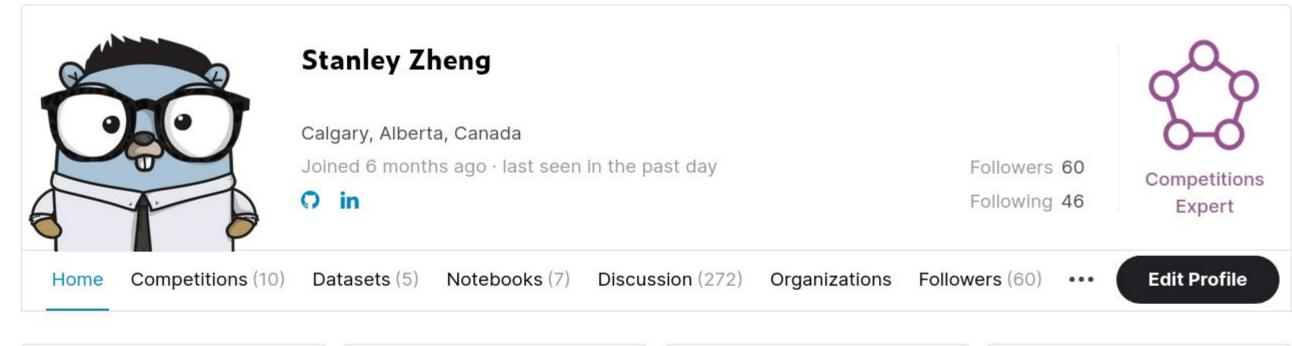
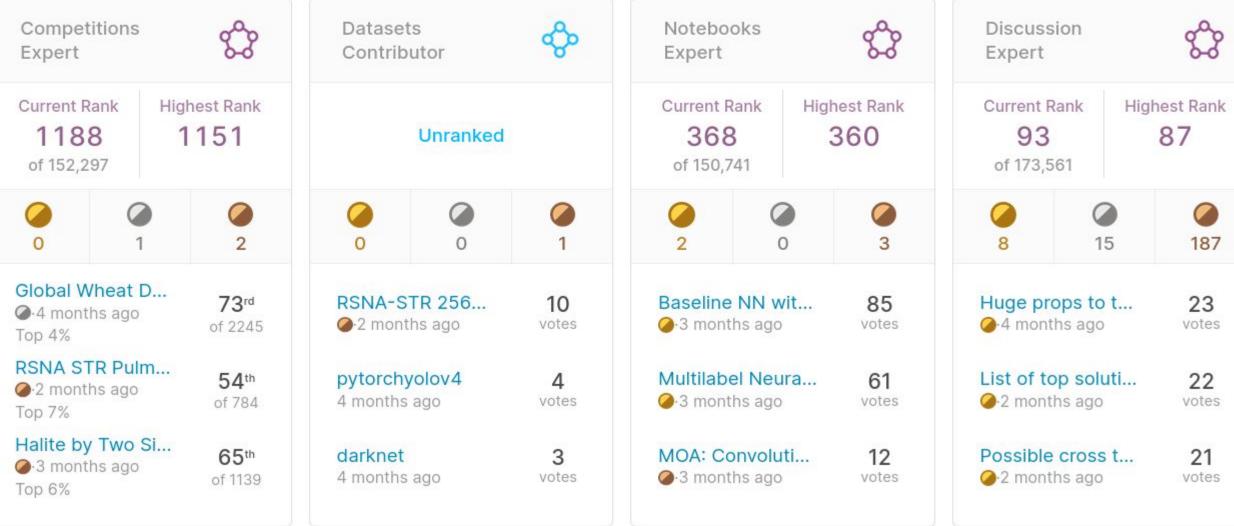


# A Guide to Pseudolabelling: How to get a Kaggle medal with only one model

Stanley Zheng

#### About Me





## GitHub/Kaggle/LinkedIn: @stanleyjzheng

#### Contents

- 1. What are pseudolabels, and why should we use them?
- 2. Effective use of pseudolabels
- 3. Applications
- 4. Minimal code example on MNIST

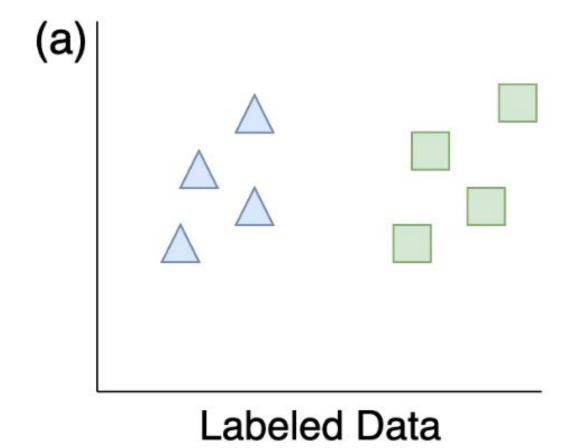
Sources and further reading at <a href="https://bydata-github">bit.ly/pydata-github</a>

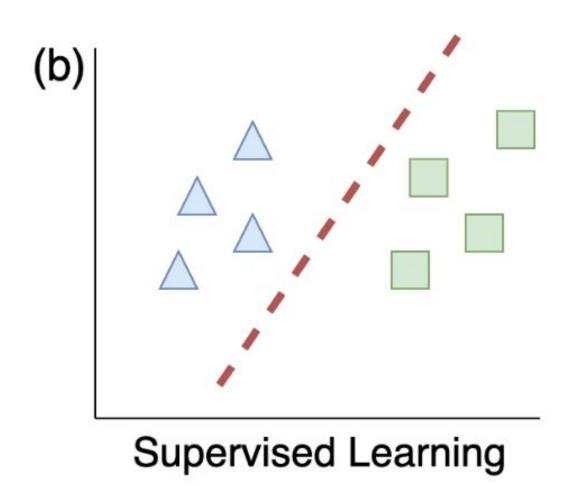
Thanks to Yauhen Babakhin for some of the graphics in this presentation [1]

#### What is Pseudolabelling?

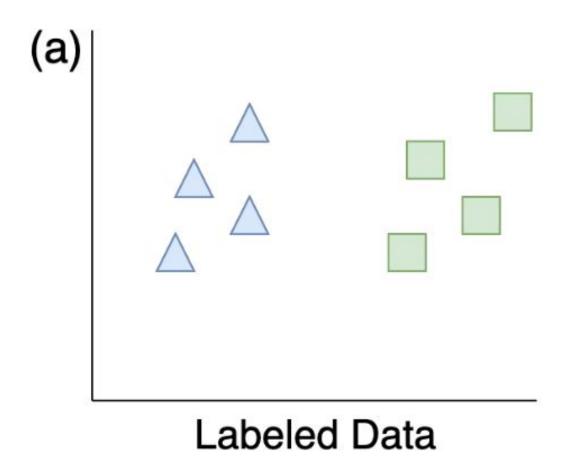
- Semi-supervised learning
- Allows models to leverage a large unlabelled dataset

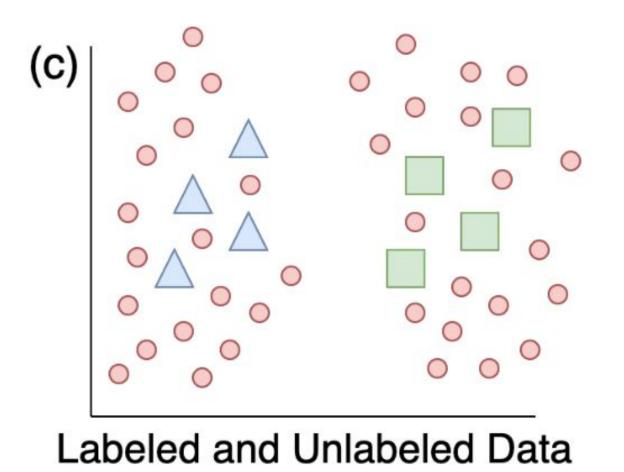
## Visual Example

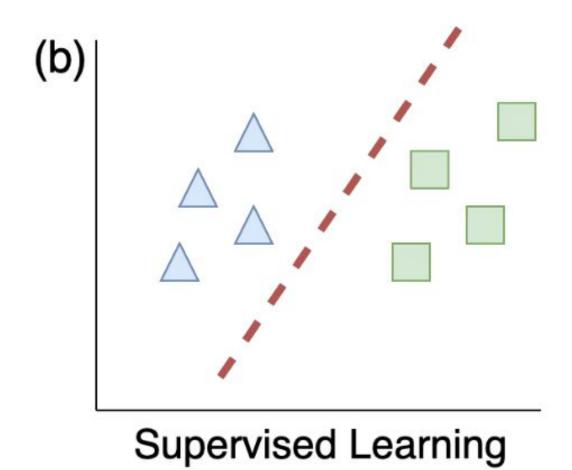




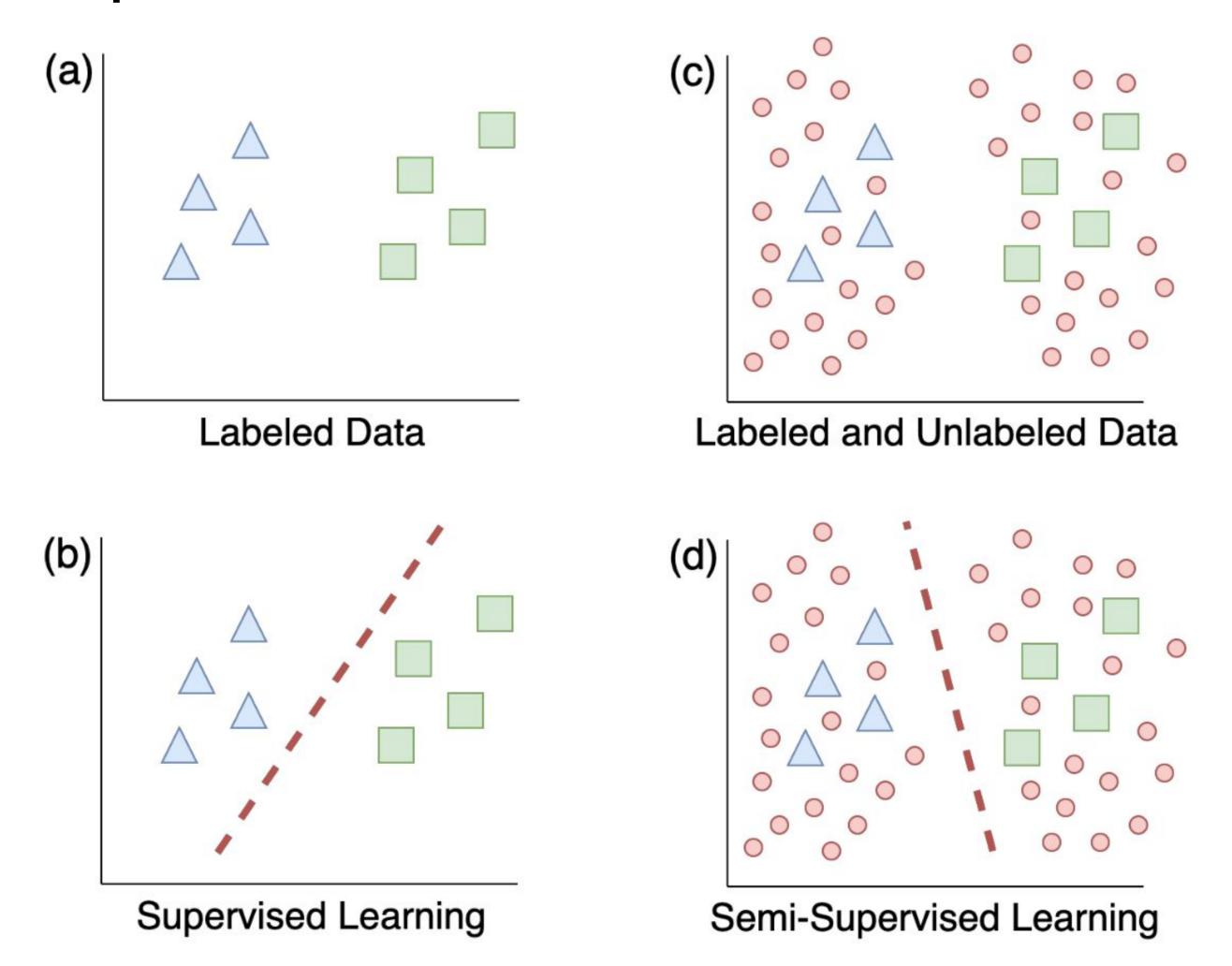
## Visual Example







#### Visual Example



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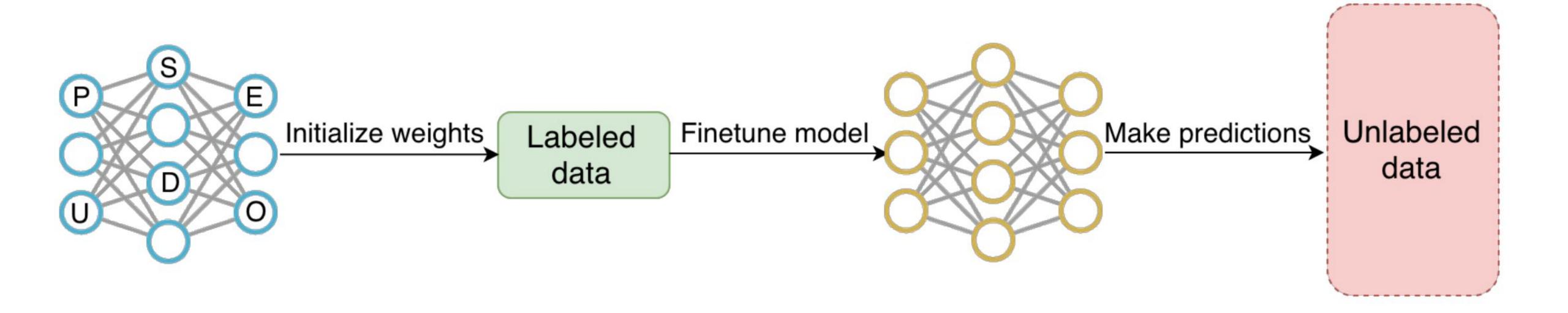
#### Why use pseudolabelling?

- Data is expensive to label
  - 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

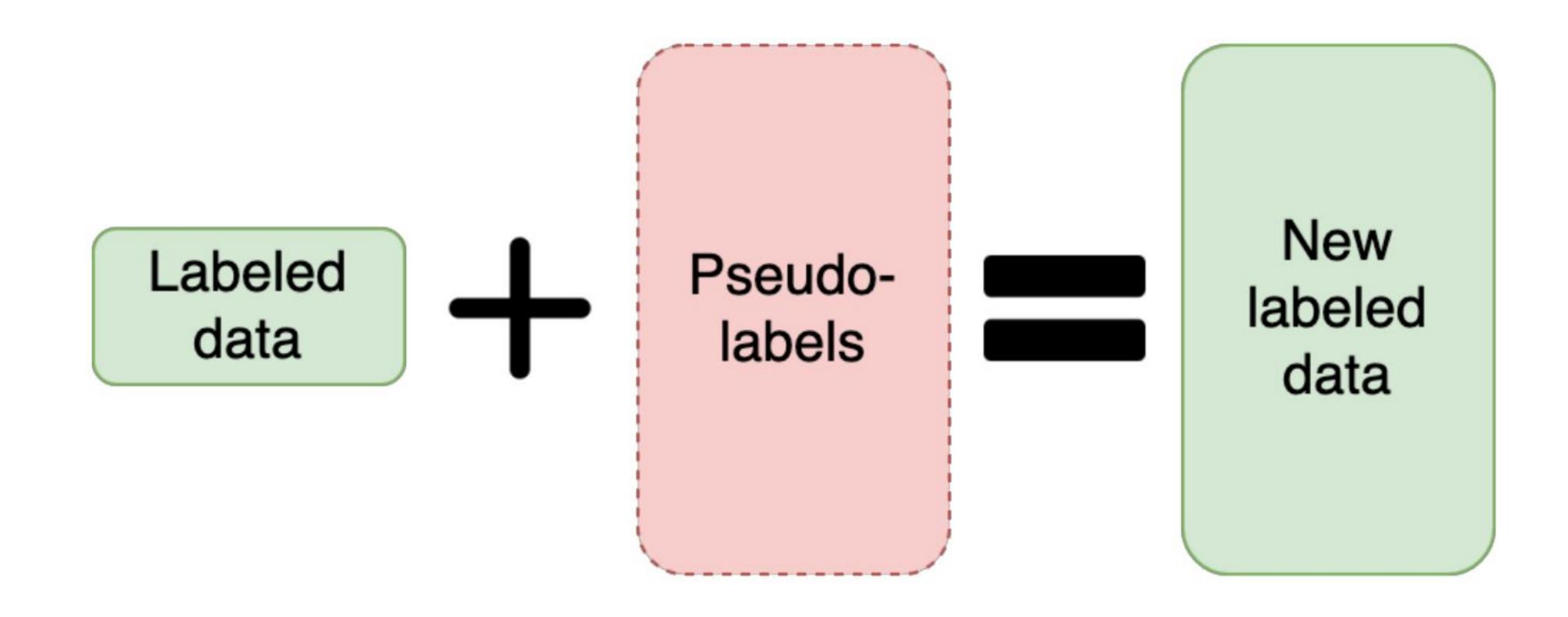
### Why use pseudolabelling? [2]

- Data is expensive to label
  - 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

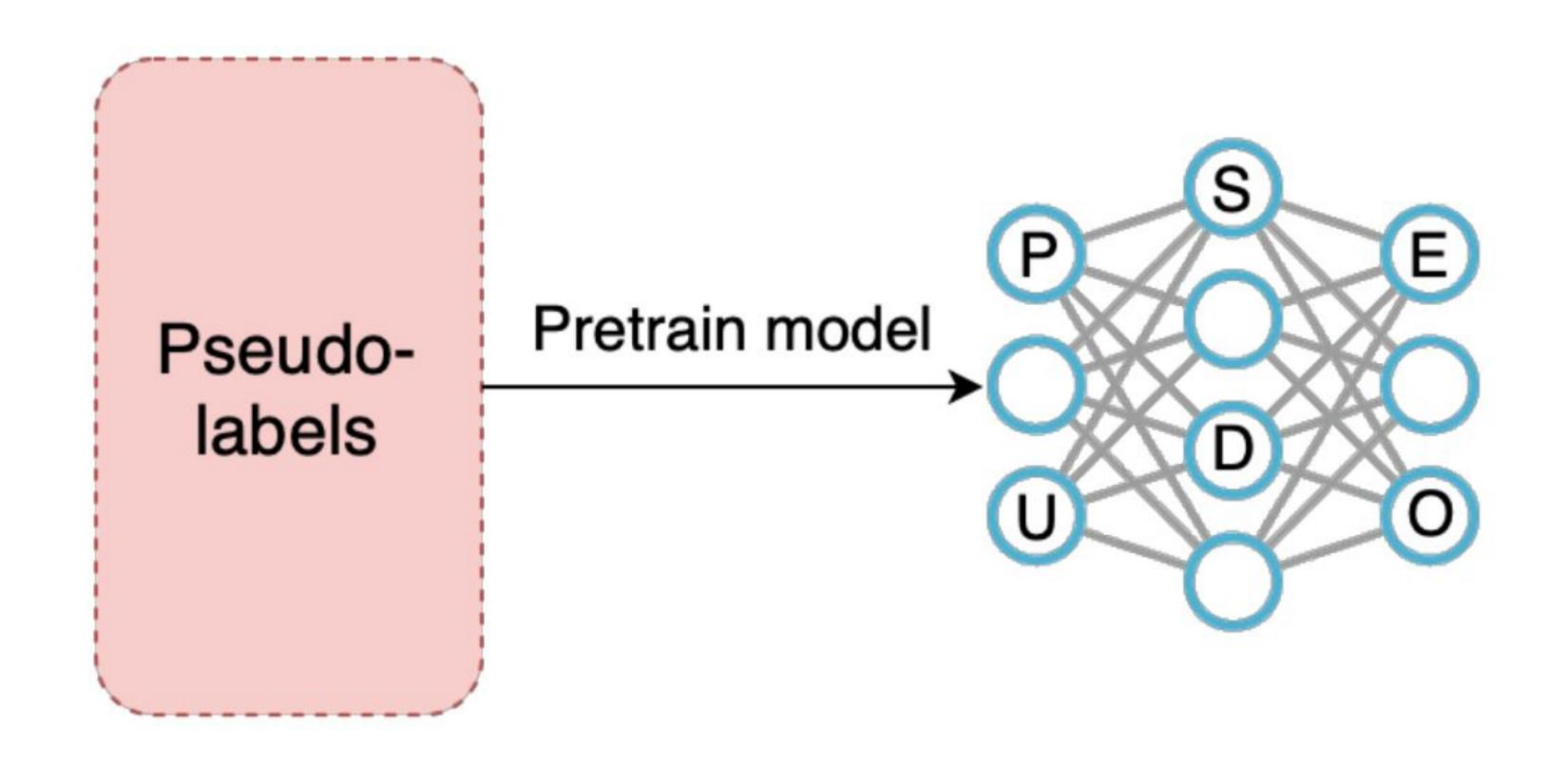
#### Training Schemes - Self Training



#### 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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- 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)

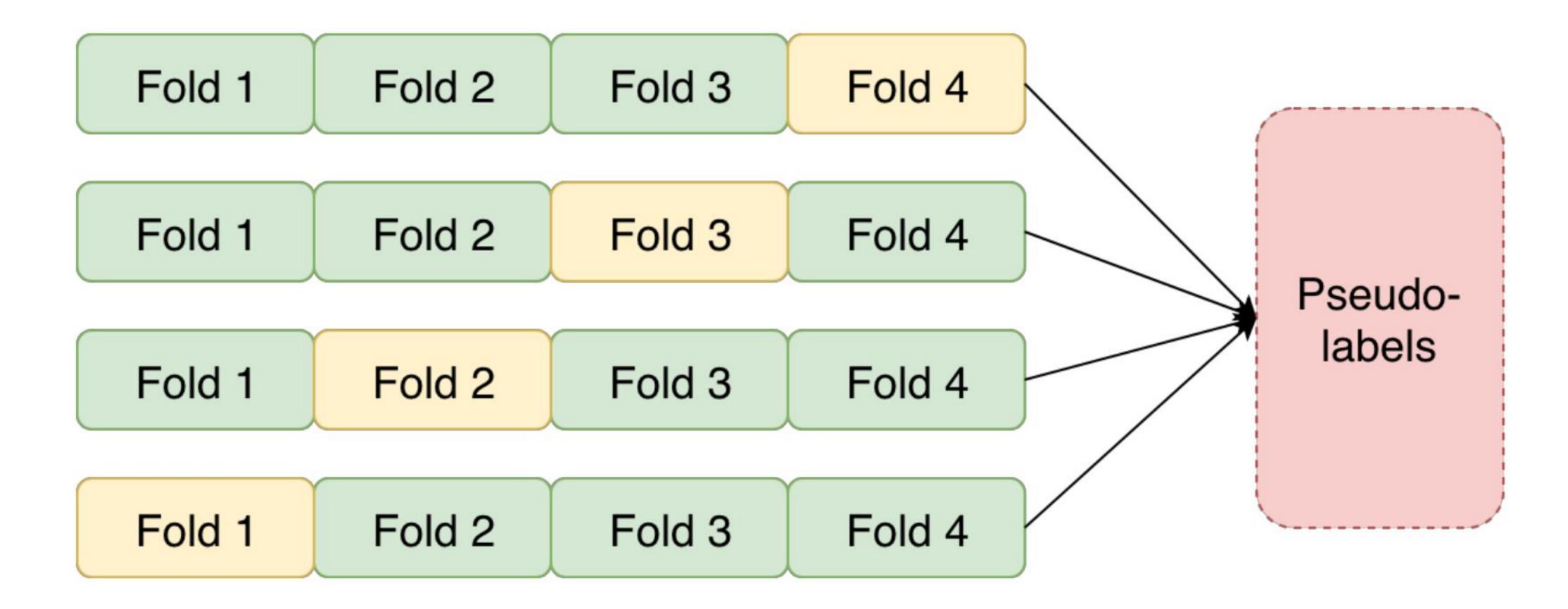
#### K-fold Cross Validation

- 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

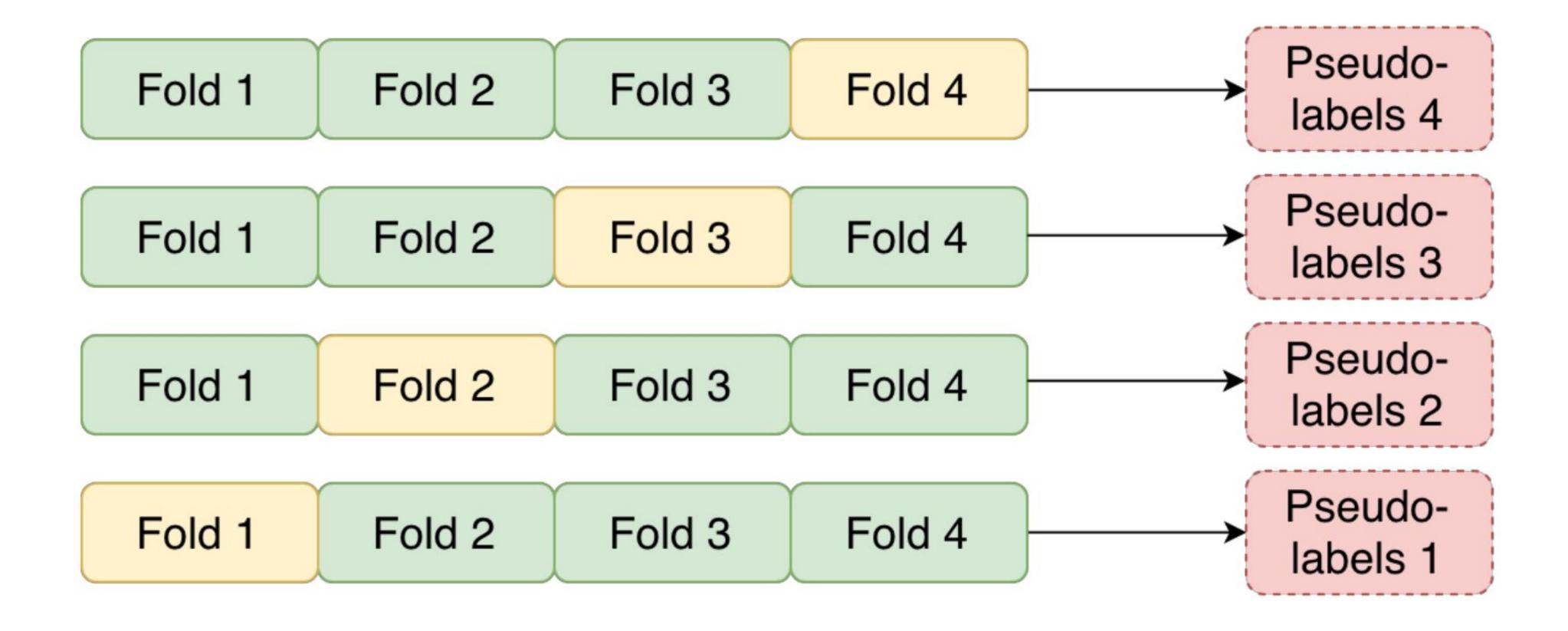
#### Ensembling folds to produce pseudolabels



#### 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]

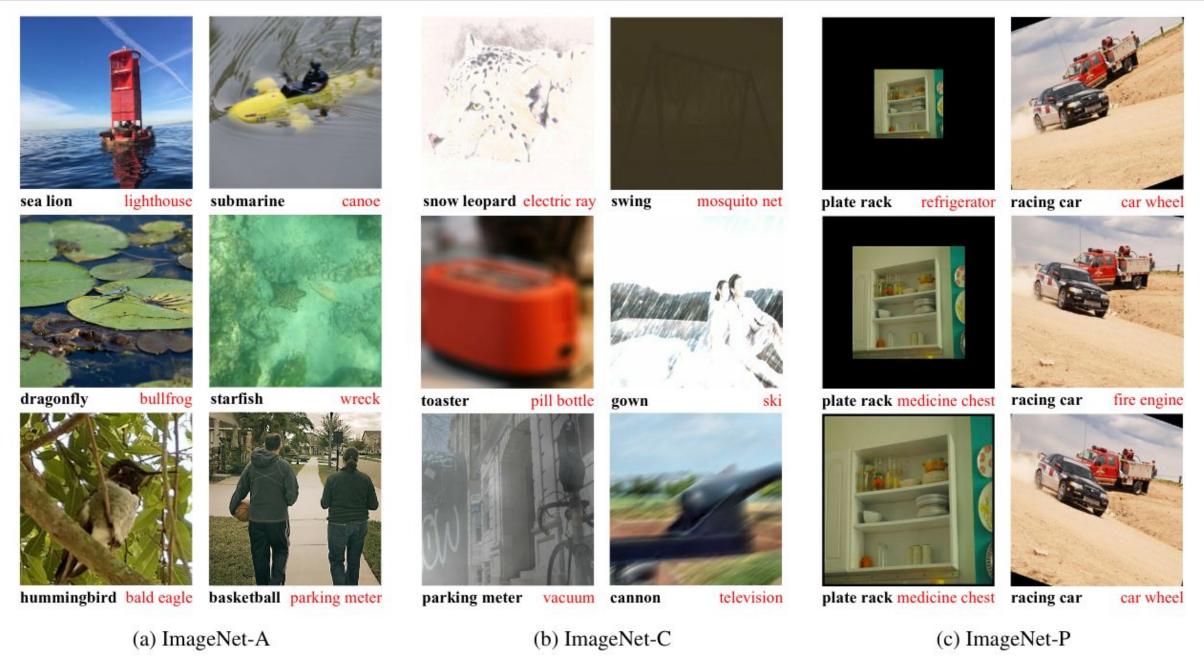
Scores of various models (Intersection over Union, higher is better)

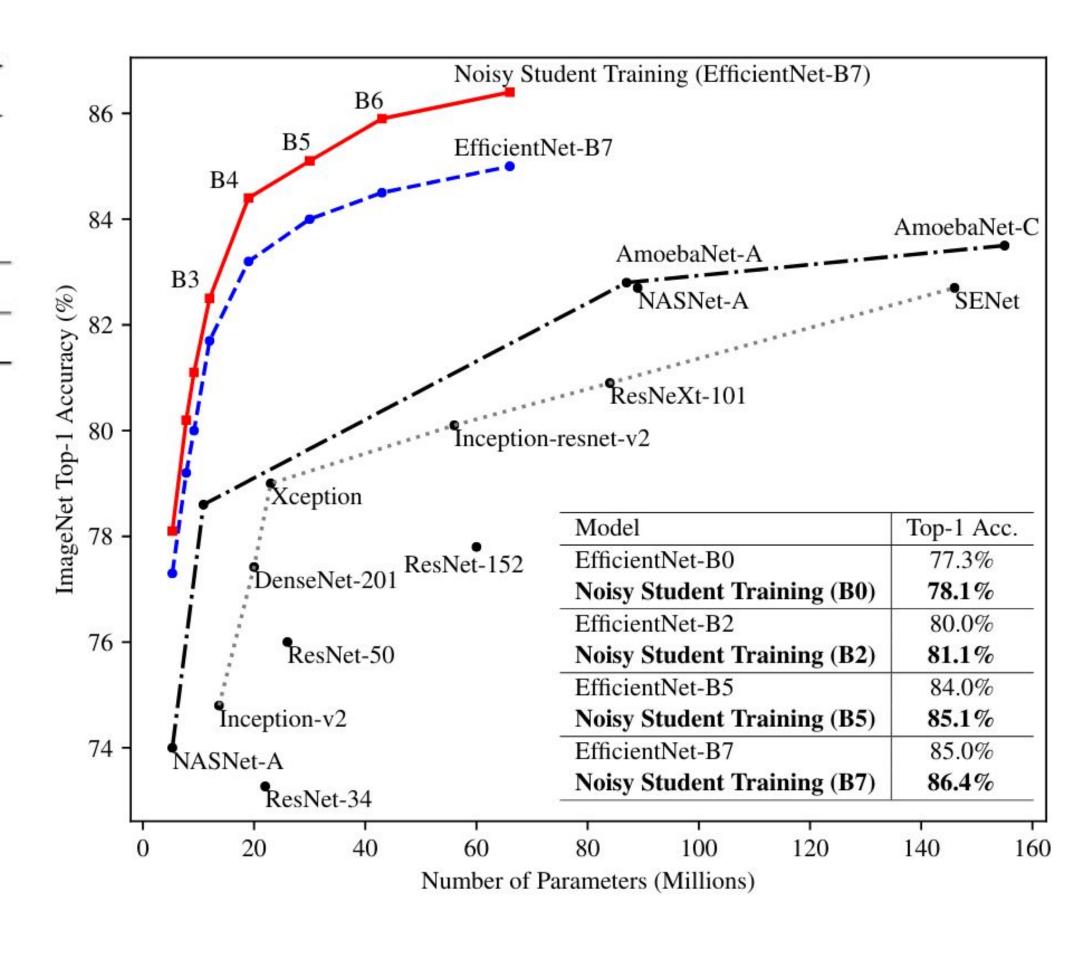
Technique	Public Leaderboard	Private Leaderboard
No pseudolabelling	0.7115 (821st)	0.6371 (327th)
Self-training	0.7406 (+4%, 207th)	0.6625 (+4%, 36th)
Pretraining	0.7562 (+6%, 61st)	0.6668 (+5%, 22nd)



## 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] <sup>†</sup>	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%





#### Simple Code Example on MNIST [6]

bit.ly/pydata-notebook

#### Thanks!

I'm looking for paid or unpaid remote internships during Winter 2020 or Summer

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