Paired-Dual Learning for Fast Training of Latent Variable Hinge-Loss MRFs

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Introduction

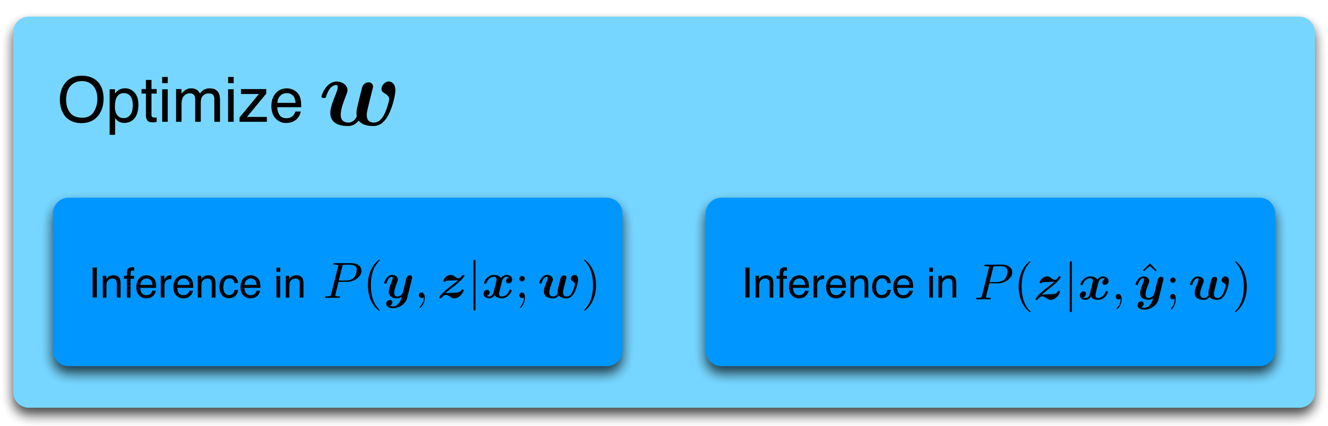
- **Latent variables** are very useful in **large-scale structured prediction**, but they **complicate learning**!
- A naive approach is not scalable, and smarter methods exist **for discrete models only**
- We introduce a **new method for continuous MRFs** that interleaves parameter and inference updates

Learning with Latent Variables

- The maximum likelihood learning objective for models with latent variables contains two inner inference problems:

$$\arg\min_{\boldsymbol{w}} \max_{\rho \in \Delta(\boldsymbol{y},\boldsymbol{z})} \min_{q \in \Delta(\boldsymbol{z})} \frac{\lambda}{2}\|\boldsymbol{w}\|^2 - \mathbb{E}_\rho\left[\boldsymbol{w}^\top \boldsymbol{\phi}(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})\right] + H(\rho) + \mathbb{E}_q\left[\boldsymbol{w}^\top \boldsymbol{\phi}(\boldsymbol{x},\hat{\boldsymbol{y}},\boldsymbol{z})\right] - H(q)$$

- At a high level, this objective has a simple structure:

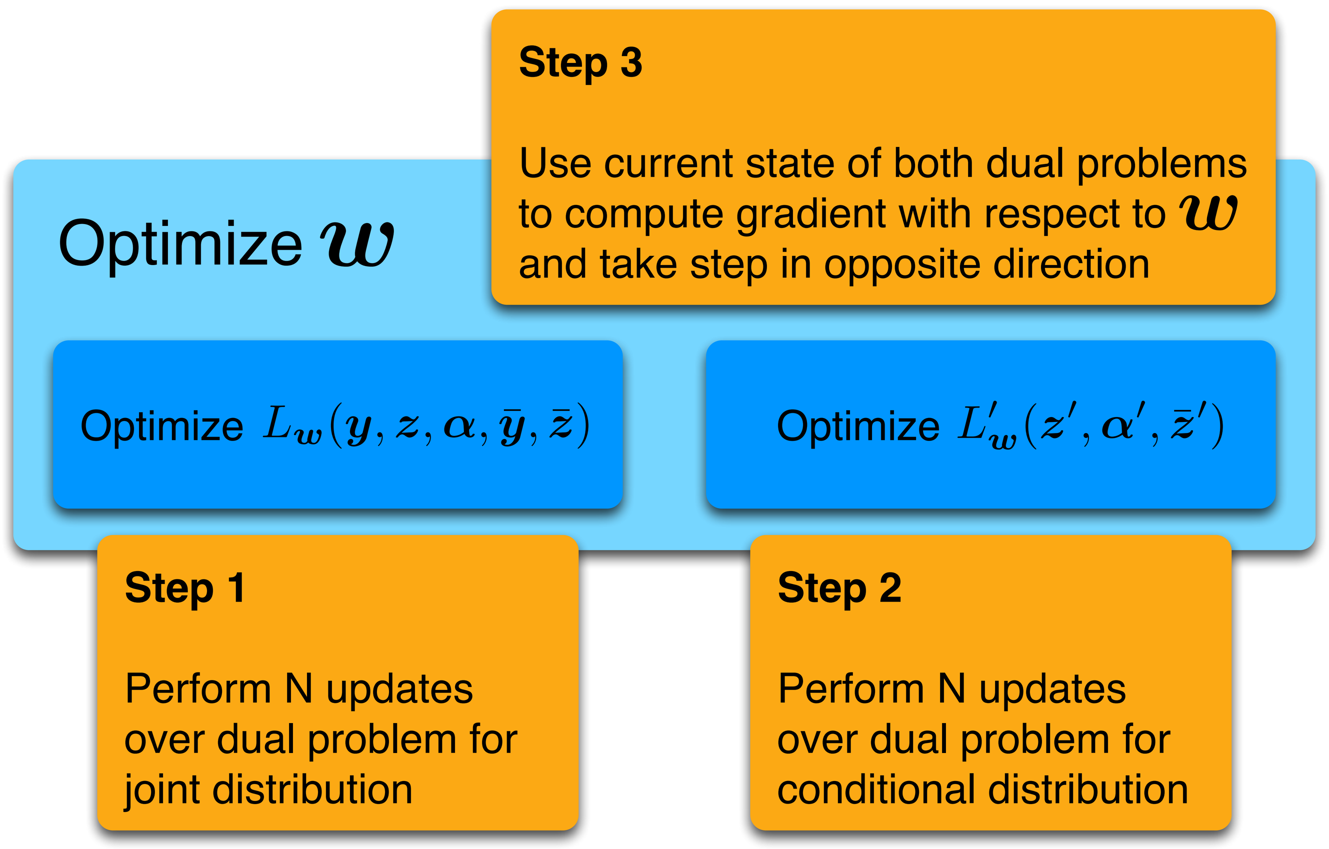


- But repeatedly performing inference is **very expensive**!
- Supervised learning can be sped up by interleaving inference and parameter updates, e.g., Taskar et al. [ICML 2005] and Meshi et al. [ICML 2010]
- Schwing et al. [ICML 2012] and Chen et al. [ICML 2015] propose interleaving updates for discrete latent models
- Any new method for continuous variables must solve the problems of **intractable expectations and entropies**

Paired-Dual Learning

- We choose point distributions for variational families and construct entropy surrogates to make objective tractable
- Paired-dual learning replaces both inner inferences with augmented Lagrangians and optimizes jointly:

$$\arg\min_{\boldsymbol{w}} \max_{\boldsymbol{y},\boldsymbol{z},\bar{\boldsymbol{y}},\bar{\boldsymbol{z}}} \min_{\boldsymbol{\alpha}} \min_{\boldsymbol{z}',\bar{\boldsymbol{z}}'} \max_{\boldsymbol{\alpha}'} \frac{\lambda}{2}\|\boldsymbol{w}\|^2 - L_{\boldsymbol{w}}(\boldsymbol{y},\boldsymbol{z},\boldsymbol{\alpha},\bar{\boldsymbol{y}},\bar{\boldsymbol{z}}) + L'_{\boldsymbol{w}}(\boldsymbol{z}',\boldsymbol{\alpha}',\bar{\boldsymbol{z}}')$$



Hinge-Loss Markov Random Fields

- Undirected graphical models over continuous variables with hinge-loss potential functions

$$P(\boldsymbol{y},\boldsymbol{z}|\boldsymbol{x};\boldsymbol{w}) \propto \exp\left(\sum_{j=1}^{m} w_j \left(\max\{\ell_j(\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}),0\}\right)^{p_j}\right)$$

where ℓ_j is a linear function and $p_j \in \{1,2\}$

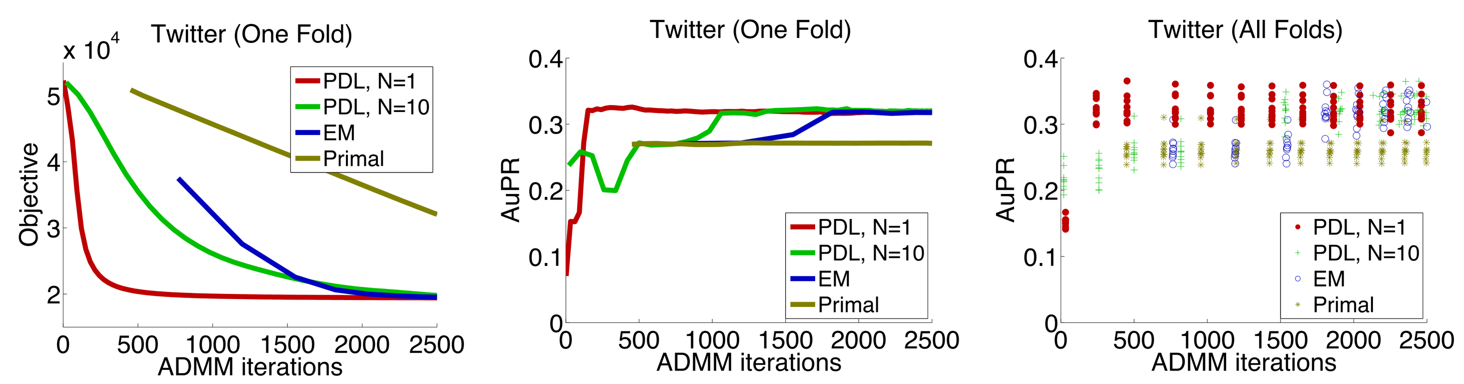
- Generalizes
  - Randomized algorithms for MAX SAT
  - Relaxed MAP for discrete, logical MRFs
  - Exact MAX SAT using soft logic
- **Highly scalable**, ADMM-based MAP inference

Code available: http://psl.cs.umd.edu

Evaluation

- Paired-dual learning is
  - **Just as accurate** as traditional methods
  - **So fast** that it often **converges before others make a single parameter update**

Interaction Prediction via Community Detection



Trust Prediction in Social Networks

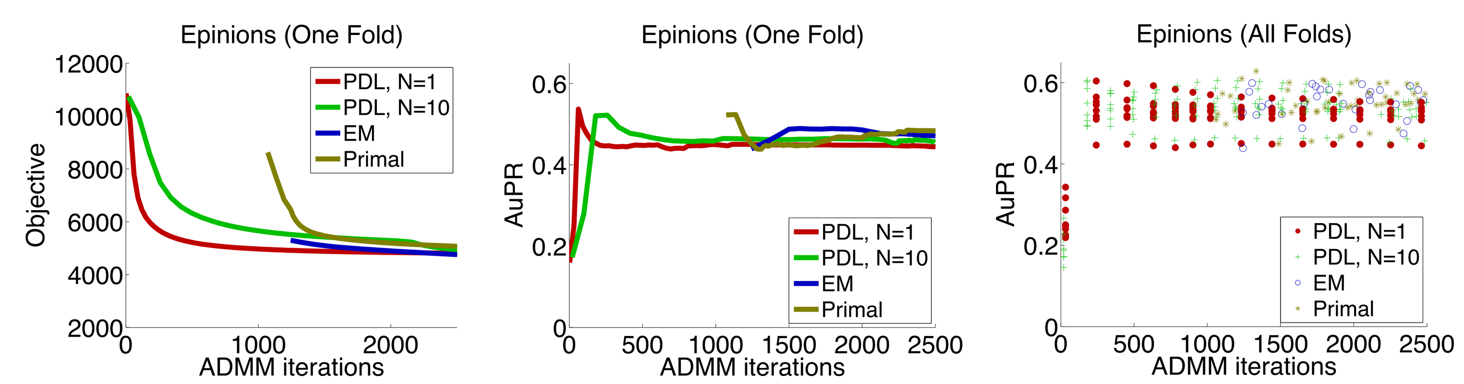
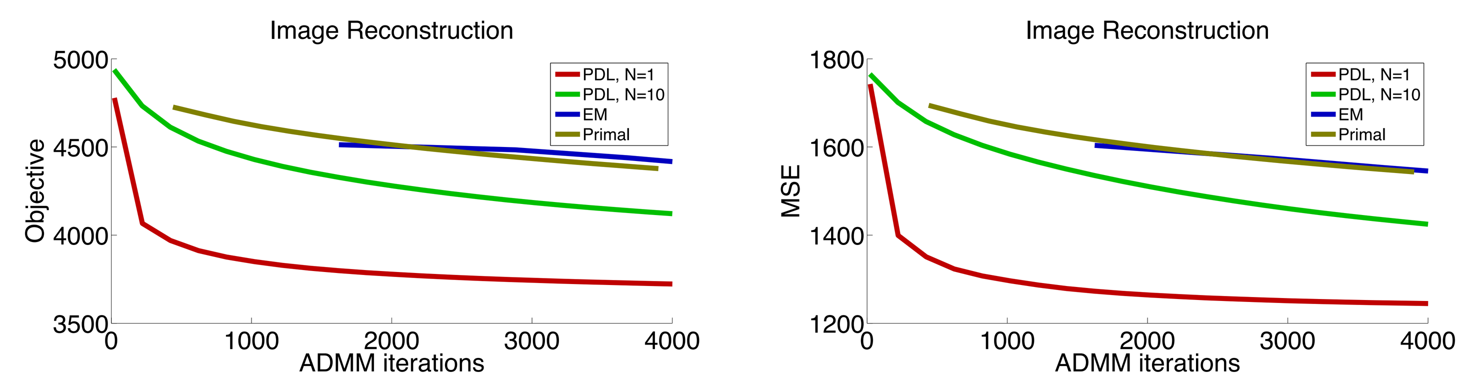


Image Reconstruction



Conclusions

- Paired-dual learning overcomes the inference bottleneck associated with learning with latent variables
- Latent variable hinge-loss MRFs are now **practical for large-scale applications!**
- Paired-dual learning is also applicable to other continuous models and even discrete models

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