2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

ID.58190

LARGE-SCALE SPATIAL-TEMPORAL ANALYSIS FOR DENSE SATELLITE IMAGE SERIES WITH DEEP LEARNING

18 OCT 2022

ID. 58190

PROJECT TITLE: LARGE-SCALE SPATIAL-TEMPORAL ANALYSIS FOR DENSE SATELLITE IMAGE SERIES WITH DEEP LEARNING

PRINCIPAL INVESTIGATORS: WEIWEI GUO, DANIELA FAUR

CO-AUTHORS: ZENGHUI ZHANG, YIN XU, SIYUAN ZHAO; CHENXUAN LI; LIU DAI

PRESENTED BY: WEIWEI GUO

同濟大學 TONGJI UNIVERSITY

UNIVERSITATEA POLITEHNICA DIN BUCURESTI 1818

上海交通大學 SHANGHAI JIAO TONG UNIVERSITY

the project's objectives

In this project, we intend to develop advanced deep learning techniques to analyze the EO data of dense satellite image time series

- Develop weakly supervised deep learning techniques for object extraction and semantic classification for remote sensing images
- Develop deep spatial-temporal network techniques for large dense SITS clustering, classification and prediction
- Exploit deep change detection techniques for multi-temporal satellite images
- Develop spatial-temporal fusion and synergic computation techniques of Multi-modal, Multiresolutions and Multi-sensor images for SITS mining, classification, and change analysis
- Two Cases: ecosystem monitoring of an UNESCO protected area, Romina, and Urban Evolution of Shanghai City

Young Scientists： 4+ PhD Students 4+ Master students

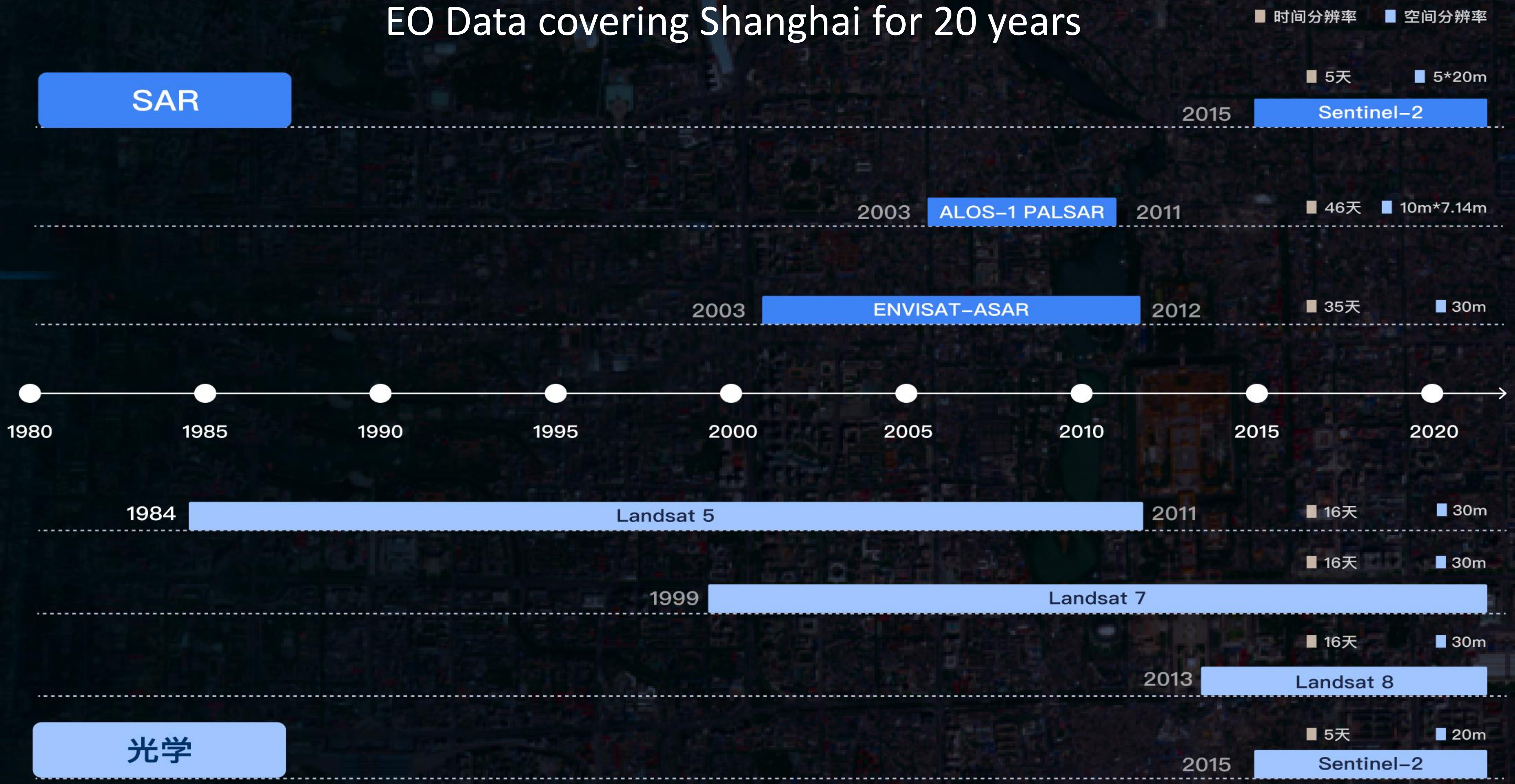
European Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Galan, Lorena	Politehnica University of Bucharest	Satellite Time Series based monitoring of the La Palma volcanic activity	In the fall of 2021 took place one of the biggest eruptions in the volcanic Canary Islands, on the La Palma island. This paper proposes the use of multispectral Sentinel 2 time series data to monitor pre and post event activity and assess vegetation's damage

Chinese Young scientists contributions in Dragon 5

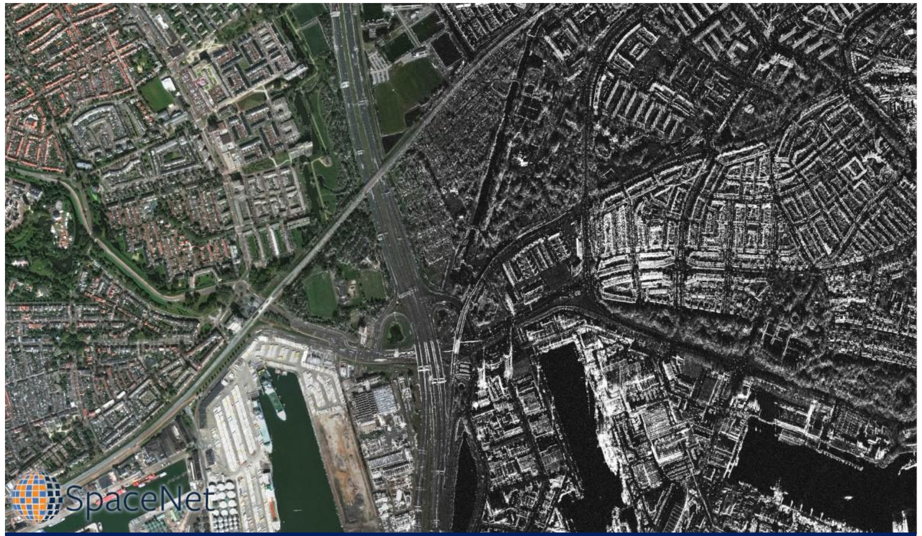
Name	Institution	Poster title	Contribution
Siyuan Zhao	Shanghai Jiao Tong University	A Feature Decomposition-based Method for Automatic Ship Detection Crossing Different Satellite SAR Images	We propose a feature decomposition-based method for automatic ship detection of SAR images crossing different satellites. Experimental results on Gaofen-3 and SSDD show that the detection performance of the method is significantly better than that of the baseline network and other DA SOTA methods

EO Data covering Shanghai for 20 years



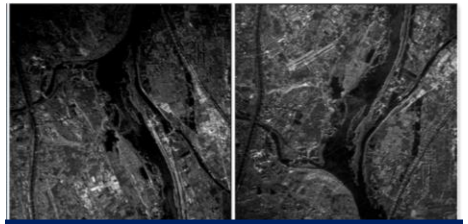
Some Challenges on EO Data and SITS Analysis

- Lack of large amount of labeled data
- Big data and small samples
- Multi-modal, heterogeneous data
- Unseen/novel categories

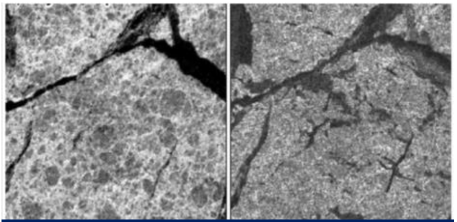


Optical and SAR

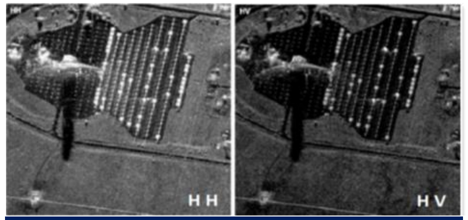
Different Resolutions



Different Imaging view



Different Frequency Bands



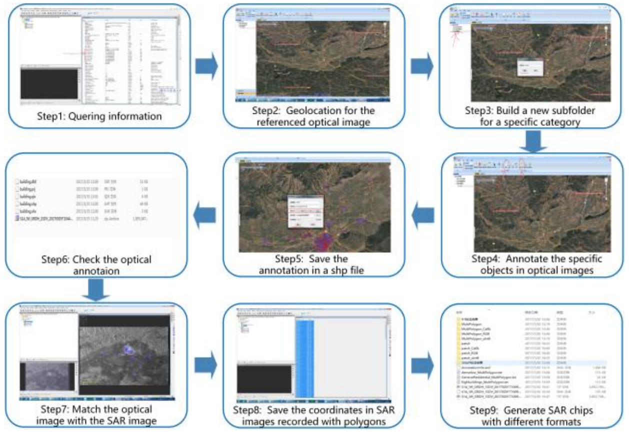
Different Polarimetric

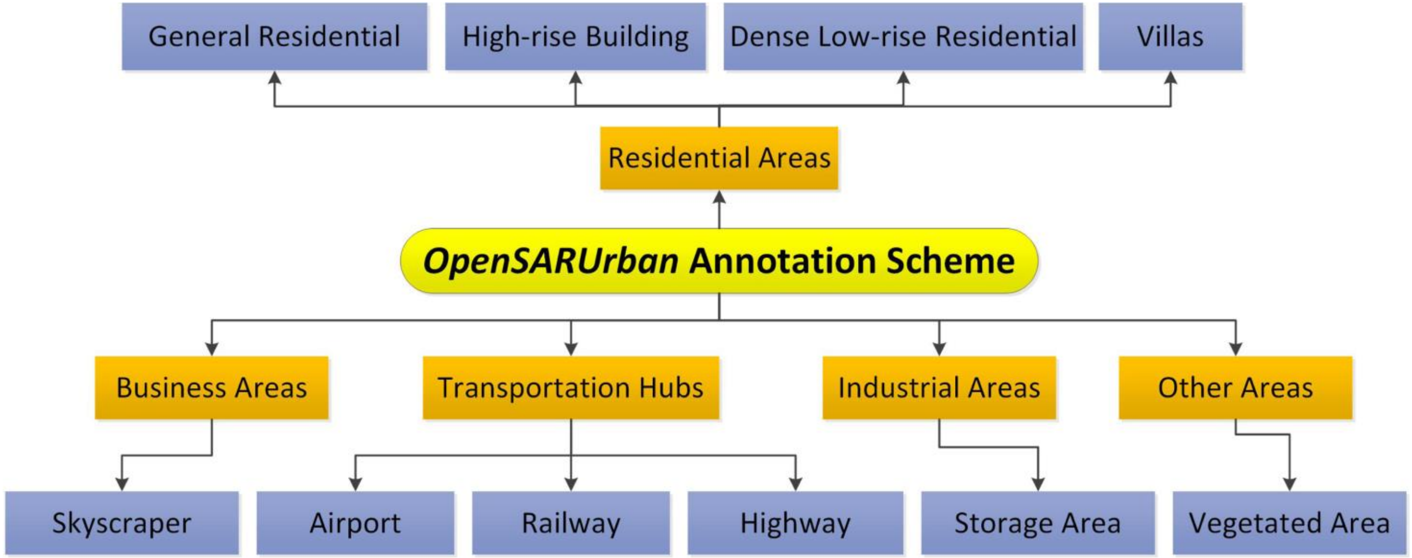
Address the Challenge 1: Lack of large amount of labeled data

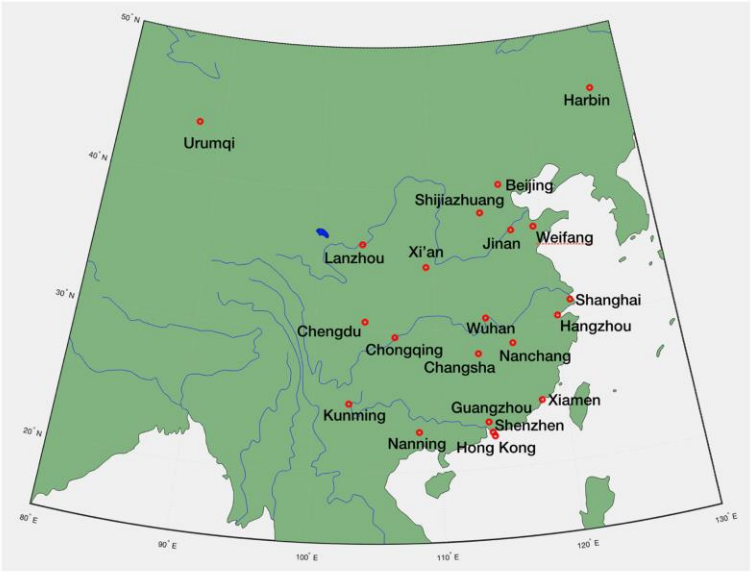
- **Building OpenSARUrban Dataset from Sentinel-1 data**

10 main Chinese Cities　　**20m** resolutions

10 classes



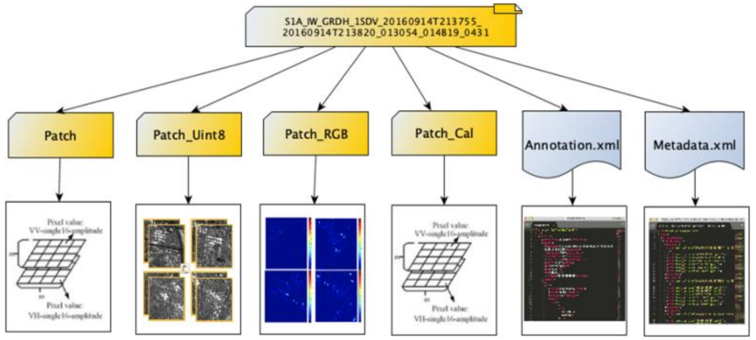




[1]Zhao, J., Zhang, Z., Yao, W., Datcu, M., Xiong, H., & Yu, W. "OpenSARUrban: A Sentinel-1 SAR image dataset for urban interpretation." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 13 (2020): 187-203.

Address the Challenge 1: Lack of large amount of labeled data

■ Building OpenSARUrban Dataset from Sentinel-1 data



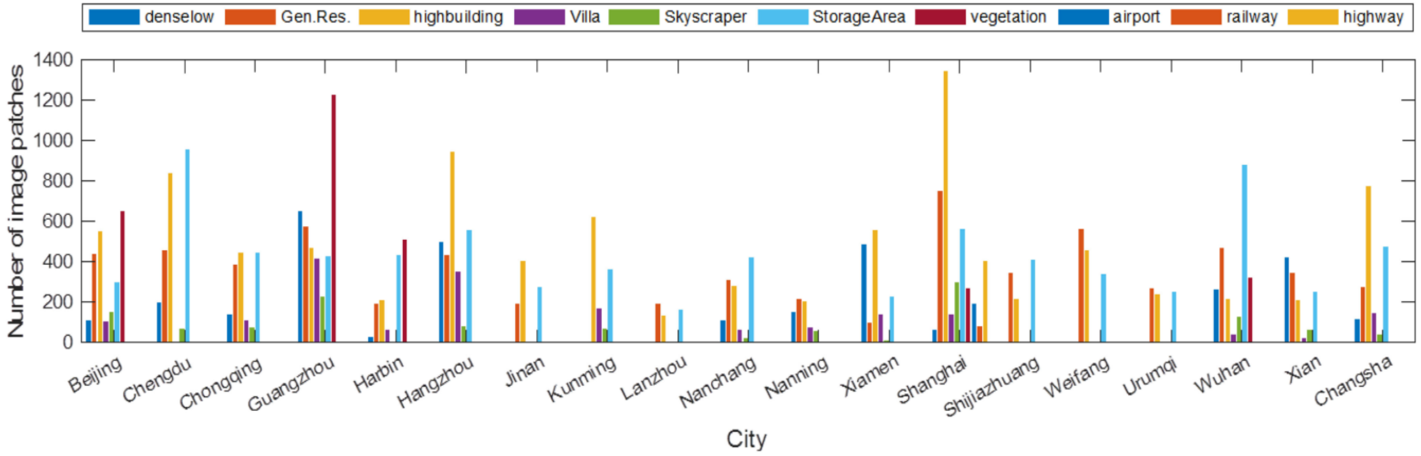
10 main Chinese Cities

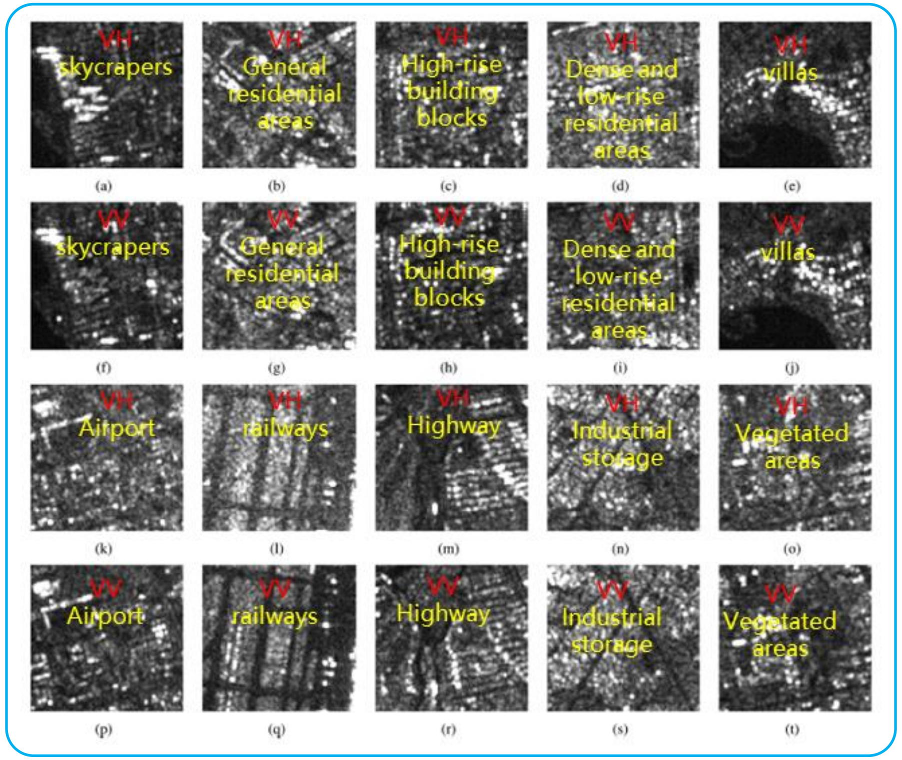
10 categories

100x100 of size

20m resolutions

30000+ tiles





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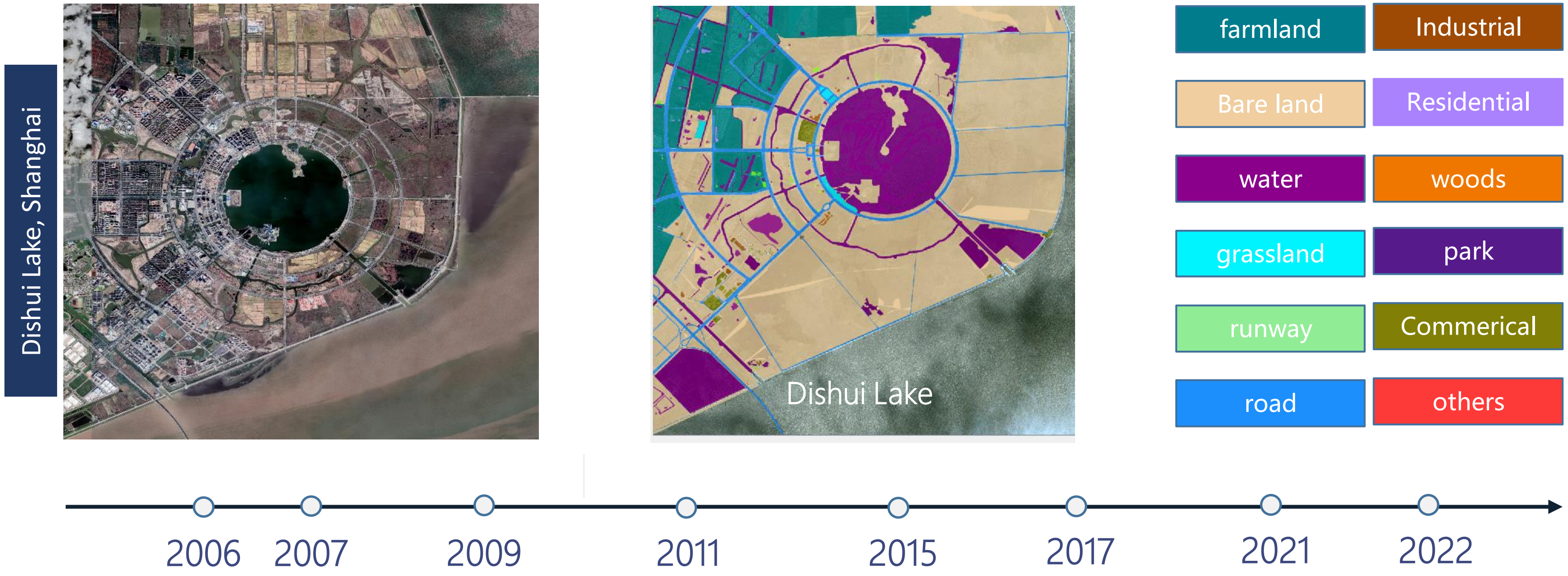
Address the Challenge 1: Lack of large amount of labeled data

■ In Processing: building dataset of LULC for SITS

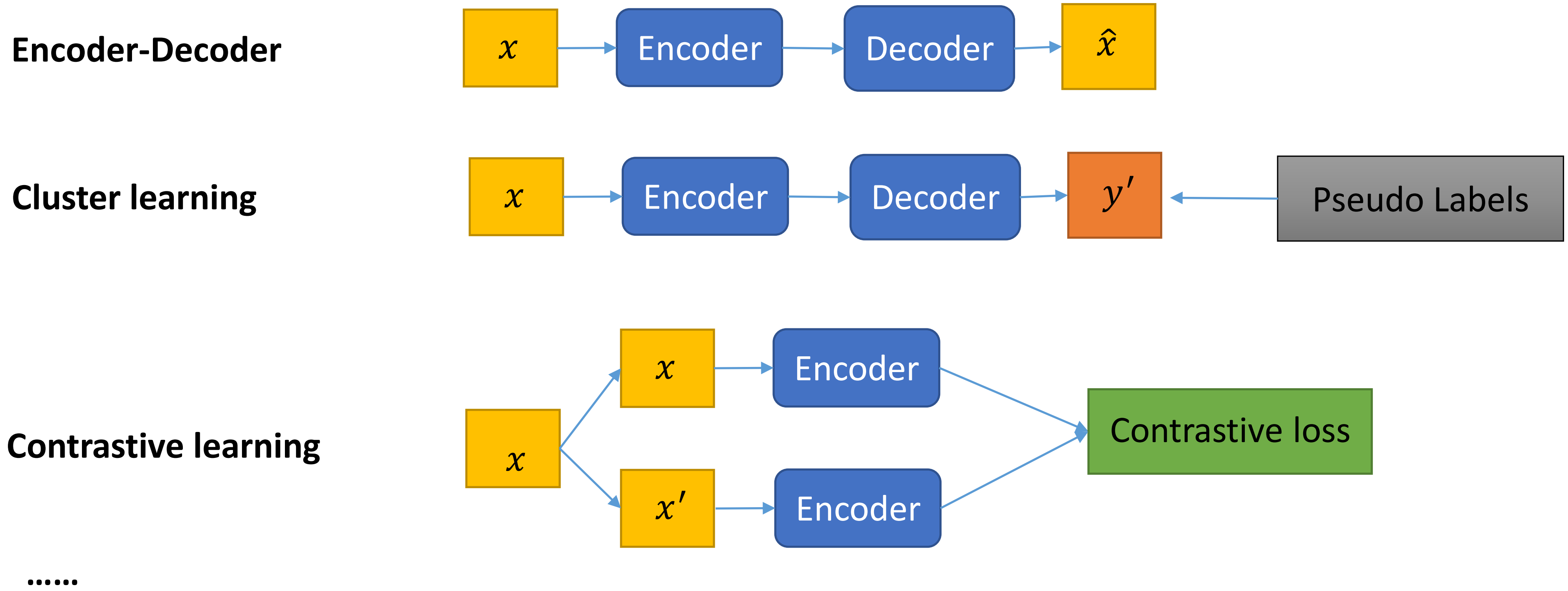
- Pixel Labeling is extremely labor expensive
- Transfer From high resolution (e.g.,Google earth) to low resolution (e.g., Sentinel, Landsat,...)
- Transfer From the optical to SAR
- Transfer For one AOI to another AOI



Address the Challenge 2: Big data and small samples

- Self-Supervised: Multi-Embedding Contrastive Pre-training Learning for Classification

Self-Supervised learning: construct self-supervised signal for representation learning and apply for the downstream tasks by fine-tuning



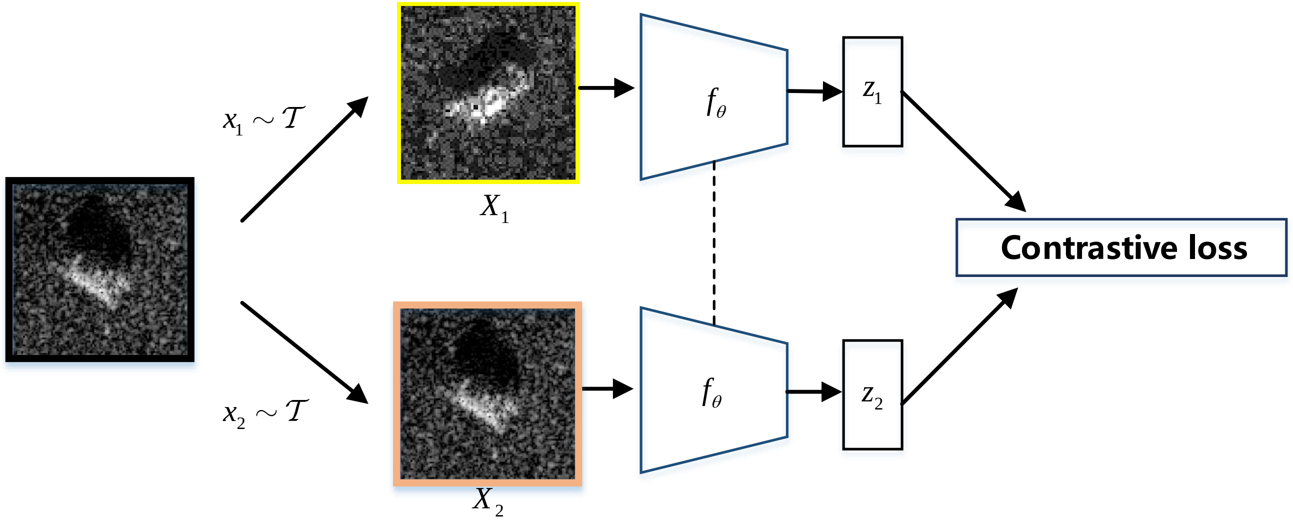
[2] Xu, Y., Guo, W., Zhang, Z., & Yu, W. "Multiple Embeddings Contrastive Pretraining for Remote Sensing Image Classification." *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1-5.

Address the Challenge 2: Big data and small samples

- Self-Supervised: Multi-Embedding Contrastive Pre-training Learning for Classification

Contrastive learning:

- Transform/Augment the same image as different views
- Push the same images close while pull the different ones away
- Learning some invariant features dependent on the augmentation transform

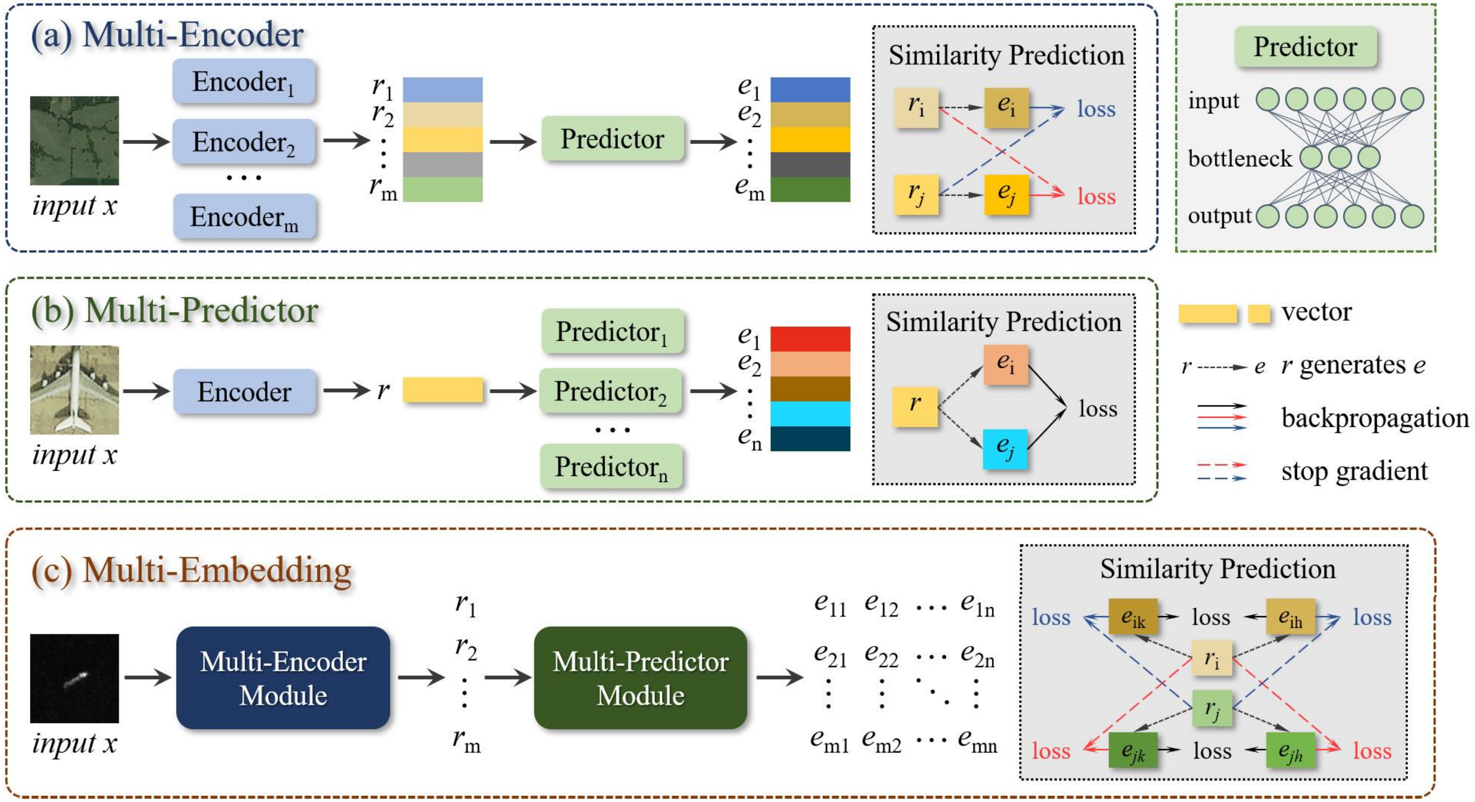


[2] Xu, Y., Guo, W., Zhang, Z., & Yu, W. "Multiple Embeddings Contrastive Pretraining for Remote Sensing Image Classification." *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1-5.

Address the Challenge 2: Big data and small samples

■ MECo: Multi-Embedding Contrastive Pre-training Learning for Classification

- **Multi-Encoder**: generate the different representations by multi encoder network instead of view augmentation
- **Predictor**: map the representation to the embedding by MLPs
- **Similarity Prediction**: Encourage the similarity between multi-encoders and multi-predictors



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Address the Challenge 2: Big data and small samples

- **MECo**: Multi-Embedding Contrastive Pre-training Learning for Classification

ACCURACY (%) OF MECO PRETRAINING AND SUPERVISED LEARNING METHOD

method	train ep.	OpenSARShip	GaoFenPlane	RSSCN7
supervised	200	71.96	47.22	70.83
supervised	1000	74.51	61.06	82.38
MECo-2-2 (ft)	200	74.71	75.68	86.67
MECo-2-2 (lin.)	200	68.82	63.86	69.40

MECO :fine-tuning accuracy of the pretrained encoder was higher than that of the encoder trained using the supervised method.

FINE-TUNING ACCURACY (%) OF MECO PRETRAINING AND OTHER SELF-SUPERVISED METHODS

method	pre-train ep.	OpenSARShip	GaoFenPlane	RSSCN7
SimCLR [9]	20	72.63	71.30	83.15
MoCo [10]	20	71.43	69.87	79.20
BYOL [11]	20	71.63	71.19	81.36
SimSiam [12]	20	74.23	70.79	81.55
SimSiam [12]	100	74.23	73.23	85.36
MECo-2-2 (ours)	20	**74.71**	**75.68**	**86.67**

MECo outperforms the SOTA self-supervised methods

[2] Xu, Y., Guo, W., Zhang, Z., & Yu, W. "Multiple Embeddings Contrastive Pretraining for Remote Sensing Image Classification." *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1-5.

Address the Challenge 3: Big data and small samples

- **MECo**: Multi-Embedding Contrastive Pre-training Learning for Classification

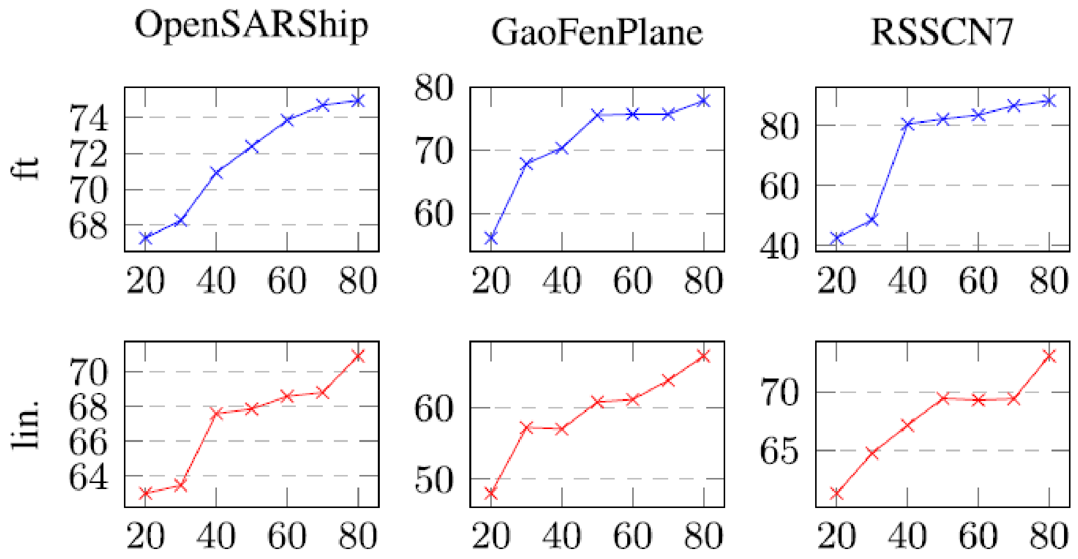


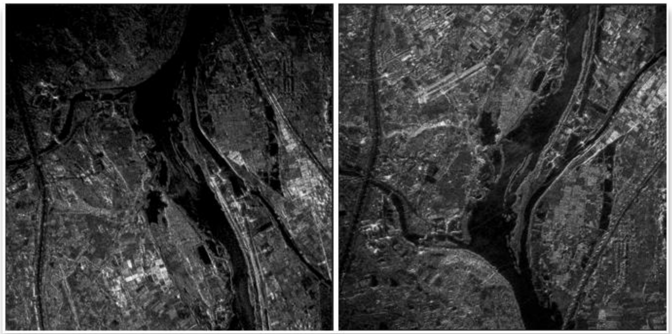
Fig. 3. Relationship between classification accuracy (vertical axis) and the percentage of training set versus total dataset in the evaluation stage (horizontal axis). We report fine-tuning accuracy (upper) and linear probing accuracy (lower). The encoders were pretrained by MECo-2-2.

Data efficient :only a small percentage of training images were used can achieve good performance

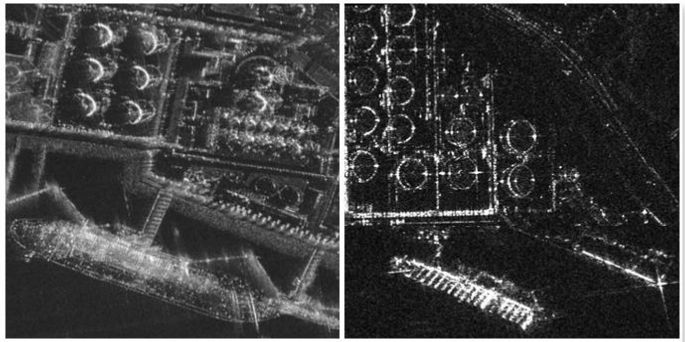
[2] Xu, Y., Guo, W., Zhang, Z., & Yu, W. "Multiple Embeddings Contrastive Pretraining for Remote Sensing Image Classification." *IEEE Geoscience and Remote Sensing Letters* 19 (2022): 1-5.

Address the Challenge 3: Multi-modal, heterogeneous data

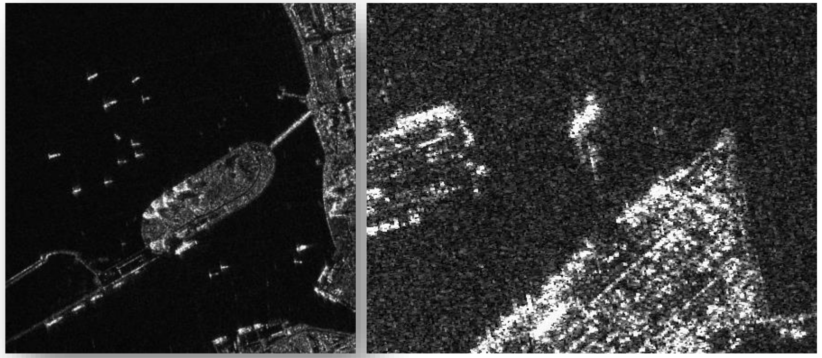
- SAR images varies greatly under different imaging parameters
- Performance degrades sharply when testing and training data have different distributions



Different imaging angles



Different resolutions



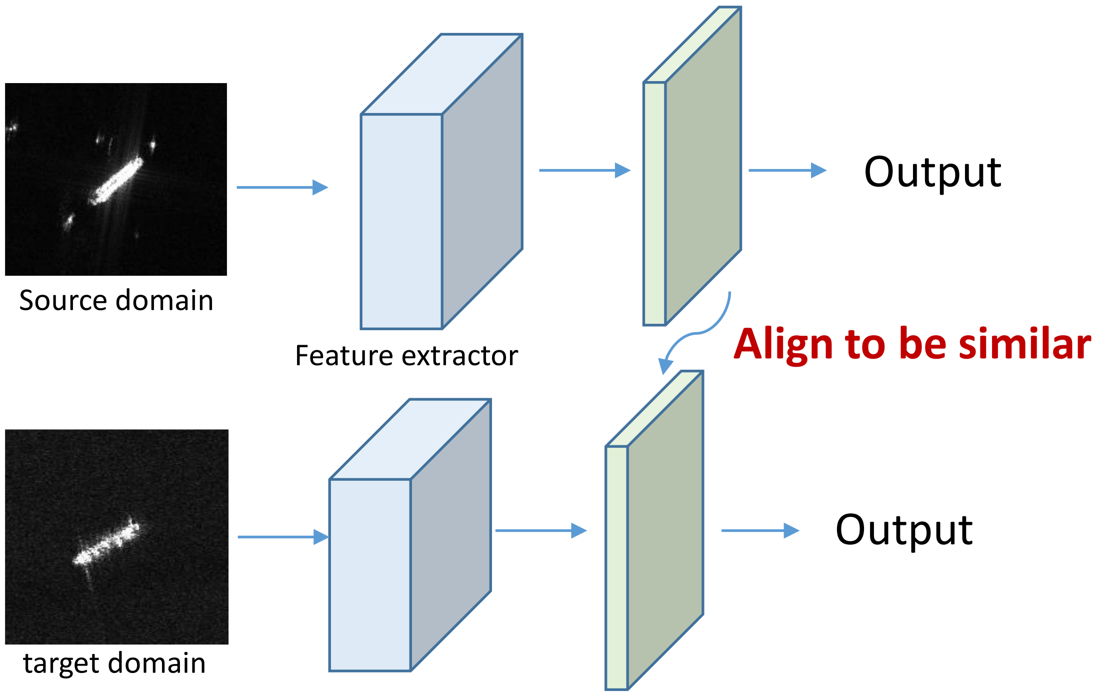
Different platform of Gaofen3 and TerreSAR

[3] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "Active Learning SAR Image Classification Method Crossing Different Imaging Platforms," in IEEE Geoscience and Remote Sensing Letters, 2022, doi: 10.1109/LGRS.2022.3208468.
[4] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "A Feature Decomposition-Based Method for Automatic Ship Detection Crossing Different Satellite SAR Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5234015, doi: 10.1109/TGRS.2022.3201628

[5] S. Zhao, Z. Zhang, W. Guo and Y. Luo, "An Automatic Ship Detection Method Adapting to Different Satellites SAR Images With Feature Alignment and Compensation Loss," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-17, 2022, Art no. 5225217, doi: 10.1109/TGRS.2022.3160727
[6] S. Zhao, Z. Zhang, T. Zhang, W. Guo and Y. Luo, "Transferable SAR Image Classification Crossing Different Satellites Under Open Set Condition," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4506005, doi: 10.1109/LGRS.2022.3159179

Address the Challenge 3: Multi-modal, heterogeneous data

- Domain Adaption and transferring learning techniques are adopted



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Address the Challenge 3: Multi-modal, heterogeneous data

- Adversarial Domain Adaptation

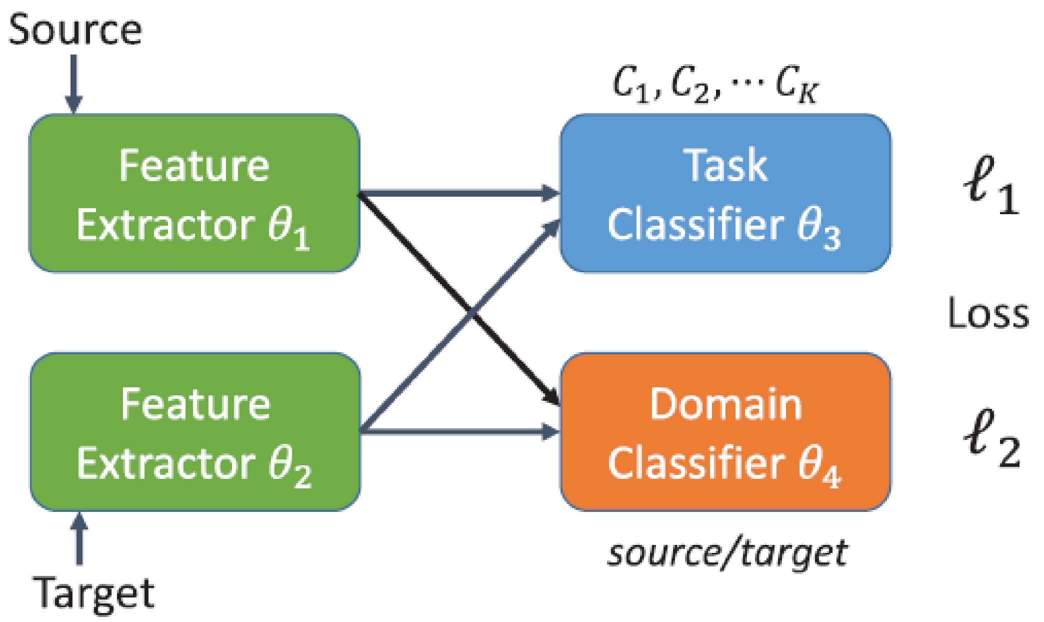
Adversarial Learning to align the target and source features

$$\theta_1 \Rightarrow \min\ l_1, \max l_2$$

$$\theta_2 \Rightarrow \min\ l_1(optional), \max l_2$$

$$\theta_3 \Rightarrow \min\ l_1$$

$$\theta_4 \Rightarrow \min\ l_2$$



Taken from ZHANG, et al. Robust pattern recognition a review

[3] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "Active Learning SAR Image Classification Method Crossing Different Imaging Platforms," in IEEE Geoscience and Remote Sensing Letters, 2022, doi: 10.1109/LGRS.2022.3208468.

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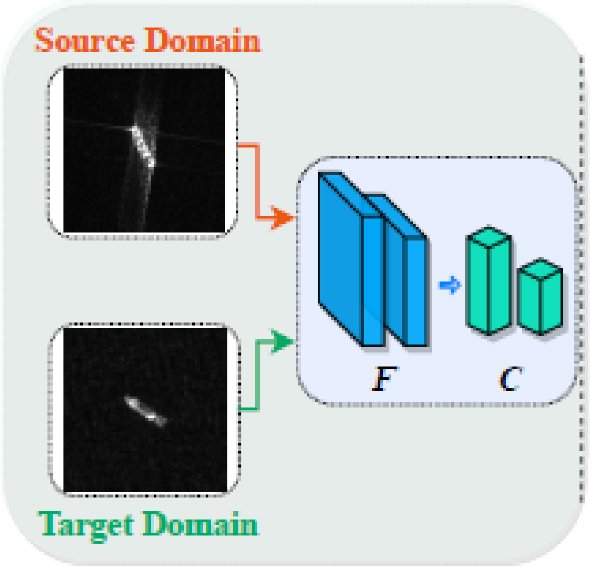
Address the Challenge 3: Multi-modal, heterogeneous data

Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

- Incorporate active learning into adversarial domain adaption to improve DA performance
- Narrow the feature gap between source and target domain by adversarial DA
- Prototype loss to improve feature discrimination in target domain
- Select "Hard" target samples to be labeled



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Address the Challenge 3: Multi-modal, heterogeneous data

- Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

Training Loss

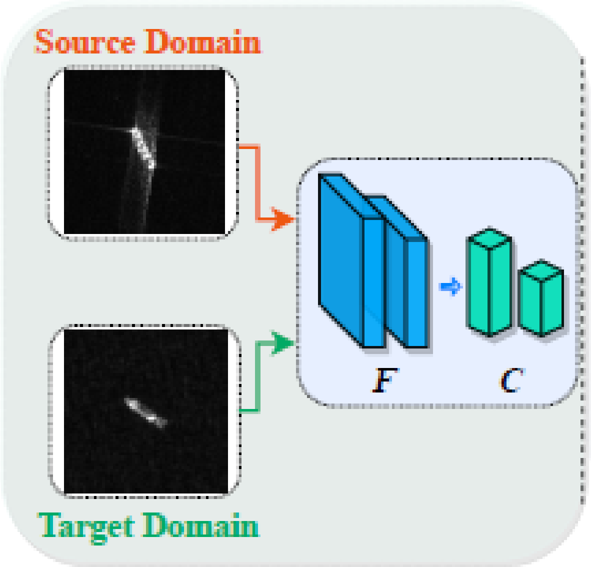
$$L = L_{adv} + L_{pr} + L_{clm}$$

$$\mathcal{L}_{clm}(x) = \sum_{i \neq j} c_{i,j} \left[m - C(F(x))_j + C(F(x))_i \right]_+$$

$$\mathcal{L}_{adv} = -\frac{1}{N_S} \sum_{i=1}^{N_S} \mathcal{L}_{ce}\left(C\left(F\left(x_i^s\right)\right), y_i^s\right) - \frac{1}{N_T} \sum_{i=1}^{N_T} \mathcal{L}_{ce}\left(1 - C\left(F\left(x_i^t\right)\right)\right)$$

$$\mathcal{L}_{pr} = -\sum_{i=1}^{N_T} \sum_{k=1}^{K} \hat{y}_{i,k}^t \log \delta(i,k)$$

$$\delta(i,k) = \frac{\exp\left(v_i^{\mathrm{T}} b_k^t\right)}{\sum_{k=1}^{K} \exp\left(v_i^{\mathrm{T}} b_k^t\right)}$$



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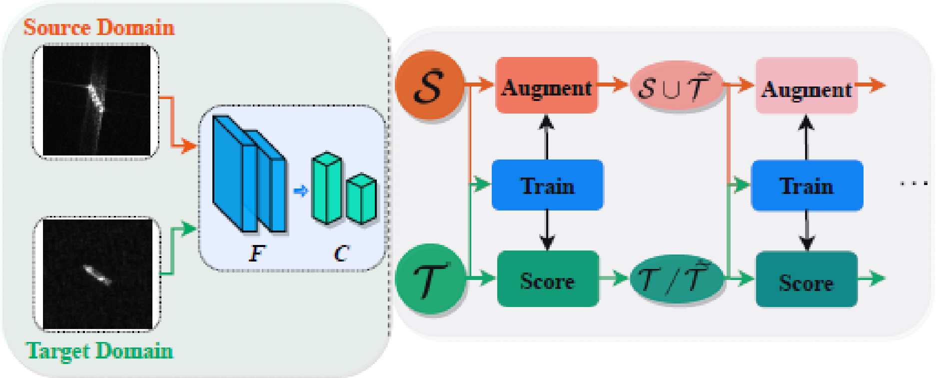
Address the Challenge 3: Multi-modal, heterogeneous data

- Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

Hard samples selection

Rank the target samples with the gap between the maximum and second maximum of classification logits

$$Q_{ms}\left(x^{t}\right)=p_{m}-p_{sm}, \forall x^{t} \in \mathcal{T}/\tilde{\mathcal{T}}$$



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Address the Challenge 3: Multi-modal, heterogeneous data

- Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

OpenSARship dataset : ESA Sentinel-1

FUSAR dataset : Chinese Gaofen-3

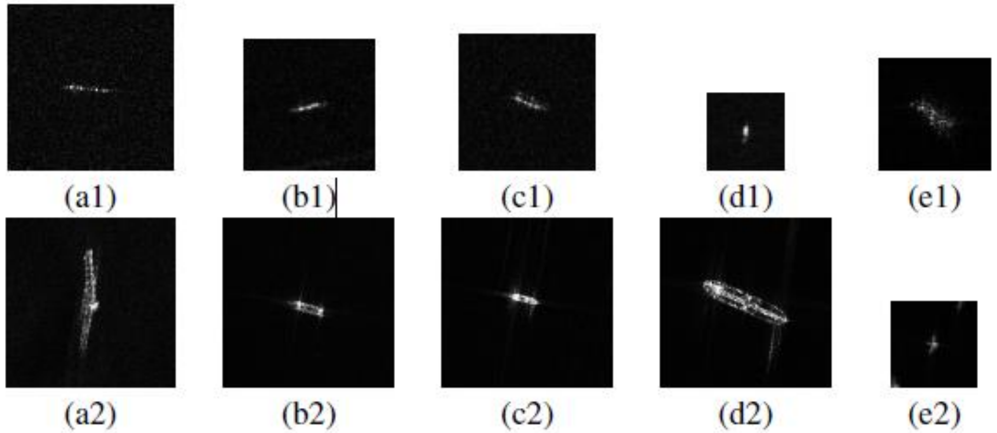

Fig. 2. Each class in the two datasets. The first row is from OpenSAR and the second row is from FUSAR. (a) Cargo. (b) Dredging. (c) Fishing. (d) Tanker. (e) Others.

[3] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "Active Learning SAR Image Classification Method Crossing Different Imaging Platforms," in IEEE Geoscience and Remote Sensing Letters, 2022, doi: 10.1109/LGRS.2022.3208468.

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Address the Challenge 3: Multi-modal, heterogeneous data

- Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

the proposed method shows the best classification performance in both DA tasks, with higher classification accuracy.

TABLE II
SAR IMAGE DATASETS FROM DIFFERENT SATELLITES CLASSIFICATION RESULTS (%) OF VARIOUS METHODS

Method	FU → O						O → FU					
	Cargo	Dredging	Fishing	Tanker	Others	Accuracy	Cargo	Dredging	Fishing	Tanker	Others	Accuracy
DLDA	87.9	42.0	75.3	68.1	70.9	68.8	87.6	49.8	61.9	76.2	69.7	69.0
MALDA	88.7	42.8	75.9	68.7	70.6	69.3	88.3	51.1	62.6	77.9	71.4	70.2
TDDA	89.4	43.2	78.6	69.3	71.0	70.3	91.5	52.0	63.4	79.6	73.1	71.9
CORAL	93.3	63.5	79.3	80.2	76.2	78.5	94.2	68.7	82.0	81.4	82.9	81.8
S3ADA	90.6	61.5	74.9	77.3	72.7	75.4	92.1	64.3	76.7	79.8	73.3	77.2
EADA	92.0	62.2	78.9	79.6	76.8	77.9	93.9	67.4	80.2	82.4	83.2	81.4
Ours	**95.5**	**84.9**	**86.8**	**88.9**	**80.4**	**87.3**	**97.8**	**86.0**	**88.1**	**91.1**	**83.5**	**89.3**

[3] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "Active Learning SAR Image Classification Method Crossing Different Imaging Platforms," in IEEE Geoscience and Remote Sensing Letters, 2022, doi: 10.1109/LGRS.2022.3208468.
[4] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "A Feature Decomposition-Based Method for Automatic Ship Detection Crossing Different Satellite SAR Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5234015, doi: 10.1109/TGRS.2022.3201628
[5] S. Zhao, Z. Zhang, W. Guo and Y. Luo, "An Automatic Ship Detection Method Adapting to Different Satellites SAR Images With Feature Alignment and Compensation Loss," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-17, 2022, Art no. 5225217, doi: 10.1109/TGRS.2022.3160727
[6] S. Zhao, Z. Zhang, T. Zhang, W. Guo and Y. Luo, "Transferable SAR Image Classification Crossing Different Satellites Under Open Set Condition," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4506005, doi: 10.1109/LGRS.2022.3159179

Address the Challenge 3: Multi-modal, heterogeneous data

- Active Learning SAR Image Classification Method Crossing Different Imaging Platforms

Variation with Different Budget Size

our approach achieves consistent improvements regardless of budget size.

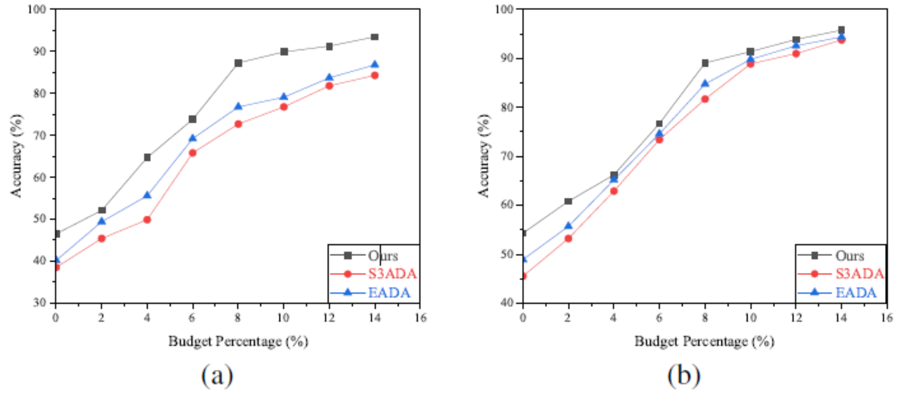


Fig. 4. Classification accuracy of the two tasks with different budget size. In two subfigures, black, red and blue indicate the proposed method, S3ADA and EADA, respectively. (a) FU → O. (b) FG → FU.

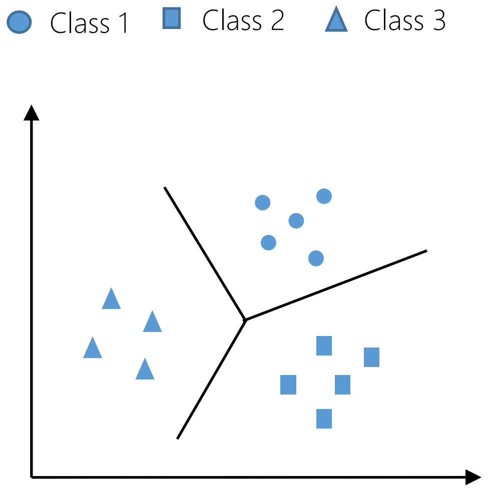
[3] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "Active Learning SAR Image Classification Method Crossing Different Imaging Platforms," in IEEE Geoscience and Remote Sensing Letters, 2022, doi: 10.1109/LGRS.2022.3208468.
[4] S. Zhao, Y. Luo, T. Zhang, W. Guo and Z. Zhang, "A Feature Decomposition-Based Method for Automatic Ship Detection Crossing Different Satellite SAR Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-15, 2022, Art no. 5234015, doi: 10.1109/TGRS.2022.3201628

[5] S. Zhao, Z. Zhang, W. Guo and Y. Luo, "An Automatic Ship Detection Method Adapting to Different Satellites SAR Images With Feature Alignment and Compensation Loss," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-17, 2022, Art no. 5225217, doi: 10.1109/TGRS.2022.3160727
[6] S. Zhao, Z. Zhang, T. Zhang, W. Guo and Y. Luo, "Transferable SAR Image Classification Crossing Different Satellites Under Open Set Condition," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 4506005, doi: 10.1109/LGRS.2022.3159179

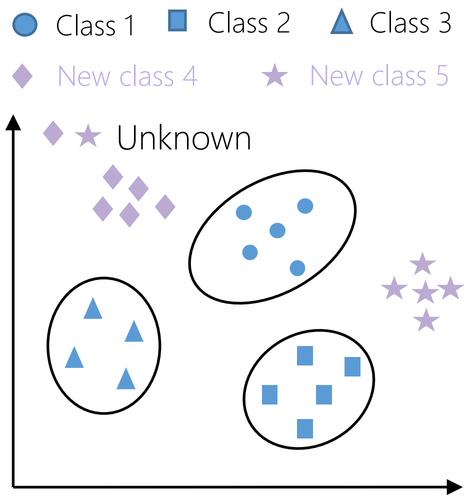
Address the Challenge 4: Unseen/novel categories

- Class definition dependent on specific application
- Novel Classes are emerging
- Traditional ML/DL assumptions: i.i.d and close set

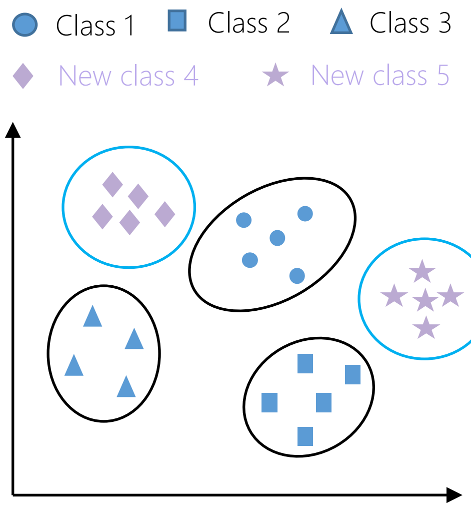
Close Set



Open Set



Novel Class Discovery



[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342

[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Open Set Recognition with variational autoencoder (VAE)
  - SAR image distributions are very complex
  - Embedding the SAR image into latent space and model the latent features as mixture of Gaussian
  - Training VAE for each class by reconstruction loss, K-L distribution loss and classification loss
  - Detect unknown class with low classification probability and large reconstruction error.

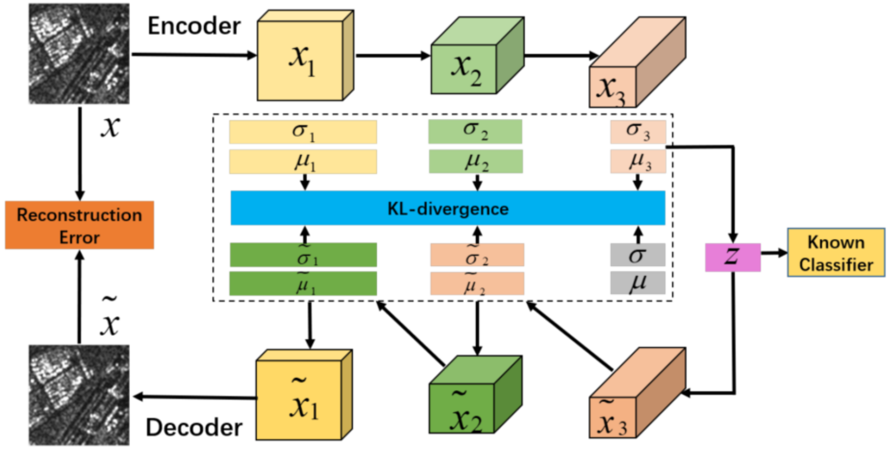


Fig. 2. SAR Distinguishability Analysor (SAR-DA)

Encoder	Decoder
	$d_{k+1} = \mathrm{Unflatten}(\tilde{z}_{k+1})$
$x_k = \mathrm{Conv}(x_{k-1})$	$x_{k+1} = \mathrm{TConv}(d_{k+1})$
$\mu_k = \mathrm{Linear}(\mathrm{Flatten}(x_k))$	$\mu_k = \mathrm{Linear}(\mathrm{Flatten}(x_{k+1}))$
$\sigma_k^2 = \mathrm{F}(\mathrm{Linear}(\mathrm{Flatten}(x_k)))$	$\sigma_k^2 = \mathrm{F}(\mathrm{Linear}(\mathrm{Flatten}(x_{k+1})))$
	$\tilde{z}_k = \mu_k + \varepsilon \cdot \sigma_k^2, \varepsilon \sim N(0, \mathbf{I})$

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342

[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Open Set Recognition with variational autoencoder (VAE)
  - OpenSARUrban dataset
  - Close classifications of 9 categories and 10 categories
  - Open recognition of 9 known categories and 1 unknown class

Classes	Unknown Classes																				All Known
	Denselow		Gen.Res		Highbuildings		SingleBuilding		Skyscraper		StorageArea		Vegetataion		Airport		Railway		Highway		
Denselow	**53.10**	—	86.10	98.66	95.12	99.64	89.21	99.64	98.40	99.02	83.32	99.10	93.00	99.91	99.87	99.73	99.62	97.28	99.14	99.91	99.46
Gen.Res	81.17	99.86	**47.74**	—	82.69	99.95	96.18	99.77	98.28	99.09	76.80	98.99	87.58	99.59	99.82	99.31	99.22	99.54	99.54	99.31	99.22
Highbuildings	91.30	99.94	80.80	99.77	**60.10**	—	98.11	99.64	93.19	99.84	64.03	99.77	92.58	99.84	99.89	96.47	98.97	99.87	99.77	99.87	99.84
SingleBuilding	85.95	99.68	95.72	98.57	98.60	99.84	**14.17**	—	97.37	99.20	79.49	99.68	81.35	99.68	99.09	99.05	98.53	99.68	98.84	98.74	99.52
Skyscraper	93.02	99.55	81.91	99.10	82.27	99.77	98.90	99.77	**13.01**	—	73.88	98.65	93.73	99.77	99.71	97.95	98.96	99.77	99.15	99.77	99.77
StorageArea	81.39	99.92	90.83	99.03	80.87	99.84	93.81	99.76	95.82	99.67	**32.88**	—	84.82	98.47	99.31	99.96	98.93	98.91	98.90	99.55	99.92
Vegetataion	88.16	99.24	94.86	99.66	95.67	99.75	83.88	99.91	95.99	99.49	66.20	99.91	**50.43**	—	99.10	99.49	99.14	99.07	97.07	99.49	99.32
Airport	95.65	98.41	97.14	98.46	92.45	98.51	88.89	98.51	97.78	96.92	78.57	98.48	78.72	95.65	**21.93**	—	97.67	96.92	97.76	97.06	95.65
Railway	86.67	96.43	85.71	93.10	00.00	96.43	87.50	96.43	82.61	96.00	95.83	96.43	80.00	89.66	96.00	96.00	**99.12**	—	96.15	96.30	96.43
Highway	84.06	99.28	78.57	97.84	96.89	99.28	89.55	99.26	88.15	99.23	85.92	99.28	86.89	99.26	99.19	97.86	99.12	97.06	**39.72**	—	99.26
m-precision	79.03	99.14	83.94	98.24	78.47	99.22	84.02	99.19	86.06	98.72	73.69	98.92	82.91	97.98	89.42	98.42	89.11	98.68	89.05	98.89	98.84
m-recall	79.61	98.56	67.72	98.44	67.90	99.23	67.67	98.91	75.86	96.67	78.72	98.84	80.62	98.40	75.11	97.19	80.08	98.24	71.60	98.62	98.92
m-fmeasure	79.32	98.85	74.96	98.34	72.79	99.22	74.96	99.05	80.64	97.68	76.12	98.88	81.75	98.19	81.64	97.80	84.35	98.46	79.38	98.75	98.88

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342
[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Open Set Recognition with variational autoencoder (VAE)
  - High accuracy under close settings. It indicates VAE can model the SAR image distribution well
  - Unknown classes lead to negative impact on the whole classification accuracy
  - The separability of SAR classification dataset can be analyzed through the open set recognition accuracy

Classes	Unknown Classes																				All Known
	Denselow		Gen.Res		Highbuildings		SingleBuilding		Skyscraper		StorageArea		Vegetataion		Airport		Railway		Highway		
Denselow	**53.10**	—	86.10	98.66	95.12	99.64	89.21	99.64	98.40	99.02	83.32	99.10	93.00	99.91	99.87	99.73	99.62	97.28	99.14	99.91	99.46
Gen.Res	81.17	99.86	**47.74**	—	82.69	99.95	96.18	99.77	98.28	99.09	76.80	98.99	87.58	99.59	99.82	99.31	99.22	99.54	99.54	99.31	99.22
Highbuildings	91.30	99.94	80.80	99.77	**60.10**	—	98.11	99.64	93.19	99.84	64.03	99.77	92.58	99.84	99.89	96.47	98.97	99.87	99.77	99.87	99.84
SingleBuilding	85.95	99.68	95.72	98.57	98.60	99.84	**14.17**	—	97.37	99.20	79.49	99.68	81.35	99.68	99.09	99.05	98.53	99.68	98.84	98.74	99.52
Skyscraper	93.02	99.55	81.91	99.10	82.27	99.77	98.90	99.77	**13.01**	—	73.88	98.65	93.73	99.77	99.71	97.95	98.96	99.77	99.15	99.77	99.77
StorageArea	81.39	99.92	90.83	99.03	80.87	99.84	93.81	99.76	95.82	99.67	**32.88**	—	84.82	98.47	99.31	99.96	98.93	98.91	98.90	99.55	99.92
Vegetataion	88.16	99.24	94.86	99.66	95.67	99.75	83.88	99.91	95.99	99.49	66.20	99.91	**50.43**	—	99.10	99.49	99.14	99.07	97.07	99.49	99.32
Airport	95.65	98.41	97.14	98.46	92.45	98.51	88.89	98.51	97.78	96.92	78.57	98.48	78.72	95.65	**21.93**	—	97.67	96.92	97.76	97.06	95.65
Railway	86.67	96.43	85.71	93.10	00.00	96.43	87.50	96.43	82.61	96.00	95.83	96.43	80.00	89.66	96.00	96.00	**99.12**	—	96.15	96.30	96.43
Highway	84.06	99.28	78.57	97.84	96.89	99.28	89.55	99.26	88.15	99.23	85.92	99.28	86.89	99.26	99.19	97.86	99.12	97.06	**39.72**	—	99.26
m-precision	79.03	99.14	83.94	98.24	78.47	99.22	84.02	99.19	86.06	98.72	73.69	98.92	82.91	97.98	89.42	98.42	89.11	98.68	89.05	98.89	98.84
m-recall	79.61	98.56	67.72	98.44	67.90	99.23	67.67	98.91	75.86	96.67	78.72	98.84	80.62	98.40	75.11	97.19	80.08	98.24	71.60	98.62	98.92
m-fmeasure	79.32	98.85	74.96	98.34	72.79	99.22	74.96	99.05	80.64	97.68	76.12	98.88	81.75	98.19	81.64	97.80	84.35	98.46	79.38	98.75	98.88

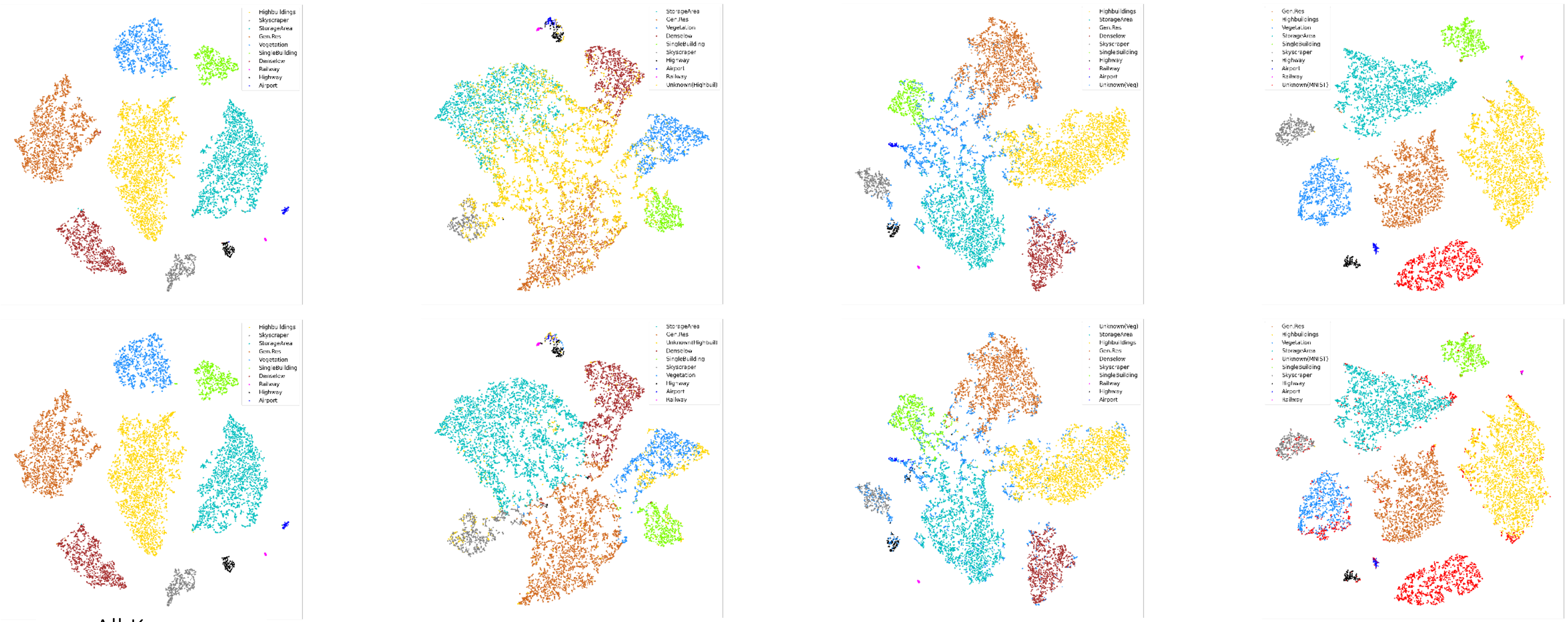
[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342
[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Open Set Recognition with variational autoencoder (VAE)

GT

Results



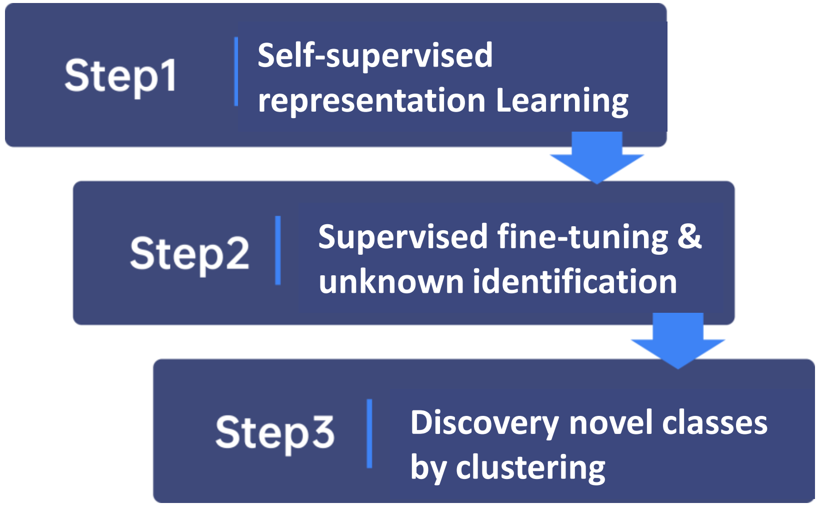
All Known | Highbuildings Unknown | Vegetation Unknown | Without Denselow+MNIST

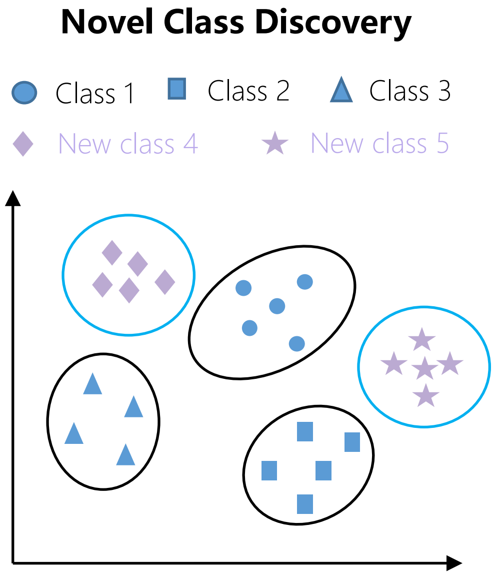
[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342

[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Novel Categories Discovery
  - Propose a novel pipeline of novel categories discovering





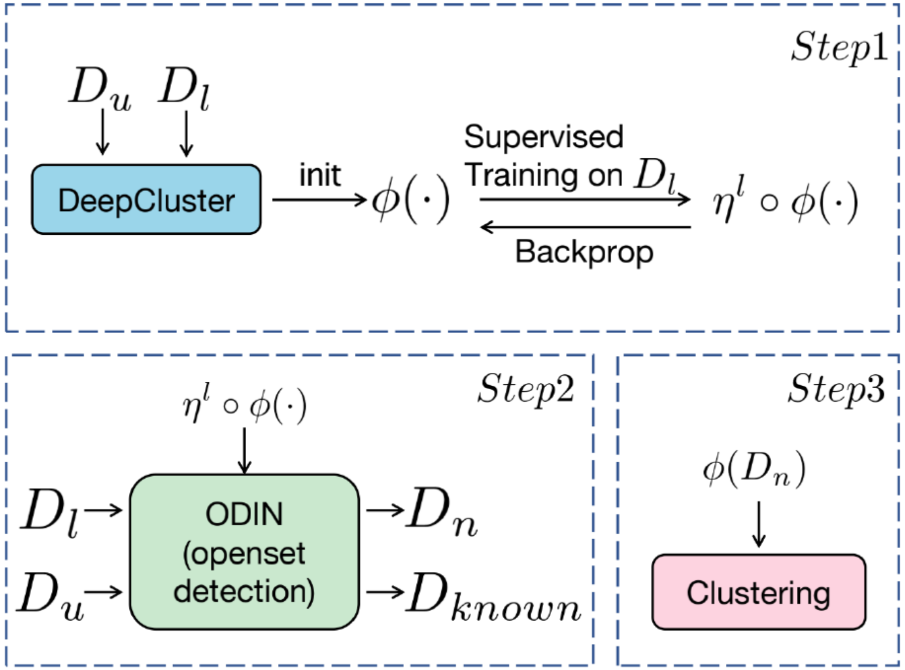


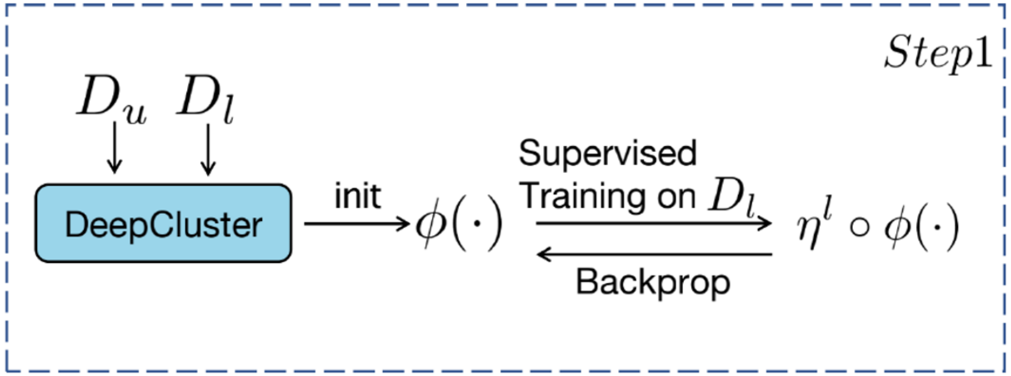
Fig. 1. The detailed pipeline of our method to pick out the new category data in SAR image dataset, conducting Step 1,2 and 3 in turn.

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342
[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Novel Categories Discovery
  - Step 1: self-supervised learning based on deep clustering

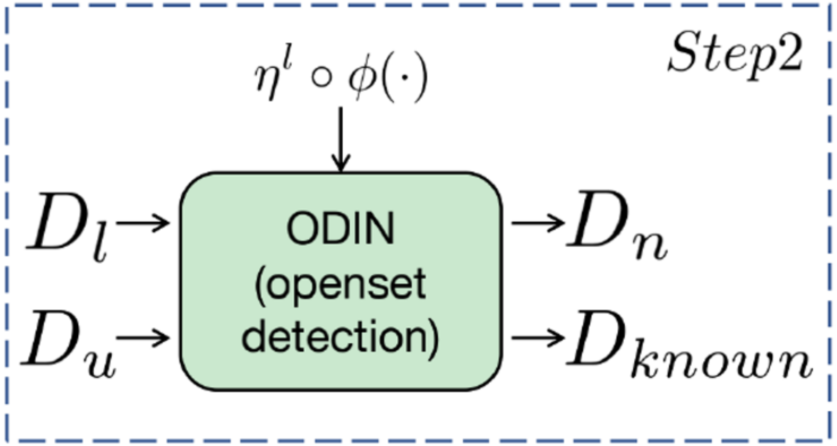
    Training on all labeled and unlabeled data to obtain good representation



[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342
[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Novel Categories Discovery
  - Step 2: fine-tuning and open set detection
    - ✓ Supervised Fine-tuning on the labeled dataset
    - ✓ In-distribution data have high softmax score while out-of-distribution data have low softmax score
    - ✓ Enlarge the difference between the out-of-distribution and in-distribution data



small controlled perturbations

temperature scaling

Open set identification by threshold

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} - \varepsilon \operatorname{sign}(-\nabla_{\boldsymbol{x}} \log S_{\hat{y}}(\boldsymbol{x}; T)), \longrightarrow S_i(\boldsymbol{x}; T) = \frac{\exp(f_i(\boldsymbol{x})/T)}{\sum_{j=1}^{N} \exp(f_j(\boldsymbol{x})/T)}, \longrightarrow g(\boldsymbol{x}; \delta, T, \varepsilon) = \begin{cases} 1 & \text{if} \max_i p(\tilde{\boldsymbol{x}}; T) \leq \delta, \\ 0 & \text{if} \max_i p(\tilde{\boldsymbol{x}}; T) > \delta. \end{cases}$$

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342

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Address the Challenge 4: Unseen/novel categories

- Novel Categories Discovery
  - Step 3: Discovery novel categories by clustering
    - ✓ Determine the number of clusters by clustering the data consist of sampled labeled data and the detected unknown data
    - ✓ Cluster the unknown the data using the estimated K by k-means

1: **Preparation:**
2: Split the probe set D^l_r into D^l_{ra} and D^l_{rv}.
3: Extract features of D^l_r and D^u using Φ.
4: **Main loop:**
5: **for** $0 \leq C^u_i \leq C^u_{\max}$ **do**
6: Run k-means on $D^l_r \cup D^u$ assuming $C^{lu}_r = C^l_r + C^u_i$ classes in semi-supervised mode (i.e. forcing data in D^l_{ra} to map to the ground-truth class labels).
7: Compute ACC for D^l_{rv} and CVI for D^u.
8: **end for**
9: **Obtain optimal:**
10: Let C^{u*}_a be the value of C^u_i that maximise ACC for D^l_{rv} and C^{u*}_v be the value that maximise CVI for D^u and let $\hat{C}^u = (C^{u*}_a + C^{u*}_v)/2$. Run semi-supervised k-means on $D^l_r \cup D^u$ again assuming $C^l_r + \hat{C}^u$ classes.
11: **Remove outliers:**
12: Look at the resulting clusters in D^u and drop any that has a mass less than τ of the largest cluster. Output the number of remaining clusters.

[7] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7895-7910, 2021, doi: 10.1109/JSTARS.2021.3100342
[8]L. Dai, W. Guo, Z. Zhang and W. Yu, "Discovering Novel Categories in Sar Images in Open Set Conditions," IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium, 2022, pp. 1932-1935, doi: 10.1109/IGARSS46834.2022.9883175.

Address the Challenge 4: Unseen/novel categories

- Novel Categories Discovery

Dataset： OpenSARUrban (10 classes)

Data split： known: unknown= 5 : 5 / 6 : 4 / 7 : 3

Feature Extractor	Number of Clustering Class	ACC	NMI	ARI
before fine-tuning	5	29.54%	0.127	0.110
after fine-tuning	5	43.22%	0.220	0.167

Self-supervised with fine-tuning

Different data spit

Table 2. The scores for clustering the novel dataset D_n.

Data Process	Data Distribution (known+unknown)	ACC	NMI	ARI
$\phi(D_n)$	7 + 3	58.94%	0.310	0.272
$\phi(D_n)$	6 + 4	53.55%	0.256	0.169
$\phi(D_n)$	5 + 5	43.22%	0.220	0.167
raw D_n	7 + 3	41.52%	0.127	0.058

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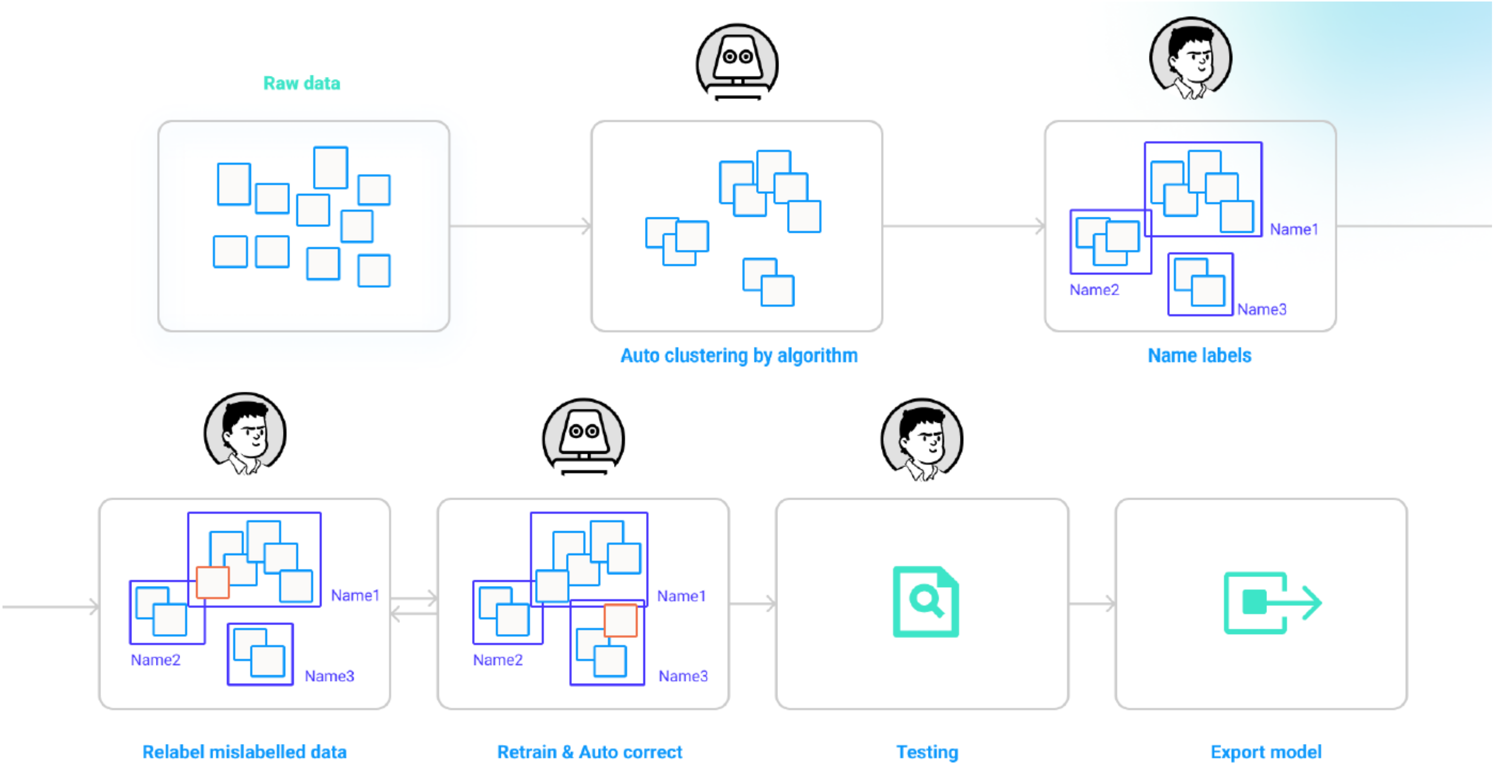
In process: Interactive Deep Learning Remote Sensing Image Annotation tool

- Human-in-loop Interactive deep learning
- Small annotation and fast training
- Good user experience.



In process: Interactive Deep Learning Remote Sensing Image Annotation tools

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■ Future Work

- Develop interactive annotation tools and complete the large-scale dataset of LULC of SITS
- Develop multi-modal change detection and spatial-temporal analyze techniques with deep learning
- Complete 2 cases : Romania - EU for ecosystem and Shanghai City Urban evolution analysis


HY
HJ-1AB
CBERS
Gaofen
Beijing-2
Sentinel-1
Sentinel-2
Sentinel-3
Sentinel-5p
Aeolus

THANK YOU !