Active Learning

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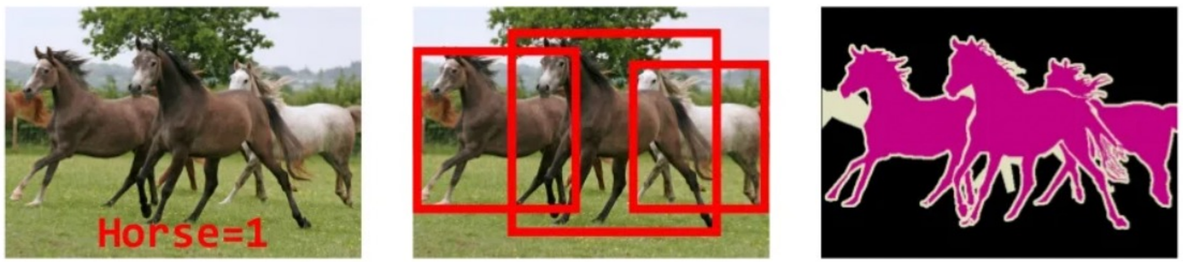
Outline

1. Motivation
2. About Active Learning
3. Recent Work
4. For Hand Pose Estimation
5. Conclusion
6. References

Motivation

- Success of Supervised Learning
  - A large number of learnable parameters
  - Availability for large-scale annotated data
- Limitations
  - Annotating requires a lot of effort
  - Expensive
  - Time-consuming



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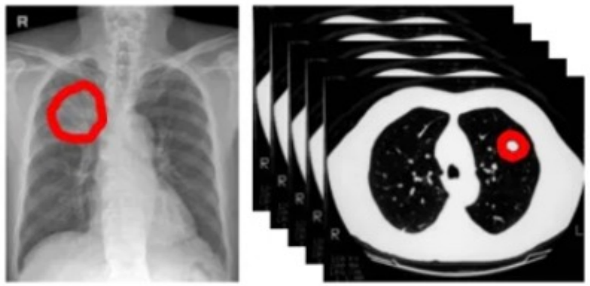

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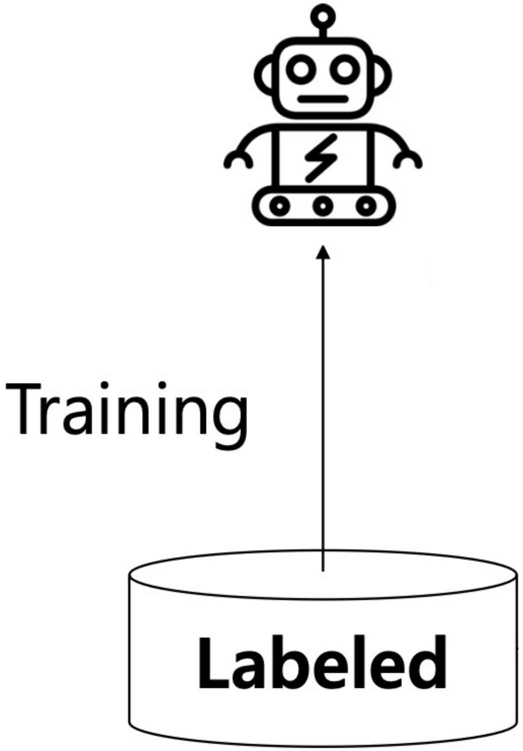
- Success of Supervised Learning
  - A large number of learnable parameters
  - Availability for large-scale annotated data
- Limitations
  - Annotating requires a lot of effort
  - Expensive
  - Time-consuming
- Solution
  - Identify the most influencing and discriminative examples to annotate.
  - Efficiently select the most meaningful samples.

➔ ***Active Learning is ABSOLUTELY NEEDED!***

About Active Learning

- Concept



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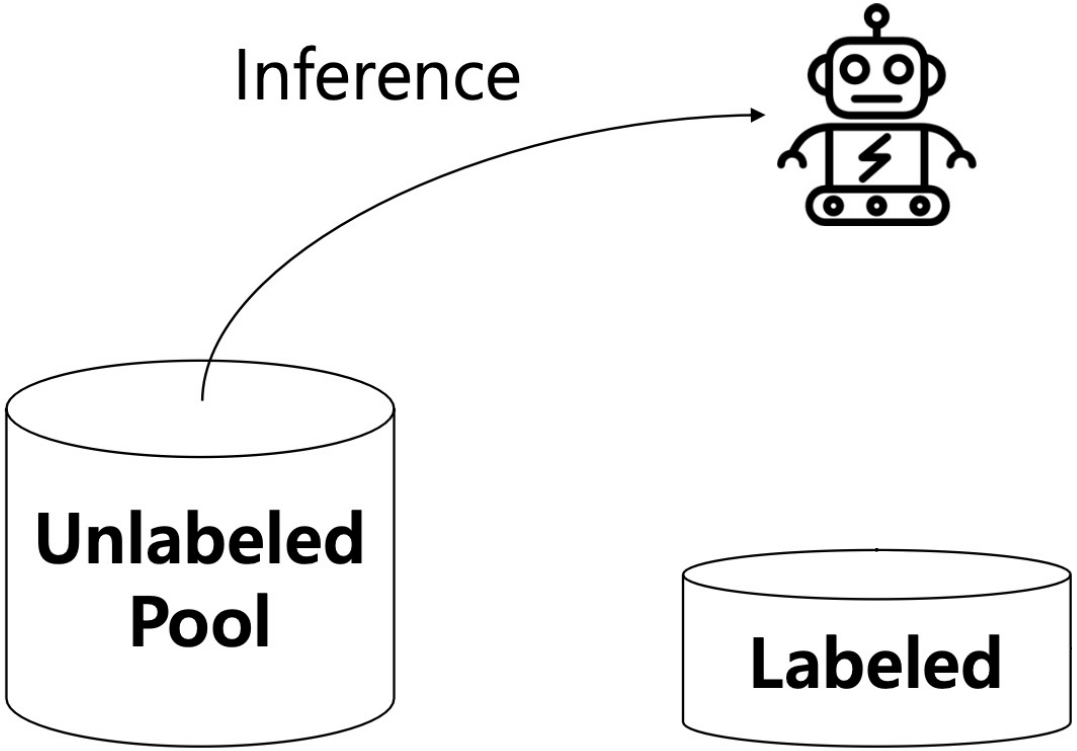

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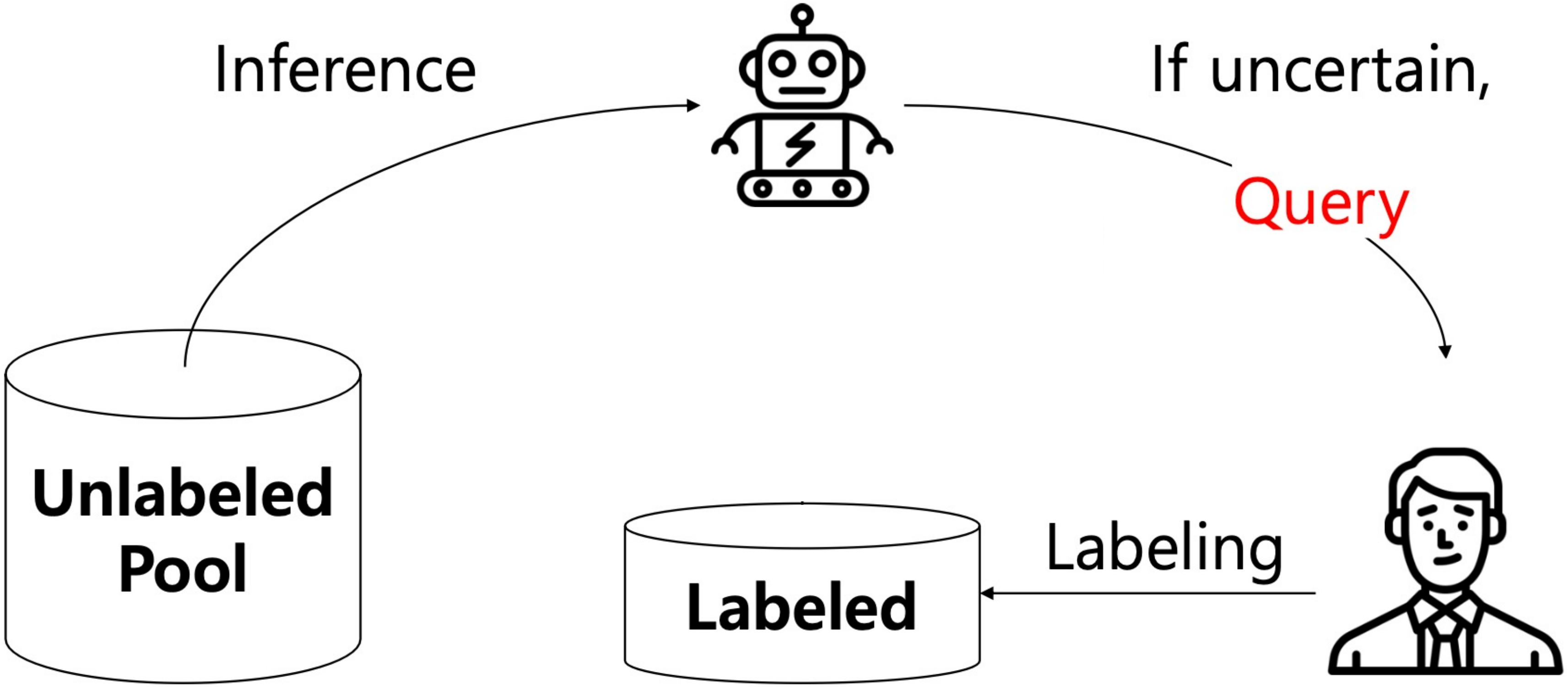

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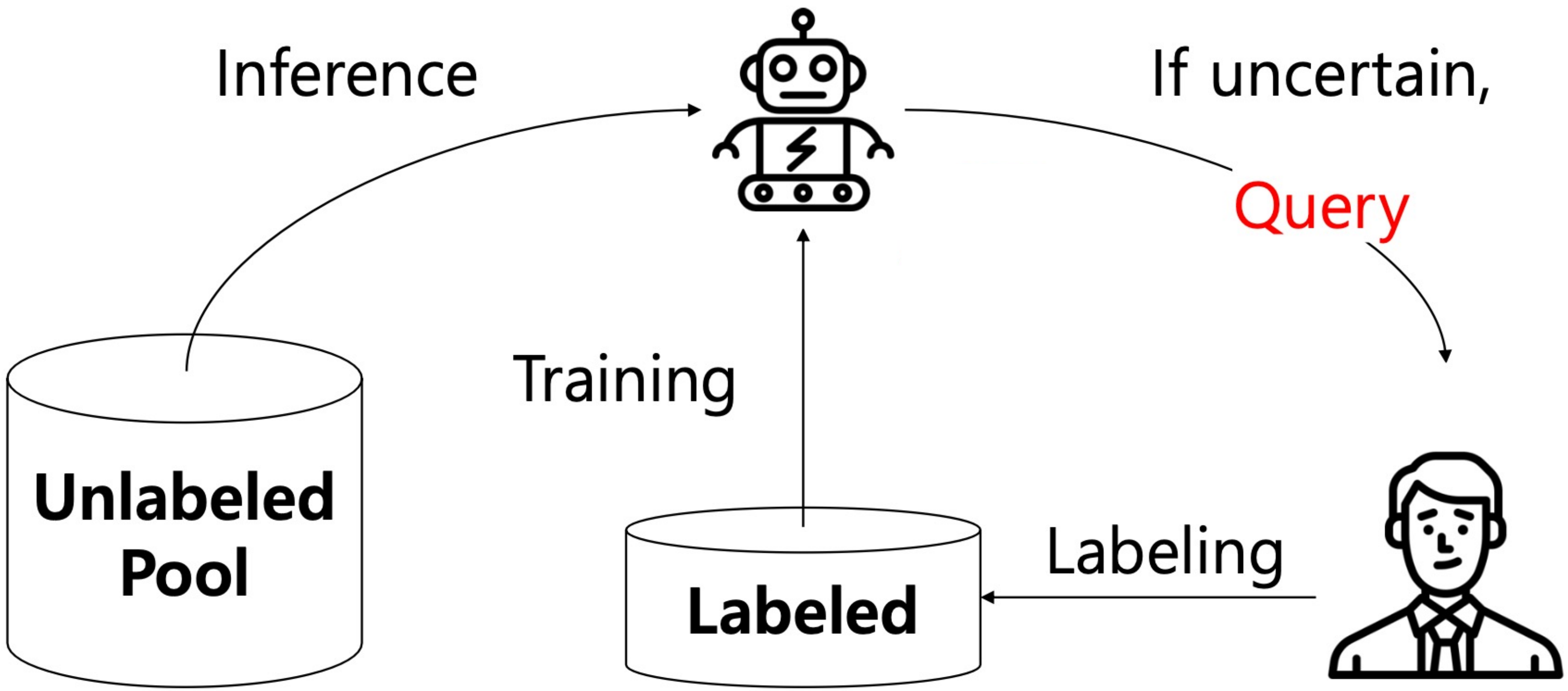

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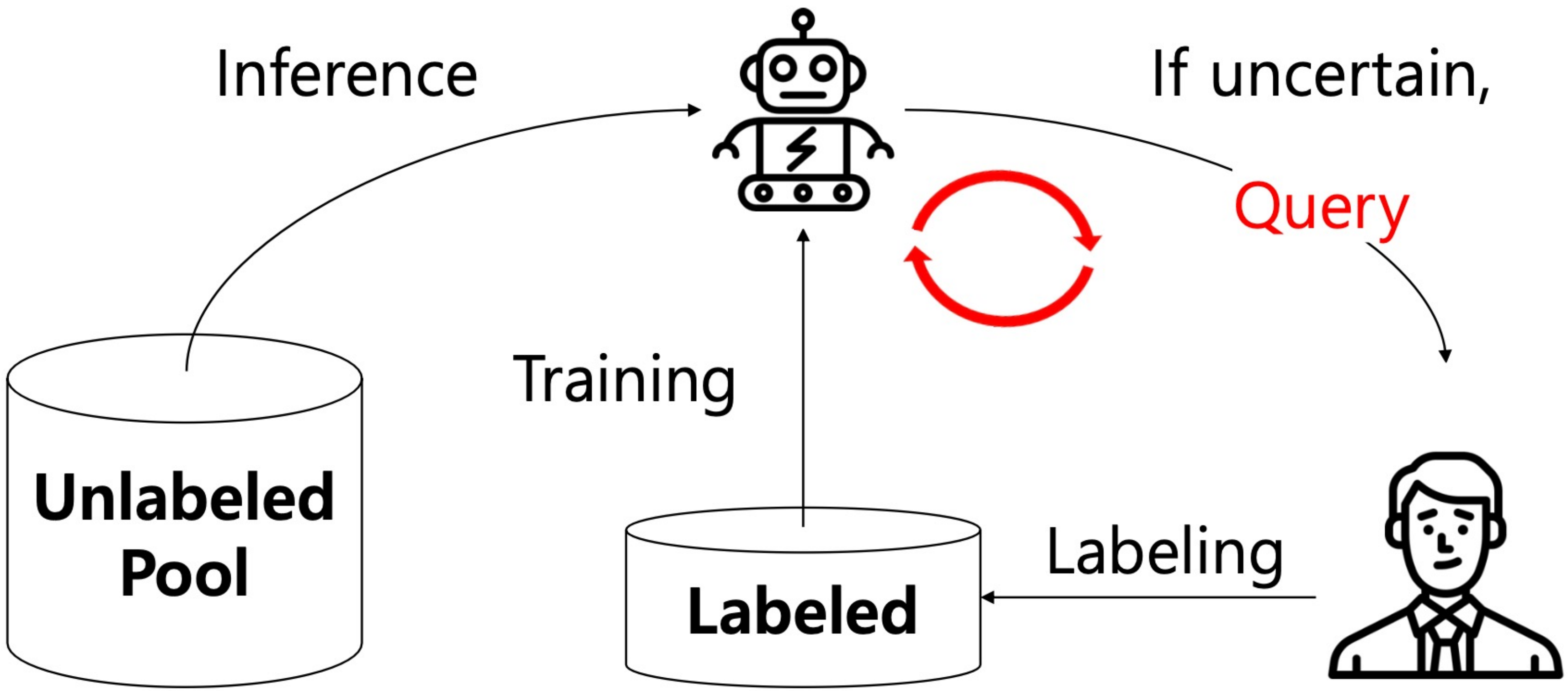

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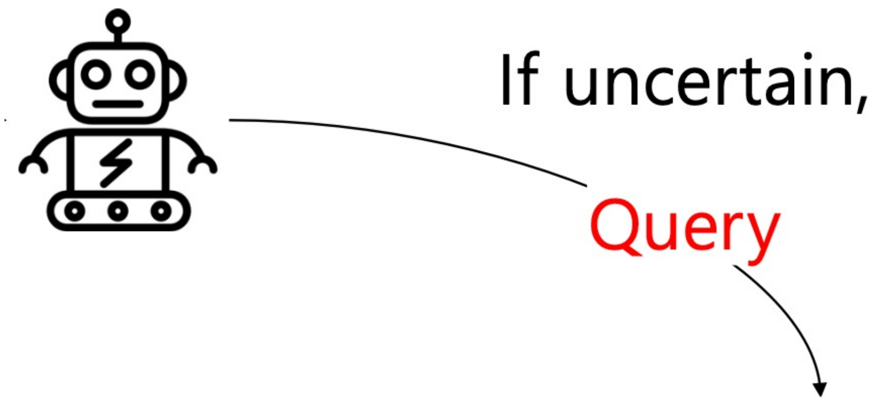
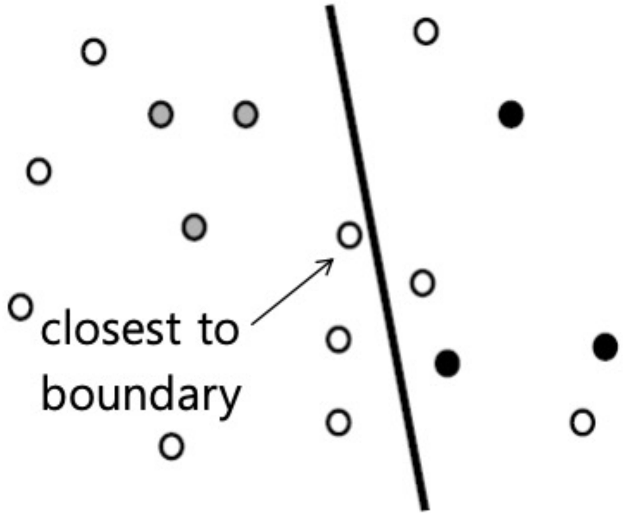


The key of active learning:
How to measure the UNCERTAINTY

Uncertainty Sampling

- Goal
  - Choosing the sample closest to the decision boundary.
- Methods
  - Least Confidence
  - Margin Sampling
  - Maximum Entropy



Uncertainty Sampling

- Least Confidence
  - Choose the example where the top label had the smallest probability.

Data ID	Class A	Class B	Class C	Top 1	Query Priority
D1	0.1	0.2	0.7	0.7	4
D2	0.33	0.33	0.34	0.34	1
D3	0.41	0.39	0.2	0.41	3
D4	0.3	0.4	0.3	0.4	2

Uncertainty Sampling

- Margin Sampling
  - The sample with the smallest difference between the top-1 confidence and the top-2 confidence is selected.

Data ID	Class A	Class B	Class C	Top 1 – Top 2	Query Priority
D1	0.1	0.2	0.7	0.5	4
D2	0.33	0.33	0.34	0.01	1
D3	0.41	0.39	0.2	0.02	2
D4	0.3	0.4	0.3	0.1	3

Uncertainty Sampling

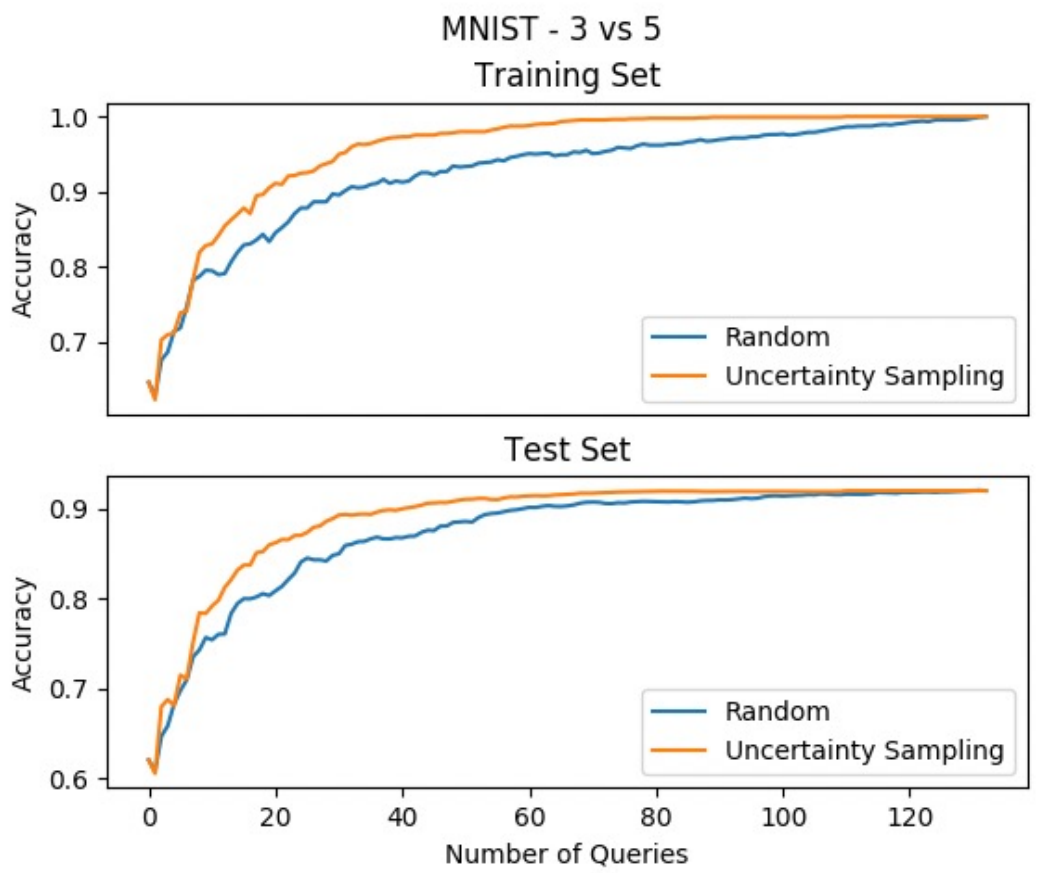
- Maximum Entropy
  - Choose the example which has the highest entropy.
  - Decision Rule:

$$\mathrm{H}(X) = -\sum_{i=1}^{n} \mathrm{P}(x_i) \log \mathrm{P}(x_i)$$

Data ID	Class A	Class B	Class C	Entropy	Query Priority
D1	0.1	0.2	0.7	0.8018	4
D2	0.33	0.33	0.34	1.0985	1
D3	0.41	0.39	0.2	1.0546	3
D4	0.3	0.4	0.3	1.0888	2

Uncertainty Sampling

- Compared with Random Sampling



Uncertainty Sampling

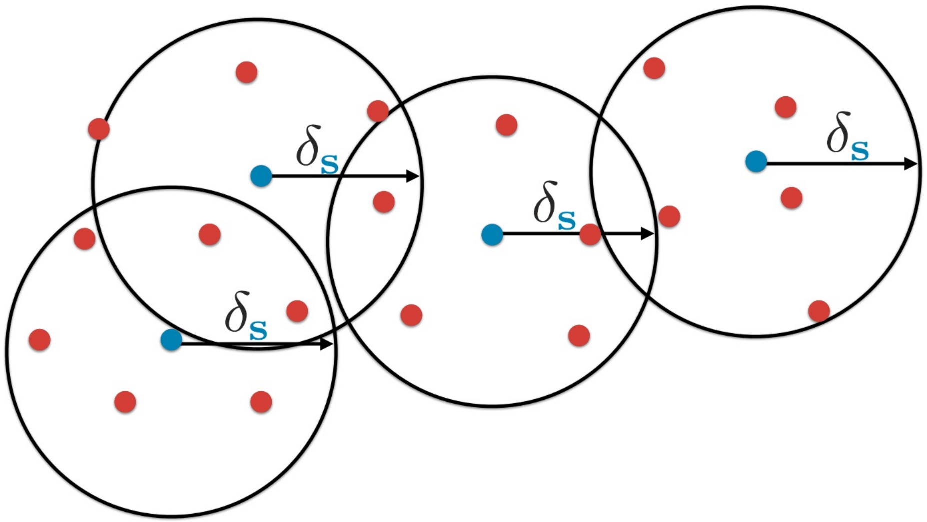
- Advantage
  - Easy to implement
  - High performance
- Disadvantage
  - Suffer from outlier
  - Ignored diversity

Recent Work

- CoreSet
  - Active Learning for Convolutional Neural Networks: A Core-set approach
  - Accepted at ICLR 2018
- Learning Loss
  - Learning Loss for Active Learning
  - Accepted as Oral at CVPR 2019

CoreSet

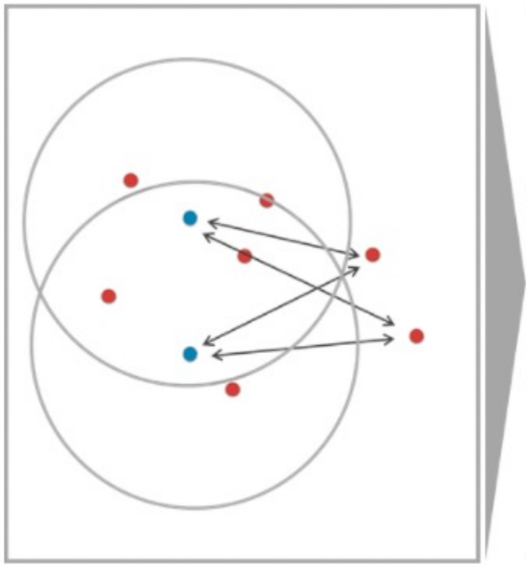
- Concept
  - Using feature in Deep Learning
  - Batch Active Learning
  - Find distinct data points from pre-selected subsets



CoreSet

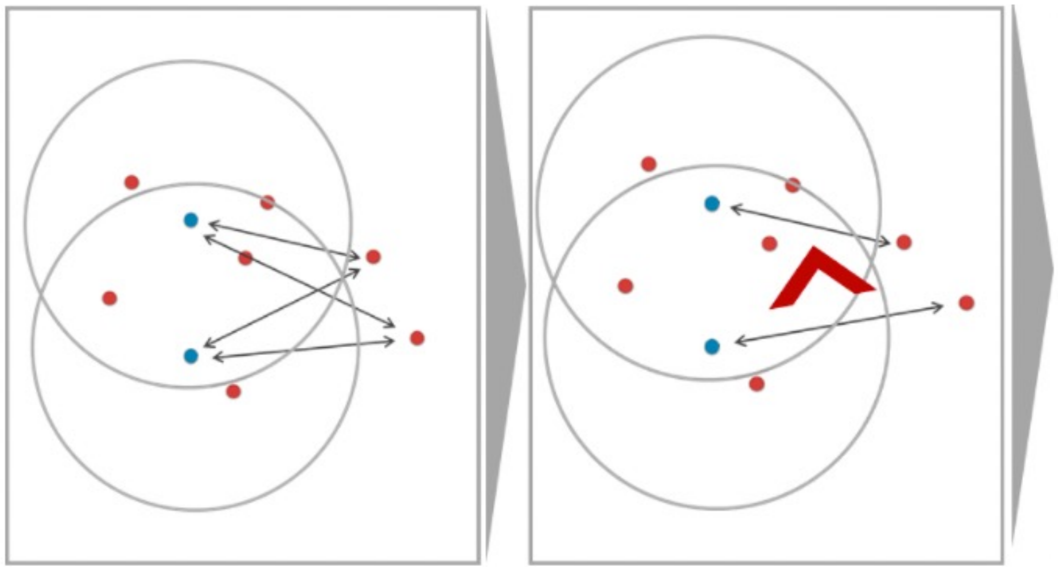
- k-Center-Greedy Algorithm

  1. Find the shortest distance between the data point and the center of the circle.



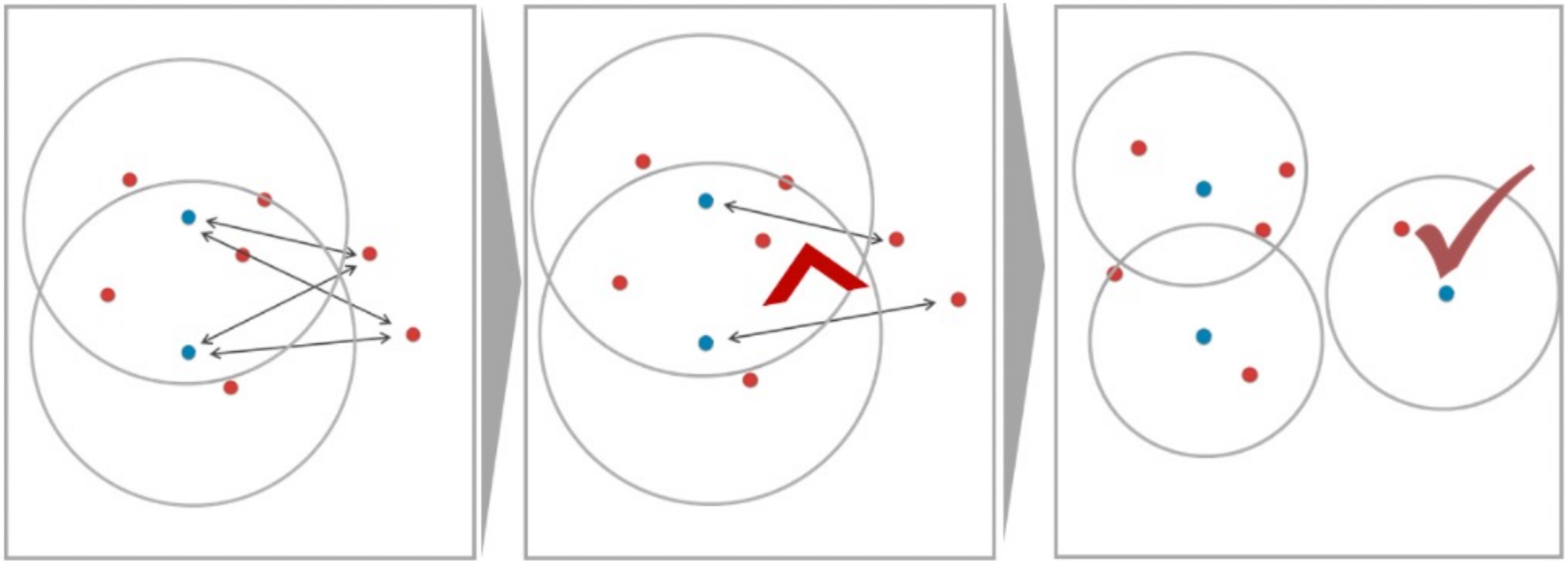
CoreSet

- k-Center-Greedy Algorithm
  1. Find the shortest distance between the data point and the center of the circle.
  2. Select the longest distance among them.



CoreSet

- k-Center-Greedy Algorithm
    1. Find the shortest distance between the data point and the center of the circle.
    2. Select the longest distance among them.
    3. Define new Core-set.

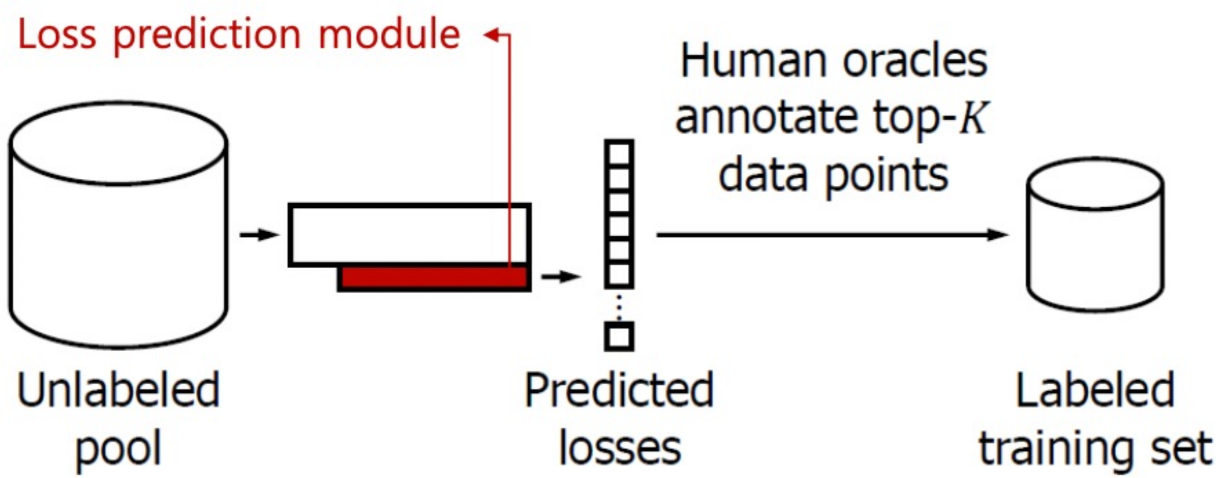


CoreSet

- Advantage
  - Easy to implement.
  - Efficient due to short search time.
- Disadvantage
  - Affected by the density of data.
  - Suffer from outlier.

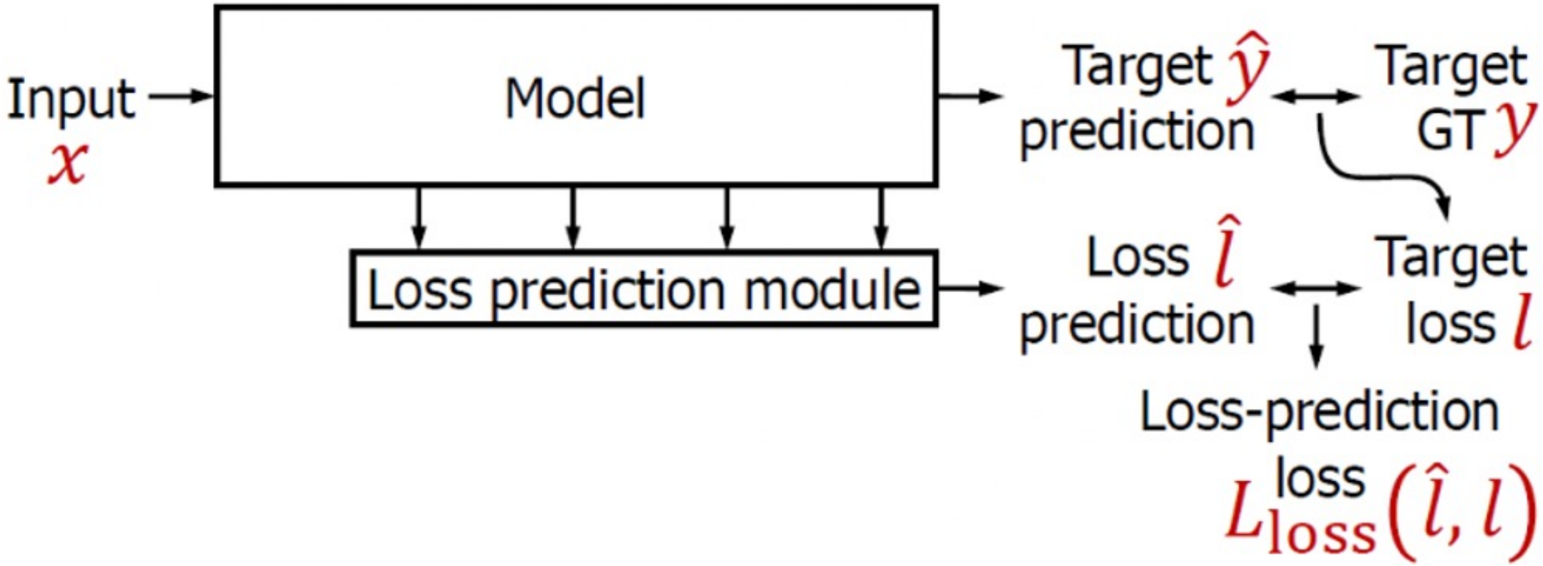
Learning Loss

- Concept
  - Query the sample which has highest loss from unlabeled data.
  - Add loss prediction module to predict top-k data points.



Learning Loss

- Loss function



Learning Loss

- Loss function
  - Constantly decreasing target loss during training.
  - Instead of MSE Loss, using Margin Ranking Loss.
  - MSE Loss:

$$L_{loss}(\hat{l}, l) = \|\hat{l} - l\|^2$$

Scale changes

  - Margin Ranking Loss:

Margin (=1)

$$L_{\text{loss}}(\hat{l}_i, \hat{l}_j, l_i, l_j) = \max\left(0, -\mathbf{1}(l_i, l_j) \cdot (\hat{l}_i - \hat{l}_j) + \xi\right)$$

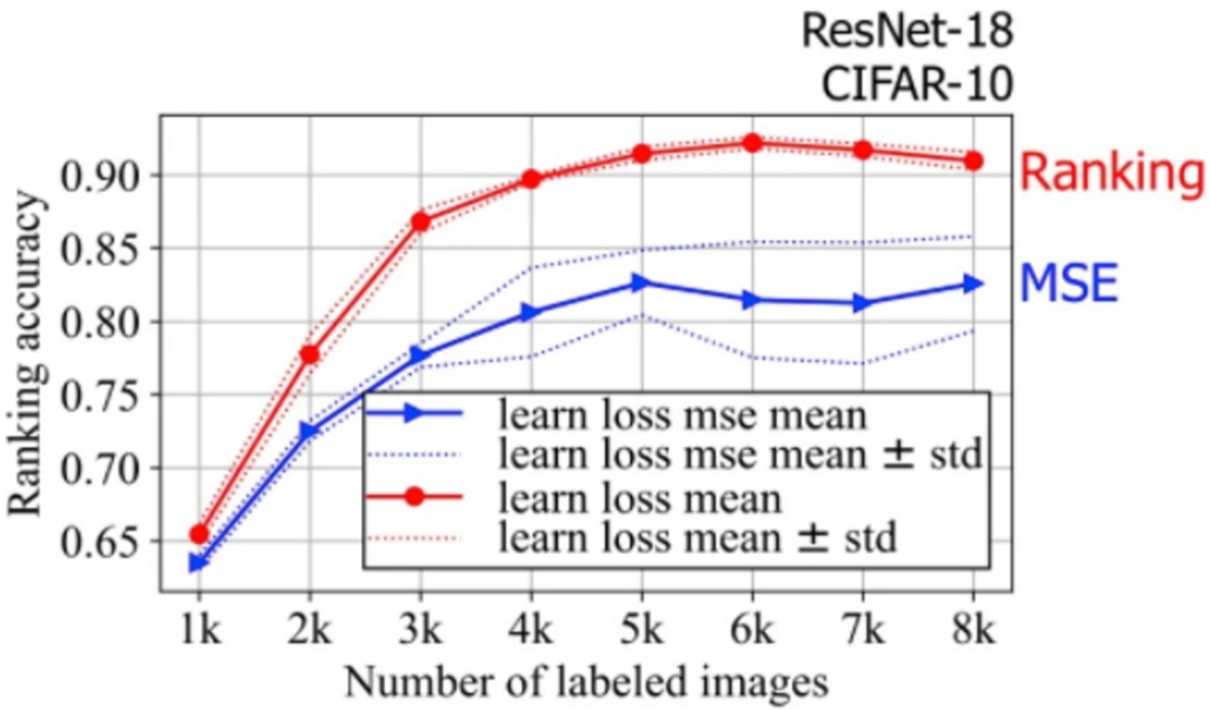
A pair of predicted losses

A pair of real losses

$$\text{where} \quad \mathbf{1}(l_i, l_j) = \begin{cases} +1, & \text{if } l_i > l_j \\ -1, & \text{otherwise} \end{cases}$$

Learning Loss

- Loss function
  - MSE Loss vs. Ranking Loss

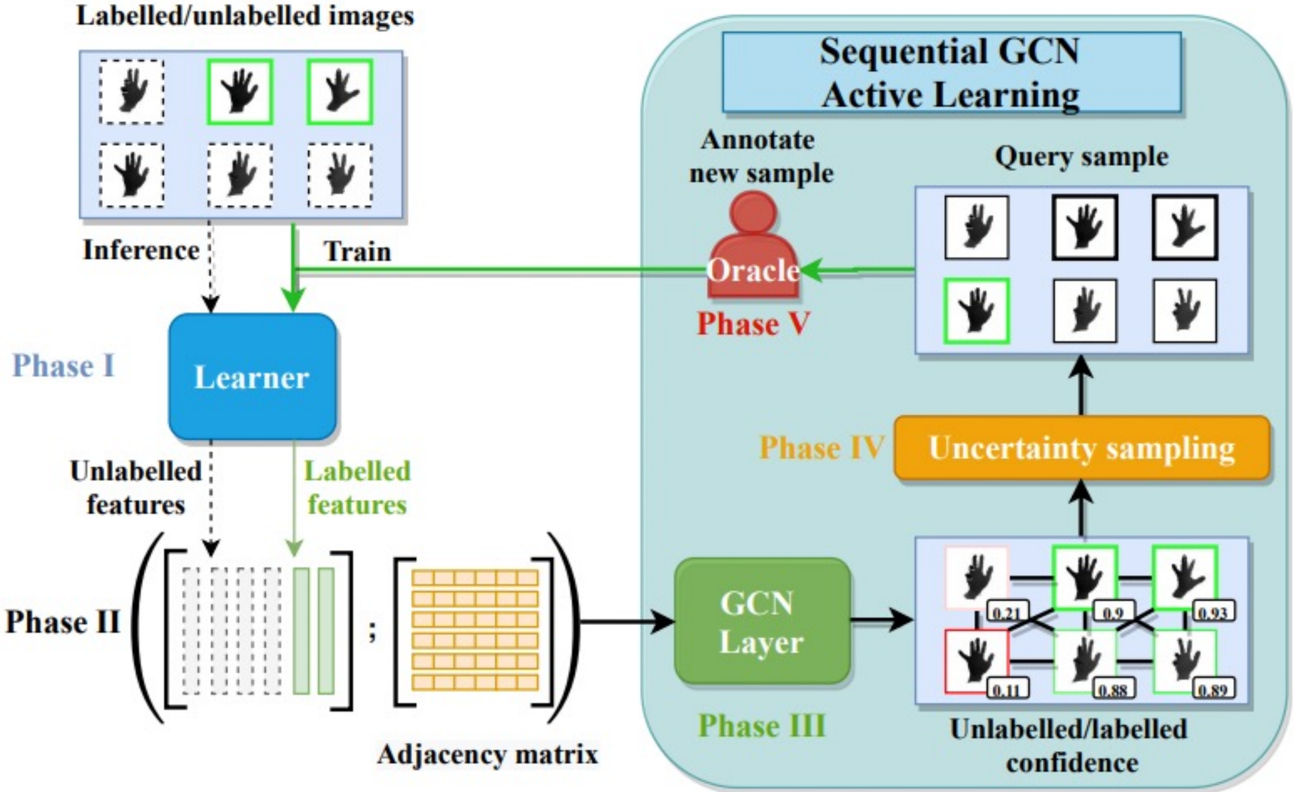


Learning Loss

- Advantage
  - Task-agnostic.
  - End-to-end training.
- Disadvantage
  - Not considered diversity and density.
  - Lack of correlation between the labeled and unlabeled data.

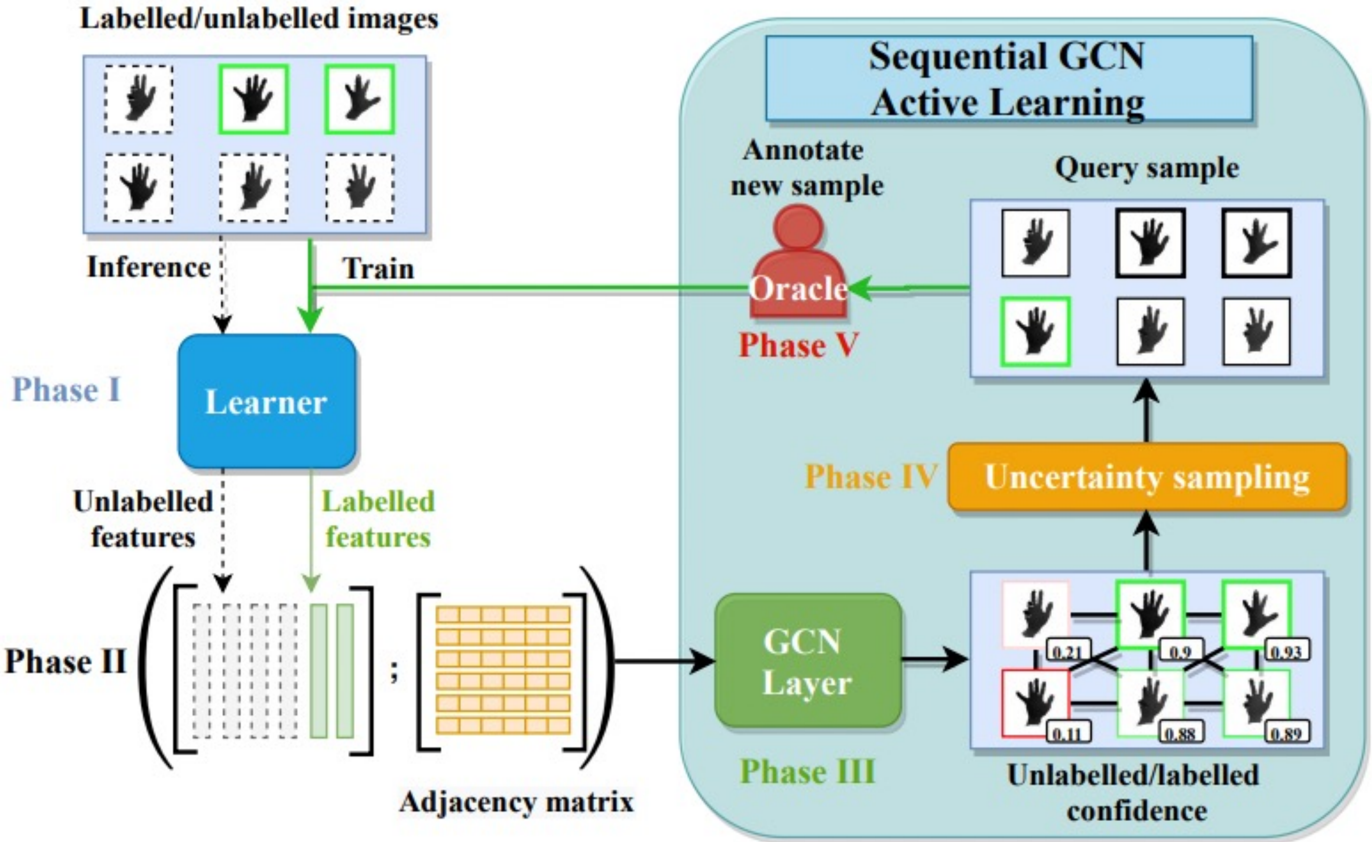
For Hand Pose Estimation

- Sequential Graph Convolutional Network for Active Learning
  - Accepted as Poster at CVPR 2021



Components of AL framework

- Learner, Sampler, Annotator



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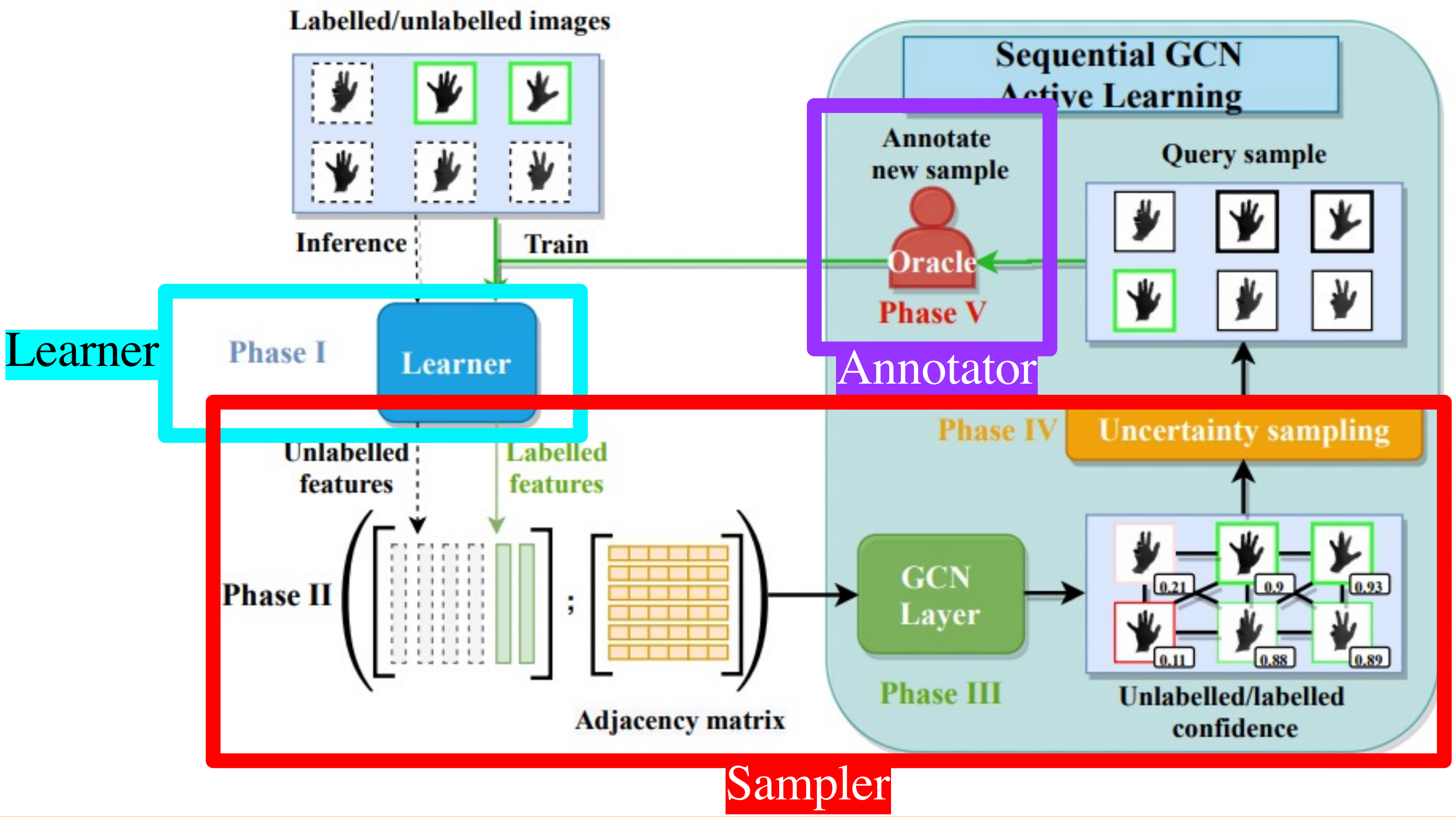


Learner

- Goal
  - Minimize the objective of target task.
  - Objective may change depending on the task to be dealt with.
- Classification
  - Objective function (cross-entropy):

$$\mathcal{L}^c_{\mathcal{M}}(\mathbf{x}, \mathbf{y}; \theta) = -\frac{1}{N_l} \sum_{i=1}^{N_l} \mathbf{y}_i \log(f(\mathbf{x}_i, \mathbf{y}_i; \theta)),$$

Learner

- Goal
  - Minimize the objective of target task.
  - Objective may change depending on the task to be dealt with.
- Regression
  - Objective function:

$$\mathcal{L}^{r}_{\mathcal{M}}(\mathbf{x}, \mathbf{y}; \theta) = \frac{1}{N_l} \sum_{i=1}^{N_l} \left(\frac{1}{J} \sum_{j=1}^{J} \| \mathbf{y}_{i,j} - f(\mathbf{x}_{i,j}, \mathbf{y}_{i,j}; \theta) \|^2 \right)$$

- Other tasks
  - Just modify the learner.
  - The rest of pipeline remains the same.

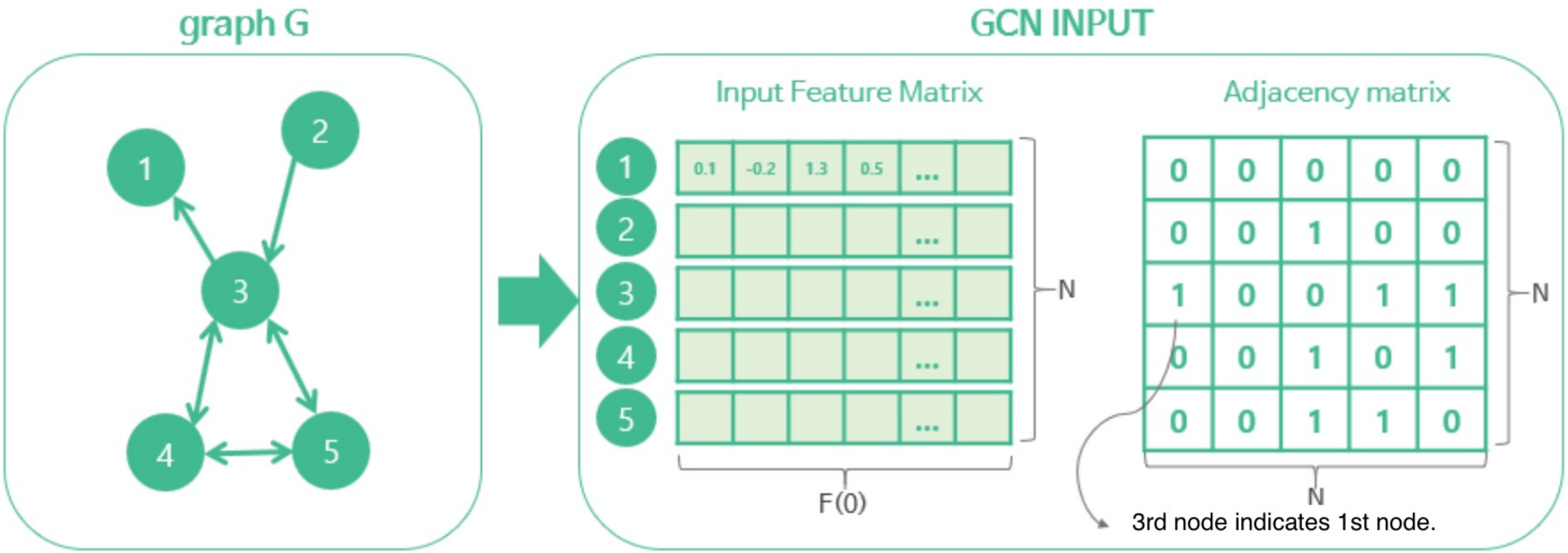
Sampler

- Goal
  - Select the representative unlabeled examples within a fixed budget to deliver the highest performance.
- Mechanism
  - From a pool of unlabeled dataset D_U, randomly select an initial batch for labelling $D_0 \subset D_U$.
  - Achieve minimum loss with the least number of batches D_n.

$$\min_{n} \min_{\mathcal{L}_{\mathcal{M}}} \mathcal{A}(\mathcal{L}_{\mathcal{M}}(\mathbf{x}, \mathbf{y}; \theta) | \mathbf{D}_0 \subset \cdots \subset \mathbf{D}_n \subset \mathbf{D}_U).$$

Sampler

- Graph Convolutional Network



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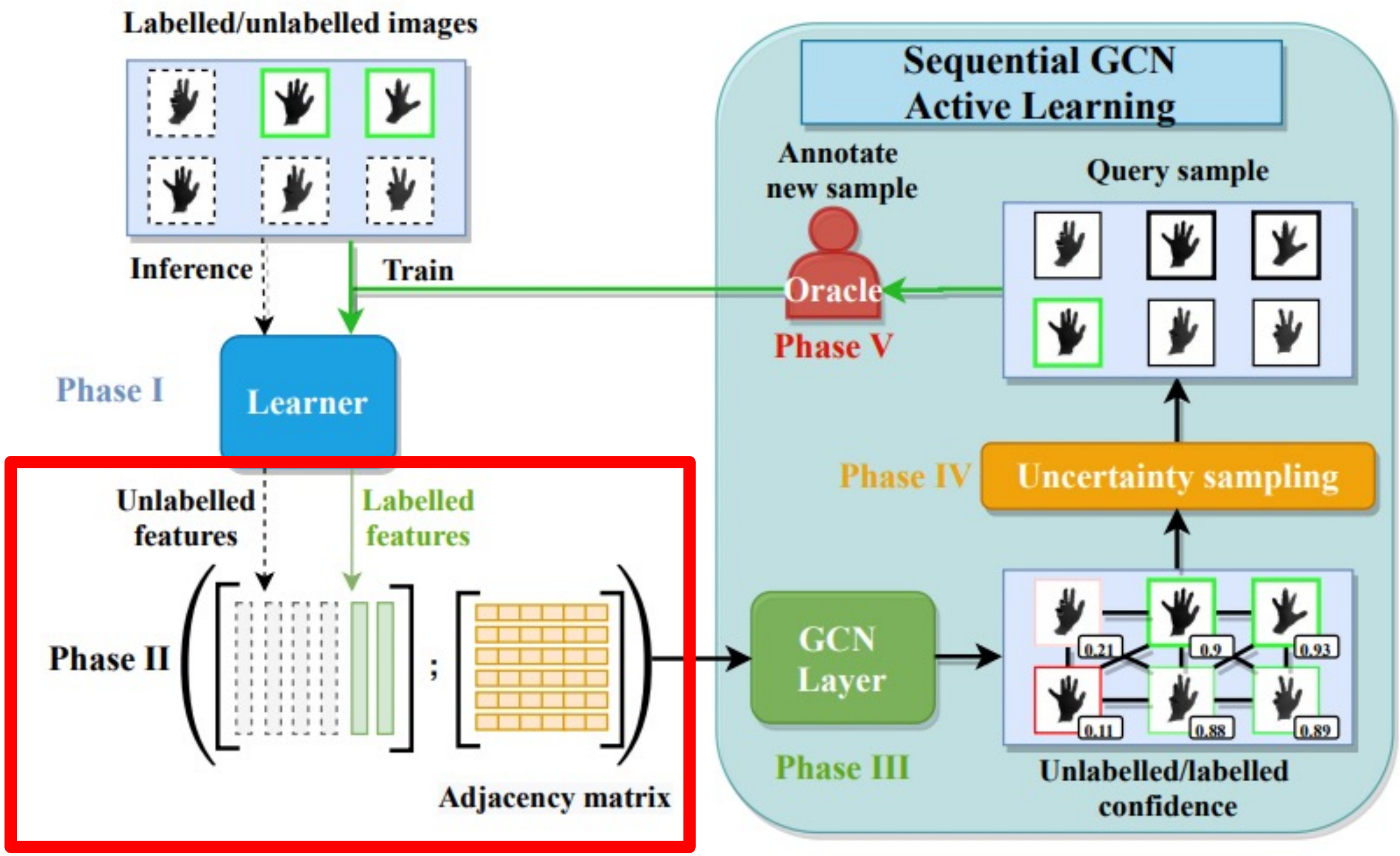
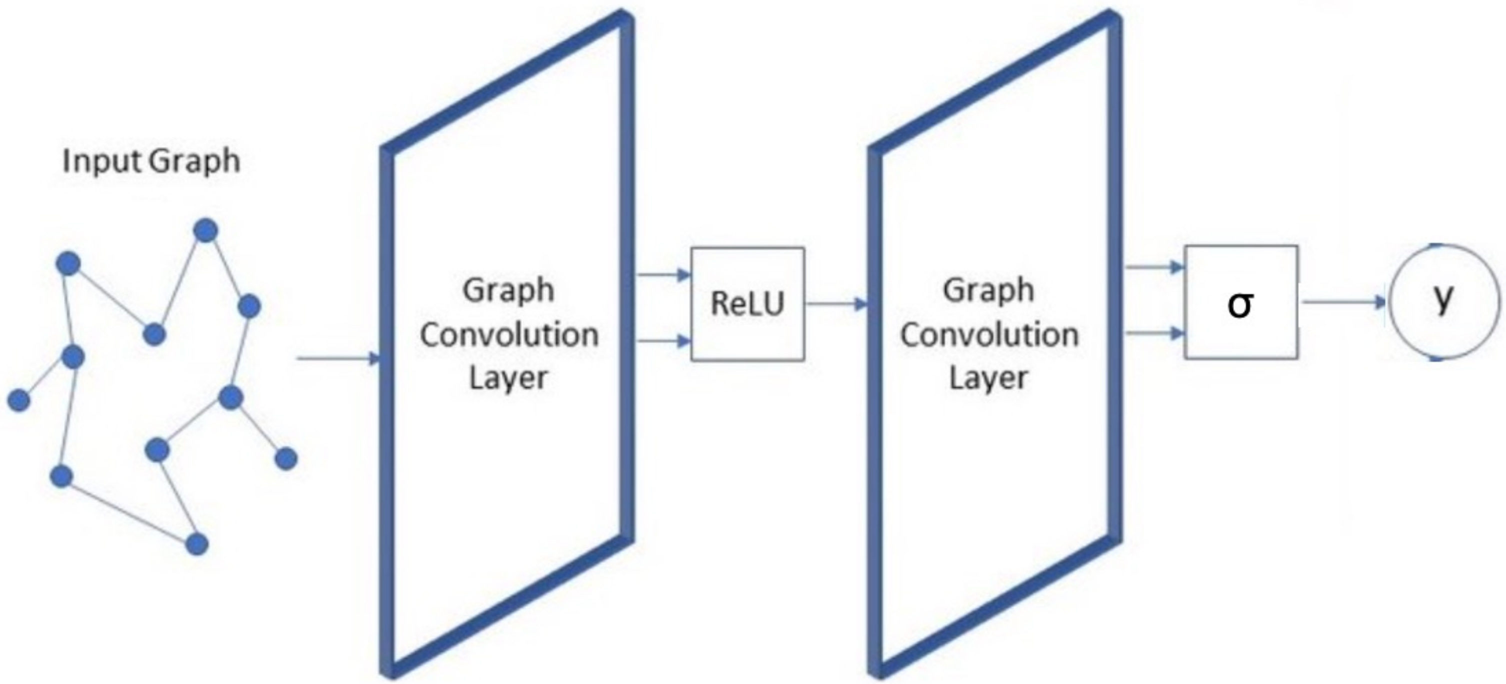


Sampler

- Graph Convolutional Network
  - Proposed Architecture



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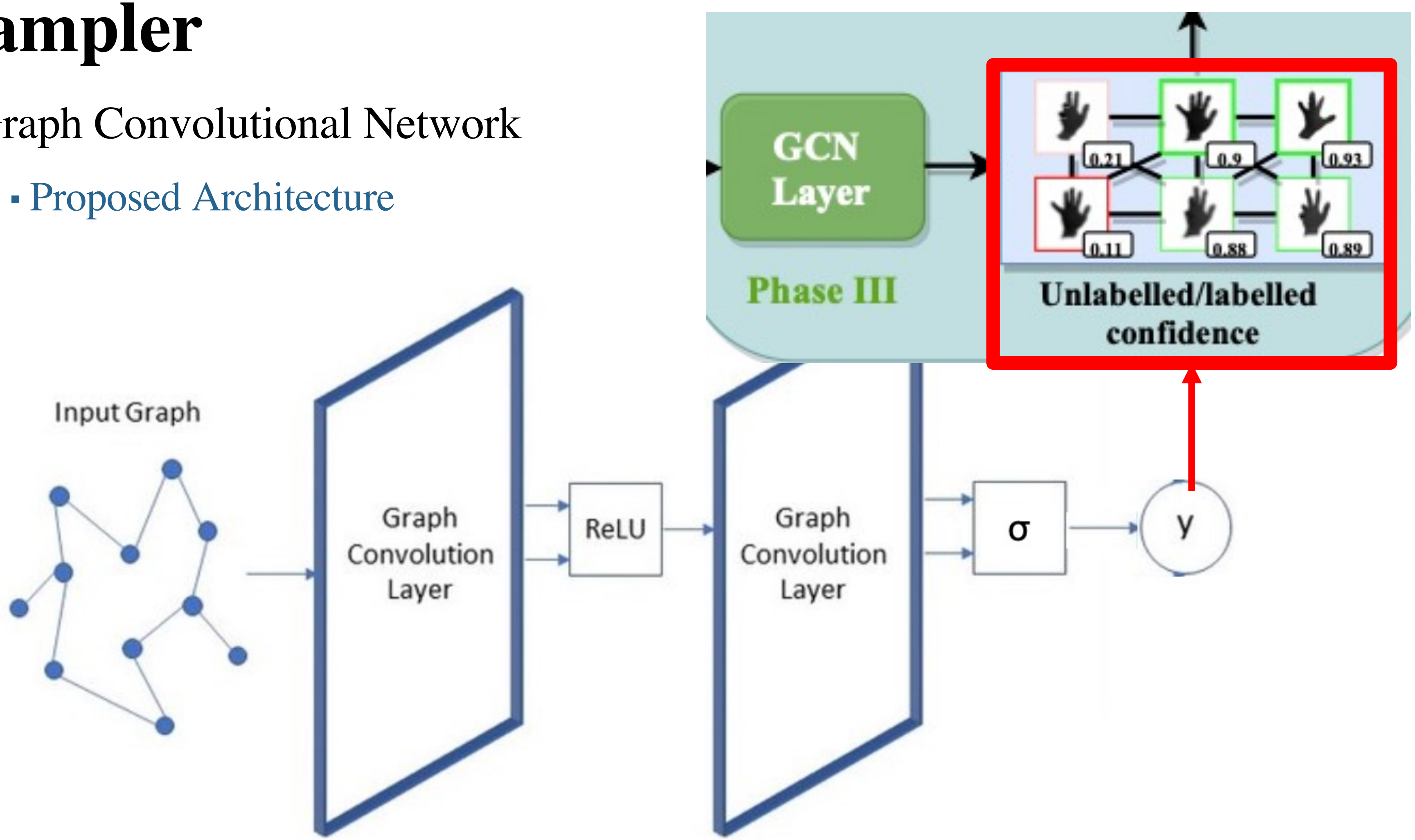

Sampler

- UncertainGCN: Uncertainty sampling on GCN

$$\mathbf{D}_L = \mathbf{D}_L \cup \underset{i=1\cdots b}{\arg\max} |s_{margin} - f_{\mathcal{G}}(\mathbf{v}_i; \mathbf{D}_U)|.$$

- CoreGCN: CoreSet sampling on GCN

$$\mathbf{D}_L = \mathbf{D}_L \cup \underset{i \in \mathbf{D}_U}{\arg\max} \min_{j \in \mathbf{D}_L} \delta(f^1_{\mathcal{G}}(A, \mathbf{v}_i; \Theta_1), f^1_{\mathcal{G}}(A, \mathbf{v}_j; \Theta_1))$$

UncertainGCN: Uncertainty sampling on GCN

- After training on GCN, move to selection.
- From D_U, draw confidence scores $f_g(v_i; D_U)$ as output of GCN.
- Using this score, select the unlabeled images with UncertainGCN.
- Apply the following equation:

$$\mathbf{D}_L = \mathbf{D}_L \cup \underset{i=1\cdots b}{\arg\max} |s_{margin} - f_{\mathcal{G}}(\mathbf{v}_i; \mathbf{D}_U)|.$$

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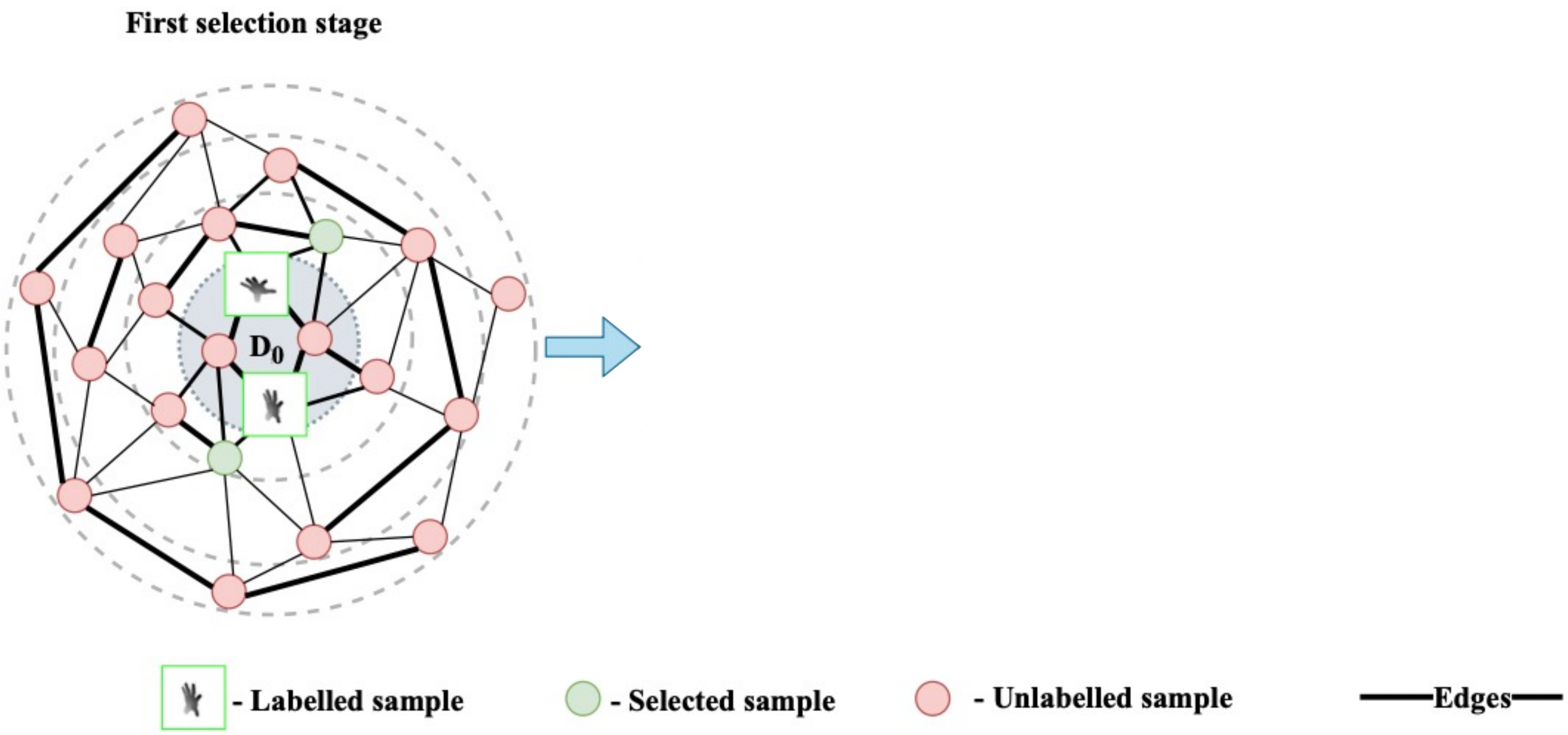

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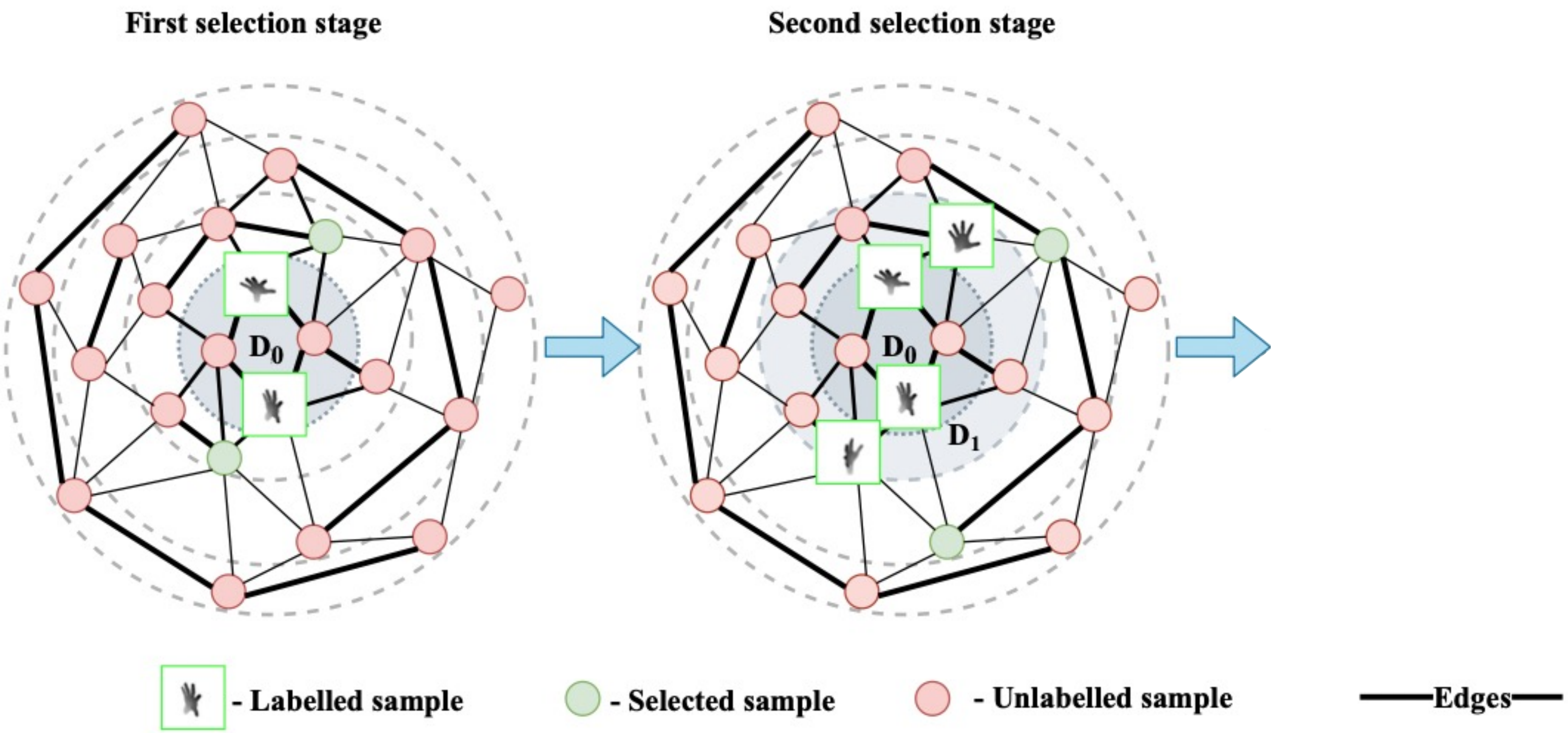

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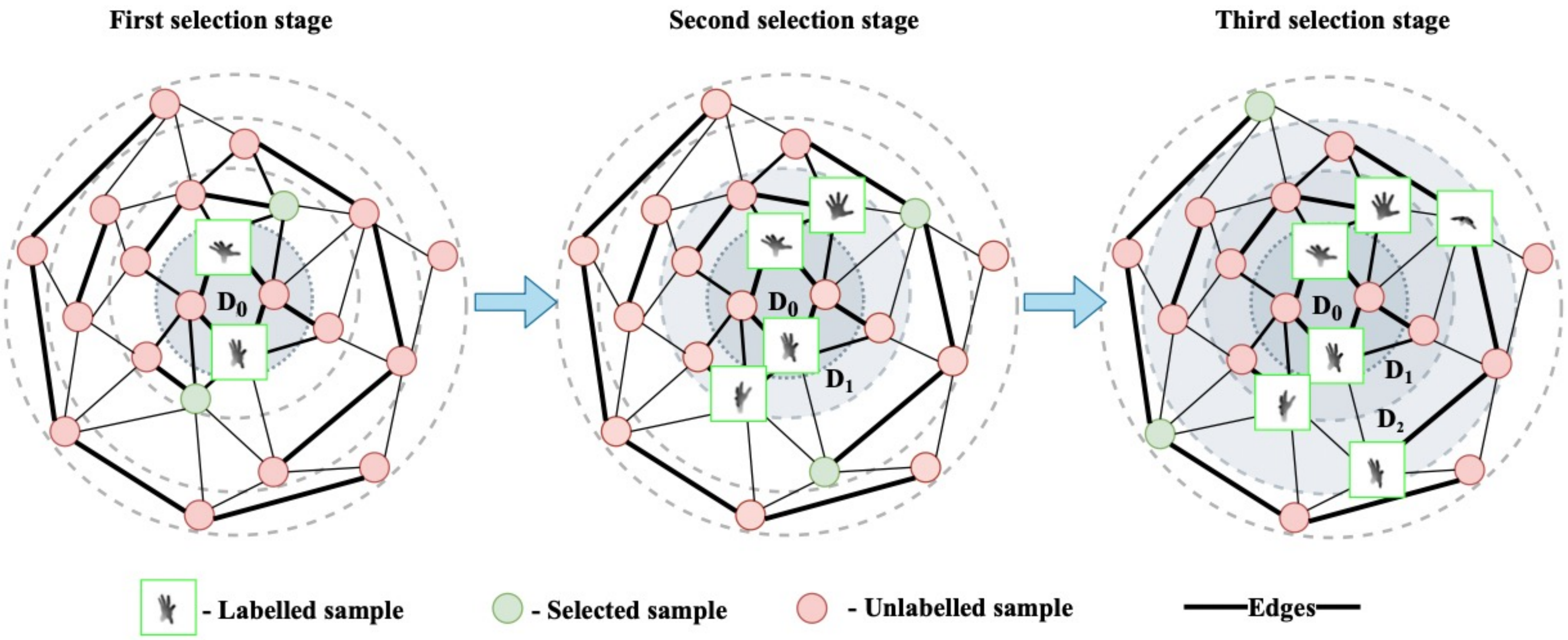

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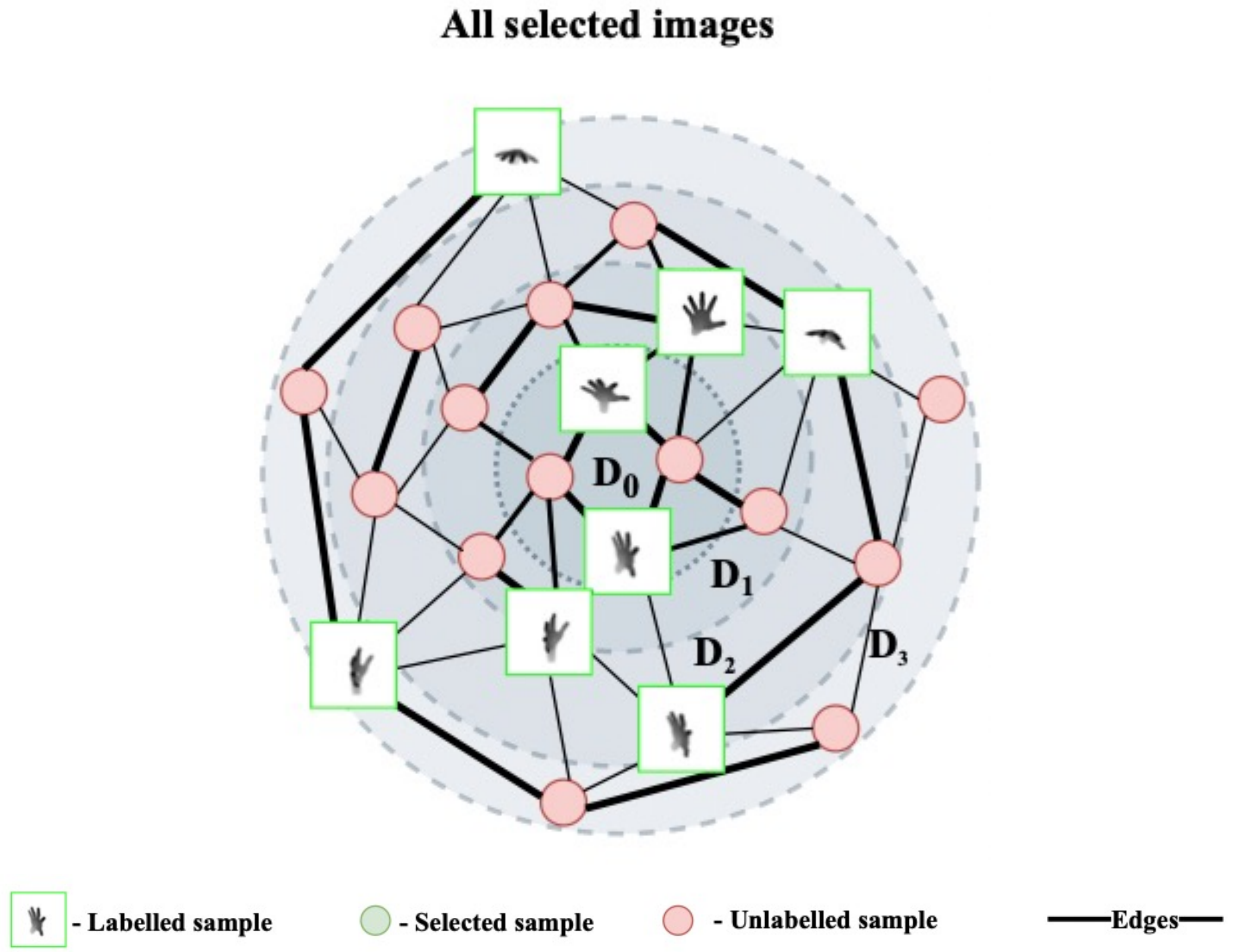

CoreGCN: CoreSet sampling on GCN

- Approach CoreSet technique
  - To integrate geometric information between the labeled and unlabeled graph representation.
  - Apply the following equation:

$$\mathbf{D}_L = \mathbf{D}_L \cup \underset{i \in \mathbf{D}_U}{\arg\max} \min_{j \in \mathbf{D}_L} \delta(f_{\mathcal{G}}^1(A, \mathbf{v}_i; \Theta_1), f_{\mathcal{G}}^1(A, \mathbf{v}_j; \Theta_1))$$

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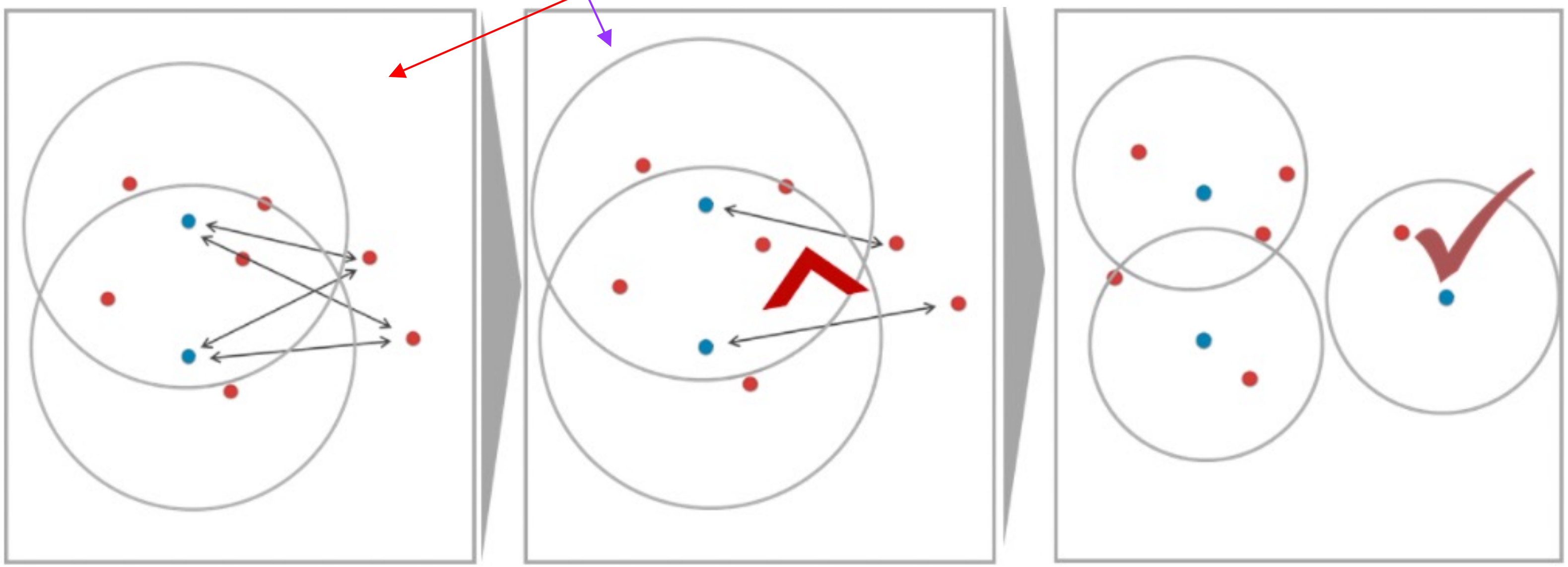
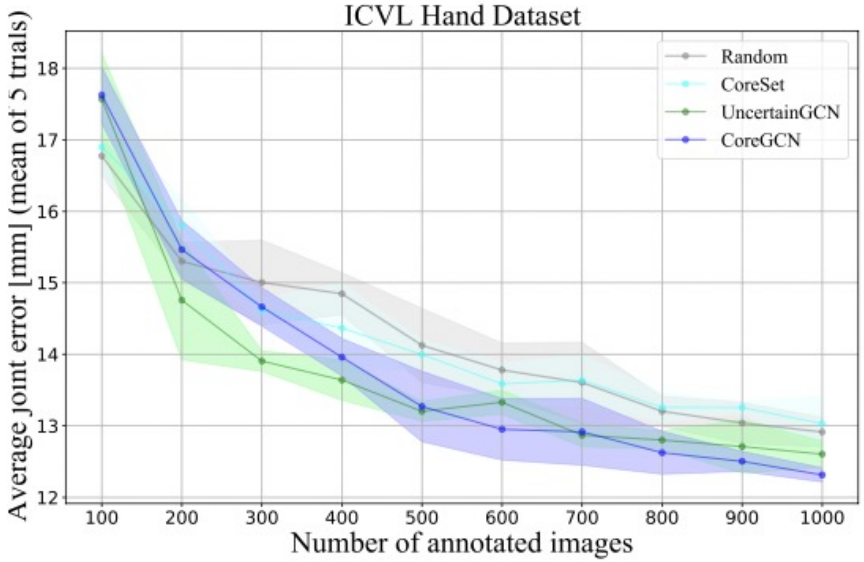


Experiment

- 3D Hand Pose Estimation



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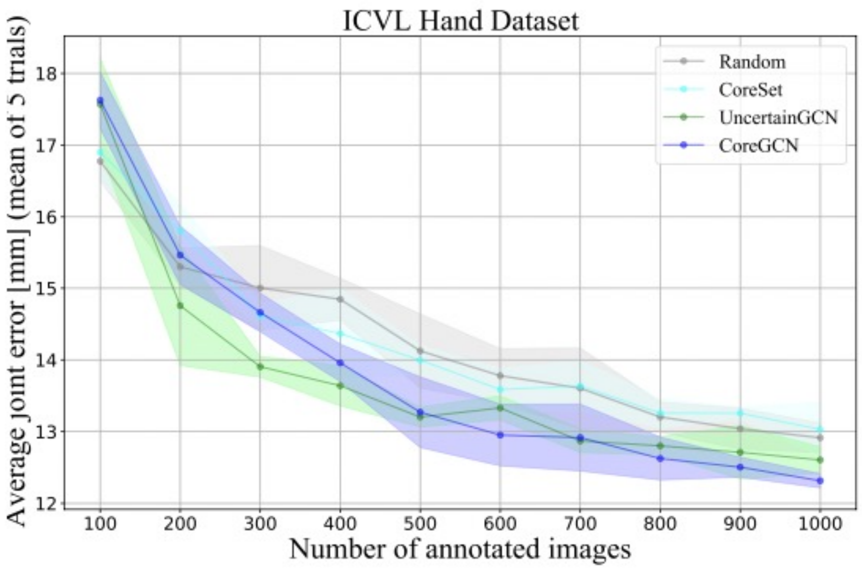

Methods	Mean error (mm)			Input	Type
	ICVL	MSRA	NYU		
DeepModel [46]	11.56	-	17.04	2D	R
DeepPrior [27]	10.4	-	19.73	2D	R
Ren-4x6x6 [14]	7.63	-	13.39	2D	R
Ren-9x6x6 [42]	7.31	9.7	12.69	2D	R
DeepPrior++ [26]	8.1	9.5	12.24	2D	R
Pose-Ren [3]	6.79	8.65	11.81	2D	R
DenseReg [42]	7.3	**7.2**	10.2	2D	D
CrossInfoNet [6]	6.73	7.86	10.08	2D	R
JGR-P2O [8]	6.02	7.55	**8.29**	2D	D
3DCNN [11]	-	9.6	14.1	3D	R
SHPR-Net [4]	7.22	7.76	10.78	3D	R
HandPointNet [9]	6.94	8.5	10.54	3D	R
Point-to-Point [12]	6.3	7.7	9.10	3D	D
V2V [24]	6.28	7.59	8.42	3D	D

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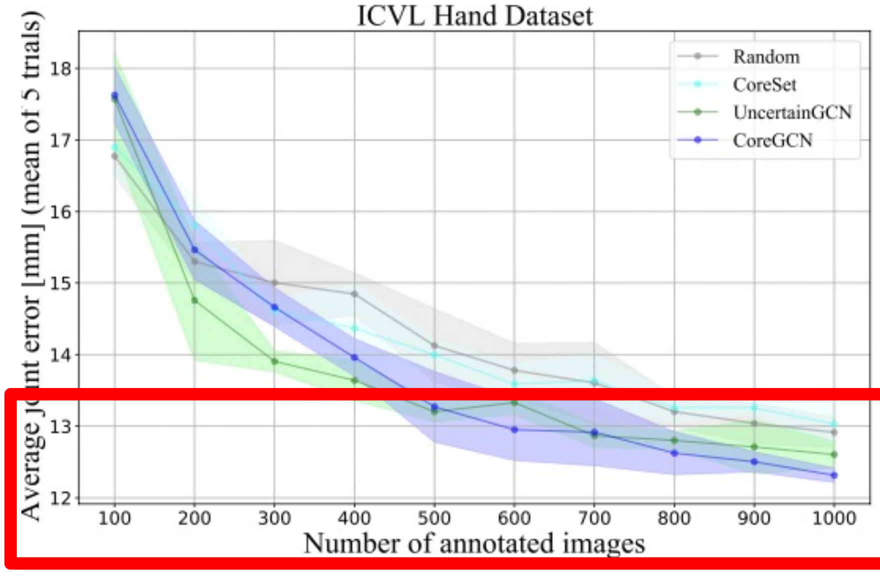

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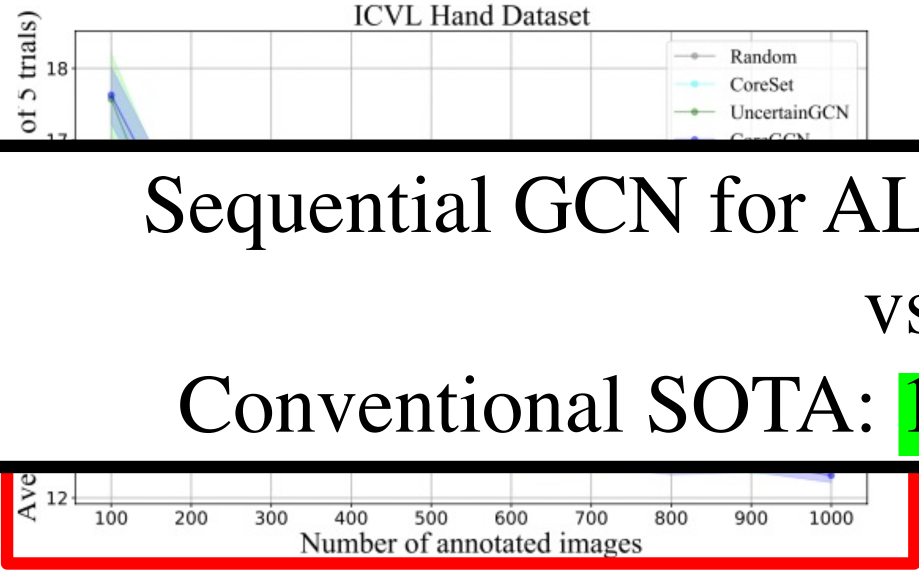

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V2V [24]	6.28	7.59	8.42	3D	D

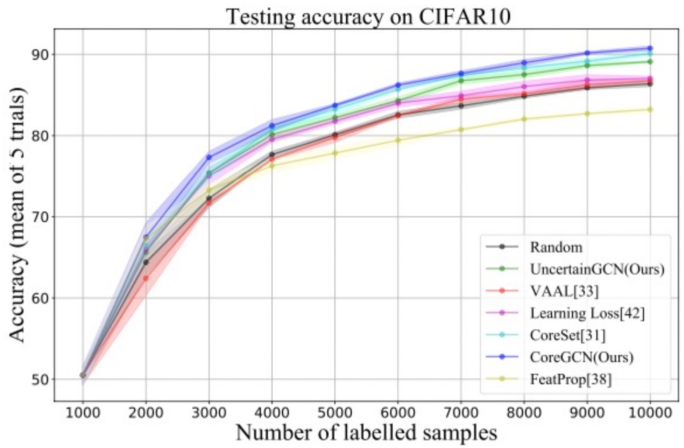
Sequential GCN for AL: 1,000 labeled images

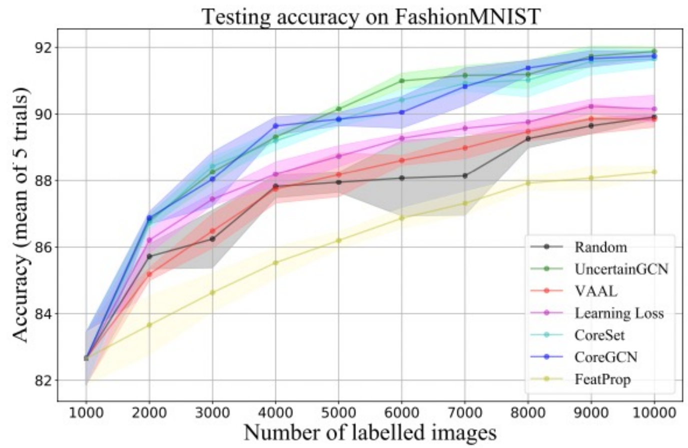
vs.

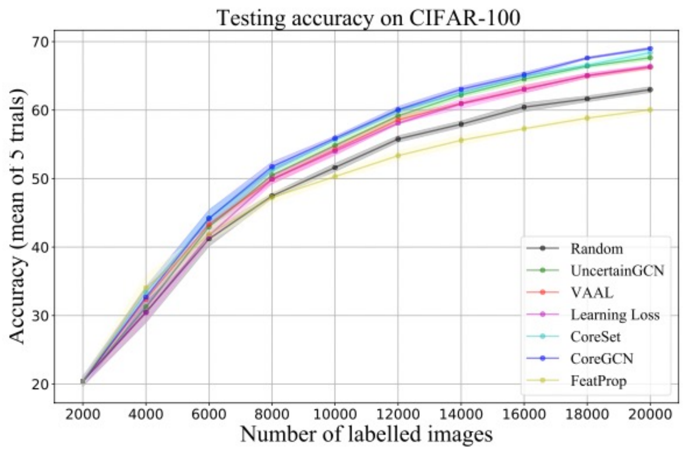
Conventional SOTA: 16,004 labeled images

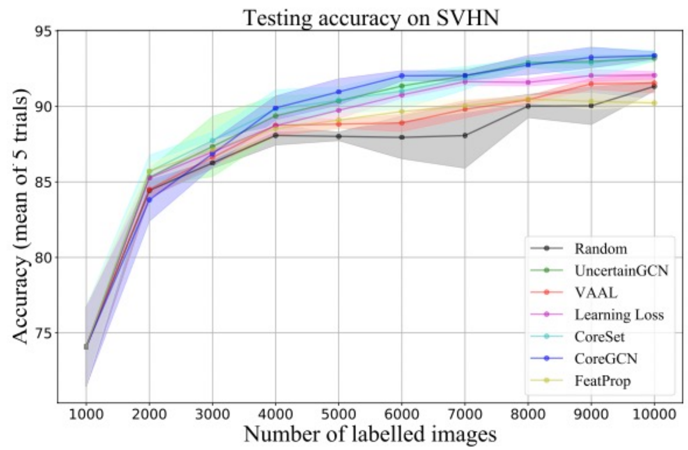
Experiment

- Image Classification









Conclusion

- Benefit of Active Learning
  - The more important data is picked, the lower the cost and the higher the performance will be.
- Compared with Semi-supervised learning
  - Active Learning with Pseudo-Labels for Multi-View 3D Pose Estimation
    - Meta Reality Labs
- Limitations
  - Need more elaborate method.
- Future work
  - Apply to Interacting-hand Pose Estimation.

References

1. Razvan Caramalau, Binod Bhattarai, and Tae-Kyun Kim. Sequential Graph Convolutional Network for Active Learning. In CVPR, 2021.
2. Sener and Silvio Savarese. Active Learning for Convolutional Neural Networks: A Core-set approach. In ICLR, 2018.
3. Donggeun Yoo and In So Kweon. Learning Loss for Active Learning. In CVPR, 2019.