Deep Semi-supervised learning (SSL) for Remote Sensing Datasets

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ICIAP 2023

About me

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- PhD. Computer Science - Computer Vision
- University Jaume I, Castellón, Spain
- Internship Helmholtz Institute Freiberg for Resource Technology (HIF)
- @itzahs

Content of this presentation

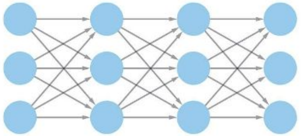
01

Introduction

Machine Learning & Deep Learning

ML

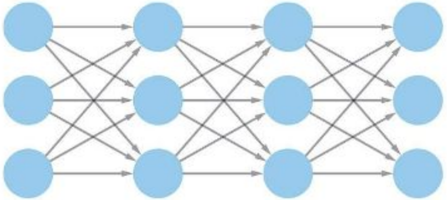
Feature extraction



Classification

Class probability

DL



Feature extraction + Classification

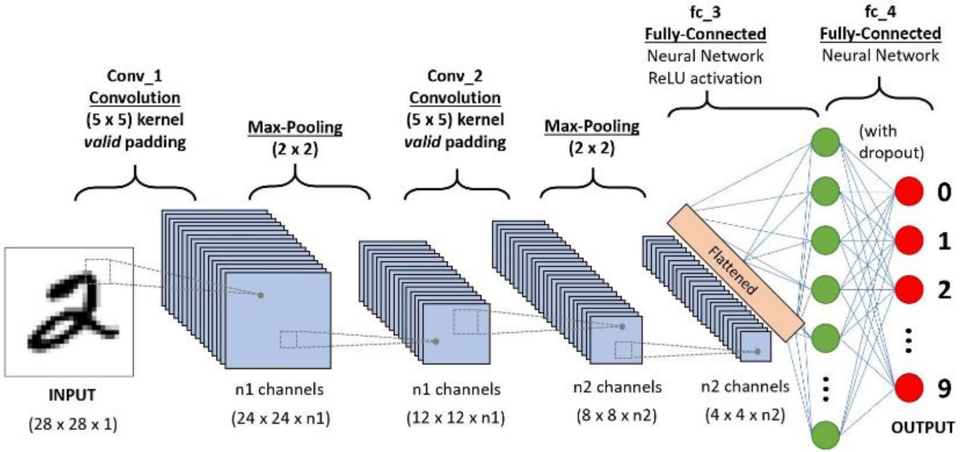
Class probability

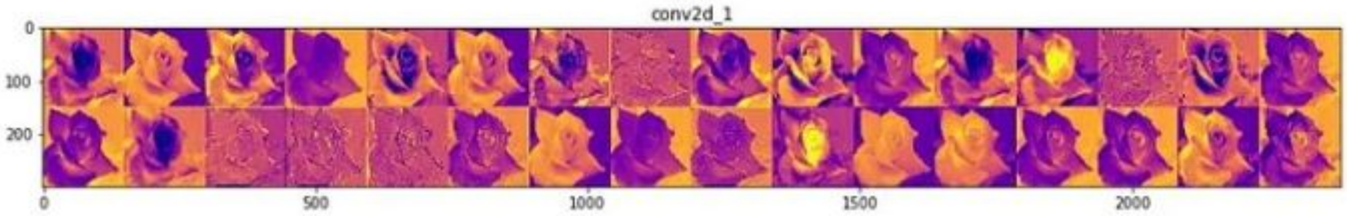
Supervised **Semi-supervised** Unsupervised

[1] Bhavsar, K. (2018, September 14). Understanding your Convolution Network with Visualizations. Towards Data Science. https://towardsdatascience.com/understanding-your-convolution-network-with-visualizations-a4883441533b

Convolutional Neural Network (CNN)

Original Image

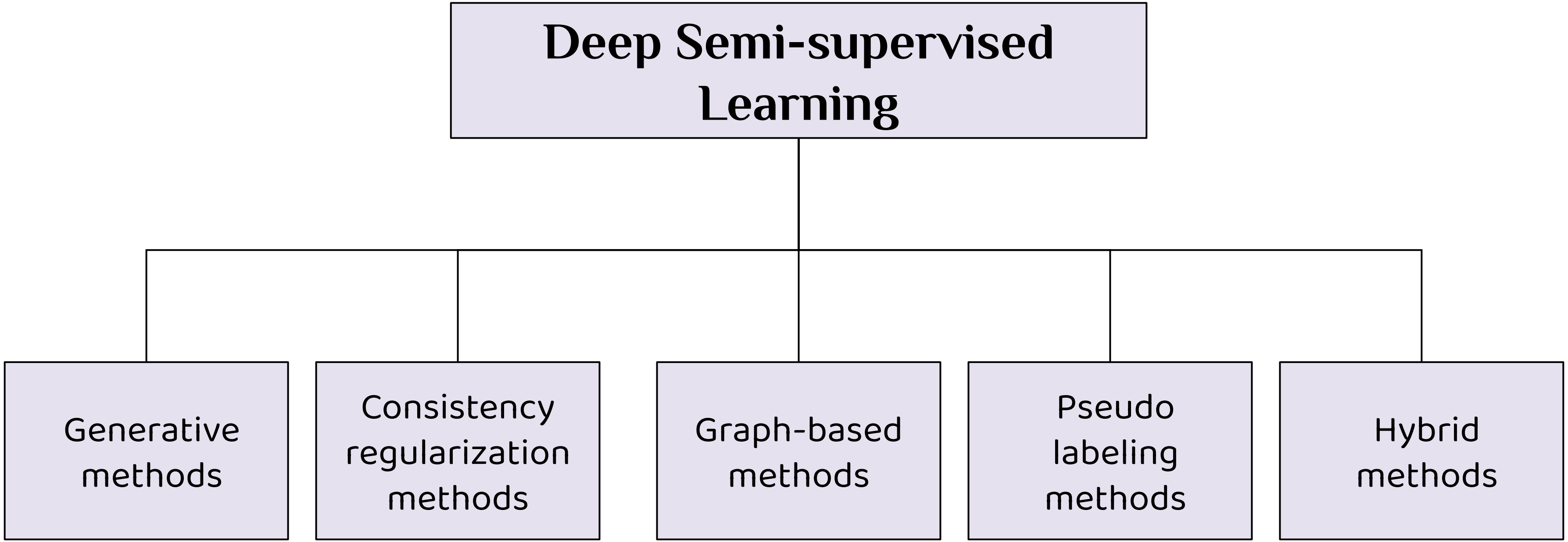




Resnet-18 Resnet-50 **WideResNet-28-2**

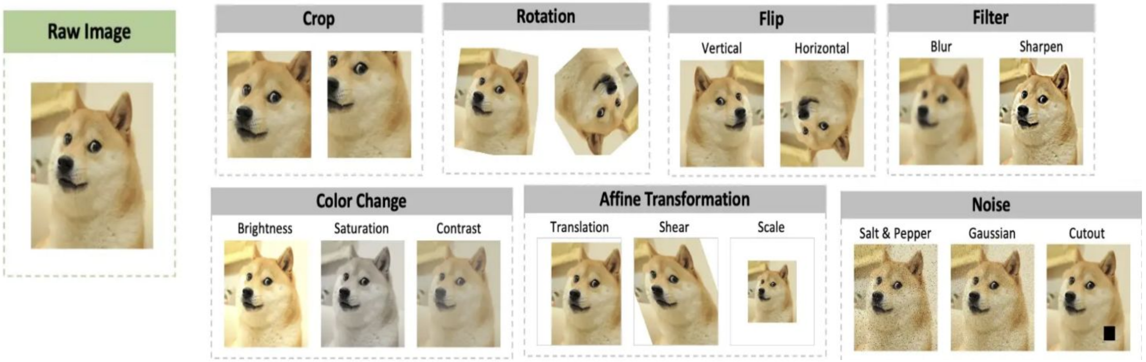
[1] Bhavsar, K. (2018, September 14). Understanding your Convolution Network with Visualizations. Towards Data Science. https://towardsdatascience.com/understanding-your-convolution-network-with-visualizations-a4883441533b

Taxonomy



[3] X. Yang, Z. Song, I. King and Z. Xu, "A Survey on Deep Semi-Supervised Learning," in IEEE Transactions on Knowledge and Data Engineering, 2022, doi: 10.1109/TKDE.2022.3220219.

Image data augmentation for DL



- **Data Warping**: transforms existing images such as the label is preserved.

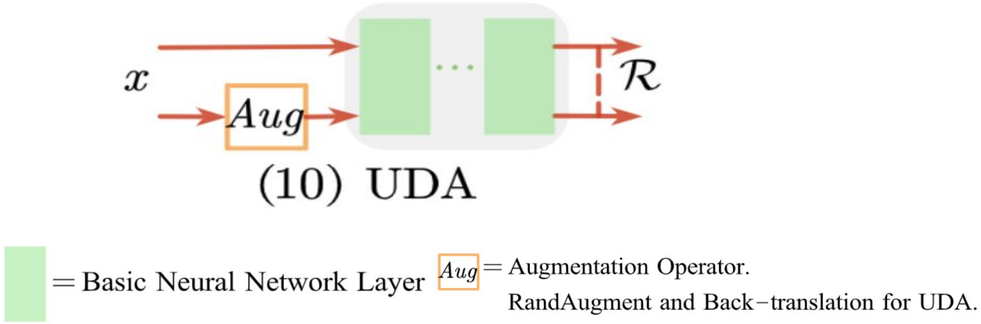
Synthetic data - CycleGANS - emotion classification

- **Oversampling**: creates synthetic instances and add them to the training set.

[4] Sharma, A. (2019, June 12). Complete Guide to Data Augmentation for Computer Vision. Towards Data Science. https://towardsdatascience.com/complete-guide-to-data-augmentation-for-computer-vision-1abe4063ad07.

[5] Shorten, C., Khoshgoftaar, T.M. A survey on Image Data Augmentation for Deep Learning. *J Big Data* 6, 60 (2019). https://doi.org/10.1186/s40537-019-0197-0

Consistency regularization

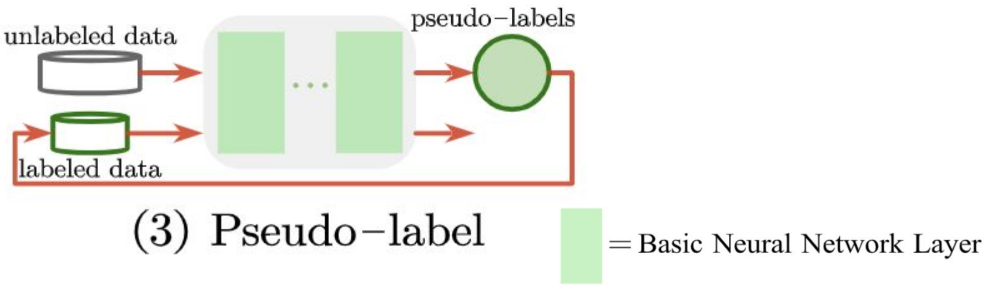


A consistency regularization term is applied to the **final loss function**. e.g. **Cross Entropy for example H(F(x), Tx).**

A realistic perturbation in the training data should not change the output of the model.

e.g. Unsupervised Data Augmentation (**UDA**).

Pseudo-labelling

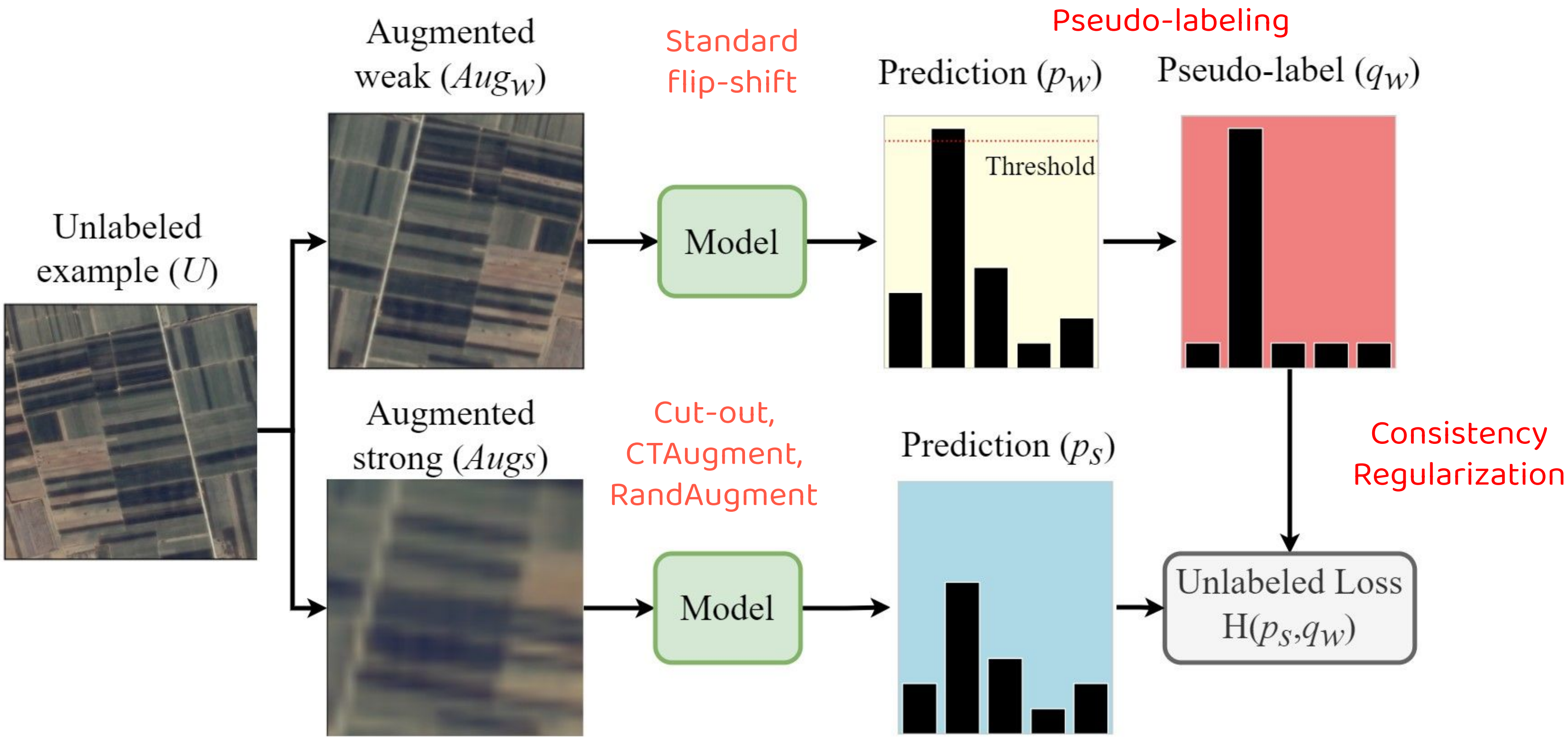


Pseudo-labeling methods rely on the **high-confidence of pseudo-labels**, which can be added to the training data set as labeled data.

Self-training: leverage model's own confident predictions to produce the pseudo-labels for **unlabeled data**.

[3] X. Yang, Z. Song, I. King and Z. Xu, "A Survey on Deep Semi-Supervised Learning," in IEEE Transactions on Knowledge and Data Engineering, 2022, doi: 10.1109/TKDE.2022.3220219.

Hybrid: Fixmatch - Consistency Regularization and Pseudo Labeling



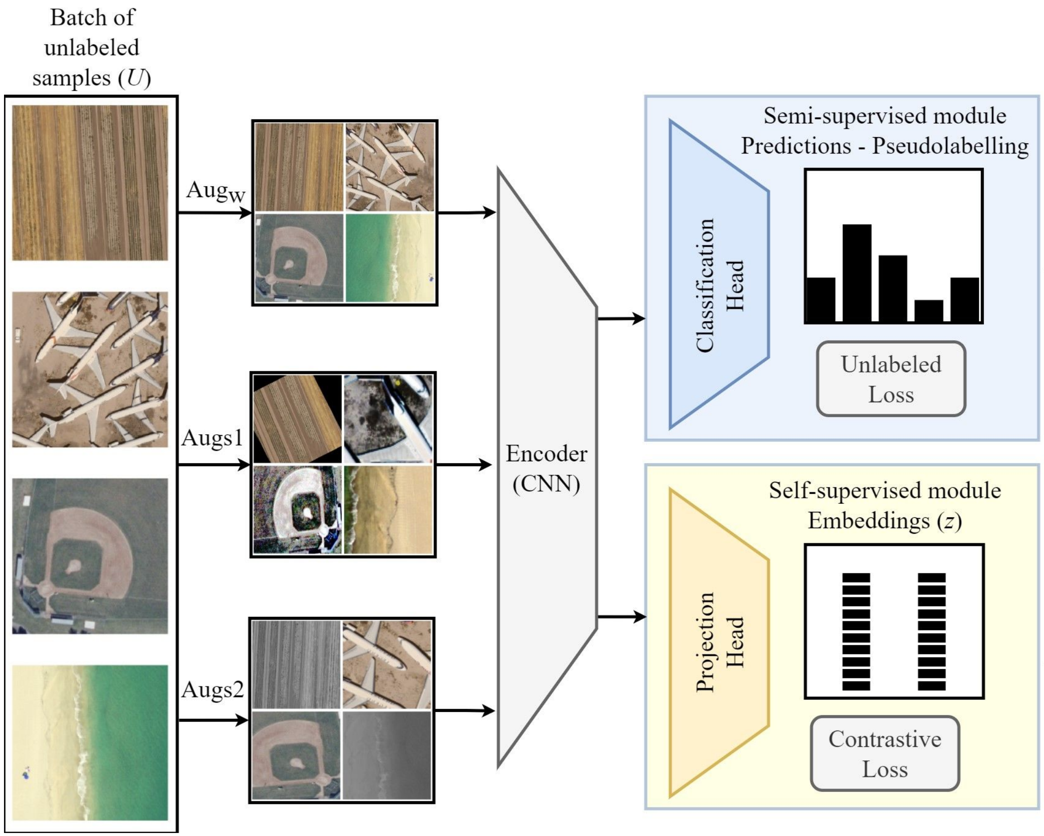
[6] Kihyuk Sohn, David Berthelot, Nicholas Carlini, Zizhao Zhang, Han Zhang, Colin A Raffel, Ekin Dogus Cubuk, Alexey Kurakin, and Chun-Liang Li. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. NeurIPS, 33, 2020.

Hybrid: CoMatch - Consistency Regularization and Pseudo Labeling

Standard flip-shift

Cut-out, CTAugment, RandAugment

Color Jittering Grayscaling

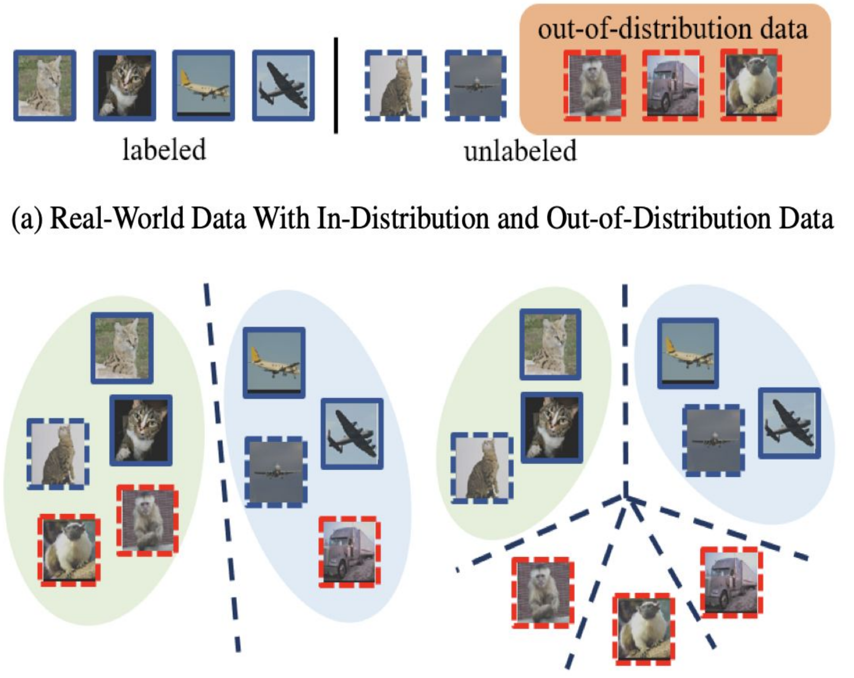


Semi-supervised

Self-supervised

[6] Kihyuk Sohn, David Berthelot, Nicholas Carlini, Zizhao Zhang, Han Zhang, Colin A Raffel, Ekin Dogus Cubuk, Alexey Kurakin, and Chun-Liang Li. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. NeurIPS, 33, 2020.

CCSSL - Class-Aware Contrastive Semi-Supervised Learning



(a) Real-World Data With In-Distribution and Out-of-Distribution Data

(b) Pseudo-Label-Based SSL (c) Class-Aware Contrastive SSL (ours)

- Assumption that the classes and distribution of the unlabeled data is close to the labeled.

- **In-distribution** (known classes and balanced datasets) → **class-wise clustering**. **High-confidence** pseudo-label should be **puller closer with the same class**.

- **Out-of-distribution** (unknown classes or unlabeled distribution) → **image-wise contrasting**. **Low-confidence pseudo-labels,** triggers contrastive learning where only **augmentation of the same image are positive pairs**.

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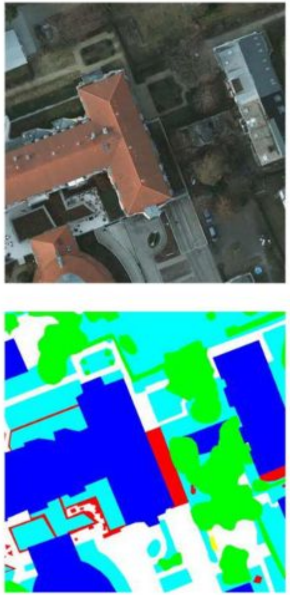
[8] F. Yang et al., "Class-Aware Contrastive Semi-Supervised Learning," 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), New Orleans, LA, USA, 2022, pp. 14401-14410, doi: 10.1109/CVPR52688.2022.01402.

02
Data & Code

DL in Aerial Image Classification

Pixel-level



Object-level

Scene-level

[2] G. Cheng, X. Xie, J. Han, L. Guo and G. -S. Xia, "Remote Sensing Image Scene Classification Meets Deep Learning: Challenges, Methods, Benchmarks, and Opportunities," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 3735-3756, 2020, doi: 10.1109/JSTARS.2020.3005403 .

Datasets

UCM Dataset [download]:

- 21 clases
- 100 images per class
- 256 x 256 pixels (0.3 m)

AID Dataset [download]:

- 30 clases
- 200 to 400 images per class
- 600 × 600 pixels

[7] Yi Yang and Shawn Newsam, "Bag-Of-Visual-Words and Spatial Extensions for Land-Use Classification," ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS), 2010.

Sampling strategy

Sampling strategy:

- 50 % training and 50% testing (Cheng, G. et al, 2020) [2].
- When using supervised 1,050 samples for UCM and 5, 000 for AID.
- When using semi-supervised 84 samples or 4 labels per class (Sohn, K. et al, 2020) [6].

Dataset	Class	# Labels per class	# Training data	# Testing data	Train/Test split
UCM	21	4/25/40	84/525/840	1, 050	50% / 50%
AID	30	4/25/40	120/750/1200	5, 000	50% / 50%

[7] Yi Yang and Shawn Newsam, "Bag-Of-Visual-Words and Spatial Extensions for Land-Use Classification," ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (ACM GIS), 2010.

Semi-supervised learning toolbox

Class-Aware Contrastive Semi-Supervised Learning

Publisher: IEEE Cite This PDF

Fan Yang ; Kai Wu ; Shuyi Zhang ; Guannan Jiang ; Yong Liu ; Feng Zheng ; Wei Zhang ; Chengjie Wang ; Long Zeng **All Authors**

Abstract:
Pseudo-label-based semi-supervised learning (SSL) has achieved great success on raw data utilization. However, its training procedure suffers from confirmation bias due to the noise contained in self-generated artificial labels. Moreover, the model's judgment becomes noisier in real-world applications with extensive out-of-distribution data. To address this issue, we propose a general method named Class-aware Contrastive Semi-Supervised Learning (CCSSL), which is a drop-in helper to improve the pseudo-label quality and enhance the model's robustness in the real-world setting. Rather than treating real-world data as a union set, our method separately handles reliable in-distribution data with class-wise clustering for blending into downstream tasks and noisy out-of-distribution data with image-wise contrastive for better generalization. Furthermore, by applying target reweighting, we successfully emphasize clean label learning and simultaneously reduce noisy label learning. Despite its simplicity, our proposed CCSSL has significant performance improvements over the state-of-the-art SSL methods on the standard datasets CIFAR100 [18] and STL10 [8]. On the real-world dataset Semi-iNat 2021 [27], we improve FixMatch [25] by 9.80% and CoMatch [19] by 3.18%. Code is available https://github.com/TencentYoutuResearch/Classification-SemiCLS.

Published in: 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)

Date of Conference: 18-24 June 2022

INSPEC Accession Number: 22095223

Date Added to IEEE *Xplore*: 27 September 2022

DOI: 10.1109/CVPR52688.2022.01402

[8] F. Yang et al., "Class-Aware Contrastive Semi-Supervised Learning," 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), New Orleans, LA, USA, 2022, pp. 14401-14410, doi: 10.1109/CVPR52688.2022.01402.

Results & Future Research

Classification accuracy

Dataset	**UCM**			**AID**		
# Labels per class	4	25	40	4	25	40
# Total samples	84	525	840	120	750	1200
Supervised	90.00	90.86	93.52	85.34	85.90	89.94
FixMatch	94.38	92.00	94.48	92.66	87.30	92.8
CoMatch	95.52	94.76	93.81	93.04	93.88	89.26
FixMatch+CCSSL	94.00	94.67	94.67	90.94	91.28	92.00
# Total samples	1, 050			5, 000		
Fully Supervised	93.71			90.2		

Classification accuracy

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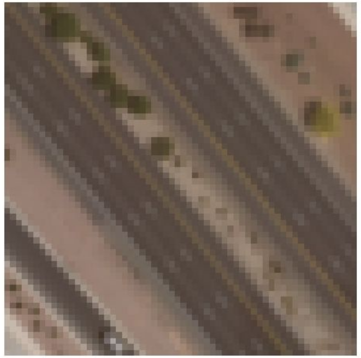
FixMatch+CCSSL	94.00	94.67	94.67	90.94	91.28	92.00
# Total samples	1, 050			5, 000		
Fully Supervised	93.71			90.2		

Classification accuracy UCM

CoMatch - 10 min inference

Easy dataset - indist

True: freeway
Predicted: runway



True: golfcourse
Predicted: tenniscourt

Confusion Matrix

True Labels \ Predicted Labels	agricultural	airplane	baseballdiamond	beach	buildings	chaparral	denseresidential	forest	freeway	golfcourse	harbor	intersection	mediumresidential	mobilehomepark	overpass	parkinglot	river	runway	sparseresidential	storagetanks	tenniscourt
agricultural	49	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
airplane	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
baseballdiamond	0	0	47	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0
beach	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
buildings	0	1	0	0	41	0	3	0	0	0	0	0	0	1	1	0	0	0	0	1	2
chaparral	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
denseresidential	0	0	0	0	3	0	41	0	0	0	0	0	1	3	0	2	0	0	0	0	0
forest	0	0	0	0	0	1	0	49	0	0	0	0	0	0	0	0	0	0	0	0	0
freeway	0	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	2	0	0	0
golfcourse	0	0	0	0	0	0	0	0	0	45	0	0	1	0	0	0	0	0	3	0	1
harbor	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0
intersection	0	0	0	0	0	0	1	0	0	0	0	46	0	0	2	1	0	0	0	0	0
mediumresidential	0	0	0	0	2	0	3	0	0	0	1	0	44	0	0	0	0	0	0	0	0
mobilehomepark	0	0	0	0	0	0	0	0	0	0	0	0	0	49	0	1	0	0	0	0	0
overpass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0
parkinglot	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	48	0	0	0	0	0
river	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0
runway	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0
sparseresidential	0	0	0	0	0	0	0	2	0	0	0	0	3	0	1	0	0	0	44	0	0
storagetanks	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	44	2
tenniscourt	0	0	1	0	1	0	3	0	0	0	0	0	1	0	0	0	0	0	0	1	43

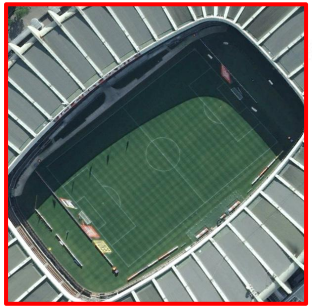
Classification accuracy AID

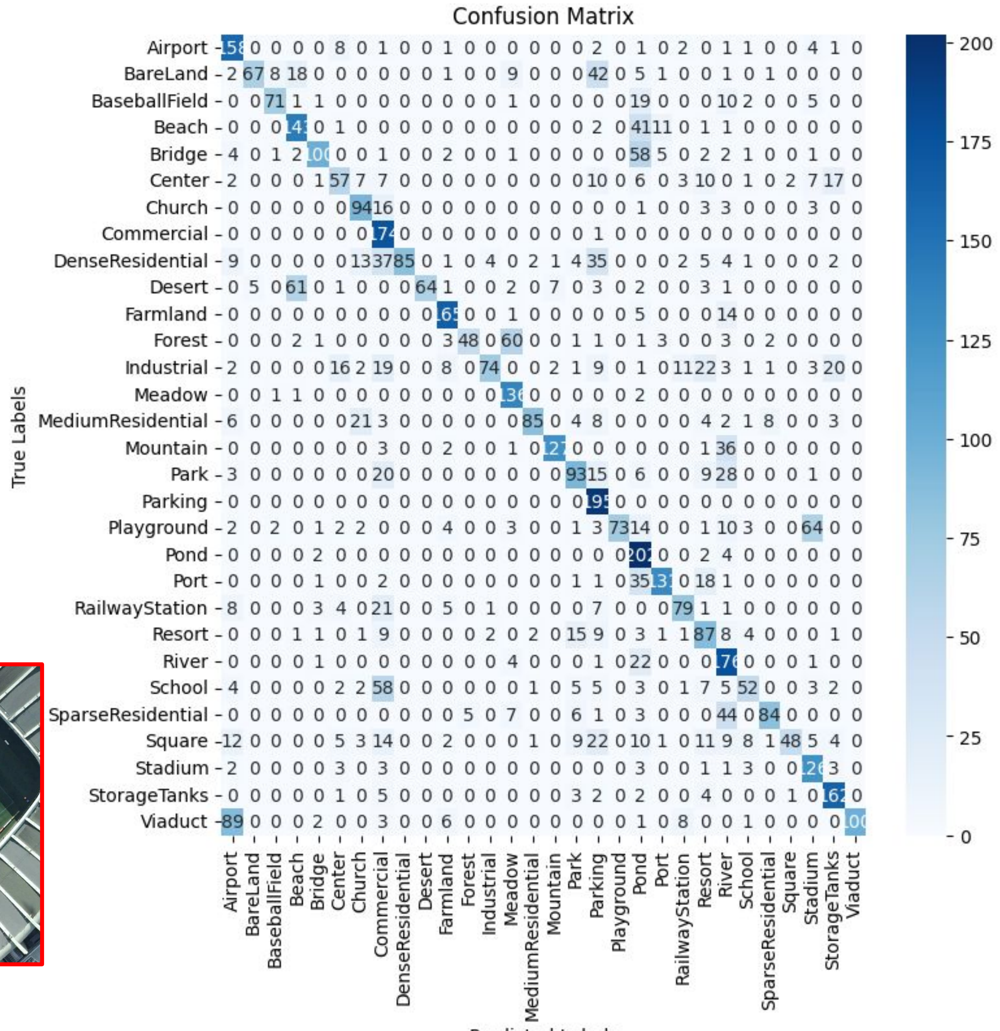
FixMatch+CCSSL, WRN-28-2, 224x224 - 30 min inference

Harder dataset but with in-distribution data

True: Playground
Predicted: Stadium

True: Playground
Predicted: Stadium





Computational cost analysis UCM

WRN-28-2

Image size: 224x224

Labeled to unlabeled ratio:

1-7

Labeled batch 8

Unlabeled batch 56

Trainer	Label	B	GPU	Ttime
Fully Supervised	50%	8	<12	50:53
Supervised	4	8	<12	12:39
Supervised	40	8	<12	66:06
FixMatch	4	8	12–24	68:17
FixMatch	40	8	12–24	67:39
CoMatch	4	8	24–40	71:08
CoMatch	40	4	12–24	59:11
FM+CCSSL	4	8	24–40	70:40
FM+CCSSL	40	4	12–24	59:49

Computational cost analysis UCM

WRN-28-2

Image size: 224x224

Labeled to unlabeled ratio:

1-7

Labeled batch 8

Unlabeled batch 56

Trainer	Label	B	GPU	Ttime
Fully Supervised	50%	8	<12	50:53
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CoMatch	40	4	12–24	59:11
FM+CCSSL	4	8	24–40	70:40
FM+CCSSL	40	4	12–24	59:49

Computational cost analysis UCM

RN-18

3.5 GB

RN-50

7 GB

WRN-28-2

12 GB

- Image size: 60x60
- Batch size: 32
- CoMatch
- Labeled to unlabeled ratio: 1-7

Codes for reproducibility

@itzahs github

SSL-for-RS Public

Configuration files for the ICIAP2023 paper "Semi-supervised classification for remote sensing datasets"

Jupyter Notebook

Configuration files & Logs of the experimental results

Step-by-step implementation in 4 notebooks:

1. Get data & software
2. Train model
3. Model evaluation
4. Model inference

15TH EDITION GEOMUNDUS CONFERENCE

20th and 21st October
Castellón, Spain

Thanks!

Do you have any questions?

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@itzahs

References

Bibliography:

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2. G. Cheng, X. Xie, J. Han, L. Guo and G. -S. Xia, "Remote Sensing Image Scene Classification Meets Deep Learning: Challenges, Methods, Benchmarks, and Opportunities," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 3735-3756, 2020, doi: 10.1109/JSTARS.2020.3005403 .
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9. S. Zagoruyko and N. Komodakis, "Wide residual networks," in Proceedings of the British Machine Vision Conference (BMVC), 2017, pp. 87.1-87.12, doi: 10.22024/UniKent/01.02.69550, arXiv:1605.07146.

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