CMPSC 584 HW 1
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Paper 1 : "Support Vector Machine Active Learning by Hessian Regularization" by W. Liu, L. Zhang, D. Tao and J. Cheng

This paper addresses the challenge of efficiently labeling multimedia data - a task critical for training machine learning models (particularly in the fields of image segmentation and activity recognition). One of the primary motivations behind this paper is the growth in the amount of multimedia data - caused in part due to the proliferation of digital sensor technology, and in part due to the increasing scope of internet-based platforms. Labeling large datasets can be expensive and time-consuming, especially in multimedia applications. The demand for more efficient techniques that can optimize learning outcomes with minimal labeled data is thus rising rapidly. Active learning is a prominent method for trying to achieve this - it involves selecting the most informative samples from a pool of unlabeled data, minimizing learning error while maintaining high accuracy. However, many active learning approaches only focus on the labeled data - leading to suboptimal results when the geometry of unlabeled data is ignored.

To solve this issue, the paper introduces a semi-supervised learning method that combines Hessian regularization with support vector machines. To exploit the underlying structure of both unlabeled and labeled data, the authors integrate Hessian regularization into SVMs. This approach takes advantage of the manifold geometry of the data distribution - which results in the classifier generalizing more effectively, even if the set of labeled examples is limited. Specifically, the Hessian regularization term ensures that the prediction function varies smoothly along the manifold, making better use of both unlabeled and labeled data. This increases the classifier's accuracy. The query strategy employed is uncertainty sampling - the most informative samples (which typically lie near the classification boundary), are selected for labeling in each iteration. Thus, with each round of active learning, the classifier is progressively refined and the performance is improved.

The key contributions of the paper are the use of Hessian regularization in an active learning context - which provides a significant improvement over traditional methods. Prior approaches like Laplacian regularization have aimed to preserve the local geometry of data. Hessian regularization, however, goes much further by making the prediction function vary linearly along the manifold. This results in better extrapolation beyond the immediate vicinity of the training samples. The paper's experimental results utilize popular datasets (GrabCut for image segmentation and USAA dataset for human activity recognition) to show that the proposed method outperforms conventional active learning techniques that solely rely on labeled data or employ less sophisticated methods like Laplacian regularization.

There are a few potential downsides to this method presented in the paper. Firstly, the computational complexity of the method is mch higher than traditional approaches - there is a need to compute Hessian matrices and solve quadratic problems. When computational efficiency is critical or desired (like with real-time applications or extremely large datasets), this could be a limiting factor. Also, the method relies on the assumption that the data lies in a low-dimensional manifold. This may not hold in all cases - particularly in more complex data spaces, and may end up impacting the performance of the classifier.

Paper 2 : "Semi-supervised learning combining transductive support vector machine with active learning" by X. Wang, J. Wen, S. Alam, Z. Jiang and Y. Wu

This paper, similar to the last one, seeks to address the problem of efficiently labeling large datasets, especially in scenarios where labeled data is scarce. However, the authors attempt to do this by improving the performance of TSVMs - Transductive Support Vector Machines, which are part of a semi-supervised learning method that leverages both labeled and unlabeled data for classification. TSVM is useful when labeled data is limited, but suffers from several deficiencies, some of which are issues with label switching, sensitivity to number of positive class samples, and the need for large amounts of unlabeled data. The motivation behind this paper is to address these shortcomings, and to enhance classifier performance with minimal human effort.

The authors propose combining TSVMs with active learning for a more robust semi-supervised learning algorithm. Activelearning can be used to select the most informative samples from the pool of unlabeled data, which can then be labeled by human annotators. This will help the algorithm focus on the most crucial data points that will help improve classification accuracy, while reducing the labeling effort required. The authors introduce adding a manifold regularization term to the TSVM's objective function, as well as a version space min-max division principle for selecting the aforementioned "most informative samples". The regularization term, in particular, helps capture the geometric structure of the data, ensuring that the decision function varies smoothly across it. This in turn enhances the classifier's generalization capabilities. The paper also provides experimental results performed on UCI datasets and a real-world book review dataset, showing that the proposed method outperformed all other State of the art active learning methods without as much human intervention at the time.

Despite the advantages, the proposed method has potential downsides. A major issue , much like the last paper, lies in the computational complexity associated with the combination of manifold regularization and active learning. The need to not only compute the regularization term, but also select the most informative samples based on the version space min-max division principle makes the algorithm less suitable for real-time applications. The process may also be disrupted by data with intricate underlying structures.

Paper 3 : "Fast Laplacian Twin Support Vector Machine with Active Learning for Pattern Classification" by R. Rastogi and S. Sharma

This paper addresses the combined challenge of improving the efficiency of semi-supervised learning algorithms, while simultaneously trying to reduce reliance on large amounts of labeled data. Labeling of data can often be costly and laborious - two examples that the paper presents are human activity recognition and content-based image retrieval. The core motivation for this research thus stems from the need to make machine learning models more efficient and robust when the available labeled data is noisy or sparse.

The authors introduce an approach called the Fast Laplacian Twin Support Vector Machine (FLap-TWSVM) - an advancement of traditional Laplacian Twin Support Vector Machines (Lap-TWSVM). The key advancement of FLap-TWSVM is the ability to increase computational efficiency greatly over its predecessor. The original Lap-TWSVM requires solving two large quadratic programming problems - a property that makes it struggle computationally leading to a high training time. FLap-TWSVM, on the other hand, only solves one (smaller) quadratic programming problem and an unconstrained minimization problem, which reduces the computational cost. This enables the algorithm to handle larger datasets much more efficiently.

The active learning framework the authors propose is a major contribution. They propose a new sampling strategy called "Minimum difference strategy" (MDS), which identifies the most informative samples (especially those that lie near the decision boundary between classes), and queries their labels from a domain expert. This approach is especially useful in scenarios which render obtaining labeled data expensive, or even impossible. The combination of semi-supervised learning and active learning in FLap-TWSVM makes it so that the model is able to generalize well with limited labeled data. This makes it much more effective for tasks that may require real time applications like human activity recognition or CBIR.

Another contribution is the ability of FLap-TWSVM to handle multi-class classification problems. Active learning models are often designed for binary classification, which may render them less useful in more complex scenarios. The authors demonstrate this through experiments on UCI benchmark datasets. Also, the model performs robustly against heteroscedastic noise - variations in data that can introduce errors in classification tasks. A distance parameter allows the model to adapt to noise in the data - a process that enables it to achieve high accuracy in noisy real-world environments.

Despite its strengths, the paper acknowledges some potential downsides to this approach. While FLap-TWSVM reduces computational complexity compared to its predecessor, it still needs to solve a quadratic problem and an unconstrained minimization problem, which could prove to be computationally intensive. Moreover, while the need for labeled data is minimized via active learning, an iterative querying process is still required - this can become time consuming when the pool of unlabeled data is large.