Learning to Active Learn by Gradient Variation based on Instance Importance

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***Abstract*—A major challenge in active learning is to select the most informative instances to be labeled by an annotation oracle at each step. In this respect, one effective paradigm is to learn the active learning strategy that best suits the performance of a meta-learning model. This strategy first measures the quality of the instances selected in the previous steps and then trains a machine learning model that is used to predict the quality of instances to be labeled in the current step.**

In this paper, we propose a new approach of learning-to-active-learn that selects the instances to be labeled as the ones producing the maximum change to the current classifier. Our key idea is to select such instances according to their importance reflecting variations in the learning gradient of the classification model. Our approach can be instantiated with any classifier trainable via gradient descent optimization, and here we provide a formulation based on a deep neural network model, which has not deeply been investigated in existing learning-to-active-learn approaches. The experimental validation of our approach has shown promising results in scenarios characterized by relatively few initially labeled instances.

I. Introduction

Supervised machine learning methods typically require a number of training data instances that is as much large as possible. However, manually labeling training instances is a costly and time consuming process, especially for specialized domains, where a deep expertise is required for correctly associating data instances with labels. *Active Learning* aims at selecting the data instances to be labeled by an expert, or annotation oracle, in order to train a machine learning model as quickly and effectively as possible. Several strategies have been proposed in the literature [1], which select the instances to be provided to the oracle for annotation using different heuristics; however, none of such heuristics has shown to outperform the others in every scenario of interest. To overcome major limitations, *meta-active learning* approaches have been proposed to automatically detect the best strategy of selection of the instances to be annotated [2], [3], [4]. Indeed, meta-learning approaches are gaining interest in several fields, for instance to coordinate the learning process in a master-slave distributed system [5] or to create algorithms for gradient descent, global black-box optimization [6], [7], or as a regression problem [8].

In this paper, we propose a new instance selection approach, modeled as a regression problem, that exploits the training gradient of a deep neural network model, and in general of any machine learning model whose training phase is based on the gradient descent algorithm. Before stating our contributions, we discuss some related work on active learning.

Related work. Active learning methods typically fall into one of the following categories: Uncertainty Sampling, Query-By-Committee, Expected Model Change, Expected Error Reduction, Variance Reduction, and Density-Weighted [1].

Uncertainty sampling aims to improve the quality of the labeled dataset by selecting as instances to be labeled those such that the trained classifier is most uncertain in assigning a class label [9], [10]. Among the uncertainty sampling methods, least confidence sampling (LCS) is very popular for statistical sequence models in information extraction tasks [11], [12]. LCS uses as uncertainty measure for an instance the difference between 100% confidence and the most confidently predicted label for the instance. Other approaches use different multi-class uncertainty sampling variants, such as margin sampling [13] or entropy [12].

Originally defined in [14] and theoretically analyzed in [15], the query-by-committee approach maintains a set of prediction models, or committee, that are used to predict the label of an instance. The instance over which there is the maximum disagreement on the labels predicted by the models in the committee is regarded as the most informative and hence selected for labeling. Several specializations of the approach have been proposed using different models for the committee members [16], [17], [18], [19].

The expected model change framework was first introduced in [20], where the goal is to define a strategy for selecting the instance that would yield the greatest change to the current model if we knew its label. The strategy computes the expected gradient length and uses it as a measure of the expected change to the model that is associated to the labeling of an instance. The key idea is to prefer instances that are likely to have the greatest influence in changing the model. The framework has shown to work well in practice, and theoretical aspects have been well studied for support vector machines and linear regression [21], although it can be computationally expensive for large feature space and set of labelings.

Expected error reduction aims to select the instance x that yields the maximum reduction of the model generalization error once it is trained using the label of x too. However, since the labels of some instances are not known, the model is usually approximated using the expectation over all possible labels under the current model. This framework has been

successfully used with a variety of models such as Naıve Bayes [22], logistic regression [23], and SVM [24].

Variance reduction methods reduce the generalization error indirectly by minimizing output variance. The early method in [25] was proposed for active learning based on the reduction of the estimated distribution of the model's output for regression. Applications of variance reduction include multi-class image classification [26].

The key idea of density-weighted methods is that informative instances should not only be the uncertain ones, but also those representative of the underlying distribution [16], [27], [28], [12], [29]. Hence, the instances to label are selected according to a combination of a base selection measure (e.g., LCS) and a density based measure (i.e., the average similarity of an instance w.r.t. the other instances).

Meta-learning algorithms have recently been proposed for the active learning tasks. In [2], several active learning heuristics are combined using a bandit algorithm exploiting a maximum entropy criterion that estimates classification performance without knowing the actual labels. This approach has been improved in [3] with the use of a new unbiased estimator of the test error. A Markov decision process is used in [4] to provide a new meta-learning strategy for active learning. Rather than combining existing heuristics, the meta-learning approach to active learning in [8] models the active learning task as a regression problem: given a trained classifier and its output for a specific unlabeled instance, it predicts the reduction in generalization error that can be expected by providing the actual label of the instance. Note that the regressor in [8] is required to be trained on a specific set of instance-driven features, such as the variance of the classifier output for the instance or the predicted probability distribution over possible labels for the instance. Our approach does not have the same constraint, since we utilize the raw features of the instances, yet we can in principle exploit instance-driven features. More importantly, for each active learning epoch, [8] requires to perform several training steps of the classifier while we perform just a single training step, which is suitably modified so as to account for the *importance* of the features.

Main contributions. We propose a learning-to-active-learn approach that originally incorporates a regression-based meta-learning approach within a maximum model change framework. Our main contributions can be summarized as follows:

- Starting from a classification model trained on a small set of instances, we define an iterative active learning scheme that, in order to decide the bunch of instances to be labeled by an annotation oracle, it predicts which instances will yield the maximum change to the current classifier.
- We define a meta-learning process upon two key ingredients: a notion of the importance of unlabeled instances (from the pool of active learning choices) that expresses the contribution that each instance provides to the learning of the classifier; and a regression model to be trained on pairs of labeled instances with associated importance scores.
- We design our approach to profitably exploit the learning capabilities of (Deep) Neural Network models trained on a classification task. Nonetheless, the proposed learning-to-active-learn approach is actually versatile w.r.t. the supervised learning model, as long as the gradient descent is used as the training optimization method.
- While taking advantage of a deep neural network model, we also face a challenge related to how to score the importance of instances to drive the active learning process. Therefore, we investigate different strategies of instance importance scoring by considering variations in the learning gradient of the neural network model. In this regard, our key idea is to account for the similarity of direction of two gradients, the one unbiased and the other one biased w.r.t. a candidate instance for labeling at each step of the active learning process.
- Our experimental evaluation conducted on CIFAR-10 image data, and including a comparison with random and LCS baselines, has shown promising results by the proposed approach in terms of percentage increase in accuracy, due to the active learning process driven by the proposed instance importance scoring strategies, which tends to improve as the number of initially available labeled instances gets smaller.

II. Proposed Approach

A classification problem consists in associating every instance taken from a predefined domain $\mathcal{D}$ with a label taken from a fixed universe of labels $\mathcal{L}$. We assume the presence of a set of instance-label pairs $LI \subseteq \mathcal{D} \times \mathcal{L}$ and a set of unlabeled instances $UI \subseteq \mathcal{D}$, where for each pair $\langle x, y \rangle \in LI$, x is an instance in $\mathcal{D}$ and y is the label associated with x.

Our proposed approach is comprised of two phases: initialization and an iterative phase. In the initialization phase, a neural network is trained with the labeled instances in LI. An initial set of unlabeled instances is randomly selected from UI and these instances are submitted to the oracle to be labeled, thus obtaining a new set of labeled instances, denoted as NLI. In the iterative phase, several pool-based active learning steps are performed. In each step, the set NLI of newly labeled instances is used to train the classifier together with the set LI. When retraining the classifier, the *importance* of every instance x in NLI during the training is measured so as to assign an *importance score* to x. Next, a regressor is trained using the instances in NLI that aim to predict the importance scores. Finally, the top-k instances having the greatest importance score are selected for oracle labeling and, once labeled, they replace the set NLI so to start the next active learning step.

The concept of importance score is at the core of our approach. Following the model change framework [20], the importance score of an instance x measures the impact of having x in the training set for the obtained classifier. That is, the importance score of a (labeled) instance x w.r.t. a set of labeled instances is a measure of the difference between the parameters of the classifier θ trained over LI and the parameters of the classifier $\hat{\theta}$ trained over $LI \cup \{\langle x, y \rangle\}$, where y is the label of x. Unfortunately, in the case of neural network classifiers, for the most commonly used training algorithm, such as the stochastic gradient, there is (almost) no difference

Algorithm 1: LAL-IGradV

Data: LI: set of labeled instances, UI: set of unlabeled instances, DNN: deep neural network model, R: importance score regressor, $epch$: maximum number of epochs, k: number of relevant instances to select

1 Train DNN on LI
2 $NLI \leftarrow$ Select k instances from UI uniformly at random
3 The oracle annotates the instances in NLI
4 **for** $i = 1 \dots epch$ **do**
5 Train DNN on $LI \cup NLI$ and compute importance score r_x, for each $x \in NLI$
6 Train R on the set of pairs $\{\langle x, r_x \rangle \mid x \in NLI\}$
7 $LI \leftarrow LI \cup NLI$
8 Apply R to UI instances to predict importance scores ($\widehat{r_x}$)
9 $topK \leftarrow$ Select top-k instances from UI by importance score $\widehat{r_x}$
10 The oracle annotates the instances in $topK$
11 $NLI \leftarrow topK$

between the parameters of the classifier trained using LI and the parameters of the classifier trained conditionally to the presence/absence of a given instance, i.e., trained using $LI \cup \{\langle x, y \rangle\}$. To overcome this issue, we define different notions of importance score (cf. Section II-B). In the next section we provide a detailed description of the proposed approach.

A. The LAL-IGradV algorithm

Algorithm 1 shows the general schema of the proposed approach, named ***L**earning to **A**ctive **L**earn by Instance **I**mportance based **Grad**ient **V**ariation* (LAL-IGradV).

LAL-IGradV receives in input a (small) set of labeled instances LI, a set of unlabeled instances UI, a deep neural network model DNN, a regressor model R, the number $epch$ of active learning epochs, and the number k of unlabeled instances to select for oracle labeling at each active learning epoch. The algorithm first trains DNN using LI (line 1), randomly selects k unlabeled instances from UI and asks the oracle to label them, thus obtaining the initial set NLI of oracle-labeled instances (lines 2- 3). Then, at each epoch (lines 4-11), LAL-IGradV performs the following steps.

- The neural network model is trained using the labeled instances in LI and NLI (line 5). During the training process, every instance $x \in NLI$ is associated with its importance score r_x. The computation of the importance scores of the instance in NLI is performed using one of the techniques described in Section II-B.
- A regressor R is trained on the set $\{(x, r_x) | x \in NLI\}$. Note that the choice of the regressor model actually used in this and the subsequent steps is orthogonal w.r.t. the proposed approach; however, it is essential that the chosen regression model must be trainable using a small set of labeled instances.
- *NLS* instances are added to *LS* (line 7).
- The regressor R is applied to the instances in UI so that, given an instance x, it predicts its importance score $\widehat{r_x}$ (line 8).
- The algorithm selects the top-k instances from UI ($topK$) having the highest predicted importance scores, and these instances in $topK$ are submitted to the oracle for labeling (lines 9-10). Finally, NLI is replaced with $topK$ (line 11).

B. Importance scoring strategies

Let $f(x_i, \theta)$ be the output of a DNN model f characterized by a vector of parameters θ for an input x_i and let $X = \{x_1, \dots, x_n\}$ be a set of instances used for training f, where each sample $x_i \in X$ is associated to a label y_i.

The training of the DNN f over X requires solving

$$\arg\min_{\theta} \left(\sum_{x_i \in X} (L(y_i, f(x_i, \theta)) + reg(\theta) \right),$$

where $L(y_i, f(x_i, \theta))$ is the loss of the model for instance x_i and $reg(\theta)$ is the regularization of the parameters. The training of f is accomplished by iteratively updating the parameters θ, through two steps: (i) computing the change in all weights w.r.t. the change in error, i.e., the *gradient*, defined as

$$\delta(X) = \frac{\partial}{\partial \theta} \sum_{x_i \in X} (L(y_i, f(x_i, \theta)) + reg(\theta)),$$

and (ii) updating θ using $\delta(X)$, i.e., $\theta_{k+1} = \theta_k - \eta \times \delta(X)$, where η is the update step size.

We define four strategies to associate each instance in NLI with its importance score during the training of the DNN classifier. The goal shared by the various techniques is to modify the training of the neural network model by accounting for the importance of the instances in NLI involved in each training step. Each of the proposed techniques makes use of the gradient corresponding to the instances currently in LI and NLI, i.e., $\delta(LI \cup NLI)$, hereinafter simply denoted as δ. The four proposed techniques differ in the way the importance of an instance x in NLI is calculated with respect to the single epoch. We will use symbol δ_x to denote the value of the gradient $\delta(\{x\})$, and $\delta_{\neg x}$ to denote the value of the gradient $\delta(LI \cup NLI \setminus \{x\})$. In the following, we describe our proposed techniques for computing the importance scores.

Direct similarity (*DS*) – given an instance x in NLI, this strategy compares the learning gradient of the neural network at the current epoch, δ, with the gradient calculated with respect to x only, i.e., δ_x. The importance score of x at the current epoch is defined as the cosine similarity between δ and δ_x, i.e., $r_x = cos(\delta, \delta_x)$. The rationale of this strategy is that an instance $x \in NLI$ is likely to be more important for the training of DNN at the current epoch if there is a small difference between the directions of the gradients δ and δ_x, as reflected by a high value of the cosine similarity between the two gradients. That is, the more the learning behavior of the neural network considering the whole training set is similar to the one of the same neural network trained on x only, the higher the importance of x is.

Ranked direct similarity (*RDS*) – this strategy first applies the *DS* technique, then the importance scores of the instances in NLI computed by *DS* are ordered and divided into three bins, which correspond to the top quartile of the importance scores, the bottom quartile, and the union of the second and

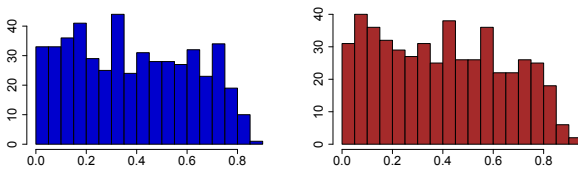


Fig. 1: Histograms of the $k = 500$ measurements of *DS* (left) and *LD* (right) strategies at the first epoch of active learning

third quartiles. The instances falling into the top quartile will be associated with score 1, the ones falling into the bottom quartile with score 0, and the other instances with score 0.5.

Leave-one-out distance (*LD*) – given an instance x in NLI, this strategy compares δ with the gradient calculated when leaving out x, i.e., $\delta_{\neg x}$. The importance score of x at the current epoch is defined as the complement of the cosine similarity (i.e., cosine distance) between δ and $\delta_{\neg x}$, i.e., $r_x = 1 - cos(\delta, \delta_{\neg x})$. The rationale of this strategy is that an instance $x \in NLI$ is likely to be more important for the training of DNN at the current epoch if leaving it out will lead to large differences between the learning behavior of the neural network considering the whole training set and the learning behavior of the same neural network trained without x, i.e., a large change in the direction of the gradient $\delta_{\neg x}$ w.r.t. the gradient δ, as reflected by a high value of the cosine distance between the two gradients.

Ranked leave-one-out distance (*RLD*) – analogously to *RDS* w.r.t. *DS*, the *RLD* strategy adds the same discretization step over the importance scores computed by *LD*.

Figure 1 shows the distributions of the importance scores yielded by *DS* and *LD* at the first epoch of active learning. As it can be observed, both distributions span over the full regime of admissible values, despite the high dimensionality of the gradient vectors being compared.

III. Experimental Evaluation

Data. We used the well-known CIFAR-10 dataset [30], which consists of 60000 instances representing 32x32 colour images, labeled using 10 mutually exclusive classes, with 6000 images per class. The dataset is organized into 50000 instances as the training set and 10000 instances as the test set. The latter contains exactly 1000 randomly-selected images from each class, while the training set is comprised of five training batches, which contain 5000 images from each class.

We divided the training set into two parts, the one corresponding to the set of labeled instances (LS), and the other corresponding to the set of unlabeled instances (US).

Baseline methods. We compare the performance of our methods with a Random baseline and the LCS method [12]. The Random baseline, hereinafter denoted as Rnd, simply selects k instances to be annotated at each epoch uniformly at random from the set of unlabeled instances. The LCS method follows an uncertainty sampling approach, therefore it estimates the uncertainty of a specific instance and exploits it as criterion for the unlabeled instance selection. More precisely, given an instance x and a classification model θ, the uncertainty of x w.r.t. θ ($\phi(x)$) is measured as $\phi(x) = (1 - P_\theta(y^*|x)) \times \frac{m}{m-1}$, where $P_\theta(y^*|x)$ denotes the probability that the model θ assigns to the label y^* for the instance x, y^* is the label for which θ yields the maximum probability on x (i.e., $y^* = \arg\max_y P_\theta(y|x)$), and m is the cardinality of the set of labels. Note that the uncertainty function ranges between $[0, 1]$, where 1 is the most uncertain score.

Settings and assessment criteria. In our experimental evaluation, we used 6 Convolutional Neural Network (CNN) 2D layers, with 3 input channels, kernel size 3, stride size 3, padding size 1, ReLU activation function. The CNN module has on top a fully-connected network with an input layer of size 4096, one hidden layer with input size 4096 and output size 1024, another hidden layer with input size 1024 and output size 512, an output layer of size 10 (i.e., number of classes), and a dropout layers with probability 0.1.

In our LAL-IGradV algorithm, the DNN model was trained using cross entropy as loss function and Adam optimizer (with learning rate 1e-4 and weight decay 5e-4), a number of epochs equal to 10 for both the initialization step of training (Line 1) and the training steps in the main loop (Line 5). Also, the maximum number of iterations of the algorithm, i.e., number of epochs in the active learning process ($epch$) was set to 10. Unless otherwise specified, the number k of instances to select from UI was set to 500; the size of LI, resp. UI, was experimentally varied. As the regressor (R), we used two models: the Gradient Boosting Regressor, with least absolute deviations (LAD) loss function and 200 estimators, for the *DS* and *LD* strategies, and the Random Forest Classifier, with maximum depth 5, for the *RDS* and *RLD* strategies.

To simulate the oracle for annotating the instances, we resorted to the availability of class label information for the CIFAR-10 data: whenever an instance was used in the UI set, we masked its actual label during the learning process, and we unveiled the label only if the instance was selected within the $topK$ set of instances to annotate.

To assess the performance of the methods, we considered the accuracy of the classifier during the various training batches, in absolute terms as well as in terms of percentage increase w.r.t. the early accuracy of the classifier itself or the accuracy of a reference method. More precisely, we computed: the *accuracy at the initial step of training* of LAL-IGradV (line 1), denoted as $A^{(0)}$, and the accuracy at the end of the active learning process, denoted as A; the *percentage increase in the accuracy* of LAL-IGradV, which is defined as $100(A - A^{(0)})/A^{(0)}$; the *percentage increase in the accuracy* of LAL-IGradV w.r.t. Rnd, resp. LCS, which is defined as $\%_{\text{Rnd}} = 100(A - A_{\text{Rnd}})/A_{\text{Rnd}}$, resp. $\%_{\text{LCS}} = 100(A - A_{\text{LCS}})/A_{\text{LCS}}$, where A_{Rnd} and A_{LCS} denote the accuracy at the end of the active learning process for Rnd and LCS.

Results. Table I reports on the performance of our LAL-IGradV variants corresponding to the four importance scoring techniques, for varying percentages of the set of unlabeled instances (UI); for example, row '10%' indicates that 10% of

TABLE I: Performance of our proposed methods: initial and final accuracy, percentage increase w.r.t. Rnd and w.r.t. LCS, and active learning time (sec) averaged over the epochs, for various percentage values of unlabeled instances

	$A^{(0)}$	*DS*				*RDS*				*LD*				*RLD*			
		A	$\%_{\text{Rnd}}$	$\%_{\text{LCS}}$	time	A	$\%_{\text{Rnd}}$	$\%_{\text{LCS}}$	time	A	$\%_{\text{Rnd}}$	$\%_{\text{LCS}}$	time	A	$\%_{\text{Rnd}}$	$\%_{\text{LCS}}$	time
10%	0.793	0.831	2.32	0.43	186	0.832	2.44	0.54	191	0.831	2.28	0.39	625	0.828	1.90	0.01	769
20%	0.783	0.826	1.90	0.75	178	0.825	1.79	0.65	217	0.824	1.72	0.57	623	0.822	1.46	0.32	796
30%	0.784	0.827	1.95	0.50	170	0.828	2.06	0.61	250	0.826	1.75	0.30	620	0.822	1.46	0.32	827
40%	0.763	0.819	4.01	1.08	170	0.811	3.04	0.13	295	0.811	3.02	0.11	620	0.811	2.96	0.05	872
50%	0.733	0.801	5.97	2.84	162	0.800	5.82	2.70	352	0.799	5.80	2.67	619	0.779	3.07	0.03	1002
60%	0.728	0.801	6.32	3.21	162	0.798	5.96	2.86	423	0.795	5.57	2.48	614	0.777	3.20	0.18	1089
70%	0.708	0.778	6.49	2.50	154	0.778	6.38	2.40	513	0.773	5.82	1.86	607	0.760	4.01	0.12	1190
80%	0.640	0.705	5.39	1.82	139	0.704	5.27	1.71	613	0.700	4.62	1.08	604	0.694	3.78	0.27	1310
90%	0.570	0.644	5.89	2.22	129	0.636	4.60	0.98	732	0.632	3.95	0.35	602	0.636	4.59	0.97	1395

the instances of the CIFAR-10 training set was used as UI and the remaining 90% of the training set as LI.

Looking at the table, several remarks stand out. First of all, it is not surprising to notice that the accuracy values (i.e., columns corresponding to A and $A^{(0)}$) tend to decrease as the percentage of unlabeled instances gets higher, since the LAL-IGradV method is forced to handle progressively reduced sets of labeled instances on its initial training. More interestingly, the percentage increase of each of the LAL-IGradV variants w.r.t. both Rnd and LCS is always positive — up to 6.5% against Rnd and up to 3.2% against LCS — and it tends to improve with higher percentages of unlabeled instances, with peaks around 70% against Rnd and around 50-60% against LCS. As concerns the impact of the importance scoring technique, we observe that all the LAL-IGradV variants are able to improve upon the accuracy at the initial training step. Moreover, the direct similarity based techniques, i.e., *DS* and *RDS*, reveal to be more efficient[1] as well as more accurate than the leave-one-out distance based techniques, for each percentage of unlabeled set. We tend to ascribe this fact to a higher sensitivity of the approach in capturing the gradient direction change due to the individual contribution of an instance rather than to the masking of a single instance in the training gradient, which would result in a more diluted signal of variation of the training gradient.

Figure 2 focuses on the percentage increase in accuracy that each active learning method achieves by varying the fraction of unlabeled instances. As expected due to the advantage of performing an active learning task, the percentage increase values tend to improve for higher fractions of unlabeled instances. The trends are steeper for our LAL-IGradV methods, particularly for *DS* and *RDS*, followed by LCS. Indeed, it is worth emphasizing that our LAL-IGradV methods achieve the best performance gain against the two baselines as the fraction of labeled instances becomes smaller.

In Figs. 3 and 4, we delve into the trends of accuracy percentage-increase obtained by a particular active learning method, for varying k, i.e., number of unlabeled instances to be selected at each epoch of the active learning process. At a first glance, in each of the plots, we notice that the curve of the percentage increase values over k is more likely to change

[1]Experiments were carried out on an Intel Core i7 CPU @2.90GHz, 32GB RAM, with NVIDIA GeForce RTX 2070 Super GPU

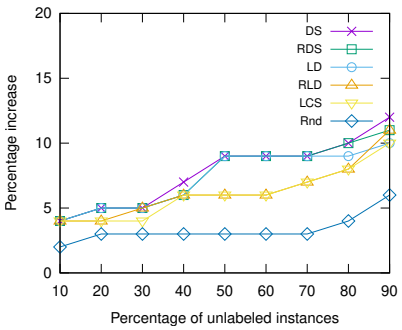
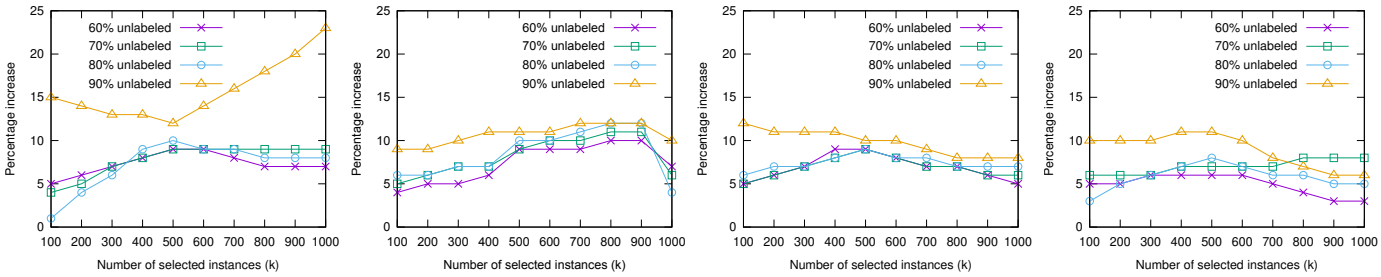


Fig. 2: Percentage increase of accuracy for the various active learning methods, with varying percentage of unlabeled instances, and number of selected instances (k) equal to 500

for larger fractions of the set of unlabeled instances, with the most evident changes corresponding to 90%.

A few interesting remarks can be drawn from Fig. 3. When portions of UI below 90% are selected, we observe a relatively small range of variation of the percentage increase values (approximately from 5% to 10%), with peaks around $k = 500$ for the *DS* and *LD* variants, and around $k = 900$ for the *RDS* and *RLD* variants. This would hint at higher requirements (i.e., higher k) needed for the importance scoring strategies that compute discretized importance scores. Another remark is on the curves corresponding to the use of 90% of the set of unlabeled instances: compared to the curves corresponding to lower fractions of UI, the percentage increase values are higher on average, and the trends are quite different, especially for the *DS* variant where we observe a minimum (rather than a maximum) for $k = 500$. Apart from this exception, it is worth noticing that better percentage increase of accuracy do not necessarily correspond to a higher number k of selected instances. This might be explained since the more unlabeled instances are selected for labeling, the more the method is less likely to make a correct choice for changing the most the current model, as the latter is being trained only on few instances, thus lacking full knowledge on the class distribution of all the instances for available training.

Concerning the baseline methods (Fig. 4), two different situations occur between the Rnd plot (on the left) and the LCS plot (on the right). The former shows a decreasing trend until mid values of k (i.e., around 500 instances) followed by



(a) *DS* (b) *RDS* (c) *LD* (d) *RLD*

Fig. 3: Percentage increase due to active learning based on our LAL-IGradV variants, by varying the number of selected instances (k) and the percentage of labeled instances

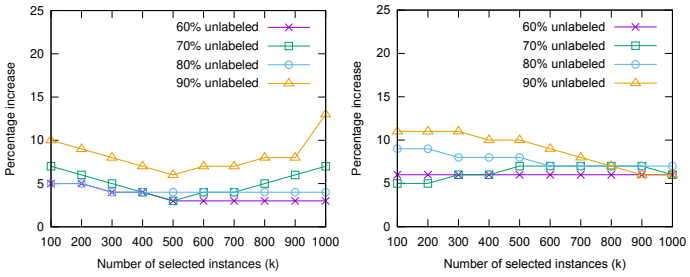


Fig. 4: Percentage increase due to active learning based on Rnd (left) and on LCS (right), by varying the number of selected instances (k) and the percentage of labeled instances

a rising trend, which sheds light on the divergent behavior of a random selection of the unlabeled instances w.r.t. all the other instance selection methods. Also, the LCS plot shows curves that tend to monotonically decrease, resp. remain substantially unchanged, for larger, resp. smaller, fractions of UI, which again puts in evidence how our LAL-IGradV variants behave differently from an uncertainty sampling approach like LCS.

Summary. Our proposed LAL-IGradV has shown that a learning-to-active-learn by instance importance based gradient variation improves significantly upon not only a random baseline but also an uncertainty sampling approach like LCS. LAL-IGradV methods are all able to increase the accuracy at the initial training step, and tend to improve with higher percentages of unlabeled instances. Yet, higher percentages of unlabeled instances lead to an increased gain against LCS and random baseline. LAL-IGradV methods are also not particularly demanding in terms of number (k) of selected instances to label at each active learning epoch.

IV. Limitations and Possible Enhancements

LAL-IGradV has shown satisfactory results in terms of a significantly positive change in the accuracy of the classifier, and this performance improvement is emphasized for increasingly large sets of unlabeled instances, which makes LAL-IGradV useful in practical scenarios.

Nonetheless, several aspects of our approach need to be further investigated and enhanced. Our importance scoring strategies might be improved in different ways. The importance of an instance could be measured not only in terms of its own contribution to the model change but also w.r.t. other instances, including both labeled and unlabeled ones, according to some instance locality principle. In this regard, it would be worthy to consider the data instance features, so as to identify an instance's neighborhood to evaluate in each step of importance scoring. Features of the regressor (meta-features) could also be incorporated into the instance selection steps, although this would require to identify those features that are suited to a specific type of regressor.

From an efficiency viewpoint, it would also be important to define theoretical properties on the gradient direction change in function of the number of top-k instances to be annotated and/or the size of the batch of unlabeled instances available for the active learning process, in order to prune the candidates thus speeding up the active learning of the model.

Besides enhancements on the importance scoring and top-k selection policies, different choices might be investigated about the architecture and setting of the deep neural network classifier. Our experimental evaluation focused on image data, for which CNN models are known to be effective; clearly, the choice of the neural network architecture might be dependent on the type of the input data and on the target learning task.

LAL-IGradV exhibited quite different behavior w.r.t. not only random instance selection, but also compared to an uncertainty sampling method like LCS. However, a more robust evaluation should be carried out to include a comparison with state-of-the-art active learning methods, such as [8] and more recently developed methods, possibly using larger data from different application domains.

V. Conclusions

We proposed a learning-to-active-learn approach whose key novelty is twofold: the integration of a regression-based meta-learning approach within a maximum model-change framework, and the definition of policies for scoring the instance importance based on the amount of change in the learning gradient of a deep neural network model.

LAL-IGradV source code is publicly available at *https://github.com/Franco7Scala/exploiting_gradient.git*.

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