Fast Incremental Learning Strategy Driven by Confusion Reject for Online Handwriting Recognition

Summary: This paper represents a new method of incremental learning algorithm with a specific criteria of sample selection, focusing on retraining the most relevant data points to improve the efficiency and adaptability of the handwriting character recognition systems model. The presented strategy is driven by using confusion detection mechanisms in order to control the learning process.

Implementation:
Sample Selection: The model selects a set of samples in order to maintain model efficiency and optimize memory use. This is achieved by selecting samples based on a criterion that evaluates their importance in defining decision boundaries. They have chosen the Fuzzy **Inference System (FSI) for classification** approach.

Incremental Update: The model is updated often to incorporate new data points while preserving previously selected significant samples, enabling it to continuously adapt without the need for retraining. It is driven by **confusion reject**, which means to assess the reliability of the classifier by detecting patterns for which the classifier is likely to misclassify.

Evaluation: The paper evaluates the methodology and shows how sample selection can reduce processing time and memory requirements for incremental learning using benchmark datasets.

Algorithm 1: Incremental learning algorithm driven by confusion reject.

```
foreach new example e do
    if e is the first example of the class C then
        create a new prototype around e;
        apply adaptation technique;
        reject_threshold[C] = initial value;
    else
        apply adaptation technique;
        calculate the confusion degree;
        if confusion reject then
            create a new prototype around e;
            reduce the value of reject_threshold[C];
        end
    end
end
```

Exploring the Open World Using Incremental Extreme Value Machines

This paper discusses the use of incremental learning techniques for open world recognition by introducing the modification of the widely known Extreme Value Machine (EVM). Mainly focuses on the models ability to recognize both known and unknown classes. The method extends the EVM with a partial model fitting function by neglecting unaffected space during an update where the model must effectively adapt to new classes without being explicitly trained on them. The paper emphasizes on the importance of handling open-set conditions, where the model must effectively adapt the new class without being explicitly known about or trained on them.

Implementation:
Open World Recognition with EVM, leverages EVM to handle unknown classes by identifying boundary conditions that classify new samples as unknowns. Then the paper proposed a step by step process that allows models to learn from the new classes without forgetting the old ones. The method is evaluated on classification accuracy, computational efficiency, and the ability to identify unknown classes, demonstrating EVM's role in balancing model accuracy with effective open world recognition.

Learn or Recall? Revisiting Incremental Learning with Pre-trained Language Models

This papers proposed a method called SEQ* for Incremental Learning with Pre-trained Language models (PLM's) after finding out that most of the methods of classification tasks (Text Classification, Intent Classification, Relation Extraction, and Named Entity Recognition) under the two most popular IL settings (ClassIncremental and Task-Incremental) severely underestimate the inherent anti-forgetting ability of PLMs. The study explores techniques to maintain knowledge retention and adapt to new data without retraining fully. It evaluates different strategies for handling the challenges in incremental learning, like forgetting previous knowledge and balancing between learning new information and recalling existing data.

Implementation:

Pre-trained Model Selection: Choose a base pre-trained language model to adapt incrementally.
Data Partitioning: Divide the training data into sequential tasks for incremental learning.
Layer-wise Fine-Tuning: Incrementally fine-tune layers of the model with new data, ensuring minimal interference with prior knowledge.
Knowledge Distillation: Apply knowledge distillation methods to retain previous knowledge by comparing outputs from the old model and the incrementally fine-tuned model.
Evaluation: Assess model performance on both new and previous tasks to verify knowledge retention and adaptation.