Project Proposal: A Hybrid Learning Framework for Continual and Sample-Efficient Computer Vision

Abstract

Modern computer vision has been revolutionized by large-scale, pre-trained Vision-Language Models (VLMs) like CLIP, which exhibit remarkable zero-shot generalization capabilities. However, these models are fundamentally static; they struggle with catastrophic forgetting when updated with new information and lack mechanisms for sample-efficient fine-tuning or self-assessment of their own competence. This proposal introduces the Continual, Adaptive Learning Model (CALM), a novel hybrid framework designed to address these critical limitations. CALM integrates a pre-trained VLM with three key components: (1) an episodic memory system to mitigate catastrophic forgetting in continual learning scenarios; (2) a Reinforcement Learning from Human Feedback (RLHF) loop for sample-efficient adaptation; and (3) a meta-learning agent for autonomous readiness assessment. We hypothesize that CALM will significantly outperform existing methods in few-shot accuracy, knowledge retention, and feedback efficiency. The system will be evaluated on a suite of benchmarks measuring these capabilities against state-of-the-art continual and meta-learning baselines.

1 Benchmarking Strategy

To validate the performance of the CALM framework, a multi-faceted benchmarking strategy will be employed, focusing on its core contributions: few-shot learning, continual learning, and domain adaptation.

1.1 Evaluation Datasets

A curated set of datasets will be used to test different aspects of the model's performance:

- **miniImageNet**: The standard benchmark for N-way, K-shot classification. This will be the primary dataset for evaluating few-shot learning performance and sample efficiency against meta-learning baselines.

- **Sequential CIFAR-100**: To measure continual learning and catastrophic forgetting, the 100 classes of CIFAR-100 will be split into 10 sequential tasks of 10 classes each. The model will be trained on these tasks sequentially, and its performance on previously seen tasks will be evaluated.
- **COCO-Text**: A complex, real-world dataset for evaluating the model's ability to adapt to a specific, challenging domain (Optical Character Recognition) using the proposed RLHF mechanism.

1.2 Baselines for Comparison (State-of-the-Art Reference)

The performance of CALM will be benchmarked against a set of established and state-of-the-art (SOTA) methods, each chosen to represent a different approach to the problem:

- **Naive Fine-tuning**: A standard CLIP/LLaVA model fine-tuned on new tasks sequentially. This baseline is expected to perform well on the current task but suffer from severe catastrophic forgetting, providing a lower bound for knowledge retention.
- **MAML (Model-Agnostic Meta-Learning)**: A classic meta-learning algorithm that explicitly trains a model to adapt quickly to new tasks with few examples. This serves as a strong baseline for few-shot learning performance (3).
- **EWC (Elastic Weight Consolidation)**: A canonical continual learning method that prevents forgetting by adding a regularization term to penalize changes to weights important for old tasks. This is a strong baseline for knowledge retention (4).
- **SOTA VLM-Continual Learning (LLaVA-CL)**: The current state-of-the-art approach for continual learning with pre-trained VLMs, as described in recent literature (e.g., 5). This provides the most challenging and relevant SOTA comparison.

2 Evaluation Metrics

To provide a comprehensive assessment, the evaluation will be based on four distinct categories of metrics, each targeting a key hypothesis of this research.

2.1 Few-Shot Learning Performance

- **N-way K-shot Accuracy**: The primary metric for sample efficiency, measuring classification accuracy on N classes after seeing only K examples of each. We will report 5-way 1-shot and 5-way 5-shot results on miniImageNet.

2.2 Knowledge Retention & Continual Learning

- **Average Accuracy**: The mean accuracy across all tasks learned so far. A high average accuracy indicates strong overall performance.
- **Backward Transfer (BWT)**: A direct measure of catastrophic forgetting. It calculates the average change in performance on previous tasks after learning a new one. A value close to zero indicates no forgetting.

$$\text{BWT} = \frac{1}{T-1}\sum(\text{Accuracy}_{\text{task}_i,\text{after}_T} - \text{Accuracy}_{\text{task}_i,\text{initial}})$$

2.3 Human Feedback Efficiency

- **Accuracy Gain per Feedback Unit**: Measures how much the model's accuracy on a specific task (e.g., COCO-Text) improves for each piece of human feedback provided. This quantifies the sample efficiency of the RLHF loop.

2.4 Readiness Assessment Performance

- **Deployment Decision Accuracy**: The accuracy of the meta-learning agent in predicting whether the main model's prediction is reliable enough for deployment (i.e., above a performance threshold).
- **False Positive Rate (FPR)**: The rate at which the agent incorrectly flags a wrong prediction as "Ready". A low FPR is critical for system safety and reliability.

3 Expected Outcomes

We hypothesize that the CALM framework will demonstrate superior performance across all key evaluation axes. The following table presents the expected quantitative results from our benchmarking experiments:

Method	**Few-Shot Acc. (5-way 1-shot)**	**Final Acc. (Seq. CIFAR-100)**	**BWT**[1]
Naive Fine-tuning	48.5%	85.3%	-0.45
EWC	52.1%	78.1%	-0.15
MAML	63.1%	75.5%	-0.21
LLaVA-CL (SOTA)	65.4%	81.2%	-0.09
CALM (Ours)	72.5%	84.9%	-0.03

Table 1: Expected quantitative results for CALM and baseline methods.

4 Experimental Results

The framework was rigorously evaluated using the CIFAR-10 dataset to assess its zero-shot and few-shot learning capabilities, executed on a system with device selection prioritizing CUDA, followed by Metal Performance Shaders (MPS), and defaulting to CPU. The evaluation process utilized the CLIP model (`openai/clip-vit-base-patch32`) with a batch size of 32 for testing.

The zero-shot evaluation achieved an accuracy of 88.80%, completed in 313 iterations over approximately 1 minute and 59 seconds, demonstrating robust generalization without task-specific training. This phase involved generating text prompts (`"a photo of a {class}"`) for the 10 CIFAR-10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck) and comparing image logits against true labels.

For the 1-shot K-Nearest Neighbors (K-NN) evaluation, the framework constructed an episodic memory by selecting one example per class from the training set, encoding these images into embeddings using the CLIP model. The K-NN classifier, with $k = 1$, was trained on these embeddings and evaluated on the test set, achieving an accuracy of 63.75% over 313 iterations in about 55 seconds.

The performance decreased from zero-shot to 1-shot by 25.05 percentage points, indicating that the basic K-NN approach with minimal data (one example per class) requires further optimization. This performance gap will be addressed through the application of our proposed methods in subsequent evaluations.

5 Bibliography

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