

# Open-world Machine Learning: A Review and New Outlooks

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## Abstract

Machine learning has achieved remarkable success in many applications. However, existing studies are largely based on the closed-world assumption, which assumes that the environment is stationary, and the model is fixed once deployed. In many real-world applications, this fundamental and rather naive assumption may not hold because an open environment is complex, dynamic, and full of unknowns. In such cases, rejecting unknowns, discovering novelties, and then incrementally learning them, could enable models to be safe and evolve continually as biological systems do. This paper provides a holistic view of open-world machine learning by investigating unknown rejection, novel class discovery, and class-incremental learning in a unified paradigm. The challenges, principles, and limitations of current methodologies are discussed in detail. Finally, we discuss several potential directions for future research. This paper aims to provide a comprehensive introduction to the emerging open-world machine learning paradigm, to help researchers build more powerful AI systems in their respective fields, and to promote the development of artificial general intelligence.

## 1 Introduction

Artificial intelligence coupled with machine learning techniques is broadly used in many fields such as medical treatment [1], industry [2], transportation and scientific discovery [3]. Typically, supervised machine learning involves isolated classification or regression task, which learns a function (model)  $f : \mathcal{X} \rightarrow \mathcal{Y}$  from a training dataset  $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$  containing pairs of feature vector and ground-truth label [4]. Then, the model  $f$  can be deployed to predict future encountered inputs. However, the current success of machine learning is largely based on the closed-world assumption [5, 6, 7], where the important factors of learning are limited to what has been observed during training. In the classification task, all the classes  $y$  that the model will encounter during deployment must have been seen in training, *i.e.*,  $y \in \mathcal{Y}$ . This assumption is often reasonable in restricted scenarios where possible classes are well-defined and unlikely to change over time. For example, in a handwritten digit recognition task, the closed-world assumption holds because the set of digits (0-9) is fixed and known in advance. Besides, this assumption also makes the data collection process easier and straightforward.

However, real-world applications often involve dynamic and open environments, where unexpected situations inevitably arise and instances belonging to unknown classes ( $y \notin \mathcal{Y}$ ) may appear [8, 9]. For example, in non-stationary environments, a self-driving car may encounter novel objects that have been never learned before; myriad novel categories would emerge continually in web usage and face recognition systems. The closed-world assumption can be problematic in such situations. Firstly, models are overconfident and predict unknowns as training classes without hesitation [10, 11, 12],

which can cause various harms from financial loss to injury and death. Secondly, models fail to extrapolate to novel classes by discovering and clustering them [13]. Thirdly, learning new stream data leads to catastrophic forgetting of previous knowledge [14]. To learn in such an endless variety of ever-changing scenarios, we need open-world learning to overcome these limitations by accommodating the dynamic and uncertain nature of real-world data. In this paradigm, a model is equipped to identify and reject inputs that deviate from training classes to keep safe, and then discovers new classes from unknowns and incrementally learns them to accumulate knowledge without re-training the whole model from scratch.

The general life cycle of an open-world learning (OWL) paradigm is illustrated in Figure 1. This process mainly consists of three key steps. The first step is unknown rejection, which requires the model to recognize test instances that belong to seen classes while also being able to detect or reject misclassified and unknown instances that do not belong to the training classes based on reliable confidence estimation [11, 15]. The second step is novel class discovery [13], which clusters the collected unknown samples in the buffer automatically based on the knowledge learned in the past. Finally, when the discovered classes have sufficient data, the system must extend the original multi-class classifier to incorporate new classes without retraining from scratch or catastrophic forgetting of previously learned knowledge [16, 17, 18]. By integrating unknown rejection, novel class discovery, and continual learning, the system is able to scale and adapt to an ever-evolving environment. In other words, the model can be aware of what it does not know and learns interactively after deployment (on the job) in the open world like humans.

In this article, we present a systematic review of recent research advances in open-world machine learning, with an emphasis on techniques concerning unknown rejection, novel class discovery, and class-incremental learning. The principles and limitations of current methods and the relation among them are discussed in detail. Finally, the possible challenges, research gaps, and outlook for the future development of open-world machine learning are presented. Our broad and insightful review will be helpful for researchers to apply this new learning paradigm in their own domains, and also be a call to build human-like, truly intelligent systems.

## 2 Background

### 2.1 Problem Formulation and Notations

Here, we give a holistic problem formulation and notations of open-world machine learning, comprising three tasks: unknown rejection, novel class discovery and class-incremental learning. Let  $\mathcal{D}_{\text{train}} = \{(x_i, y_i)\}_{i=1}^N \subset \mathcal{X} \times \mathcal{Y}_{\text{train}}$  denote the training dataset, and  $\mathcal{D}_{\text{test}} = \{(x_i, y_i)\}_{i=1}^M \subset \mathcal{X} \times \mathcal{Y}_{\text{test}}$  denote the test dataset. By default, the training data only contains labeled data from old and known classes, *i.e.*,  $\mathcal{C}_{\text{old}} = \mathcal{Y}_{\text{train}}$ . We represent a deep neural network (DNN) based model  $f$  with two components: a feature extractor  $h$  and a unified classifier  $g$ , *i.e.*,  $f = g \circ h$ . In the canonical closed-world setting, the test dataset shares categories with training data with no additional classes, *i.e.*,  $\mathcal{Y}_{\text{test}} = \mathcal{Y}_{\text{train}}$ . By contrast, in the open-world, samples from new classes emerge, *i.e.*,  $\mathcal{Y}_{\text{train}} \neq \mathcal{Y}_{\text{test}}$ , we further express it as  $\mathcal{Y}_{\text{train}} \subset \mathcal{Y}_{\text{test}}$ . In this paper, we not only consider how to classify the seen and known classes, but also focus on how to handle samples from new classes  $\mathcal{C}_{\text{new}} = \mathcal{Y}_{\text{test}} \setminus \mathcal{Y}_{\text{train}}$ , which is divided into three progressive ways: unknown rejection, novel class discovery and class-incremental learning. In unknown rejection, models only need to reject unknowns, while in novel class discovery and class-incremental, models are further required to classify/cluster samples from new classes. Considering the clustering objective, in novel class discovery,  $\mathcal{D}_{\text{train}}$  could also contain some unlabeled data from  $\mathcal{C}_{\text{new}}$ . While in class-incremental learning, the training scheme could be divided into several stages, models are trained on streaming data, and we add a superscript  $t$  to the dataset  $\mathcal{D}_{\text{train}}^t$  and  $\mathcal{D}_{\text{test}}^t$  to indicate each incremental step. Considering the differences among the three tasks, we will also give task-specific notations for three tasks when discussing them.

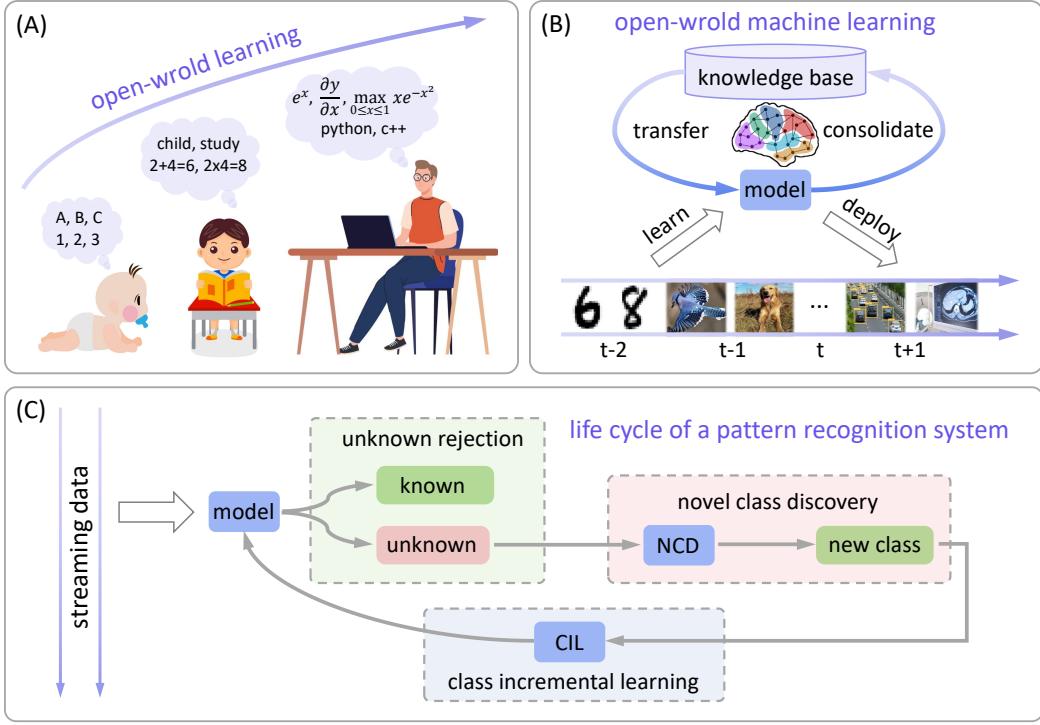


Figure 1: Illustrations of the life cycle of a learning system in the open-world applications. (A) Humans continually learn new knowledge throughout their lives and maintain/use the previous knowledge, becoming increasingly smarter and more skillful over time. (B) Open-world machine learning aims to build a human-like system that can transfer and consolidate knowledge incrementally during deployment. (C) An open-world learning paradigm mainly includes three parts, *i.e.*, unknown rejection, novel class discovery (NCD) and class-incremental learning (CIL).

## 2.2 Canonical Use Cases

In this section, we discuss several canonical applications of open-world machine learning. An illustration is provided in Figure 2.

**Autonomous Driving.** Self-driving cars in real-world scenarios can encounter a nearly infinite number of unexpected and novel objects [19], and open-world learning can provide them with the adaptability needed to navigate safely and effectively. Specifically, when encountering a novel object on the road, *e.g.* a deer or even a hole on the road that does not appear in the training class set, the car should stop or slow down. This involves leveraging an unknown rejection algorithm that provides reliable confidence scores. If the confidence score is lower than a threshold, the system should raise an alarm so that the car takes a predefined safety action. Then, novel class discovery techniques are used to create the class identity for the unknown, new object. Finally, based on incremental learning methods, the car can continue to learn from a single or few samples of the object, enabling autonomous systems to quickly adapt to unexpected new environments without forgetting the skills already mastered. In conclusion, open-world learning allows the vehicle to learn from dynamic real-world environments and adapt its decision-making process, improving its driving behavior over time.

**Medical Diagnosis.** Real-time medical applications require the AI system to address many heterogeneous problems that involve multiple, complex tasks. For example, a pulmonary model trained on existing lung data would not be able to reliably predict newly emerged pulmonary diseases like COVID-19, and the medical diagnostic tools can easily make mistakes [20]. In such cases, the model

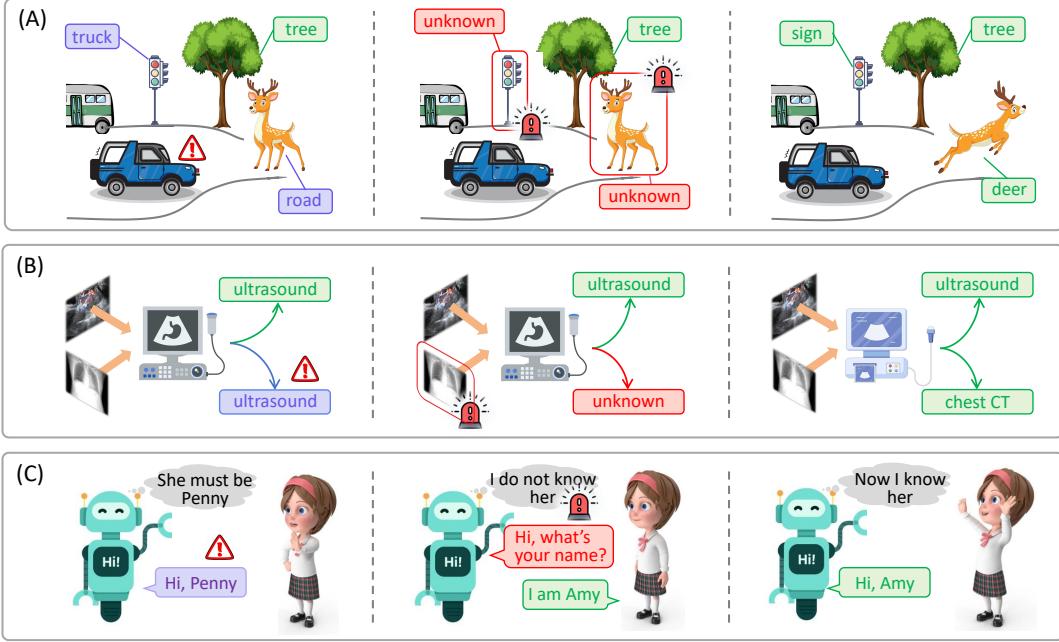


Figure 2: Example applications of open-world machine learning systems such as (A) autonomous driving, (B) medical diagnosis, and (C) AI chatbot.

should be equipped with unknown rejection ability to output reliable and human-interpretable confidence scores along with its predictions, which helps doctors or participants to make safe decisions. For example, the input should be handed over to human doctors when the confidence of a disease diagnosis is low. When encountering more and more unknowns, the medical diagnosis system is supposed to continually learn from those unknowns or more data to improve its performance progressively [21, 22]. Since manual image grading is time-consuming, novel class discovery methods would largely accelerate the processing of labeling new data. The above adaptive capability ensures that medical diagnosis systems can learn from on-the-job experiences and apply this knowledge to similar situations in the future, which is very similar to the ways that human clinicians learn. In conclusion, open-world learning enables medical diagnoses to make more reliable clinical decisions and be more responsive to evolving environments.

**AI Chatbot.** With the launch of large language models like ChatGPT [23], AI chatbots have become widely used in many scenarios to help with daily tasks for users. In practice, it is critical for a chatbot to know what it doesn't know. Specifically, if the chatbot does not know the answer, it is better to reject to response rather than provide incorrect information that may cause very serious mistakes in fields like clinical and legal matters [24, 25]. One way to avoid providing misleading information is to abstain from making a prediction based on unknown rejection methods. Further, if the user provides the correct answer or more data is available, the chatbot should improve its conversational skills continually without forgetting previously learned knowledge. A typical example is the hotel guest-greeting bot [5], where a chatbot greets known hotel guests, detects new guests, and then incrementally learns them by asking their names and taking photos. As can be seen, open-world learning makes the AI Chatbot more knowledgeable and powerful over time.

### 2.3 Overall Challenges of Open-world Learning

As illustrated in Figure 1 and Figure 2, open-world learning involves performing unknown rejection, novel class discovery, and class-incremental learning sequentially and periodically. The core challenge

is enabling the above process to automatically proceed through the interactions between the model and the open environments without relying on human engineers [26]. Unfortunately, under the close-world assumption [7], a model is overconfident and can hardly be aware of the unknown. Specifically, from the perspective of representation learning, the model is trained only on the current dataset with data-driven optimization, the learned representations are task-specific and less generic; from the perspective of classifier learning, current discriminative classifiers leave little room for the unknown, making it hard to characterize, discover and adapt to novelty. Consequently, examples from unknown classes would be mapped to the region of known classes, leading to catastrophic forgetting of previous knowledge in the latter incremental learning process.

### 3 Unknown Rejection

Unknown rejection is the first step towards open-world machine learning, which is also a fundamental ability of the classifier in the open-world. Considering that a training set comprises of  $K$  classes, *i.e.*,  $\mathcal{D}_{\text{train}} = \mathcal{D}_{\text{in}} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N \subset \mathcal{X} \times \mathcal{Y}_{\text{in}}$ , where  $\mathcal{Y}_{\text{in}} = \{1, 2, \dots, K\}$ . Once trained on  $\mathcal{D}_{\text{in}}$ , models are supposed to reject unknown samples from classes outside of  $\mathcal{Y}_{\text{in}}$ , rather than classifying it irresponsibly into one of  $K$  categories. The philosophy behind unknown rejection is that when encountering unfamiliar knowledge, it is essential to bravely acknowledge the limitations rather than feign understanding and give arbitrary answers.

Many efforts have been made to enhance the unknown rejection ability of machine learning systems. There are multiple research areas related to unknown rejection, such as anomaly detection [27, 28], out-of-distribution (OOD) detection [29, 30], and open-set recognition [31, 32] (OSR). Among them, anomaly detection is widely used in early work, while OOD detection and OSR are more often used in recent works. The differences between OOD detection and OSR lie in two aspects. First, in OOD detection, the semantic distance between the OOD data and in-distribution (ID) data is relatively larger, *e.g.*, the OOD dataset is usually completely unrelated. While in OSR, a subset of classes from a dataset is viewed as ID and other classes from the same dataset are viewed as OOD data. Second, OOD detection mainly concentrates on distinguishing OOD samples from ID samples, whereas OSR also evaluates closed-world classification performance on known classes. We overview the recent advances in OOD detection and OSR in the remaining part of this section, and different types of methods are illustrated in Figure 3.

**Key Challenges.** The inherent challenge of unknown rejection is that OOD samples are agnostic during training. Even though some methods [33, 34] resort to auxiliary outlier OOD samples, it is impossible to exhaustively encompass all OOD distributions. As a consequence, models need to reverse some open space for potential unknown samples to reduce the open space risk [31, 32]. Secondly, when the semantic similarity [35] between OOD and ID samples is minimal, their separability decreases, resulting in a decline in rejection capability. Such samples are referred to as *near-ood* samples in the literature [36]. Furthermore, some issues could impact the rejection of unknown samples, including covariate shifts [37] and spurious correlations [38], for example, ID samples from another distribution domain might be mistakenly detected as OOD samples, and spurious correlations learned from training data could mislead the models to focus on irrelevant features and areas.

#### 3.1 Out-of-distribution Detection

OOD detection focuses on whether a test example is outside the distribution of the training data and aims to improve the separability between ID and OOD samples. The most widely used metric for OOD detection is the Area Under the Receiver Operating Characteristic curve [39] (AUROC), which is a threshold-independent metric that can be interpreted as the probability that a positive example (ID) is assigned a higher prediction score than a negative example. In addition, there are many other metrics like TNR-95%-TPR, AUPR-In and AUPR-Out [10] to imply how the in-distribution and OOD

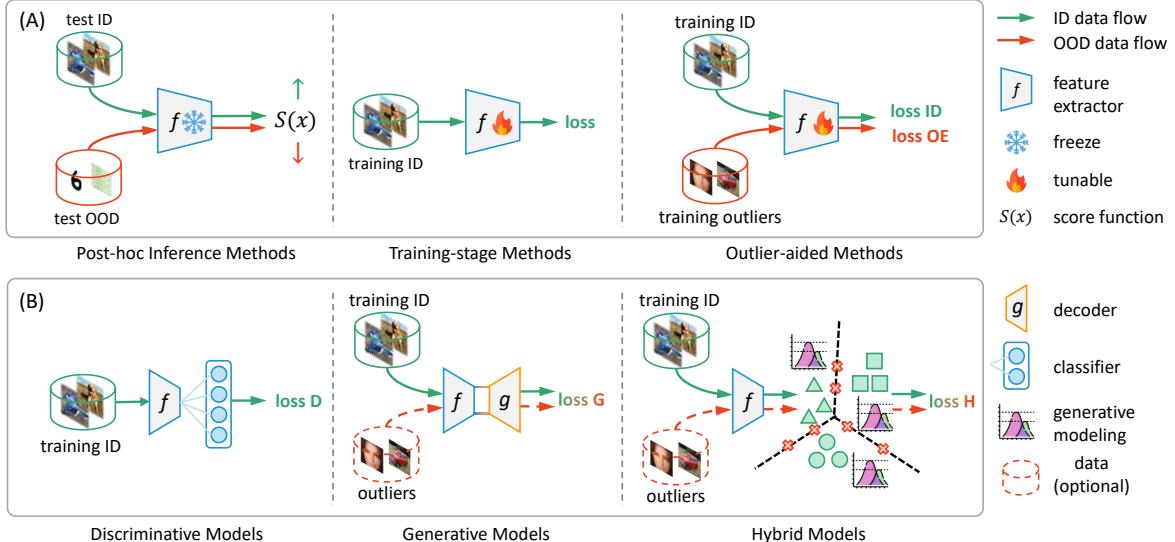


Figure 3: Illustrations of different types of methods of (A) OOD detection and (B) OSR. In OOD detection, methods are divided according to training and inference strategies while modeling perspectives in OSR. In OSR, “loss D”, “loss G” and “loss H” denote loss functions for discriminative, generative and hybrid models, respectively.

samples are separated. Technically, the common practice is to assign each sample with a score function  $S(x)$  indicating the *otherness* of each sample. If the score is above a pre-defined threshold  $\delta$ , then the sample is recognized as ID, otherwise detected as OOD and rejected. OOD detection methods can be categorized into three classes [36, 40] based on different training and inference techniques.

**Post-hoc Inference Methods.** One natural and simple way is to design appropriate score functions  $S(x)$  that have the most significant separability between ID and OOD samples. Post-hoc methods are simply implemented on the trained models, without interfering with the training phase, as a result, they are orthogonal to the training-stage methods discussed below. Many characteristics of the trained models could be designed as score functions, such as posterior probabilities of the classification head, activations and dynamics in the feature space. Early works design  $S(x)$  based on probabilities, *i.e.*,  $p(c|x) = \frac{\exp(z_c(x))}{\sum_{j=1}^K \exp(z_j(x))}$  where  $z_c(x)$  denotes the logits of sample  $x$ . Hendrycks *et al.* [10] proposed a simple score function, namely maximum softmax probability (MSP), *i.e.*  $S(x) = \max_c p(c|x)$ , which is regarded a baseline method in the literature. MSP could be enhanced by input perturbation which aims to increase the softmax score for the true label and temperature scaling [41]. Apart from softmax probabilities, energy score [42] derived from energy-based models [43] is less susceptible to the overconfidence issue of classifiers, achieving better OOD detection abilities. Similar to probabilities, logits also serve as the belongingness of each class without the normalization process in MSP, and maximum logit score (MLS) [44] is reported better than MSP score. Instead of the probability distribution, characteristics in the feature space could also be exploited for OOD detection. Lee *et al.* [45] designed the Mahalanobis distance-based confidence score by modeling layer-wise Gaussian distribution of features, which could be substituted by flow-based [46] generative modeling for more flexible expressivity [47]. These methods still impose certain assumptions on the distribution of the feature spaces, which limits the performance to some extent. By contrast, non-parametric nearest-neighbor distance [48] is more general and flexible without relying on any distributional assumptions. Activations in the penultimate layer [49] could also be considered. The methods above design  $S(x)$  from only one of the two aspects. We could also combine the above two perspectives [50], namely posterior probabilities and feature embeddings, for a more remarkable separation between ID and OOD samples.

**Training-stage Methods.** Training-based methods directly explore the training of models with inherent capabilities to discriminate between ID and OOD samples. This line of works are complementary to the post-hoc methods dedicated to designing OOD scores, they could be combined for better OOD detection performance. In general, advanced training tricks including self-supervised learning [51] and normalization [52], provide outstanding OOD detectors. Self-supervised learning, like rotation prediction [53] and contrastive learning [54], could help improve robustness and uncertainty estimation, which also greatly boost OOD detection [51, 55] with alleviated overconfidence issues. Another technique namely logit normalization [52] helps to mitigate the overconfidence issue for both ID and OOD samples. Models could also be encouraged for greater inter-class separation and intra-class compactness [56] in the feature space, which leaves more room for open space and helps separate ID and OOD samples. Recently, flat minima has been demonstrated to be a good optimization objective for the detection of misclassified examples from known classes and OOD examples from unknown classes [15]. When scaling OOD detection to large-scale datasets, a key insight is to decompose the large semantic space into many small groups and train models with group-based learning [57].

**Outlier-aided Methods.** It is also intuitive for better OOD performance by directly training models on auxiliary OOD samples  $\mathcal{D}_{\text{out}}$  and maximizing the uncertainty on them. Outlier exposure [33] (OE) is a pioneer work to explicitly require and learn on the auxiliary outliers. Specifically, OE proposes to maximize the uncertainty on the outliers. The loss function of OE is  $\mathcal{L} = \mathbb{E}_{(\mathbf{x}, y) \in \mathcal{D}_{\text{in}}} \mathcal{L}_{ce}(y, f(\mathbf{x})) + \lambda \mathbb{E}_{\mathbf{x} \in \mathcal{D}_{\text{out}}} \mathcal{L}_{ce}(\mathcal{U}, f(\mathbf{x}))$ , where  $f(\mathbf{x})$  is the predictive probability,  $\mathcal{L}_{ce}$  is the cross-entropy loss, and  $\mathcal{U}$  is the uniform distribution. Practically, OE performs to minimize the cross-entropy between the uniform distribution and the model’s predictions to encourage uncertain predictions. The authors [33] found that once learned on  $\mathcal{D}_{\text{out}}$ , the model could generalize to detect unseen OOD samples and anomalies and achieves remarkable OOD detection performance. Recently, Zhu *et al.* [58] revealed that popular OOD detection methods like OE often make it harder to detect misclassified examples from known classes, and proposed a unified misclassification and OOD detection approach named OpenMix.

## 3.2 Open-Set Recognition

OSR [31, 32] aims to recognize known classes (ID) while detecting unknown classes (OOD) at the same time. In the literature of OSR, ID and OOD are conventionally drawn from different class sets within the same dataset. Early OSR works are mainly based on support vector machine [31], nearest class mean classifiers [59] and extreme value machine [60]. Those traditional machine learning-based OSR approaches have been well reviewed and discussed [32]. In recent years, various deep learning-based OSR methods have been developed, and we mainly focus on them in this paper. The methods could be divided into three types from the modeling perspective: discriminative, generative and hybrid models.

**Discriminative Models.** Discriminative models perform relatively well in classification tasks, it is natural to employ them to handle OSR, *i.e.*, classify among known classes and reject unknown classes. One direct and intuitive method is to leave room for the modeling of unknown classes. A pioneer work OpenMax [61] re-calibrates the logits of top classes from known to assign the probability to the appended class zero representing unknown classes. OpenMax [61] resorts to extreme value theorem and utilizes Weibull distribution to compute the re-calibration weights. Dummy classifiers [62] for unknown samples could mimic the novel classes as data placeholders and augment the closed-set classifier with classifier placeholders. From another perspective, similar to OOD detection, models could also be trained on both known and auxiliary unknown classes to behave differently on knowns and unknowns and improve the ability to distinguish between them. Dhamija *et al.* [63] leveraged samples from background classes as unknown samples and proposed two novel loss functions to make ID and OOD well-separated in both probability space and feature space. DTL [64] proposes membership loss to substitute cross-entropy loss for class-wise probability modeling, and also relies on outlier data to train a parallel network for providing global negative filtering. The methods discussed above mainly employ the output of classifiers as a proxy to discern ID and OOD samples. Besides, auto-encoders are proven good indicators for OSR, the fundamental principle is that models are trained on known samples to minimize reconstruction errors and will produce relatively higher

reconstruction errors on unknown samples. C2AE [65] divides OSR into closed-set classification and open-set identification, and the test sample is rejected as unknown if the reconstruction error is below the threshold.

**Generative Models.** Generative models provide different perspectives from discriminative models and could be utilized mainly in two ways, *i.e.*, one is generative and probabilistic modeling of known and unknown classes, and the other is to explicitly generate fake unknown samples for greater separation between known and unknown classes. From the perspective of generative modeling, the basic idea is to model posterior distributions in the latent space to approximate conditional Gaussian distributions [66] and the probability of test samples could be used for unknown rejection. However, directly modeling the distribution is difficult, and most existing methods employ off-the-shelf generative models to generate pseudo-unknown samples to augment classifiers. For example, G-OpenMax [67] generates unknown samples with GANs [68] and fine-tunes the model with OpenMax [61] loss. OpenGAN [69] adopts an adversarial training framework to generate pseudo-unknown samples on the deep feature space. By further taking the difficulty [70] of the generated unknown samples into consideration, models could grasp fine-grained concepts of unknowns for results. Besides, without using explicit generative models, pseudo-unknown samples could be generated by optimizing a latent vector to have a small distance to training samples but produce low confidence on known categories [71]. These samples could be viewed as difficult open-space samples which are similar to known samples. A  $(K + 1)$ -way classifier is trained on the combination of training samples and the generated counterfactual samples.

**Hybrid Models.** Discriminative and generative models are complementary to each other, and both have their specific advantages. In principle, discriminative models perform better on classification tasks than generative models. On the other hand, generative models could formalize the distribution of known and unknown samples, and additionally generate fake samples to augment discriminative models. As a consequence, combining both discriminative and generative models into hybrid models results in enormous potential for performing OSR tasks. Zhang *et al.* [72] proposed to train a flow-based generative model [73] and an inlier classifier on a shared feature space of the encoder. The flow-based model and the classifier are targeted to detect outliers and classify inliers respectively without intervention. The flow-based model is trained on the feature space using the maximum likelihood loss function, which avoids the issue of assigning OOD with high probability [74] when learned in the input pixel space. Yang *et al.* [75, 76] creatively proposed convolutional prototype networks (CPN) for OSR with learnable class-wise prototypes serving as a classifier, which is different from conventional linear classifiers. The prototypical classifier could be viewed as Gaussian generative modeling for each class, and leaves more room for open set samples in the feature space. CPN is trained on both discriminative and generative loss functions to encourage inter-class separation and intra-class compactness respectively, resulting in less open set risk and remarkable OSR performance. ARPL [77, 78] takes the similar spirit of CPN [76], but models class-wise reciprocal points representing the extra-class space, *i.e.*, modeling the open-space of each category. ARPL [78] additionally employs adversarial enhancement to generate diverse confusing samples to further reduce the open space risk caused by confusing samples. The class-wise points of CPN [76] and ARPL [78] could be generalized to class-wise continuous manifolds [79], which are constructed by class-wise auto-encoders upon the feature space. Each class-wise manifold could be viewed as an infinite number of prototype/reciprocal points, and thus more flexible and generalizable.

### 3.3 Analysis of Unknown Rejection

The ability of a classifier to reject unknowns has been verified as highly correlated with its closed-set classification accuracy [35]. As a result, when applying some training tricks to the classifier for better closed-set classification, *e.g.*, longer training, RandAugment [80], learning rate warmup, and label smoothing [81], the classifier consequently performs better in OSR. The authors [35] further found that applying baseline methods like MSP [10] and MLS [44] on a well-trained closed-set classifier could achieve competitively with or even outperform state-of-the-art OSR methods. Cen *et al.* [82] further

revealed that wrong-classified ID samples have similar uncertainty distribution to unknown samples, which limits the performance of OSR, and pre-training could enhance both the separation between ID and OOD samples and the separation between the correctly- and wrongly-classified ID samples.

Regarding the difficulty of unknown rejection, existing works predominantly resort to *openness* [31]  $O^*$  defined by the number of known and unknown classes, *i.e.*,  $O^* = 1 - \sqrt{\frac{2 \times K_{ID}}{K_{ID} + K_{OOD}}}$ , where  $K_{ID}, K_{OOD}$  denote the number of known and unknown classes, respectively. The more unknown categories compared to the number of known categories, the more challenging the unknown rejection task becomes. Vaze *et al.* [35] proposed a more rational metric namely semantic similarity [83]. Open-set samples that share a greater number of visual features, such as attributes, color, and shape, with known training samples, are more difficult to reject.

## 4 Novel Class Discovery

Novel class discovery [13, 84] is the second step in open-world machine learning, which aims to automatically discover novel categories from unlabeled data based on the model’s prior knowledge. Novel class discovery is an extension of unknown rejection, requiring models to not only reject unknown samples, but also further extrapolate to classify the rejected samples. Given a dataset  $\mathcal{D}_{\text{train}} = \mathcal{D}_l \cup \mathcal{D}_u$  with two subsets, where  $\mathcal{D}_l = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_l} \subset \mathcal{X} \times \mathcal{Y}_l$  is the labeled dataset and  $\mathcal{D}_u = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N_u} \subset \mathcal{X} \times \mathcal{Y}_u$  is the unlabeled data. It is worth noting that  $\mathcal{Y}_u \neq \mathcal{Y}_l$ , *i.e.*, there are novel classes in the unlabeled data outside the old classes in  $\mathcal{D}_l$ . Let  $\mathcal{C}_{\text{old}}, \mathcal{C}_{\text{new}}$  denote the old and new classes in the labeled and unlabeled dataset, with the number of classes  $K_{\text{old}} = |\mathcal{C}_{\text{old}}|, K_{\text{new}} = |\mathcal{C}_{\text{new}}|$ , respectively. The objective is to cluster and discover  $\mathcal{C}_{\text{new}}$  in  $\mathcal{D}_u$  leveraging the knowledge learned on  $\mathcal{D}_l$ .

In essence, novel class discovery is a clustering task on  $\mathcal{D}_u$ . Regarding its differences from unsupervised clustering [85, 86], the latter aims to cluster unlabeled data in a purely unsupervised manner without any prior knowledge of classification criterion, as a result, unsupervised clustering is not a fully learnable task. For example, in the absence of any external information, the model might face a dilemma, confusing whether to cluster red flowers and red cars together according to colors or to cluster red flowers and yellow flowers together according to species. From this perspective, some labeled data  $\mathcal{D}_l$  is necessary and could provide some prior knowledge indicating what constitutes a class to clarify the clustering criterion and eliminate ambiguity. In a word, novel class discovery is a more reasonable and pragmatic task, and could be referred to as deep transfer clustering [87], models are supposed to transfer the knowledge learned from old and labeled classes to cluster novel categories in the unlabeled data.

**Key Challenges.** Intrinsically, the semantic similarity between new and old categories determines the extent of knowledge transferable from old to new categories, thereby influencing the performance of category discovery. If the semantic similarity is limited, the labeled old class may degrade the performance novel class discovery [88]. Technically, novel category discovery could be referred to as open-world semi-supervised learning [89], where unlabeled samples contain new classes, which makes the conventional pseudo-labeling mechanism [90] not applicable due to the non-shared categories between labeled and unlabeled data. Moreover, in practical scenarios, the number of novel categories is always unknown, which makes the task challenging.

### 4.1 Novel Category Discovery

Novel Category Discovery [13] (NCD) is a basic setting where  $\mathcal{Y}_u = \mathcal{C}_{\text{new}}$  and  $\mathcal{Y}_u \cap \mathcal{Y}_l = \Phi$ , *i.e.*, unlabeled data only contain novel classes and has no class overlap with the labeled data. NCD mainly concerns category discovery in  $\mathcal{D}_u$ .

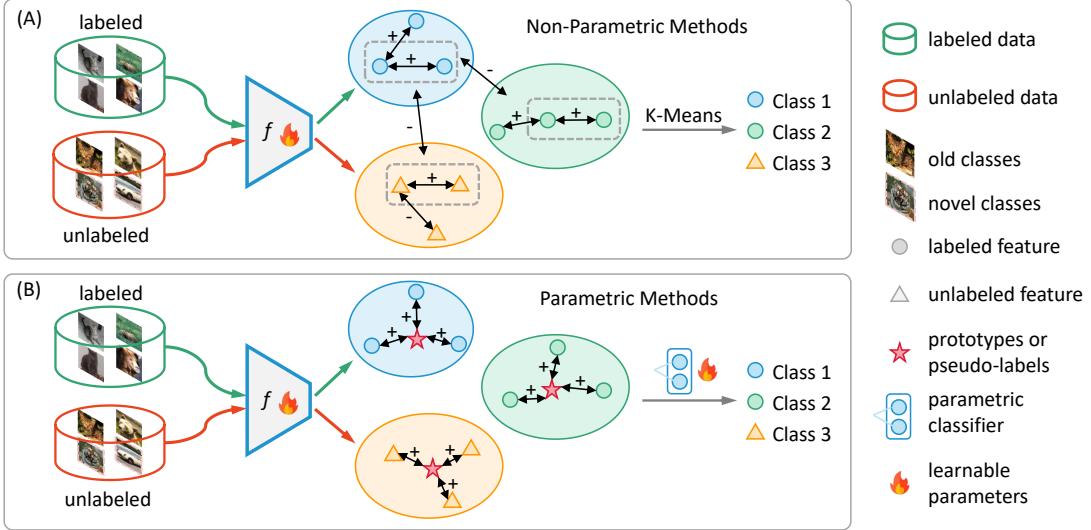


Figure 4: Illustrations of two types of methods of GCD, *i.e.*, (A) non-parametric methods with K-means clustering and (B) parametric methods with learnable classification heads (bottom).

**Multi-stage Methods.** Early works in NCD mainly transfer knowledge from  $\mathcal{D}_l$  to  $\mathcal{D}_u$  for category discovery in multi-steps. A pioneer work DTC [87] formalizes NCD as a deep transfer clustering task, and builds the method upon unsupervised clustering DEC [85]. DTC first trains a model on  $\mathcal{D}_l$  which is then utilized to extract features of  $\mathcal{D}_u$  to initialize cluster centroids. Then DTC performs alternative optimization between the soft targets and model parameters together with cluster centroids. Later works predominantly resort to pseudo-labels to transfer knowledge from labeled samples from old classes to unlabeled samples from novel classes. However, due to the disjoint classes, one could not simply adopt the naive pseudo-labels [90] in semi-supervised learning [91]. To overcome this issue, several methods rely on pairwise pseudo-labels [92] indicating whether two samples are similar or not. Specifically, the model is firstly trained on  $\mathcal{D}_l$  to assign pairwise pseudo-labels on  $\mathcal{D}_u$ , if the similarity is larger than a pre-defined threshold, then such pair of samples are recognized as similar pair. Then the model is trained on  $\mathcal{D}_u$  with the binary pseudo-labels for novel category discovery. Such type of methods rely on an implicit assumption that general knowledge of what constitutes a good class is shared across old and new classes. AutoNovel [13] is a representative work in NCD, dividing NCD into three steps. The model is firstly pre-trained on  $\mathcal{D}_l$  and  $\mathcal{D}_u$  collectively with self-supervision on rotation-prediction [53] to grasp fundamental representation. They proposed a novel pseudo-labeling criteria namely ranking statistics to obtain pairwise similarities. Concretely, two samples are deemed to be similar if the top-k ranked dimensions of feature magnitudes are identical, which is robust and stable for knowledge transfer from old to novel classes. In the last step, the model is jointly optimized on  $\mathcal{D}_l$  with classification loss and  $\mathcal{D}_u$  with pseudo-labels, together with consistency regularization [93] for better representation learning. Some other methods advance NCD from different perspectives, including local part-level information [94], and neighborhood [95] in the feature space containing more potential positive samples. The adjacent samples in the feature space are valuable for constructing pseudo-positives and hard negatives for substantially better representation learning.

**One-stage Methods.** More recent works learn  $\mathcal{D}_l$  and  $\mathcal{D}_u$  simultaneously in a joint optimization manner. Zhong *et al.* [96] proposed to model old and novel classes into a joint label distribution, and leverage the mixup of labeled and unlabeled samples to generate more credible data for learning. UNO [97] is a simple yet effective method with a unified objective for NCD. UNO employs a swapped prediction task like SwAV [98] for pseudo-labeling followed by Sinkhorn-Knopp algorithm [99] to avoid trivial solutions. Kullback–Leibler divergence terms [100] to maximize the inter-class divergence and minimize the intra-class divergence could be incorporated to boost the performance.

## 4.2 Generalized Category Discovery

Generalize category discovery (GCD) is a more pragmatic and challenging task, relaxing the strong assumption in NCD that unlabeled data all come from novel classes, *i.e.*,  $\mathcal{Y}_u = \mathcal{C}_{\text{old}} \cap \mathcal{C}_{\text{new}}$  and  $\mathcal{Y}_l \subset \mathcal{Y}_u$ . The challenge in GCD lies in that models are supposed to simultaneously recognize unlabeled samples from old classes and cluster samples from novel categories. Illustrations of two canonical types of methods are shown in Figure 4.

**Non-parametric Classification.** Most methods in GCD predominantly rely on contrastive learning for feature representation and resort to K-means [101, 102] clustering as a non-parametric classifier for classification. Vaze *et al.* [103] firstly introduced the task of GCD, and proposed to employ supervised contrastive learning [104] on  $\mathcal{D}_l$  and unsupervised contrastive learning [54] on  $\mathcal{D}_u$ , respectively. Then semi-supervised K-means [101] is performed on the learned representations for classification of old samples and clustering of novel samples. They argue that parametric classifiers are prone to overfitting to old classes. This work could be further augmented by performing contrastive learning on sub-datasets partitioned by clustering in advance [105]. However, purely unsupervised contrastive learning neglects substantial positive pairs and suffers from the class collision issue, later works exploit more potential positive pairs to better feature representation. For example, a dynamic conceptional contrastive learning [106] framework is introduced to exploit the underlying relationships between samples of similar concepts. In this framework, dynamic conception generation and conception-level contrastive learning are alternatively performed for better feature representations. Zhao *et al.* [107] integrated class number estimation and representation learning into a unified EM-like framework to learn semi-supervised Gaussian mixture models. To further achieve better performance, PromptCAL [108] employs visual prompt tuning [109] with stronger representation ability.

**Parametric Classification.** Recently, Wen *et al.* [110] rethought parametric classifiers for GCD and attributed the failure of parametric classifiers to two biases, *i.e.*, the bias to predicting old classes more often and the bias to imbalanced pseudo-labels. They proposed to implement self-distillation [111] for unlabeled data and employ entropy regularization to mitigate imbalanced pseudo-labels. By avoiding severe biases, the proposed method achieves remarkable performance with the parametric classifier.

## 4.3 Estimating the Number of Novel Classes

In the literature of NCD and GCD, most methods require the number of novel classes  $|\mathcal{C}_{\text{new}}|$  is known *a-priori*, which is impractical in real-world applications. It is of vital importance to precisely estimate the number of classes. AutoNovel [13] devise a sophisticated data splitting and clustering scheme. In particular, they first split the probe (labeled) data  $\mathcal{D}_l^r$  into  $\mathcal{D}_l^{ra}$  and  $\mathcal{D}_l^{rv}$ , and run semi-supervised K-means on  $\mathcal{D}_l^r \cup \mathcal{D}_u$  with ground-truth constraints on  $\mathcal{D}_l^{ra}$ , subsequently, they proposed to compute clustering accuracy on  $\mathcal{D}_l^{rv}$  and cluster validity index (CVI) [112] on  $\mathcal{D}_u$ , respectively. Finally, they average the cluster numbers maximizing accuracy and CVI respectively as the estimation of class number. Vaze *et al.* [103] proposed to run the clustering algorithm on the learned representations with different numbers of classes and choose the one that maximizes the accuracy on the labeled data as an estimate of  $|\mathcal{C}_{\text{new}}|$ . Recent methods adopt a more elegant way, which seamlessly integrates representation learning and category number estimation into a unified learning framework. DCCL [106] utilizes infomap algorithm [113] for dynamic conception generation, where the number of conceptions is dynamically changed throughout training, as the algorithm converges, and the resulting number of clusters represents the estimation. Zhao *et al.* [107] formalized EM-like framework, wherein prototype and class number are estimated in the E-step with a variant of Gaussian mixture model, and they employ prototypical contrastive learning [114] in the M-step.

#### 4.4 Analysis of Category Discovery

Novel class discovery is implicitly guided by knowledge transferred from old classes to novel categories for clustering and category discovery. How much knowledge could be transferred essentially influences the performance of category discovery. Li *et al.* [88] questioned the viewpoint that supervised knowledge is always helpful at different levels of semantic relevance. They proposed a metric called transfer flow to quantitatively assess the semantic similarity between labeled and unlabeled categories and give the theoretical analysis of semantic similarity and conclude that supervised knowledge might hurt the performance of NCD in circumstances with low semantic similarity between old and new classes and further suggest utilizing transfer flow as a reference to indicate how to use data.

It is intuitive that the difficulty of NCD is determined by the semantic similarities between old and novel categories, *i.e.*, how much knowledge is helpful and could be transferred for NCD. Besides, the number of novel classes also influences the difficulty. The greater the semantic similarity and the fewer the novel categories, the simpler the NCD task becomes. Interestingly, the impact of semantic similarity on the difficulty of novel class discovery is opposite to the conclusion of the unknown rejection task, in essence, unknown rejection is a discriminative task to distinguish between ID and OOD samples, while NCD is a transfer learning task to transfer the knowledge from ID to guide the clustering of OOD samples.

### 5 Class-incremental Learning

After detecting unknown samples via OOD detection or open-set recognition techniques, those samples should be labeled by humans or novel class discovery strategies. Then the system must continually extend the multi-class classifier to learn those new classes, which is referred to as class-incremental learning (CIL), being the third step in the open-world recognition process. Typically, an incremental learner learns several tasks sequentially, and only the data of the current task can be accessed by the learner. Most early studies [115, 116, 117] focus on task-incremental learning (TIL) scenario, in which the task identity is provided at inference time and the model only performs classification in each single task. Differently, the more challenging CIL problem involves the sequential learning of tasks that consist of disjoint class sets, and the model has to learn a unified classifier that can classify all seen classes. Formally, at incremental step  $t$ , a dataset  $\mathcal{D}_{\text{train}}^t = \{(x_i^t, y_i^t)\}_{i=1}^{N_t}$  is given, where  $x$  is an instance in the input space  $\mathcal{X}$  and  $y \in \mathcal{C}^t$  is its corresponding label.  $\mathcal{C}^t$  is the class set of task  $t$  and the class sets of different task are disjoint, *i.e.*,  $\mathcal{C}^i \cap \mathcal{C}^j = \emptyset$  if  $i \neq j$ . The general objective at each incremental step  $t$  is to learn new classes  $\mathcal{C}^t$  without interfering and with possibly improving previously learned knowledge [118].

**Key Challenges.** The central challenge of CIL is the training data of old classes is assumed to be unavailable due to memory limits or privacy issues [119, 120] when learning new classes. However, without accessing old training data, directly updating the model on new classes would cause the catastrophic forgetting problem [121, 14], *i.e.*, the classification accuracy on old classes drops dramatically after learning new classes. By taking a closer look at catastrophic forgetting in CIL, we find that there are mainly three issues, and each of them represents an aspect of forgetting, while the concurrence of them results in the performance degradation of old classes after learning new classes (as shown in Figure 5 (A)): (1) Representation and classifier mismatch. Directly updating the model on new classes could dramatically change the learned representations and class weights for old classes, which leads to the mismatch between old classes' features and weights. (2) Representation confusion. After learning new classes, the feature extractor would no longer be suitable for old classes. As a result, the input from old and new classes would be confused and overlapped in the deep feature space. (3) Classifier imbalance. The class weights of old and new classes can not be jointly optimized because of the lack of old data. Therefore, the class weights of old and new classes are imbalanced, and the decision boundary can easily shift toward novel classes. The above analysis would not only give a deeper understanding of catastrophic forgetting in CIL but also provide a unified perspective to understand

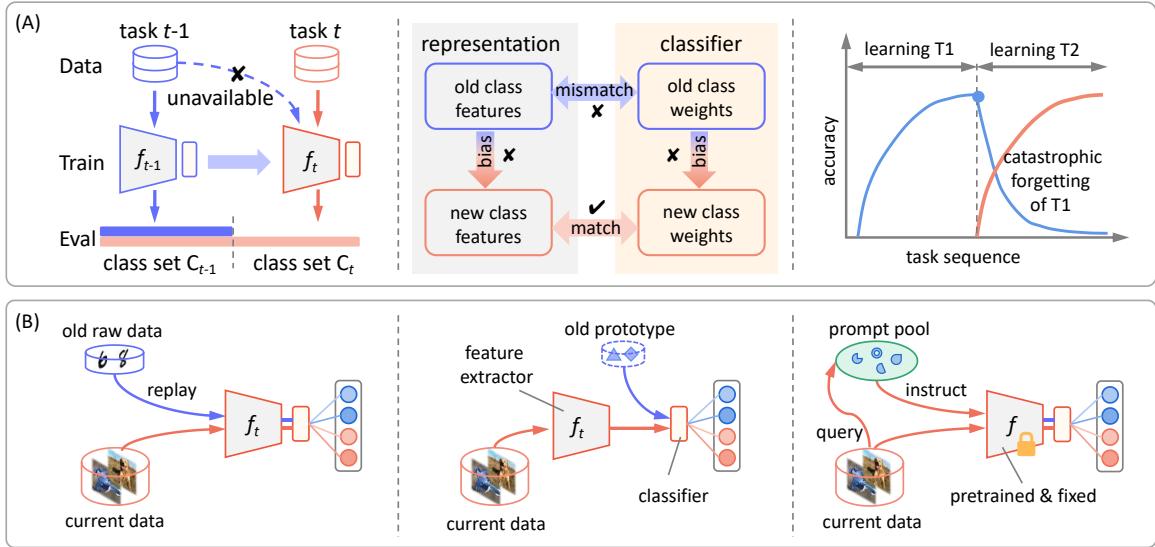


Figure 5: Illustrations of (A) the problem setting and (B) Key challenges of class-incremental learning. Existing technique methods mainly include exemplar replay, feature replay based and prompt-based methods.

existing methods. Despite the grand challenges, considerable progress has been made to enable the continual ability of DNNs recently. As illustrated in Figure 5 (B), existing methods can be grouped into four main categories: regularization based, exemplar replay, feature replay based and prompt-based methods. In what follows, we review the principles and limitations of different approaches.

## 5.1 Regularization based CIL

Both the parameters of a model and its input-output behavior provide distinct measures of what the model has learned from different perspectives. As a result, methods in this domain can be categorized into two groups: explicit and implicit regularization, each aimed at preserving specific forms of knowledge. Explicit regularization seeks to prevent substantial alteration of crucial network parameters, while implicit regularization focuses on maintaining the input-output behavior of the network.

**Explicit Regularization.** For explicit regularization, the central and challenging work is to estimate the importance of network parameters. After learning each task, the importance of individual parameters in the model is estimated to regularize the new class learning process by penalizing the change of important parameters. The general regularization loss is can be formalized as  $\mathcal{L}_{\text{EReg}}^t = \sum_i^P \Omega_i (\theta_i^t - \theta_i^{t-1})^2$ , where  $\Omega_i$  is the estimated importance factor for parameter  $\theta_i$ , and  $P$  is the number of parameters in the network. The first work to achieve this goal is elastic weight consolidation (EWC) [115], which uses the diagonal of the Fisher information matrix to compute the importance  $\Omega_i$ . Alternatively, parameter importance can be estimated by quantifying the sensitivity of the predicted output function to changes in each parameter [117]. These methods can be interpreted as metaplasticity-inspired [122] from a neuroscience point of view [123]. Nonetheless, designing a reasonable importance metric within a neural network remains challenging. Another line of works [124, 125, 126] avoid interfering with previously learned knowledge from a parameter space perspective by projecting and updating the parameters in the null space of the previous tasks. Those methods assume that the capacity of a neural network is high enough to learn new tasks effectively, which would not always hold in practice, especially for incremental learning with long sequences.

**Implicit Regularization.** Rather than directly constraining the parameters of the network, implicit regularization approaches focus on keeping the input-output behavior of the network based on current train-

ing data. The general regularization loss can be formalized as  $\mathcal{L}_{\text{IReg}}^t = \mathbb{E}_{(x,y) \sim \mathcal{D}^t} [D(f^{t-1}(x), f^t(x))]$ , where  $D(\cdot)$  denotes the distance metric such as Euclidean distance, Cosine distance, or Kullback-Leibler divergence. To realize this idea, Li *et al.* proposed learning without forgetting (LwF) which firstly incorporates the knowledge distillation (KD) [127] technique into incremental learning to consolidate old knowledge by distilling the outputs of the previous model to that of the updated model. Noteworthy, although KD [127] was originally developed for model compression, it has been widely used in CIL and served as a basic building block in many methods. Later, several works followed the teacher-student distillation framework to address the catastrophic forgetting in CIL by modifying the KD technique. For example, some approaches distill important features in the deep feature space [128, 129]. Specifically, important features can be identified via attention mechanisms [129, 130] or feature projection [128]. By distilling knowledge from important features, the model not only preserves the crucial information of old classes but also provides flexibility for adapting to new classes. Other works explore methods to distillate knowledge from multi-models [131, 132] or auxiliary data [131, 133, 134].

## 5.2 Exemplar Replay based CIL

Rebuffi *et al.* [135] firstly investigated exemplar replay strategy, and proposed iCaRL that learns both new data and stored old data at each incremental stage. Due to the strong performance, various exemplar replay methods have been developed, mainly focusing on four different aspects: classifier calibration, distilled knowledge, model structure and generative replay.

**Imbalance Calibration.** Due to the memory limitation, the number of saved samples is usually much fewer compared with that of new classes. Therefore, there exists the class imbalance problem [136] between new and old classes. Visually, the norms of the weight vectors of old classes are much smaller than those of new classes [137]. To calibrate the bias, some approaches aim to learn a balanced classifier during training, while other approaches use post-hoc methods to calibrate the classifier. For training-time imbalance calibration, a classical way is under-sampling [138, 139], which reduces the number of new data to construct a balanced training set. However, this is undesirable because many samples of new classes remain unused. A better way is using the balanced training set to fine-tune the model with a small learning rate [140, 133, 141]. Recent work also shows that the memory management policy for imbalance calibration can also be learned via reinforcement learning. Besides focusing on data, other methods explore to modify the classifier directly such as cosine normalization [142] and separated softmax [143, 134]. For post-hoc imbalance calibration, iCaRL [135] introduces the nearest class mean classifier [59] to replace the original classifier, which effectively mitigates the class imbalance problem. A more direct way is to calibrate the classifier via bias correction layer [144] or output scaling [137, 145, 146]. For example, scaling the output logits based on logit norm [137] or rectifying softmax probabilities [146] for old classes to ensure a more balanced treatment of old and new classes during inference.

**Distilled Knowledge.** Knowledge distillation (KD) is a widely used technique to avoid catastrophic forgetting in exemplar replay methods, and it is often applied to both the saved old data and new data. A natural question is: What kind of knowledge should be distilled to maintain the performance on old classes? Indeed, many approaches have been developed from the perspective of distilled knowledge: some focus on unstructured KD, while more recent works focus on structured KD. For unstructured KD, early methods [135, 140, 144] adopt a straightforward and naive way that distills the soft probability distribution, while others [141] also prevent changes in the final or intermediate feature representations to maintain spatial information. To better preserve the previous knowledge, structural KD techniques penalize structural differences in relation of data examples. For instance, the neighborhood relations of samples [147] can be distilled to preserve the topology of the feature space during incremental learning. An alternative way is to penalize the change of ranking order of similarities [148] or instance-wise similarity [149]. Besides explicitly penalizing the change of neighborhood relation, GeoDL [150] models and punishes the gradual changes between two different tasks with the geodesic flow, while DDE [151] implicitly constrains the neighborhood relation by

predicting a sample with its neighborhood.

**Model Architecture.** In task incremental learning (TIL) setting, dynamically extending the network architecture has been demonstrated to be quite effective [152, 153]. Specifically, when learning a new task, the old parameters are frozen and new branches are allocated to learn new tasks. However, those methods are often impractical for CIL because the task identity is not available at inference time, and one can not know which group of parameters should be used for inference given an input. Recently, based on exemplar replay, several architecture-based methods have been proposed for CIL. Liu *et al.* [154] designed two types of residual blocks that have different levels of learnability: a stable block is to maintain the knowledge of old classes, and a plastic block is to learn new classes. A similar idea has been explored in [155], which designed a dual networks architecture that includes a slow learning module for generic representation learning and a fast learning module for task-specific representation learning. Indeed, a simpler and more effective way is dynamically expanding feature extractor to preserve old knowledge while learning new concepts [156]. Specifically, at each incremental stage, the old feature extractor is frozen and a new feature extractor is introduced for learning new classes. However, incrementally creating new models leads to an increase in the number of parameters, while KD can be an effective way to remove redundant parameters [157].

**Generative Exemplar Replay.** Despite the success of real exemplar replay methods in alleviating catastrophic forgetting, they may bring issues such as violation of data privacy and memory limitation: storing a fraction of old raw data would be unsuitable for privacy-sensitive applications in the field of healthcare and security [119, 158], and suffer from memory limitation for long-step incremental learning and applications with limited computational budget. Moreover, directly storing some old training samples is less human-like from the biological perspective [159, 160, 124]. To address privacy and memory limitation concerns of real data replay, researchers have started to consider generative data replay. Early approaches [161, 162] leverage generative model to generate pseudo-samples for old classes. Particularly, the generative model is trained simultaneously with the classification model at each incremental stage. However, those approaches perform poorly for CIL and the generated pseudo-examples rely heavily on the quality of the generative model. Besides, it is computational and memory intensive to train generative models, which also suffer from catastrophic forgetting in the incremental learning process. Recently, rather than leveraging an additional complex generative model, some works [163, 164] explore to use of the classification model itself to generate pseudo-samples. In those works, a crucial challenge is to address the distribution shift between real and generated samples.

### 5.3 Feature Replay based CIL

Exemplar replay methods suffer from memory limitation and privacy concerns in real-world applications, and generating exemplars in input space is quite challenging and highly depends on the quality of generative models. To avoid directly storing and replaying old data, recent works explore feature replay strategies that store and replay features of old classes. Compared with exemplar replay, feature replay has advantages in terms of computation efficiency, memory footprint and privacy safety. However, with the continual updating of feature extractor in the incremental learning process, the saved old features would be less valid and representative. Therefore, maintaining the effectiveness of saved features is a challenge.

**Real and Generative Feature Replay.** In DNNs, there exist many features with different levels of depth or semantics. Therefore, both feature instances in intermediate [165, 166] or final layer [167] can be saved. For feature replay in the intermediate layer, to keep the stored features valid and stable when learning new classes, one can directly freeze the layers between input and feature replay layer [166], or assign a lower learning rate for those layers [165]. For feature replay in the final layer, freezing all layers or assigning a lower learning rate would make the model hard to learn new knowledge. To keep the stored features valid, a feature adaptation module can be constructed to map the saved features to the updated feature space [167], and the classifier can be then jointly optimized over new and old classes in the same space. Besides, inspired by generative exemplar replay, some works [168, 169, 170]

explored generative feature replay, which generates pseudo features of old classes for replay when learning new classes. In particular, generating the final features has been shown to be more effective than generating features in shallower layers [170].

**Prototype Replay.** To further reduce the memory cost of feature replay, prototype replay methods [120, 171, 172] only memorize one class-representative prototype (class mean in deep feature space) for each old class. However, the saved prototypes become increasingly outdated when updating the model on new classes. To address this issue, Zhu *et al.* [120] proposed prototype augmentation to regularize the model, and leveraged self-supervised learning to learn more generic and transferable features, which in turn reduce the feature drift when learning new classes. Other works explicitly model and constrain the feature drifts of old classes via linear [172] or nonlinear transformations [173]. In addition to saving only the prototypes of old classes, more distribution information can be beneficial for maintaining the decision boundary of previous tasks, and an infinite number of pseudo-feature instances can be generated implicitly [174]. More recent works [175, 176] explore directly learning discriminative prototypes for incremental learning.

## 5.4 Prompt-based CIL

Recent works [177, 178, 179, 180] leverage pre-trained frozen models and learn a set of prompts (*i.e.*, small learnable parameters) to dynamically instruct models in tackling tasks sequentially. L2P [177] stands as the pioneering work that formulates the problem of learning new tasks as training small prompt parameters attached to a pre-trained frozen model. To further improve the plasticity of the model, CODA-Prompt [179] introduces an attention-based end-to-end key-query scheme, wherein a collection of input-conditioned prompts is learned. Wang *et al.* [181] proposed a hierarchical decomposition prompt framework to explicitly optimize the within-task prediction, task-identity inference, and task-adaptive prediction with task-specific prompts. Nevertheless, it is worth noting that prompt-based methods are largely reliant on pre-trained models. As highlighted recently by Kim *et al.* [182] the information leak both in terms of features and class labels can exert a substantial influence on the results of those approaches.

# 6 Future Directions

Open-world machine learning is an active and long-term research topic, and there are a number of critical open directions worthy of further investigation. In this section, we briefly outline a few promising research directions that enable OWL in a unified framework and more complex scenarios, *e.g.* structured data and applications such as detection, segmentation, etc. Besides, additional directions considering brain-inspired OWL and machine unlearning are also discussed. Figure 6 presents an illustration of the future directions.

## 6.1 Unified OWL

A desirable open-world learner has to learn and adapt continuously in its interaction with the environment. Specifically, during deployment, the model should correctly classify the known (classes seen at the current stage) and reject the unknown (misclassified samples from known classes and OOD samples from unseen classes), discover and label these unknowns in the buffer as novel known classes, and then incremental learning these new classes while maintaining the discrimination ability on old classes. Nevertheless, existing studies mostly focus on an isolated task without considering the whole learning process. Here we discuss some typical examples. For unknown rejection, current approaches aim to detect and filter out known samples from unseen classes, while they often lower a model’s ability to reject misclassified samples from known classes [58, 183, 184]. This is undesirable because real-world applications require the rejection of both widely existing misclassified and OOD samples,

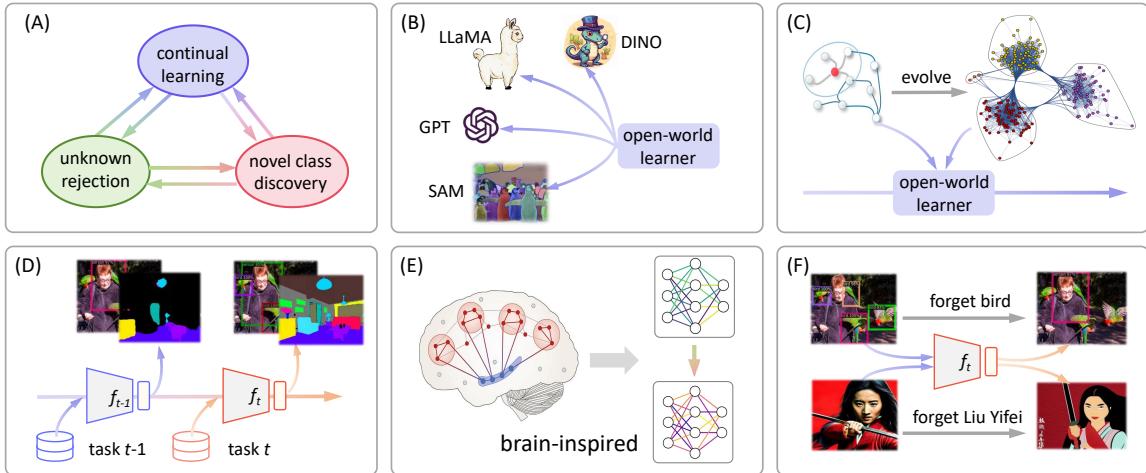


Figure 6: Illustrations of future research directions of open-world learning. (A) Unified open-world learner. (B) OWL for foundation models such as GPT, SAM and LLaMA. (C) OWL for structured data with graph neural networks. (D) OWL beyond classification, such as object detection and segmentation. (E) Brain-inspired OWL models that mimic biological learning systems. (F) Open-world unlearning actively and selectively forgetting or erasing specific knowledge.

and there is a long way to go towards developing unified unknown rejection methods [185]. For class-incremental learning, when learning new classes, the training samples are well-labeled manually and clean, *i.e.*, only contain given class in  $\mathcal{C}^t$ . In practice, the users often are not aware of novelty and the model is supposed to discover novel classes from the buffer which contains various samples without labels. Some works [186, 187] propose the task of incremental novel category discovery, where the samples from new classes are unlabeled at each incremental step. More recent works [188] consider a more challenging scenario where the unlabeled data could also contain samples from the old classes at each incremental step. In addition, a better understanding of the relationship between unknown rejection, novel class discovery and class-incremental learning is needed. A recent study [182] has shown that OOD detection techniques can help CIL, and designs an algorithm that explicitly performs OOD detection in the incremental learning process. A more interesting question is how rejection performance change when a model continually adapts and learn in the open environment. Intuitively, incremental learning could profoundly affect the rejection ability because newly accumulated knowledge will affect the border of the unknown [12]. In summary, it is worth studying the relation or interaction among those three tasks in OWL and developing a unified framework that can deal with those open-world problems simultaneously, *i.e.*, correctly recognize known, reject unknown, discover new classes from unknown and then incrementally learn them.

## 6.2 OWL for Foundation Models

Recent years have witnessed the significant progress of foundation models [189]. CLIP [190], ChatGPT [23], and SAM [191] have demonstrated remarkable zero-shot and few-shot learning. However, if we consider open-world learning ability, there still remain important limitations. On the one hand, OpenAI has pointed out that ChatGPT can be easily overconfident in its incorrect predictions [23]. When faced with questions it cannot answer, ChatGPT tends to make meaningless guesses rather than refusing to respond [192], propagates false information or provides unethical advice in fields such as clinical and legal matters [24]. Indeed, there is still a lack of clear understanding of the reliability and failure cases of foundational models. On the other hand, foundational models yield poor performance in certain tasks [190, 193]. Nevertheless, they still lack the ability for incremental learning, and direct fine-tuning may deteriorate the model’s performance on other classes or tasks [194]. Furthermore,

without the continual updating of model weights, the knowledge within foundational models can become outdated, resulting in the provision of incorrect information. For example, ChatGPT is trained on data up to 2021 and has limited knowledge of the world and events after that time. If you ask ChatGPT who won the World Cup in 2022, it won't be able to give you a response. Another example is that although ChatGPT is good at writing code, it can not generate code with the latest version, which largely limits its power. Unfortunately, the computational burden of training from scratch makes it impossible to directly retrain the model on both old and new data. The aforementioned issues highlight the limitations associated with the practical applications of foundation models, making it a grand challenge for future research. To enhance the reliability and adaption ability of foundation models in open environments, innovations in both learning objectives and model architectures are needed to develop novel OWL techniques.

### 6.3 OWL for Structured Data

Most existing OWL methods assume that inputs (*e.g.* images in computer vision) are independently sampled. However, in practice, data is often structured and inter-connected, such as traffic networks and social networks. However, existing methods are hard to apply to structured data because they mainly focus on individual samples but neglect the topological structure and the interconnections among different samples. There have been some studies that attempt to improve the OWL ability for structured data learning with graph neural networks. To name a few, Stadler *et al.* [195] designed Bayesian graph neural networks models to detect OOD nodes on graphs, while Wu *et al.* [196] proposed energy function based OOD discriminator for unknown reject on graph-structured data. For CIL, Liu *et al.* [197] introduced a topology-aware weight-preserving strategy that explicitly looks into topological aggregation and propagation to reduce the forgetting of old knowledge. Besides, a comprehensive continual graph learning benchmark that contains both node-level and graph-level continual learning tasks has been established recently [198]. Open-world learning on structured data is an emerging research area, and inevitably work will be needed to facilitate its development based on a deeper understanding of structured data.

### 6.4 OWL Beyond Classification

Existing works mainly focused on image classification tasks. Recently, there has been noticeable attention in addressing open-wold learning challenges in other applications such as object detection [199, 200] and semantic segmentation [201, 202]. In image classification, a single image typically only contains one object. In contrast, object detection and semantic segmentation tasks typically involve input images that contain multiple objects, and some of them are labeled during the initial learning stage, while others should be classified as unknown. This implies that many unknown classes would have been already seen by the object detector. During the incremental learning process, information (labels) about these new classes within the background becomes available, the model should incrementally learn them to incorporate novel knowledge [203]. Therefore, the advances in open-world classification cannot be trivially adapted to open-world object detection or segmentation, and it is important to leverage background information and explore feature representations that could facilitate future learning of new classes. Besides, OWL is also important for natural language processing domain, where out-of-vocabulary words or novel concept vocabulary may emerge over time. To design effective algorithms for those tasks beyond classification, it is helpful to combine existing methods with task-specific domain knowledge.

### 6.5 Brain-inspired OWL

Compared to DNN based artificial intelligence systems, biological organisms like humans naturally have the strong ability of open-world learning, enabling them to interact with the environment

throughout their lifetime [160]. For example, humans can be aware of when they are likely to be wrong and then refuse to make a high-risk decision; they can discover novel knowledge based on what they have learned previously, and last but not least, humans excel at learning from a dynamically changing environment incrementally without suffering from catastrophic forgetting. In light of this, some works [123, 124, 204, 205, 206] aim to design brain-inspired open-world machine learning models. For example, van de Ven *et al.* [123] proposed a brain-inspired feature replay method that uses the original classification model itself to generate features of old classes, avoiding using additional generative models and showing promising performance for CIL. Recently, inspired by biological learning systems, Wang *et al.* [204] built a continual model with the ability of stability protection and active forgetting. We believe that the biological cognitive system will inspire more advanced OWL models to narrow the gap between artificial and natural intelligence.

## 6.6 Open-world Unlearning

Most of the focus in machine learning is on training models to acquire new knowledge, *e.g.*, incremental learning aims to incorporate new knowledge without forgetting previously learned ones. On the contrary, there are scenarios where machine unlearning may be required for various reasons: (1) Sensitive information removal. In some cases, machine learning models may inadvertently memorize sensitive or private information from the training data [207]. Unlearning can be used to erase such information from the model’s memory to ensure data privacy and compliance with regulations. (2) Bias mitigation. If a model exhibits undesirable biases in its predictions [208], unlearning can be employed to eliminate these biases or align the model better with desired behaviors by removing some patterns learned during training. (3) Selective forgetting. Unlearning allows models to discard some outdated information to leave more room for learning new tasks. This is different from the well-known catastrophic forgetting [121, 14] which may forget important information that we want to memorize. Indeed, machine unlearning is challenging because it involves determining which parts of knowledge to remove, developing algorithms for knowledge erasure, and ensuring that unlearning does not adversely affect the model’s overall performance [209, 210]. Therefore, it is a long-term research goal to perform open-world learning and unlearning flexibly and simultaneously.

## 7 Conclusion

Open-world learning stands as a critical frontier in the field of artificial intelligence, particularly as AI systems increasingly operate in complex, real-life environments (*e.g.* self-driving cars, mobile robots, chatbots, etc.), and engage with humans and automated systems. The essence of open-world learning lies in the ability to detect and adapt to new diverse and ever-changing scenarios, like a self-motivated learner. In this article, we provided an overview of open-world learning, with an emphasis on techniques concerning unknown rejection, novel class discovery, and class-incremental learning. Finally, we outlined several challenging open problems that merit substantial research endeavors in the future.

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