Paper 1: Active Learning and Machine Teaching for Online Learning: A Study of Attention and Labelling Cost

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

The paper focuses on high labeling and monitoring efforts required by the human involvement in interactive machine learning. Active learning view humans as passive and always right, and Machine teaching view humans to constantly monitor, which are unrealistic expectations. The cost of labelling budget in interactive ML is measured only in number of labelled samples, while the cost of the workload of the annotator which includes monitoring the system is not considered. The main objective of the paper is to produce more realistic models of human efforts in labelling and attention along with maintaining high classification performance.

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

The problem is solved using an interactive online learning framework that combines elements of both active learning and machine teaching. This framework considers both labeling cost and attention cost which are expected by the human. The framework test various strategies in cold start scenario, considering the tradeoff between labelling effort and attention cost. Labelling is considered only when the current labelling expense along with the query cost and the estimated labelling cost is less than the labelling budget. This framework is used with different strategies to get the optimized costs and classification performance.

3. **A list of novelties/contributions**
    - This framework distinguishes between attention cost and labelling cost which is often ignored in other models.
    - Provides results demonstrating the advantage of the combined approach of active learning and machine teaching strategies to traditional methods.
    - The cold start scenario which is used ensures that the framework works even when the model is not trained and has limited data.
    - The experiments are done on real world datasets (mHealth and HAR) which proves the practical ability of this framework.

4. **What do you think are the downsides of the work?**
    - The results are specific to mHealth and HAR datasets, and it is not clear about how it performs with larger data sets and other different tasks.
    - The results may not be applicable to all Machine Learning applications because of their complexities.

- The costs may differ according to the skill of the annotator which is not considered.
- The framework is conducted in a cold start scenario which is not a real-world scenario where the models are continuously learning and are pretrained.

Paper 2: Active Learning Based on Transfer Learning Techniques for Text Classification

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

The paper focuses on training text classification machine learning models with limited labeled data. Large amounts of labeled data are required by methods like deep learning which is time consuming. The paper presents a model which combines active learning (AL) and transfer learning (TL) techniques to develop an effective text categorization method.

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

The problem is solved using a combination of active learning and transfer learning which is active transfer learning for text classification. The training points are selected using random selection, uncertainty sampling, and active transfer (AT) which is proposed in this paper. Active transfer uses learned models of earlier data sets to identify the new data point. The active transfer method performed better than traditional methods when evaluated on five varied datasets from different domains.

3. **A list of novelties/contributions**
    - Introduced Active Transfer Criterion which combines active and transfer learning, which selects items that contain most of the information about the current task, using models learned on similar tasks.
    - The method was tested on five different datasets from various domains and performed well across various contexts.
    - The AT criterion gave better results than the traditional methods such as random selection, uncertainty sampling criterion in various metrics like accuracy, precision, recall, and F1 score.

- The proposed method was applied in image classification and in text classification. This method of selecting the training points by combining active and transfer learning can be integrated into models that use images and text as input.

4. **What do you think are the downsides of the work?**
    - The combination of active and transfer learning might add complexity especially where access to related task's models is limited.
    - While AT criterion performs well with the given data sets, it might not perform well across different types of data or tasks beyond those tested, especially if task similarity is low.
    - The AT criterion might get negatively impacted If the pre trained models from similar tasks are not available.
    - Very large datasets might require high cost of updating models which might prevent the usage of this method in real large-scale applications.

Paper 3: Exploring Active Machine Learning Techniques to Boost Classification Accuracy in Image and Text Models

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

The paper focuses on enhancing the classification accuracy of image and text models which has large and diverse datasets. The traditional supervised learning does not have high accuracy because of the large amount of labeled data required and the classification is complicated. The paper proposes the use of active learning to optimize the annotation process by reducing the cost required to label data along with improving model performance.

2. How does it solve the problem?

Query-by-Committee method, which is an active learning technique is used to select the most useful data sample for annotation. The committee of models prioritizes the data points which are more informative. This active learning strategy is integrated into the text and image classification models using ALiPy (Active Learning in Python) library, along with neural networks (CNN) for image data (CIFAR-10) and Bag-of-Words (BoW) models for text data (AG News dataset).

3. A list of novelties/contributions

- QBC Method: Implementing this method ensured the selection and annotation of uncertain data points which resulted in increased accuracy.
- Datasets: This method is tested on CIFAR-10 dataset for images and AG News dataset for text which are the standard real-world datasets.
- Performance: In QBC models (QBC-CNN and QBC-BoW) resulted in higher accuracy, precision, recall, and F1-scores compared to non-QBC models.
- Efficiency: The efficiency and convergence rates show that active learning is cost effective compared to traditional approaches.

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

- The QBC approach needs more computational power compared to a single-model training.
- The performance of the models in the committee has a lot of effect on QBC method. If the committee is poorly selected, the method would have a huge negative impact.
- Testing on large and complex datasets might result in high computational demand and may require a lot of time for annotation.
- QBC is not compared to other active learning methods which might indicate that other methods might work well for few dataset types.