Master Thesis

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

H. C. Zarza

zarza@cmu.edu

http://www.andrew.cmu.edu/user/zarza/

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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.

Motivation

Motivation

- 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

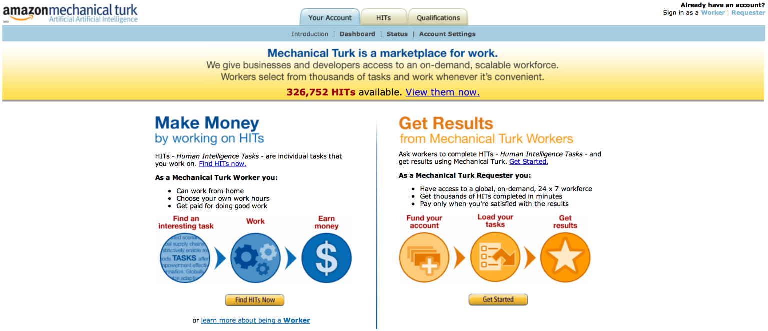


Figure: AMTurk.

Local Binary Patterns

Detect facial points using Supervised Descend (Xiong and De La Torre 2013) and then extract LBP Features around them.

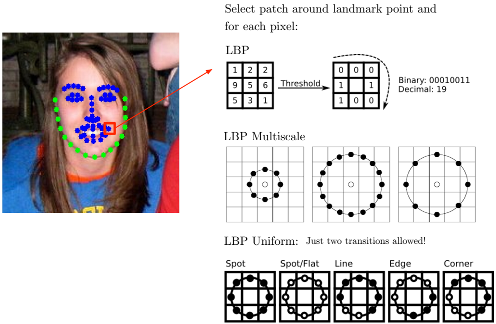


Figure: LBP.

Local Binary Patterns

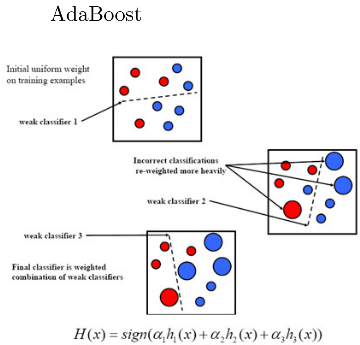
LBP Features:

- 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

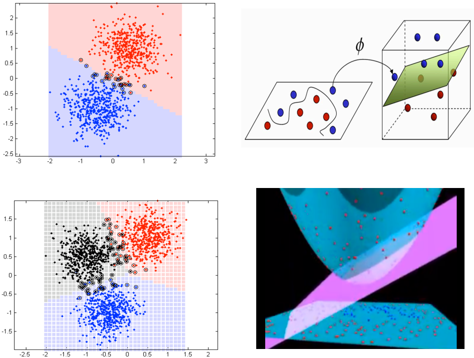
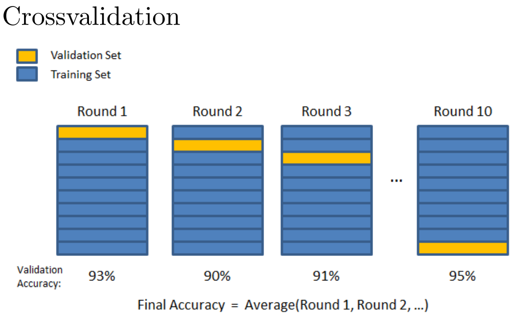


Figure: SVM.

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. 2013) 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. 2013) 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

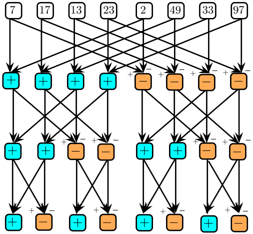
- B entries 1 and -1.
- H Walsh Hadamard. FWH maximizing cache hits and CPU performance. SIMD Intel Intrinsics.

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 matrix of permutation using Fisher-Yates ($O(n)$).
- G entries following distribution Normal $N(0,1)$.
  Distributed-oriented version: BOX MULLER Transform (Box and Muller 1958)

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

- S entries random numbers Chi with d degrees of freedom.
  Distributed version: approximation by (Wilson and Hilferty 1931)

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

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.

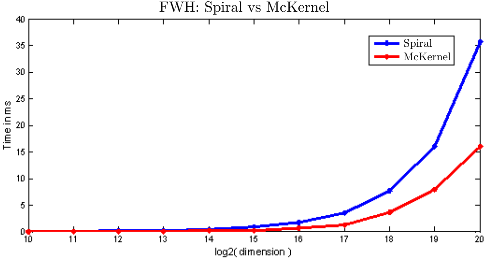


Figure: Comparison between Spiral and McKernel.

Application to Computer Vision

The mapping of features for McKernel is defined as:

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

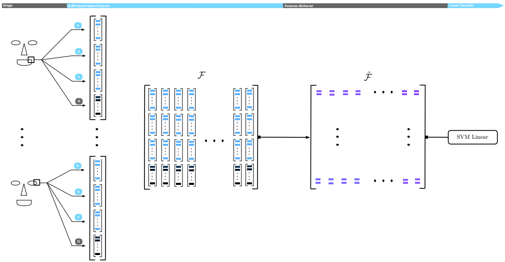
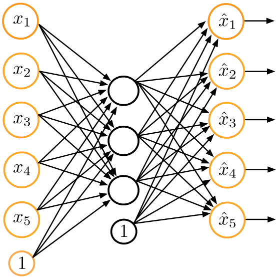


Figure: McKernel Embedded in a System for Classification of Ethnicity.

Application to Deep Learning

Autoencoders

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



Stacked Autoencoders: Multiple Layers of Sparse Autoencoders.

Multi-layer Neural Network

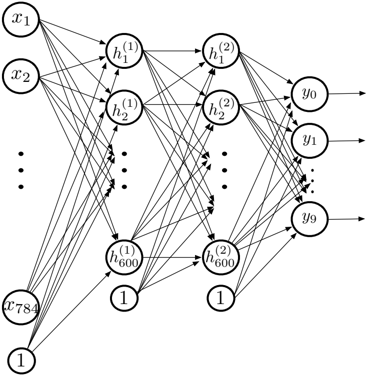


Figure: Multi-layer Neural Network.

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

DE 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.