PAISE 2021

Argonne NATIONAL LABORATORY

Addressing the Constraints of Active Learning on the Edge

Enrique Nueve
enrique.iv@northwestern.edu
Seongha Park
seongha.park@anl.gov
Sean Shahkarami
sshahkarami@uchicago.edu
Nicola Ferrier
nferrier@anl.gov

Intro

- Enrique (Rick) Nueve ~ pre-doc on the SAGE project (Ph.D. student at CU Boulder this fall)
- SAGE is a NSF-funded project to develop a novel cyberinfrastructure to exploit dramatic improvements in artificial intelligence technology.
- SAGE website: https://sagecontinuum.org/

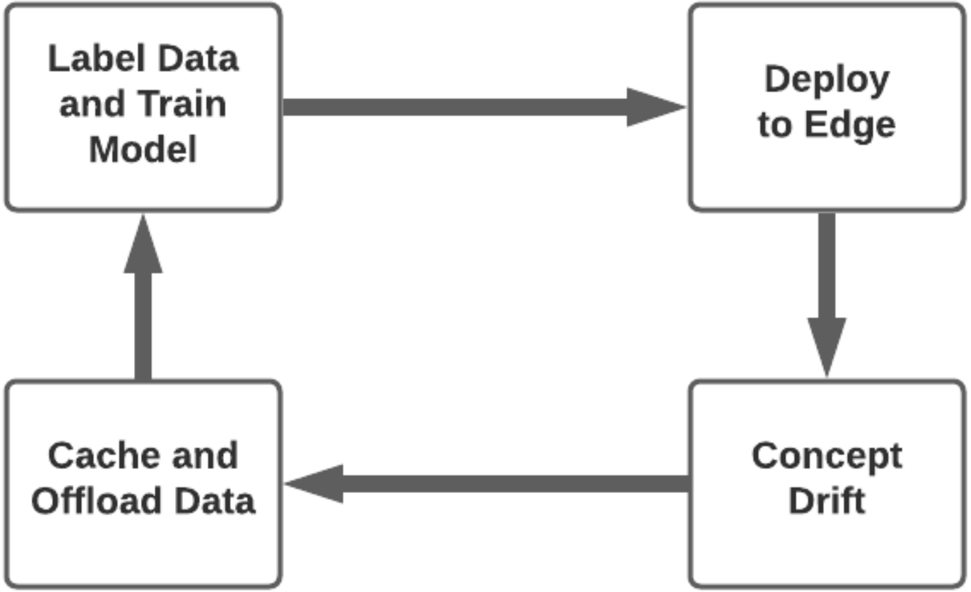
A Software-Defined Sensor Network Cyberinfrastructure for AI at the Edge

Overview

1. Machine learning at the edge
2. Why perform active learning on the edge?
3. Active learning on the edge
4. Edge compatible active learning framework
5. Future work

1. Machine learning at the edge

Life on the edge



1. Machine learning at the edge

Life before the edge

Where do we get the initial data to train the model?

2. Why perform active learning on the edge?

What is active learning?

Active learning is an approach for training a machine learning model with the objective of maximizing the model's performance while using the least amount of data.

2. Why perform active learning on the edge?

How could active learning help on the edge?

- Improve model performance
- Edge caching (memory)
- Edge offloading (bandwidth)

3. Active learning on the edge

Current state of the art methods for active learning

- Discriminative Active Learning (Gissin & Shalev-Shwartz, 2019)
- Adversarial Active Learning (Ducoffe & Precioso, 2018)
- Deep Bayesian Active Learning (Gal, Islam, & Ghahraman, 2017)
- Multi-class Active Learning by Uncertainty Sampling with Diversity Maximization (Yang, Ma, Nie, Chang, & Hauptmann, 2015)
- Learning to Sample (Shao, Wang, & F. Liu, 2019)

3. Active learning on the edge

Constraints of active learning on the edge

- Separated data, labeled data on the cloud, and unlabeled data on the edge
- Cold starting or low initial model performance
- Limited budget size due to bandwidth and memory constraints
- Limited computational resources

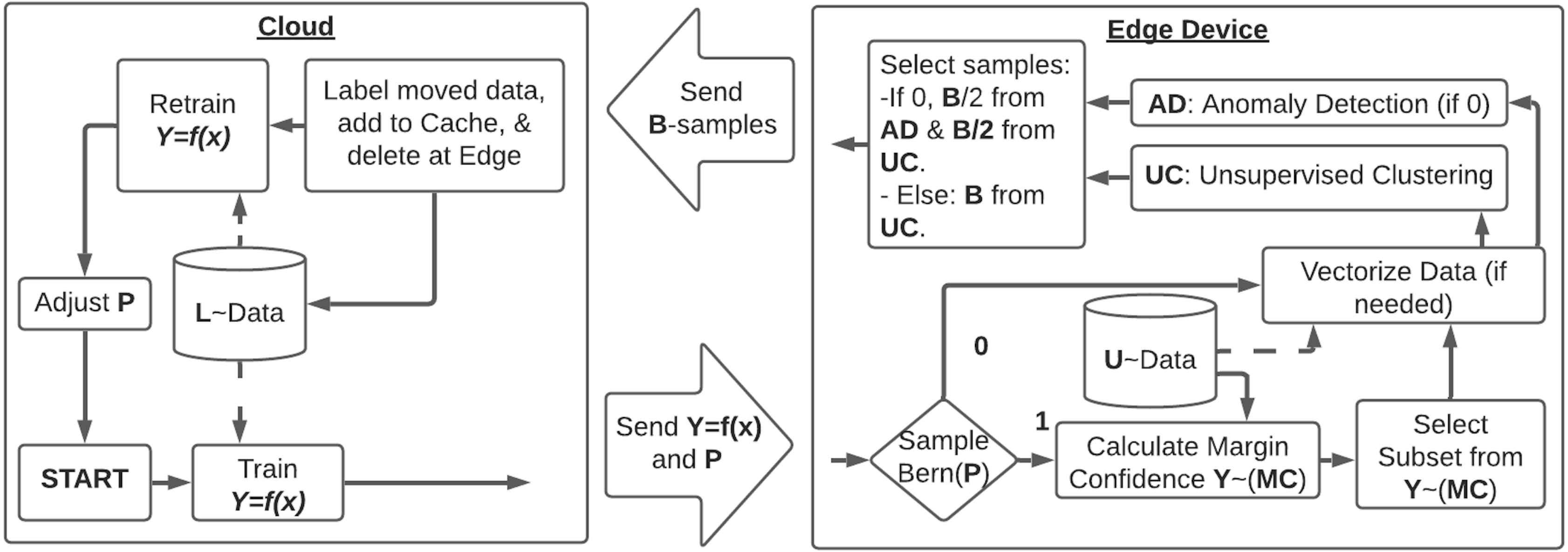
4. Edge compatible active learning framework

Focus of method

- Method focused around computational feasibility
- Scalable to resources
- Takes into account budget size and cold starting
- Tries to balance uncertainty and representative sampling

4. Edge compatible active learning framework

Framework diagram



4. Edge compatible active learning framework

Experiment datasets

- MNIST: 70,000 total samples, budget size of 100
- Bee images: 4,744 total samples, budget size of 100
- Monkey images: 1,368 total samples, budget size of 50

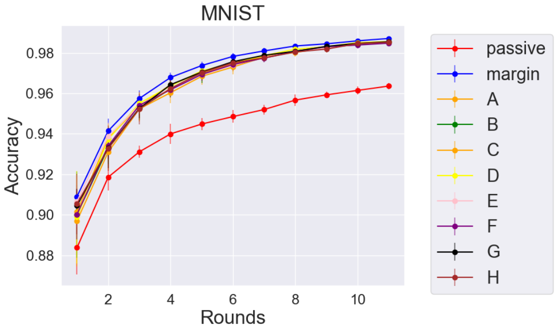
4. Edge compatible active learning framework

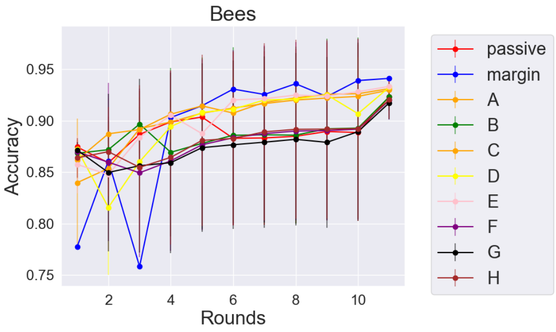
Experiment configurations

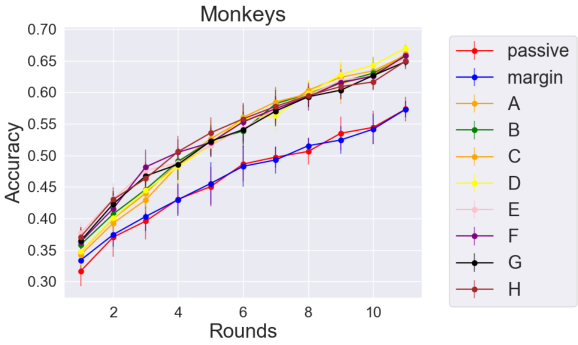
	A	B	C	D	E	F	G	H
Vector	HOG	HOG	HOG	HOG	Flat	Flat	Flat	Flat
Cluster	Gaussian Mixture	Gaussian Mixture	K-means	K-means	Gaussian Mixture	Gaussian Mixture	K-means	K-means
Anomaly	Isolation Forest	One Class SVM	Isolation Forest	One Class SVM	Isolation Forest	One Class SVM	Isolation Forest	One Class SVM

4. Edge compatible active learning framework

Results







4. Edge compatible active learning framework

Results

Best configurations

- MNIST ~ D
- Bees ~ D
- Monkeys ~ E

Data set (size)	Proposed	Passive	Margin
MNIST (100)	0.99 ± 0.00	0.96 ± 0.00	0.99 ± 0.0
Bees (100)	0.93 ± 0.012	0.92 ± 0.01	0.94 ± 0.00
Monkeys (50)	0.67 ± 0.01	0.57 ± 0.02	0.57 ± 0.01

5. Future work

- Leveraging multiple edge devices and fog devices
- Exploring the trade-off of budget and performance
- Hybrid active/federated learning approach

References

[1] D. Gissin and S. Shalev-Shwartz, “Discriminative active learning,” arXiv preprint arXiv:1907.06347, 2019

[2] M. Ducoffe and F. Precioso, “Adversarial active learning for deep networks: a margin based approach,” arXiv preprint arXiv:1802.09841,2018.

[3] Gal, R. Islam, and Z. Ghahramani, “Deep Bayesian active learning with image data,”arXiv preprin arXiv:1703.02910, 2017.

[4] . Yang, Z. Ma, F. Nie, X. Chang, and A. G. Hauptmann, “Multi-class active learning by uncertainty sampling with diversity maximization,” International Journal of Computer Vision, vol. 113, no. 2, pp. 113–127, 2015

[5] J. Shao, Q. Wang, and F. Liu, “Learning to sample: an active learning framework,” in 2019 IEEE International Conference on Data Mining (ICDM). IEEE, 2019, pp. 538–547.

Questions?