An Investigation of Classification Techniques For Handwritten Digit Recognition

Deric Pang
dericp@cs.washington.edu

Saidutt Nimmagadda
nimmas@cs.washington.edu

Abstract

TODO

1 Introduction

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2 Project Description

2.1 Goal

Our goal for this project is quite simple—we want to take pixel data from images of hand-drawn digits and classify them as a number from 0 to 9.

2.2 Data

The data for our project was taken from the MNIST dataset. As written on a Kaggle competition using the MNIST dataset, "The MNIST ('Modified National Institute of Standards and Technology') dataset is a classic within the Machine Learning community that has been extensively studied. More detail about the dataset, including Machine Learning algorithms that have been tried on it and their levels of success, can be found at http://yann.lecun.com/exdb/mnist/index.html."

Each handwritten digit is vectorized. Each vector is composed of a label which represents the label classification (i.e. numbers from 0 to 9) and 783 pixel features of integer values between 0 and 255. Since all of the data is already normalized and centered, we did not need to take those steps ourselves to start building models against. The training data set consists of 60,000 data points, while the test set consists of 10,000 data points.

The specific flavor of the MNIST dataset that we used came from https://pjreddie.com/projects/mnist-in-csv/ where the data is formated as a CSV.

3 First Considerations

3.1 Machine Learning Techniques

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3.2 Related Work

Before we began implementing any classifiers, we wanted to investigate what material already existed in the domain of digit recognition. We discovered that digit recognition, especially on the

MNIST database, is an extremely well studied problem. As such, we had no trouble finding a plethora of detailed papers.

Going into the project, we had intuition that the most accurate classifier we could build was a convolutional neural network. This was confirmed in most of the related work [1 - 3]. However, we wanted to determine which techniques would be the most insightful, interesting, and performant to implement for our project even though the readings pointed out a clear state-of-the-art.

We found from the conclusions of Lecun [1] that the k-Nearest Neighbors classifier would not only pose serious scaleability difficulties when it came to runtime and memory usage, but it would also be a comparatively unreliable classifier. We decided that it would be interesting to see just how difficult it would be to deal with the runtime and what kind of accuracy we could achieve with limited computation resources.

We also saw that according to Maji [2], "with improved features a low complexity classifier, in particular an additive-kernel SVM, can achieve state of the art performance." This inspired us to implement a support vector machine as a lightweight, high accuracy classifier.

4 Approach

4.1 Baselines

We used scikit-learn [6] to implement baselines for the k-NN classifier and the SVM. Even though scikit-learn is presumably optimized very well, these classifiers took a very long time to train and evaluate. As a result, we tuned hyperparameters with only 17% of our training data. Once we settled upon optimal hyper parameters, we trained the scikit-learn k-NN and SVM on 25% of the training set and evaluated them on the entirety of the test set.

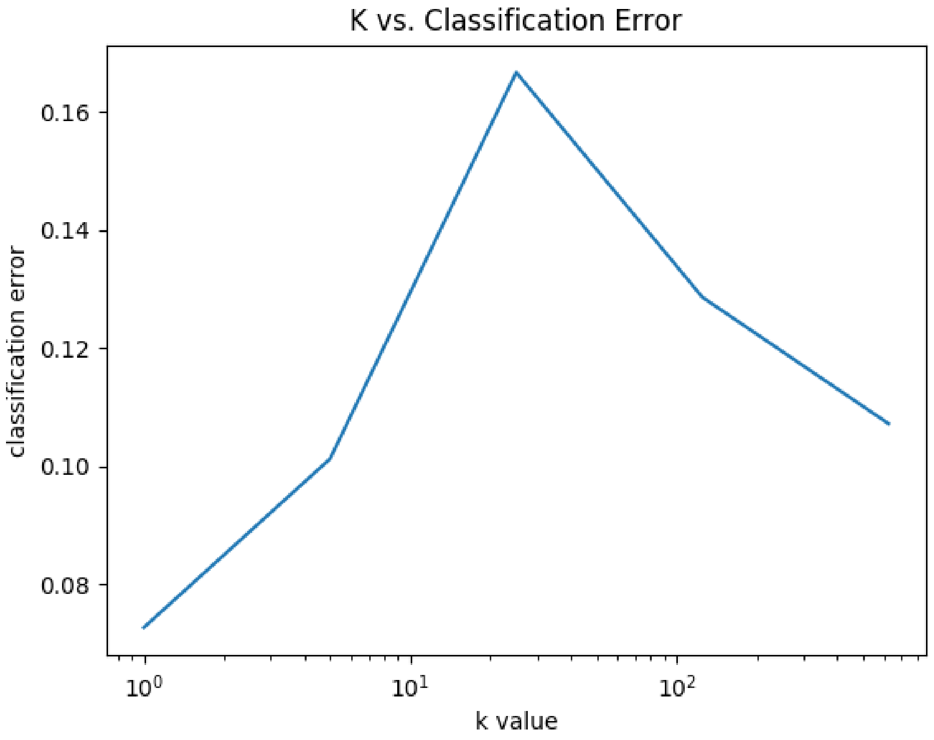
4.2 Evaluation

To tune hyperparameters, we used cross-validation with random 80-20 splits. We consistently report the validation errors from the cross-validation and the test error on the MNIST test set.

4.3 k-Nearest Neighbors

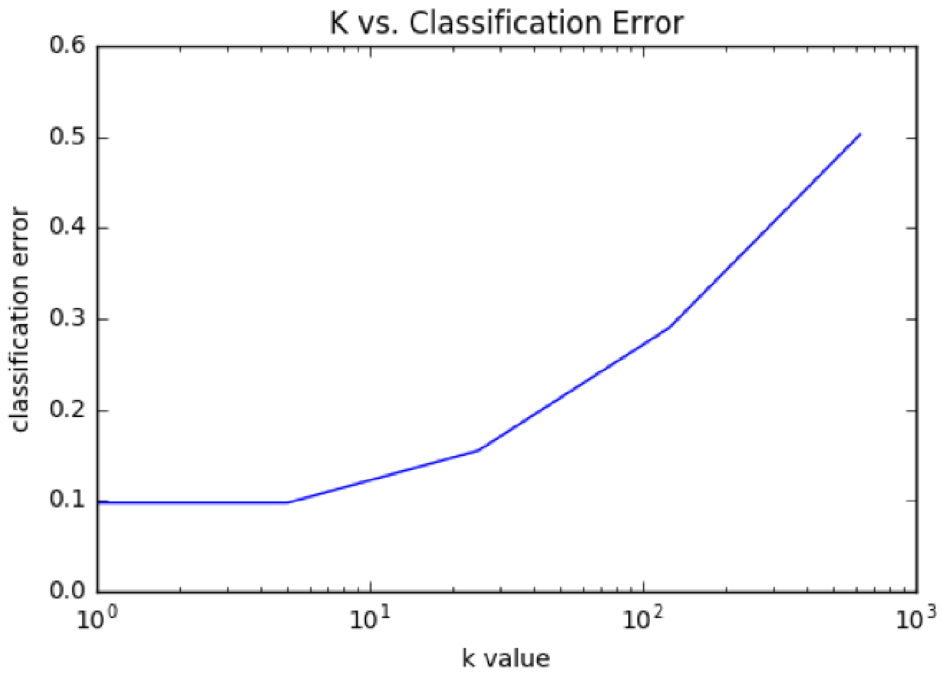
We implemented a k-nearest neighbors (k-NN) classifier using k-nearest neighbors regression. The first issue we ran into was the intractable runtime needed to run k-NN over the large training set of 60,000 images. Given runtime constraints, we ran the algorithm on 10% of the training set. For each value of k, we found the classification error on the validation set.

TODO these graphs say classification error when it should be VALIDATION error.

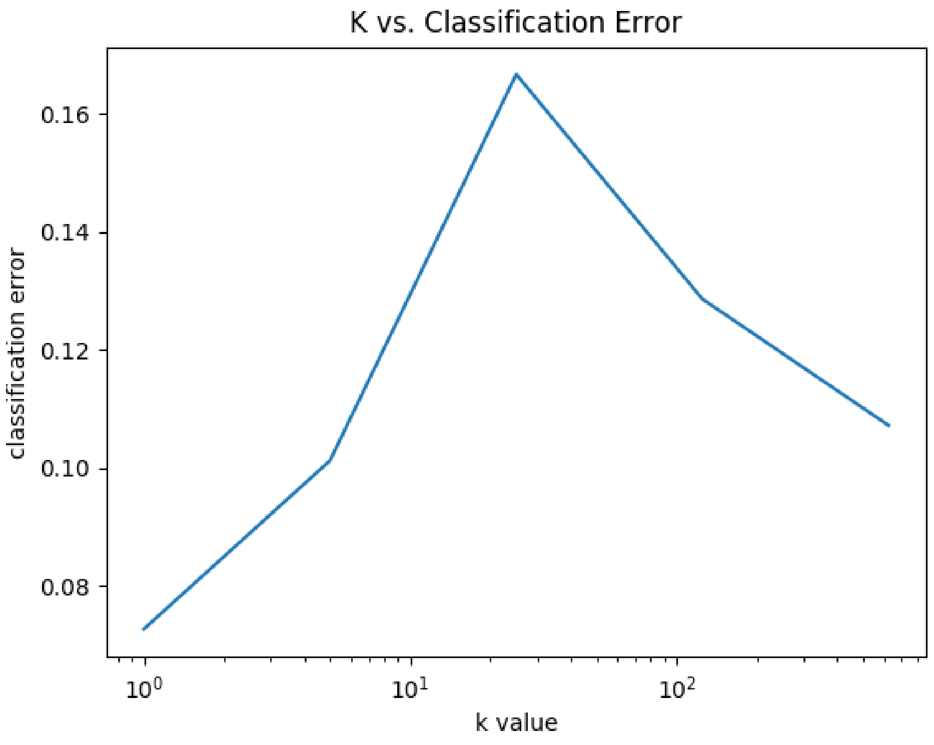


Surprisingly, we can see that with $k = 1$ we achieve the lowest classification error. This is most likely due to the lack of a kernel to weigh the points according to how far they are from the query. We would expect that as k increases, our classification error would decrase. However, without a proper kernel to weigh the data points, this is unlikely.

We first tackled nearest neighbor regression. For baselining, we used the scikit-learn NearestNeighbors functionality. Rather than choosing a particular nearest neighbors algorithm, we let scikit-learn decide which nearest neighbors algorithm to use after analysis of the training model. Algorithms available include brute force, the K-D tree, and Ball tree. The latter two trade precision off for efficiency by using heuristics to prune which points are considered when evaluating nearest neighbors. The decision on which algorithm to use is based on the number of samples, the structure of the data (e.g. sparsity, intrinsic dimensionality), the number of neighbors requested for a query point, and the number of query points. The baseline library ended up choosing the K-D tree algorithm because of the k values we cross validated over, and the one we ended up using for our final model, being less than N/2. We ran cross-validation over a small subset of our training set (1/10th of the training set). Running cross validation over a set of k values from 1 to 625, we found that a k of 1 minimized our validation error.



After running cross validation on our baseline, we implemented our own K-Nearest Neighbors algorithm. We used a brute force algorithm that scans every point in the training set to find the k neighbors with the lowest Euclidean distances from the query point. Then, amongst those k neighbors, we found the classification with the lowest average Euclidean distance from the query point. That classification was the classification wed assigned to the query point.

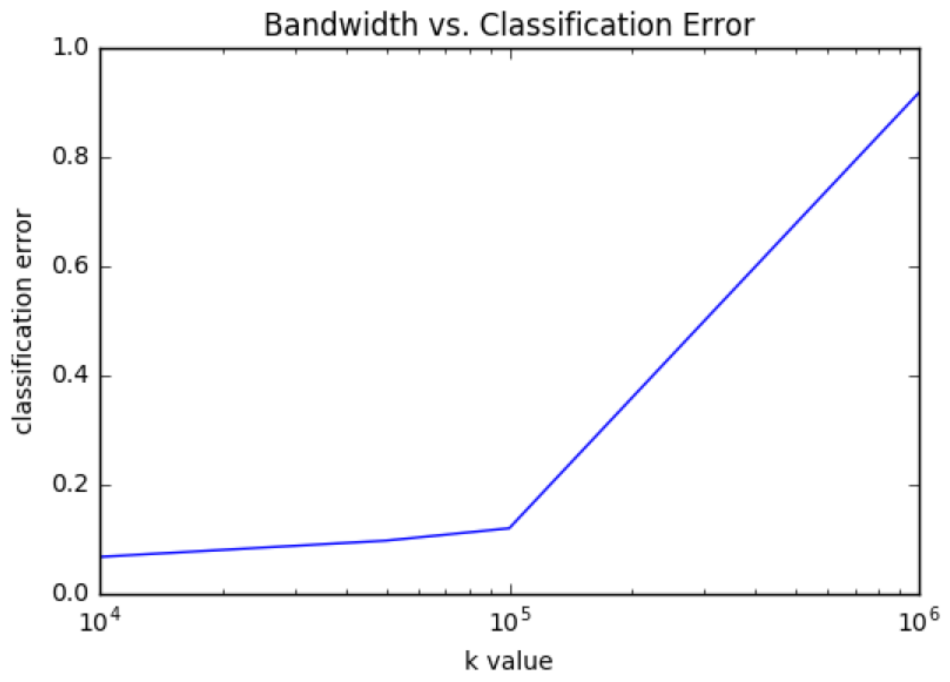


We ran cross-validation over a small subset of our training data (once again, 1/10th). The results backed up the results from the library implementation with a k of 1 minimizing our validation error. Afterwards, we implemented a Gaussian kernel and classified query points based off of the Nadaraya Watson Kernel Weighted Average. Instead of finding the k nearest neighbors to classify a query point, we used this Kernelized Regression to calculate the classification for each query point.

TODO include kernel formulation here

Since we didnt have to just find the k nearest neighbors, but instead iterated through every point and kernelized its distance as a weight to its classification, we had to tune our bandwidth value λ rather than a k. As a result of overflow and underflow errors, we could only test a range of bandwidths from 10^4 to 10^6.

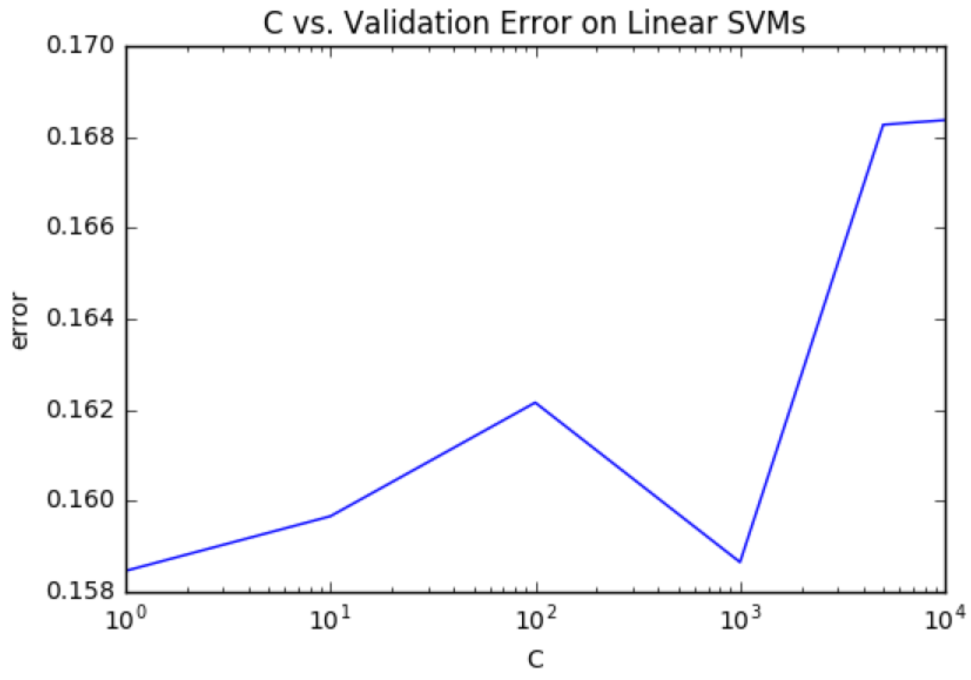
TODO this x-axis is mislablbed, it should be BANDWIDTH

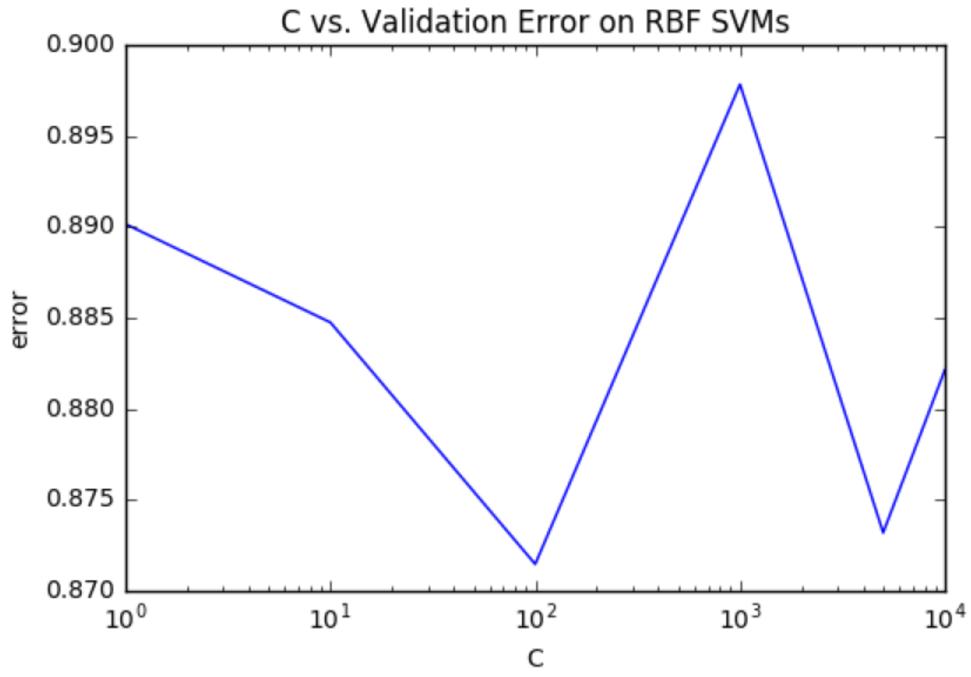


Running cross validation on 1/10th of our training set, we found that a bandwidth of 104 not only avoided overflow errors, it also minimized validation error.

4.4 SVM

We then tackled Support Vector Machines. For baselining, we used scikit-learns LinearSVC and SVC functionality. The former trains a Support Vector Machine until convergence with a Linear kernel, and the latter with a Radial Basis function kernel.





Running cross-validation for each C value over a small subset of the training set (10000 rows), we found that C values of 1 and 100 minimized validation error in the Linear and RBF SVMs respectively. This was surprising to us, especially the former C-value, and we suspected after some tinkering around that the differences in validation error can be ascribed to differences in the validation blocks data rather than differences in C value. Nonetheless, we used those respective C-values for creating our model against the the training data and running it against the test data.

4.5 CNN

TODO

5 Results

References

[1] LeCun, Yann, et al. ”Comparison of learning algorithms for handwritten digit recognition.” International conference on artificial neural networks. Vol. 60. 1995.

[2] Maji, Subhransu, and Jitendra Malik. ”Fast and accurate digit classification.” EECS Department, University of California, Berkeley, Tech. Rep. UCB/EECS-2009-159 (2009).

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