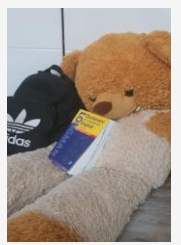


# Robust multi-label learning for weakly labeled data

## Background information

- **Multi-label learning (MLL)** is a type of supervised learning in which each input example could be assigned to more than output label.
- **Weak labels** are a type of multi-label data corruption where not only all the relevant (true) labels are presented but also some of the irrelevant ones.



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Bike
Bed
Backpack
Book

Bear
Backpack
Book

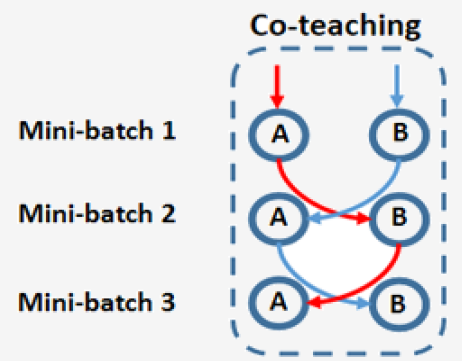
Example image      Weak labels      Correct labels

**Overfitting problem** - The deep neural networks used to solve MLL problems could be quite complex and often have a huge capacity. This enormous capacity, however, could also be a negative, as they tend to eventually **overfit** the undesirable corrupted labels.

## Method: Co-ASL

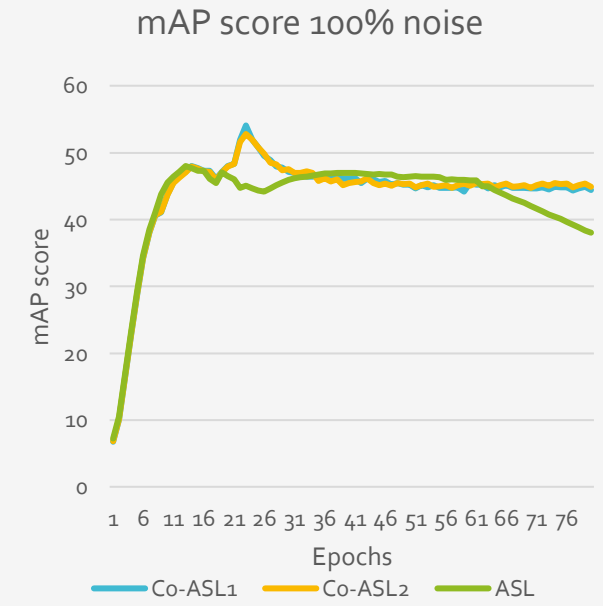
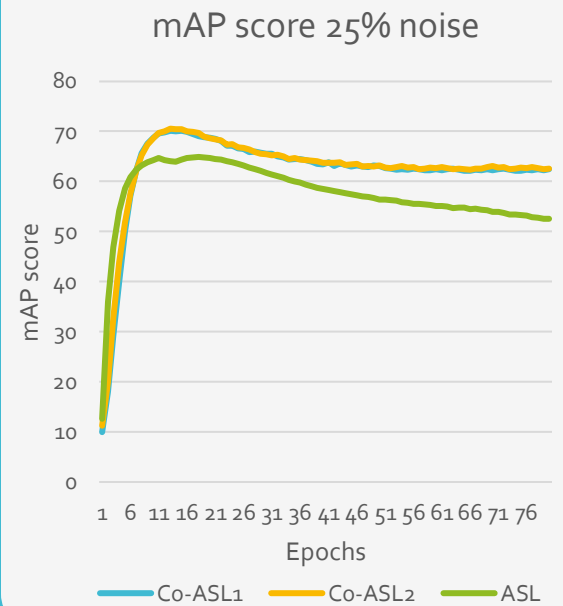
**Co-ASL** solves the problem by combining the most prominent solutions in the two fields - **ASL**[1], the state-of-the-art MLL approach, and **Co-teaching**[2], an eminent robust training strategy.

- Initialize the two peer networks;
- The data is fed in a mini-batch manner;
- Each network forwards the entire mini-batch and remembers the portion with the lowest loss (small-loss instance);
- The networks swap their small-loss instances and adjust their weights using only the instance of their peer.



## Results

- **MS-COCO**[3] was used as a dataset for the experiments.
- It is a clean dataset and, therefore, an **artificial noise** was injected into it.
- The experiments were running for **80 epochs**.



## Conclusions

- Co-ASL proves to be an MLL algorithm robust for weakly labeled data.
- **Does not overfit** even after 80 epochs.
  - Achieves an improvement of **8-9 mAP score** over ASL.