

# Master Thesis

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

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# Outline

Motivation

C&Z Dataset

Fast Kernel Expansions: Randomized Features

McKernel

Applications

Conclusions

# 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.
- Extraction of features: LBP Handcrafted Features around landmark facial points.
- Step of preprocessing: gamma correction, filter DoG and contrast equalization.
- Classification: SVM Linear.
- K-fold crossvalidation.

# AMTurk

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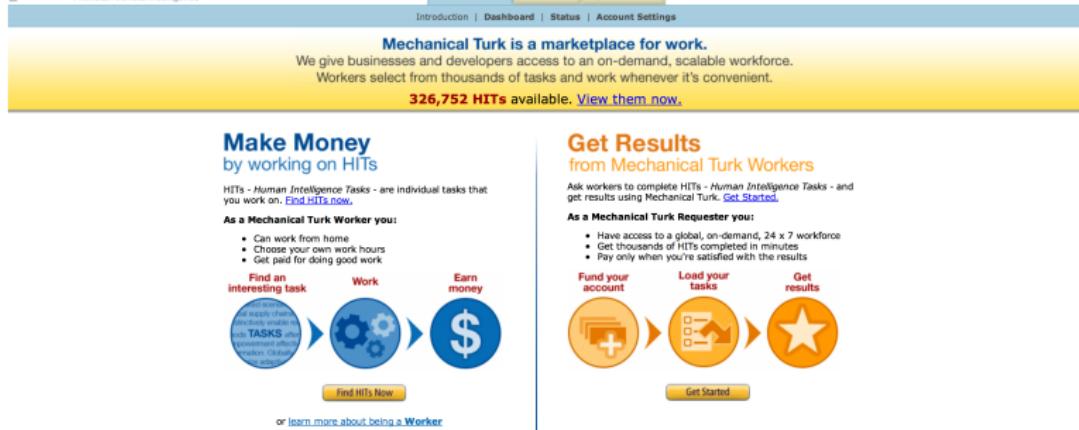


Figure: AMTurk.

# Local Binary Patterns

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

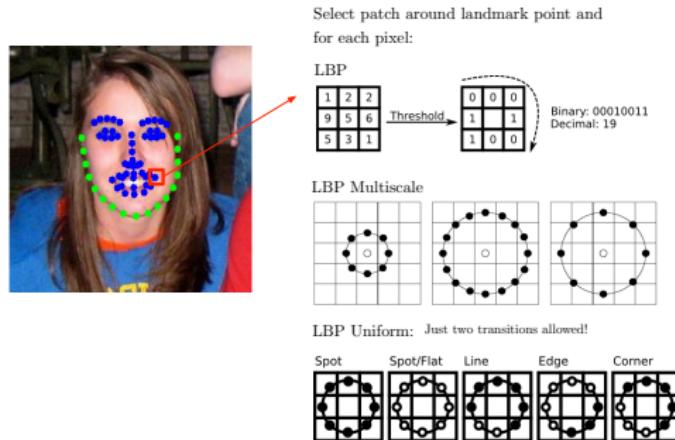


Figure: LBP.

# Local Binary Patterns

## LBP Features:

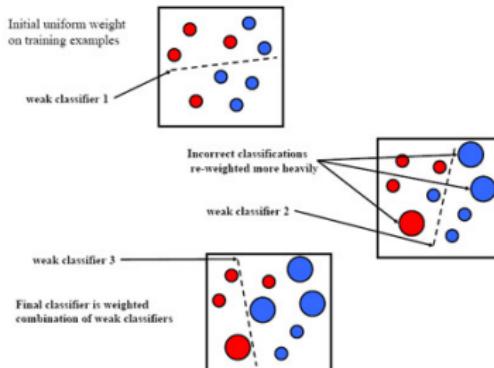
- LBP.
- ULBP: less memory and computational time.
- ULBP Multiscale: use of different radius to extract local and global information.

**Improvement in the performance using a step of preprocessing.**

# Classifier

## 1. AdaBoost.

AdaBoost

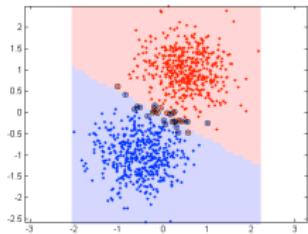


$$H(x) = \text{sign}(\alpha_1 h_1(x) + \alpha_2 h_2(x) + \alpha_3 h_3(x))$$

## 2. SVM Linear and Non-linear.

# Support Vector Machines

SVM Linear



SVM Kernel

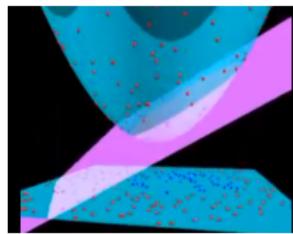
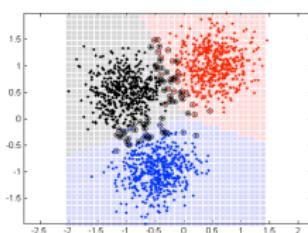
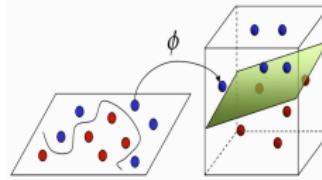
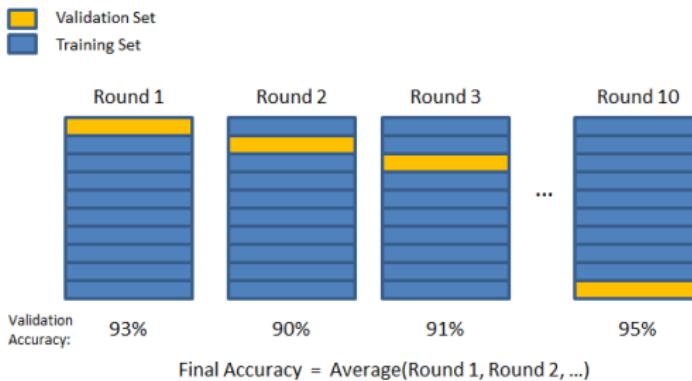


Figure: SVM.

# Crossvalidation

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

## Crossvalidation



# 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.

	Accuracy (%)
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 is 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

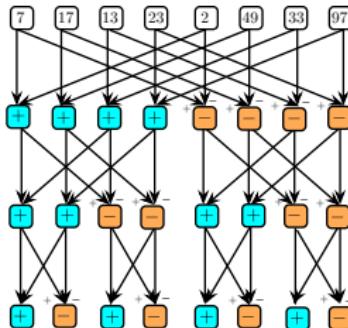
- $B$  entries 1 and -1.
- $H$  Walsh Hadamard. FWH maximizing cache hits and CPU performance. SIMD Intel Intrinsics.

Defining the  $1 \times 1$  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

- $\Pi$  matrix of permutation using Fisher Yates ( $O(n)$ ).
- $G$  entries follow distribution Normal  $N(0, 1)$ .

Distributed-oriented version: BOX MULLER Transform (Box and Muller 1958)

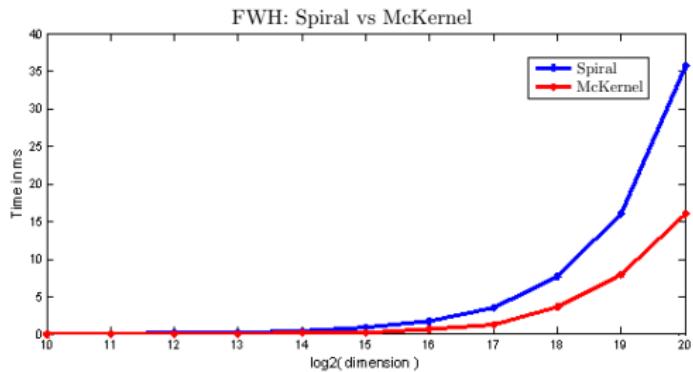
$$P_{cz} = (-2 \log h_1(c, z)/N)^{1/2} \cos(2\pi h_2(c, z)/N).$$

- $S$  entries are random numbers Chi with  $d$  degrees of freedom.  
Distributed version: approximation by (Wilson and Hylferty 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. The results have been computed averaging the time performance of 300 random vectors float for each given length.

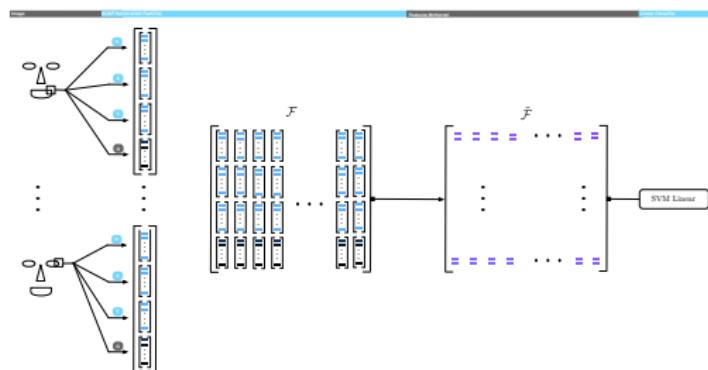


**Figure:** Comparison between Spiral and McKernel.

# Application to Computer Vision

The mapping of features for McKernel is defined as:

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

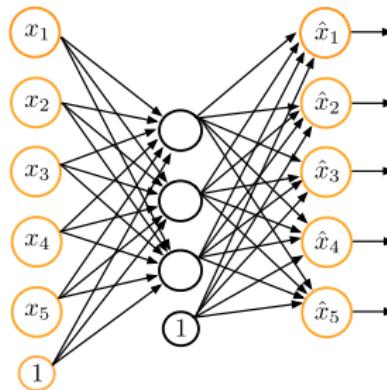


**Figure:** McKernel Embedded in a System for Classification of Ethnicity.

# Application to Deep Learning

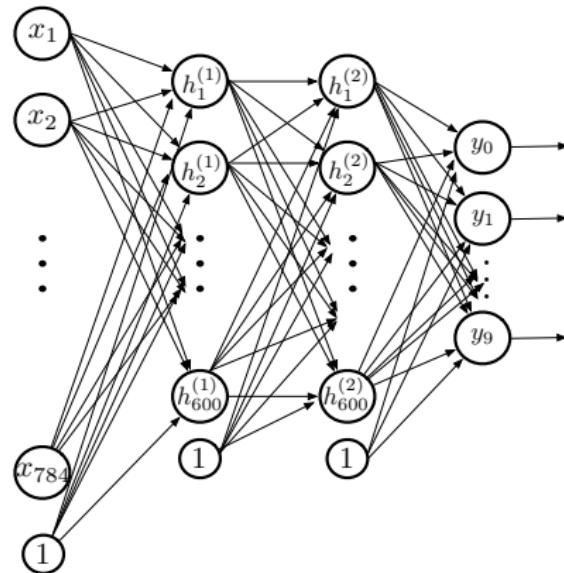
## Autoencoders

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

## Highlights of the Code:

- MNIST Loading.
- Implemented function to compute the risk and gradients for the sparse autoencoder, logistic regression and overall deep network.
- Implemented functions to check gradients are well computed.
- Train layers of the autoencoder 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.