

## Homework #1

### Paper 1: [Deep Bayesian Active Learning with Image Data](#)

#### 1. What problem does this paper try to solve, i.e., its motivation?

This paper is motivated by the need to solve the problem of deep learning in the context of active learning, where there is excessive dependence on large datasets, and there is no good way to quantify model uncertainty. The purpose is to advance the innovative active learning methods through Bayesian deep learning techniques that will be enough to effectively address high dimensional datasets which have been a challenge. It is seen that this framework is able to enhance the active learning task especially in the tasks of image classification and skin cancer detection and diagnosis.

#### 2. How does it solve the problem?

The Work develops a Bayesian based approach to active learning which implements selective deep neural networks that replace the need for long computational layers with Monte Carlo dropout that achieves deep network Bayesian inference. Using this technique, the user can represent the image classifier training set posterior using the outputs resulting from dropout at evaluation phase rather than a single output. The technique is implemented by choosing the most informative data points to add to the existing training set. As a result, deep learning is combined with the basic idea of active learning to quantify the uncertainty of classification and then utilize it effectively.

#### 3. A list of novelties/contributions:

- Bayesian approaches for active learning with deep neural networks
- Practical use of integrated deep architectures for Bayesian models using Monte Carlo dropout
- Use acquisition functions for deep Bayesian models

#### 4. What do you think are the downsides of the work?

The possible disadvantages are overhead costs associated with extended periods for training because it includes the model resetting processes after every acquisition, which implies additional computation. Furthermore, there is the risk of not resetting the system to cut down running time risks of being trapped in local optima, which may lead to sub-optimal model performance and accuracy of the acquisition functions that need further exploration.

Paper 2: [Active Learning for Convolutional Neural Networks: A Core-Set Approach](#)

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

The objective of this work is to respond to the progress of traditional applications of CNN, which have limitations as they depend on collecting a large set of labeled images, which is very expensive. By using active learning as a learning process to improve the model, the focus is on the core-set selection problem where only a subset, representative core-set of data is selected that can provide performance competitive to that obtained using the whole dataset. It solves the problems associated with active learning strategies currently applied in CNNs.

**2. How does it solve the problem?**

The paper presents the problem of active learning as the selection of a core-set from the feature space of the CNN. It proposes a greedy algorithm that selects samples to minimize the maximum distance between any datapoint and its corresponding nearest core-set point. This ensures that a more informative sub-sample is selected for labeling that will cover the feature space adequately and even enhance the performance of the models trained with fewer labels.

**3. A list of novelties/contributions:**

- It developed a greedy algorithm for core-set selection
- It compared with other active learning methods and random sampling

**4. What do you think are the downsides of the work?**

There may be an overfitting risk if the core-set is not truly representative of the full dataset, there's a risk that the model could overfit to this subset, leading to poor generalization on new data.

Paper 3: [Learning Loss for Active Learning](#)

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

The motivation for this work is the need to enhance the performance of deep networks when dealing with a limited number of annotations. Active learning can minimize the cost of labeling, but it is restricted in that it often asks human to annotate data that it perceived as uncertain, and some approaches are not very efficient when dealing with large networks. This paper proposes a task-agnostic, loss prediction active learning designed to improve active learning for deep networks across a variety of tasks including image classification, object detection, and pose estimation.

**2. How does it solve the problem?**

The paper suggests creating an additional neural network or "loss prediction module" that will be trained concurrently with the main model. This module is trained to predict an arbitrary loss for unlabeled samples, thus provides an indicator of sample informative value. In such approach each query is assigned an expected value of the loss and samples with high predicted values of loss are chosen for labeling. In this way, the model learns how to self-determine the data that it is most likely to classify wrongly so that such data can be marked for labeling, therefore, saving on the total labeling cost.

**3. A list of novelties/contributions:**

- Introduction of a new loss prediction module for active learning
- Development of a task-agnostic method applicable to deep learning problems
- Exploration of the method's applicability to different types of tasks (e.g., classification, regression)

**4. What do you think are the downsides of the work?**

The possible disadvantages of the described method are that they do not incorporate in data the concept of their diversity or density, which decreases the effectiveness. The other challenge is that the prediction of the loss is not very accurate for such prediction tasks as the object detection and the estimation of the human pose, hence there are limitations in the architecture and objective function that need to be addressed to enhance performance.