Zaid Alayedy

Patricia Mcmanus

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Image Classification with SVM

Understanding of SVM Algorithm:

Support Vector Machine (SVM) is a type of supervised learning algorithm that solves classification tasks by finding the most suitable hyperplane to partition data from classes. In this lab, I gained a lot of insights about SVM and its use with high-dimensional datasets such as images. I have come to admire the mathematical elegance of SVM, in that it combines non-linearly separable data via kernel manipulation.

Data Preparation Steps:

The data preparation process involved several key steps:

Loading and Preprocessing: Images were resized, normalized, and converted into a format suitable for SVM.

Splitting the Dataset: Data was split into training and testing sets to evaluate model performance.

Dimensionality Reduction: To manage computational costs, PCA (Principal Component Analysis) was used to reduce feature dimensions, a step that was both challenging and insightful in understanding data transformation.

Model Training and Evaluation:

Model training was an active learning experience about SVM hyperparameters (kernel choice, C-parameter tuning). I tried out different kernels (linear, polynomial, RBF) and saw how they affected decision margins and performance. This was followed by testing using accuracy, precision, recall, and cross-validation, which influenced model robustness.

Challenges Faced:

Among the problems was that the dataset size and compute overhead was really taking a toll on the runtime of training. I assumed the code was buggy, but when I looked into it, I discovered it was loading needed data in the background. This taught me to be patient and to keep track of progress logs. The other problem was how to get a handle on how hyperparameters affected performance, this involved experimenting and evaluating outcomes.

Insights and Reflections:

This lab further strengthened my confidence in SVM’s ability to process small- or medium-sized data with distinct class margins. But I saw its weakness in image classification tasks like CIFAR-10, where higher level architectures like CNNs are superior. The lab also reiterated that preprocessing of data and feature engineering are key to getting things right. What really caught my attention was the use of kernel tricks to compress the data into higher dimensions for classification.

Critical Analysis:

While SVM performed reasonably well, its scalability is a limitation for large datasets like CIFAR-10. I learned that for image classification tasks with complex patterns, models like Convolutional Neural Networks (CNNs) are more suitable due to their ability to learn hierarchical features. If I were to repeat this lab, I would explore hybrid models or incorporate transfer learning to improve performance.

Visual Outputs:

To make things easier to digest, I also included visuals such as confusion matrixes and plots of accuracy over time (attached). These images represent the model’s performance in all classes and provide feedback on what we can improve upon.

Conclusion:

This lab was a valuable learning experience, offering practical insights into SVM and its role in classification tasks. It taught me to approach algorithms critically, reflecting on their strengths, limitations, and applicability to real-world problems.

Reference:

Scikit-learn documentation (https://scikit-learn.org/stable/modules/svm.html)

AI Black Box for conceptual understanding.

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