CS771 Mini Project-II

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1 Introduction

The field of machine learning has witnessed significant advancements, yet challenges persist in leveraging partially labeled data and adapting to varying data distributions effectively. This project addresses these challenges using a unique setting based on the CIFAR-10 image classification dataset, emphasizing incremental learning and domain adaptation.

The primary problem involves utilizing a labeled dataset to train an initial model and iteratively refining this model with predictions on subsequent unlabeled datasets. This process is carried out across datasets with two distinct properties: one group of datasets sharing the same input distribution and another exhibiting different but related distributions. The overarching aim is not only to maximize accuracy but also to maintain stability in model performance across earlier datasets as the model evolves.

The dataset comprises subsets of CIFAR-10 images, a well-established benchmark dataset for object classification tasks. It includes 32×32 RGB images spanning ten classes such as airplanes, automobiles, and birds. The dataset is divided into two distinct groups:

1. **Homogeneous Distribution (D1 to D10):**
   - These ten datasets originate from the same input distribution ($p(x)$), ensuring uniform feature characteristics across datasets.
   - The first dataset, $D1$, is fully labeled, providing a foundation for model training. The subsequent datasets ($D2$ to $D10$) are unlabeled but share similar underlying characteristics.
2. **Heterogeneous Distribution (D11 to D20):**
   - These ten datasets come from varying input distributions, exhibiting degrees of similarity with the distribution of $D1$ to $D10$.
   - This variation introduces domain adaptation challenges, as models must account for distributional shifts while maintaining predictive accuracy.

Each dataset has corresponding held-out labeled subsets ($\hat{D}_1$ to $\hat{D}_{20}$) strictly reserved for performance evaluation, prohibiting their use during model training or cross-validation. This separation ensures unbiased assessment of the models' generalization capabilities.

The problem's structure leverages these datasets to investigate the effectiveness of Learning with Prototypes (LwP) classifiers and their potential extensions for continual learning tasks. The project thus bridges the gap between incremental learning, domain adaptation, and prototype-based classification, providing a practical framework for exploring these interconnected areas.

2 Task 1

This section presents the methodology and results for Task 1, where we iteratively trained and updated the model f_1 using Learning with Prototypes (LwP) and evaluated its performance across datasets D_1 to D_{10}.

2.1 Feature Extraction

The provided datasets D_1 to D_{10} consist of 32×32 RGB images from CIFAR-10. To prepare the datasets for feature extraction and enhance model generalization, the following steps were performed:

- Images were normalized to have zero mean and unit variance.
- Data augmentation techniques, including random cropping and horizontal flipping, were applied to expand the diversity of the training data.
- Deep feature representations were extracted using pre-trained models, including **ResNet50**, **DenseNet**, and **ConvNeXt**, trained on ImageNet.
- Among these models, ResNet50 achieved an accuracy of 79%, DenseNet reached 80%, and ConvNeXt outperformed with 87% accuracy when evaluated using the LwP classifier.

2.2 Model Selection and Variants of LwP

We experimented with multiple variants of LwP to identify the most suitable approach:

1. **Kernelized LwP:** Multiple kernels were explored (e.g., sigmoid, exponential and polynomial), but accuracy showed no significant improvement over the baseline.
2. **Mahalanobis Distance:** This variant performed well on dataset D_1, achieving good accuracy; however, it failed to generalize across datasets D_2 to D_{10}.
3. **GMM with PCA:** A Gaussian Mixture Model (GMM) was implemented with PCA to reduce dimensionality and mitigate the curse of high dimensionality in GMM. This approach achieved the highest accuracy of **88%** on D_1 and demonstrated superior generalization when extended to datasets D_2 to D_{10}.

2.3 Hyperparameter Tuning

The primary hyperparameter for PCA, the number of components, was tuned empirically. Setting the number of components to 50 provided the best trade-off between computational efficiency and accuracy.

2.4 Results and Evaluation

The accuracy matrix for models f_1 to f_{10} evaluated on held-out datasets $\hat{D}_1$ to $\hat{D}_{10}$ is shown in Table 1. The results highlight the effectiveness of GMM with PCA in achieving consistent and high accuracy across datasets.

The results underscore the robustness of the GMM with PCA approach, which consistently outperformed other LwP variants across datasets.

3 Task 2

In Task 2, we extended the methodology from Task 1 to datasets D_{11} to D_{20}. Unlike Task 1, where datasets D_1 to D_{10} shared the same input distribution, datasets D_{11} to D_{20} originate from different input distributions. This introduced significant domain adaptation challenges, which required modifications to the original approach to maintain accuracy and stability.

Table 1: Accuracy Matrix for Models f_1 to f_{10} on Held-Out Datasets $\hat{D}_1$ to $\hat{D}_{10}$

Model/Dataset	$\hat{D}_1$	$\hat{D}_2$	$\hat{D}_3$	$\hat{D}_4$	$\hat{D}_5$	$\hat{D}_6$	$\hat{D}_7$	$\hat{D}_8$	$\hat{D}_9$	$\hat{D}_{10}$
f_1	88.40	-	-	-	-	-	-	-	-	-
f_2	87.96	89.04	-	-	-	-	-	-	-	-
f_3	88.16	89.12	88.92	-	-	-	-	-	-	-
f_4	87.64	89.28	88.56	89.52	-	-	-	-	-	-
f_5	87.96	89.36	88.76	89.12	88.80	-	-	-	-	-
f_6	88.40	89.28	88.84	89.68	88.80	89.56	-	-	-	-
f_7	87.76	89.60	88.80	89.56	88.64	89.72	88.76	-	-	-
f_8	87.72	89.80	89.08	89.40	88.68	89.32	88.72	88.08	-	-
f_9	87.52	89.52	88.88	89.68	88.68	89.40	88.88	88.12	88.48	-
f_{10}	87.52	89.48	88.84	89.60	88.72	89.68	89.24	87.68	88.60	88.24

3.1 Adapting the Methodology for Domain Shift

The primary challenge in Task 2 was handling the domain shift between datasets. To address this:

- The final model f_{10} from Task 1 was used as the initial model f_{11}.
- Feature representations were updated using a **ConvNeXt model pre-trained on ImageNet**, as it provided the best features in Task 1.
- A **Gaussian Mixture Model (GMM)** with PCA was extended, with the number of components set to 50 to balance dimensionality reduction and preservation of feature variance.
- Domain adaptation was explicitly considered by updating GMM parameters using the predicted labels of each dataset while incorporating soft cluster assignments to reduce the impact of noisy predictions.

3.2 Model Update Procedure

The model update procedure was iterative, similar to Task 1. For each dataset D_i, $i \in \{11, \dots, 20\}$:

1. Model f_i was used to predict labels for D_{i+1}.
2. Predicted labels were incorporated into the GMM with soft assignments to update the model for D_{i+1}.
3. PCA was reapplied to the feature space of D_{i+1} before training the updated GMM.
4. The updated model f_{i+1} was evaluated on all held-out datasets $\hat{D}_1$ to $\hat{D}_{20}$.

3.3 Results and Evaluation

The performance of models f_{11} to f_{20} was evaluated in terms of their accuracy on held-out datasets $\hat{D}_1$ to $\hat{D}_{20}$. The accuracy matrix is presented in Table 2 and Table 3.

3.4 Analysis of Results

The results indicate a gradual decrease in accuracy as domain shifts increase across datasets. However, the GMM with PCA model demonstrated resilience, maintaining reasonable performance on earlier datasets while adapting to new ones. The use of soft cluster assignments in GMM reduced the impact of noisy predictions, particularly in later datasets.

Overall, the results validate the effectiveness of extending the approach from Task 1 to handle domain adaptation challenges in Task 2.

4 YouTube Video Description

As part of Problem 2, a concise video presentation was created to summarize the key ideas and results of the selected research paper. The video provides an overview of the problem studied, the

Table 2: Accuracy Matrix for Models f_{11} to f_{20} on Held-Out Datasets $\hat{D}_1$ to $\hat{D}_{10}$

Model/Dataset	$\hat{D}_1$	$\hat{D}_2$	$\hat{D}_3$	$\hat{D}_4$	$\hat{D}_5$	$\hat{D}_6$	$\hat{D}_7$	$\hat{D}_8$	$\hat{D}_9$	$\hat{D}_{10}$
f_{11}	87.60	89.00	88.72	89.00	88.60	89.28	88.32	87.64	88.28	88.12
f_{12}	87.32	89.04	88.40	88.44	88.24	88.48	88.28	87.48	87.56	87.32
f_{13}	87.00	88.24	87.88	87.92	87.68	88.16	87.40	87.20	87.00	87.08
f_{14}	86.20	87.88	87.44	87.68	87.12	87.60	87.40	86.68	86.32	86.88
f_{15}	85.80	87.68	87.08	87.00	86.76	87.40	86.68	86.16	86.12	86.52
f_{16}	85.76	87.36	86.88	86.68	86.56	86.88	86.32	85.44	86.40	86.60
f_{17}	85.63	87.07	86.73	86.55	86.41	86.31	85.91	85.25	86.11	86.47
f_{18}	85.60	86.88	86.57	86.49	86.28	86.12	85.72	85.00	85.78	86.26
f_{19}	85.41	86.76	86.41	86.27	86.15	85.87	85.57	84.78	86.50	86.19
f_{20}	85.37	86.64	86.29	86.09	86.01	85.54	85.33	84.59	86.43	85.99

Table 3: Accuracy Matrix for Models f_{11} to f_{20} on Held-Out Datasets $\hat{D}_{11}$ to $\hat{D}_{20}$

Model/Dataset	$\hat{D}_{11}$	$\hat{D}_{12}$	$\hat{D}_{13}$	$\hat{D}_{14}$	$\hat{D}_{15}$	$\hat{D}_{16}$	$\hat{D}_{17}$	$\hat{D}_{18}$	$\hat{D}_{19}$	$\hat{D}_{20}$
f_{11}	69.92	-	-	-	-	-	-	-	-	-
f_{12}	69.16	44.16	-	-	-	-	-	-	-	-
f_{13}	68.24	44.08	75.40	-	-	-	-	-	-	-
f_{14}	67.12	44.60	74.88	81.48	-	-	-	-	-	-
f_{15}	66.80	45.08	74.02	81.40	85.48	-	-	-	-	-
f_{16}	66.40	44.20	73.16	81.20	85.40	71.48	-	-	-	-
f_{17}	66.21	44.13	74.24	81.51	85.13	71.21	75.83	-	-	-
f_{18}	66.07	43.86	74.11	81.13	84.88	70.86	73.68	69.40	-	-
f_{19}	65.97	44.10	73.84	81.04	84.53	70.65	74.97	69.88	63.04	-
f_{20}	65.97	44.06	73.52	80.87	84.32	70.41	74.84	69.36	60.40	76.32

proposed methodologies, and the results presented in the paper. It also includes insights into how the research aligns with the settings explored in Problem 1 of this mini-project.

The video was created using a combination of presentation slides and voice-over explanations to ensure clarity and engagement. The video can be accessed using the following YouTube link:

`https://youtu.be/wvOdvgIQsa0?si=M_r9onfJCImkHaiS`

References

- Lifelong Domain Adaptation via Consolidated Internal Distribution
- Deja Vu: Continual Model Generalization for Unseen Domains
- CIFAR-10 Dataset