

# Learning to Distinguish Samples for Generalized Category Discovery

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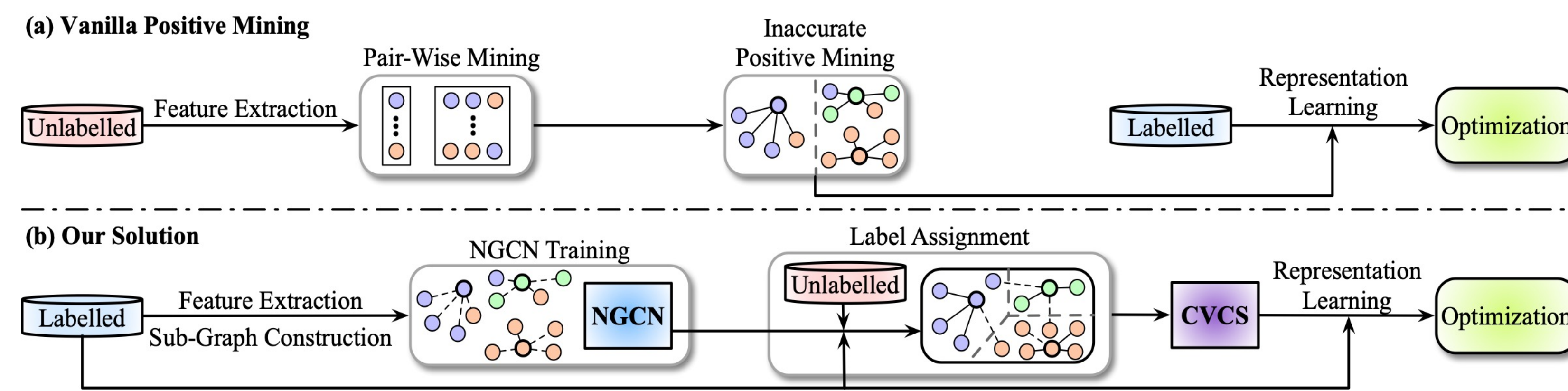
## Problem Formulation



**Definition:** Using partially labelled data to optimize model and recognize known / unknown categories [a].

**Approach:** Assigning pseudo-labels for representation learning.

## Contributions



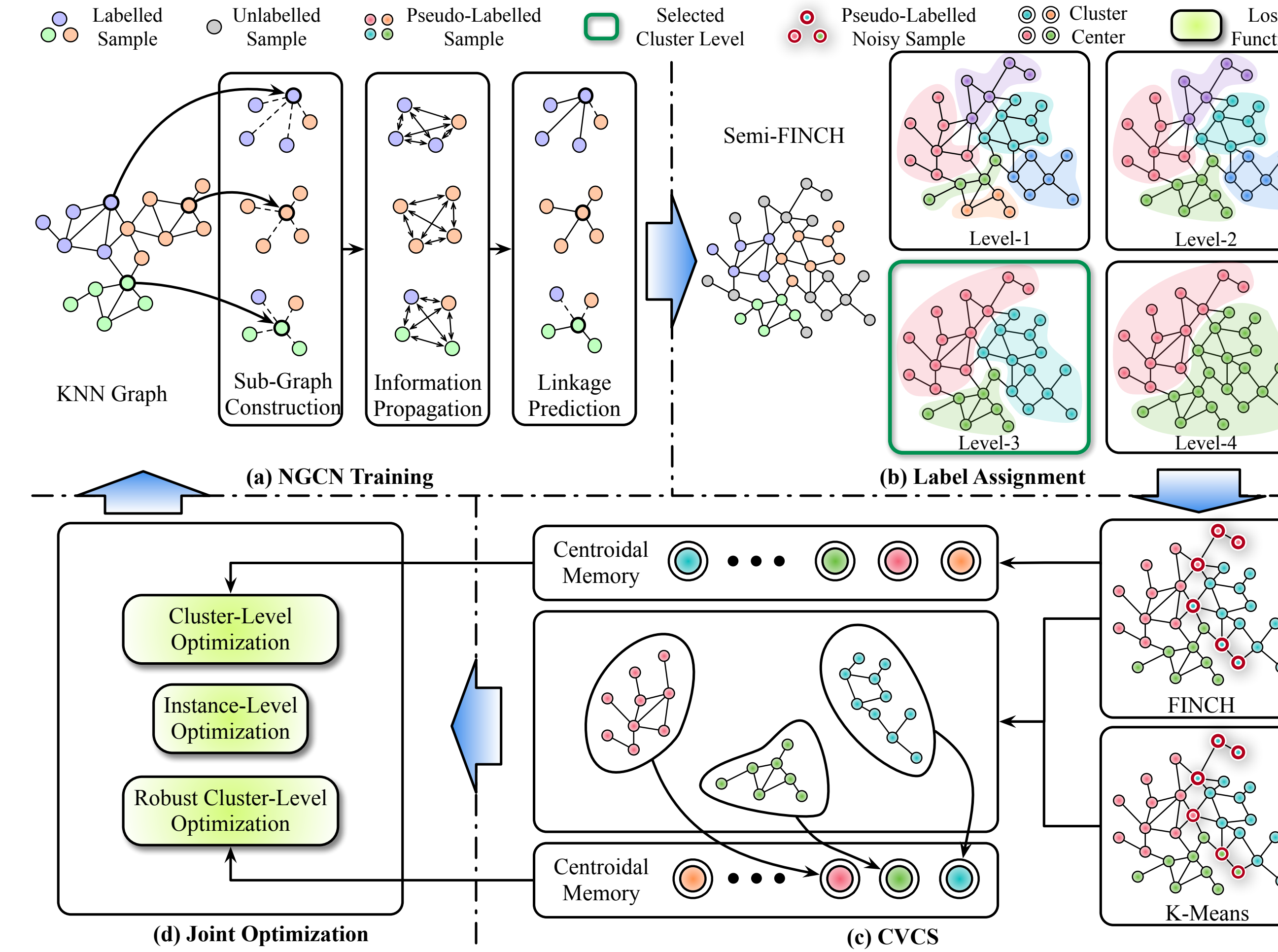
### Background

- (1) Concurrent methods [a,b] predict pseudo-labels based on pairwise similarities, while the overall relationships within each instance's neighbors are largely overlooked.
- (2) Moreover, the inaccurate pseudo labels may hinder the further improvement of GCD accuracies.

### Contributions

- (1) We construct sub-graphs based on each labelled instance's  $k$ -nearest neighbors and optimize Neighbor Graph Convolutional Network (NGCN) to extract neighbor-wise relations for pseudo labelling. NGCN is then used to predict pseudo labels of unlabelled data.
- (2) We propose Cross-View Consistency Strategy (CVCS) to locate and exclude noisy labels from training, which is achieved by comparing clusters from two different clustering algorithms.
- (3) NGCN and CVCS are plug-and-play modules, which can be easily incorporated into other GCD methods for better accuracies.

## Framework



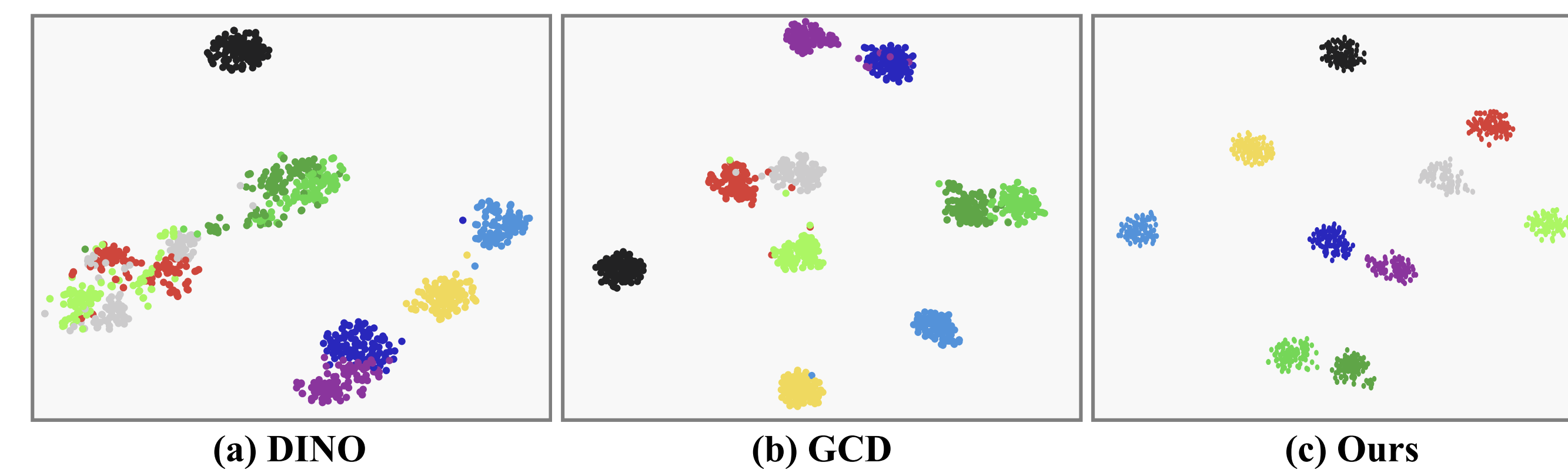
Step 1: Optimizing NGCN with  $k$ NN of labelled data.

Step 2: Adopting NGCN to predict linkage of unlabelled data for clustering.

Step 3: Using CVCS and another clustering method to exclude noisy labels.

Step 4: Optimizing GCD model to recognize known / unknown categories.

## Visualization



**Conclusion:** Features learned with our method is more discriminative and shows clear inter-class boundary than others.

## Contact Us

If you have any problem, please send an email to us ([yangfx@stu.xmu.edu.cn](mailto:yangfx@stu.xmu.edu.cn)) or ask in Github.

Scan QR code for code and other resources.



## Experiments

Methods	CF10			CF100			IN100		
	All	Old	New	All	Old	New	All	Old	New
UNO+ [10]	68.6	<b>98.3</b>	53.8	69.5	80.6	47.2	70.3	95.0	57.9
RankStats+ [13]	46.8	19.2	60.5	58.2	77.6	19.3	37.1	61.6	24.8
GCD [35]	91.5	97.9	88.2	73.0	76.2	66.5	74.1	89.8	66.3
XCon [9]	96.0	97.3	95.4	74.2	81.2	60.3	77.6	93.5	69.7
DCCL [28]	96.3	96.5	<b>96.9</b>	<b>75.3</b>	<b>76.8</b>	<b>70.2</b>	<b>80.5</b>	90.5	<b>76.2</b>
This Work	<b>96.5</b>	97.6	94.4	74.6	76.5	69.4	78.1	<b>91.3</b>	70.5

Methods	Pets			CUB			SCars		
	All	Old	New	All	Old	New	All	Old	New
UNO+ [10]	-	-	-	35.1	49.0	28.1	35.5	<b>70.5</b>	18.6
RankStats+ [13]	-	-	-	33.3	51.6	24.2	28.3	61.8	12.1
GCD [35]	80.2	85.1	77.6	51.3	56.6	48.7	39.0	57.6	29.9
XCon [9]	86.7	91.5	84.1	52.1	54.3	51.0	40.5	58.8	31.7
DCCL [28]	<b>88.1</b>	88.2	88.0	<b>63.5</b>	60.8	<b>64.9</b>	43.1	55.7	36.2
This Work	87.2	<b>91.2</b>	<b>89.6</b>	61.3	<b>60.8</b>	62.1	<b>44.3</b>	58.2	<b>39.1</b>

**Tab. 1** Results under “ $k$ -unknown” Scenario

Methods	CF100			IN100		
	All	Old	New	All	Old	New
SimGCD [37]	80.1	81.2	77.8	83.0	93.1	77.9
PromptCAL [41]	81.2	84.2	75.3	83.1	92.7	78.3
Ours + PromptCAL	<b>82.5</b>	<b>86.6</b>	<b>78.2</b>	<b>83.8</b>	<b>93.2</b>	<b>79.0</b>

Methods	CUB			SCars		
	All	Old	New	All	Old	New
SimGCD [37]	60.3	65.6	57.7	53.8	<b>71.9</b>	45.0
PromptCAL [41]	62.9	64.4	62.1	50.2	70.1	40.6
Ours + PromptCAL	<b>63.8</b>	<b>68.4</b>	<b>63.7</b>	<b>54.7</b>	69.6	<b>45.5</b>

**Tab. 2** Results under “ $k$ -known” Scenario

Method	Attributes		CUB-200			Pets		
	NGCN	CVCS	All	Old	New	All	Old	New
Baseline ( $L_{ins}$ )	×	×	51.3	56.6	48.7	80.2	85.1	77.6
NGCN ( $L_{ins}$ and $L_{ccl}$ )	✓	×	58.3	56.4	59.2	83.3	82.3	83.8
CVCS ( $L_{ins}$ and $L_{rcl}$ )	×	✓	53.5	57.2	52.8	82.6	80.2	83.7
Ours ( $L_{ins}$ , $L_{ccl}$ , and $L_{rcl}$ )	✓	✓	<b>61.3</b>	<b>60.8</b>	<b>62.1</b>	<b>87.2</b>	<b>91.2</b>	<b>86.8</b>

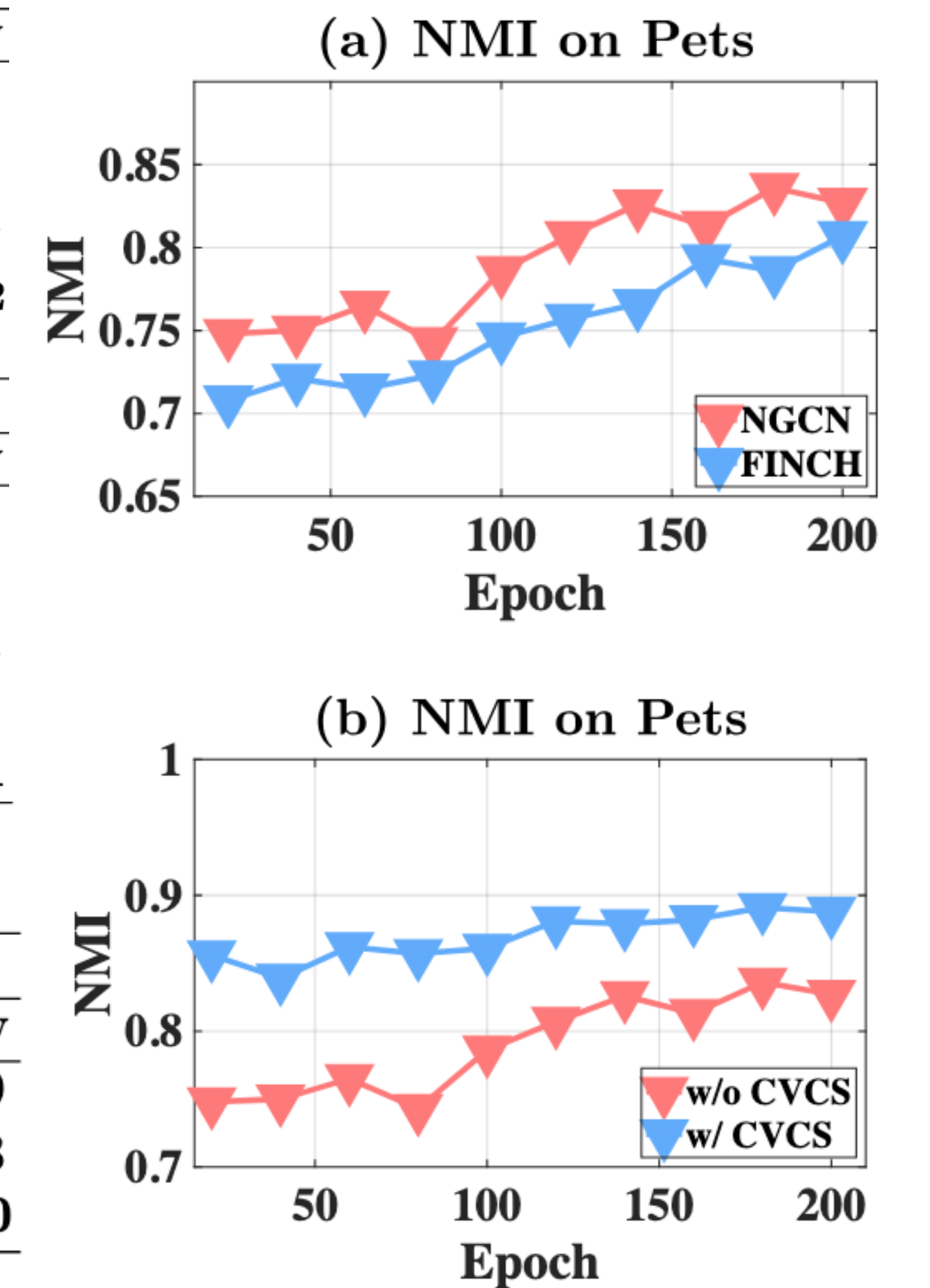
**Tab. 3** Ablation Study

### Conclusions:

- Our method achieves competitive results and can be further incorporated into SoTA methods for better accuracies under both “ $k$ -known” and “ $k$ -unknown” scenario.
- Ablation study show the efficacy of each component. Moreover, visualization of NMI show the efficacy of NGCN and CVCS in terms of clustering.

## References

- [a] Vaze et al. Generalized Category Discovery. CVPR'22.  
 [b] Pu et al. Dynamic Conceptual Contrastive Learning for Generalized Category Discovery. CVPR'23.



**Fig. 1** Quantitative results for (a) NGCN prediction accuracy (b) NMI for clusters before and after using CVCS