Master Thesis

A Library for Fast Kernel Expansions with Applications to Computer Vision and Deep Learning

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Outline

Introduction

Description

- Time period: 26th May 2014 - 5th December 2014
- Carnegie Mellon
- Location: Pittsburgh, Pennsylvania
- Office 8018, GATES HILLMAN Center
- School of Computer Science
  ML Department

- Advisor at City University of Hong Kong: **C. W. Ngo**

Motivation

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- Explore the limitations of traditional Computer Vision
- Study novel techniques to accelerate learning in Large-scale Machine Learning: Fast Kernel Expansions
- Implement a library fast and easy-to-use
- Supplement with applications to Computer Vision and Deep Learning

Traditional Computer Vision

- Building our own dataset: Exploiting Flickr
- Getting the labels: AMTurk
- Feature extraction: LBP Handcrafted Features around Landmark Facial Points
- Preprocessing step: Gamma Correction, Filter DoG and Contrast Equalization
- Classification: SVM Linear
- K-Fold Crossvalidation

AMTurk

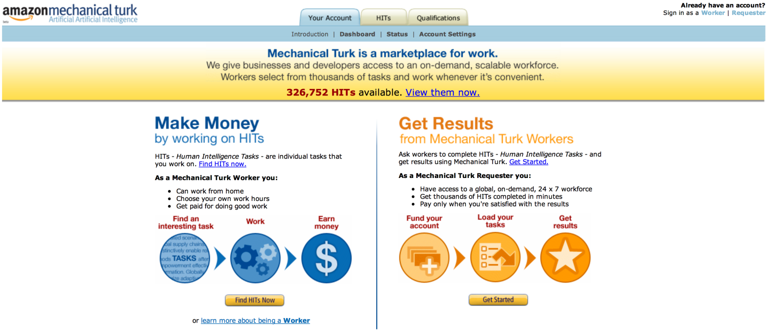


Figure: AMTurk

Local Binary Patterns

Detect Facial Points using Supervised Descend [Xiong and De La Torre 2013] and then extract LBP Features around them

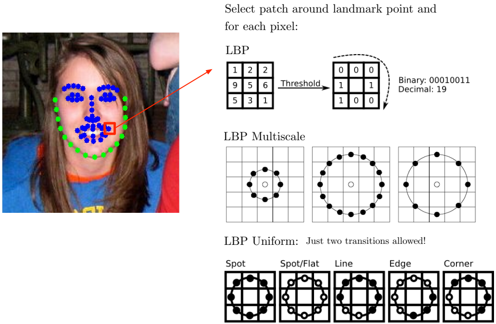


Figure: LBP

Local Binary Patterns

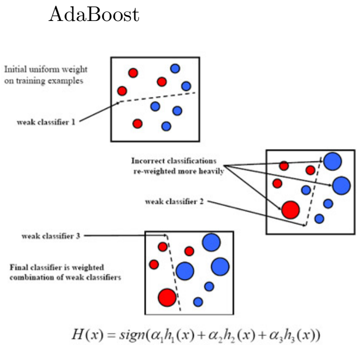
LBP Features

- LBP
- ULBP: less memory and computational time
- ULBP Multiscale: use of different radius to extract local and global information

Performance improvement using a preprocessing step

Classifier

1. AdaBoost



2. SVM Linear and non-Linear

Support Vector Machines

SVM Linear SVM Kernel

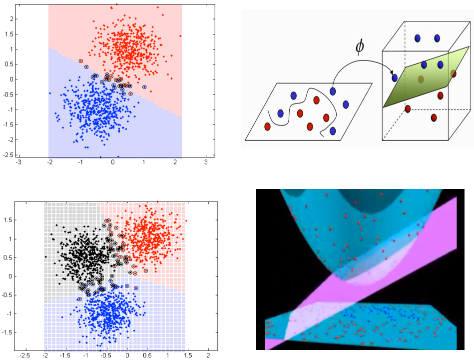
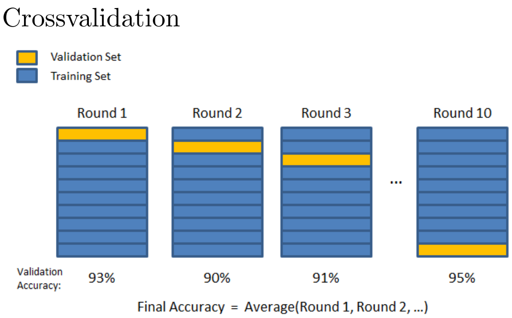


Figure: SVM

Crossvalidation

Color Space, LBP parameters (radius, neighbors, patch size) and weak learners (AdaBoost)



Best Results

Color space	RGB	LUV	YCrCb	HSV
Accuracy (%)	77.4983	78.1971	78.2669	81.4116

Table: Color space K-Fold crossvalidation applied to classification of ethnicity

Test Explanation	Accuracy achieved (%)
ULBP, SVM Linear	77.71
ULBP Multiscale(3), SVM Linear	78.27
ULBP Multiscale(3), SVM Linear, HSV	81.42
ULBP Multiscale(3), SVM Linear, HSV, preprocessing	82.36
ULBP Multiscale(3), SVM Linear, HSV, optimized preprocessing	85.02

Table: Experimental Results System of Ethnicity

Drawbacks and Solutions

Drawbacks

- SVM non-linear entangles high cost in training step
- SVM not recommended for large datasets ($>$ 50.000 instances)

Solutions

- Use Random Features to leverage learned training parameters
- Le et al propose Fastfood

Fast Kernel Expansions: Randomized Features

In Random Kitchen Sinks instead of computing RBF GAUSSIAN Kernel

$$k(x, x') = \exp(-||x - x'||^2/(2\sigma^2))$$

the method computes

$$k(x, x') = \exp(i[Zx]_c)$$

where z_c is drawn from a random distribution normal.
In Le et al Z is parametrized by V as

$$V := \frac{1}{\sigma\sqrt{d}} SHG\Pi HB$$

McKernel

Characteristics

- API following a design in Factory.
- Distributed-oriented version: Pseudo-random Numbers are generated using hash functions, no need to re-compute the matrices.
- Optimized library: cache-friendly code, unrolled loops, SIMD Intel Intrinsics for vectorized operations and in-place routines.

$$V := \frac{1}{\sigma\sqrt{d}} SHG\Pi HB$$

where

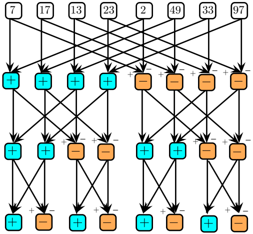
- B entries 1 and -1.
- H Walsh Hadamard. FWH maximizing cache hits and CPU performance. SIMD Intel Intrinsics.

Defining the 1×1 Hadamard by the identity $H_0 = 1$, then $\forall m > 0$, H_m is defined as:

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix}$$

and for $m > 1$ we have

$$H_m = H_1 \otimes H_{m-1}$$



McKernel

- Π permutation matrix using Fisher-Yates ($O(n)$).
- G entries following distribution Normal $N(0,1)$.
  Distributed-oriented version: BOX MULLER Transform

$$P_{cz} = (-2\log h_1(c,z)/N)^{1/2}\cos(2\pi h_2(c,z)/N)$$

- S entries random numbers chi with d degrees of freedom.
  Distributed version: Approximation by Wilson and Hilferty

$$\chi_d^2 = d\left(\sqrt{\frac{2}{9d}}z + \left(1 - \frac{2}{9d}\right)\right)^3$$

Benchmarks

The experiments have been done using an Intel Core i5-4200 CPU @ 1.60 GHz machine. The results have been computed averaging the time performance of 300 random float vectors for each given length.

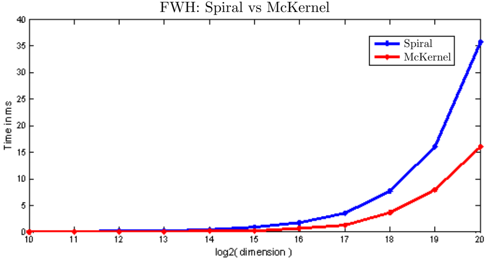


Figure: Comparison between Spiral and McKernel

Application to Computer Vision

The feature map for McKernel is defined as:

$$\phi_c(x) = n^{-\frac{1}{2}} \exp(i[Vx]_c)$$

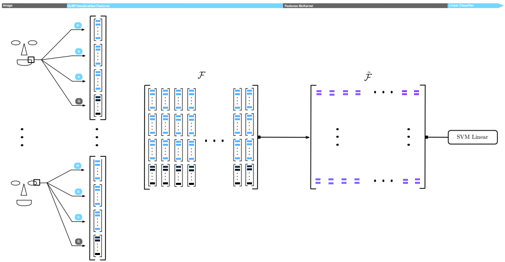
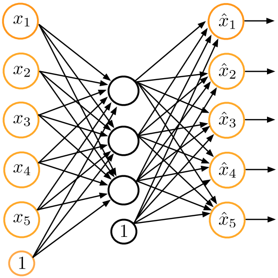


Figure: McKernel embedded in a System for Classification of Ethnicity.

Application to Deep Learning

Autoencoders

Extract the internal representation of the data by applying back propagation and setting $y_{(z)} = x_{(z)}$.



Stacked Autoencoders: Multiple layers of Sparse Autoencoders.

Multi-layer Neural Network

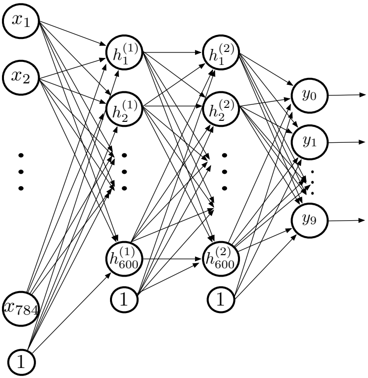


Figure: Multi-layer Neural Network

Applications to Deep Learning

Code Highlights:

- MNIST Loading
- Implement function to compute the cost function and gradients for the sparse autoencoder, logistic regression and overall deep network.
- Implement the functions to check gradients are well computed.
- Train autoencoder layers and softmax regression.
- Fine-tune the network by backpropagation.

Where does McKernel fit in?

We use McKernel as a non-linear mapping to the activation function.

Results

MNIST Average Accuracy 96.31 %
3 % Improvement just by wiring McKernel.
Additional gain by enlarging the number of Kernel Expansions.

Conclusions

Achievements

- C&Z Dataset
- SIMD FWH that performs better than current state-of-the-art libraries (Spiral)
- Fast Implementation of Approximate Kernel Expansions. Library McKernel
- McKernel embedded in a System for Estimation of Ethnicity
- McKernel wired in Deep Learning

Thank you

ZARZA I CUBERO Irene

Thank you

Warm thank you to all the people at the ML Department, Robotics and Carnegie Mellon that made this possible. Thanks to Dr. C. W. Ngo. A heartfelt thanks to Dr. C. F. Chan, T. Chow and S. Tsui.