A Simple Parametric Classification Baseline for Generalized Category Discovery

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Abstract

Generalized category discovery (GCD) is a problem setting where the goal is to discover novel categories within an unlabelled dataset using the knowledge learned from a set of labelled samples. Recent works in GCD argue that a non-parametric classifier formed using semi-supervised k-means can outperform strong baselines which use parametric classifiers as it can alleviate the over-fitting to seen categories in the labelled set. In this paper, we revisit the reason that makes previous parametric classifiers fail to recognise new classes for GCD. By investigating the design choices of parametric classifiers from the perspective of model architecture, representation learning, and classifier learning, we conclude that the less discriminative representations and unreliable pseudo-labelling strategy are key factors that make parametric classifiers lag behind non-parametric ones. Motivated by our investigation, we present a simple yet effective parametric classification baseline that outperforms the previous best methods by a large margin on multiple popular GCD benchmarks. We hope the investigations and the simple baseline can serve as a cornerstone to facilitate future studies. Our code is available at: https://github.com/CVMI-Lab/SimGCD.

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1. Introduction

With large-scale labelled datasets, deep learning methods can surpass humans in recognising images [20]. However, it is not always possible to collect large-scale human annotations for training deep learning models. Therefore, there is a rich body of recognition models that focus on learning with a large number of unlabelled data. Among them, semi-supervised learning (SSL) [3, 26, 28] is regarded as a promising approach, yet with the assumption that labelled instances are provided for each of the categories the model needs to classify. Generalized category discovery (GCD) [33] is recently formalised to relax this assumption by assuming the unlabelled data can also contain similar yet distinct categories from the labelled data. The goal of GCD is to learn a model that is able to classify the already-seen categories in the labelled data, and more importantly, jointly discover the new categories in the unlabelled data and make correct classifications. Developing a strong method for this problem could help us better utilise the easily available large-scale unlabelled datasets.

Previous works [4, 14, 17, 33] approach this problem from two perspectives: learning generic feature representations to facilitate the discovery of novel categories and generating pseudo clusters/labels for unlabelled data to guide the
learning of a classifier. The former is often achieved by using self-supervised learning methods [7, 15, 17, 19, 40, 41] to improve the generalization ability of features to novel categories. For constructing the classifier, earlier works [4, 14, 17, 40, 43] adopt a parametric approach that builds a learnable classifier on top of the extracted features. The classifier is jointly optimised with the backbone using labelled data and pseudo-labelled data.

However, recent research shows [13, 33] that parametric classifiers are prone to overfit to seen categories and thus promote the use of a non-parametric classifier such as k-means clustering. Albeit obtaining promising results, the non-parametric classifiers suffer from heavy computation costs on large-scale datasets due to the quadratic complexity of the clustering algorithm. For instance, it takes up to 3 hours to obtain a result on the Herbarium 19 dataset [29] with ∼30k images. Besides, unlike a learnable parametric classifier, the non-parametric approach loses the ability to jointly optimise the separating hyperplane of all categories in a learnable manner, potentially being sub-optimal.

This motivates us to revisit the reason that makes previous parametric classifiers fail to recognise new classes for GCD. In a series of investigations (Sec. 3), we find that both the design of prototypical classifiers and the joint representation-classifier training paradigm are not to blame, and the misuse of representations and the unreliable pseudo-labelling strategy contribute to previous methods’ degraded performance. Based on these findings, we thus present a simple parametric classification baseline for generalized category discovery (see Figs. 1 and 7). The representation learning objective follows GCD [33], and the classification objective is simply cross-entropy for labelled samples and self-distillation [1, 7] for unlabelled samples.

The baseline is simple, yet strong, leading to around 10 points’ gains in new class accuracy on both generic image self-distillation [1, 7] for unlabelled samples. It is pointed out in [33] that a non-parametric classifier formed using semi-supervised k-means can outperform strong parametric classification baselines for NCD [14, 17, 40, 42, 43] can be adopted for the GCD problem by extending the classification head to have more outputs [33]. It is pointed out in [33] that a non-parametric classifier formed using semi-supervised k-means can outperform strong parametric classification baselines from NCD [14, 17] because it can alleviate the overfitting to seen categories in the labelled set. In this paper, we revisit this claim and show that parametric classifiers can reach stronger performance than non-parametric classifiers.

Generalized Category Discovery (GCD) is a relatively new problem recently formalised in Vaze et al. [33]. Different from the common assumption of SSL [26], GCD does not assume the unlabelled dataset comes from the same class set as the labelled dataset, posing a greater challenge for designing an effective model. GCD can be seen as a natural extension of the novel category discovery (NCD) problem [18] where it is assumed that the unlabelled dataset and the labelled dataset do not have any class overlap, thus baselines for NCD [14, 17, 40, 42, 43] can be adopted for the GCD problem by extending the classification head to have more outputs [33].

2. Related Works

Semi-Supervised Learning (SSL) has been an important research topic where a number of methods have been proposed [3, 28, 30]. SSL assumes that the labelled instances are available for all possible categories in the unlabelled dataset; the objective is to learn a model to perform classification using both the labelled samples as well as the large-scale available unlabelled data. One of the most effective methods for SSL is the consistency-based method, where the model is forced to learn consistent representations of two different augmentations of the same image [3, 28, 30]. Furthermore, it is also shown that self-supervised representation learning is helpful for the task of SSL [27, 39] as it can provide a strong representation for the task.

Figure 2. Comparisons with representative methods in terms of new class clustering accuracy and label assignment time cost (including post-training clustering time and inference time). Our method (SimGCD) achieves top performance in both metrics.
Deep clustering has shown strong potential for unsupervised representation learning [1, 5–7, 38], unsupervised semantic segmentation [9, 37], semi-supervised learning [2], and novel category discovery [14]. In this work, we explore the techniques that make strong parametric classifiers for GCD with inspirations from deep clustering.

3. What Makes Parametric Classification Fail?

In this section, in order to explore the reason that makes previous parametric classifiers fail to recognise new classes for generalized category discovery, we study four perspectives: classifier architecture (Sec. 3.2), the representation it builds on (Sec. 3.3), the training paradigm and pseudo-labelling strategy (Sec. 3.4). We conclude that: both the design of prototypical classifiers and the joint representation-classifier training paradigm adopted in previous methods are not to blame, and the misuse of representations and the unreliable pseudo-labelling strategy are keys to parametric classifiers’ degraded performance. This is then verified in later ablation studies (Sec. 5.3) and leads to a state-of-the-art parametric classifier for generalized category discovery.

3.1. Investigation Setting

Generalized Category Discovery. Given an unlabelled dataset \( D^u = \{ (x^u_i, y^u_i) \} \in \mathcal{X} \times \mathcal{Y}_u \) where \( \mathcal{Y}_u \) is the label space of the unlabelled samples, the goal of GCD is to learn a model to categorise the samples in \( D^u \) using the knowledge from a labelled dataset \( D^l = \{ (x^l_i, y^l_i) \} \in \mathcal{X} \times \mathcal{Y}_l \) where \( \mathcal{Y}_l \) is the label space of labelled samples and \( \mathcal{Y}_l \subseteq \mathcal{Y}_u \). We denote the number of categories in \( \mathcal{Y}_u \) as \( K_u = |\mathcal{Y}_u| \), it is common to assume the number of categories is known a-priori [14,17,40,43], or can be estimated using off-the-shelf methods [18,33].

Representation Learning. For representation learning, we follow GCD [33], which applies supervised contrastive learning [21] on labelled samples, and self-supervised contrastive learning [8] on all samples (detailed in Sec. 4.1).

Classifiers. We study two types of parametric classifiers: the linear classifier and the prototypical classifier. Considering \( f(x) \) as the feature vector of an image \( x \) extracted using from the backbone, \( f \), the procedure for producing logits is \( l = w^\top f(x) + b \) for a linear classifier parameterised by \( w \) and \( b \), and \( l = \frac{1}{\tau} (w/||w||)^\top (f(x)/||f(x)||) \) for a prototypical classifier. Here \( 1/\tau \) is a factor that scales up the norm of \( l \) and facilitates optimisation of the cross-entropy loss [36]. The major difference between the two classifiers is that the latter has no bias term, and both the weight and the feature are normalised. Therefore, it can be interpreted as a set of learnable prototypes in the same space with the features, and \( l \) is the scaled cosine similarity between them. Besides that, we also adopt a mean classifier, which denotes the \( \ell_2 \)-normalised class-mean prototypes produced from the feature of all samples, and use it to estimate the upper bound of \( k \)-means-style non-parametric classifiers.

Training Settings. We analyse the upper bound of different classifiers by utilising full supervision (The labels in both \( D^l \) and \( D^u \)), and study the lower bound of different settings using minimal supervision (Only the labels in \( D^l \)). For both the full supervision setting and the minimal supervision setting, by default, we only employ a cross-entropy loss on the labelled samples on hand for classification. Note that unless otherwise stated, this is done on detached features, thus representation learning is not affected.

3.2. Why Prototypical Classification?

Motivation. While linear classifiers have been a common choice [28,30] in supervised and semi-supervised learning, prototypical classifiers take a dominant role in deep clustering [6,9,37] and generalized category discovery [4,14]. In this section, we revisit this option by exploring the upper bound and lower bound of different classifiers with different levels of supervision.

Figure 3. Results on the upper bound of different classifiers. In this setting, all labels are available. While the linear classifier conquers this setting, the prototypical classifier still outperforms the mean classifier (upper bound of \( k \)-means). Since all samples are labelled, the difference between ‘Old’ and ‘New’ classes is meaningless, and please refer to the ‘All’ result.

Result & Discussion. In Fig. 3, we show the results with full supervision and explore the upper bound of different classifiers. In this case, the linear classifier easily approaches 100% accuracy on both datasets, which is expected because of the full supervision, and the linear classifier has more flexibility to adjust its parameters without imposing any regularisation as the prototypical classifier
does. However, if imposing minimal supervision (Fig. 4) with only labelled data $D^l$, it does not show as strong performance on new classes as the prototypical classifier. One explanation is that normalisation helps overcome the optimisation bias towards old categories. In our further experiments combined with self-labelling techniques for the unlabelled samples, instability in optimisation is commonly observed for the linear classifier, mainly due to its nature that the norms of the logits are not bounded. Therefore, we endorse the trend of prototypical classification.

**Takeaway Message.** Though linear classifiers have a higher upper bound if full supervision is available, prototypical classifiers are more favoured since they can better recognise new categories with minimal supervision thanks to the natural logit calibration from feature normalisation.

3.3. Which Representation to Build Your Classifier?

**Motivation.** Following the trend of deep clustering that focuses on self-supervised representation learning [6], previous parametric classification work UNO [14] fed the classifier with representations taken from the projector. While in GCD [33], significantly stronger performance is achieved with a non-parametric classifier built upon representations taken from the backbone. We revisit this choice as follows.

**Setting.** Consider $f$ as the feature backbone, and $g$ is a multi-layer perceptron (MLP) projection head. Given an input image $x_i$, the representation from the backbone can be written as $f(x_i)$, and that from the projector is $g(f(x_i))$. We train a prototypical classifier under the full supervision setting with either representation.

![Figure 5](image)

**Figure 5.** Results on classification upper bound with different representations. The larger gap in ‘New’ classes is a result of GCD [33]’s default sampling strategy, and only the full supervision setting is affected. Please refer to the ‘All’ results since the ‘Old’-’New’ split is meaningless in this setting.

**Result & Discussion.** As shown in Fig. 5, the post-backbone feature space has a significantly higher upper bound for learning prototypical classifiers than the post-projector feature space. The use of a projector in self-supervised learning lets the projector focus on solving pretext tasks and allows the backbone to keep as much information as possible (which facilitates downstream tasks) [10]. However, when good classification performance is all you need, our results suggest that the classification objective should build on post-backbone representations directly before the projector. The features after the projector might focus more on solving the pretext task, which might not be necessarily useful for the classification objective.

**Takeaway Message.** The post-backbone feature space, which is not directly optimised for the pretext task, is favourable for the classification objective than the post-projector feature space.

3.4. Decoupled or Joint Representation Learning?

**Motivation.** Previous parametric classification methods, e.g., UNO [14], commonly tune the representations jointly with the classification objective. However, in the non-parametric method GCD [33] where the performance in new classes is notably higher, the representations can be viewed as unaltered by classification when forming the classifier. In this part, we discuss how the classification performance would change if we allow the backbone to be jointly optimised with the classification objective, and explore whether the joint learning strategy contributes to previous parametric classifiers’ degraded performance in new classes.

**Setting.** Consider $f(x)$ as the representation fed to the classifier, decoupled training, as the previous settings adopted, indicates $f(x)$ is detached when computing the logits $l$, thus the classification objective won’t supervise representation learning. While for joint training, the representations are not detached. We train a prototypical classifier under the minimal supervision setting with either the decoupled or joint training paradigm. If w/o self-label, as before, we do not utilise the unlabelled samples; and if w/ self-label, we predict the pseudo-labels for the unlabelled samples with the Sinkhorn Knopp algorithm following [14]. Further, we evaluate the setting w/ self-distill, which depicts another pseudo-labelling strategy as in Fig. 7 and will be introduced in detail in Sec. 4.2.

**Result & Discussion.** The results are illustrated in Fig. 6. When only the ground-truth labels (which are absolutely correct) on hand are utilised, for both datasets, jointly supervising the representation with classifier learning can improve the performance on new categories (1% for CIFAR100 and 5% for CUB), while the results of old classes can drop by a relatively small margin. This is acceptable since we care more about new classes. However, if we also adopt the pseudo-labels (which can be unreliable) produced online for the unlabelled samples, there is a sharp drop in old-class performance on both datasets, while for the new classes, it can improve by 13 points on CIFAR100, and drop by a small margin on CUB. This means that the joint training strategy does not necessarily result in UNO [14]’s low
Figure 6. Results with or without joint training. We adopt the minimal supervision setting and train a prototypical classifier with only labelled samples (w/o self-label) or also utilise the unlabelled samples by either self-labelling (w/ self-label, UNO [14]-style) or self-distillation (w/ self-distill, as in Fig. 7). Decouple denotes the classifier adopts detached features, while Joint indicates the classification objective can affect representation learning.

**Takeaway Message.** Jointly supervising the representation with a classification objective is helpful for parametric classifiers to recognise new classes. One key factor to blame in previous parametric methods is the paradigm for producing pseudo-labels, and when equipped with a more advanced one, the help from joint training can be even more significant.

4. Method

In this section, we present the whole picture of this simple yet effective method (see Fig. 7). And in Sec. 5.3, we discuss the step-by-step changes that lead a simple baseline to our design for generalized category discovery.

4.1. Representation Learning

Our representation learning objective follows GCD [33], which is supervised contrastive learning [21] on labelled samples, and self-supervised contrastive learning [8] on all samples. Formally, given two views (random augmentations) \( x_i \) and \( x'_i \) of the same image in a mini-batch \( B \), the self-supervised contrastive loss is written as:

\[
\mathcal{L}_{\text{rep}} = \frac{1}{|B|} \sum_{i \in B} - \log \frac{\exp \left( \frac{x_i^T z_i'}{\tau_u} \right)}{\sum_{n \neq i} \exp \left( \frac{x_i^T z_n'}{\tau_u} \right)},
\]

where \( \tau_u \) is a temperature value. The supervised contrastive loss is similar, and the major difference is that positive samples are matched by their labels, formally written as:

\[
\mathcal{L}_{\text{rep}}^s = \frac{1}{|B|} \sum_{i \in B} \frac{1}{|N_i|} \sum_{q \in N_i} - \log \frac{\exp \left( \frac{x_i^T z_q'}{\tau_c} \right)}{\sum_{n \neq i} \exp \left( \frac{x_i^T z_n'}{\tau_c} \right)},
\]

where \( N_i \) indexes all other images in the same batch that hold the same label as \( x_i \). The overall representation learning loss is balanced with \( \lambda \):

\[
\mathcal{L}_{\text{rep}} = (1 - \lambda) \mathcal{L}_{\text{rep}}^u + \lambda \mathcal{L}_{\text{rep}}^s,
\]

where \( B^l \) corresponds to the labelled subset of \( B \).

4.2. Parametric Classification

Our parametric classification paradigm follows the self-distillation [1, 7] fashion. Formally, with \( K = |\mathcal{Y}| \cup \mathcal{Y}_u \) denoting the total number of categories, we randomly initialise a set of prototypes \( \mathcal{C} = \{c_1, \ldots, c_K\} \), each standing for the prototype of one category. During training, for each augmented view \( x_i \), we calculate its soft class prediction by softmax on cosine similarity between the hidden feature \( h_i = f(x_i) \) and the prototypes \( \mathcal{C} \) scaled by \( 1/\tau_s \):

\[
p_i^{(k)} = \frac{\exp \left( \frac{1}{\tau_s} \langle h_i, c_k \rangle \right)}{\sum_{k'} \exp \left( \frac{1}{\tau_s} \langle h_i, c_{k'} \rangle \right)},
\]

where
and the soft pseudo-label \( q_i^* \) is produced by another view \( x_i \) with a sharper temperature \( \tau_t \) in a similar fashion. The classification objectives are then simply cross-entropy loss \( \ell(q_i^*, p_i) = - \sum_k q_i^{(k)} \log p_i^{(k)} \) between the predictions and pseudo-labels or ground-truth labels:

\[
\mathcal{L}_{\text{cls}}^u = \frac{1}{|B|} \sum_{i \in B} (\ell(q_i^*, p_i) + \varepsilon H(\overline{p})^u), \quad \mathcal{L}_{\text{cls}}^l = \frac{1}{|B'|} \sum_{i \in B'} (\ell(y_i, p_i)),
\]

(5)

where \( y_i \) denote the one-hot label of \( x_i \). We also adopt a mean-entropy maximisation regulariser [1] for the unsupervised objective. Here \( \overline{p} = \frac{1}{2|B|} \sum_{i \in B} (p_i + p_i') \) denotes the mean prediction of a batch, and the entropy \( H(\overline{p}) = - \sum_k \overline{p}^{(k)} \log \overline{p}^{(k)} \). As we will show in Secs. 5.3 and 5.4, this term helps calibrate the predictions’ class distribution and avoid the presence of “dead” prototypes (to which only one or even none of the samples is assigned), which is commonly observed in previous works [33, 37].

Then the classification objective is \( \mathcal{L}_{\text{cls}} = (1 - \lambda)\mathcal{L}_{\text{cls}}^u + \lambda \mathcal{L}_{\text{cls}}^l \) and the overall objective is simply \( \mathcal{L}_{\text{rep}} + \mathcal{L}_{\text{cls}} \).

**Discussions.** It should be clarified that this work doesn’t aim to promote new methods but to examine existing solutions, provide insights on their failures and build a simple yet strong baseline. The philosophy of producing pseudo-labels from sharpened predictions of another augmented view appears to resemble consistency-based methods [3, 28, 30] in the SSL community. However, despite differences in augmentation strategies and soft/hard pseudo-labels, our approach jointly performs category discovery and self-training style learning, while the SSL methods purely focus on bootstrapping itself with unlabelled data, and does not discover novel categories.

## 5. Experiments

### 5.1. Experimental Setup

**Datasets.** We validate the effectiveness of our method on the generic image recognition benchmark (including CIFAR10/100 [23] and ImageNet-100 [31]), the recently proposed Semantic Shift Benchmark [34] (SSB, including CUB [35], Stanford Cars [22], and FGVC-Aircraft [25]), and also Herbarium 19 [29]. For each dataset, we follow [33] to sample a subset of all classes as the old classes \( \mathcal{Y}_1 \); 50% of the images from these labelled classes are used to construct \( D^l \), and the remaining images are regarded as the unlabelled data \( D^u \). See Tab. 1 for statistics of the datasets we evaluate on.

**Evaluation Protocol.** We evaluate the model performance with clustering accuracy (ACC) following standard practice [33]. During evaluation, given the ground truth \( y^* \) and the predicted labels \( \hat{y} \), the ACC is calculated as \( \text{ACC} = \frac{1}{M} \sum_{i=1}^M \mathbb{1}(q_i^* = p(\hat{y}_i)) \) where \( M = |D^u| \), and \( p \) is the optimal permutation that matches the predicted cluster assignments to the ground truth class labels. Besides, since the split for evaluation of Herbarium 19 is imbalanced, we also report the balanced ACC (calculated as the average of per-class ACCs) to avoid biased evaluation.

**Implementation Details.** Following GCD [33], we train all methods with a ViT-B/16 backbone [12] pre-trained with DINO [7]. We use the output of \( \text{CLS} \) token with a dimension of 768 as the feature for an image, and only fine-tune the last block of the backbone. We train with a batch size of 128, and an initial learning rate of 0.1 decayed with a cosine schedule. For a fair comparison, we train for 200 epochs on each dataset, and the best-performing model is selected using the accuracy on the validation set of the labelled classes. Aligning with [33], the balancing factor \( \lambda \) is set to 0.35, and the temperature values \( \tau_{s, u} \) set to 0.07, 1.0, respectively. For the classification objective, we set \( \tau_u \) to 0.1, and \( \tau_t \) is initialised to 0.07, then warmed up to 0.04 with a cosine schedule in the starting 30 epochs. Besides, the weight \( \varepsilon \) of the regulariser is set to 2. All experiments are done with an NVIDIA GeForce RTX 3090 GPU.

## 5.2. Comparison with the State of the Arts

We compare with state-of-the-art methods in generalized category discovery (ORCA [4] and GCD [33]), strong baselines derived from novel category discovery (RankStats+ [17] and UNO+ [14]), and direct k-means [24] on DINO [7] features. On both the generic image recognition datasets (Tab. 2a) and the harder SSB benchmark (Tab. 2b), our method achieves notable improvements in recognising new classes (across the instances in \( D^u \) that belong to classes in \( \mathcal{Y}_1 \setminus \mathcal{Y}_2 \)), outperforming the SOTAs by around 10%. The results in old classes are relatively lower, yet they are still competitive against the best-performing baselines. Given that the ability to discover new classes is a more desirable ability, the results are quite encouraging.

In Tab. 3, we also report the results on Herbarium 19 [29], a naturally long-tailed fine-grained dataset that is closer to the real-world application of generalized category discovery. One concern is that its test split is also long-tailed, which may conceal the bias of models. Thus we also report the balanced ACC, which is simply the average of per-class vanilla ACCs and avoids the imbalance between...
classes in the metric. Still, our method shows consistent improvements in all metrics. In Fig. 2, we compare the time cost for label assignment with GCD [33], one iconic non-parametric classification method. Let the number of all samples and unlabelled samples be $N$ and $N_u$, the number of classes $K$, feature dimension $d$, and the number of $k$-means iterations to be $t$, the time complexity of GCD is $O(N^2d + NKd t)$ (including $k$-means++ initialisation), while our method only requires a nearest-neighbour prototype search for each instance, with time complexity $O(N_uKd)$. All methods adopt GPU implementation and omit the cost for feature extraction.

5.3. Ablation Study

In Tab. 4, we ablate the key components that bring the baseline method step-by-step to a new SOTA.

Baseline. We start from UNO+ [14], a two-stage parametric classification framework. In the first stage, the backbone is trained with a cross-entropy loss with the labelled samples to learn discriminative features; and in the second stage, it adopts a SwAV [6]-like self-labelling strategy and a classification objective to learn a classifier. The classifier consists of two heads: one for the old classes built on the backbone, and one for the new classes built on the projector. The backbone is jointly tuned in the classifier learning stage.

Improving the Representations. In rows (2) and (3), we explore improving the representations of UNO+. We first align its representation learning objective with GCD [33] (see Sec. 4.1). We jointly train this objective with the classification objective in a decoupled manner, thus simplifying the training schedule while maintaining fair comparison. As in row (2), this makes little difference for CIFAR100, but significantly improves CUB in both old classes (5%) and new classes (8%). As suggested in Sec. 3.3, we then simplify the classifier into a single head built on the backbone. As shown in row (3), this makes notable improvements in old classes for both datasets (5%, 7%).

Improving the Pseudo Labels. In rows (4), (5), and (6), we explore improving the pseudo-labelling strategy. We start with replacing the Sinkhorn-Knopp algorithm with a vanilla self-distillation paradigm (Eq. (5) with $\varepsilon = 0$). Though this results in a sharp performance drop, when combined with a mean-entropy maximisation regulariser, as in row (5), we achieve consistent improvements over row (3) by a large margin (26% in CIFAR100, 13% in CUB) in new classes. Our intuition is that this regulariser can be viewed as a softened counterpart of the Sinkhorn-Knopp algorithm, and helps calibrate the predictions’ class distribution in a more suitable way. We then further adopt a teacher temperature warmup strategy to lower the confidence of the pseudo-labels at an earlier stage. The intuition is that at the beginning, both the classifier and the representation are not well fitted to the target data, thus the pseudo-labels are not quite reliable. As reported in row (6), this is indeed helpful for CUB, resulting in an improvement of 5% in new classes. While for CIFAR100, which is much similar to the pre-training data (ImageNet), the unreliable pseudo label is not a problem, thus lowering the confidence results in 3 points’ drop in new classes. For simplicity, we keep the training strategy consistent with CUB.

Jointly Training the Representation. Previous settings adopt a decoupled training strategy for consistent representations with GCD [33] and fair comparison. Finally, as confirmed in Sec. 3.4, we jointly supervise the representation with the classification objective. As in row (7), this results in a significant improvement in new classes for CIFAR100 (15%), with also a considerable drop in old classes (8%).
The overall gain for CUB is, in contrast, relatively small. We leave the discussions in Sec. 5.4. For simplicity, we keep the training strategy consistent with CIFAR100.

The model used in row (7) is the same as the final model for experimental results and is introduced in detail in Sec. 4.

5.4. Discussions

What Makes for the Significant Improvements Over GCD Given the Same Representations? One interesting message from row (6) of Tab. 4 is that, even with the same representations, for SSB [34] datasets like CUB, we can already improve GCD overall by 10%. We thus study the classification predictions and the major components that lead to the performance gap. As shown in Fig. 8, the non-parametric classifier (semi-supervised k-means) adopted by GCD [33] produces highly imbalanced predictions, while our method better fits the true distribution. Further analysis shows that our method significantly improves over the tail classes of GCD. Concerning why this improvement is relatively small on CIFAR100, our intuition is: for generic classification, the number of instances per class is much more abundant, therefore semi-supervised k-means can be more robust, and our improvement is not as notable.

Figure 8. Classification result analysis on CUB [35]. Left: Based on identical representations, the non-parametric classifier (semi-supervised k-means) adopted by GCD [33] produces highly imbalanced predictions, while our method better fits the true distribution. Right: our method significantly improves GCD’s tail classes.

Concerning why this is not as helpful for SSB: we hypothesise that one important factor lies in how transferable the features learned in old classes are to novel classes. While it may be easier for a cat classifier to be adapted to dogs, things can be different for fine-grained bird recognition. Besides, the small scale of CUB, which contains only 6k images while holding a fine-grained class split (200), might also make it hard to learn transferrable features.

Jointly training the representations with the classification objective can lead to \( \sim 15\% \) boost in new classes on CIFAR100. We study this difference by visualising the representations before and after tuning with t-SNE [32]. As illustrated in Fig. 9, jointly tuning the feature leads to less ambiguity, larger margins, and more compact clusters.

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Figure 10. We observe a trade-off between the performance in ‘Old’ and ‘New’ categories, which is common across datasets.

Trade-off Between Old and New Categories. We plot the performance evolution throughout the model learning process in Fig. 10. It can be observed that the performance on the ‘Old’ categories first climbs to the highest point at the early stage of training and then slowly degrades as the performance on the ‘New’ categories improves. We believe this demonstrates an important aspect of the design of models for the GCD problem: the performance on the ‘Old’ categories may be in odd with the performance on the ‘New’ categories, how to achieve a better trade-off between these two could be an interesting investigation for future works.

6. Conclusion

In this work, we revisit the reason that makes previous parametric classifiers fail to recognise new classes for GCD. Our investigations show that the less discriminative representations and unreliable pseudo-labelling strategy are key factors that make parametric classifiers lag behind non-parametric ones. We then present a simple yet effective parametric classification baseline that outperforms previous SOTAs by a large margin on multiple GCD benchmarks.

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A Simple Parametric Classification Baseline for Generalized Category Discovery

Appendix

### A. Extended Ablation Study

**Pseudo-labelling strategy.** In Tab. 5a, we ablate the pseudo-labelling strategy. Compared with the self-labelling method (Sinkhorn Knopp algorithm) adopted by UNO [14], the self-distillation-style pseudo-labelling strategy shows consistently better results on all metrics. Notably, the gains on new classes of both datasets can reach around 20 points. This indicates that the self-distillation strategy is significantly favourable for generalized category discovery.

**Learning paradigm.** In Tab. 5b, we show the results of different learning paradigms. By jointly supervising the representation with the classification objective, we see a significant improvement in new classes for CIFAR100 (15%), with also a considerable drop in old classes (8%). The overall gain for CUB is, in contrast, relatively small. Discussions on this can be found in the main text.

**Representation for the classifier.** In Tab. 5c, we ablate the effect of different representations. For CUB, taking the post-backbone representations yields consistent improvements (20% on old classes, 7.6% on new classes). While for CIFAR100, the post-projector representations can be helpful for recognising new classes (5.8%). As discussed in the main text, the features after the projector focus more on solving the pretext task, which can be helpful for the classification objective if the pretext task well fits the criterion for the new classes, *e.g.*, CIFAR100, but not for the fine-grained CUB.

**Teacher temperature schedule.** In Tab. 5d, we show the effect of different teacher temperature schedules. A smaller value indicates sharper pseudo-labels. A warmup strategy that lowers the confidence of the pseudo-labels at early stages results in an improvement of 5% in new classes on CUB. While for CIFAR100, which is much similar to the pre-training data (ImageNet), the unreliable pseudo label is not a problem, thus lowering the confidence results in 3 points’ drop in new classes.

**Mean-entropy maximisation regulariser weight.** Tab. 5e ablates the weight for the mean-entropy maximisation regulariser. A higher weight enforces the mean predictions of a batch to imitate uniform distribution, which resembles the Sinkhorn Knopp algorithm’s hard uniform partition constraint. While a lower weight may result in extremely long-tailed predictions as GCD [33] does. Generally, we found setting the weight to 2 reaches a good balance, and shows the best performance in new classes.
B. Unknown Number of Categories

In the main text, we assumed the number of categories is known a-priori following prior works [14, 17, 40, 43]. In this section, we report the results with the number of categories estimated using an off-the-shelf method [33] (Tab. 6). Since the estimated $K$ is identical to the real $K$ for CIFAR100, we omit the results on it. The results on CIFAR10 [23], ImageNet-100 [11], CUB [35], and Stanford Cars [22] are available in Tabs. 7 and 8.

| Methods          | Known $K$ | CIFAR10 All | Old | New | ImageNet-100 All | Old | New |
|------------------|-----------|-------------|-----|-----|------------------|-----|-----|
| GCD [33]         | ✓         | 91.5        | 97.9| 88.2| 74.1             | 89.8| 66.3 |
| SimGCD (Ours)    | ✓         | 93.2        | 82.0| 98.9| 82.4             | 90.7| 78.3 |
| GCD [33]         | ✗         | 88.6        | 96.2| 84.9| 72.7             | 91.8| 63.8 |
| SimGCD (Ours)    | ✗         | 82.8        | 93.9| 77.2| 81.5             | 89.7| 77.5 |

Table 7. Results on generic image recognition datasets.

| Methods          | Known $K$ | CUB All | Old | New | Stanford Cars All | Old | New |
|------------------|-----------|---------|-----|-----|-------------------|-----|-----|
| GCD [33]         | ✓         | 51.3    | 56.6| 48.7| 39.0              | 57.6| 29.9 |
| SimGCD (Ours)    | ✓         | 60.3    | 65.6| 57.7| 46.8              | 64.9| 38.0 |
| GCD [33]         | ✗         | 47.1    | 55.1| 44.8| 35.0              | 56.0| 24.8 |
| SimGCD (Ours)    | ✗         | 61.5    | 66.4| 59.1| 49.1              | 65.1| 41.3 |

Table 8. Results on the Semantic Shift Benchmark [34].

Generally speaking, if the estimated $K$ is smaller than the real $K$, the model tends to sacrifice the performance of new classes, and focus more on the old classes. On the other hand, if the estimated $K$ is larger than the real $K$, the results are generally robust. Notably, the inaccurate $K$ estimation can cause gains $\sim 3$ points in new classes in CUB and Stanford Cars. This motivates us to further analyse the influence of the estimated category number, detailed as follows.

In Fig. 11, we present the results with different numbers of categories on four representative datasets. A category number lower than the ground truth significantly limits the ability to discover new categories, and the model tends to focus more on the old classes. On the other hand, increasing the number of categories results in less harm to the generic image recognition datasets and can even be helpful for the fine-grained SSB datasets.

Generally speaking, increasing the number of predicted classes can produce more robust prototypes, thus decreasing the number of false positives (misclassified instances), and on the other hand, increasing the number of false negatives (instances classified into redundant classes). It is interesting to see that on CUB and Stanford Cars, even using $2\times$ of the real number of categories does not result in a notable performance drop (caused by the increase in false negatives). This motivates us to further investigate the size of different clusters with different category numbers (Fig. 12). While a larger category number introduces more active classes ($\sim 50\%$) to the coarse-grained CIFAR100, it is interesting to see the network prefers to keep the number of active prototypes low and close to the real category number (200) for the fine-grained CUB.
C. Limitations and Potential Future Works

**Representation Learning.** This paper mainly targets improving the classification ability for generalized category discovery. The representation learning, however, follows the prior work GCD [33]. It is expectable that the quality of representation learning can be improved. For instance, generally, by using more advanced geometric and photometric data augmentations [16], and even multiple local crops [6]. Further, can the design of data augmentations be better aligned with the classification criteria of the target data? For another example, a large batch size has been shown to be critical to the performance of contrastive learning-based frameworks [8]. However, the batch size adopted by GCD [33] is only 128, which might limit the quality of learned representations. Moreover, is the supervised contrastive learning plus self-supervised contrastive learning paradigm the ultimate answer to form the feature manifold? We believe that advances in representation learning can lead to further gains.

**Unknown Category Number.** This paper assumes the number of categories is known *a-priori* [14, 17, 40, 43], or can be estimated using off-the-shelf methods [18, 33]. In Figs. 11 and 12, we discovered that even given a large category-number estimation, the model could fit well to the real number of categories on the semantic shift benchmark [34]. We believe that further explorations on this phenomenon might motivate improvements that can allow the model to jointly estimate the number of categories in an end-to-end manner.

**Ethical Considerations.** Current methods commonly suffer from low-data or long-tailed scenarios. Depending on the data and classification criteria of specific tasks, discrimination against minority categories or instances is possible.