OBJECT CLASSIFICATION FOR AUTONOMOUS VEHICLE NAVIGATION

SJSU SAN JOSÉ STATE UNIVERSITY

Math 285 Final Project
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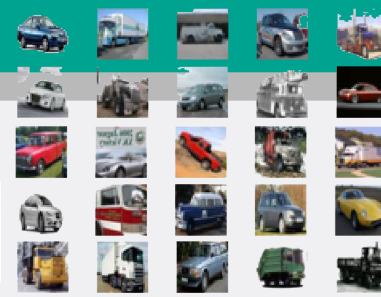


Introduction

* A lot of autonomous vehicles are equipped with on-board digital cameras to capture pictures (data) of objects on the roads;
* I implemented and compared the methods learned in this semester. The following classifiers yields some better results:

1. Principal Component Analysis (PCA)+Local kMeans
2. Random Forests
3. Principal Component Analysis (PCA) + Quadratic Discernment Analysis (QDA)
4. PCA + Support Vector Machine (SVM) with Gaussian Kernel + One vs. All Extension

Data

CIFAR 10: 32 x 32 pixels x 3 Layers (Red, Green & Blue); Color Images

	# of Classes	Data Size
Training	10	50000
Test	10	10000

Algorithm

The Algorithm:
PCA + Local kMeans

- Applied Principal component Analysis (PCA) to both of the training and test data
  - Input: data set $X = [x_1 \ldots x_n]^T \in R^{n\times d}$ and integer s (with $0 < s < d$)
  - Output: compressed data $Y \in R^{n\times s}$
  - Steps:
    - Center data: $\widetilde{\boldsymbol{X}} = [x_1 \ldots x_n]^T - [m \ldots m]^T$ where $\mathbf{m} = \frac{1}{n}\sum x_i$;
    - Perform Singular Value Decomposition (SVD): $\widetilde{\boldsymbol{X}} = \boldsymbol{U\Sigma V^T}$, where $\boldsymbol{U}$ consists of the eigenvectors of $\boldsymbol{XX^T} \in \boldsymbol{R^{n\times n}}$, V consists of the eigenvectors of $\boldsymbol{X^TX} \in \boldsymbol{R^{d\times d}}$, and $\boldsymbol{\Sigma}$ consists of the square roots of the eigenvalues of either matrix (and zero).
    - Return: $\boldsymbol{Y} = \widetilde{\boldsymbol{X}}\,\boldsymbol{V}(:,\mathbf{1}:\boldsymbol{s}) = \boldsymbol{U}(:,\mathbf{1}:\boldsymbol{s})\boldsymbol{\Sigma}(\mathbf{1}:\boldsymbol{s},\mathbf{1}:\boldsymbol{s})$, where s is the top number of principal components.
- Use the k nearest points in each class to represent the corresponding class
- Perform $k$means classification based on the reduced data
  - Assign labels to test images based on the most similar centers

$$\hat{y} = argmin_y dist(\mathbf{x}, C_y)$$

in which $dist(x, C_y)$ represents the distance from a test point $\mathbf{x}$ to a training class C_y.

The Algorithm:
Random Forests

- Build a classification tree on a separate bootstrap sample of the training data
  - Bootstrap sample: random sample with replacement
- Every tree in the ensemble to randomly select features of the training data for its nodes

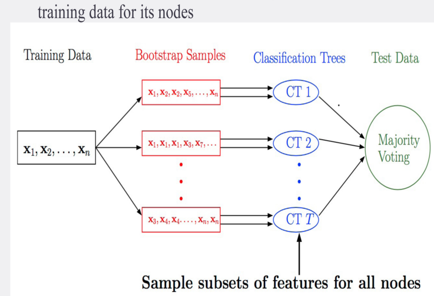


Photo Credit: Chen, Guangliang. "Lecture 8: Classification trees and ensemble learning". Math 285 – Spring 2016

The Algorithm:
PCA + QDA

- Applied Principal component Analysis (PCA) to both of the training and test data as usual
- Applied Quadratic Discriminant Analysis (QDA) classifier to the training data:
  - Model the distribution of each training class C_i by a pdf $f_i(\mathbf{x})$, and assign the label based on the posterior probability

$$i^* = argmax_i f_i(\mathbf{x})\pi_i;$$

  - For QDA, we use multivariate Gaussian distributions to estimate $f_i(\mathbf{x})$.

The Algorithm:
PCA + SVM Kernel + One vs. All

- Applied PCA to the training and test data as usual
- Construct the classifier for each class against the rest of training set
  - The "most clearly winning" class is adopted as the final prediction
- Applied SVM with Gaussian kernel
  - Solve the following quadratic program

$$\max_{\lambda_1,\ldots,\lambda_n} \sum_i \lambda_i - \frac{1}{2}\sum_{i,j} \lambda_i\lambda_j y_i y_j k(\mathbf{x_i}, \mathbf{x_j})$$

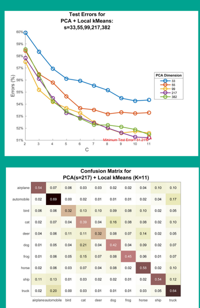
subject to $0 \le \lambda_i \le 0$ and $\sum \lambda_i y_i = 0$
where $k(\mathbf{x_i}, \mathbf{x_j})$ is the Gaussian kernel function

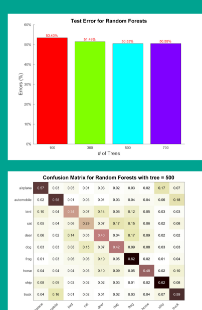
  - Classify new data $\mathbf{x}$ based on the following decision rule:

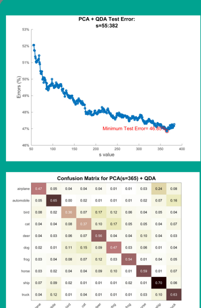
$$y = sgn(\sum \lambda_i y_i k(\mathbf{x_i}, \mathbf{x}) + b)$$

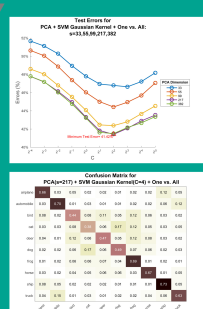
where b can be determined from any support vector with $0 \le \lambda_i \le C$.

Results









The Best Results from This Project

Test Error	Method
51.21%	PCA(s=217)+Local kMeans(k=11)
50.03%	Random Forests with tree = 500
46.85%	PCA(s=365)+QDA
41.42%	PCA(s=217)+SVM Gaussian Kernel(C=4)+One vs. All

Conclusions

- PCA + SVM method produces the lowest test error rate but the computation time is the longest
- Test Error is relatively high by using methods learned from this semester;
- The CIFAR 10 data only contains low resolution pictures;
- Should collect my own photos as test data in future studies.

Some outstanding research results

Test Error	Method
21.14%	Enhanced Image Classification With a Fast-Learning Shallow Convolutional Neural Network
20.40%	An Analysis of Single-Layer Networks in Unsupervised Feature Learning
17.82%	Convolutional kernel Network
3.46%	Fractional Max-Pooling

References

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