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A Survey of Deep Active Learning

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Active learning (AL) attempts to maximize the performance gain of the model by marking the fewest samples. Deep learning (DL) is greedy for data and requires a large amount of data supply to optimize massive parameters, so that the model learns how to extract high-quality features. In recent years, due to the rapid development of internet technology, we are in an era of information torrents and we have massive amounts of data. In this way, DL has aroused strong interest of researchers and has been rapidly developed. Compared with DL, researchers have relatively low interest in AL. This is mainly because before the rise of DL, traditional machine learning requires relatively few labeled samples. Therefore, early AL is difficult to reflect the value it deserves. Although DL has made breakthroughs in various fields, most of this success is due to the publicity of the large number of existing annotation datasets. However, the acquisition of a large number of high-quality annotated datasets consumes a lot of manpower, which is not allowed in some fields that require high expertise, especially in the fields of speech recognition, information extraction, medical images, etc. Therefore, AL has gradually received due attention.

A natural idea is whether AL can be used to reduce the cost of sample annotations, while retaining the powerful learning capabilities of DL. Therefore, deep active learning (DAL) has emerged. Although the related research has been quite abundant, it lacks a comprehensive survey of DAL. This article is to fill this gap, we provide a formal classification method for the existing work, and a comprehensive and systematic overview. In addition, we also analyzed and summarized the development of DAL from the perspective of application. Finally, we discussed the confusion and problems in DAL, and gave some possible development directions for DAL.

CCS Concepts: • **Computing methodologies** → **Machine learning algorithms**.

Additional Key Words and Phrases: Deep Learning, Active Learning, Deep Active Learning.

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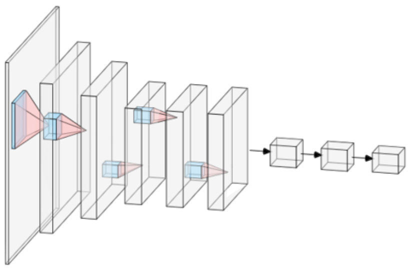
1 INTRODUCTION

Both DL and AL have important applications in the machine learning community. With their excellent characteristics, they have attracted the interest of a large number of researchers. Specifically, DL has achieved unprecedented breakthroughs in various challenging tasks, but this is largely due to the disclosure of massive labeling datasets [16, 87]. Therefore, DL is limited by the high sample labeling cost in some professional fields that require rich knowledge. On the other hand, in theory, an effective AL algorithm can achieve exponential acceleration in labeling efficiency [12]. This huge label cost saving potential is fascinating. In addition, the classic AL algorithm is also difficult to handle high-dimensional data [100, 101, 162, 179]. Therefore, the combination of DL and AL, DAL, has also been given high expectations by researchers. DAL has been widely used in various fields, such as image recognition [35, 47, 53, 68], text classification [147, 183, 188], visual question answering [98] and object detection [3, 39, 123], etc. Although the related work has been quite rich, DAL still lacks a unified classification framework. In order to fill this gap, in this article we will give a comprehensive overview of the existing DAL related work and provide a formal classification method. Next, we will first briefly review the development status of DL and AL in their respective fields. Then, in Section 2, the necessity and challenges of combining DL and AL are further given.

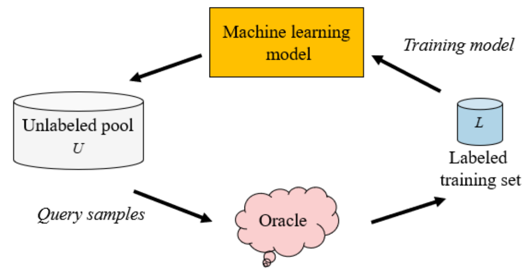
1.1 Deep Learning

DL attempts to build corresponding models by simulating the structure of the human brain. In 1943, the McCulloch-Pitts (MCP) model proposed by [40] was regarded as the beginning of modern DL. Subsequently, in 1986, [131] introduced backpropagation into the optimization of neural networks, which laid the foundation for the subsequent vigorous development of DL. In the same year, Recurrent Neural Networks (RNNs) [75] were proposed. In 1998, the LeNet [92] network appeared, and it was one of the earliest uses of deep neural networks (DNN). However, these pioneering work in the early days were limited by the computing resources at the time and did not receive as much attention and application as they should [90]. In 2006, Deep Belief Networks (DBNs) [62] were proposed and used to explore deeper networks than before, which prompted the name of neural networks as DL. In 2012, in the ImageNet competition, the DL model AlexNet [87] won the championship in one fell swoop. It uses the ReLU activation function to effectively suppress the problem of gradient disappearance, while using multiple GPUs greatly improves the training speed of the model. Subsequently, DL began to win championships in various competitions and constantly refresh records in various tasks. From the perspective of automation, the emergence of DL has transformed the manual design of features [30, 104] in machine learning into automatic extraction [58, 151]. It is precisely because of the powerful automatic feature extraction ability of DL that it has shown unprecedented advantages in many fields. After decades of development of DL, related research work has been quite rich. In Fig.1a, we show a standard deep learning model example: convolutional neural network (CNN) [91, 132]. Based on this, similar CNNs are applied to various image processing tasks. In addition, RNNs and Generative Adversarial Networks (GANs) [134] are widely used. Starting in 2017, DL gradually changed from the initial feature extraction automation to the automation of model architecture design [11, 126, 192]. However, this still has a long way to go.

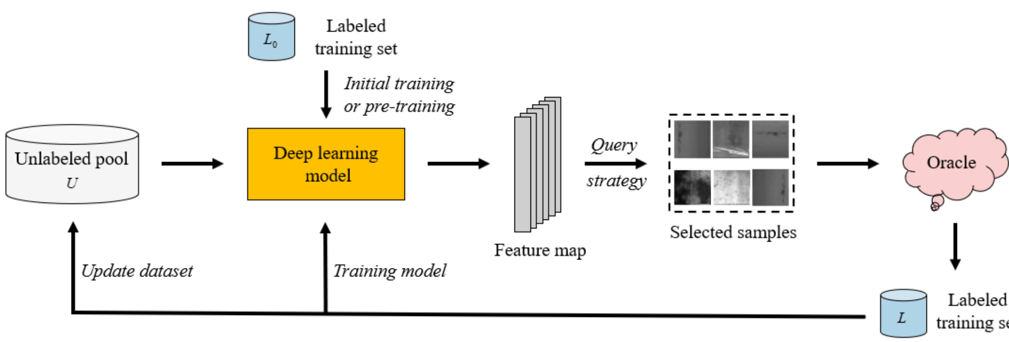
Thanks to the publication of a large number of existing annotation datasets [16, 87], in recent years, DL has made breakthroughs in various fields such as machine translation [4, 13, 161, 170], speech recognition [112, 118, 122, 138], and image classification [60, 108, 117, 176]. However, this is at the cost of a large number of manually labeled datasets, and DL has a strong greedy attribute to the data. In the real world, obtaining a large number of unlabeled datasets is relatively simple, but manual labeling of datasets faces a high price. Especially those fields that require high professional



(a) Structure diagram of convolutional neural network.



(b) The pool-based active learning cycle.



(c) A typical example of deep active learning.

Fig. 1. Comparison of typical architectures of DL, AL and DAL. (a) A common DL model: Convolutional Neural Network.(b)The pool-based AL cycle: Use the query strategy to query the sample in the unlabeled pool U and hand it over to oracle for labeling, then add the queried sample to the labeled training dataset L and train, and then use the newly learned knowledge for the next round of query. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached. (c) A typical example of DAL: The parameters θ of the DL model are initialized or pre-trained on the label training set L_0, and the samples of the unlabeled pool U are used to extract features through the DL model. Then select samples based on the corresponding query strategy, and query the label in oracle to form a new label training set L, then train the DL model on L, and update U at the same time. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached.

knowledge [64, 155], such as the labeling and description of lung lesion images of COVID-19 patients require experienced clinicians to complete. Obviously, it is impossible to require them to complete a large amount of medical image labeling. Similar fields also include speech recognition [1, 191], medical imaging [64, 93, 111, 178], recommender systems [2, 26], information extraction [17], satellite remote sensing [99] and robotics [7, 22, 160, 189], etc. Therefore, we urgently need a way to maximize the performance gain of the model when annotating a small number of samples.

1.2 Active Learning

AL is such a method. It tries to select the most useful samples from the unlabeled dataset and hand it over to oracle (e.g., human annotator) for labeling, so as to reduce the cost of labeling as much as possible while maintaining performance. AL can be divided into membership query synthesis [8, 82], stream-based selective sampling [29, 85] and pool-based [95] AL from application scenarios

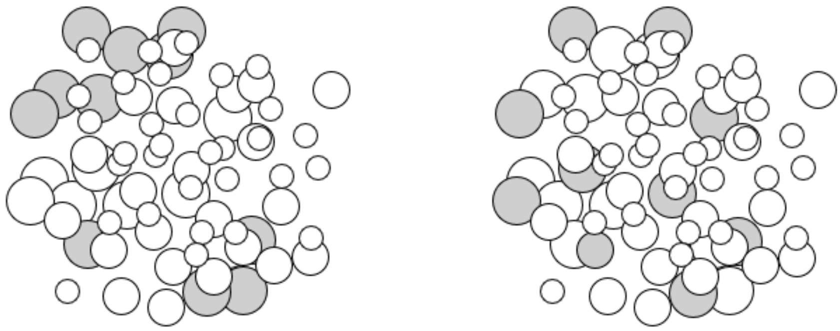
[141]. Membership query synthesis means that the learner can request to query the label of any unlabeled sample in the input space, including the sample generated by the learner. The difference between stream-based selective sampling and pool-based is mainly that the former is to make an independent judgment on whether each sample in the data stream needs to query the labels of unlabeled samples, while the latter can choose the best query sample based on the evaluation and ranking of the entire dataset. In contrast, the pool-based scenario seems to be more common in the application of the paper, but it is clear that the application scenario of stream-based selective sampling is more suitable for small mobile devices that require timeliness. In Fig.1b, we illustrates the framework diagram of the pool-based active learning cycle. In the initial state, we can randomly select one or more samples from the unlabeled pool U and give it to the oracle query label to get the labeled dataset L, and then train the model on L by supervised learning. Next, use the new knowledge to select the next sample to be queried, and add the newly queried sample to L and train. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached.

It is different from DL by using manual or automatic methods to design models with high-performance feature extraction capabilities. AL starts with datasets, mainly by designing elaborate query rules to select the best samples from unlabeled datasets and query their labels, in an attempt to reduce the labeling cost as much as possible. Therefore, the design of query rules is crucial to the performance of AL. Related research is also quite rich. For example, in a given set of unlabeled datasets, the main query strategies include uncertainty-based approach [14, 76, 95, 125, 144, 163], diversity-based approach [18, 47, 55, 113] and expected model change [43, 129, 143]. In addition, there are many works to study hybrid query strategies [10, 148, 180, 186], taking into account the uncertainty and diversity of query samples, and trying to find a balance between these two strategies. Because separate sampling based on uncertainty often results in sampling bias [31]: The currently selected sample is not representative in the distribution of unlabeled datasets. On the other hand, considering only diversity strategies may lead to increased labeling costs: There may be a considerable number of samples with low information content will be selected. More classic query strategies can be queried in [142]. Although the research related to AL has been quite rich, AL still faces the problem of expanding to high-dimensional data (e.g., images, text and video, etc.) [162], so most AL work is mainly concentrated on low-dimensional problems [61, 162]. In addition, AL often queries high-value samples based on features extracted in advance, and does not have the ability to extract features.

2 THE NECESSITY AND CHALLENGE OF COMBINING DL AND AL

DL has a strong learning ability in high-dimensional data processing and automatic feature extraction, and AL also has great potential in effectively reducing labeling costs. Therefore, an obvious idea is to combine DL and AL, which will greatly expand their application potential. DAL was proposed by considering the complementary advantages of the two, and related research has also been placed high hopes by researchers. Although AL's research on query strategy is quite rich, it is still quite difficult to directly apply this strategy to DL. This is mainly due to:

- Insufficient data for label samples. AL often relies on a small amount of labeled sample data to learn and update the model, and DL is often very greedy for the data [63]. The labeled training samples provided by the classic AL method are not sufficient to support the training of traditional DL. In addition, the one-by-one sample query method commonly used in AL is also not applicable in DL [186].
- Model uncertainty. The query strategy based on uncertainty is an important direction of AL. In the classification task, although DL can use the softmax layer to obtain the probability



(a) Batch query strategy considering only the amount of information.

(b) Batch query strategy considering both information volume and diversity.

Fig. 2. A comparison diagram of a batch query strategy that only considers the amount of information and considers both the amount of information and diversity. The size of the dots indicates the amount of information of the samples, and the distance between the dots indicates the similarity between the samples. The gray solid points indicate the sample points to be queried in a batch.

distribution on the label, the facts show that they are too confident. The softmax response (SR) [168] of the final output is unreliable as a measure of confidence, and the performance of this method will be even worse than that of random sampling [167].

- The processing pipeline is inconsistent. The processing pipelines of AL and DL are inconsistent. Most AL algorithms mainly focus on the training of classifiers, and various query strategies are largely based on fixed feature representations. In DL, feature learning and classifier training are jointly optimized. Only fine-tuning the DL models in the AL framework or treating them as two separate problems may cause divergent issues [168].

For the first problem, researchers consider using generative networks for data augmentation [164] or assigning pseudo-labels to high-confidence samples to expand the labeled training set [168]. Some researchers also consider using labeled datasets and unlabeled datasets to combine supervised training and semisupervised training across AL cycles [65, 150]. In addition, previous heuristic-based AL [141] query strategies have proved to be ineffective when applied to DL [140]. Therefore, for the one-by-one query strategy in classic AL, many researchers focus on the improvement of the query strategy of batch samples [10, 51, 84, 186], taking into account the amount of information and the diversity of samples in batch samples. In order to solve the neglect of model uncertainty in DL, some researchers use Bayesian deep learning [45] to deal with the high-dimensional mini-batch samples with fewer queries in the context of AL [47, 84, 120, 164], thereby effectively alleviating the problem of the DL model being too confident about the output results. To deal with the problem of inconsistent pipelines, researchers consider modifying the combined framework of AL and DL to make the proposed DAL model as general as possible, which can be extended to various application fields. This is of great significance to the promotion of DAL. For example, [181] embeds the idea of AL into DL and proposes a task-independent architecture design.

We will focus on the detailed discussion and summary of the various strategies used in DAL in the Section 3.

3 DEEP ACTIVE LEARNING

In this section, we will provide a comprehensive and systematic overview of DAL related work. Fig.1c illustrates a typical DAL model architecture example. The parameters θ of the deep learning model are initialized or pre-trained on the label training set L_0, and the samples of the unlabeled pool U are used to extract features through the deep learning model. Then select samples based on the corresponding query strategy, and query the label in oracle to form a new label training set L, then train the deep learning model on L, and update U at the same time. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached. From the DAL framework example in Fig.1c, we can roughly divide the DAL framework into two parts: the AL query strategy on the unlabeled dataset and the DL model training method. To this end, we will discuss and summarize them in the following Section 3.1 and 3.2 respectively. Finally, we will discuss the efforts made by DAL on the generalization of the model in Section 3.3.

3.1 Query Strategy Optimization in DAL

In the pool-based method, we define $U^n = \{\mathcal{X}, \mathcal{Y}\}$ as an unlabeled dataset with n samples, where $\mathcal{X}$ is the sample space, $\mathcal{Y}$ is the label space, and $P(x, y)$ is a potential distribution, where $x \in \mathcal{X}, y \in \mathcal{Y}$. $L^m = \{X, Y\}$ is the current labeled training set with m samples, where $\mathrm{x} \in X, \mathrm{y} \in Y$. Under the standard supervision environment of DAL, our main goal is to design a query strategy Q, $U^n \xrightarrow{Q} L^m$, using the deep model $f \in \mathcal{F}, f : \mathcal{X} \to \mathcal{Y}$, the optimization problem of DAL in a supervised environment can be expressed as:

$$\underset{L\subseteq U, (\mathrm{x},\mathrm{y})\in L}{\arg\min} \ \mathbb{E}_{(x,y)}[\ell(f(\mathrm{x}), \mathrm{y})], \tag{1}$$

where $\ell(\cdot) \in \mathcal{R}^+$ is the given loss equation, and expect $m \ll n$. Our goal is to make m as small as possible while ensuring a certain level of accuracy. Therefore, the query strategy Q in DAL is crucial to reduce the labeling cost.

3.1.1 Batch Mode DAL (BMDAL). The main difference between DAL and classic AL is that DAL uses batch-based sample query. In traditional AL, most algorithms use one-by-one query, which leads to frequent training of the learning model, but the training data has little change. The training set obtained by this query method is not only inefficient in the training of the DL model but also easily causes overfitting. Therefore, the research of BMDAL is necessary. In the context of BMDAL, at each acquisition step, we score the batch of candidate unlabeled data samples $\mathcal{B} = \{x_1, x_2, ..., x_b\} \subseteq U$ based on the acquisition function used a and the deep model $f_\theta(L)$ trained on L, to select a new batch of data samples $\mathcal{B}^* = \{x_1^*, x_2^*, ..., x_b^*\}$. This problem can be formulated as follows:

$$\mathcal{B}^* = \underset{\mathcal{B}\subseteq U}{\arg\max}\, a_{batch}(\mathcal{B}, f_\theta(L)). \tag{2}$$

A naive idea is to continuously query a batch of samples based on the one-by-one strategy. For example, [46, 73] adopts the method of batch acquisition, and chooses to query Bayesian Active Learning by Disagreement (BALD) [67] to obtain the top b samples with the highest scores. Obviously, this method is not feasible because it is very likely to choose a set of information-rich but similar samples. The information provided by the similar samples to the model is basically the same, which not only wastes labeling resources, but also makes it difficult for the model to really learn useful information. Therefore, the core of BMDAL is to query a set of information-rich and diverse samples. Fig.2 illustrates a schematic diagram of this idea.

The batch-based query strategy forms the basis of the combination of AL and DL, and related research is also very rich. We will give a detailed overview and discussion of the query strategy on BMDAL in the following sections.

3.1.2 Uncertainty-based and hybrid query strategy. Because the method based on uncertainty is simple in form and has low computational complexity, it is a very popular query strategy in AL. This query strategy is mainly used in some shallow models (eg, SVM [163] or KNN [72]). This is mainly because the uncertainty of this model can be accurately obtained by traditional uncertainty sampling methods (eg, Margin Sampling, Least Confidence and Entropy [142]) measuring.

There are many DAL [9, 59, 116, 125] methods that directly use this uncertainty-based sampling strategy. However, as analyzed in Section 3.1.1, this can easily lead to insufficient diversity of batch query samples (not fully utilizing relevant knowledge of data distribution), which in turn leads to low or even invalid DL model training performance. A feasible strategy is to use a hybrid query strategy in a batch query, taking into account both the information volume and diversity of samples in an explicit or implicit manner.

Early Batch Mode Active Learning (BMAL) [20, 77, 113, 173, 175] algorithm performance often relies too much on the measurement of similarity between samples. In addition, these algorithms are often only good at exploitation (learners tend to focus only on samples near the current decision boundary, corresponding to high-information query strategies), resulting in the samples in the query batch sample set cannot represent the true data distribution of the feature space (insufficient diversity of batch sample sets). To this end, Exploration-P [180] uses a deep neural network to learn the feature representation of the samples, and explicitly calculates the similarity between the samples. At the same time, the process of exploitation and exploration (in the early days of model training, learners use random sampling strategies to explore) is balanced to measure the similarity between samples more accurately. On the other hand, DBAL [186] adds the informativeness to the optimization goal of K-means by weight, and deeply studies the hybrid query strategy that considers the sample information volume and diversity under the sample query setting of mini-batch. DBAL [186] can easily complete the expansion from the generalized linear model to DL, which not only increases the scalability of DBAL [186] but also increases the diversity of active query samples in mini-batch. This hybrid query strategy is quite popular. For example, WI-DL [99] mainly considers the two stages of DBN. In the unsupervised feature learning stage, the representativeness of the data is mainly considered, while in the supervised fine-tuning stage, the uncertainty of the data is considered, and then the two indicators are integrated, and finally optimized using the proposed weighted incremental dictionary learning (WI-DL) algorithm.

Although the above improvements have achieved good performance, there is still a hidden danger to be solved. In fact, diversity-based strategies are not appropriate for any dataset. The richer the category content of the dataset, the larger the batch size, the better the effect of diversity-based methods. On the contrary, the query strategy based on uncertainty performs better. These characteristics depend on the statistical characteristics of the dataset. In BMAL, the data are unfamiliar and potentially unstructured. Therefore, it is impossible to know which AL query strategy is more appropriate. Based on this, Batch Active learning by Diverse Gradient Embeddings (BADGE) [10] samples point groups that are disparate and high magnitude when represented in a hallucinated gradient space, so that the prediction uncertainty of the model and the diversity of the samples are simultaneously considered in a batch. Most importantly, BADGE can achieve an automatic balance between forecast uncertainty and sample diversity without the need for manual hyperparameter adjustments. Different from BADGE [10] considering this hybrid query strategy in an implicit way, Wasserstein Adversarial Active Learning (WAAL) [148] proposes a hybrid query strategy that explicitly compromises uncertainty and diversity. In addition, WAAL [148] uses Wasserstein distance to model the interactive procedure in AL as a distribution matching, and derives losses from it, and then decomposes WAAL [148] into two stages: DNN parameter optimization and query batch selection. Task-Aware Variational Adversarial Active Learning (TA-VAAL) [81] also explores the balance of this hybrid query strategy. TA-VAAL believes that the uncertainty-based method does not make good use of the overall data distribution, while the data distribution-based method often ignores the structure of the task. Therefore, TA-VAAL proposes to integrate the loss prediction module [181] and the concept of RankCGAN [135] into Variational Adversarial Active Learning (VAAL) [152] in order to consider both the data distribution and the model uncertainty. TA-VAAL has achieved good performance on various balanced and unbalanced benchmark datasets. The structure diagram of TA-VAAL and VAAL is shown in Fig.6a.

In fact, although the hybrid query strategy shows more excellent performance. But in contrast, because the AL query strategy based on uncertainty is more convenient to combine with the output of the softmax layer of DL, the query strategy based on uncertainty is still widely used.

3.1.3 Deep Bayesian Active Learning (DBAL). As described in the analysis of the challenge of combining DL and AL in Section 2, the acquisition function based on uncertainty is an important research direction of many classic AL algorithms, and traditional DL methods rarely represent such model uncertainty.

For this reason, Deep Bayesian Active Learning appeared. In the given input set X and the output Y belonging to the c class, the probabilistic neural network model can be defined as $f(\mathrm{x};\theta)$, $p(\theta)$ is a prior on the parameter space θ (usually Gaussian), and the likelihood $p(\mathrm{y}=c|\mathrm{x},\theta)$ is usually determined by $softmax(f(\mathrm{x};\theta))$ given. Our goal is to obtain the posterior distribution over θ:

$$p(\theta|X,Y)=\frac{p(Y|X,\theta)p(\theta)}{p(Y|X)}. \tag{3}$$

For a given new data point x^*, $\hat{\mathrm{y}}$ is predicted by

$$p\left(\hat{\mathrm{y}}|\mathrm{x}^*,X,Y\right)=\int p\left(\hat{\mathrm{y}}|\mathrm{x},\theta\right)p(\theta|X,Y)d\theta=\mathbb{E}_{\theta\sim p(\theta|X,Y)}[f(\mathrm{x};\theta)]. \tag{4}$$

DBAL [47] combines Bayesian convolutional neural networks (BCNNs) [45] with AL methods to adapt BALD [67] to the deep learning environment, thus developing a new AL framework for high-dimensional data. It adopts the above method to first perform Gaussian prior modeling on CNNs weights, and then use variational inference to obtain the posterior distribution of network prediction. In addition, in practice, researchers often also use a powerful and low-cost Monte-Carlo dropout (MC-dropout) [158] stochastic regularization technique to obtain posterior samples, and have a good performance on real datasets [80, 94]. Moreover, this regularization technique has been proved to be equivalent to variational inference [46]. However, A core-set approach [140] points out that DBAL [47] is not suitable for large datasets due to the need for batch sampling. It should be pointed out that DBAL [47] allows the use of dropout in testing for better confidence estimation, but the analysis of [51] believes that the performance of this method is similar to the performance of using neural network softmax response (SR) [168] as uncertainty sampling, this requires vigilance. In addition, DFAL [36] pointed out that the uncertainty-based DBAL [44, 46] method may be fooled by adversarial examples, and a slight disturbance may cause unacceptable performance loss. DEBAL [120] believes that the pattern collapse phenomenon [157] in the variational inference method leads to the overconfident prediction of the DBAL method. For this reason, DEBAL combines the expressive power of ensemble methods with MC-dropout to obtain better uncertainty in the absence of trading representativeness. On the other hand, BatchBALD [84] chose to expands BALD [67] to batch query, no longer calculates the mutual information between a single sample and model parameters, but recalculates the mutual information between the batch smaples and the model parameters to jointly score the batch of samples. Therefore, BatchBALD can more accurately evaluate the joint mutual information. Inspired by the latest research on the Bayesian coresets [23, 69], ACS-FW [119] reconstructed the batch structure to optimize the sparse subset approximation of the log posterior induced by the entire dataset. By using this similarity, ACS-FW uses Frank-Wolfe [42] algorithm to enable effective Bayesian AL at scale, and the use of random projection makes ACS-FW further popularized. Compared with other query strategies (e.g. maximizing the predictive entropy (MAXENT) [47, 140] and BALD [67]), ACS-FW has better coverage in the entire data maniflod. DPEs [28] introduces an expandable Deep Probabilistic Ensembles (DPEs) technology, which uses a regularized ensemble to approximate deep BNN, and evaluates the classification effect of DPEs in a series of large-scale visual AL experiments.

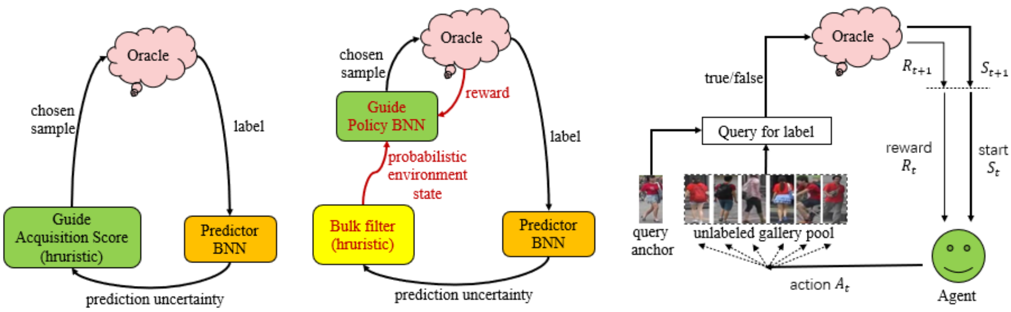
ActiveLink [116] is inspired by the latest advances in Bayesian deep learning [46, 174]. It adopts the Bayesian view of the existing neural link predictors, and expands the uncertainty sampling method by using the basic structure of the knowledge graph, thereby realizing a novel DAL method. And ActiveLink noticed that although AL can sample efficient samples, the model needs to be retrained from scratch for each iteration in the process of AL, which is unacceptable for DL model training. A simple solution is to use newly selected data to train the model incrementally, or to combine it with existing training data [147]. But this will cause the model to either be biased towards a small amount of newly selected data or towards data selected early in the process. In order to solve this bias problem, ActiveLink adopts a principled and unbiased incremental training method based on meta-learning. That is, in each AL iteration, ActiveLink uses the newly selected samples to update the model parameters, and approximates the meta-objective of the model's future prediction by generalizing the model based on the samples selected in the previous iteration. This allows ActiveLink to strike a balance between the importance of the newly selected data and the previously selected data, thereby achieving unbiased estimation of model parameters.

In addition to the above-mentioned DBAL work, due to the lesser parameter of BNN and the uncertainty sampling strategy similar to traditional AL, the research of DBAL is quite extensive, and there are many related DBAL work [54, 107, 128, 149, 177, 182].

3.1.4 Density-based Methods. The density-based method mainly refers to the selection of sample from the perspective of the set (core set). The construction of the core set is such a representative query strategy. This idea is mainly inspired by the compression idea of the coreset dataset, and attempts to use the coreset to represent the distribution of the feature space of the entire original dataset, thereby reducing the labeling cost of AL.

Farthest First Active Learning (FF-Active) [49] is based on this idea and uses the farthest-first traversals in the space of neural activation over a representation layer to query consecutive points from the pool. It is worth mentioning that FF-Active [49] and Exploration-P [180] are similar to the use of random queries in the early stages of AL to enhance AL's exploration ability, thereby avoiding AL from falling into the trap of insufficient sample diversity. Similarly, in order to solve the sampling bias problem in batch query, the diversity of batch query samples is increased. The Core-set approach [140] attempts to solve this problem by constructing a core subset. And further solve the k-Center problem [38] to build a core subset, so that the model learned on the selected core set is more competitive than the rest of the data. However, because the Core-set approach requires a large distance matrix to be built on the unlabeled data set, this search process is computationally expensive. And this disadvantage will become more apparent on large-scale unlabeled datasets [10].

Active Palmprint Recognition [35] applies DAL to high-dimensional and complex palmprint recognition data. Similar to the idea of the core set, Active Palmprint Recognition [35] regards AL as a binary classification task. It is expected that the labeled sample set and the unlabeled sample set have the same data distribution and make the two difficult to distinguish. That is, trying to find a subset of core labeled with the same distribution as the original dataset. Specifically, due to the heuristic generative model simulation data distribution is difficult to train and is not suitable for



(a) Active learning pipeline.

(b) Reinforced Active Learning (RAL) [57].

(c) Deep Reinforcement Active Learning (DRAL) [102].

Fig. 3. Comparison of standard AL, RAL [57] and DRAL [102] pipelines. (a) The standard AL pipeline usually consists of three parts. Oracle provides a set of labeled data, the predictor (here, BNN) is used to learn these data, and provides predictable uncertainty for the guide. The guide is usually a fixed, hard-coded acquisition function, which picks the next sample for oracle to restart the cycle. (b) RAL replaces the fixed acquisition function with the policy BNN. The policy BNN learns in a probabilistic state, and obtains feedback from the oracle, and learns how to select the next optimal sample point (new parts in red) in a reinforcement learning manner. Therefore, RAL can adjust the acquisition function more flexibly to adapt to the existing dataset. (c) DRAL designed a deep reinforcement active learning framework for the person Re-ID task. For each query anchor (probe), the agent (reinforcement active learner) will select sequential instances from the gallery pool during the active learning process and hand it to oracle to obtain manual annotation with binary feedback (positive/negative). The state evaluates the similarity relationship between all instances, and calculates rewards based on oracle feedback to adjust agent queries.

high-dimensional and complex data such as palm prints. Therefore, the author considers whether the sample can be highly positively distinguished from the unlabeled dataset or the labeled dataset. Those samples that can be clearly distinguished are obviously different from the data distribution of the core annotation subset. These samples will be added to the annotation dataset for the next round of training. The previous coreset-based methods [49, 140] often just try to query data points as far as possible to cover all points of data manifold without considering the density, resulting in the queried data points overly representing sample points from manifold sparse areas. Similar to [35], Discriminative Active Learning (DAL) [51] also regards AL as a binary classification task, trying to make the queried labeled dataset indistinguishable from the unlabeled dataset. The highlight of DAL is that it can sample from unlabeled data set in proportion to the density, without biasing the sample points in the sparse popular domain. And the method proposed by DAL [51] is not limited to classification tasks, which are conceptually easy to transfer to other new tasks.

In addition to the corresponding query strategy, some researchers also consider the impact of batch query size on query performance. For example, [10, 84, 119, 186] mainly studies the optimization of query strategies in smaller batches, while [27] recommended to expand the query scale of AL for large-scale sampling (10k or 500k sampling at a time). And by integrating hundreds of models and reusing intermediate checkpoints, the distributed search of training data on large-scale labeled datasets is efficiently realized with a small computational cost. [27] also proved that the performance of using the entire dataset for training is not the upper limit of performance, and AL based on subsets may have better performance.

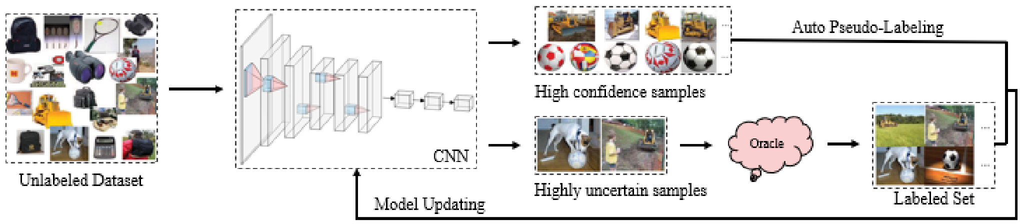


Fig. 4. In CEAL [168], the overall framework of DAL. CEAL [168] gradually feeds the samples from the unlabeled dataset to the initialized CNN, and the CNN classifier outputs two types of samples: a small number of uncertain samples and a large number of high prediction confidence samples. Labeling a small number of uncertain samples through orcal, and using the CNN classifier to automatically assign pseudo-labels to a large number of high-prediction confidence samples. Then, use these two types of samples to fine-tune CNN and repeat this update process.

Density-based methods mainly consider the selection of core subsets from the perspective of data distribution, and there are relatively few related research methods, which provide a new possibility for sample query.

3.1.5 Other methods. There are some studies that are not as focused as the above query methods, we will summarize them below.

For example, [37] redefine the heuristic AL algorithm as a reinforcement learning problem and introduce a new description through a clear selection strategy. Unlike most previous uncertainty-based methods, DFAL [36] believes that these methods are easily fooled by adversarial examples, so DFAL will focus on the study of examples near the decision boundary. And actively use the information provided by these adversarial examples on the input spatial distribution to approximate their distance to the decision boundary. This adversarial query strategy can effectively improve the convergence speed of training CNN. On the other hand, AL aims to use the relative importance of the data to label as little data as possible to efficiently train a model with satisfactory performance. Therefore, the attributes of the dataset itself also have an important impact on the performance of DAL. To this end, GA [166] has studied the relative importance of image data in common datasets and proposed a general data analysis tool that can help us better understand the diversity of training examples in the dataset. GA found that not all datasets can be trained on a small sub-sample set, because the relative difference of sample importance in some datasets can be almost ignored. Therefore, it is not advisable to blindly use smaller sub-data sets in AL. [14] found that compared with Bayesian deep learning approach (Monte-Carlo dropout [47]) and density-based [139] methods, ensemble-based AL can effectively offset the imbalance of categories in the dataset during the acquisition process, resulting in more calibration prediction uncertainty, and thus better performance.

Some researchers have also noticed that in traditional AL workflows, the acquisition function is often regarded as a fixed known prior, and whether this acquisition function is appropriate can only be observed when the label budget is exhausted. This makes it impossible to flexibly and quickly tune the acquisition function. Therefore, it may be a good choice to use reinforcement learning to dynamically tune the acquisition function. RAL [57] proposes to choose BNN as a learning predictor for acquisition functions. Then, all the probability information provided by the BNN predictor will be combined to obtain a comprehensive probability distribution, and then the probability distribution is sent to a BNN probabilistic policy network, which performs reinforcement learning based on the oracle feedback in each labeling round. This feedback will fine-tune the acquisition function to continuously improve the quality of the acquisition function. DRAL [102] adopted a similar idea and designed a deep reinforcement active learning framework for the person Re-ID task. DRAL uses the idea of reinforcement learning to dynamically adjust the acquisition function to obtain high-quality query samples. Fig.3 shows the comparison between traditional AL, RAL and DRAL pipelines.

On the other hand, Active-iNAS [50] notices that most of the previous DAL methods [3, 5, 89] assume that a suitable DL model has been designed for the current task, so it mainly focuses on how to design an effective query mechanism. In fact, the existing DL model is not necessarily optimal for the current DAL task. To this end, Active-iNAS [50] challenges this hypothesis and uses neural architecture search (NAS) [126] technology to dynamically search for effective model architectures while conducting active learning. There is also some work devoted to providing a convenient performance comparison platform for DAL. [110] discusses and studies the robustness and reproducibility of the DAL method in detail, and gives many useful suggestions.

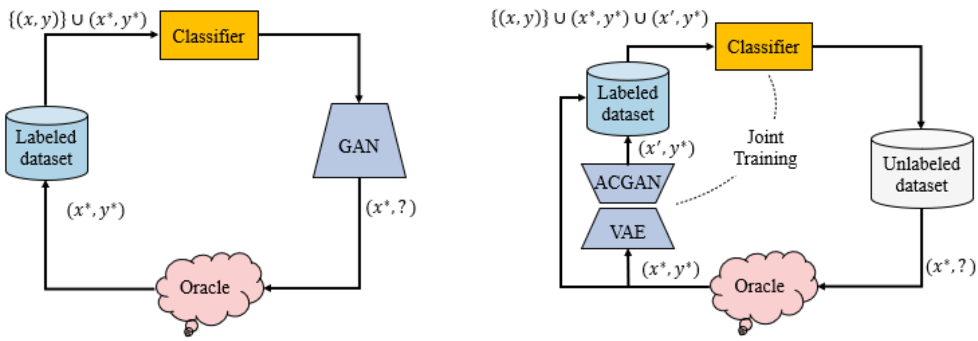
In general, these query strategies are not independent of each other, but interrelated. Batch-based BMDAL provides the basis for the update training of AL query samples on the DL model. Although the query strategies in DAL are rich and complex, they are mostly designed to take into account the diversity and uncertainty of query batches in BMDAL. The previous methods based on uncertainty often ignore the diversity in the batch, so these methods can be roughly divided into two categories. They either design a mechanism that explicitly encourages batch diversity in the input or learning representation space, or directly measure the mutual information (MI) of the entire batch.

3.2 Insufficient Data in DAL

AL often requires only a small amount of labeled sample data to realize learning and update the model, while DL requires a large amount of labeled data to effectively train. Therefore, the combination of AL and DL requires as much as possible to use the data strategy without consuming too much human resources to achieve DAL model training. Most previous DAL methods [184] often only train on the labeled sample set sampled by the query strategy. It ignores the existence of existing unlabeled data sets, and the corresponding data expansion and training strategies are not fully utilized. These strategies help to improve the problem of insufficient label data in DAL training without adding additional manual labeling costs. Therefore, the study of these strategies is also quite meaningful.

For example, CEAL [168] enriches the training set by assigning pseudo-labels to samples with high confidence in model prediction in addition to the labeled data set sampled by the query strategy. Use the expanded training set to train the DL model together. This strategy is shown in Fig.4. Another very popular strategy is to perform unsupervised training on labeled and unlabeled datasets and combine other strategies to train the entire network structure. For example, WI-DL [99] notes that a full training of DBN requires a large number of training samples, and it is impractical to apply DBN to a limited training set in AL context. Therefore, in order to improve the training efficiency of DBN, WI-DL uses a combination of unsupervised feature learning on all datasets and supervised fine-tuning on labeled datasets to train DBN.

At the same time, some researchers are considering using Generative Adversarial Networks (GAN) for data augmentation. For example, GAAL [190] introduced the Generative Adversarial Network (GAN) to the query method of AL for the first time. GAAL aims to use generative learning to generate samples with more information than the original dataset. However, random data augmentation does not guarantee that the generated samples have more information than the original data, which will waste computing resources. Therefore, BGADL [164] expands the idea of GAAL [190] and proposes a Bayesian generative active deep learning method. Specifically, the BGADL combines Generative adversarial active learning (GAAL) [190], Bayesian data augmentation [165], Auxiliary-classifier



(a) Generative adversarial active learning (GAAL).

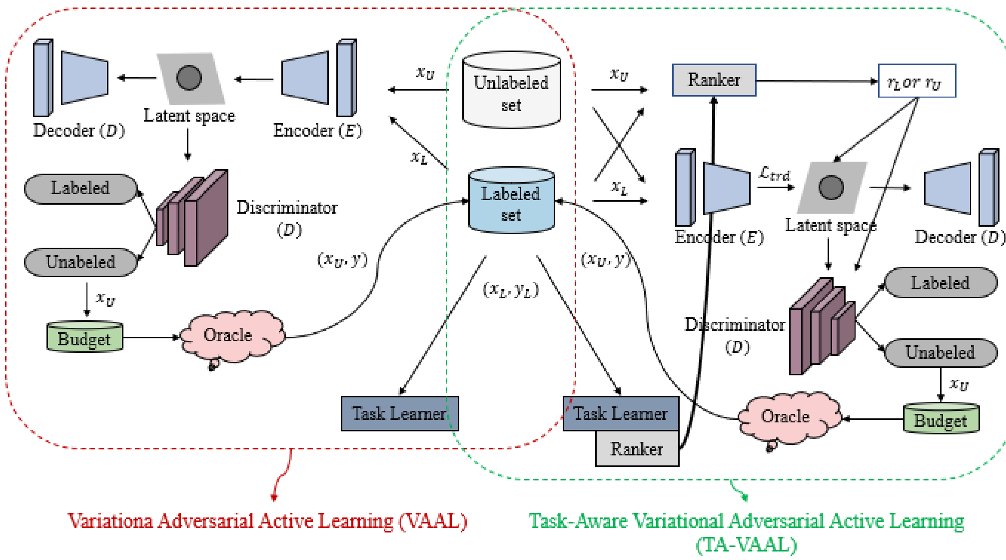
(b) Bayesian generative active deep learning (BGADL).

Fig. 5. Structure comparison chart of GAAL [190] and BGADL [164]. For more details, please check BGADL.

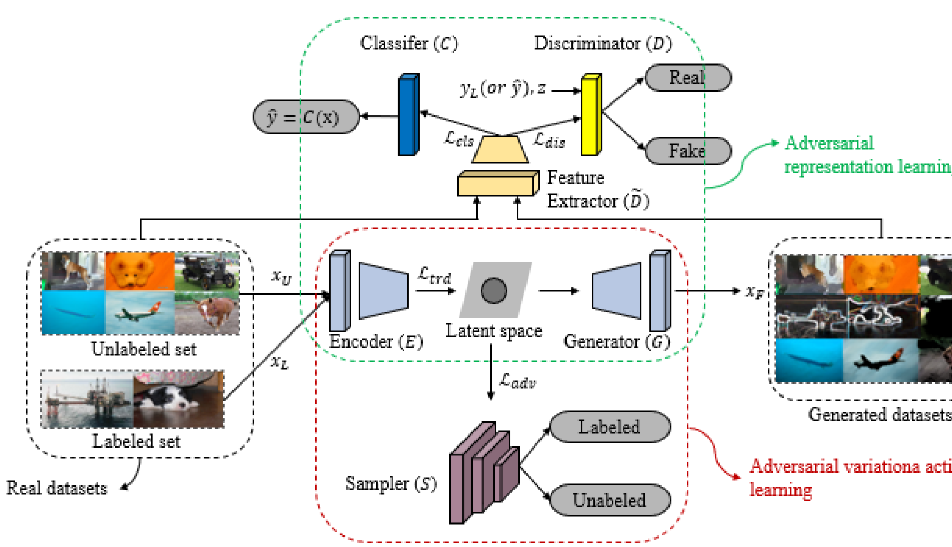
generative adversarial networks (ACGAN) [115] and Variational autoencoder (VAE) [83] method, which aims to generate samples of disagenment regions [142] belonging to different categories. The structure comparison between GAAL and BGADL is shown in Fig.5.

Subsequently, VAAL [152] and ARAL [109] borrowed from previous methods [99, 164, 190] not only to train the network using labeled datasets and unlabeled datasets, but also to introduce generative adversarial learning into the network architecture for data augmentation, so as to further improve the learning ability of the network. Specifically, VAAL [152] noticed that the batch-based query strategy based on uncertainty is not only easy to cause the problem of insufficient sample diversity, but also very susceptible to interference from outliers. In addition, density-based methods [140] for high-dimensional data are susceptible to p-norm limitations, resulting in calculation distances that are too concentrated [6]. To this end, VAAL [152] proposes to use the method of adversarial learning representation to distinguish the potential spatial coding features of labeled data and unlabeled data, thus weakening the interference of outliers. And VAAL [152] uses labeled data and unlabeled data to jointly train variational autoencoder (VAE) [83, 156] in a semi-supervised manner, trying to deceive the adversarial network [52] to predict that all data points come from the labeled pool, in order to solve the problem of distance concentration. VAAL [152] can learn an effective low-dimensional latent representation on a large-scale dataset, and provides an effective sampling method by jointly learning the representation form and uncertainty.

Then, ARAL [109] expanded VAAL [152], aiming to use as few manual annotation samples as possible but make full use of the existing or generated data information to improve the learning ability of the model. In addition to using labeled and unlabeled datasets, ARAL [109] also uses samples produced by deep production networks to jointly train the entire model. ARAL [109] is composed of VAAL [152] and adversarial representation learning [33]. By using VAAL [152] to learn the potential feature representation space of labeled and unlabeled data, the unlabeled samples with the largest amount of information are selected accordingly. At the same time, real data and generated data are used to enhance the learning ability of the model through confrontational representation learning [33]. Similar TA-VAAL [81] also extends VAAL. TA-VAAL uses the global data structure from VAAL and local task-related information from learning loss for sample query. We show the frames of VAAL [152], ARAL [109] and TA-VAAL [81] in Fig.6.



(a) Structure comparison chart of VAAL [152] and TA-VAAL [81]. 1) VAAL uses labeled data and unlabeled data in a semi-supervised way to learn the latent representation space of the data, and selects the unlabeled data with the largest amount of information according to the latent space for labeling. 2) TA-VAAL expands VAAL and integrates the loss prediction module [181] and RankCGAN [135] into VAAL in order to simultaneously consider data distribution and model uncertainty.



(b) The overall structure of ARAL [109]. ARAL has also expanded VAAL. ARAL not only uses real datasets (composed of labeled datasets and unlabeled datasets) and also uses generated datasets to jointly train the network. The whole network consists of encoder (E), generator (G), discriminator (D), classifier (C) and sampler (S), and all parts of the model are trained together.

Fig. 6. The structure comparison of VAAL [152], ARAL [109] and TA-VAAL [81].

Unlike ARAL [109] and VAAL [152] which use labeled and unlabeled datasets for adversarial representation learning, SSAL has tried a new training method. SSAL uses unsupervised, supervised and semi-supervised learning methods across AL cycles, and makes full use of existing information for training without increasing the cost of labeling as much as possible. Specifically, before the AL starts, first use labeled data and unlabeled data for unsupervised pre-training. In each AL learning cycle, first perform supervised training on the labeled dataset, and then perform semi-supervised training on all datasets. This is a new attempt in the training method, and the author found that compared with the difference between the sampling strategy, this model training method has a surprising improvement in performance.

As analyzed above, this kind of exploration in training methods and data utilization skills is also very necessary, and its performance gains may even exceed the performance gains generated by changing the query strategy. This is actually a full use of existing data without increasing the cost of labeling, which helps to alleviate the problem that the number of AL query samples is not enough to support the update of the DL model.

3.3 Common Framework DAL

As mentioned in 2.3, due to the inconsistency of the processing pipeline between AL and DL, only fine-tuning the DL model in the AL framework or simply combining AL and DL to treat them as two separate problems may cause divergence. As described in Section 2, due to the inconsistency of AL and DL in the processing pipeline, only fine-tuning the DL models in the AL framework or simply combining AL and DL to treat them as two separate problems may cause divergence. For example, [9] first conducts offline supervised training of the DL model on two different types of session datasets to make the backbone network have basic conversational capabilities, and then enables the online AL stage to interact with human users, improve the model in an open way based on user feedback. AL-DL [167] proposes an AL method for DL models with DBNs. ADN [187] proposes an active deep network architecture for sentiment classification. [159] proposed an AL algorithm using CNN for captcha recognition. However, the above methods often first perform routine supervised training on the depth model on the labeled dataset, and then actively sample based on the output of the depth model. There are many similar related works [39, 146], this split-and-splitting approach that treats the training of AL and deep models as two independent problems increases the possibility that the two problems will diverge. Although this method also achieved some success at the time, a general framework that closely combines the two tasks of DL and AL plays a vital role in the performance improvement and promotion of DAL.

CEAL [168] is one of the first work to combine AL and DL to solve the problem of depth image classification. CEAL [168] merges deep convolutional neural network into AL, and proposes a novel DAL framework. It sends samples from the unlabeled dataset to the CNN step by step, and the CNN classifier outputs two types of samples: a small number of uncertain samples and a large number of high prediction confidence samples. Labeling a small number of uncertain samples through orcal, and using the CNN classifier to automatically assign pseudo-labels to a large number of high-prediction confidence samples. Then, use these two types of samples to fine-tune CNN and repeat this update process. In Fig.4, we show the overall framework of CEAL. Similarly, HDAL [96] uses a similar framework for face recognition tasks. It combines AL with a deep CNN model to integrate feature learning and AL query model training.

In addition, Fig.1c shows a very common general framework for DAL tasks. Related work includes [35, 59, 105, 178, 185] and so on. Specifically, [178] proposes a framework that uses a fully convolutional network (FCN) [103] and AL to solve the problem of medical image segmentation using a small amount of annotations. It first trains FCN on a small number of labeled datasets, and then extracts the features of the unlabeled datasets through FCN, and use these features to estimate

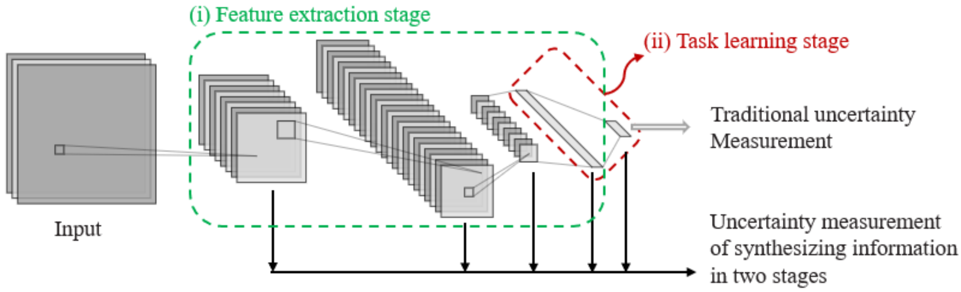


Fig. 7. Taking a common CNN as an example, it shows the comparison between the traditional uncertainty measurement method [35, 105, 178] and the uncertainty measurement method of synthesizing information in two stages [59, 181, 185] (ie, feature extraction stage and task learning stage).

the uncertainty and similarity of unlabeled samples. This strategy, similar to that in Section 3.1.2, helps to select highly uncertain and diverse samples to be added to the labeled dataset to start the next stage of training. Active Palmprint Recognition [35] proposes a similar DAL framework for the palmprint recognition task. The difference is that inspired by domain adaptation [15], Active Palmprint Recognition [35] regards AL as a binary classification task. It is expected that the labeled sample set and the unlabeled sample set have the same data distribution and make the two difficult to distinguish. Supervision training can be performed directly on a small amount of labeled datasets, thereby reducing the burden of labeling. [105] proposes a DAL framework for defect detection. It performs uncertainty sampling based on the features output by the detection model to generate a list of candidate samples for annotation. In order to further take into account the diversity of defect categories in the sampled samples, [105] designed an average margin method to control the sampling ratio of each defect category.

Different from the above methods, only the final output of the DL model is often used as the basis for determining the uncertainty or diversity of the sample (Active Palmprint Recognition [35] uses the output of the first fully connected layer). [59, 181, 185] also used the output of the middle hidden layer of the DL model. As analyzed in Section 3.1.2 and Section 2, due to the difference in the learning paradigm between the deep model and the shallow model, the traditional query strategy based on uncertainty cannot be directly applied to the DL model. In addition, unlike the shallow model, the deep model can be regarded as composed of two stages: the feature extraction stage and the task learning stage. It is inaccurate to use only the output of the last layer of the DL model as the basis for evaluating the uncertainty of sample prediction. Because the uncertainty of the DL model is actually composed of the uncertainty of the two stages of feature extraction and task learning. A schematic diagram of this idea is shown in Fig.7. To this end, AL-MV [59] treats the features from different hidden layers in the middle of CNN as multi-view data, taking into account the uncertainty of the two stages, and designed the AL-MV algorithm to achieve the The certainty is adaptively weighted to measure the uncertainty of the sample more accurately. LLAL [181] also used a similar idea. LLAL designed a small parameter module of the loss prediction module to attach to the target network, using the output of multiple hidden layers of the target network as the input of the loss prediction module. The loss prediction module is learned to predict the target loss of the unlabeled dataset, and the top-K strategy is used to select query samples. LLAL achieves task-agnostic AL framework design at a small parameter cost, and has achieved competitive performance on a variety of mainstream visual tasks (ie, image classification, target detection, and human pose estimation). Similar [185] uses a similar strategy to implement a DAL

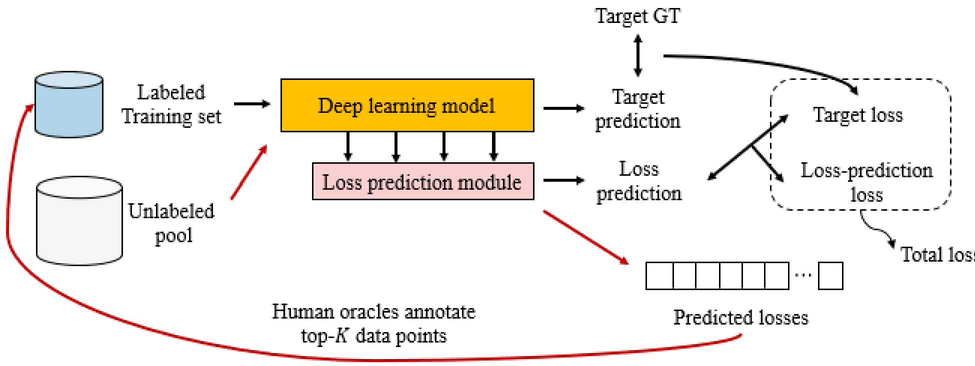


Fig. 8. The overall framework of LLAL [181]. The black line represents the stage of training model parameters, optimizing the overall loss composed of target loss and loss-prediction loss. The red line represents the sample query phase of AL. The output of multiple hidden layers of the DL model is used as the input of the loss prediction module, and the top-K unlabeled data points are selected according to the predicted losses and assigned labels by oracle.

framework for finger bone segmentation tasks. [185] uses Deeply Supervised U-Net [127] as the segmentation network, then uses the output of the multi-level segmentation hidden layer and the output of the last layer as the input of AL, and integrate these input information as the basis for the evaluation of the sample information size. We take LLAL [181] as an example to show the overall network structure of this idea in Fig.8.

The research on the general framework is very beneficial to the development and promotion of DAL. This task-independent framework can be transplanted to other fields more conveniently. The current fusion between DL and AL is mainly focused on DL is mainly responsible for feature extraction, and AL is mainly responsible for sample query, so deeper and tighter fusion will help DAL achieve better performance. Of course, this requires more exploration and effort by researchers.

4 VARIOUS APPLICATIONS OF DAL

Today, DAL has been applied including but not limited to visual data processing (such as object detection, semantic segmentation, etc.), NLP (such as sentiment analysis, question and answer, etc.), speech and audio processing, social network analysis, medical image processing, wildlife protection, industrial robots and disaster analysis and other fields. In this section, we give a systematic and detailed overview of DAL's related work from an application perspective.

4.1 Visual Data Processing

Just as DL is widely used in the field of computer vision, the first field in which DAL is expected to exert its potential is computer vision. In this section, we mainly discuss the research of DAL in the field of visual data processing.

4.1.1 Image classification and recognition. Similar to the research of DL, the classification and recognition of images in DAL is a basis for the research of other vision tasks. How to efficiently query samples on high-dimensional data that traditional AL is not good at, and obtain satisfactory performance at the smallest possible labeling cost is an important problem that DAL faces in the field of image vision tasks.

To solve this problem, CEAL [168] assigns pseudo labels to samples with high confidence and adds them to the highly uncertain sample set queried using the uncertainty-based AL method, and uses the expanded training set to train the DAL model image classifier together. [125] first integrated the criteria of AL into the deep belief network, and conducted extensive research on classification tasks on a variety of uni-modal and multi-modal real datasets. WI-DL [99] uses the DAL method to simultaneously consider the two selection criteria of maximizing representativeness and uncertainty on hyperspectral image (HSI) datasets for remote sensing classification. Similar [32, 97] also studied the classification of HSI. [97] introduces AL to initialize HSI, and then performs transfer learning. At the same time, it is recommended to construct and connect higher-level features to source and target HSI data to further overcome the cross-domain disparity. [32] proposed a unified deep network combined with active transfer learning, using only less label training data to train HSI classification well.

In addition, medical image analysis is also an important application. For example, [41] explore the use of AL instead of random learning to train convolutional neural networks for tissue (eg., stroma, lymphocytes, tumor, mucosa, keratin pearls, blood, and background/adipose) classification tasks. [21] has conducted a comprehensive review of related DAL methods in the field of medical image analysis. For similar reasons, since the annotation of medical images requires strong professional knowledge, the time of well-trained experts is usually very expensive and very scarce. In addition, DL has achieved impressive performance on various image feature tasks. Therefore, there is still a lot of work focused on combining DL and AL to apply DAL to the field of medical image analysis [25, 34, 89, 133, 136, 137, 153, 154]. The DAL method is also used to classify in situ plankton [19], and the automatic counting of cells [5].

In addition, DAL also has a wide range of applications in our daily life scenes. For example, [159] proposed an AL algorithm that uses CNN for verification code recognition. It can use the ability to obtain labeled data for free to avoid human intervention and greatly improve the recognition accuracy when less labeled data is used. HDAL [96] combines the excellent feature extraction capabilities of deep convolutional neural networks (CNN) and the saving of AL labeling costs to design a heuristic deep active learning framework for face recognition tasks.

4.1.2 Object detection and semantic segmentation. Object detection and semantic segmentation have important application values in various fields such as autonomous driving, medical image processing, and wildlife protection. However, these fields are also limited by the higher sample labeling cost, and the smaller labeling cost of DAL is expected to accelerate the application of corresponding DL models in some real-world areas that are more difficult to label.

[130] designed a DAL framework for object detection, which uses the layered architecture used in object detection as an example of "query by committee" to select the image set to be queried, and at the same time introduces a similar exploration/exploitation trade-off strategy to [180]. DAL is widely used in natural biological fields and industrial applications. For example, [114] uses deep neural networks to quickly, transferably and automatically extract information, and combines transfer learning and AL to design a DAL framework for species identification and counting in camera trap images. [79] use unmanned aerial vehicles (UAV) to obtain images for wildlife detection. In order to be able to reuse this animal detector, [79] uses AL and introduces transfer sampling (TS) to find the corresponding area between the source and target datasets, so as to realize the transfer of data to the target domain. [39] proposes a DAL framework for deep object detection in autonomous driving to train LiDAR 3D object detectors. [105] proposes a very common DAL framework for defect detection in real industries, and proposes an uncertainty sampling method to generate candidate label categories. It uses the average margin method to set the sampling scale of each defect category, and can obtain the required performance with less labeled data.

In addition, DAL also has important applications in medical image segmentation. For example, [48] proposes an AL-based transfer learning mechanism for medical image segmentation, so that this method can effectively improve the image segmentation performance on a limited labeled dataset. [178] combines fully convolutional networks (FCN) and AL to propose a DAL framework for biological image segmentation. It uses the uncertainty and similarity information provided by FCN to give an extension of the maximum set cover problem, and significantly reduces the workload of labeling by pointing out the most effective labeling areas. DASL [172] proposes a deep region-based network Nodules R-CNN for pulmonary nodule segmentation tasks to generate segmentation masks for examples, and at the same time, combines AL and Self-Paced Learning (SPL) [88] to propose a new Deep Active Self-paced Learning (DASL) strategy to reduce the workload of labeling. [171] proposes a Nodule-plus Region-based CNN for pulmonary nodules detection and segmentation in 3D thoracic Computed Tomography (CT). Nodule-plus Region-based CNN combines AL and self-paced learning (SPL) strategies, and proposes a new deep self-paced active learning (DSAL) strategy, which reduces the workload of annotation and make effective use of unannotated data. [185] proposes a new deep-supervised active learning method for finger bones segmentation tasks, which can be fine-tuned in an iterative and incremental learning manner, and uses the output of the intermediate hidden layer as the basis for selecting samples. Compared with the complete markup, [185] only used fewer samples to obtain comparable segmentation results.

4.1.3 Video processing. Compared with images, in addition to processing spatial features, video tasks also need to process temporal features. Therefore, the annotation work of video tasks is more expensive, and the expectation of introducing AL is more urgent. DAL also has broader application scenarios in this field.

For example, [70] proposes to use imitation learning to perform navigation tasks. The visual environment and actions taken by the teacher from the first-person perspective are used as the training set. Through training, it is hoped that students can predict and execute corresponding actions according to their environment. When performing tasks, students use deep convolutional neural networks for feature extraction, learn imitation strategies, and use the AL method to select samples with insufficient confidence to add to the training set to update the action strategy. [70] uses fewer samples to significantly improve the initial strategy. DeActive [66] proposed a DAL activity recognition model. Compared with the traditional DL model for activity recognition, DeActive requires fewer labeled samples, consumes less resources, and has high recognition accuracy. [169] minimizes the annotation cost of the video-based person Re-ID dataset by integrating AL into the DL framework. Similarly, [102] proposes a deep reinforcement active learning method for the person Re-ID task, using oracle feedback to guide the agent (the model in the reinforcement learning process) to select the next uncertainty sample. Continuously optimize the agent selection mechanism through alternately refined reinforcement learning strategies. [3] proposes an active learning object detector method based on convolutional neural network for pedestrian target detection in video and static images.

4.2 Natural Language Processing (NLP)

NLP has always been a very challenging task. NLP aims to make computers understand complex human language and help humans deal with various tasks related to natural language. Insufficient data labeling is also a key challenge faced by NLP tasks. Below we introduce some of the most famous DAL methods in the NLP field.

4.2.1 Sentiment Analysis. It is a typical task in NLP, which aims to make the computer understand a natural language description and extract and analyze the meaning information.

The relevant application scenarios are very rich, including but not limited to sentiment classification, news identification, named entity recognition (NER), etc. More specifically, for example, [187] uses restricted Boltzmann machines (RBM) to construct an active deep network (ADN), and conduct unsupervised training on the labeled and unlabeled datasets. ADN uses a large number of unlabeled datasets to improve the generalization ability of the model, and uses AL in a semi-supervised learning framework, unifying the selection of labeled data and classifiers in a semi-supervised classification framework, and competitive results are obtained on sentiment classification tasks. [17] proposes a human-computer collaborative learning system for news accuracy detection tasks (that is, identifying misleading and false information in news) with only a limited number of annotation samples. The system is a deep model based on AL, which uses 1-2 orders of magnitude less annotation samples than fully supervised learning, which greatly accelerates the convergence speed of the model and achieves an astonishing 25% average performance gain in detection performance.

In addition, [24, 145, 147] uses the combination of DL and AL to study how to improve the technical level of NER in the case of a small training set. [121] uses relevant tweets from the disaster-stricken area to extract information for the identification of infrastructure damage during the earthquake. For this reason, [121] combines the RNN and GRU-based models with AL, and use AL-based methods to pre-train the model to retrieve tweets from infrastructure damage in different regions, thereby significantly reducing the workload of manual labeling. Entity resolution (ER) is the task of recognizing the same real entities with different representations across databases, and is a key step in knowledge base creation and text mining. [78] developed a DL-based method for ER, which combines transfer learning and AL to design an architecture that allows learning a transferable model from high-resource environments to low-resource environments.

4.2.2 Question answering and summarization. Question answering systems and automatic summarization are also common processing tasks in NLP. DL has achieved impressive results in these areas. However, the performance of these applications still relies on massive labeled datasets, and AL is expected to bring new hope to this challenge.

The automatic question answering system has a very wide range of applications in the industry, and DAL also has important research value in this field. For example, [9] uses the online AL strategy combined with the DL model to achieve an opendomain dialogue by interacting with real users and learning from usersâĂŹ feedback in an incremental manner in each round of dialogue. [74] found that AL strategies designed for specific tasks (eg., classification) often have only one correct answer, and these uncertainty-based measurements are often calculated based on the output of the model. Many real-world vision tasks often have multiple correct answers, leading to overestimation of uncertainty measures, and sometimes even worse performance than random sampling baselines. For this reason, [74] proposes to estimate the uncertainty in the hidden space inside the model instead of the uncertainty in the output space of the model in the Visual Question Answer generation (VQA), thus overcoming the paraphrastic nature of language.

Automatic summarization aims to extract useful and most important information from large texts. [106] proposes a novel active learning policy neural network (ALPNN) for recognizing the concepts and relationships in large electroencephalogram (EEG) reports, which can help humans extract available clinical knowledge from a large number of EEG reports.

4.3 Other Applications

The emergence of DAL is exciting, and it is expected to reduce the annotation cost by orders of magnitude while maintaining performance. For this reason, DAL is also widely used in other fields.

These applications include, but are not limited to, gene expression, robotics, wearable device data analysis, social networking, ECG signal analysis, etc. More specifically, for example, MLFS [71] combines DL and AL to select genes/miRNAs based on expression profiles and proposes a novel multi-level feature selection method. MLFS also considers the biological relationship between miRNAs and genes, and applies this method to miRNA expansion tasks. The failure risk of real-world robots is expensive. For this reason, [7] proposed a risk-aware resampling technique. It uses AL together with existing solvers and DL to optimize the robot's trajectory in order to effectively deal with the collision problem in the scene of moving obstacles, and verify the effectiveness of the DAL method on a real nano-quadcopter. [189] proposes an active trajectory generation framework for the inverse dynamics model of the robot control algorithm, which allows [189] to systematically design the information trajectory used to train the DNN inverse dynamics module.

In addition, [54, 65] uses sensors on wearable devices or mobile terminals to collect user movement information for human activity recognition. [65] proposes a DAL framework for activity recognition with context-aware annotator selection. ActiveHARNet [54] proposes a resource-efficient deep ensembled model ActiveHARNet, which supports incremental learning and inference on the device, using the approximation in the BNN to represent the uncertainty of the model, and proves the feasibility of ActiveHARNet deployment and incremental learning on two public datasets. DALAUP [26] designs a DAL framework for anchor user prediction in social networks to reduce the annotation cost of anchor users and improve the accuracy of prediction. DAL is also used in the classification of electrocardiogram (ECG) signals. For example, [124] proposes an active classification method for ECG signals based on DL. [56] proposed an AL-based ECG classification method using eigenvalues and DL. By using the AL method, the cost of marking ECG signals by medical experts can be effectively reduced. The cost of label annotation in the speech and audio fields is also relatively high. [1] found that the model trained on a corpus composed of thousands of recordings collected by a small number of speakers cannot be generalized to new domains. Therefore, [1] studied the practical scheme of using AL to train deep neural networks for speech emotion recognition tasks under the condition of limited label resources.

In general, the current applications of DAL are mainly concentrated in visual image processing tasks, and there are relatively scattered applications in NLP and other fields. Compared with DL and AL, DAL is still in the preliminary stage of research, and the corresponding classic works are relatively few, but it still has the same broad application scenarios and practical value as DL.

5 DISCUSSION AND FUTURE DIRECTIONS

DAL combines the common advantages of DL and AL, not only inherits DL's ability to process high-dimensional image data and automatic feature extraction, but also inherits the potential of AL to effectively reduce the cost of annotation. Therefore, DAL has fascinating potential especially in areas where labels require high expertise and are difficult to obtain.

Most recent work shows that DAL has been successful in many common tasks. DAL has attracted the interest of a large number of researchers by reducing the cost of annotation and inheriting the powerful feature extraction capabilities of DL, and the related research work is also extremely rich. But there are still a lot of unanswered questions here. As [110] discovered, the results reported on the random sampling baseline (RSB) are quite different in different studies. For example, under the same settings, using 20% of the label data of CIFAR 10, the RSB performance reported by [181] is 13% higher than that of [164]. Secondly, the same DAL method may report different results in different studies. For example, using 40% of the label data of CIFAR 100 [86] and VGG16 [151] as the extraction network, the reported results of [140] and [152] differ by 8%. In addition, the latest DAL research is also inconsistent with each other. For example, [140] and [36] point out that diversity-based methods have always been better than uncertainty-based methods, and uncertainty-based methods are worse than RSB. However, the latest research of [181] shows that this is not the case.

Compared with AL's strategic selection of high-value samples, RSB has been regarded as a strong baseline [140, 181]. The above problems show that we urgently need to design a general performance evaluation platform for DAL work and determine a unified high-performance RSB.

Secondly, the reproducibility of different DAL methods is also an important issue. The highly reproducible DAL method helps to evaluate the performance of different DALs. The common evaluation platform should be used for experiments under consistent settings, and snapshots of experimental settings should be shared. In addition, multiple repetitive experiments with different initializations under the same experimental conditions are required, which can effectively avoid misleading conclusions caused by experimental setup problems. Those inconsistent studies need to arouse enough attention by researchers in order to clarify the principles. on the other hand, adequate ablation experiments and transfer experiments are also necessary. The former can make it easier for us to see which improvements have brought performance gains, and the latter can ensure that AL selection strategy can indeed select high-value samples indiscriminately for the dataset.

The current research directions on DAL methods mainly focuses on the improvement of AL selection strategies, the optimization of training methods and the improvement of task-independent models. As analyzed in Section 3.1, the improvement of AL selection strategy is currently mainly focused on taking into account the query strategy based on uncertainty and diversity in an explicit or implicit manner. And hybrid selection strategies are more and more favored by researchers. The optimization of training methods mainly focuses on labeled datasets, unlabeled datasets, or using methods such as GAN to expand data, and then the hybrid training method of unsupervised learning, semi-supervised learning, and supervised learning across the AL cycle. This training method even shows a more promising performance improvement than the selection strategy improvement. In fact, this makes up for the problem that the DL model requires a large number of labeled training samples and the AL selects a limited number of labeled samples. In addition, the use of unlabeled datasets or generated datasets is also conducive to making full use of existing information without adding additional annotation costs. In addition, the incremental training method is also an important research direction. It is unacceptable in terms of computing resources to train a deep model from scratch in each cycle. The simple incremental training will cause the deviation of model parameters, but the huge temptation to save resources is quite attractive. However, related research is still quite scarce, but it is still a very promising research direction.

Task independence is also an important research direction, which helps to make DAL models more directly and widely extended to other tasks. However, the related research is still insufficient, and the corresponding DAL methods often only focus on the uncertainty-based selection method. Because DL itself is easier to integrate with the uncertainty-based AL selection strategy, we believe that uncertainty-based methods will continue to dominate in the future in the research direction that is not related to the task. On the other hand, it may also be a good choice to explicitly take the selection strategy based on diversity into account. Of course, this also faces great challenges. In addition, it needs to be pointed out that it is not advisable to blindly pursue the idea of training models on smaller subsets, because the relative difference in sample importance in some datasets with a large variety of content and a large number of samples can almost be ignored.

Obviously, there is no conflict between the above-mentioned improvement directions, so a mixed improvement strategy is an important development direction in the future. In general, DAL research has great practical application value in both labeling costs and application scenarios, but the current DAL research is still in its infancy, and there is still a long way to go in the future.

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