S^4AD-Learning: Self-supervised Semi-supervised Active Deep Learning

Joao Fonseca[*]
NOVA Information Management School
Universidade Nova de Lisboa
jpfonseca@novaims.unl.pt

Fernando Bacao
NOVA Information Management School
Universidade Nova de Lisboa
bacao@novaims.unl.pt

Abstract

TODO

1 Introduction

This is an introduction.

Learning-based AL selection is an important yet under-explored problem [1].

The proposed method extends the model described in [2] in the following ways: (1) Add a Semi-supervised learning loss to leverage the informativeness of both labeled and unlabeled data in the iterative process, (2) Extend the Self-supervised Active Learning model using data augmentation as a regularization method, (3) Combine the LADA-LearningLoss data acquisition method proposed in [3] with the VAAL model [4].

2 Background

2.1 Problem Formulation

2.2 Data Augmentation in AL

Data Augmentation in AL has been recently explored for different domains [3, 5, 6]. LADA [3]. They test two data augmentation methods, one using Spatial Transformer Networks **[CITATION]**, and another using the Mixup method.

The Variational Adversarial Active Learning model [7]

The Task-aware VAAL model [4] improves over the VAAL model via…

Copy/pasted from the LADA paper: "BayesianGenerative Active Deep Learning (BGADL) combines acquisition and augmentation in a pipelinedapproach [11]; BGADL selects data instances viafacq, and BGADL augments the selected instancesviafaug, which is VAE-ACGAN. However, BGADL limits the vicinity to preserve the label validity.Also, a large number of labeled instances are demanded to train the generative model, VAE-ACGAN,of BGADL at every acquisition round. More importantly, BGADL does not consider the potentialgain from data augmentation in the process of acquisition."

[*]Correponding author.

35th Conference on Neural Information Processing Systems (NeurIPS 2021), Sydney, Australia.

2.3 Semi-supervised Learning in AL

Consistency-based semi-supervised active learning [1]. Combining mixmatch and active learning for better accuracy with fewer labels [8].

S^4L [9] combines self-supervised and semi-supervised learning training losses simultaneously, which assumes existence of a small labeled training dataset.

2.4 Self-supervised Learning in AL

SimCLR [10]

BYOL [11]

SubTab [12]

Active Learning (AL) using self-supervised learning was explored in [13]. They used a pretrained BERT model [14] with a task-specific classification layer to natural language processing classification tasks. They proposed an Uncertainty Criterion based on the use of the average Kullback-Leibler (KL) divergence between an unlabeled observation x_p, from the unlabeled data pool $\mathcal{D}_{pool}$, and its k-nearest neighbors (KNN), $x_l^{(i)}, i = 1, \ldots, k$, from the set of labeled data $\mathcal{D}_{lab}$ in the feature space, produced via an encoder $\Phi(\mathcal{D}_{lab})$ and $\Phi(\mathcal{D}_{pool})$. They select b observations from $\mathcal{D}_{pool}$ with the highest average KL divergence score to be labeled and moved into $\mathcal{D}_{lab}$ for the next AL iteration.

An earlier attempt to joining AL with self-supervised is proposed in [15].

Another method was proposed in [2]

2.5 Active Deep Learning

A literature review of Deep AL can be found in [16].

Learning Loss in AL was proposed in [17], which replaces the traditional Uncertainty Criterion module. However, in [18], a second iteration of this module, LearningLoss++, improves it using a KL divergence based objective by comparing gradients. **[To be clarified later]**

The core-set model [19]

3 Methodology

3.1 The S^4AD-Learning Model

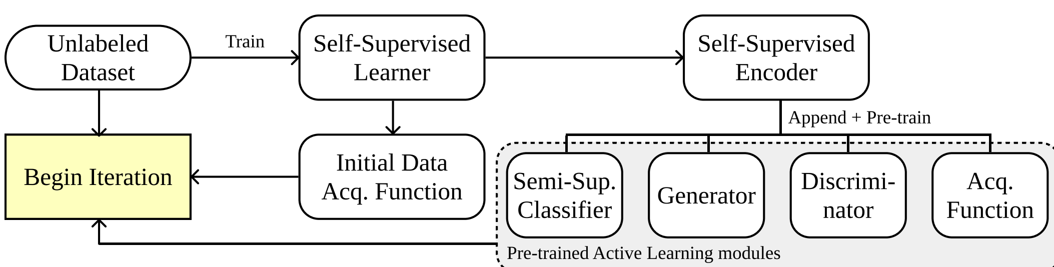

Figure 1: Diagram depicting the initialization of the proposed model.

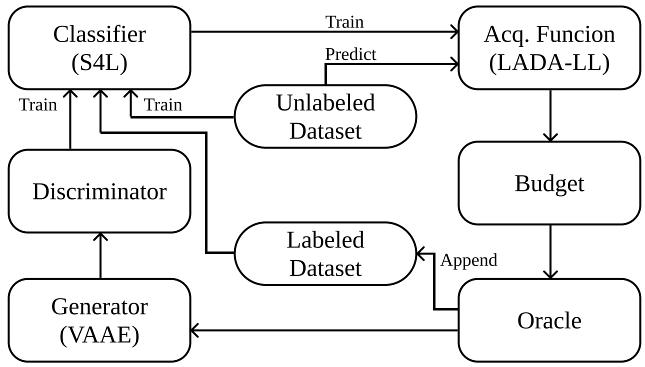

Figure 2: Diagram depicting the iterative procedure of the proposed model.

3.2 Self-supervised initialization

3.2.1 Initial Data Acquisition Function (TBD)

3.2.2 Pseudo-labeling fine tuning

3.3 Integrated Augmentation and Acquisition

3.3.1 Variational Adversarial Autoencoder

3.3.2 Look-Ahead Data Acquisition with LearningLoss++

4 Experiments

4.1 Baselines and Datasets

Datasets planned for use:

- CIFAR-10
- CIFAR-100
- FashionMNIST
- SVHN

Baseline models planned for use:

- Random
- Coreset
- LearningLoss++
- LADA
- CAL (Contrastive Active Learning)
- BALD

4.2 Quantitative Performance Evaluations

4.3 Qualitative Analysis on Acquired Data Instances

5 Conclusions

6 Broader Impact

7 Acknowledgements

References

[1] M. Gao, Z. Zhang, G. Yu, S. Ö. Arık, L. S. Davis, and T. Pfister, "Consistency-based semi-supervised active learning: Towards minimizing labeling cost," in *European Conference on Computer Vision*, pp. 510–526, Springer, 2020.

[2] J. Z. Bengar, J. van de Weijer, B. Twardowski, and B. Raducanu, "Reducing label effort: Self-supervised meets active learning," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 1631–1639, 2021.

[3] Y.-Y. Kim, K. Song, J. Jang, and I.-c. Moon, "Lada: Look-ahead data acquisition via augmentation for deep active learning," *Advances in Neural Information Processing Systems*, vol. 34, 2021.

[4] K. Kim, D. Park, K. I. Kim, and S. Y. Chun, "Task-aware variational adversarial active learning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 8166–8175, 2021.

[5] H. Quteineh, S. Samothrakis, and R. Sutcliffe, "Textual data augmentation for efficient active learning on tiny datasets," in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 7400–7410, 2020.

[6] Q. Li, Z. Huang, Y. Dou, and Z. Zhang, "A framework of data augmentation while active learning for chinese named entity recognition," in *International Conference on Knowledge Science, Engineering and Management*, pp. 88–100, Springer, 2021.

[7] S. Sinha, S. Ebrahimi, and T. Darrell, "Variational adversarial active learning," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 5972–5981, 2019.

[8] S. Song, D. Berthelot, and A. Rostamizadeh, "Combining mixmatch and active learning for better accuracy with fewer labels," *arXiv preprint arXiv:1912.00594*, 2019.

[9] X. Zhai, A. Oliver, A. Kolesnikov, and L. Beyer, "S4l: Self-supervised semi-supervised learning," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 1476–1485, 2019.

[10] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A simple framework for contrastive learning of visual representations," in *International conference on machine learning*, pp. 1597–1607, PMLR, 2020.

[11] J.-B. Grill, F. Strub, F. Altché, C. Tallec, P. H. Richemond, E. Buchatskaya, C. Doersch, B. A. Pires, Z. D. Guo, M. G. Azar, *et al.*, "Bootstrap your own latent: A new approach to self-supervised learning," *arXiv preprint arXiv:2006.07733*, 2020.

[12] T. Ucar, E. Hajiramezanali, and L. Edwards, "Subtab: Subsetting features of tabular data for self-supervised representation learning," *Advances in Neural Information Processing Systems*, vol. 34, 2021.

[13] K. Margatina, G. Vernikos, L. Barrault, and N. Aletras, "Active learning by acquiring contrastive examples," in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pp. 650–663, 2021.

[14] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 4171–4186, 2019.

[15] M. Yuan, H.-T. Lin, and J. Boyd-Graber, "Cold-start active learning through self-supervised language modeling," *arXiv preprint arXiv:2010.09535*, 2020.

[16] P. Ren, Y. Xiao, X. Chang, P.-Y. Huang, Z. Li, B. B. Gupta, X. Chen, and X. Wang, "A survey of deep active learning," *ACM Computing Surveys (CSUR)*, vol. 54, no. 9, pp. 1–40, 2021.

[17] D. Yoo and I. S. Kweon, "Learning loss for active learning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 93–102, 2019.

[18] M. Shukla and S. Ahmed, "A mathematical analysis of learning loss for active learning in regression," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 3320–3328, 2021.

[19] O. Sener and S. Savarese, "Active learning for convolutional neural networks: A core-set approach," *arXiv preprint arXiv:1708.00489*, 2017.

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section 1.
- Did you include the license to the code and datasets? [No] The code and the data are proprietary.
- Did you include the license to the code and datasets? [N/A]

Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? **[TODO]**
   (b) Did you describe the limitations of your work? **[TODO]**
   (c) Did you discuss any potential negative societal impacts of your work? **[TODO]**
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? **[TODO]**
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? **[TODO]**
   (b) Did you include complete proofs of all theoretical results? **[TODO]**
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **[TODO]**
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **[TODO]**
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **[TODO]**
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **[TODO]**

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? **[TODO]**
   (b) Did you mention the license of the assets? **[TODO]**
   (c) Did you include any new assets either in the supplemental material or as a URL? **[TODO]**
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? **[TODO]**
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **[TODO]**
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? **[TODO]**
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? **[TODO]**
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? **[TODO]**

A Appendix

Optionally include extra information (complete proofs, additional experiments and plots) in the appendix. This section will often be part of the supplemental material.