CSE 584 HW1

**Paper 1: Less is More: Active Learning with Support Vector Machines**

Reference: Vlachos, A., 2004. Active learning with support vector machines. Master of Science, School of Informatics, University of Edinburgh, UK.

1.

This paper is trying to address the problem of the need for an efficient way to train Support Vector Machines (SVMs) for document classification tasks. They want to use a simple active learning heuristic which greatly enhances the generalization behavior of support vector machines (SVMs) on several practical document classification tasks. Typically, SVMs require a large number of labeled examples for training, which can be time-consuming and costly.

The primary motivation for active learning comes from the time or expense of obtaining labeled training examples. In most domains, either generating training examples is costly or labeling the examples is spending too much. The promise of active learning is this: when the examples to be labeled are selected properly, the data requirements for some problems decrease drastically.

2.

The paper proposes using an active learning heuristic to enhance SVM training. Instead of randomly selecting examples to label, the method involves selectively labeling examples that lie closest to the SVM's dividing hyperplane. Selecting training examples by their proximity to the dividing hyperplane is computationally inexpensive: if they explicitly compute the dividing hyperplane, evaluating each candidate requires only a single dot product computation. This heuristic aims to identify the most informative examples, which can improve the classifier's performance with fewer labeled samples. By training on a strategically chosen subset of data, the SVM can generalize better and often outperforms SVMs trained on the entire dataset.

3.

-Simple Active Learning Heuristic: Introduction of a simple and computationally efficient heuristic for selecting the most informative examples to label, which lies closest to the SVM's dividing hyperplane.

-Improved Performance with Less Data: Demonstration that an SVM trained on a well-chosen subset of the available corpus can perform better than one trained on all available data.

-Heuristic Stopping Criterion: Identification of a stopping criterion that indicates when peak generalization performance has been reached, allowing the process to stop before adding unnecessary labels.

-Advance Strategy in Chunking and Shrinking: They disregard already-labeled examples that are unlikely to be support vectors, purely for computational gain. In active learning, they avoid asking for those (expensive) labels in the first place — saving not only computation, but the time and expense of labelling unneeded data.

4.

-Limited Scope of Heuristic: The heuristic used is specific to linear SVMs and may not generalize well to other types of classifiers or non-linear problems.

-Potential for Degraded Performance: If the active learning approach continues to add examples beyond the optimal point, generalization performance may degrade, leading to reduced accuracy compared to using the entire dataset.

**Paper 2: Active Learning for Speech Emotion Recognition Using Deep Neural Network**

Reference: Mohammed Abdel-Wahab and Carlos Busso. 2019. Active learning for speech emotion recognition using deep neural network. In Proceedings of the 8th International Conference on Affective Computing and Intelligent Interaction. IEEE, 1–7.

1.

This study explores practical solutions to train DNNs for speech emotion recognition with limited resources by using active learning (AL). Specifically, this study focuses on active learning to select the most informative samples to improve DNN models. They consider cases where the resources to annotate samples in the new domain are limited.  DNNs typically require large amounts of annotated data to achieve good performance, but obtaining emotional labels for speech data is costly and time-consuming.

The motivation behind this work is to find a practical way to train DNNs for SER using a limited amount of labeled data by employing active learning, thereby reducing the annotation cost while maintaining or improving model performance.

2.

In this context, active learning approaches offer appealing solutions for models to reach their potential performance, while minimizing the amount of labelled data. This study demonstrated that active learning can significantly reduce the amount of labeled data needed to achieve a reasonable performance in a new domain. They explore different active learning strategies, including uncertainty-based methods and greedy sampling. Specifically, they focus on regression problems predicting emotional attributes like arousal and valence. The paper evaluates the performance of various acquisition functions, including uncertainty (variance)-based acquisition and greedy sampling based on feature and label diversity.

3.

-Application of Active Learning in SER: Implementation of active learning for deep learning-based SER, focusing on regression tasks for emotional attributes.

-Evaluation of Acquisition Functions: Comparative analysis of different data acquisition functions (uncertainty-based and greedy sampling) in the context of SER using DNNs.

-Greedy Sampling Effectiveness: Evidence that greedy sampling in the feature space outperforms random sampling and provides more consistent results across multiple initializations.

-Pretraining with Autoencoders: Introduction of a multitask autoencoder network structure that uses unlabeled data for pretraining, further enhancing the performance of the active learning approach.

4.

-Computational Cost: Some greedy sampling methods, especially in the feature space, can be computationally expensive due to the need to calculate distances between samples, particularly in high-dimensional spaces.

-Dependence on Model Predictions: The performance of certain acquisition functions, such as greedy sampling on the label space, relies heavily on the accuracy of the model's predictions, making them less reliable when the training set is very limited.

-Uncertainty of Sample Space: Uncertainty present in difficult samples as well as the uncertainty caused by the lack of data may influence the experimental results. The model may not generalize well in special cases.

**Paper 3: Dissimilarity-based active learning for embedded weed identification**

Reference: Yang, Y.; Li, Y.; Yang, J.; Wen, J. Dissimilarity-based active learning for embedded weed identification. Turk. J. Agric. For. 2022, 46, 390–401.

1.

The paper addresses the challenge of weed identification in precision agriculture using deep learning. Although the deep learning-based methods have achieved high performance, their needed large-scale annotated data is difficult to obtain, and the massive parameters lead to difficulties in model deployment in embedded applications. There are two main problems with the current deep learning methods. First, deep CNNs based on deep learning require a huge mass of data. In addition, when facing large amounts of datasets, labelling them is difficult and costs much of the time. Second, as the depth of the network increases, there are more than millions of parameters in the deep model. High-performance servers with GPUs are indispensable.

Therefore, the motivation is to develop an efficient weed classification system that works with a limited number of labeled samples while being deployable on embedded devices with constrained computational resources. The goal is to reduce the need for extensive labeled datasets and computational power, making deep learning-based weed identification more practical for real-world agricultural applications.

2.

In this paper, they introduce a new method for weed classification, named dissimilarity-based active learning (DBAL), which can pick out a few samples yet consider the overall diversity of the dataset. This method can choose valuable samples from the unlabeled pool, using fewer samples to cover the diversity of the whole dataset, which is related with the current few-shot learning and then they remove the unimportant channels of the network to reduce the parameters and model size. By calculating the distance between each sample in unlabeled pool and the cluster centroid of labelled pool, their method DBAL can choose samples that are dissimilar to those in the labelled pool, which can contain more valuable information.

The active learning process involves training a binary classification network to differentiate between labeled and unlabeled samples, using a well-trained classification network to extract feature embeddings. The method employs K-means clustering and Euclidean distance to identify samples that are most dissimilar to the labeled pool, thereby choosing those that are expected to provide the most value in training the classifier.

3.

-Dissimilarity-Based Active Learning (DBAL): DBAL method is competitive. Introduction of a novel active learning approach that selects samples based on their dissimilarity to the labeled pool, aiming to maximize the diversity of the dataset and improve classifier performance with fewer labeled samples. Their method can achieve 90.75% test accuracy with 32% amount of the dataset, up to 99.18% of the baseline accuracy.

-Model Compression: Then model compression is executed to reduce the number of parameters and model size. With a compression ratio of 92.7%, the model is compressed from 117.9 MB to 8.6 MB, with 1% accuracy drop.

-Practical Deployment: Successful deployment of the compressed model on an NVIDIA Jetson AGX Xavier, achieving real-time processing speeds of 192 frames per second (fps), making it suitable for practical smart agricultural applications.

4.

-Limited to Specific Datasets: The effectiveness of the proposed method is demonstrated on only two specific weed datasets, which may limit its generalizability to other agricultural datasets or different domains.

-Model Pruning Sensitivity: The model compression process involves pruning convolutional channels based on scale factors. This process is sensitive to the chosen pruning threshold, which may require careful tuning to avoid significant drops in accuracy.