Many problems in computer vision and Machine Learning can be formulated using Markov Random Fields (MRFs) and Integer Quadratic Programs (IQPs).

**Proposed Approach:**
- No restrictions on the pairwise clique potentials
- Linear in the description length of the clique potentials
- Improved general optimality bounds

**MRFs and IQP/QP Formulation**

$$\text{max} \ P(X) = \frac{1}{Z} \prod_{i \in E} \prod_{j \in V} \phi_j(X_i, X_j) \prod_{i \in V} \phi_i(X_i)$$

$$x_{ia} = 1 \iff X_i = a \quad (\epsilon(x) = x^TWx + VTx)$$

**Proposition:** IQP is equivalent to QP

(generalizes a result from Ravikumar & Lafferty, 2006)

given a solution to IQP, we can construct a solution to QP

**Solution**

1. **Linear Constraint:** $Cx = 0$ (and $V = 0, \beta = 0$) $\Rightarrow$ SQP
2. **Affine Constraint:** $Cx = b$ $\Leftrightarrow$ $\sum_a x_{ia} = 1$ $\Rightarrow$ L2QP

**Experiments**

Comparison between SQP, L2QP, BP, ICM, Relaxation Labeling on random MRF problems with controlled parameters

**Previous Work**

Linear relaxations: LP, SDP, SOCPLP rewritten as (linear) matrix inner product, approximating rank 1 constraint $x^TWx + VTx = \langle X, W_{eq} \rangle$ where $X = [x_1 \ldots x_n]^T$

Quadratic relaxations: L2QP and COP COP: convexification of objective using $(W, V)^{\geq 0} (W \text{-diag}(D), V + D)$