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

Yizheng Huang *
Institute for Infocomm Research
A*STAR
huangyz0918@ieee.org

Huaizheng Zhang *
Nanyang Technological University
huaizhen001@e.ntu.edu.sg

Yuanming Li
Institute of High Performance Computing
A*STAR
yuanminglee@gmail.com

Chiew Tong Lau
Nanyang Technological University
asctlau@ntu.edu.sg

Yang You
National University of Singapore
youy@comp.nus.edu.sg

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 1) require users to manually select AL strategies, and 2) can not perform AL tasks efficiently. To this end, this paper presents an automatic and efficient MLOps system for AL, named ALaaS (Active-Learning-as-a-Service). Specifically, 1) ALaaS implements an AL agent, including a performance predictor and a workflow controller, to decide the most suitable AL strategies given users’ datasets and budgets. We call this a predictive-based successive halving early-stop (PSHEA) procedure. 2) 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. Extensive experiments show that ALaaS outperforms all other baselines in terms of latency and throughput. Also, guided by the AL agent, ALaaS can automatically select and run AL strategies for non-expert users under different datasets and budgets. Our code is available at https://github.com/MLSysOps/Active-Learning-as-a-Service.

1 Introduction

Data-centric AI is an emerging topic that focuses on engineering data to develop AI applications with off-the-shelf machine learning (ML) models [14]. 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 [16]. However, real-world AI applications are facing more complicated scenarios, which can not be adequately addressed by model-centric AI. For instance, researchers and practitioners have to spend

*Equal contribution.

Preprint. Under review.
a lot of time on data preparation, including data labeling, and error detection. Meanwhile, they also need to monitor the data, so that they can update models in time when a distribution drift is detected. Treating these issues only from a model-centric view will lead to a sub-optimal solution. Therefore, to further improve and democratize AI applications, a lot of efforts are now turning to data-centric or combining model-centric and data-centric approaches.

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. Among them, one vital direction is active learning (AL). The motivation of AL is to reduce manual labeling efforts while maintaining and even improving ML models’ performance. 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. 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 labeled 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 is a non-trivial task. First, selecting a suitable AL strategy for a specific scenario given the budget and target accuracy is hard for both experts and non-experts. As a result, users have to run AL in a trial-and-error manner, resulting in huge time and monetary waste. Second, applying AL to AI application development is not simply searching for, selecting, or implementing AL strategies. Instead, users have to build a backend to run the AL pipeline, tailored for their applications in their environment (e.g., a private cluster and AWS). In other words, they need to undertake much repetitive engineering work with boilerplate code. Third, users have to consider the efficiency and cost issues, as AL often runs on a vast dataset, and some AL strategies (e.g., committee-based) 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 lower the barrier of applying AL, and they can meet neither automation nor efficiency requirements.

To address these issues, we propose an automatic and efficient backend for AL. Our AL system, named Active-Learning-as-a-Service (ALaaS), can select AL strategies automatically given the budget and target accuracy without specifying an AL strategy. Also, it can run AL strategies on large datasets efficiently by utilizing single or distributed multiple devices. Specifically, ALaaS adopts the server-client architecture to perform AL tasks and can be deployed easily on both laptops and public clouds as a service. To achieve high efficiency, it implements a stage-level parallelism method to run AL tasks by fully utilizing hardware resources and reducing waiting time. Meanwhile, more acceleration techniques such as data cache and batching are utilized to further speed up the AL process. Besides, for users who have difficulty selecting a suitable AL strategy, ALaaS provides a predictive-based successive halving early-stop (PSHEA) procedure to automatically select and run AL with an only budget and target accuracy inputs. In addition to that, our system also considers accessibility and modularity, so that users can use many AL strategies in our AL zoo with ease, and experts can propose more advanced AL strategies for new scenarios. Experiments show that 1) our ALaaS outperforms all other baselines in terms of latency and throughput, and 2) the PSHEA procedure can predict future accuracy and select suitable AL strategies under different settings. 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.

2.1 AL Algorithms and Tools

We categorize AL strategies into three classes, namely, diversity-based, uncertainty-based, and hybrid sampling. Diversity-based methods are designed to select the most diverse samples from the whole dataset to represent it. Uncertainty-based methods aim to select the samples that can not be identified confidently by current ML models and then use these samples to further
improve ML models. Hybrid methods [22, 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 [12], DeepAL [20], LibACT [51], and ALiPy [47]. Our ALaaS is inspired by these tools and further improves 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 competitions and workshops [14] demonstrate many exciting studies from academia and industry. Inspired by the pioneering work, many data-centric methods have been proposed for different areas, including Natural Language Processing (NLP) [50, 44], Computer Vision (CV) [21, 7], Robotics [30], etc. Also, a new benchmark [16] 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 [29]. From a data-centric view, labeling tools (e.g., labelme [41]), data cleaning tools (e.g., ActiveClean [25]), data drift monitors and many others, can all be regarded as MLOps systems. From a model-centric view, there are model store systems [48], model continuous integration [54, 38] tools, training platforms [24], and deployment platforms [8], etc. Different from these systems, ALaaS is designed specifically for executing human-involved AL tasks more efficiently.

In addition, tech giants start to build end-to-end cloud platforms for MLOps (e.g., TFX [3], SageMaker [13], Ludwig [33]). Our ALaaS can be a good plugin complementary to these systems.

3 System Design and Architecture

This section first highlights our Active-Learning-as-a-Service (ALaaS) with two key features, then details the workflow and the core optimizations of the system as shown in Figure 1.
Table 1: Comparison of AL open-source tools. Our ALaaS offers an automated Machine-Learning-as-a-Service experience and largely improves AL efficiency.

| AL Open-source Tool | Pipelined Data Processing | Automatically Strategy Selection | Server-Client Architecture | Data Cache | PyPI Install | AL Strategy Zoo |
|---------------------|---------------------------|---------------------------------|-----------------------------|------------|--------------|----------------|
| DeepAL [20]         | ✓                         |                                 |                             |            |              | ✓              |
| ModAL [12]          | ✓                         |                                 |                             | ✓          | ✓            | ✓              |
| ALiPy [47]          | ✓                         |                                 |                             | ✓          | ✓            | ✓              |
| libact [51]         | ✓                         |                                 |                             | ✓          | ✓            | ✓              |
| ALaaS (Ours)        | ✓                         | ✓                               | ✓                           | ✓          | ✓            | ✓              |

3.1 ALaaS Highlights

We highlight two key features provided by our system, namely efficiency and automation. These features are also our design principles, leading the implementation to consider both experts (e.g., data scientists and machine learning engineers) and non-experts (e.g., customers with little domain knowledge) all the time. Besides, we list the main differences between our system and other existing tools in the table.

**Efficiency.** Different from previous ALaaS python tools, our system is developed as a machine learning service. As a service, in addition to providing various AL strategies, our ALaaS offers efficiency to users by employing a lot of optimization technologies, including a pipeline process [34], ML serving backend adoption [36], and caching.

**Automation.** To further lower the barrier to use, an AL system should ensure that it can be utilized by non-AL experts with minimal effort and without writing much code. To this end, we design an AL agent to automate the AL strategy selection and the data selection procedures. With the AL agent, non-experts only need to input target accuracy and budget, then sit and wait for the final results.

3.2 ALaaS Workflow

As shown in Figure 1, ALaaS adopts the service-client architecture to abstract complex AL algorithms into web-based services, enabling an out-of-the-box user experience. Specifically, first, users only need to prepare a configuration file including basic settings like model name and serving device by following the provided templates, as shown in Figure 2. 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 to the AL server. The dataset can be stored either in the local disk or AWS S3 [45]. Meanwhile, if users do not specify an AL strategy, ALaaS will invoke an AL agent to automatically select suitable strategies to perform data selection tasks to approach users’ accuracy targets constrained by budget. Finally, the AL server will return a selected dataset for human labeling as well as further model updating.
3.3 ALaaS Optimization

Different from previous methods only providing AL strategy for accessibility, our ALaaS achieves high efficiency and automation by implementing a pipeline processing with a data cache, and an AL agent including a performance predictor and a loop controller.

**Pipeline.** As shown in Figure 3, we divide the processing into three stages, downloading (red color), pre-processing (blue color), and AL (green color). Once users start to send datasets, the ALaaS server will parse the datasets’ Uniform Resource Identifier (URI) in the AL client and pipeline the data downloading and data pre-processing to reduce the hardware waiting time and improve the processing speed. Meanwhile, we implement a data cache to temporarily store the processed samples. By doing so, we further improve the processing speed. The reason is public clouds usually adopt the computation and storage separation design, and transferring the data back and forth between the current computation node to the storage node is very time-consuming. After the AL server receive a batch (batch size depends on users’ settings) of raw samples, it will send them to optimized inference workers with ML serving backend for pre-processing (e.g., embedding calculation). Finally, those workers can return the processed data to the AL server for final data selection, then send the selected results back to the AL client. We observe that even with such a simple pipeline optimization, ALaaS’s processing speed can become 10x times faster than the other open-source platforms (see Section 4.2).

**AL agent.** The AL agent implements a Predictive-based Successive Halving Early-stop (PSHEA) procedure (as shown in the Algorithm 1) to help users who are unsure about selecting AL strategies. Specifically, it includes a performance predictor and a loop controller. The performance predictor is a negative exponential forecasting model. It predicts the next-round accuracy that can be achieved by a certain AL strategy under certain budget settings. The loop controller is to run many AL strategies as ‘candidates’ first and then decide which one should be eliminated at the current round (i.e., an early-stopping mechanism). After several rounds of reaching pre-defined targets (e.g., budget or accuracy), most AL strategies will be eliminated and the left strategies with the selected data samples will be suggested to users. This design is mainly based on the conclusion that no AL strategy can outperform all others under all settings. With this AL agent, non-experts can utilize ALaaS in a cost-efficient manner rather than trying all AL strategies in a brute force manner.

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.
Algorithm 1 Predictive-based Successive Halving Early-stop (PSHEA)

1: Input: 1. user target accuracy \(a_t\);
2: 2. unlabeled data set \(\xi\) with size \(\tau\);
3: 3. the maximum labeling budget \(b_{\text{max}}\) (\(b_{\text{max}} \leq \tau\));
4: 4. active learning strategy set \(L\);
5: \(a_0 \leftarrow\) pre-train the deep active learning model and get the initial evaluation accuracy.
6: initialize 1. the maximum evaluation accuracy \(a_{\text{max}} = a_0\);
7: 2. active learning round \(r = 0\);
8: 3. labeled data set \(d_l \leftarrow \emptyset\) for strategy \(l\);
9: 4. consumed total budget \(b_{\text{total}} = 0\);
10: while True do
11: if \(a_{\text{max}} \geq a_t\) then break; end if /* stop when reaches the target learning accuracy. */
12: if \(b_{\text{total}} \geq b_{\text{max}}\) then break; end if /* stop when labeling budget is not enough. */
13: if converge then break; end if /* stop when active learning accuracy does not increase. */
14: for strategy \(l\) in \(L\) do /* estimate the future performance of each strategy. */
15: \(d_l \leftarrow d_l \cup d_{l_r}\), select and label data \(d_{l_r}\) from \(\xi\) (cost budget \(b_{l_r}\)), merge labeled data into \(d_l\).
16: \(a_l \leftarrow\) update the AL model with \(d_l\), get and record the evaluation accuracy \(a_l\);
17: \(a^*_l \leftarrow\) train a negative exponential forecasting model on historical \(a_l\) and predict the active learning accuracy \(a^*_l\) in the next round;
18: \(b_{\text{total}} \leftarrow b_{\text{total}} + b_{l_r}\) calculate the consumed total budget.
19: end for
20: \(r \leftarrow r + 1\)
21: \(a_{\text{max}} \leftarrow\) update the best evaluation accuracy among all strategies;
22: if number of strategy in \(L > 1\) then /* strategy-level early-stopping */
23: stop and remove the strategy \(l'\) with the least \(a^*_{l'}\) from \(L\);
24: end if
25: end while

4.1 Evaluation setup

We implement our ALaaS with Python, gRPC, etc., and conduct a set of benchmark studies with the following settings.

**Hardware & Software.** We conduct experiments on AWS EC2 and an Apple Mac Mini (M1 Chip). Our integrated data processing worker is NVIDIA Triton Inference Server [36].

**Dataset.** We evaluate our system on CIFAR-10 [28] and SVHN datasets. CIFAR-10 includes 50,000 training images and 10,000 test images. SVHN contains 600,000 images and we randomly sample 3,000 images as the test set and 10,000 images as the AL set to be labeled.

**Model.** We use the widely deployed ResNet-18 [19] model to benchmark systems under many settings. We only fine-tune ResNet-18’s last layer with the AL-selected and human-labeled samples.

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 at one-time. This sub-pool includes samples that will be used to improve an existing ML model further. 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 whole AL pipeline on an AWS 3x.large CPU/GPU EC2. For all tools, we use the same AL strategy named least confidence sampling [29]. Finally, these tools will select 10,000 samples from the rest 40,000 images in the training set and we will compare their latency and throughput for an efficiency evaluation.

**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 updated model evaluation 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 allows us-
Table 2: Performance comparison among different AL open-source tools. Compared to all baselines, ALaaS has the lowest latency and the highest throughput.

| AL Open-source Tool | Top-1 Accuracy (%) | Top-5 Accuracy (%) | One-round AL Latency (sec) | End-to-end Throughput (Image/sec) |
|---------------------|---------------------|---------------------|----------------------------|---------------------------------|
| DeepAL [20]         | 72.40               | 75.46               | 2287.00 ± 179.37          | 17.49                           |
| ModAL [12]          | 72.40               | 75.46               | 2006.95 ± 37.98           | 19.93                           |
| ALify [47]          | 72.40               | 75.46               | 2410.85 ± 77.81           | 16.59                           |
| libact [51]         | 71.34               | 72.32               | 1771.33 ± 109.77          | 22.58                           |
| ALaaS (Ours)        | 72.40               | 75.46               | 552.45 ± 30.385           | 72.40                           |

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 system efficiency on different batch sizes. The third experiment evaluates the proposed AL strategy auto-selection procedure with an early-stopping algorithm.

4.3.1 AL strategy impact

Our ALaaS already provides many out-of-the-box AL strategies in AL Strategy Zoo for users. This experiment evaluates 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 evaluation model accuracy of different methods is shown in Figure 4a. Core-Set [43] achieves the highest accuracy with no surprise as it is designed for CNNs in Computer Vision (CV) tasks. Meanwhile, Diverse Mini-Batch (DBAL) [55] and Margin Confidence sampling (MC) [29] have the second and the third highest accuracy respectively, though they have proposed for a long time. This indicates that even in the deep learning (DL) era, conventional methods (e.g., calculating margins) still play a vital role and can cooperate with DL well.

The throughput comparison is shown in Figure 4b. The least confidence sampling (LC) has the highest throughput while Core-Set selection achieves the lowest throughput. Given the accuracy 4a and the throughput 4b results, we can conclude that the accuracy improvement of Core-Set comes from its heavy design while conventional sampling methods like MC balances the trade-off between the accuracy and the efficiency well.

In summary, ALaaS provides many strategies with the right accuracy and can run them efficiently.

Figure 4: Performance of one-round AL for ResNet-18 [19] on CIFAR-10 dataset [28] using different AL strategies (i.e., Least Confidence (LC) [29], Margin Confidence (MC) [42], Ratio Confidence (RC) [46], Entropy Sampling (ES) [46], K-Center Greedy (KCG) [33], Core-Set [43], and Diverse Mini-Batch (DBAL) [55]) (see Figures 4a, 4b) and AL inference batch size (see Figure 4c). 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 the public cloud (i.e., AWS with S3). We first store the CIFAR-10 dataset on an AWS S3 bucket. We then start ALaaS on a laptop to simulate an end-to-end AL process, including downloading data from other devices, pre-processing data, and selecting samples with an AL strategy. The other settings are the same as the first experiment.

Results & Insights. Our ALaaS can manage the whole process steadily and efficiently with different batch sizes, as shown in Figure 4c. We can observe many interesting phenomena. First, BS = 1 and BS = 2 have very close throughput. Second, the increasing trend from BS = 4 to BS = 16 is dramatic. Third, after BS = 16, the increasing trend will stop. We attribute the reason that the transmission time accounts for a large proportion of the total processing time when the batch size is small. Therefore, the throughput improvement is marginal at the beginning. Then, as the batch computation time becomes the largest part of the total processing time, the improvement is dramatic. Finally, when the batch size reaches the computation capacity, this increasing diminishes.

4.3.3 PSHEA procedure evaluation.

Settings. We evaluate our AL agent with the PSHEA procedure on both CIFAR-10 and SVHN datasets. For both CIFAR-10 and SVHN experiments, we simulate an 8-round AL procedure.

Results & Insights. We first use the least confidence sampling strategy to evaluate the effectiveness of our accuracy prediction model mentioned in the Algorithm 1. From Figure 5a, we observe that the prediction model can foresee the accuracy very accurately, laying a solid foundation for later AL strategy auto-selection. Then, we run our AL agent with PSHEA. The AL agent will launch all 7 AL strategies as candidates in the first round and then eliminate strategies round by round. As shown in Figure 5b, for two different datasets, our AL agent selects different AL strategies under different budgets (i.e., the percentage of the labeled data in this experiment). This observation aligns with the conclusion from previous studies [18] and further shows the necessity of multi-round auto-selection, as no AL method can always outperform others under different budgets and datasets. Our method early stops many of the AL selection processes and helps to save running costs.

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, our system employs stage-level parallelism, data cache, and batching to improve AL running efficiency. Furthermore, it includes an AL agent with a predictive-based successive halving early-stop (PSHEA) procedure to select suitable AL strategies for users under different budgets and accuracy targets. Experiments show that our system has lower latency and higher throughput compared to all other baselines. Experiments also show that the auto-selection process can help users eliminate low-performing AL strategies earlier and save cost. We release our code at GitHub to facilitate the AL research.
References

[1] Sharat Agarwal, Himanshu Arora, Saket Anand, and Chetan Arora. Contextual diversity for active learning. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, *Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part XVI*, volume 12361 of *Lecture Notes in Computer Science*, pages 137–153. Springer, 2020. doi: 10.1007/978-3-030-58517-4_9. URL https://doi.org/10.1007/978-3-030-58517-4_9.

[2] Jordan T. Ash, Chicheng Zhang, Akshay Krishnamurthy, John Langford, and Alekh Agarwal. Deep batch active learning by diverse, uncertain gradient lower bounds. In *8th International Conference on Learning Representations, ICLR 2020*, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net, 2020. URL https://openreview.net/forum?id=ryghZJBKPS.

[3] Denis Baylor, Eric Breck, Heng-Tze Cheng, Noah Fiedel, Chuan Yu Foo, Zakaria Haque, Salem Haykal, Mustafa Ispir, Vihan Jain, Levent Koc, Chiu Yuen Koo, Lukasz Lew, Clemens Mewald, Akshay Naresh Modi, Neoklis Polyzotis, Sukriti Ramesh, Sudip Roy, Steven Euijong Whang, Martin Wicke, Jakub Wilkiewicz, Xin Zhang, and Martin Zinkevich. TFX: A tensorflow-based production-scale machine learning platform. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Halifax, NS, Canada, August 13 - 17, 2017, pages 1387–1395. ACM, 2017. doi: 10.1145/3097983.3098021. URL https://doi.org/10.1145/3097983.3098021.

[4] William H. Beluch, Tim Genewein, Andreas Nürnberger, and Jan M. Köhler. The power of ensembles for active learning in image classification. In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018*, Salt Lake City, UT, USA, June 18-22, 2018, pages 9368–9377. Computer Vision Foundation / IEEE Computer Society, 2018. doi: 10.1109/CVPR.2018.00976. URL http://openaccess.thecvf.com/content_cvpr_2018/html/Beluch_The_Power_of_CVPR_2018_paper.html.

[5] Tim Berners-Lee, Roy Fielding, and Larry Masinter. Uniform resource identifier (uri): Generic syntax. Technical report, 2005.

[6] Razvan Caramalau, Binod Bhattarai, and Tae-Kyun Kim. Sequential graph convolutional network for active learning. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021*, virtual, June 19-25, 2021, pages 9583–9592. Computer Vision Foundation / IEEE, 2021. URL https://openaccess.thecvf.com/content_CVPR2021/html/Caramalau_Sequential_Graph_Convolutional_Network_for_Active_Learning_CVPR_2021_paper.html.

[7] Ria Chakraborty, Madhur Popli, Rachit Lamba, and Rishi Verma. A first look towards one-shot object detection with spot for data-efficient learning. In *NeurIPS 2021 Workshop on Data-Centric AI*, 2021. URL https://www.amazon.science/publications/a-first-look-towards-one-shot-object-detection-with-spot-for-data-efficient-learning.

[8] Tianqi Chen, Thierry Moreau, Ziheng Jiang, Liannin Zheng, Eddie Q. Yan, Haichen Shen, Meghan Cowan, Leyuan Wang, Yuwei Hu, Luis Ceze, Carlos Guestrin, and Arvind Krishnamurthy. TVM: an automated end-to-end optimizing compiler for deep learning. In Andrea C. Arpaci-Dusseau and Geoff Voelker, editors, *13th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2018*, Carlsbad, CA, USA, October 8-10, 2018, pages 578–594. USENIX Association, 2018. URL https://www.usenix.org/conference/osdi18/presentation/chen.

[9] Rob Chew, Michael Wenger, Caroline Kery, Jason Nance, Keith Richards, Emily Hadley, and Peter Baumgartner. SMART: an open source data labeling platform for supervised learning. *J. Mach. Learn. Res.*, 20:82:1–82:5, 2019. URL http://jmlr.org/papers/v20/18-859.html.

[10] Daniel Crankshaw, Xin Wang, Giulio Zhou, Michael J. Franklin, Joseph E. Gonzalez, and Ion Stoica. Cliper: A low-latency online prediction serving system. In Aditya Akella and Jon Howell, editors, *14th USENIX Symposium on Networked Systems Design and Implementation*, NSDI 2017, Boston, MA, USA, March 27-29, 2017, pages 613–627. USENIX Association,
[11] Ido Dagan and Sean P. Engelson. Committee-based sampling for training probabilistic classifiers. In Armand Prieditis and Stuart Russell, editors, Machine Learning. Proceedings of the Twelfth International Conference on Machine Learning, Tahoe City, California, USA, July 9-12, 1995, pages 150–157. Morgan Kaufmann, 1995. doi: 10.1016/b978-1-55860-377-6.50027-x. URL https://doi.org/10.1016/b978-1-55860-377-6.50027-x.

[12] Tivadar Danka and Péter Horváth. modal: A modular active learning framework for python. CoRR, abs/1805.00979, 2018. URL http://arxiv.org/abs/1805.00979.

[13] Piali Das, Nikita Ivkin, Tanya Bansal, Laurence Rouesnel, Philip Gautier, Zohar S. Karnin, Leo Dirac, Lakshmi Ramakrishnan, Andre Perunicic, Iaroslav Shcherbatyi, Wilton Wu, Aida Zolic, Huibin Shen, Amr Ahmed, Fela Winkelhoven, Miroslav Miladinovic, Cédric Archambeau, Alex Tang, Bhaskar Dutt, Patricia Grao, and Kumar Venkateswar. Amazon sagemaker autopilot: a white box auto ml solution at scale. In Sebastian Schelter, Steven Whang, and Julia Stoyanovich, editors, Proceedings of the Fourth Workshop on Data Management for End-To-End Machine Learning, In conjunction with the 2020 ACM SIGMOD/PODS Conference, DEEM@SIGMOD 2020, Portland, OR, USA, June 14, 2020, pages 2:1–2:7. ACM, 2020. doi: 10.1145/3399579.3399870. URL https://doi.org/10.1145/3399579.3399870.

[14] Landing Ai. deeplearning.ai. Data-centric ai competition. URL https://deeplearning-ai.github.io/data-centric-comp/. Accessed: 2022-07-05.

[15] Melanie Ducoffe and Frédéric Precioso. Adversarial active learning for deep networks: a margin based approach. CoRR, abs/1802.09841, 2018. URL http://arxiv.org/abs/1802.09841.

[16] Sabri Eyuboglu, Bojan Karlas, Christopher Ré, Ce Zhang, and James Zou. debench: a benchmark for data-centric AI systems. In Matthias Boehm, Paroma Varma, and Doris Xin, editors, DEEM ’22: Proceedings of the Sixth Workshop on Data Management for End-To-End Machine Learning, Philadelphia, PA, USA, 12 June 2022, pages 9:1–9:4. ACM, 2022. doi: 10.1145/3533028.3533310. URL https://doi.org/10.1145/3533028.3533310.

[17] Yarin Gal, Riashat Islam, and Zoubin Ghahramani. Deep bayesian active learning with image data. volume abs/1703.02910, 2017. URL http://arxiv.org/abs/1703.02910.

[18] Guy Hacohen, Avihu Dekel, and Daphna Weinshall. Active learning on a budget: Opposite strategies suit high and low budgets. Thirty-ninth International Conference on Machine Learning, 2022.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 770–778. IEEE Computer Society, 2016. doi: 10.1109/CVPR.2016.90. URL https://doi.org/10.1109/CVPR.2016.90.

[20] Kuan-Hao Huang. Deepal: Deep active learning in python. CoRR, abs/2111.15258, 2021. URL https://arxiv.org/abs/2111.15258.

[21] Phoenix X. Huang, Wenze Hu, William Brendel, Mannmohan Chandraker, Li-Jia Li, and Xiaoyu Wang. YMIR: A rapid data-centric development platform for vision applications. CoRR, abs/2111.10046, 2021. URL https://arxiv.org/abs/2111.10046.

[22] Sheng-Jun Huang, Rong Jin, and Zhi-Hua Zhou. Active learning by querying informative and representative examples. pages 892–900, 2010. URL https://proceedings.neurips.cc/paper/2010/hash/5487315b1286f907165907aa8fc96619-Abstract.html.

[23] Yizheng Huang, HuaiZheng Zhang, Yonggang Wen, Peng Sun, and Nguyen Binh Duong Ta. Modelci-e: Enabling continual learning in deep learning serving systems. CoRR, abs/2106.03122, 2021. URL https://arxiv.org/abs/2106.03122.
[24] Yimin Jiang, Yibo Zhu, Chang Lan, Bairen Yi, Yong Cui, and Chuanxiong Guo. A unified architecture for accelerating distributed DNN training in heterogeneous GPU/CPU clusters. In 14th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2020, Virtual Event, November 4-6, 2020, pages 463–479. USENIX Association, 2020. URL https://www.usenix.org/conference/osdi20/presentation/jiang.

[25] Yuchen Jin, Tianyi Zhou, Liangyu Zhao, Yibo Zhu, Chuanxiong Guo, Marco Canini, and Arvind Krishnamurthy. Autolrs: Automatic learning-rate schedule by bayesian optimization on the fly. ICLR 2021, 2021.

[26] Sanjay Krishnan, Jiannan Wang, Eugene Wu, Michael J. Franklin, and Ken Goldberg. Activeclean: Interactive data cleaning for statistical modeling. Proc. VLDB Endow., 9(12): 948–959, 2016. doi: 10.14778/2994509.2994514. URL http://www.vldb.org/pvldb/vol9/p948-krishnan.pdf.

[27] Sanjay Krishnan, Michael J. Franklin, Ken Goldberg, and Eugene Wu. Boostclean: Automated error detection and repair for machine learning. CoRR, abs/1711.01299, 2017. URL http://arxiv.org/abs/1711.01299.

[28] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

[29] David D. Lewis and William A. Gale. A sequential algorithm for training text classifiers. In W. Bruce Croft and C. J. van Rijsbergen, editors, Proceedings of the 17th Annual International ACM-SIGIR Conference on Research and Development in Information Retrieval. Dublin, Ireland, 3-6 July 1994 (Special Issue of the SIGIR Forum), pages 3–12. ACM/Springer, 1994. doi: 10.1007/978-1-4471-2099-5_1. URL https://doi.org/10.1007/978-1-4471-2099-5_1.

[30] Qinjie Lin, Guo Ye, Jiayi Wang, and Han Liu. Roboflow: a data-centric workflow management system for developing ai-enhanced robots. In Aleksandra Faust, David Hsu, and Gerhard Neumann, editors, Conference on Robot Learning, 8-11 November 2021, London, UK, volume 164 of Proceedings of Machine Learning Research, pages 1789–1794. PMLR, 2021. URL https://proceedings.mlr.press/v164/lin22c.html.

[31] Chen Change Loy, Timothy M. Hospedales, Tao Xiang, and Shaogang Gong. Stream-based joint exploration-exploitation active learning. In 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence, RI, USA, June 16-21, 2012, pages 1560–1567. IEEE Computer Society, 2012. doi: 10.1109/CVPR.2012.6247847. URL https://doi.org/10.1109/CVPR.2012.6247847.

[32] Prem Melville and Raymond J. Mooney. Diverse ensembles for active learning. In Carla E. Brodley, editor, Machine Learning. Proceedings of the Twenty-first International Conference (ICML 2004), Banff, Alberta, Canada, July 4-8, 2004, volume 69 of ACM International Conference Proceeding Series. ACM, 2004. doi: 10.1145/1015330.1015385. URL https://doi.org/10.1145/1015330.1015385.

[33] Piero Molino, Yaroslav Dudin, and Sai Sumanth Miryala. Ludwig: a type-based declarative deep learning toolbox. CoRR, abs/1909.07930, 2019. URL http://arxiv.org/abs/1909.07930.

[34] Deepak Narayanan, Aaron Harlap, Amar Phanishayee, Vivek Seshadri, Nikhil R. Devanur, Gregory R. Ganger, Phillip B. Gibbons, and Matei Zaharia. Pipedream: generalized pipeline parallelism for DNN training. In Tim Brecht and Carey Williamson, editors, Proceedings of the 27th ACM Symposium on Operating Systems Principles, SOSP 2019, Huntsville, ON, Canada, October 27-30, 2019, pages 1–15. ACM, 2019. doi: 10.1145/3341301.3359646. URL https://doi.org/10.1145/3341301.3359646.

[35] Hieu Tat Nguyen and Arnold W. M. Smeulders. Active learning using pre-clustering. In Carla E. Brodley, editor, Machine Learning. Proceedings of the Twenty-first International Conference (ICML 2004), Banff, Alberta, Canada, July 4-8, 2004, volume 69 of ACM International Conference Proceeding Series. ACM, 2004. doi: 10.1145/1015330.1015349. URL https://doi.org/10.1145/1015330.1015349.
[36] Nvidia. The triton inference server provides an optimized cloud and edge inferencing solution. https://github.com/triton-inference-server/server. Accessed: 2022-07-05.

[37] Pengzhen Ren, Yun Xiao, Xiaojun Chang, Po-Yao Huang, Zhihui Li, Brij B. Gupta, Xiaojiang Chen, and Xin Wang. A survey of deep active learning. ACM Comput. Surv., 54(9):180:1–180:40, 2022. doi: 10.1145/3472291. URL https://doi.org/10.1145/3472291.

[38] Cédric Renggli, Bojan Karlas, Bolin Ding, Feng Liu, Kevin Schawinski, Wentao Wu, and Ce Zhang. Continuous integration of machine learning models with ease.ml/ci: Towards a rigorous yet practical treatment. 2019. URL https://proceedings.mlsys.org/book/266.pdf.

[39] Cedric Renggli, Luka Rimanic, Nezihe Merve Gürel, Bojan Karlaš, Wentao Wu, and Ce Zhang. A data quality-driven view of mlops, 2021. URL https://arxiv.org/abs/2102.07750.

[40] Dan Roth and Kevin Small. Margin-based active learning for structured output spaces. In Johannes Fürnkranz, Tobias Scheffer, and Myra Spiliopoulou, editors, Machine Learning: ECML 2006, 17th European Conference on Machine Learning, Berlin, Germany, September 18-22, 2006, Proceedings, volume 4212 of Lecture Notes in Computer Science, pages 413–424. Springer, 2006. doi: 10.1007/11871842_40. URL https://doi.org/10.1007/11871842_40.

[41] Bryan C. Russell, Antonio Torralba, Kevin P. Murphy, and William T. Freeman. Labelme: A database and web-based tool for image annotation. Int. J. Comput. Vis., 77(1-3):157–173, 2008. doi: 10.1007/s11263-007-0090-8. URL https://doi.org/10.1007/s11263-007-0090-8.

[42] Tobias Scheffer, Christian Decomain, and Stefan Wrobel. Active hidden markov models for information extraction. In Frank Hoffmann, David J. Hand, Niall M. Adams, Douglas H. Fisher, and Gabriela Guimarães, editors, Advances in Intelligent Data Analysis, 4th International Conference, IDA 2001, Cascais, Portugal, September 13-15, 2001, Proceedings, volume 2189 of Lecture Notes in Computer Science, pages 309–318. Springer, 2001. doi: 10.1007/3-540-44816-0_31. URL https://doi.org/10.1007/3-540-44816-0_31.

[43] Ozan Sener and Silvio Savarese. Active learning for convolutional neural networks: A core-set approach. In 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net, 2018. URL https://openreview.net/forum?id=H1aIuk-RW.

[44] Jaehyung Seo, Chanjun Park, Sugyeong Eo, Hyeonseok Moon, and Heuiseok Lim. Automatic knowledge augmentation for generative commonsense reasoning. arXiv preprint arXiv:2111.00192, 2021.

[45] Amazon Web Service. Amazon s3 - object storage built to retrieve any amount of data from anywhere, 2002. URL https://aws.amazon.com/s3/. Accessed: 2022-07-05.

[46] Burr Settles. Active learning literature survey. 2009. URL http://digital.library.wisc.edu/1793/60660.

[47] Ying-Peng Tang, Guo-Xiang Li, and Sheng-Jun Huang. Alipy: Active learning in python. CoRR, abs/1901.03802, 2019. URL http://arxiv.org/abs/1901.03802.

[48] Manasi Vartak. MODELDB: A system for machine learning model management. In 8th Biennial Conference on Innovative Data Systems Research, CIDR 2017, Chaminade, CA, USA, January 8-11, 2017, Online Proceedings. www.cidrdb.org, 2017. URL http://cidrdb.org/cidr2017/gongshow/abstracts/cidr2017_112.pdf.

[49] Dan Wang and Yi Shang. A new active labeling method for deep learning. In 2014 International Joint Conference on Neural Networks, IJCNN 2014, Beijing, China, July 6-11, 2014, pages 112–119. IEEE, 2014. doi: 10.1109/IJCNN.2014.6889457. URL https://doi.org/10.1109/IJCNN.2014.6889457.
[50] Liang Xu, Jiacheng Liu, Xiang Pan, Xiaojing Lu, and Xiaofeng Hou. Dataclue: A benchmark suite for data-centric NLP. *CoRR*, abs/2111.08647, 2021. URL https://arxiv.org/abs/2111.08647.

[51] Yao-Yuan Yang, Shao-Chuan Lee, Yu-An Chung, Tung-En Wu, Si-An Chen, and Hsuan-Tien Lin. libact: Pool-based active learning in python. *CoRR*, abs/1710.00379, 2017. URL http://arxiv.org/abs/1710.00379.

[52] Yi Yang, Zhigang Ma, Feiping Nie, Xiaojun Chang, and Alexander G. Hauptmann. Multi-class active learning by uncertainty sampling with diversity maximization. *Int. J. Comput. Vis.*, 113(2):113–127, 2015. doi: 10.1007/s11263-014-0781-x. URL https://doi.org/10.1007/s11263-014-0781-x.

[53] Huaizheng Zhang, Yuanming Li, Qiming Ai, Yong Luo, Yonggang Wen, Yichao Jin, and Ta Nguyen Binh Duong. Hysia: Serving dnn-based video-to-retail applications in cloud. In Chang Wen Chen, Rita Cucchiara, Xian-Sheng Hua, Guo-Jun Qi, Elisa Ricci, Zhengyou Zhang, and Roger Zimmermann, editors, *MM '20: The 28th ACM International Conference on Multimedia*, Virtual Event / Seattle, WA, USA, October 12-16, 2020, pages 4457–4460. ACM, 2020. doi: 10.1145/3394171.3414536. URL https://doi.org/10.1145/3394171.3414536.

[54] Huaizheng Zhang, Yuanming Li, Yizheng Huang, Yonggang Wen, Jianxiong Yin, and Kyle Guan. Mlmodelci: An automatic cloud platform for efficient mlaas. In Chang Wen Chen, Rita Cucchiara, Xian-Sheng Hua, Guo-Jun Qi, Elisa Ricci, Zhengyou Zhang, and Roger Zimmermann, editors, *MM '20: The 28th ACM International Conference on Multimedia*, Virtual Event / Seattle, WA, USA, October 12-16, 2020, pages 4453–4456. ACM, 2020. doi: 10.1145/3394171.3414535. URL https://doi.org/10.1145/3394171.3414535.

[55] Fedor Zhdanov. Diverse mini-batch active learning. *CoRR*, abs/1901.05954, 2019. URL http://arxiv.org/abs/1901.05954.

[56] Indre Zliobaite, Albert Bifet, Bernhard Pfahringer, and Geoffrey Holmes. Active learning with drifting streaming data. *IEEE Trans. Neural Networks Learn. Syst.*, 25(1):27–39, 2014. doi: 10.1109/TNNLS.2012.2236570. URL https://doi.org/10.1109/TNNLS.2012.2236570.