Kernel-Based Approaches for Image Classification

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Abstract

This study investigates the effectiveness of kernel methods for non-linear classification tasks, particularly in the context of image classification. Through hyperparameter optimization and score analysis, we assess their performance, aiming to achieve significant accuracy on the test set. Our findings highlight the potential of these methods in capturing intricate data relationships and achieving promising results in image classification tasks.

Introduction

In this project [1], we explore the effectiveness of kernel methods for classification tasks involving non-linear data relationships. We consider well-known techniques such as Kernel Ridge Regression (KRR), Kernel Logistic Regression (KLR), Kernel k Nearest Neighbors (KNN), and Support Vector Machines (SVM). By optimizing hyperparameters and analyzing resulting scores, our objective is to gain insights into how these methods perform and their suitability for image classification tasks.

1 Kernel Methods

Kernel methods offer a powerful approach for modeling data in classification tasks characterized by complex and non-linear feature relationships. By transforming input features into a higher-dimensional space, these techniques enhance the feasibility of achieving linear separation. The essence of kernel methods lies in computing the similarity, or "kernel", between pairs of data points in the input space, facilitating classification within a transformed feature space.

1.1 Kernels

In the context of classification tasks using kernel methods, selecting the appropriate kernel function is pivotal for achieving optimal model performance and effectively capturing complex data relationships. Here, we introduce several common kernel functions utilized in kernel-based classifiers.

- The **linear** kernel
- The **polynomial** kernel
- The **Gaussian** kernel
- The **sigmoid** kernel
- The **Gaussian-polynomial** kernel

1.2 One-vs-Rest (OvR) strategy

In multi-class classification scenarios, the One-vs-Rest (OvR) strategy [2] complements kernel methods. Here, the problem is decomposed into binary classification tasks, treating each class as a separate problem. Individual classifiers are then trained to discern instances of a specific class from all others. During prediction, the highest score from the classifiers determines the assigned class. Through the integration of kernel methods and the OvR strategy, accurate predictions in multi-class classification tasks with non-linear decision boundaries are achievable across diverse domains.

1.3 Methods

In our study, we explored several kernel methods to tackle image classification. These methods are powerful for capturing complex patterns in data that aren't easily described by simple linear relationships, which makes them popular in machine learning.

- **Kernel Ridge Regression (KRR):** KRR aims to minimize a regularized squared error loss function. It's commonly used for regression and classification tasks.
- **Kernel Logistic Regression (KLR):** KLR adjusts model parameters to maximize the likelihood of observed data. It's effective for classifying data into multiple categories.
- **Kernel k Nearest Neighbors (KNN):** KNN assigns labels to data points based on the majority vote of their nearest neighbors. It's a flexible method for classification tasks.
- **Support Vector Machines (SVM):** SVM constructs a hyperplane in a high-dimensional space to separate data points of different classes. It's useful for finding complex decision boundaries.

These methods offer flexibility in handling diverse data patterns, making them valuable for various classification tasks like image classification. Throughout our study, we evaluated these methods' performance and fine-tuned their parameters to improve classification accuracy.

2 Experiments [3]

2.1 Dataset

- 'Xtr.csv' contains a 5000×3072 matrix representing color images. Each row represents an image of size 32×32 pixels. Pixel intensities are arranged in three channels: the first 1024 values for the red channel, the next 1024 for green, and the last 1024 for blue.
- 'Xte.csv' includes 2000 test images, where each row corresponds to an image ($Id = 1$ to $Id = 2000$).
- 'Ytr.csv' contains labels for the training data, crucial for model training and evaluation.

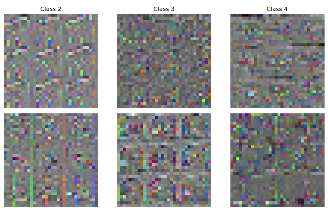

Figure 1: *Original images (standardized)*

Note: Preprocessing has been applied to these images, altering their appearance from natural images.

2.2 Methodology

In image classification, raw pixel data may lack depth for accurate classification, mainly representing basic features like color intensity. Thus, feature extraction is vital to convert raw pixel data into a more informative form by identifying key details like edges, textures, shapes, or patterns. This step can reduce data dimensionality while retaining critical information, enhancing algorithm performance by providing more discriminative features.

To tackle this challenge, we drew inspiration from Convolutional Neural Networks (CNNs), utilizing convolution and pooling techniques to capture crucial patterns from images. We then employed Principal Component Analysis (PCA) on the extracted features to reduce dimensionality and generate distinct datasets.

The resulting features, though not directly interpretable as images, were visualized to observe modifications and identify consistent patterns within the same class.

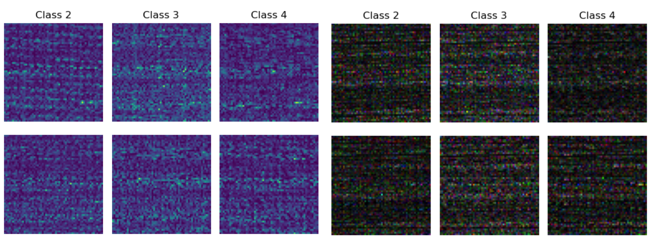

Figure 2: *ConvPool features 2D (left) and 3D (right)*

3 Results

The table below presents the results obtained after optimizing hyperparameters, including kernel parameters and regularization parameters. The **Gaussian kernel** has been consistently selected for the predictions due to its superior performance.

Method	Public	Private
KRR (2D)	0.426	0.446
KRR (3D)	0.445	**0.45**
KLR (PCA)	0.105	0.084
KNN (3D)	0.209	0.186
SVM (3D)	0.439	**0.458**

Table 1: *Kaggle public and private scores*

Based on the Kaggle public and private scores presented in the table, it appears that Kernel KNN and KLR may not be the most suitable approaches for our classification task. These methods achieved lower scores compared to others, suggesting they may not effectively capture the underlying patterns in the data. On the other hand, SVM and KRR demonstrated better performance, although not optimal, indicating their potential suitability for the classification task at hand.

Conclusion

In our project, we explored how well kernel methods work for classifying images. By studying techniques like Kernel Ridge Regression (KRR), Kernel Logistic Regression (KLR), Kernel k Nearest Neighbors (KNN), and Support Vector Machines (SVM), we learned about their performance. While SVM and KRR showed promise, KNN and KLR had some trouble capturing complex patterns in the data. Further analysis and optimization may be necessary to improve their effectiveness.

References

[1] Michael Arbel. *Data Challenge - Kernel methods (2023-2024)*. 2024. URL: https://kaggle.com/competitions/data-challenge-kernel-methods-2023-2024.

[2] Jason Brownlee. *One-vs-Rest and One-vs-One for Multi-Class Classification*. Apr. 2021. URL: https://machinelearningmastery.com/one-vs-rest-and-one-vs-one-for-multi-class-classification/.

[3] Nils Baillie and Abdoul-Hakim Ahamada. *Code for Data Challenge - Kernel methods (2023-2024)*. 2024. URL: https://github.com/Hakim506/M2-MVA/tree/main/KM/Data%20Challenge.