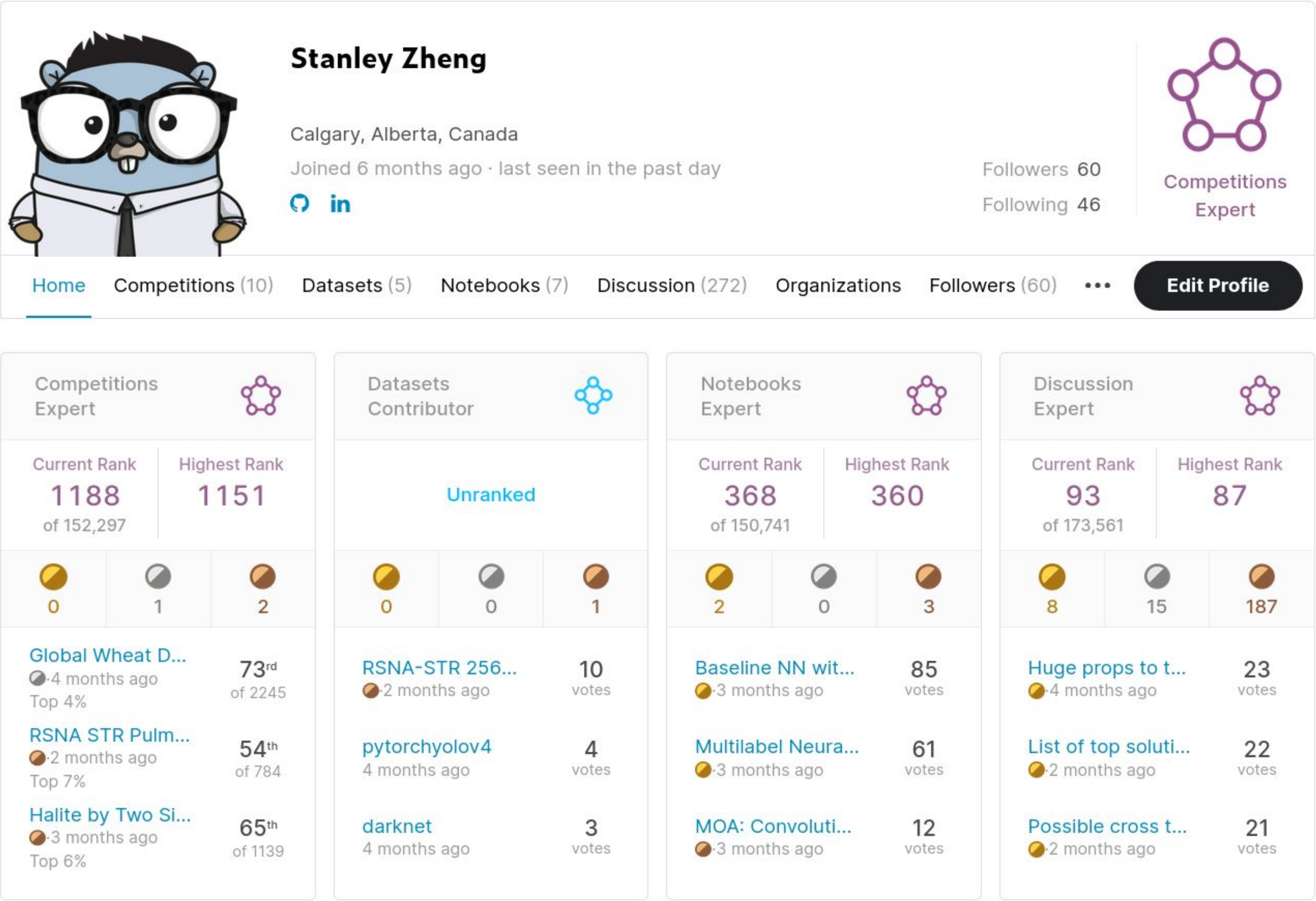
A Guide to Pseudolabelling: How to get a Kaggle medal with only one model

Stanley Zheng

About Me



GitHub/Kaggle/LinkedIn:
@stanleyjzheng

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2. Effective use of pseudolabels
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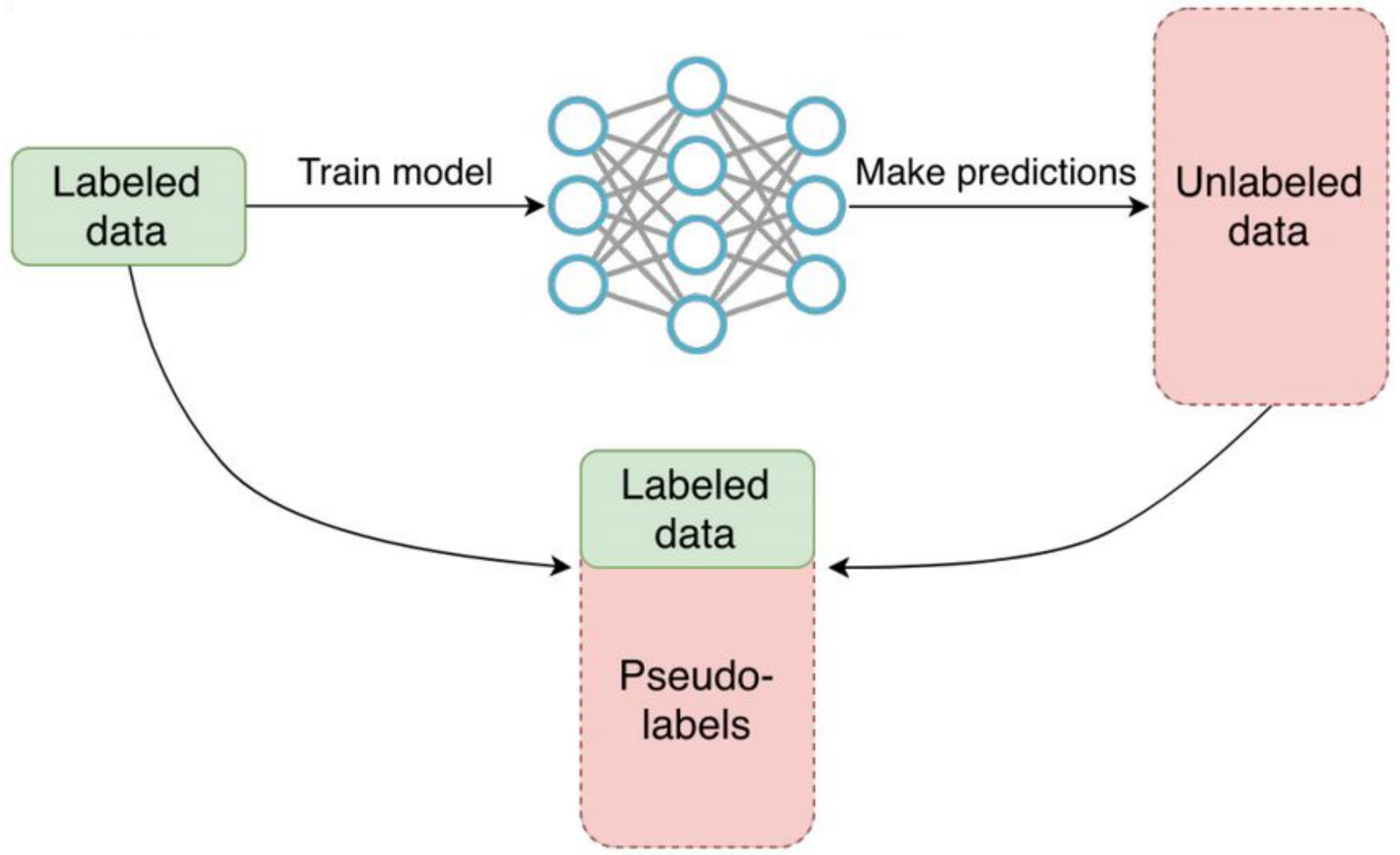
Sources and further reading at bit.ly/pydata-github

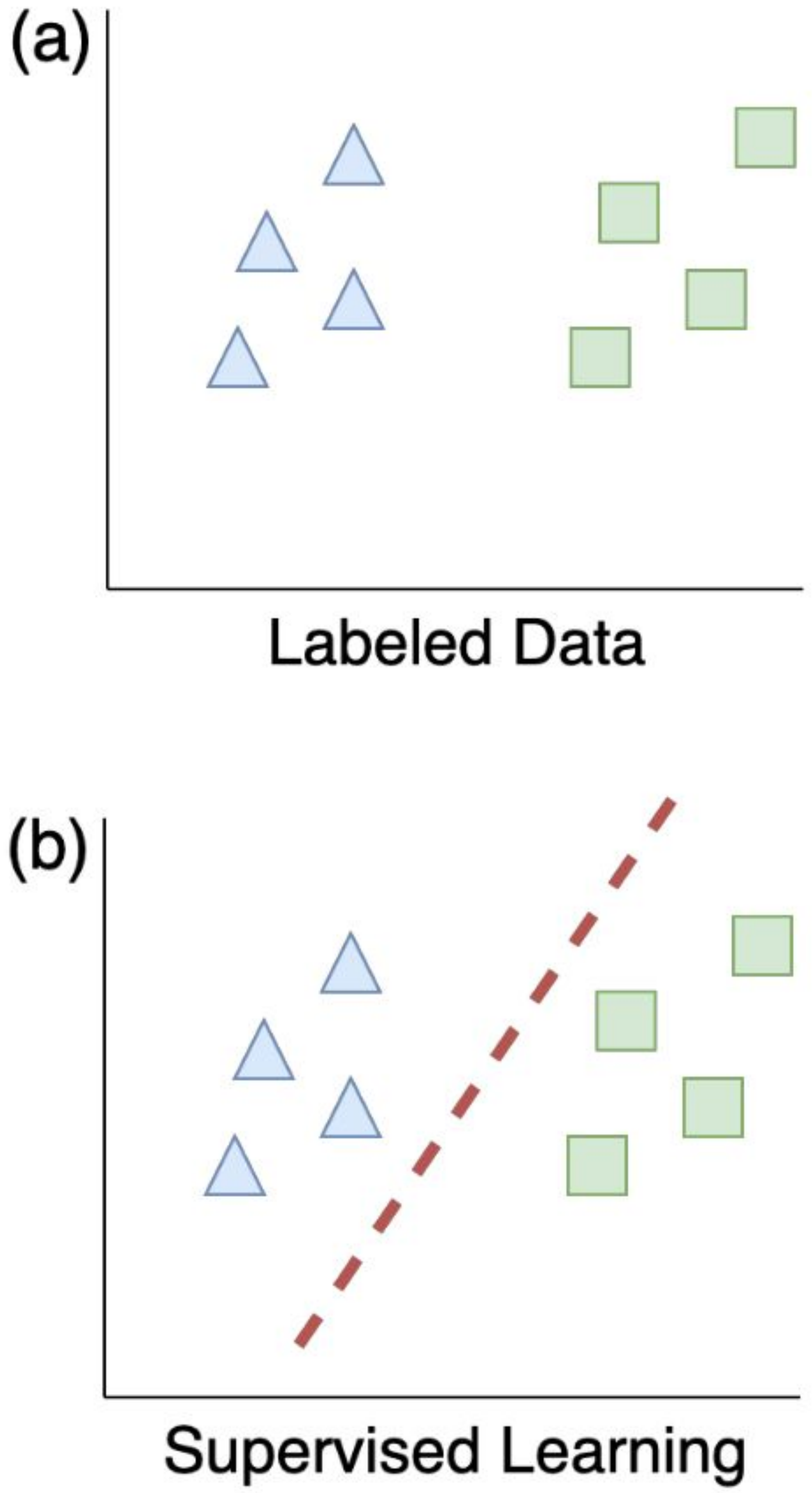
Thanks to Yauhen Babakhin for some of the graphics in this presentation [1]

What is Pseudolabelling?

- Semi-supervised learning
- Allows models to leverage a large unlabelled dataset



Visual Example



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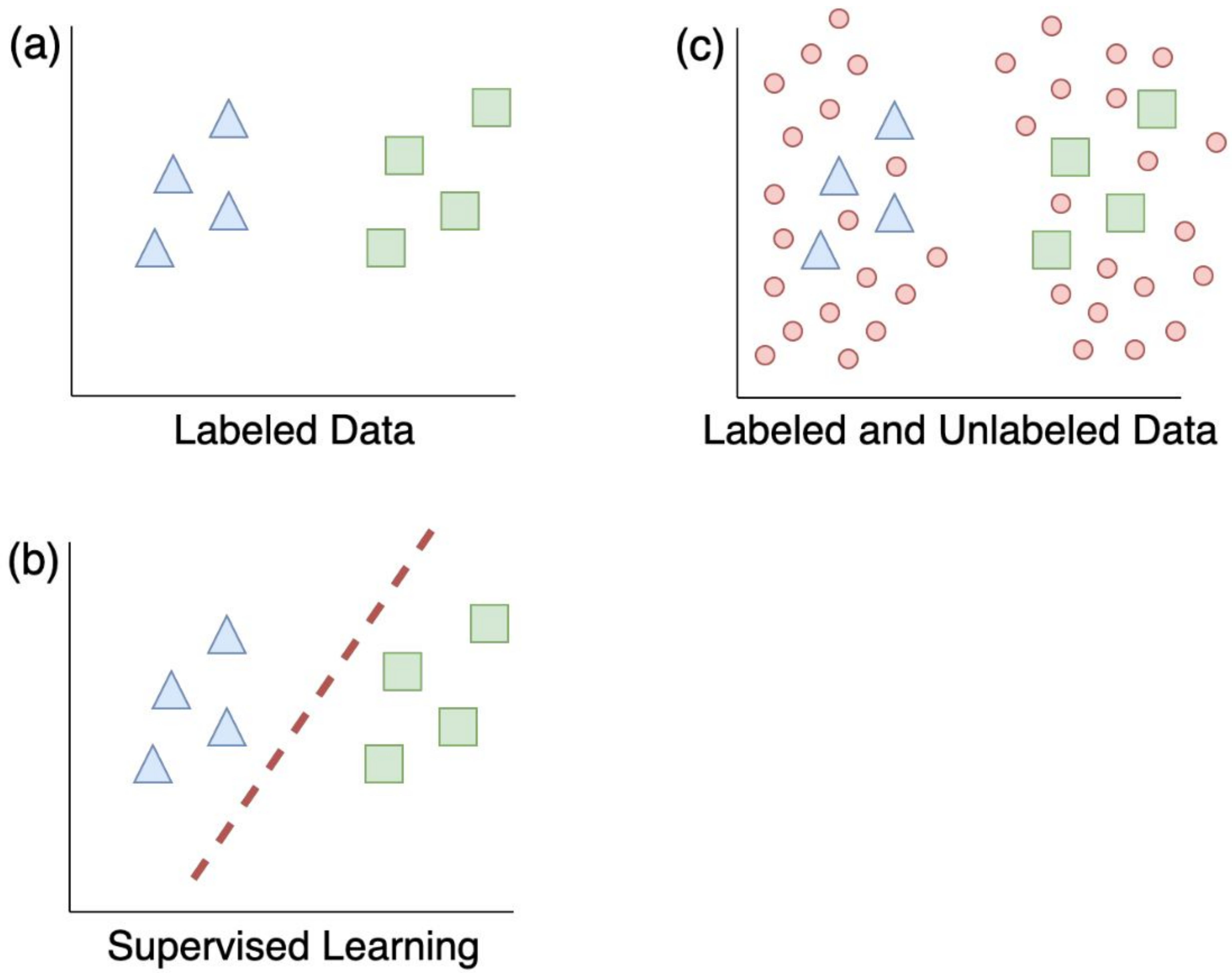

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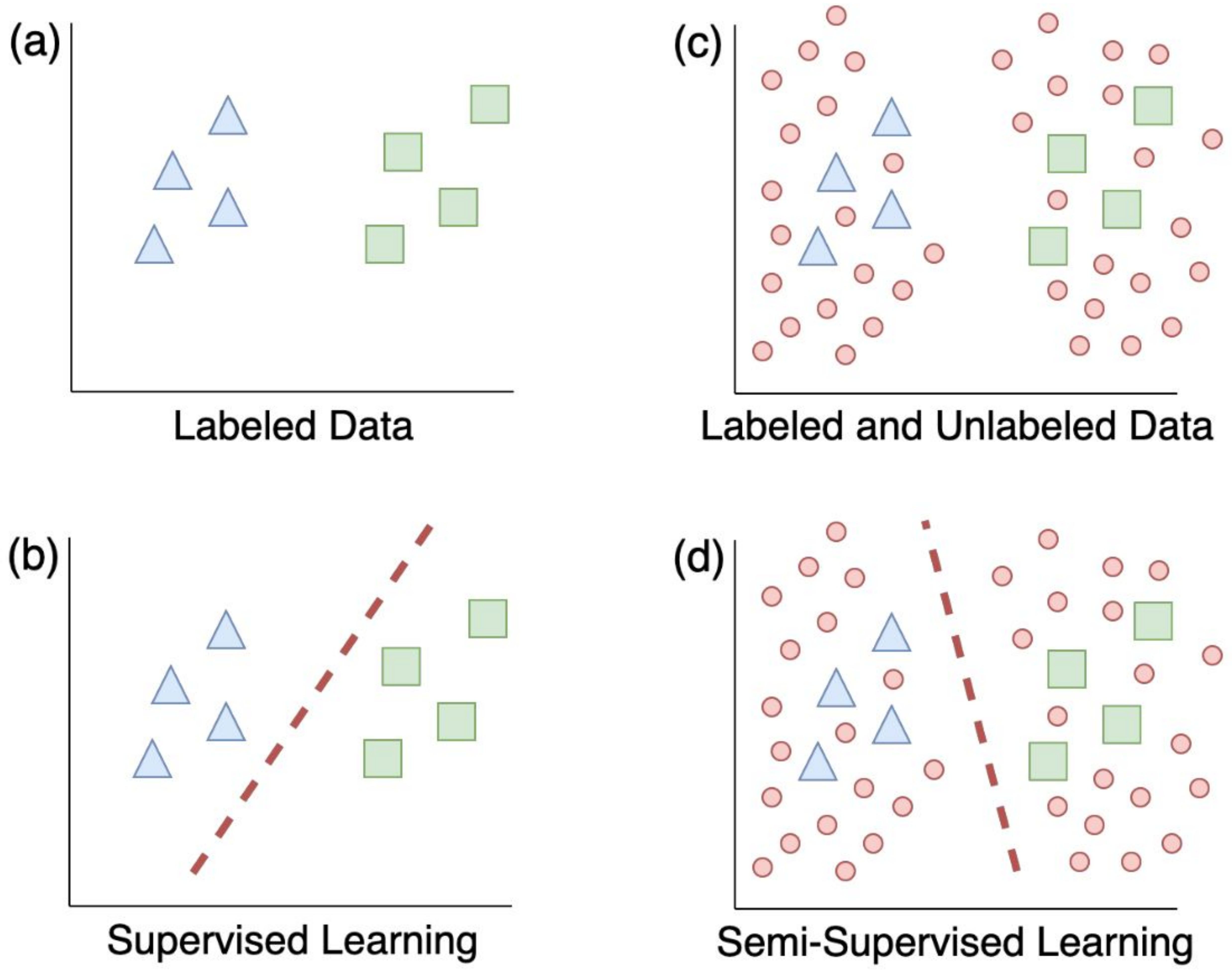

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  - Training images are from one use case, while test images are from another

Why use pseudolabelling? [2]

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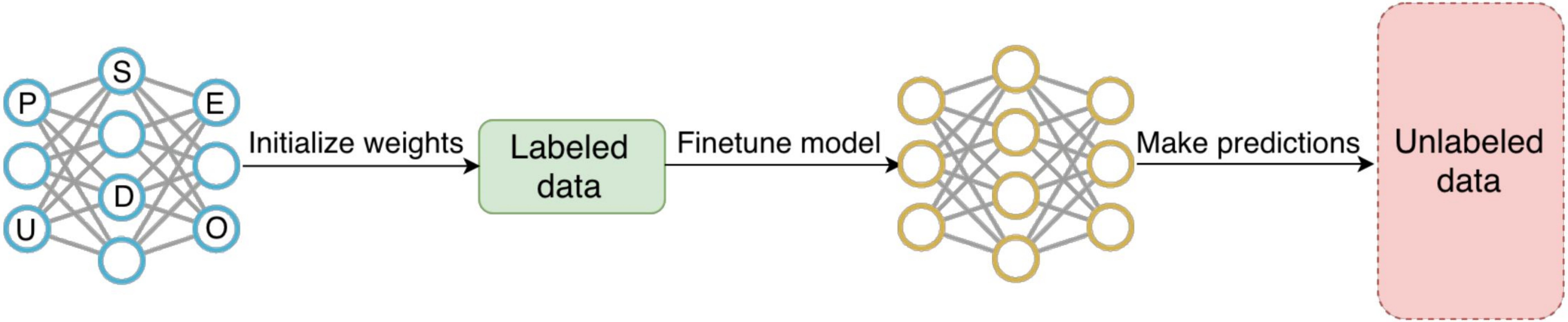
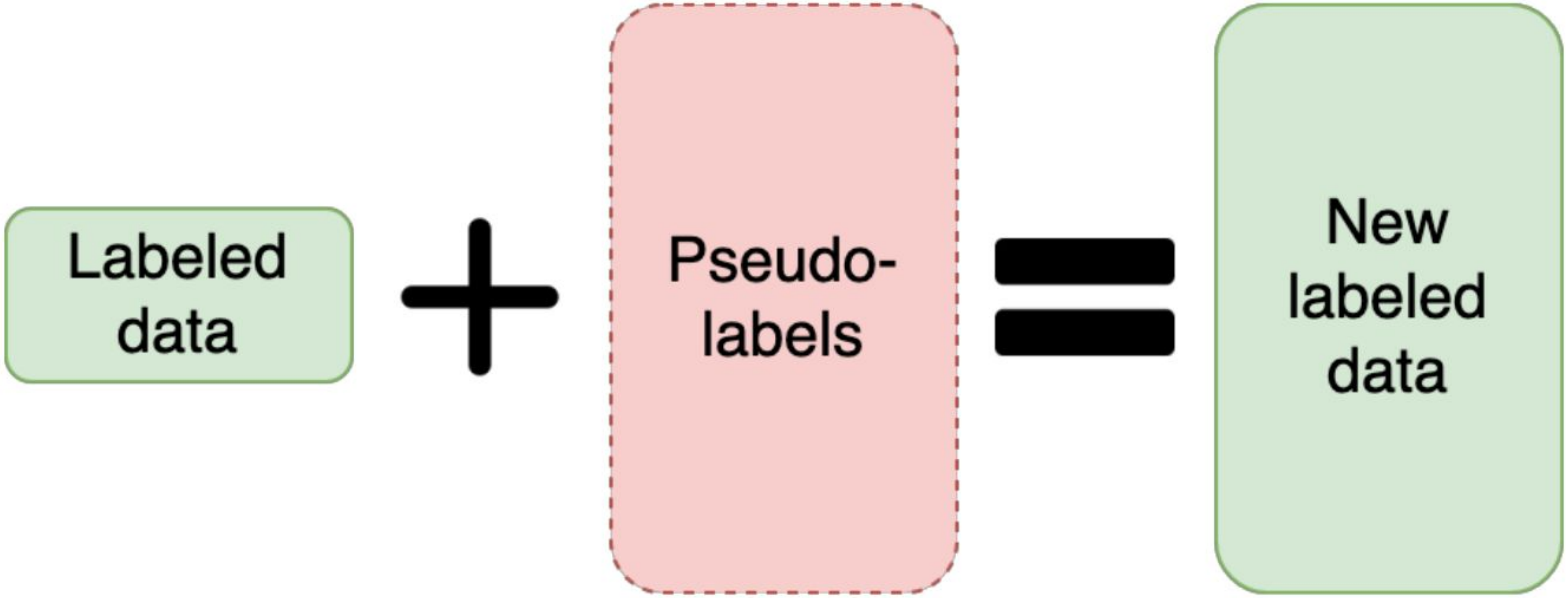
    - Requires expert labelling or is time consuming
- Data is time-sensitive
    - Model needs to be made now but data is time consuming to label
- There is a large diversity in the datasets
    - Training images are from one use case, while test images are from another
- Any application with a small training set and a large test set

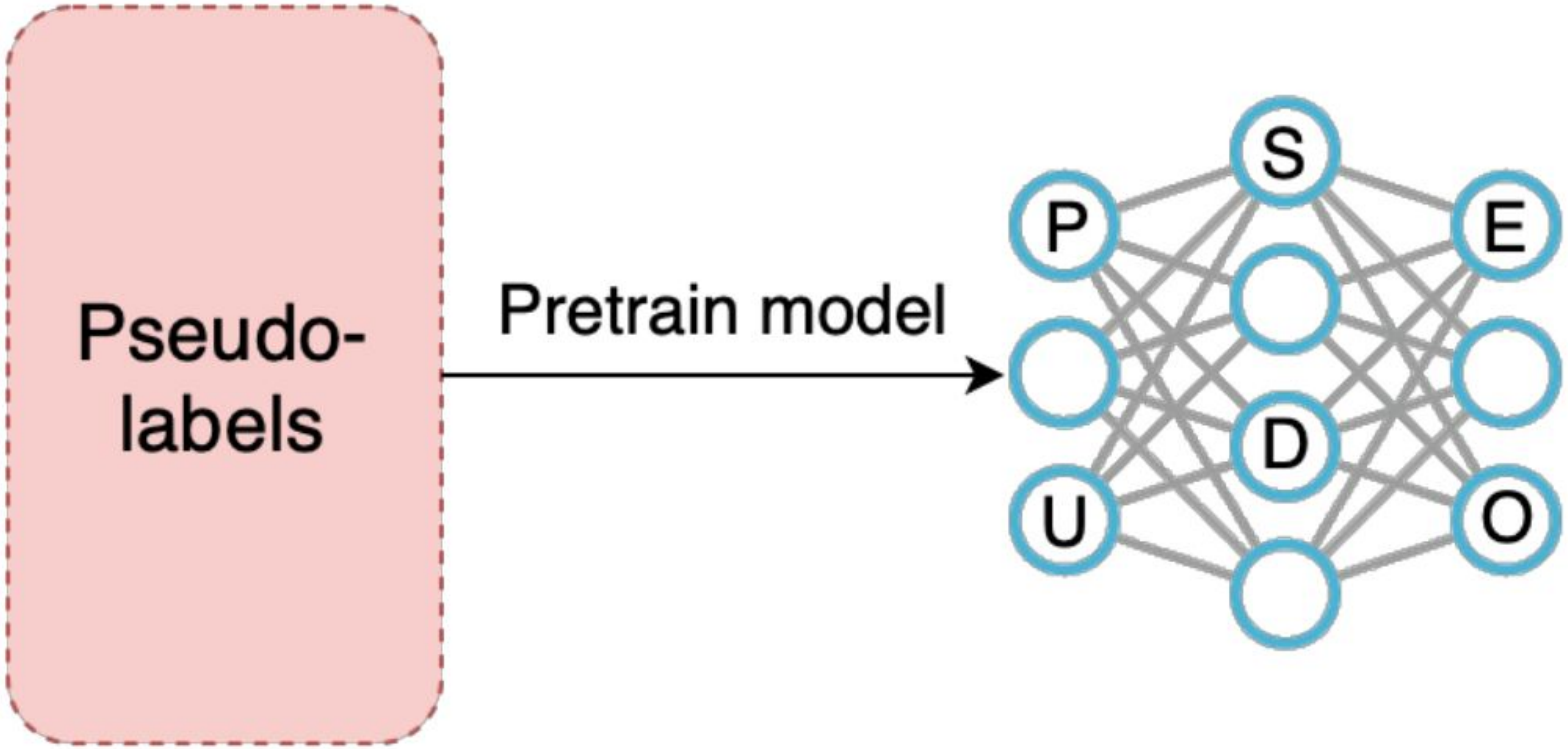
Training Schemes - Self Training



Training Schemes - Simultaneous training



Training Schemes - Pretraining [3]



General tips and tricks with pseudolabels

- For uncleaned datasets, use confidence thresholds to ensure labels are less noisy

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General tips and tricks with pseudolabels [4]

- For uncleaned datasets, use confidence thresholds to ensure labels are less noisy
- Where possible, use soft pseudolabels over hard pseudolabels
- Reduce variance with ensemble
- Use iterative pseudolabels, not one shot
    - Make sure to reinitialize the weights after each iteration
- Take measures to reduce overfitting (dropout/stochastic depth, augmentations)

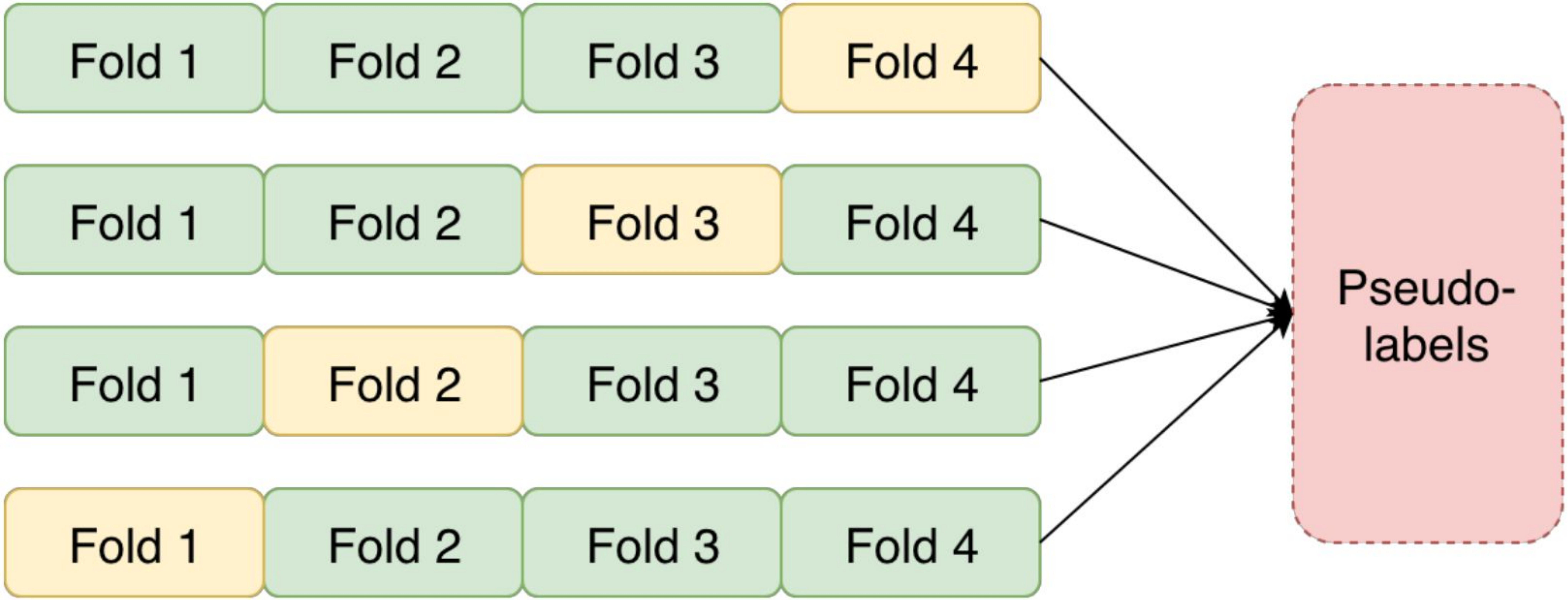
K-fold Cross Validation

1. Split the dataset into k groups
2. For each unique group:
    i. Take the group as a test data set
    ii. Take the remaining groups as a training data set
    iii. Fit a model on the training set and evaluate it on the test set
3. Find model's out-of-fold performance and save the model.

Ensembling folds to produce pseudolabels

1. Split the dataset into k groups
2. For each unique group:
   i. Take the group as a test data set
   ii. Take the remaining groups as a training data set
   iii. Fit a model on the training set
3. Ensemble all models together to produce one set of pseudolabels
4. Train models on pseudolabels and evaluate

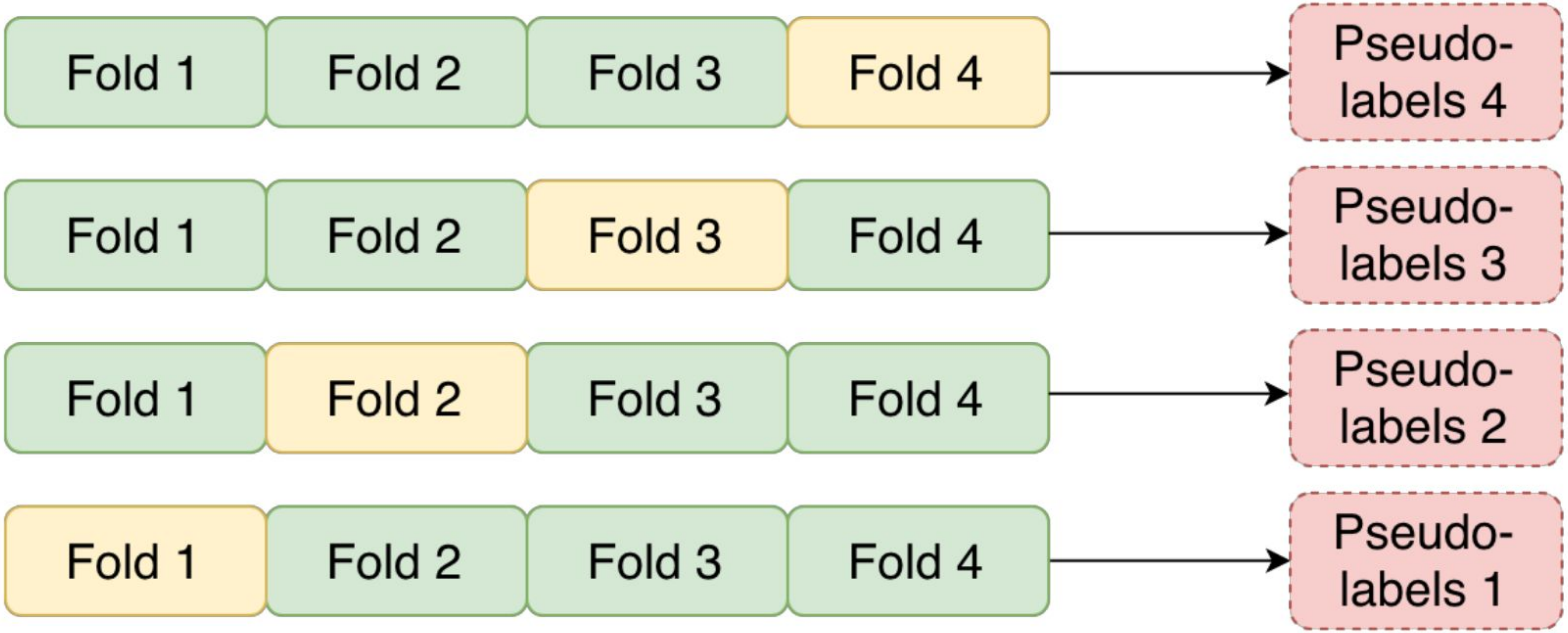
Ensembling folds to produce pseudolabels



Non-leaky approach

1. Split the dataset into k groups
2. For each unique group:
    i. Take the group as a test data set
    ii. Take the remaining groups as a training data set
    iii. Fit a model on the training set
    iv. Infer pseudolabels for the test set and train on it
    v. Evaluate the model
3. Find model’s out-of-fold performance and save the model.

Non-leaky approach



Global Wheat Detection [5]

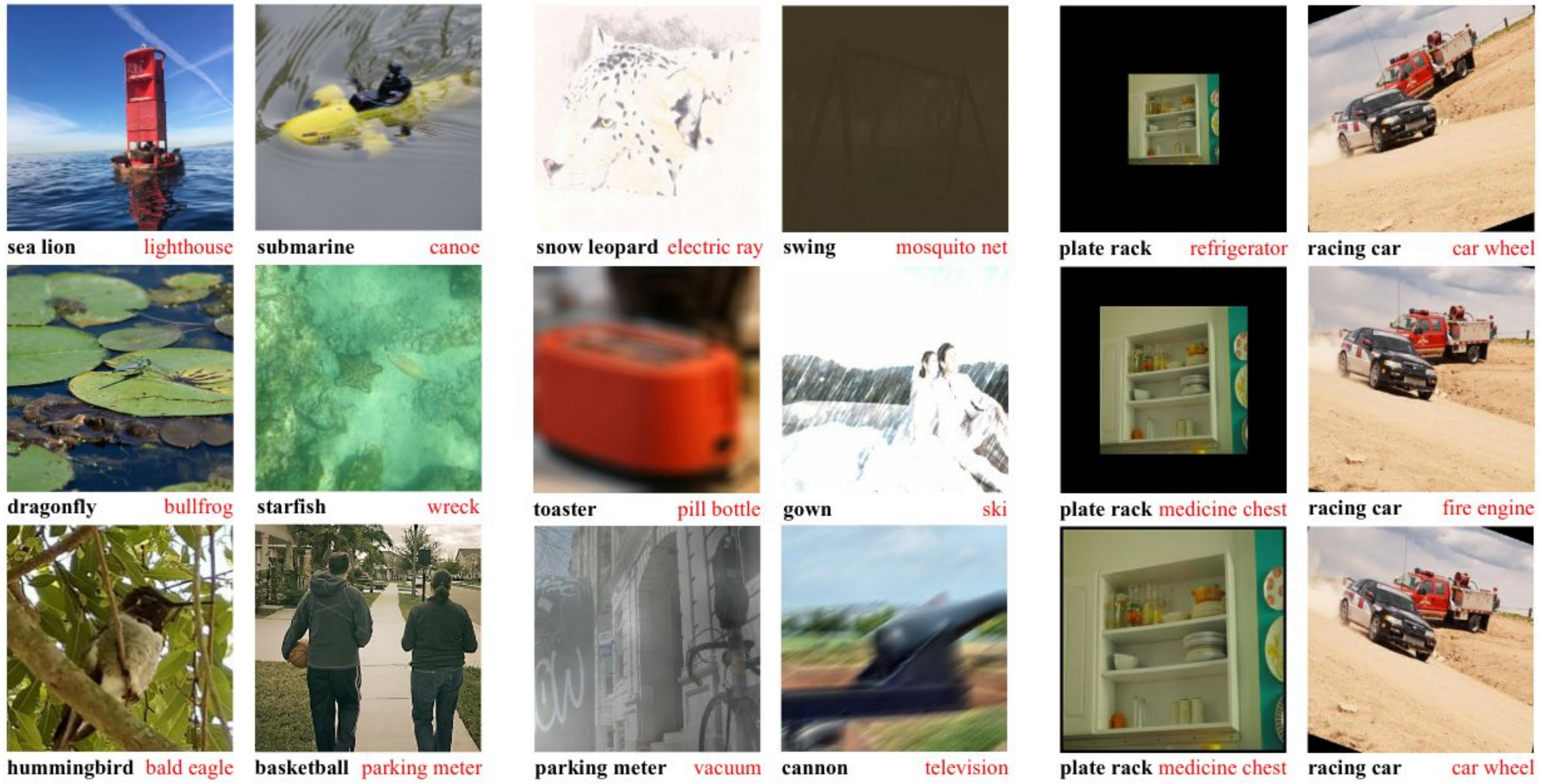
Scores of various models (Intersection over Union, higher is better)

Technique	Public Leaderboard	Private Leaderboard
No pseudolabelling	0.7115 (821st)	0.6371 (327th)
Self-training	0.7406 (+4%, 207th)	0.6625 (+4%, 36th)
Pretraining	0.7562 (+6%, 61st)	0.6668 (+5%, 22nd)

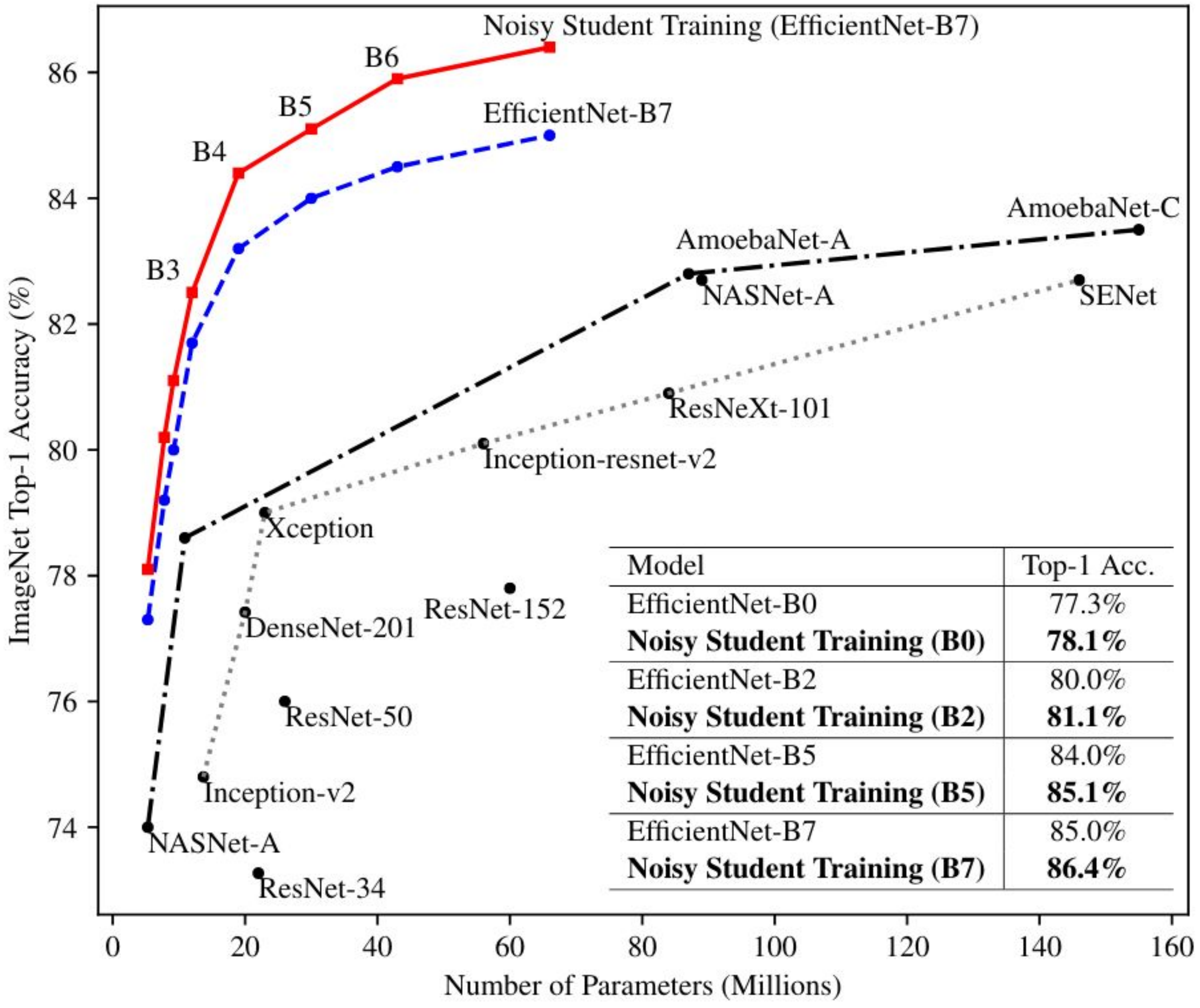
Countless other winners using pseudolabelling [6]

EfficientNet Noisy Student [4]

Method	# Params	Extra Data	Top-1 Acc.	Top-5 Acc.
ResNet-50 Billion-scale [93]	26M	3.5B images labeled with tags	81.2%	96.0%
ResNeXt-101 Billion-scale [93]	193M		84.8%	-
ResNeXt-101 WSL [55]	829M		85.4%	97.6%
FixRes ResNeXt-101 WSL [86]	829M		86.4%	98.0%
Big Transfer (BiT-L) [43]†	928M	300M weakly labeled images from JFT	87.5%	98.5%
Noisy Student Training (EfficientNet-L2)	480M	300M unlabeled images from JFT	**88.4%**	**98.7%**



(a) ImageNet-A (b) ImageNet-C (c) ImageNet-P



Simple Code Example on MNIST [7]

bit.ly/pydata-notebook

Thanks!

I'm looking for paid or unpaid remote internships during Winter 2020 or Summer 2021 - szheng3@athabasca.edu

Find me on GitHub/Kaggle/LinkedIn: @stanleyjzheng