Dissolve^{struct} - A Library for Distributed Structured Prediction

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Short Summary

Motivation: *Structured* SVMs have wide applicability, but distributed optimization in machine learning is challenging.

Contributions

New ***open source*** library for training large scale structured SVMs. *(Available on github soon)*

- Same **simple interface** as SVM^{struct}
- allows **approximate inference**
- scales to very large systems and **commodity clusters**, Amazon EC2 and others.
- automatic **fault tolerance** by running on Spark

Interface: *(same as SVM^{struct})*

User provides 3 functions:

- *Feature Map (x,y)*
- *Loss function (y,y')*
- *(approx.) Max Oracle*

Distributed and data-parallel execution is handled automatically

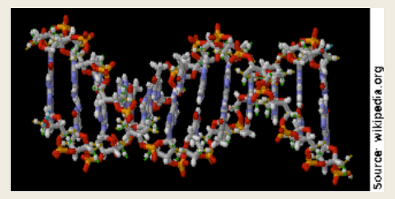
Many Applications

Text

- Parsing
- POS tagging, chunking
- sentence alignment
- named entity recognition

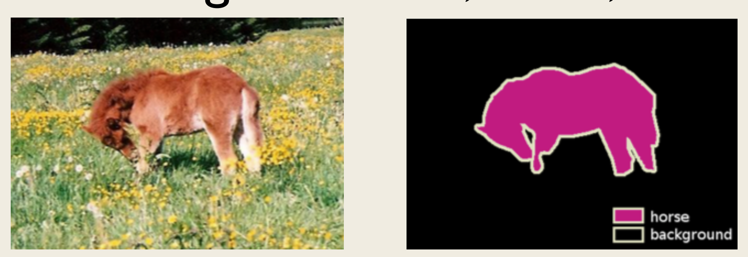
Biology

Protein structure & function prediction



Vision

Horse Segmentation, OCR, …



more?

- Scene understanding
- object localization & recognit.

We want your application!

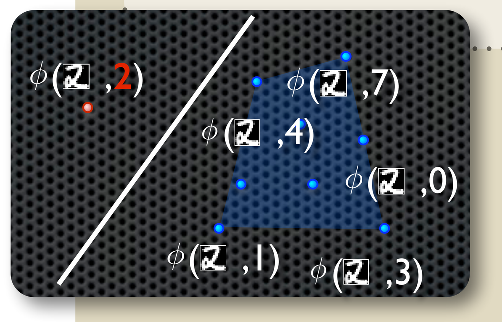
- 3D? max-cut? GPU decoding?

Structured SVM

Structured Prediction:

Goal: Given a joint "structured" feature map $\phi : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}^d$, construct a good linear classifier of the form

$$h_{\boldsymbol{w}}(\boldsymbol{x}) = \underset{\boldsymbol{y}\in\mathcal{Y}}{\operatorname{argmax}} \langle \boldsymbol{w}, \boldsymbol{\phi}(\boldsymbol{x}, \boldsymbol{y}) \rangle$$



Large margin separation

Primal

maximization oracle *(loss augmented decoding)*

$$\min_{\boldsymbol{w}} \ \frac{\lambda}{2}\|\boldsymbol{w}\|^2 + \frac{1}{n}\sum_{i=1}^{n} \underbrace{\max_{\boldsymbol{y}\in\mathcal{Y}} \left\{ L(\boldsymbol{y}_i, \boldsymbol{y}) - \langle \boldsymbol{w}, \ \boldsymbol{\phi}(\boldsymbol{x}_i, \boldsymbol{y}_i) - \boldsymbol{\phi}(\boldsymbol{x}_i, \boldsymbol{y}) \rangle \right\}}_{=\text{ structured hinge loss } =: \psi_i(\boldsymbol{y})}$$

primal-dual correspondence $w = A\alpha$

Dual

$$\min_{\alpha\in\mathbb{R}^{n\cdot|\mathcal{Y}|}} \ f(\alpha) := \frac{\lambda}{2}\|A\alpha\|^2 - \boldsymbol{b}^T\alpha$$

$$\text{s.t.} \quad \textstyle\sum_{\boldsymbol{y}\in\mathcal{Y}} \alpha_i(\boldsymbol{y}) = 1 \quad \forall i \in [n]$$

$$\text{and} \quad \alpha_i(\boldsymbol{y}) \geq 0 \quad \forall i \in [n], \forall \boldsymbol{y} \in \mathcal{Y}$$

block-structure!

Challenge: exponential # of variables

$A := \left\{ \frac{1}{\lambda n}\psi_i(\boldsymbol{y}) \in \mathbb{R}^d \ \middle|\ i \in [n], \boldsymbol{y} \in \mathcal{Y} \right\}$ $\qquad$ $\boldsymbol{b} := \left(\frac{1}{n}L_i(\boldsymbol{y})\right)_{i\in[n],\boldsymbol{y}\in\mathcal{Y}}$

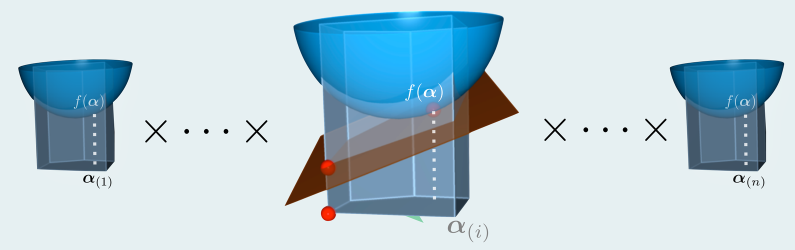
Block-Coordinate Frank-Wolfe

[ICML 2013]

Problem: Minimize a convex function over block-separable compact constraints

$$\min_{\substack{\alpha\in\mathcal{M}^{(1)}\times\ldots\times\mathcal{M}^{(n)} \\ \mathbb{R}^{m_1} \qquad \mathbb{R}^{m_n}}} f(\alpha) \qquad \alpha = (\alpha_{(1)}, \ldots, \alpha_{(n)})$$

Idea: Combine Coordinate Descent with cheaper Frank-Wolfe steps



(pick one single block at random, and perform a Frank-Wolfe step affecting only this block)

Algorithm 4 BCFW for Structural SVM

new

Let $\boldsymbol{w}^{(0)} := \boldsymbol{w}_i{}^{(0)} := \boldsymbol{0}$
for $k = 0 \ldots K$ **do**
  Pick $i \in_{u.a.r.} [n]$
  Solve $\boldsymbol{y}_i^* := \underset{\boldsymbol{y}\in\mathcal{Y}_i}{\operatorname{argmax}} \ H_i(\boldsymbol{y}; \boldsymbol{w}^{(k)})$
  Let $\boldsymbol{w}_s := \frac{1}{\lambda n}\psi_i(\boldsymbol{y}_i^*)$
  Let $\gamma := \frac{2n}{k+2n}$, or find the optimal γ
  Update $\boldsymbol{w}_i{}^{(k+1)} := (1-\gamma)\boldsymbol{w}_i{}^{(k)} + \gamma\,\boldsymbol{w}_s$
  Update $\boldsymbol{w}^{(k+1)} := \boldsymbol{w}^{(k)} + \boldsymbol{w}_i{}^{(k+1)} - \boldsymbol{w}_i{}^{(k)}$
end for

iteration cost: ***one** oracle call*

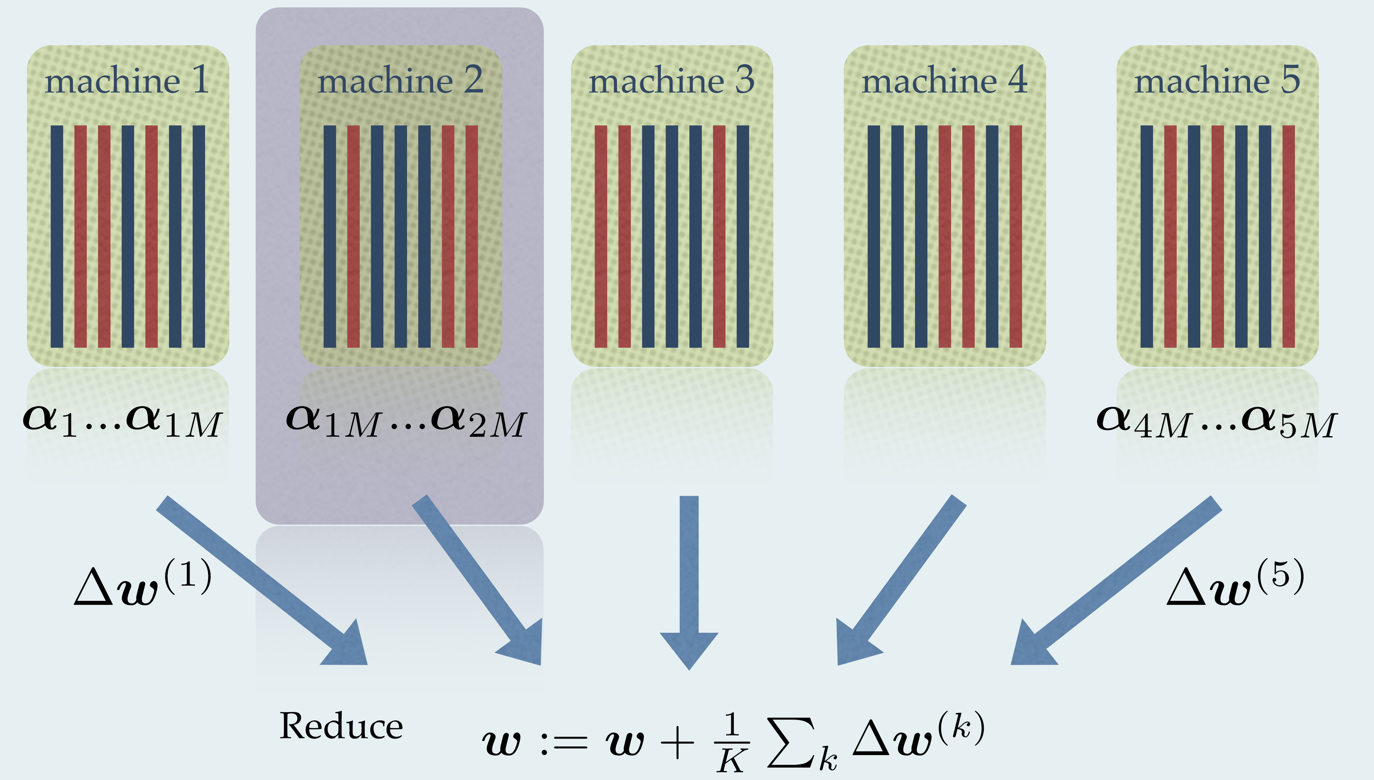
Error $\leq \varepsilon$ after $O\left(\frac{R^2}{\lambda\varepsilon}\right)$ iterations

Approximate Oracles *allowed!*

Communication Efficient Distributed Coordinate Ascent

CoCoA [NIPS 2014]

Fixing the **communication bottleneck** for distributed optimization in (generalized linear) machine learning.



Applications: State of the art in theory and practice, for SVM, Logistic Reg., Ridge Regression, Lasso / Sparse Reg.

Approximate Inference

inexact max-decoding oracles

Algorithm automatically detects if the oracle answer was accurate enough

Implemented Oracles so far:

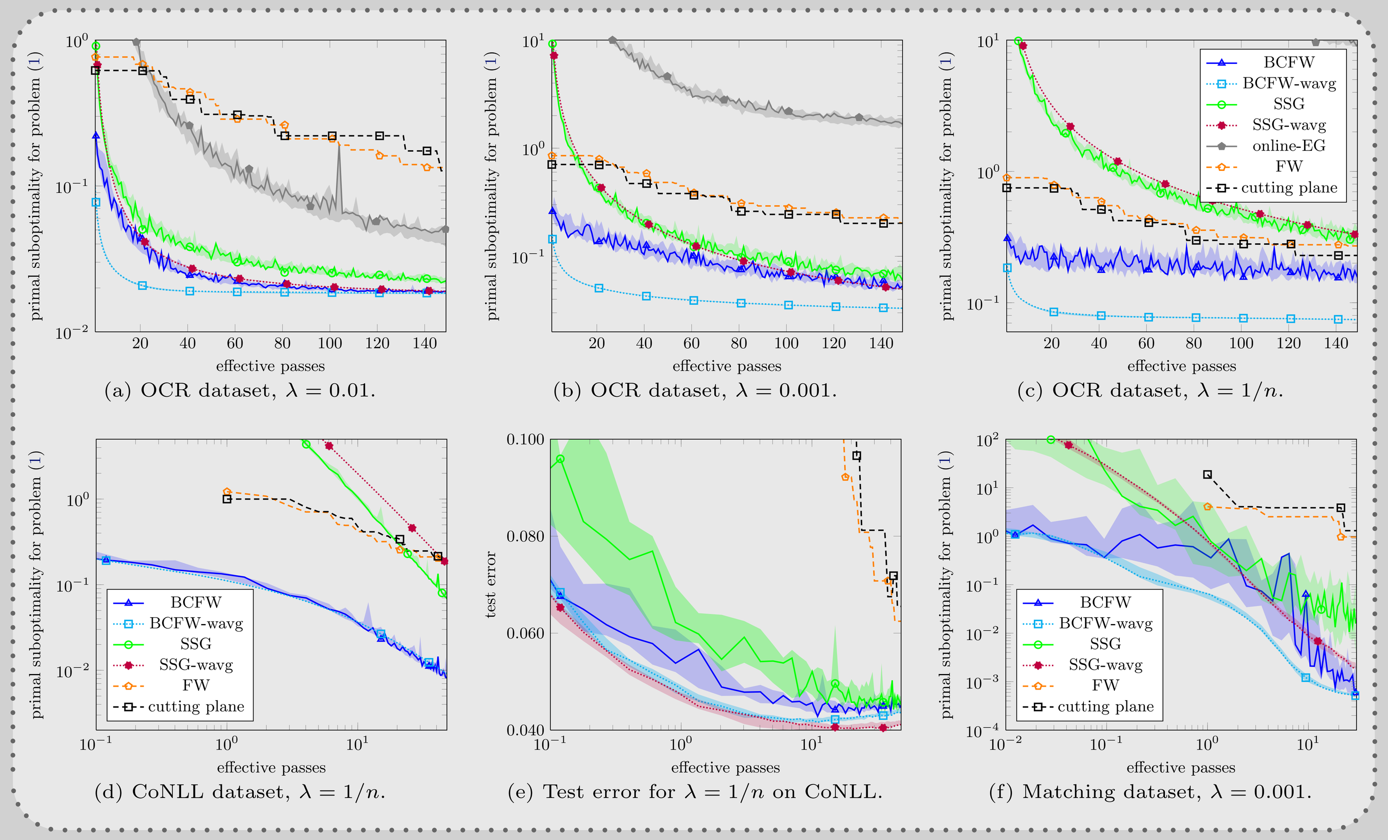
- Chain (Viterbi)
- Belief Propagation (using *Factorie* library)

Scala FACTORIE

add more oracles? need your help!

Single Machine Performance

dataset		n	d
OCR	sequence labeling	6251	4082
CoNLL	NLP chunking	8936	1643026
Matching	word alignment	5000	82



(a) OCR dataset, $\lambda = 0.01$. (b) OCR dataset, $\lambda = 0.001$. (c) OCR dataset, $\lambda = 1/n$.
(d) CoNLL dataset, $\lambda = 1/n$. (e) Test error for $\lambda = 1/n$ on CoNLL. (f) Matching dataset, $\lambda = 0.001$.

comparing *block-coordinate Frank-Wolfe* (BCFW) to *stochastic subgradient* (SSG), *online exponentiated gradient* (EG), *batch Frank-Wolfe* (FW) and *cutting plane* (wavg = weighted averaging of the iterates)