

Parallel Dual Coordinate Descent Method for Large-scale Linear Classification in Multi-core Environments



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Introduction

- Dual coordinate descent (CD) method is one of the most effective approaches for large-scale linear classification (e.g., linear SVM).
- However, its **sequential** design makes the parallelization difficult.
- In this work,
 - We investigate **multi-core dual CD** methods for linear classification.
 - We propose a new framework to parallelize dual CD and establish its **theoretical convergence properties**.
- Further, we demonstrate through experiments that the method is robust and efficient.

Formulations

- Given training data $(\mathbf{x}_i, y_i) \in \mathcal{R}^n \times \{-1, 1\}$, $i = 1, \dots, l$.
- Linear classification obtains its model vector \mathbf{w} by solving:

$$\min_{\mathbf{w}} \frac{1}{2} \mathbf{w}^T \mathbf{w} + CL(\mathbf{w}) \quad (1)$$

$$\text{where } L(\mathbf{w}) = \sum_{i=1}^l \xi(\mathbf{w}; \mathbf{x}_i, y_i). \quad (2)$$

Eq. (2) is the loss function, and two losses are considered:

$$\xi(\mathbf{w}; \mathbf{x}_i, y_i) \equiv \begin{cases} \max(0, 1 - y_i \mathbf{w}^T \mathbf{x}_i) & \text{L1-loss SVM,} \\ \max(0, 1 - y_i \mathbf{w}^T \mathbf{x}_i)^2 & \text{L2-loss SVM.} \end{cases}$$

- If (1) is referred to as the primal problem, then a dual CD method solves the following dual problem:

$$\min_{\alpha} \frac{1}{2} \alpha^T \bar{Q} \alpha - \sum_{i=1}^l \alpha_i$$

subject to $0 \leq \alpha_i \leq U, \forall i = 1, \dots, l$,

where $\bar{Q} = Q + D$ with $Q_{ij} = y_i y_j \mathbf{x}_i^T \mathbf{x}_j$, and D is diagonal with

$$D_{ii} = \begin{cases} 0 & \text{for L1-loss SVM,} \\ \frac{1}{2C} & \text{for L2-loss SVM.} \end{cases}$$

- Each time an α_i is selected and a one-variable subproblem is solved:

$$\min_d f(\alpha + d e_i) \text{ subject to } 0 \leq \alpha_i + d \leq U, \quad (3)$$

where $e_i = [\underbrace{0, \dots, 0}_{i-1}, 1, 0, \dots, 0]^T$. Clearly,

$$f(\alpha + d e_i) = \frac{1}{2} \bar{Q}_{ii} d^2 + \nabla_i f(\alpha) d + \text{constant}.$$

The solution of (3) can be easily seen as

$$d = \min \left(\max \left(\alpha_i - \frac{\nabla_i f(\alpha)}{\bar{Q}_{ii}}, 0 \right), U \right) - \alpha_i.$$

- A crucial observation in Hsieh et al. [2008] notes that if

$$\mathbf{w} \equiv \sum_{j=1}^l y_j \alpha_j \mathbf{x}_j \quad (4)$$

is maintained, then $\nabla_i f(\alpha)$ can be easily calculated by

$$\begin{aligned} \nabla_i f(\alpha) &= (\bar{Q} \alpha)_i - 1 = \sum_{j=1}^l \bar{Q}_{ij} \alpha_j - 1 \\ &= y_i \mathbf{w}^T \mathbf{x}_i - 1 + D_{ii} \alpha_i. \end{aligned} \quad (5)$$

We can then update α and maintain the weighted sum in (4) by

$$\alpha_i \leftarrow \alpha_i + d \quad \text{and} \quad \mathbf{w} \leftarrow \mathbf{w} + d y_i \mathbf{x}_i. \quad (6)$$

- The main computation for updating an α_i includes two $O(n)$ operations in (5) and (6).
- Unfortunately, the procedure is inherently **sequential**.

A Practical Implementation for Dual CD

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1: Specify a feasible  $\alpha$  and calculate  $\mathbf{w} = \sum_j y_j \alpha_j \mathbf{x}_j$ 
2: while true do
3:   for  $i = 1, \dots, l$  do
4:      $G \leftarrow y_i \mathbf{w}^T \mathbf{x}_i - 1 + D_{ii} \alpha_i$   $\triangleq O(n)$ 
5:      $PG \text{ (proj. grad.)} = \begin{cases} G & \text{if } 0 < \alpha_i < U, \\ \min(0, G) & \text{if } \alpha_i = 0, \\ \max(0, G) & \text{if } \alpha_i = U. \end{cases}$ 
6:     if  $|PG| \geq 10^{-12}$  then
7:        $d \leftarrow \min(\max(\alpha_i - G/\bar{Q}_{ii}, 0), U) - \alpha_i$ 
8:        $\alpha_i \leftarrow \alpha_i + d$ 
9:        $\mathbf{w} \leftarrow \mathbf{w} + d y_i \mathbf{x}_i$   $\triangleq O(n)$ 

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Existing Works: Mini-batch Dual CD

- Instead of running through $i = 1, \dots, l$ in line 3 one by one, run a batch of i in parallel.
- For convergence, the step size d in line 7 is scaled down

$$\alpha_i \leftarrow \alpha_i + \beta d, \text{ where } \beta < 1$$

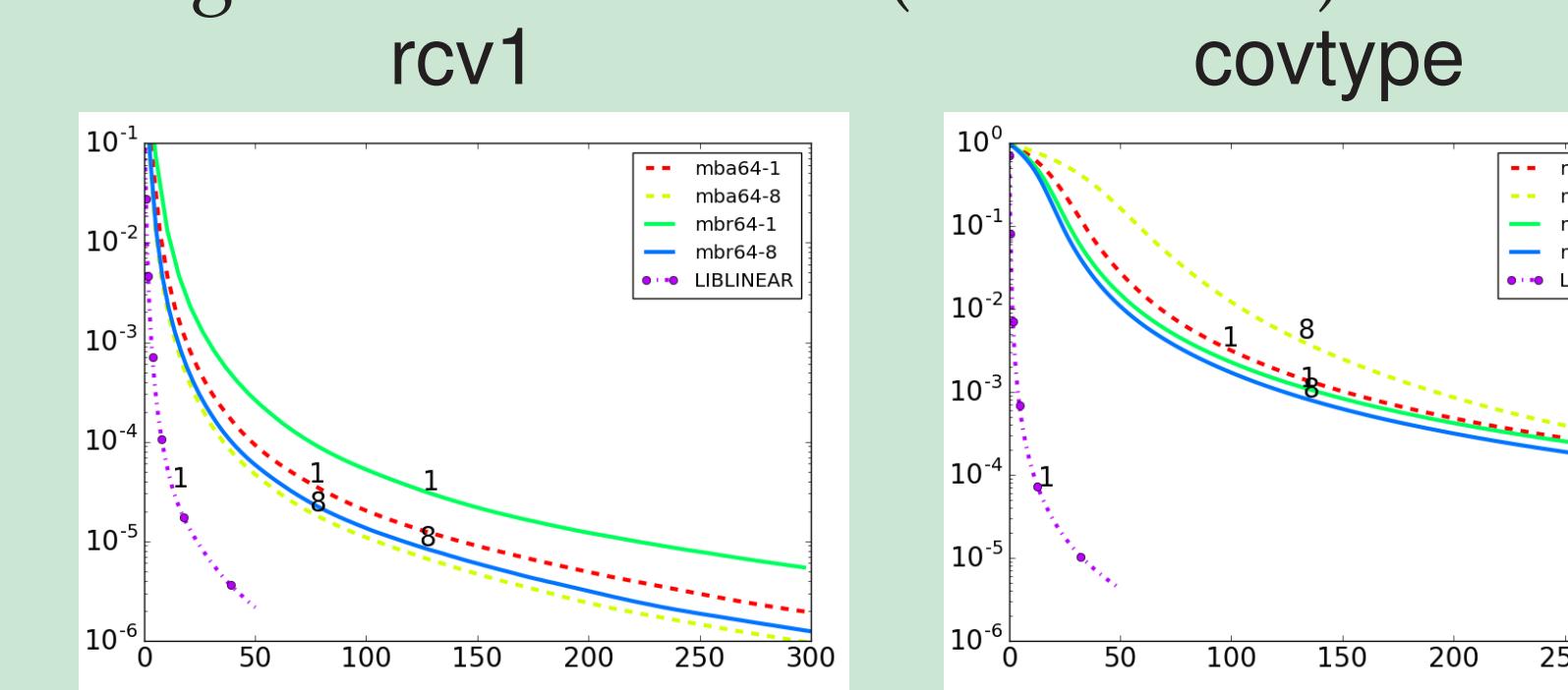
Takáč et al. [2015] discussed the condition of β and proved the convergence with suitable β .

- However, using conservative steps may cause **slower convergence**.
- In line 9, race conditions occur for multi-threading.

$$\mathbf{w} \leftarrow \mathbf{w} + \sum_{i \text{ in a batch}} d_i y_i \mathbf{x}_i \quad (7)$$

Lee et al. [2015] detailed study this issue in a multi-core Newton method. They consider atomic and reduce operations.

- However, even with careful settings, the overhead of (7) is significant because of the small batch size.
- A simple comparison between parallel mini-batch CD and single-thread dual CD (LIBLINEAR)



- Therefore, we may give up parallelizing (7) in multi-core environments.

Existing Works: Asynchronous Dual CD

- To address the slow convergence of mini-batch CD, Hsieh et al. [2015] and Tran et al. [2015] parallelize the for loop (line 3) so each thread updates α_i **asynchronously**. For line 9, \mathbf{w} can be updated by **atomic operations**.

- Since the processors are running concurrently, \mathbf{w} may change between the start (line 4) and the end (line 9) of one CD step.

- For convergence, the iteration lag τ is the key variable for analysis. Specifically, the sequence $\{\alpha^k\}$ should satisfy

$$k \leq \bar{k} + \tau$$

where \bar{k} is the iteration index when iteration k starts.

- The iteration lag τ must satisfy some conditions. However, the conditions may not hold, so asynchronous CD **may diverge**.

Our Idea and Design

- For convergence, we don't use asynchronous updates.
- We sequentially update \mathbf{w} due to the race condition in (7). However, we ensure that this takes a **small portion** while others are **parallelizable**.

Proposed Parallel Dual CD Method

- In CD a selected α_i may not need to be updated. After calculating $\nabla_i f(\alpha)$, we know if that's the case in line 6. Practically we have

$$\underbrace{\alpha_1^k, \dots, \alpha_{i-1}^k}_{\text{unchanged}}, \underbrace{\alpha_{i+1}^k, \dots, \alpha_{j-1}^k}_{\text{unchanged}}, \underbrace{\alpha_j^k, \dots, \alpha_{j+1}^k, \dots}_{\text{unchanged}}$$

- If we know α_i^k is unchanged, then $\nabla_i f(\alpha)$ doesn't need to be calculated.

- Idea: a setting to guess that some α_i are unchanged
 - Calculate $\nabla_i f(\alpha), \forall i \in \bar{B}$ **in parallel**.
 - Select a **much smaller** subset B from \bar{B} to do **sequential** CD updates.

That is, we conjecture $\alpha_i, i \in \bar{B} \setminus B$ need not be updated.

- A new framework:

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1: while true do
2:   Select a set  $\bar{B}$ 
3:   Calculate  $\nabla_{\bar{B}} f(\alpha)$  in parallel
4:   Select  $B \subset \bar{B}$  with  $|B| \ll |\bar{B}|$ 
5:   Sequentially update  $\alpha_i, i \in B$ 

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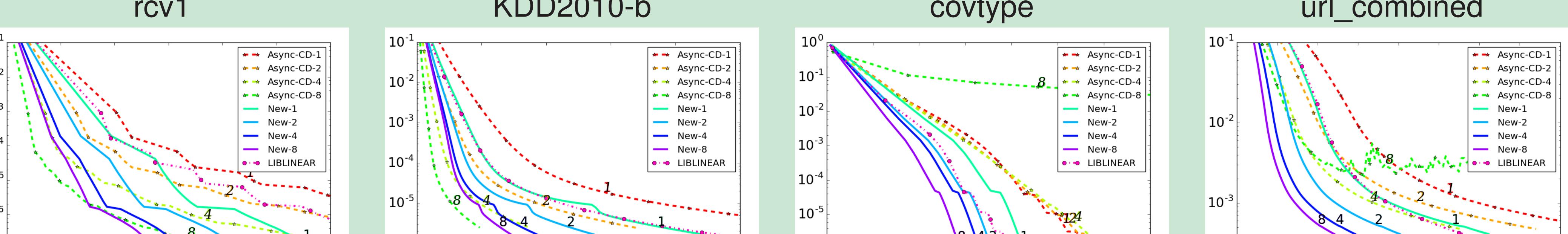
Implementation of the Proposed Framework

- The selection of B is essential. An example:
 - $\{1, \dots, l\}$ splits to $\bar{B}_1, \dots, \bar{B}_T$
 - For each \bar{B} in $\bar{B}_1, \dots, \bar{B}_T$ select elements in \bar{B} with larger project gradient as B .
- Theoretical convergence** is established.
- Other selections of B are possible.
- The block size $|\bar{B}|$ is also important
 - too small $|\bar{B}|$ may cause parallelization overhead
 - too large $|\bar{B}|$ may cause slower convergence
- Fortunately, we found that the training time is about the same when $|\bar{B}|$ is set to be a few hundreds.
- Shrinking technique in Hsieh et al. [2008] for removing some unnecessary α_i can be incorporated.

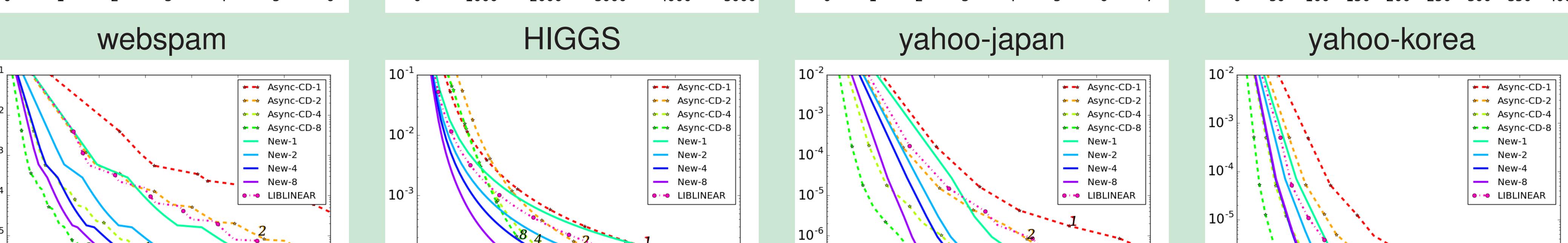
Comparison: asynchronous CD, our proposed method and single-core LIBLINEAR

- x-axis is the training time in seconds, y-axis is the relative error, and "New" is our method.

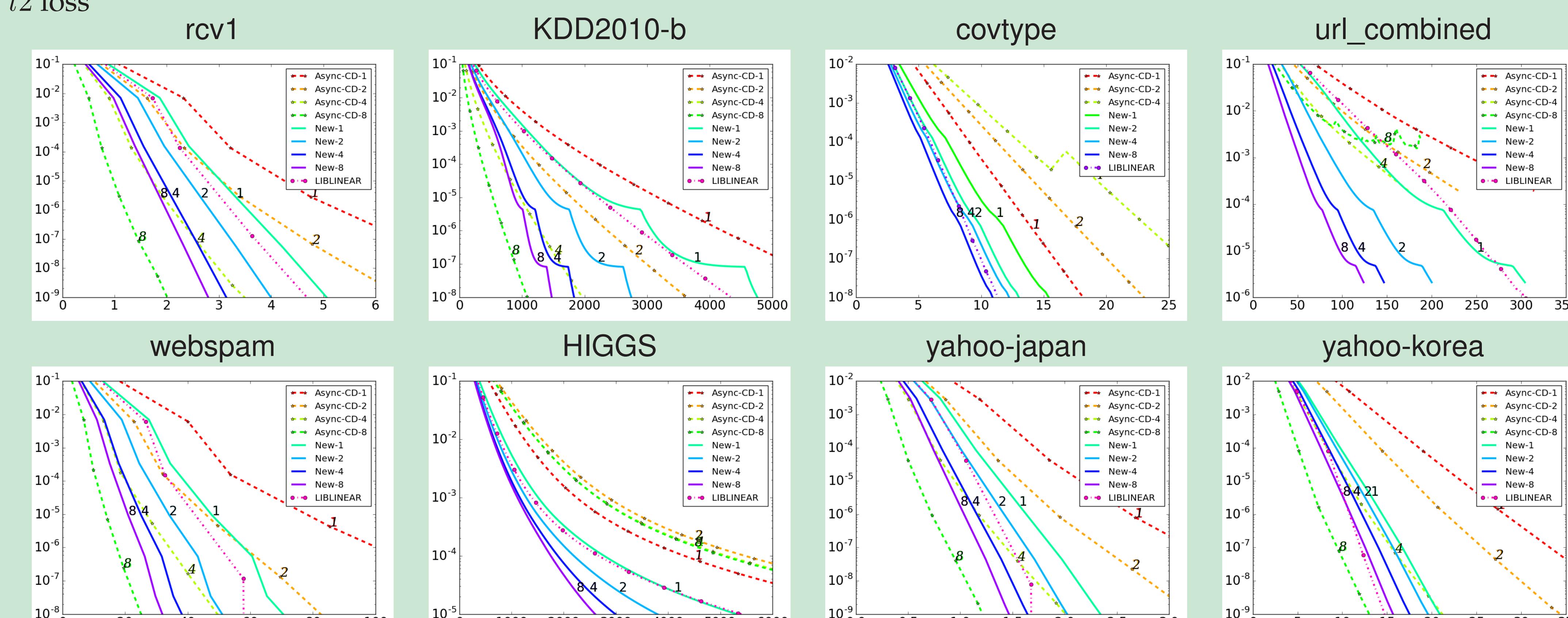
- l1 loss



- l2 loss



- Asynchronous CD is efficient, but may fail when using more threads.



Conclusions

- We propose an effective parallel dual CD framework for multi-core environments.
- Future direction: dual CD in multi-CPU environments.
- Multi-core LIBLINEAR is available at:
 <http://www.csie.ntu.edu.tw/~cjlin/libsvmtools/multicore-liblinear>