# THE UNIVERSITY OF TEXAS AT AUSTIN College of Natural Sciences

# Anna Panyu Peng, Department of Mathematics and Computer Science /CNS, ICES panyuanna@gmail.com

## Background

Dual coordinate descent method is a classic and effective optimization technique for solving empirical risk minimization problems such as Linear SVM where number of data and features are large i.e. text classification<sup>1</sup>. Several papers have studied specific implementations of the method i.e. stochastic DCD<sup>2</sup> or adaptive DCD where parallel techniques are exploited to reduce time complexity. Few have studied greedy DCD back then on a single machine. As I found out that when solving kernel SVM, computing kernel matrix is too slow so is convergence rate of objective function, I was motivated to parallelize greedy DCD in a multi-core shared memory

setting.

- Comparisons (Latest Version Used) DCDL1: Dual coordinate descent (DCDL1-S: with
- Pegasos [Shalev-Shwartz et al., 2007]: stochastic
- SVM<sup>perf</sup> [Joachims, 2006]: cutting plane
- DCDL2: Dual coordinate descent (DCDL2-S: with
- PCD [Chang et al., 2008]: Primal coordinate RON [Lin et al., 2007]: Newton method



### **Research Questions**

I am parallelizing greedy DCD for kernel SVM. Since DCD embeds the sequential idea in it, when deliberately paralleled, several obstacles confronted:

- How to partition gradient of objective function
- How to avoid conflict write
- How to load dense kernel matrix
- How to prove convergence of new algorithm

## **Methods and Materials**

- Parallel Paradigm: Open Multi-Processing in C++
- Partition method: Even partition of the vector of gradient of objective function into number of threads
- Kernel selection: Gaussian/RBF kernel:  $K(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$
- Atomic: Apply atomic operation for gradient update:





# **Parallel ASynchronous Greedy** dual Coordinate Descent



- parallel method
- fast algorithm

# Austin

The Institute for Computational Engineering and Sciences (ICES), University of Texas at Austin **Department of Mathematics and Computer Science/ CNS,** University of Texas at Austin

1. Kai-Wei Chang, C.-J. Hsieh, C.-J. Lin, S. S. Keerthi, and S. Sundararajan A Dual Coordinate Descent Method for Large-scale Linear SVM. ICML, 2008 2. Cho-Jui Hsieh, Hsiang-Fu Yu, Inderjit S. Dhillon PASSCoDe: Parallel ASynchronous Stochastic dual Co-ordinate Descent. ICML, 2015

# **# of Threads vs. Speedup**

## **Future Directions**

Preliminary outcomes point out further work:

As observed from the results, four-thread

convergence rate is only approximately 10% faster

than single thread, which is incoherent with speedup.

So I need to accelerate the convergence rate of the

To provide theoretical guarantee and analysis of our

## Acknowledgments

Inderjit S. Dhillon, Director, Center for Big Data Analytics, Department of Computer Science, University of Texas at Austin **Cho-Jui Hsieh, Professor, UC Davis; Ph.D, University of Texas at** 

### References