CSE 584 - MACHINE LEARNING

HOMEWORK - 1

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❖ From the first paper **"Active Learning for Convolutional Neural Networks: A core-set approach"**, the following observations can be drawn for listed questions -

➢ **What problem does this paper try to solve, i.e., its motivation.**
In general, Convolutional Neural Networks need a lot of labeled data to perform well, but labeling that data is mostly time consuming and costly. This paper mainly addresses the challenge of data labeling especially in CNNs. Main motivation of this paper is to find out the most efficient way to choose which data points are needed to be labeled in the datasets for boosting the accuracy, while keeping labeling costs down using Active learning approach.One more point to be noted from the paper is traditional active learning techniques don't work as effectively for CNNs in batch mode.

➢ **How does it solve the problem?**
An approach named "Core-set selection" is used to do active learning for CNNs.This approach takes a fully labeled dataset and tries to select a smaller, more manageable portion so that the model trained on it performs almost as well as if it had been trained on the whole dataset.
The formulation of this problem is "K-Center problem", with the objective of minimizing the maximum distance between every unlabeled data point and its closest labeled data point.To approximate the k-Center solution, a greedy algorithm is used to train the CNN by selecting batch-wise for the most representative data points.This method is scalable and applicable in both weakly-supervised and fully-supervised learning environments.

➢ **A list of novelties/contributions**
The following are the contributions of this paper -

- Core-Set Selection for Active Learning: A theoretical structure is introduced in this paper and it redefines active learning as a core-set selection problem.
- K-Center Problem Application: The authors relate the K-Center problem to the core-set selection problem and solve it by using an effective approximation approach.
- Theoretical Guarantees: The research provides theoretical guarantees that the chosen subset of data points functions well throughout the whole dataset for the core-set approach.
- Scalability: This approach is scalable and practical for large-scale CNNs, in contradiction to earlier active learning techniques.

- Empirical Outcome: On several datasets (CIFAR-10, CIFAR-100, and SVHN), the method significantly beats state-of-the-art active learning techniques.

➢ **What do you think are the downsides of the work?**

- Although the greedy approach is effective, it can still be computationally expensive to solve the K-Center problem on large-scale, especially if the dataset is very huge.
- The technique mostly depends on the geometric structure of the data, which is determined by how well the CNN learns features. If the feature space is represented poorly, the core-set selection may not be the best option.
- In theory, the core-set is assumed to have zero training error,but this condition may not hold in real-world situations.This assumption simplifies the analysis but may limit applicability in real-world noisy datasets.
- Uncertainty information in active learning is not included in this approach. Future research might investigate the combination of uncertainty-based techniques and this geometric approach.

❖ From the paper **“A Survey of Deep Active Learning”**, the following observations can be drawn for listed questions -

➢ **What problem does this paper try to solve, i.e., its motivation.**

To train effective models, there is a requirement for large labeled datasets.This paper addresses the problem of high labeling costs in Deep learning(DL). Main motivation of this paper is to explore how Active Learning (AL) can help in lowering the number of labeled samples that are needed without compromising on performance.This makes AL especially useful in fields like speech recognition and medical imaging where labeling is expensive and needs expertise.The approach is to combine DL with Active Learning(i.e., DeepAL) to take advantage on their complimentary benefits.

➢ **How does it solve the problem?**

This paper proposes a formal classification strategy for several methods in DeepAL, and provides a comprehensive overview of existing methods in this field.
It discusses the challenges of combining DL with AL, such as:

- Model Uncertainty: The exact assessment of uncertainty in DL models to enable effective sample selection.
- Data Efficiency: Handling the reality that DL models often require large volumes of labeled data, while AL models typically use fewer samples.
- Inconsistency in Pipelines: How to link DL's (feature extraction and model learning) with AL's (data querying) processes.

This paper solves the problem and offers several recommendations for fixes, such as:

- To use Batch-based strategies for querying several samples simultaneously.
- Using Hybrid approaches that strike a balance between sample variety and uncertainty.
- To enhance data and performance using Generative Models without increasing expenses associated with manual labeling.

➢ **A list of novelties/contributions**

This paper contributes to an in-depth review of DeepAL methods by categorizing them systematically. Using query strategies such as batch mode, uncertainty-based methods, density-based approaches, The research suggests a framework to classify different DeepAL methods.In integrating AL with DL, key obstacles like inconsistent processing, inadequate labeled data, and uncertainty estimation are identified.This survey also examines the uses of DeepAL in domains such as object detection, medical imaging, and image recognition in real world, offering insights into the practical performance of these approaches.Overall this paper contributes to discuss open issues and throw some light on potential research ideas needed to further develop DeepAL.

➢ **What do you think are the downsides of the work?**

- Even Though this paper covers a wide range of techniques to enhance DeepAL, some methods like density-based may still need a good investment in computing power to handle large-scale datasets.
- Other downsides of the work in this paper include lack of distinct benchmarks, limited examination of certain fields. For instance - As mentioned in the paper, Image recognition is the main area of concentration but DeepAL's applicability wasn't given much attention in NLP and robotics.Additionally, Pipeline inconsistency between AL and DL is identified but haven't resolved entirely in the study.

❖ From the paper **"Adaptive Active Learning for Image Classification"**, the following observations can be drawn for listed questions -

➢ **What problem does this paper try to solve, i.e., its motivation**

Main motivation of this paper is to explore the challenge of lowering the annotation effort in computer vision tasks in the ML domain.The objective is to minimize the cost of getting labeled data by choosing the most informative examples to be labeled and centered around active learning. It is not practical to assume that all samples have identical annotation costs in real world applications, as the paper points out while discussing traditional active learning algorithms. This work looks for reality that various images or data points can have different annotation costs into active learning.

- **How does it solve the problem?**

  A framework named “Adaptive Active Learning” is suggested in this paper to solve the problem. Expense of annotating a sample in addition to its informativeness is taken into account for this framework. With the help of trade-off between these two parameters, the technique dynamically chooses samples for labeling, improving learning by reducing annotation costs while preserving high accuracy. The “cost-sensitive approach” to active learning that the authors use to model the problem makes use of an algorithm that adjusts to the uncertainty of the model's predictions as well as the fluctuating costs of annotation.

- **A list of novelties/contributions**

  Firstly, This paper contributes to the Introduction of Cost-sensitive active learning for situations in which sample-to-sample variations exist in annotation costs. Trade-offs between sample informativeness and annotation cost are balanced by developing an adaptive strategy. This framework is applied to computer vision tasks like visual recognition tasks, showing that it may reduce annotation effort without sacrificing accuracy. Overall the suggested method makes use of an information gain metric that changes according to the labeling cost of each sample as well as the uncertainty of the classifier.

- **What do you think are the downsides of the work?**

  In large-scale settings, the adaptive algorithm adds additional computational overhead since it is required to maintain a balanced trade-off between the two parameters - cost and informativeness of each sample. Other drawbacks of this research are - annotation cost estimations are known beforehand(which is unknown in real-world and a challenging task), scalability of this framework to large datasets is not thoroughly explored and it is unclear how well the approach generalizes to a broader range of applications or highly imbalanced datasets.