

Linear Programming Relaxations and Belief Propagation - An Empirical Study

CS295P

Linear Programming(LP) Relaxations

- Finding MAP in a graphical model
 - For an arbitrary graph: NP hard.
 - Need approximation.
- Linear Programming Relaxations
 - Used for approximating the MAP problem
 - guaranteed optimality

However,

- Limited problem size
- Requires powerful machines

Tree-Reweighted Belief Propagation

- TRBP
 - An alternative approximation
 - A variant of BP
- Advantages
 - Finds the same solution as LP relaxations
 - Applicable to large scale problems
 - Significantly faster than CPLEX

MAP

Conditional distribution: $\Pr(x | y) = \frac{1}{Z} \prod_{\langle i, j \rangle} \Psi_{ij}(x_i, x_j) \prod_i \Psi(x_i)$

Define: $\Psi_{ij}(x_i, x_j) = e^{-E_{ij}(x_i, x_j)}$

So:

$$x^* = \arg \min_x \sum_{\langle ij \rangle} E_{ij}(x_i, x_j) + \sum_i E_i(x_i)$$

LP Relaxation

Define indicator function: $q_i(x_i), q_{ij}(x_i, x_j)$

LP relaxation of MAP:

minimize

$$J(\{q\}) = \sum_{\langle ij \rangle} \sum_{x_i, x_j} q_{ij}(x_i, x_j) E_{ij}(x_i, x_j) + \sum_i \sum_{x_i} q_i(x_i) E_i(x_i)$$

subject to

$$0 \leq q_{ij}(x_i, x_j) \leq 1$$

$$\sum_{x_i, x_j} q_{ij}(x_i, x_j)$$

$$\sum_{x_i} q_{ij}(x_i, x_j) = q_j(x_j)$$

However..

The number of variables in LP relaxation:

Denote K_i the number of possible states of node i ,
 $N_{\text{variables}} = \sum(K_i) + \sum(K_i K_j)$ for pairs of $\langle i, j \rangle$

number of constraints:

$N_{\text{constraints}} = \sum(k_i + k_j + 1)$ for pairs of $\langle i, j \rangle$

For a 200×200 pixel image, each pixel takes on 30 values:

$N_{\text{variables}} \sim 72$ million

$N_{\text{constraints}} \sim 4$ million

Tree-Reweighted BP

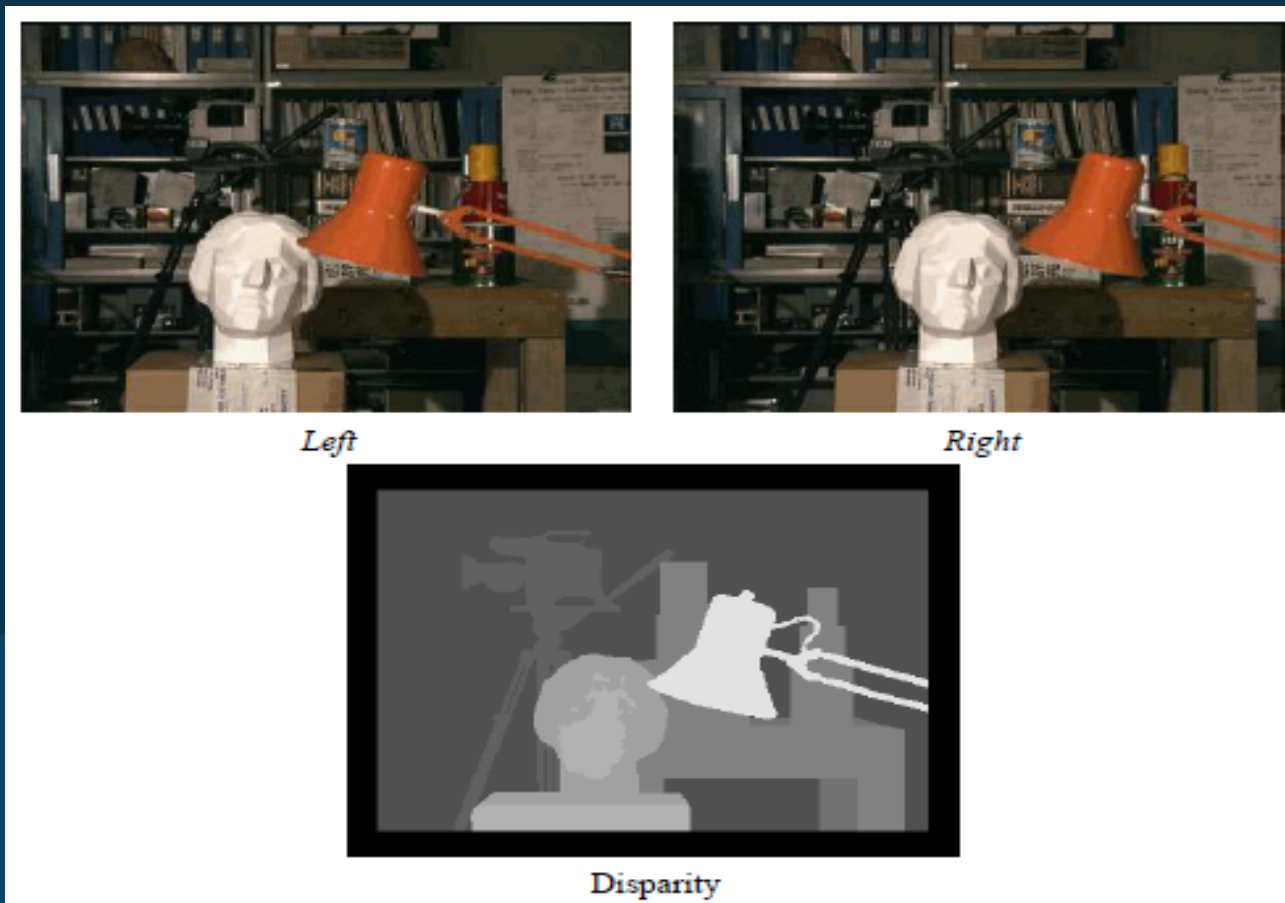
- Theory: [lecture by Prof. Sudderth]
- Number of iterations to converge:
Not sure, but somehow faster than LP relaxation..
- Memory consumption:
Implementation dependent

Benchmark Problems - Stereo Vision

<http://vision.middlebury.edu/stereo/data/scenes2001/data/imagehtml/tsukuba.html>

[edu/stereo/data/scenes2001/data/imagehtml/tsukuba.html](http://vision.middlebury.edu/stereo/data/scenes2001/data/imagehtml/tsukuba.html)

Goal: find the disparity of each pixel in a reference image.
The disparity can be translated into depth from the camera.



Benchmark Problems - Side-Chain Prediction and protein design

- Side-chain:

Proteins = chain(amino acid)

amino acid = Carbon base + NH₂ + COOH + side-chain

side-chain is bounded to the carbon base, etc..

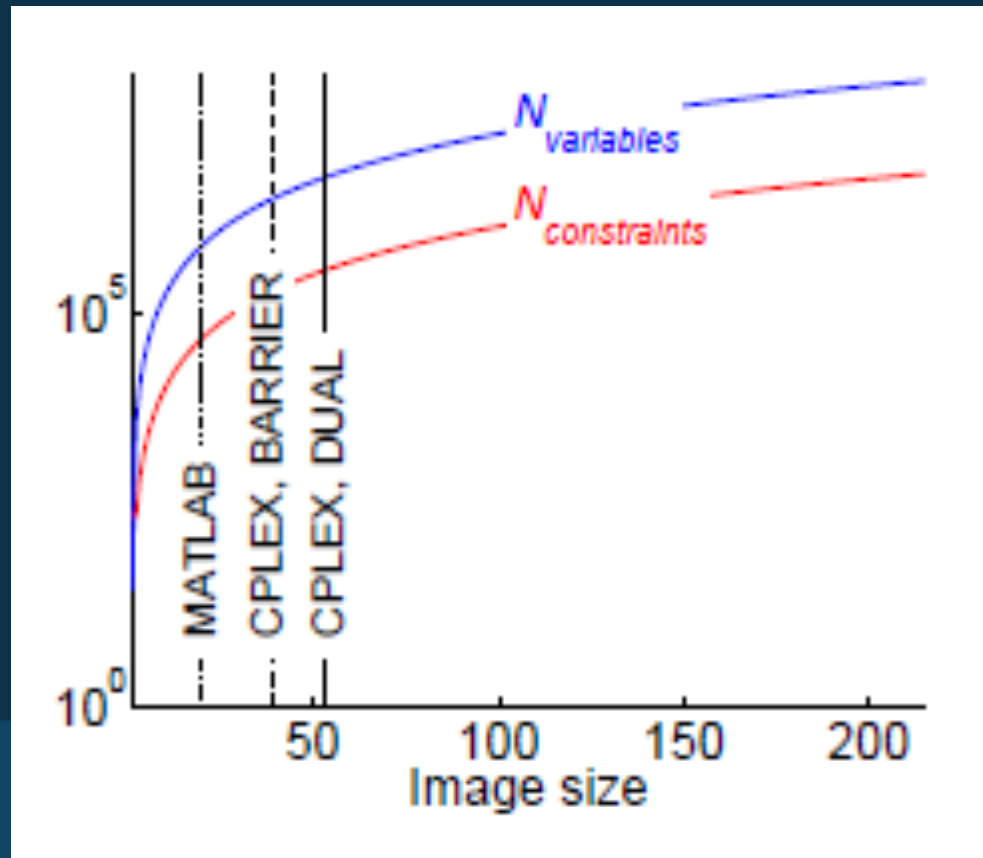
Anyway:

- Important in protein folding and protein design
- Prediction is NP-complete

CPLEX vs TRBP in Stereo Vision

CPLEX: 50*50

TRBP: 250*250

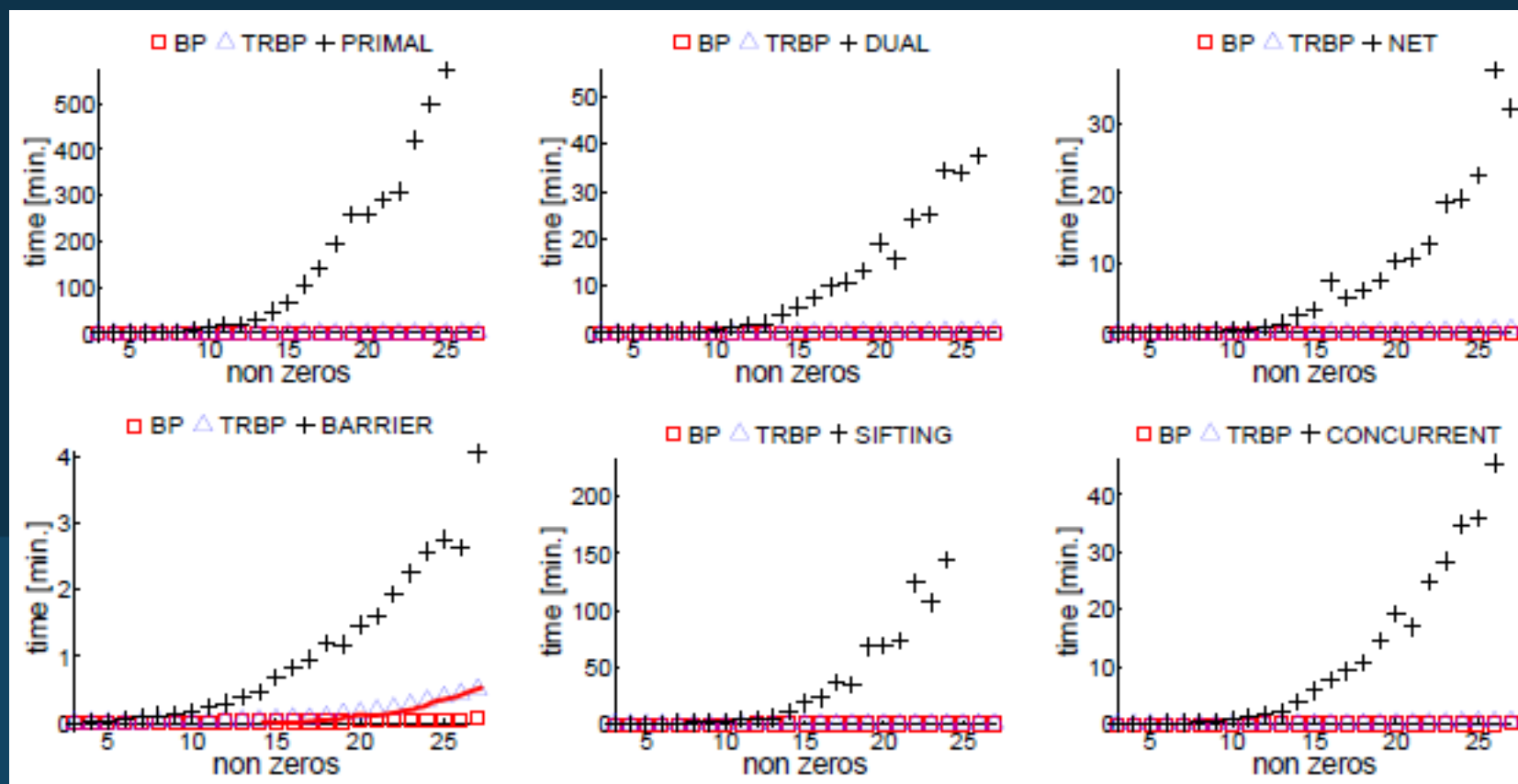


CPLEX vs TRBP in side-chain prediction and protein design

- For side-chain prediction, both CPLEX and TRBP can solve the LP relaxation for all proteins
- For protein design:
 - CPLEX: 3/97
 - TRBP: all

Runtime

Data set: a set of subproblems from the stereo benchmark set.



Summary

- TRBP is faster and memory efficient. -- Why?

The authors are not sure.. ("empirical study")

TRBP is not a general purpose LP solver. It can only solve a tiny fraction of linear programs with a very special structure.

Assumption:

LP Problem: minimize $[c^T]q$ subject to $Aq=b$ and $Cq < d$

TRBP explicitly represents the graph, while CPLEX solvers explicitly represent A .