Introduction to Deep Learning for Computer Vision

Adhyayan '23 - ACA Summer School
Department of Computer Science and Engineering
Indian Institute of Technology Kanpur

Lecture 9

Semi-Supervised Learning!

Semi-Supervised Learning

- Training on **labeled** data is mostly easy. (Supervised Learning)
- Getting labeled data is hard!
- Real Life Scenario: Some **labeled** data. A LOT of **unlabeled** data!
- How can we utilize the unlabeled data?

Semi-Supervised Learning: Assumptions

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- **(H2) Cluster Assumptions:** The feature space has both dense regions and sparse regions. Densely grouped data points naturally form a cluster. Samples in the same cluster are expected to have the same label.
- **(H3) Low-density Separation Assumptions:** The decision boundary between classes tends to be located in the sparse, low density regions, because otherwise the decision boundary would cut a high-density cluster into two classes, corresponding to two clusters, which invalidates H1 and H2.

Semi-Supervised Learning: Techniques

- **Self-training:** is a simple and popular semi-supervised learning technique.
- It involves training a model initially on the labeled data and then using this model to predict labels for the unlabeled data.
- The predicted labels are treated as pseudo-labels and used to augment the labeled dataset for further training iterations.

Semi-Supervised Learning: Techniques

- **Co-training:** is a semi-supervised learning technique suitable for scenarios with multiple views or feature sets.
- It involves training multiple models independently on different subsets of features or views of the data.
- The models then collaborate and exchange predictions on unlabeled data to improve overall performance.

Semi-Supervised Learning: Techniques

- **Consistency regularization:** assumes that randomness within the neural network (e.g. with Dropout) or data augmentation transformations should not modify model predictions given the same input.
- It enforces that small changes in input should lead to small changes in the model's output, promoting smooth predictions and improving robustness.

Semi-Supervised Learning: Techniques

- **Virtual Adversarial Training:** introduces adversarial perturbations to both labeled and unlabeled data.
- The model is trained to maximize the disagreement between its predictions on the original and perturbed inputs, leading to improved generalization.

Semi-Supervised Learning: Considerations

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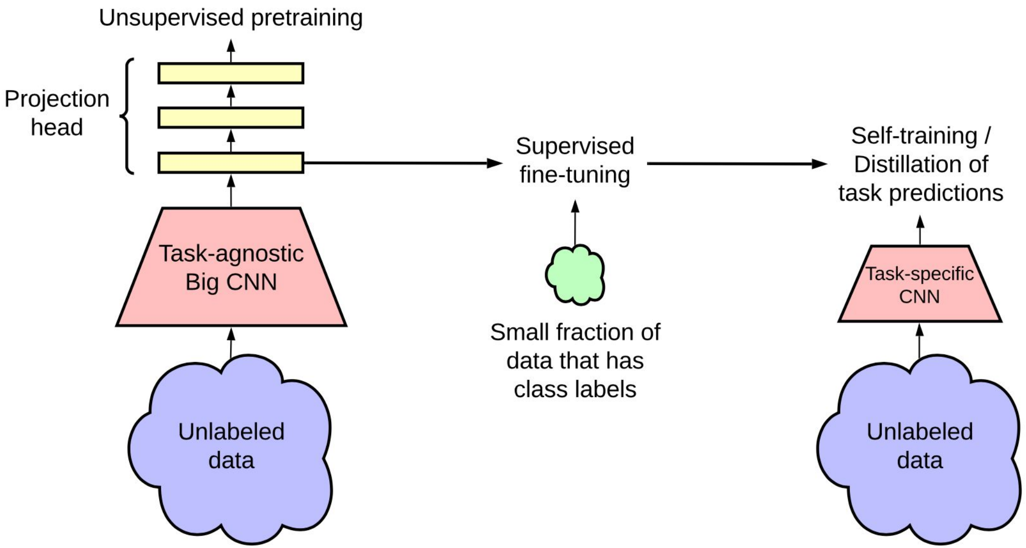
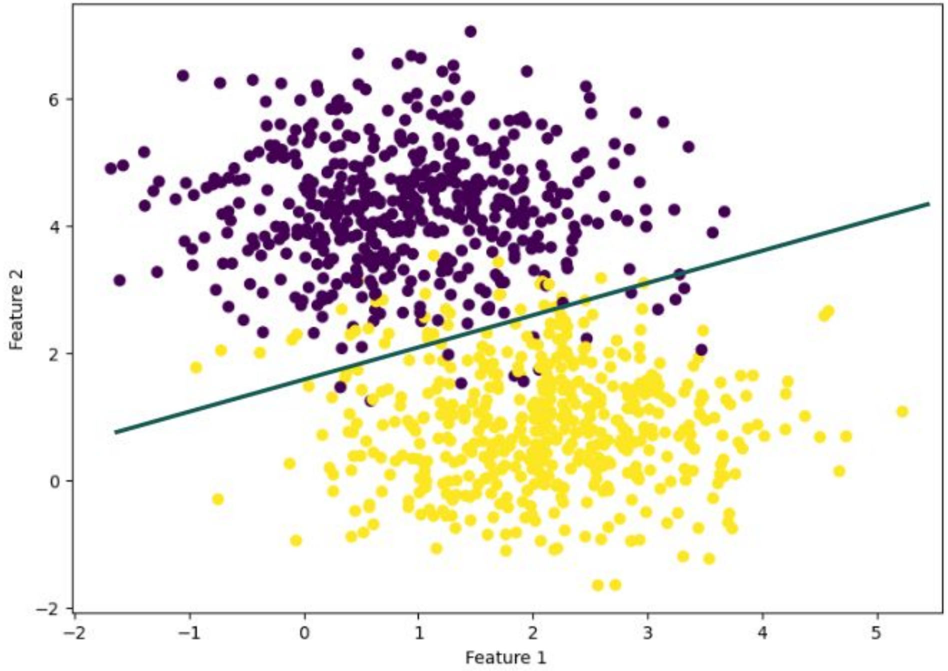


Nice Survey Paper:
https://arxiv.org/pdf/2006.05278.pdf

Active Learning

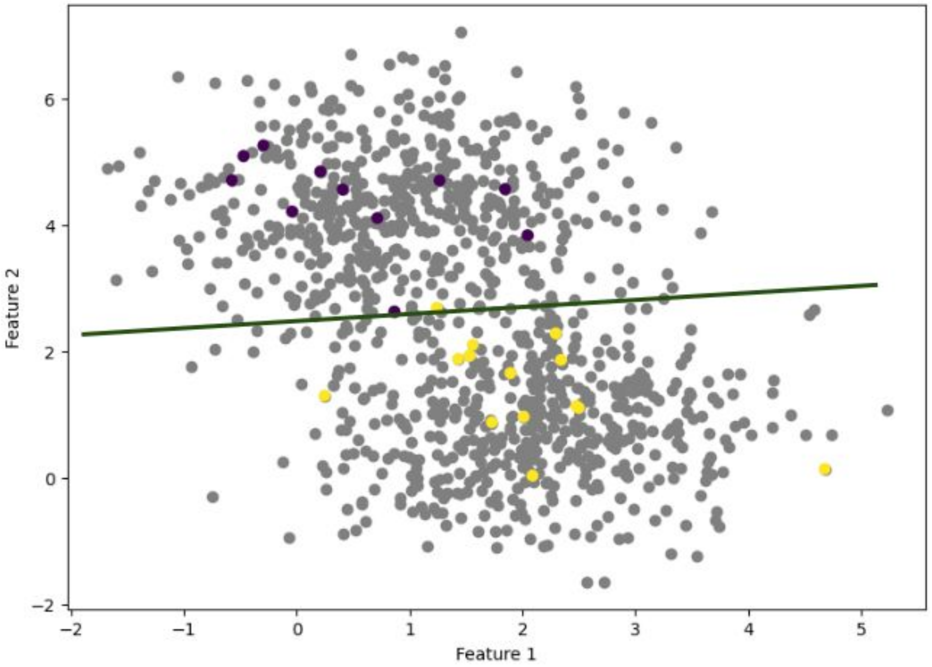
Active Learning

- All the data are labeled. Belongs to either **purple** class or **yellow** class.
- Drawing a decision boundary is easy.

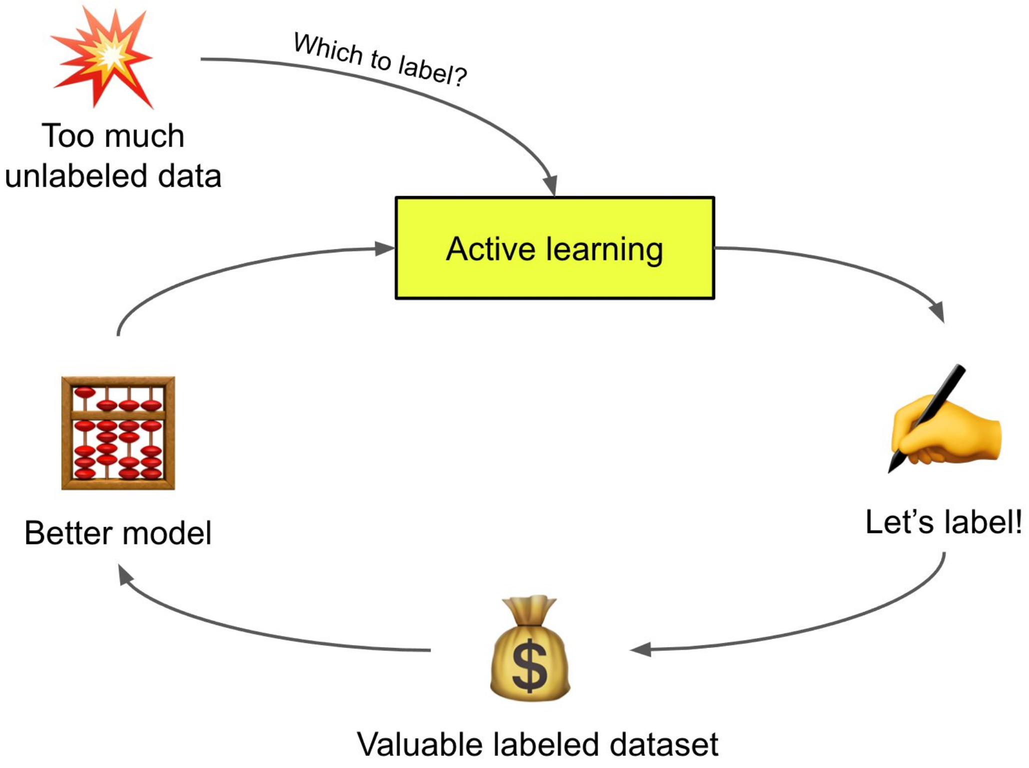


Active Learning

- Now what if most data points are unlabeled?
- Deciding on drawing the boundary is not so easy now.



Active Learning



Active Learning: Uncertainty Sampling

- Select samples that the model is uncertain about - typically with high entropy or low confidence.
- gain more knowledge and improve performance in challenging regions by labeling those samples.

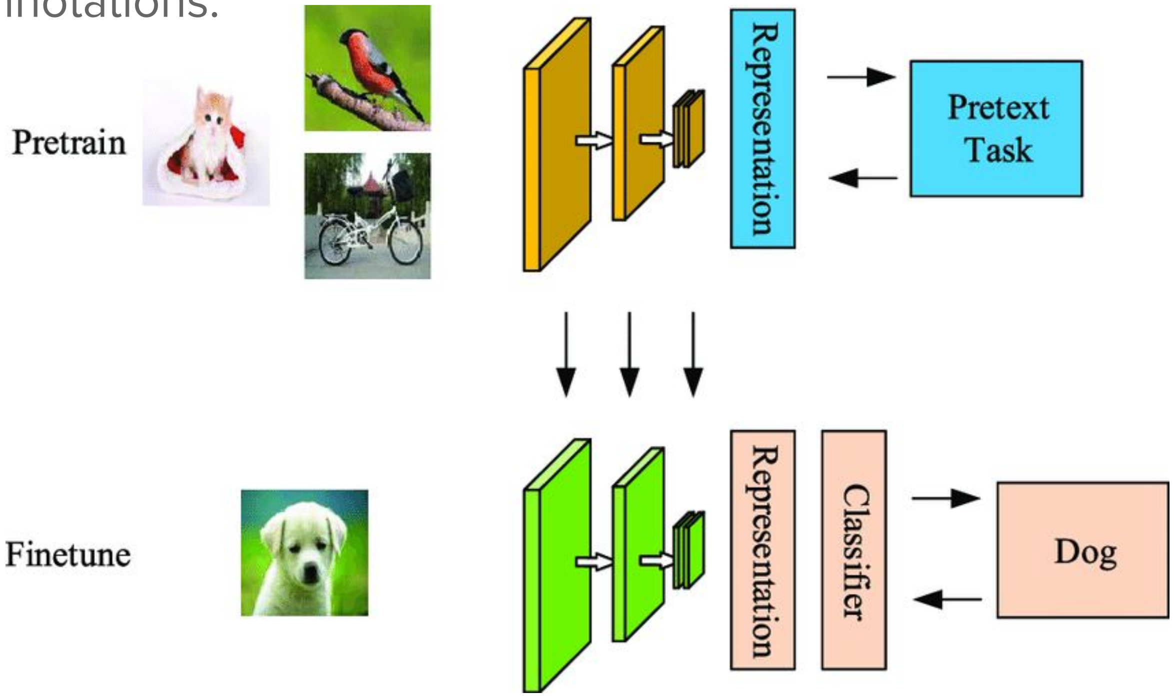
Active Learning: Query by Committee

- Maintain an **ensemble** or **committee** of *multiple models*.
- Select uncertain samples based on disagreement or consensus among the committee members.

Self-Supervised Learning

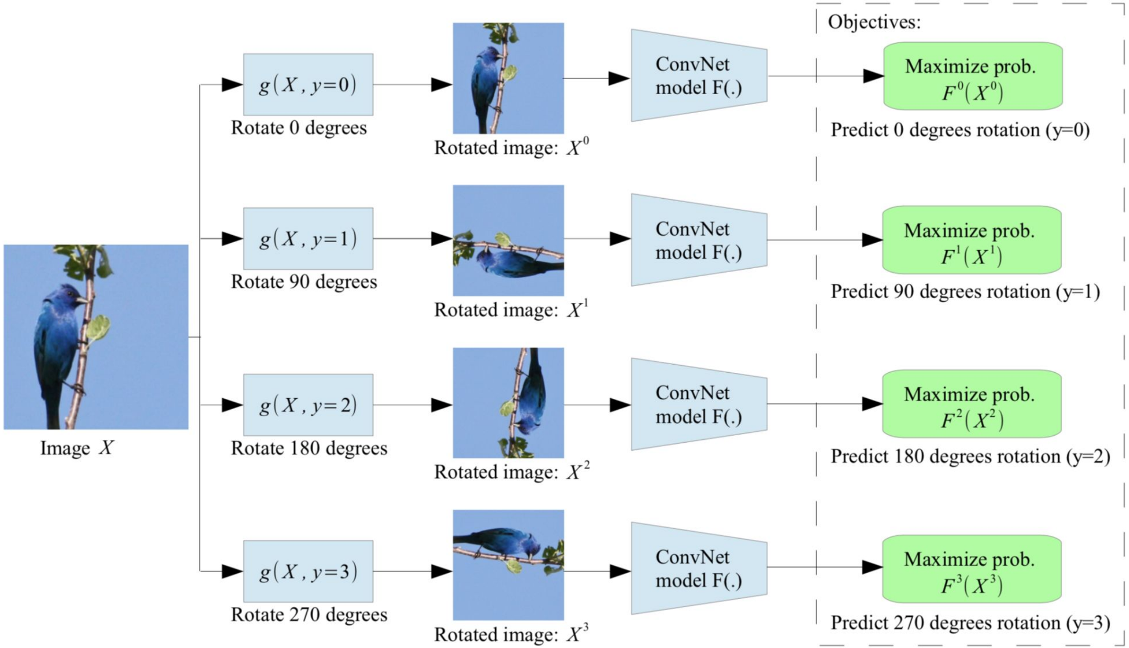
Self-Supervised Learning

- leverage unlabeled data to learn meaningful representations without explicit human annotations.



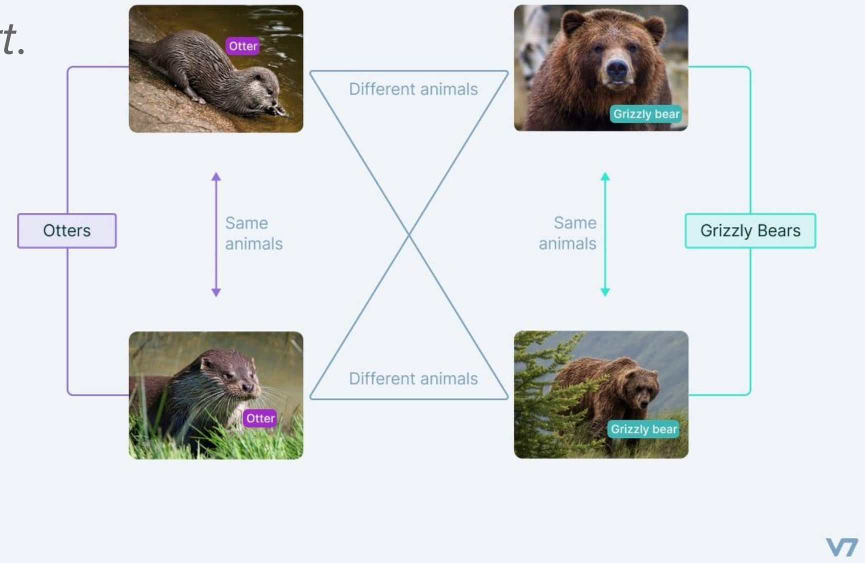
Self-Supervised Learning: Rotation Loss

- Predict the rotation angle of an image.
- Images randomly rotated by 90, 180, or 270 degrees.



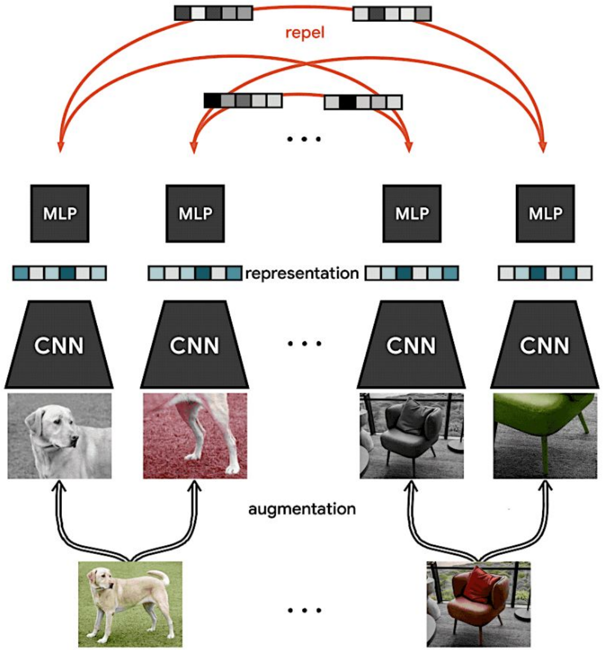
Self-Supervised Learning: Contrastive Learning

- Learn representations by **maximizing** the similarity between *positive* pairs and **minimizing** the similarity between *negative* pairs.
- Bring positive pairs *closer together* in the embedding space and push negative pairs *farther apart*.

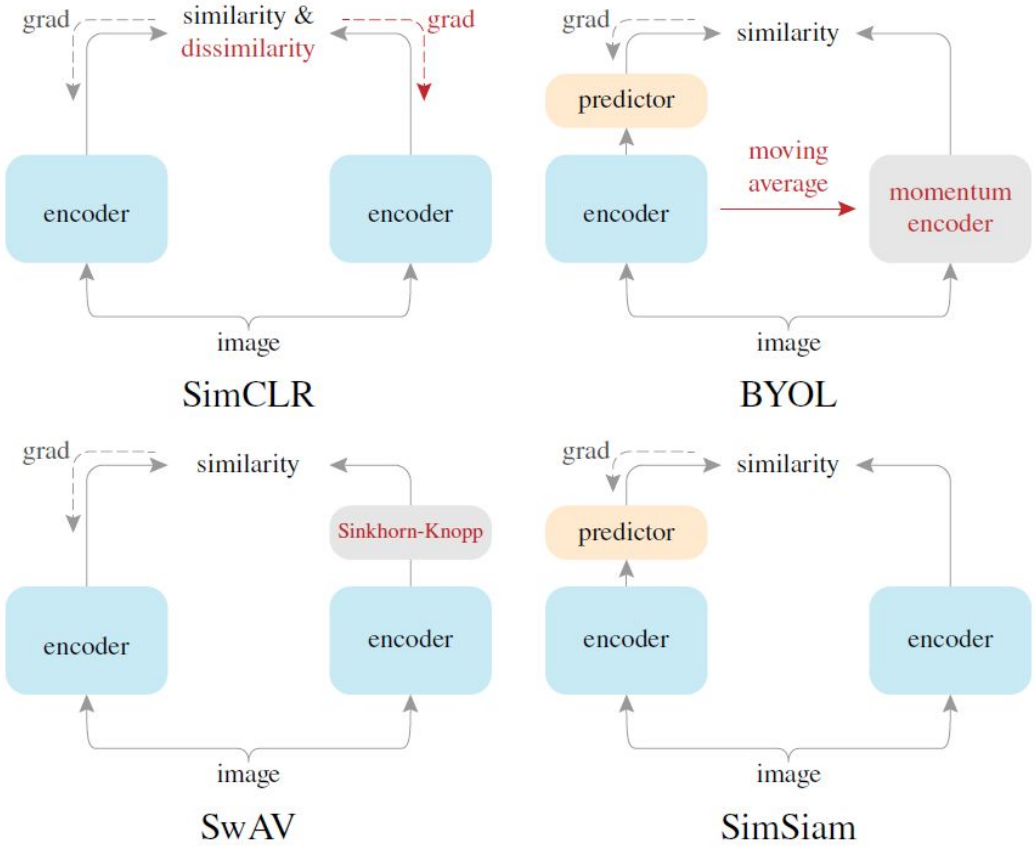


Contrastive Learning: SimCLR

- **Data Augmentation:** Apply various augmentations to create multiple versions of the same input.
- **Base Encoder:** To map the augmented inputs into an embedding space.
- **Contrastive Loss:** *maximize* the agreement between *positive pairs* and *minimize* the agreement between *negative pairs*.



Contrastive Learning: Other Techniques



Thank You!