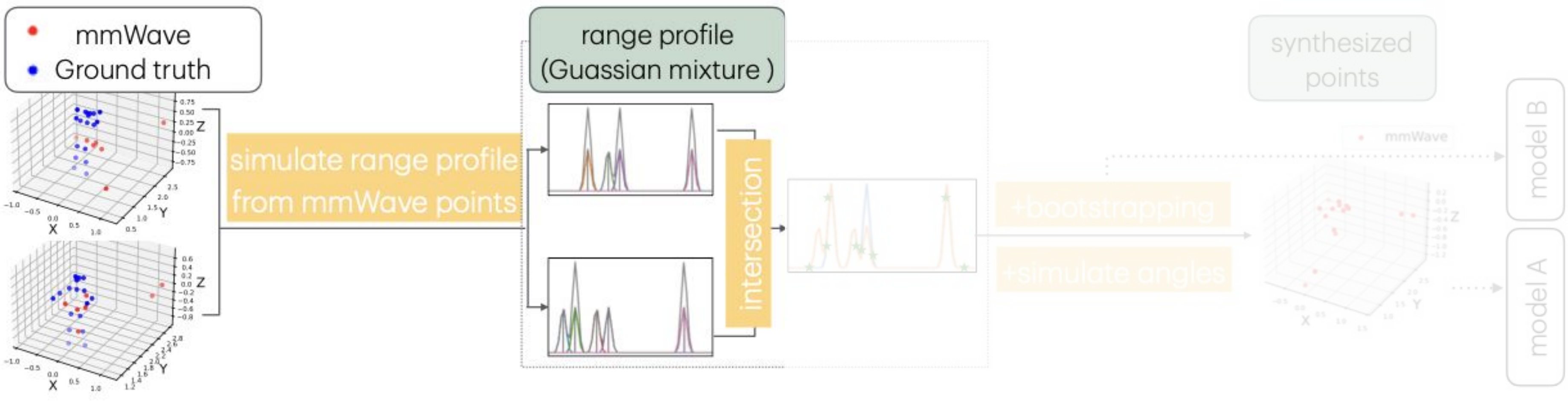


Method

- A demonstration of the data mixing pipeline of WixUp.



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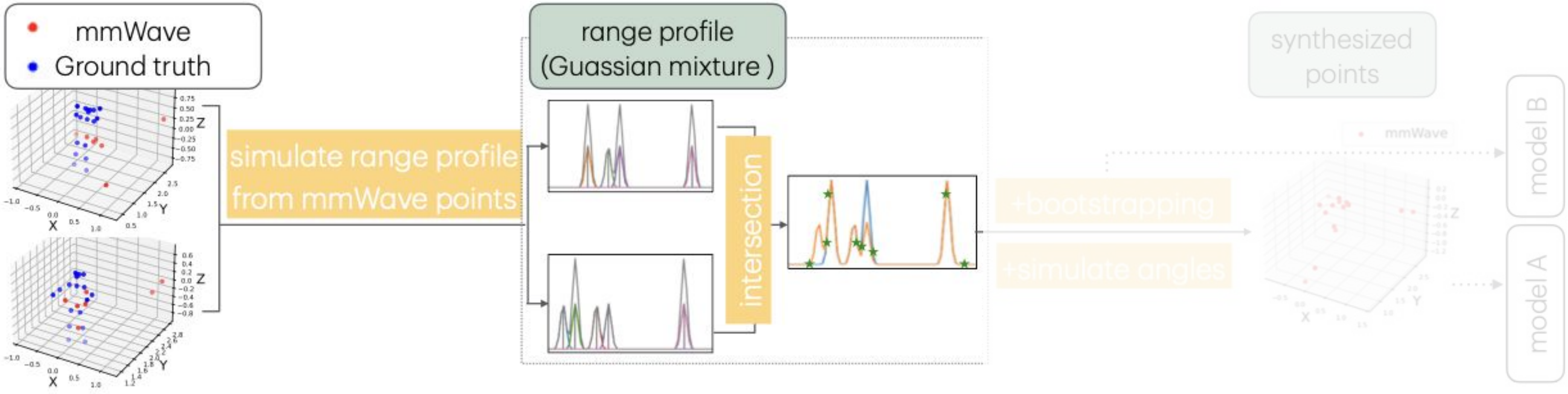

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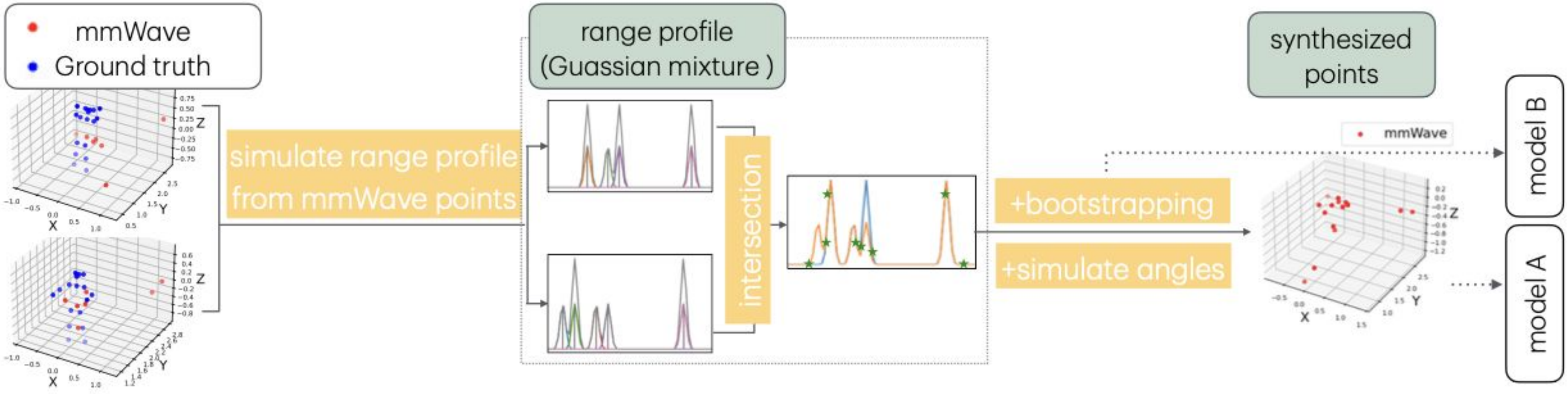


03
Experiments

Experiment
- setup

Datasets:

mmWave: MiliPoint [17], MARS [6], MMFi [54]

Acoustics: Custom Hand Tracking Dataset [31]

- **MiliPoint**: fitness movements, 49 actions, 545K frames, 11 subjects, 77–81GHz radar, stereo camera, 3D point clouds only, 24Hz
- **MARS**: rehabilitation, 10 movements, 40K frames, 4 subjects, 76–81GHz radar, Kinect V2, 64 5D points, 30Hz.
- **MMFi**: multimodal, 27 actions, 320K frames, 40 subjects, mmWave + LiDAR + WiFi CSI + RGB/IR, 30Hz,.
- **Acoustic**: hand tracking, 21 finger joints, 64 mins, 11 users, ultrasound 17–20kHz, 7-mic array, Leap Motion, 90–110Hz, 3.57mm resolution.

Experiment
- setup

Datasets:

mmWave: MiliPoint [17], MARS [6], MMFi [54]

Acoustics: Custom Hand Tracking Dataset [31]

Tasks & Metrics:

Pose Estimation (MPJPE / MLE in cm)

Action Recognition (Accuracy %)

User Identification (Accuracy %)

Models: DGCNN, PointTransformer; CNN+LSTM

Baselines: a global scaling augmentation(CGA), no-augmentation, (stacking)

Experiment results

Supervised Learning (Generalizability: Datasets, Models)

	DGCNN			PointTransformer		
	MiliPoint	MARS	MMFi	MiliPoint	MARS	MMFi
Null	24.36	28.89	28.53	17.15	25.64	24.69
CGA	23.26(+4.55%)	22.89(+20.76%)	26.25(+8.00%)	16.88(+1.60%)	20.74(+19.10%)	24.03(+2.68%)
WixUp	23.25(+4.58%)	22.65(+21.60%)	25.84(+9.42%)	16.81(+1.97%)	**20.35(+20.64%)**	**22.73(+7.96%)**
WixUp^{+}	**23.10(+5.18%)**	**21.10(+26.95%)**	**25.60(+10.28%)**	**16.67(+2.79%)**	21.35(+16.72%)	23.26(+5.80%)

Experiment results
Supervised Learning (Generalizability: Tasks, Modalities)

	Keypoint (MLE in cm)	Identification (Acc%)	Action (Acc%)
Null	24.36	0.8766	0.1305
CGA	23.26(+4.55%)	0.9097(+3.77%)	0.2143(+64.17%)
WixUp	23.25(+4.58%)	0.9031(+3.03%)	0.1924(+47.44%)
WixUp^{+}	**23.10(+5.18%)**	**0.9229(+5.29%)**	**0.2405(+84.25%)**

Experiment results

Unsupervised Domain Adaptation (UDA) via self-training

Goal:

Reduce labeling effort for new users/environments

Experiment results

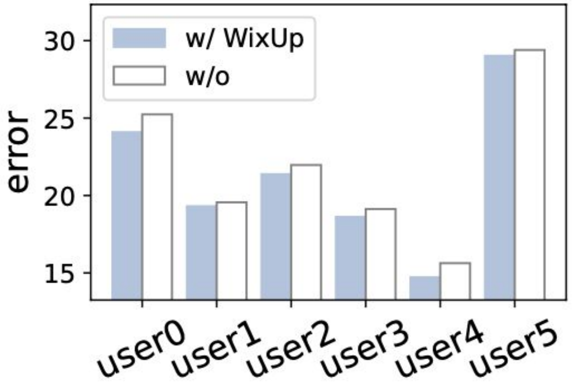
Unsupervised Domain Adaptation (UDA) via self-learning

Goal:

Reduce labeling effort for new user

UDA **Across Users:**

- Leave-one-user-out setup.
- WixUp UDA consistently improves performance vs. no adaptation baseline.
- Average Improvement: +3.04% (Range: 1.26% - 5.83%).



Experiment results

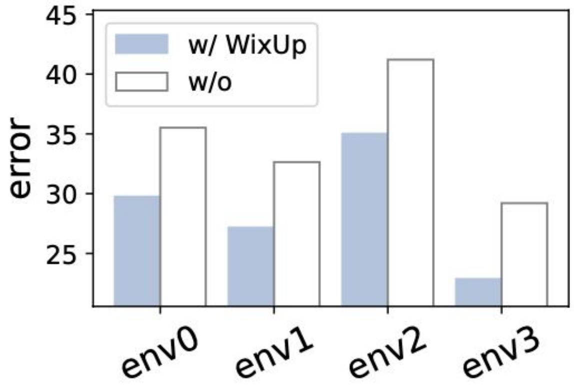
Unsupervised Domain Adaptation (UDA) via self-learning

Goal:

Reduce labeling effort for new environment

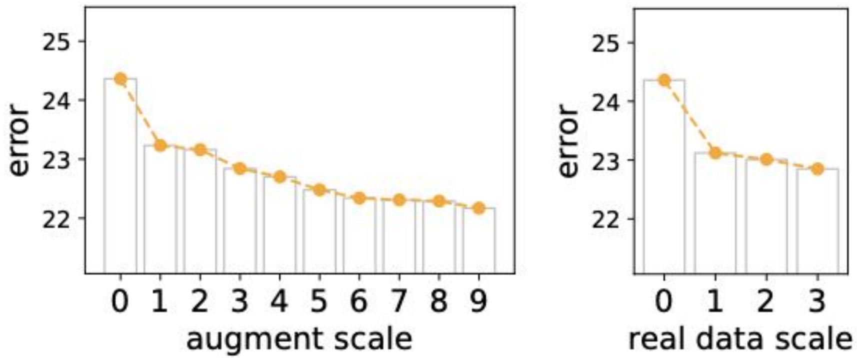
UDA **Across Environments:**

- Leave-one-scene-out setup (new scene implies new user too).
- WixUp UDA provides significant improvements v.s. no-adaptation baseline
- Average Improvement: +17.45% (Range: 15.04% - 21.73%).



Experiment results

Benefits scale up



Expanding the augment data size by tweaking WixUp bring further drops in errors.

Experiment results
Comparison with generative data augmentations

	Action (body)	Identification	Domain adaptation (Action/Keypoint)
NeRF2 [65]	NA	NA	NA
RF-Gen [13]	-	NA	(6.04%~56.42%)
RF-Diffusion [15]	1.8%~8.7%(1.98%~11.01%)	-	(5.34%~16.20%)
WixUp	11%(84.25%)	2.0% (5.29%)	(1.26%~21.73%)

Comprehensive comparison with generative data augmentation (**NA**: not applicable; **-**: not reported)

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Conclusion

Conclusion and future work

Conclusion

- **Problem**: Data scarcity limit deep learning in wireless sensing.

- **WixUp**: A generic, training-free, mixing-based, semi-real data augmentation framework.
  - Handles diverse data formats via mixture of Gaussian simulation.
  - Performs augmentation at the information-rich range-profile level.

- **Key Results**:
  - Consistent supervised performance gains (2.79%-84.25%) across datasets, models, tasks, modalities.
  - Demonstrated significant improvements via unsupervised domain adaptation for unseen users (+3.04%) and environments (+17.45%).

Future work

- **Scope**:

  Potential for extension to other domains (healthcare, agriculture) & modalities (WiFi).

- **Methods**:
  - Add kinematic constraints/filters for pose feasibility.
  - Explore cross-dataset / cross-modality un-supervised domain adaptation..
  - Adapt WixUp for non-FMCW signal types.

Thanks! Q&A

Feel free to reach out:

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- 📧 yl3243@cornell.edu
- 🌐 lynneli.xyz

Questions

	Action (body)	Identification	Domain adaptation (Action/Keypoint)
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RF-Gen [13]	-	NA	(6.04%~56.42%)
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Table 5: Comprehensive comparison with generative DA. [NA = not applicable; - = not reported]

	MiliPoint	MARS	MMFi
Null	24.36	28.89	28.53
vanilla	24.29(+0.29%)	22.8(+21.08%)	25.93(+9.11%)
+Boostrap	23.25(+4.58%)	22.65(+21.60%)	25.84(+9.42%)
+CGA	**23.10 (+5.18%)**	**21.10(+26.95%)**	**25.60(+10.28%)**

Table 6: Ablation study on incremental versions of WixUp proves the effectiveness of each component.