Active-Learning-as-a-Service: An Efficient MLOps System for Data-Centric AI

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Abstract

The success of today’s AI applications requires not only model training (Model-centric) but also data engineering (Data-centric). In data-centric AI, active learning (AL) plays a vital role, but current AL tools can not perform AL tasks efficiently. To this end, this paper presents an efficient MLOps system for AL, named ALaaS (Active-Learning-as-a-Service). Specifically, ALaaS adopts a server-client architecture to support an AL pipeline and implements stage-level parallelism for high efficiency. Meanwhile, caching and batching techniques are employed to further accelerate the AL process. In addition to efficiency, ALaaS ensures accessibility with the help of the design philosophy of configuration-as-a-service. It also abstracts an AL process to several components and provides rich APIs for advanced users to extend the system to new scenarios. Extensive experiments show that ALaaS outperforms all other baselines in terms of latency and throughput. Further ablation studies demonstrate the effectiveness of our design as well as ALaaS’s ease to use. Our code is available at [https://github.com/MLSysOps/alaas](https://github.com/MLSysOps/alaas).

1 Introduction

Data-centric AI is an emerging topic that focuses on engineering data to develop AI applications with the off-the-shelf machine learning (ML) models [13]. Previous efforts are mainly model-centric AI that assumes a static environment. In this environment, 1) the data collection and engineering are done, 2) and continuously developing ML models to achieve high performance on test sets is the main target [15]. However, real-world AI applications are facing more complicated scenarios, which can not be adequately addressed by model-centric AI. For instance, researchers have to spend a lot of time on data preparation, including data labeling [8], error detection [24], etc. Meanwhile, they also need to monitor data to detect the distribution drift so as to update models in time [21]. Treating these issues only from a model view will lead to a sub-optimal solution. Therefore, to further

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improve and democratize AI applications, a lot of efforts are now turning to data-centric or combining model-centric and data-centric [13].

Though the concept of data-centric AI has been proposed very recently, many pioneering studies whose core contributions lie in data engineering have already been proposed [40, 49]. Among them, one vital direction is active learning (AL) [34]. The motivation of AL is to reduce manual labeling efforts while maintaining and even improving ML models’ performance [47, 40, 16, 5, 2, 1, 55, 28]. Specifically, it is well-known that ML models are very data-hungry. Therefore, to reach a high performance (e.g., accuracy) that meets application requirements, people always need to label a large amount of data during data collection. This process is extremely time-consuming and labor-intensive and thus often becomes the bottleneck of ML application development. To cope with the issue, AL selects the most representative yet diverse training samples from a large training data pool by utilizing AL strategies. Then it only sends the selected samples to an oracle (e.g., human annotators) to label. Next, ML models will only be trained on these sub-datasets. By doing so, we can still obtain an ML model with competitive performance but save labeling and training costs a lot.

However, utilizing AL methods is a non-trivial task. Essentially, applying AL to AI application development is not simply searching for, selecting, or implementing the AL algorithms. Instead, users have to build a backend to run the AL pipeline, tailored for their applications in their own environment (e.g., a private cluster and AWS). In other words, they need to undertake much repetitive engineering work with boilerplate code. Moreover, users have to consider the efficiency and cost issues, as AL often runs on a vast dataset, and some AL algorithms (e.g., committee-based [10, 29]) require running more than one ML model for data selection. Under-consideration will result in a long process time and additional cost. Though several open-source AL tools [11, 18, 50, 45] lower the barrier to applying AL, they can not meet the efficiency requirement.

To address these issues, we propose to build an efficient backend for AL. Our AL system, named Active-Learning-as-a-Service (ALaaS) (see Figure [1]), is able to run AL strategies on large datasets efficiently by utilizing single or distributed multiple devices. Specifically, it adopts server-client architecture to perform AL tasks. As a result, the system can be easily installed on both laptops and the public cloud. After the installation, users can start the system with a simple configuration file by following our templates. Then the system will run AL tasks in an efficient pipeline manner. Meanwhile, more acceleration techniques such as data cache and batching [9, 53, 52] will be utilized to further speed up the AL process. In addition to that, our system also considers the accessibility and modularity so that non-experts can use AL strategies stored in our AL zoo with ease, and experts can propose more advanced AL strategies for more scenarios. Experiments show that our ALaaS outperforms all other baselines in terms of latency and throughput. Further ablation studies show the effectiveness of our design and reveal more insightful conclusions.

2 Related Work

This section presents the related work, including three categories: active learning (AL) algorithms and tools, Data-centric AI, and MLOps.
Table 1: Comparison of Active Learning (AL) open-source tools. Our ALaaS provides a Machine-Learning-as-a-Service experience and improves AL efficiency a lot.

| AL Open-source Tool | Pipelined Data Processing | Elastic AL Serving | Server-Client Architecture | PyPI Install | Data Cache | AL Zoo |
|---------------------|---------------------------|--------------------|----------------------------|--------------|-----------|--------|
| DeepAL [18]         | ✓                         | ✓                  |                            |              |           | ✓      |
| ModAL [11]          | ✓                         | ✓                  |                            | ✓            |           | ✓      |
| ALiPy [45]          | ✓                         | ✓                  |                            | ✓            | ✓         | ✓      |
| libact [50]         | ✓                         | ✓                  |                            | ✓            | ✓         | ✓      |
| ALaaS (Ours)        | ✓                         | ✓                  | ✓                          | ✓            | ✓         | ✓      |

2.1 AL Algorithms and Tools

We categorize AL strategies into three classes, namely, diversity-based, uncertainty-based, and hybrid sampling. Diversity-based methods [51, 40] are designed to select the most informative samples from the whole dataset to represent it. Uncertainty-based methods [37, 37, 16] aim to select the samples that cannot be identified confidently by current ML models and then use these samples to further improve ML models. Hybrid methods [20, 4] combine both the above-mentioned methods. Our system supports all of these methods and runs them more efficiently.

Many open-source AL tools have been developed to benefit both academia and industry, including ModAL [11], DeepAL [18], Libact [50], and ALiPy [45]. Our ALaaS is inspired by these tools and further improves the AL efficiency and accessibility by adopting the MLOps concept. The detailed comparison is summarized in Table 1.

2.2 Data-centric AI

Data-centric AI is proposed to improve AI application performance by engineering datasets rather than only focusing on models. Recent Data-centric AI competition and workshop [13] from Landing.ai demonstrates many exciting studies from both academia and industry. Inspired by the pioneering work, many data-centric methods have been proposed for different areas, including NLP [49, 41], CV [19, 6], Robot [27], etc. Also, a new benchmark [15] has been built for pushing forward data-centric AI research. To the best of our knowledge, ALaaS is the first MLOps system for efficient AL from the data-centric view.

2.3 MLOps

MLOps (Machine Learning Operation) aims to streamline the ML model development and reduce the AI application maintenance cost. Many MLOps systems have been proposed for both data-centric AI and model-centric AI. From a data-centric view, labeling tools (e.g., labelme [38]), data cleaning tools (e.g., ActiveClean [23]), data drift monitors, and so on, can all be regarded as MLOps systems. From a model-centric view, we have model store systems [46], model continuous integration [53, 55] tools, training platforms [22], deployment platforms [7], etc. Different from these systems, ALaaS is designed specifically for running AL tasks more efficiently.

In addition, tech giants start to build end-to-end cloud platforms for MLOps (e.g., TFX [3], SageMaker [12], Ludwig [30]). Our ALaaS can be a good plugin that is complementary to these systems.

3 System Design and Architecture

This section first highlights our Active-Learning-as-a-Service (ALaaS) with three key features, then details the design of core modules of the system as shown in Figure 1.

3.1 ALaaS Highlights

We highlight three key features, namely efficiency, accessibility, and modularity, provided by our system. These features are also our design principles, leading the implementation to consider both
experts (e.g., data scientists and machine learning (ML) engineers) and non-experts (e.g., customers with little domain knowledge) all the time.

**Efficiency.** Active Learning (AL) always faces large-scale datasets to be labeled [34] and some AL even employ multiple computational intensive deep learning (DL) models (e.g., Query-By-Committee [10, 29]). Thus, it is critical to efficiently process these datasets and models to accelerate ML application development and save users’ AL use cost. Our ALaaS offers an extremely efficient AL service to users by employing a lot of optimization technologies, including a pipeline process [31], ML serving backend adoption [33], etc.

**Accessibility.** To further lower the application barrier as well as to improve the adoption rate, an AL system should ensure AL non-experts can easily use it with minimal effort and avoid writing much code. Our ALaaS follows this principle and enables a smooth user experience by implementing a containerized AL service with rich configuration temples to help users quickly get started.

**Modularity.** AL is evolving fast, especially driven by the advance in Deep Learning, which requires a large amount of data to train. Making AL accessible should not hinder its advanced use by AL or ML experts. Therefore, our system is designed in a highly modular manner, enabling experts to prototype, extend and deploy state-of-the-art (SOTA) AL methods with ease.

### 3.2 ALaaS Architecture

The system adopts service-client architecture to abstract complex AL algorithms into web-based services, enabling an out-of-the-box user experience. Besides, our system provides a modular data manager and an AL strategy zoo, decoupling two key processes, large data operation (e.g., data index and storage) and AL strategy development and selection, in AL utilization.

**Server-Client.** The server-client architecture makes the AL accessible for different level users ranging from domain experts to ML beginners with almost no knowledge. It can be deployed to a personal laptop as well as a public cloud. We take an ALaaS deployed to AWS [42] (see Figure 2) as an example to detail the whole workflow. First users only need to prepare a configuration file including basic settings like dataset path and AL methods by following provided templates, as shown in Figure 3. Then, with very few lines of code (LoCs), users can start both the AL client and AL server. Next, users will push their unlabeled datasets, which can be stored either in the local disk or AWS S3 [43], to the AL server.

After getting the dataset Uniform Resource Identifier (URI) from the AL client, the AL server will download the dataset and process it with specific AL strategies in a pipeline manner as shown in Figure 4. With this frustratingly simple optimization, the processing speed can become 10x times faster than the other open-source platform (see Section 4.2). Meanwhile, the AL server will index every sample in the dataset by assigning unique IDs to them with the help of the data manager. These IDs will be utilized by AL strategies.
1. Configure AL server at example.yml

```python
from alaas import Client 
al_client = ...    worker: 
      type: docker 
      docker_repo: "nvcr.io/nvidia/tritonserver" 
      tag: "22.03-pyt-python-py3"
```

2. Start Server

```python
from alaas import Server
al_server = Server(config_path="example.yml")
al_client.start()
```

3. Start Client

```python
al_client = Client(al_server_url="localhost:8888")
selected_data_list = al_client.query(budget=10)
```

Figure 3: An AL service can be easily configured and started with YML files.

Finally, the server will distribute the downloaded samples to an optimized inference worker with ML serving backend to do inference. According to pre-defined AL strategies, the AL server will make decisions and generate a report including the URIs of selected samples to be labeled. As a result, the AL server only needs to return the URIs to the AL client, avoiding downloading selected samples from the AL server.

**Data Manager.** The data manager manages the lifecycle of the dataset in our system. First, it accepts users’ datasets and persists their metadata (e.g., name, owner, etc.) for data housekeeping. Second, during the system running, it will index data samples to avoid redundant data movement and batch data for an efficient GPU process. Meanwhile, it provides rich data transformation functions for different tasks like NLP, CV, and Audio. Moreover, for different kinds of AL methods, the data manager can equip the corresponding processing methods to improve usability.

**AL Strategy Zoo.** The AL strategy zoo abstracts and stores many AL strategies, including uncertainty-based, Bayesian, density-based, batch mode, etc. It also provides a base class for advanced users to inherit and extend AL to new scenarios.

Figure 4: Dataflow comparison among conventional pool-based learning methods (a), (b), and proposed ALaaS (c). These workflows show how data flows in machines in multiple rounds of AL with different methods. A red box represents a data sample at a download stage, a blue box represents a data sample at a process stage, a green box represents a data sample at an AL inference stage, and a box with a diagonal fill indicates there is no process. The numbers inside the box indicate different rounds of AL.
Other Utilities. To further lower the barrier of using AL and improve efficiency, the system further offers many useful utility functions. For example, as shown in Figure 1, model repository is designed to connect many public model hubs like HuggingFace [48] and TorchHub [36] and obtain pre-trained models from them. Second, as shown in Figure 2, the data cache is employed to improve AL computation efficiency, and workers with serving engine are to call different ML serving backend to speed up ML model inference.

4 System Evaluation

This section presents the quantitative evaluation of our systems. We first compare our system with other open-source platforms. Then we benchmark our system from different perspectives to demonstrate its efficiency and accessibility.

4.1 Evaluation setup

Hardware&Software. We evaluate the system on AWS EC2 and a MacBook laptop. The backend inference software is Triton Inference Server [33].

Dataset. We use the CIFAR-10 dataset [25] to conduct experiments. It includes 50,000 training images and 10,000 test images.

Model. We use the widely deployed ResNet-18 [17] model to evaluate system performance as well as benchmark different AL strategies and AL settings.

4.2 Comparison with other AL open source tools

The first experiment compares the efficiency of ALaaS with that of other baselines.

Settings. In this experiment, we simulate a one-round AL process, which applies AL methods to scan the whole dataset to generate a sub-pool. This sub-pool includes samples that will be used to further improve an existing ML model. Specifically, we first train an ML model with randomly selected 10,000 images from the CIFAR-10 training set as the initial model. Next, we use different AL tools to serve the trained model on an AWS 3x.large CPU/GPU EC2. For all tools, we use the same AL strategy named least confidence sampling [26]. Finally, we utilize these tools to select 10,000 samples from the rest 40,000 images in the training set and compare their latency and throughput.

Results & Insights. The results are shown in Table 2. Compared to other tools, our ALaaS achieves the lowest latency and highest throughput while still maintaining the same accuracy. This efficiency improvement can be attributed to two sides. First, our ALaaS implements stage-level parallelism which reduces the device idle time extremely. Second, ALaaS adopts the existing ML inference servers to accelerate the model inference.

Furthermore, we evaluate the intermediate results with different budgets of our ALaaS. As shown in Figure 5, as the budget increases, more samples will be selected and the accuracy will also be increased. This further proves the effectiveness of our system.

4.3 ALaaS Characterization

We further benchmark our ALaaS with different system settings. The first experiment is to evaluate different AL strategies re-implemented in our system. The second experiment explores the batch size’s impact on system efficiency.
Table 2: Performance evaluation among different AL open-source tools. Compared to all baselines, ALaaS has the lowest latency and highest throughput.

| AL Open-source Tool | Top-1 Accuracy (%) | Top-5 Accuracy (%) | One-round AL Latency (sec) | End-to-end Throughput (Image/sec) |
|---------------------|--------------------|--------------------|-----------------------------|----------------------------------|
| DeepAL [18]         | 86.90              | 89.67              | 2287.00 ± 179.37            | 17.49                            |
| ModAL [21]          | 86.90              | 85.72              | 2006.95 ± 37.98             | 19.93                            |
| ALiPy [45]          | 86.90              | 83.46              | 2410.85 ± 77.81             | 16.59                            |
| libact [50]         | 85.14              | 81.23              | 1771.33 ± 109.77            | 22.58                            |
| ALaaS (Ours)        | 86.90              | 88.12              | 552.45 ± 30.385             | 72.40                            |

4.3.1 AL strategy impact

Our ALaaS already provides many out-of-the-box AL strategies in ModelZoo for users. This experiment evaluate these strategies re-implemented by ALaaS from accuracy and efficiency views to provide more insights. All settings are the same as in the previous experiment.

**Results & Insights.** The accuracy of different methods is shown in Figure 6a. Core-set [40] achieves the highest accuracy with no surprise as it is designed for CNNs in computer vision (CV) tasks. Meanwhile, K-Center Greedy (KCG) [32] and Least Confidence (LC) [26] are the second and the third accuracy though proposed very early. This tells us that even in the deep learning (DL) era, traditional methods still play a vital role and can cooperate with DL very well.

The throughput is shown in Figure 6b. LC has the highest throughput while Core-set achieves the lowest throughput. Combining the accuracy and the throughput results, we can draw the conclusion that the accuracy improvement of Core-set comes from the heavy design while LC balances the trade-off between accuracy and efficiency well.

In summary, ALaaS provides many methods with clear accuracy and efficiency reports so users can choose them based on their own scenarios accordingly.

![Figure 6: Performance of one-round AL for ResNet-18 on CIFAR-10 dataset using different AL strategies](image)

Figure 6: Performance of one-round AL for ResNet-18 on CIFAR-10 dataset using different AL strategies (i.e., Least Confidence (LC) [26], Margin Confidence (MC) [59], Ratio Confidence (RC) [44], Entropy Sampling (ES) [44], K-Center Greedy (KCG) [32], K-Means Sampling (KMeans) [32], Core-set [40], and Diverse Mini-Batch (DBAL) [54]). The lower-bound baseline is using random sampling (Random) strategy, while the upper-bound baseline is using the entire dataset for training.

4.3.2 Batch size impact.

**Settings.** We evaluate the batch size (BS) impact on two deployment scenarios, the private server and the AWS cloud. Specifically, we first store the CIFAR-10 dataset on a private FTP server and an AWS S3, respectively. We then start ALaaS on a laptop to simulate the end-to-end AL process,
including downloading data from other devices, pre-processing data, and selecting AL with an AL strategy. The other settings are the same as the first experiment.

Results & Insights. Our ALaaS can manage the whole process in both environments with different batch sizes steadily and efficiently, as shown in Figure 7. Also, from the Figure 7, we have many interesting phenomena. First, BS = 1 and BS = 2 have very close throughput. Second, the increasing trend from BS = 2 to BS = 8 is the most dramatic. Third, after BS=16, the increase will stop. We attribute the reason to that the transmission time accounts for a large proportion of total processing time when the batch size is small. Therefore, the throughput improvement is marginal at the beginning. Then the batch computation time becomes the largest part of the total processing time, so the improvement is dramatic. Finally, when the batch size reaches the computation capacity, the increase stops.

5 Conclusion

This paper presents a new MLOps system, named ALaaS, for data-centric AI. ALaaS adopts the philosophy of Machine-Learning-as-Service and implements a server-client architecture, so users can use AL as a web service. Meanwhile, it abstracts the AL process into multiple components and develops several modules, including a data manager, an AL strategy zoo, and utility functions, to support them. More importantly, ALaaS employ stage-level parallelism (a pipeline manner), cache, and batching to improve AL running efficiency. Experiments show that our system has lower latency and higher throughput than all other baselines. We release our code to facilitate the AL research.
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