Learning structural objects from unknown probability distribution is becoming popular in recent years. Tsochantaridis et al.\cite generalized multiclass SVMs\cite to structural SVMs by extending feature vectors to joint feature vectors which map features extracted jointly over input-output pairs to discrete output. The exact maximum a posteriori (MAP) problem thus becomes an NP-hard problem. They overcome this by using a method called “Soft-Margin Maximization” and found an upper bound of the loss function.

Based on the previous research, Yu and Joachims\cite developed latent SVM by introducing a hidden variable into the joint feature vector. They observed a fact that in real world applications hidden variables are usually intermediate results and are not required as an output. With this fact they followed “Soft-Margin” method and found an upper bound for the loss function with latent variables. However, the resulted object function is still non-convex.

Yuille and Rangarajan \cite developed the Concave-Convex Procedure (CCCP) which is guaranteed to find a local minimum for a Difference-Convex (DC) program. Yu and Joachims\cite combined CCCP algorithm by writing their non-convex object function into a difference of two convex function and came up with a EM like 2 steps optimizing algorithm. For each iteration, they first compute latent variables utilizing current parameter vectors and then in turn optimizing parameter vectors using the standard Structural SVM algorithm with previously computed latent variables.

Higher order potentials are raising interests due to their capability to represent dependencies between complex objects. Kohli and Kumar\cite proposed a method to represent a class of higher order potentials with lower (upper) linear envelope potentials. By introducing auxiliary variables, they reduced the linear representation to a pairwise form and proposed an approximate algorithm with standard LP program methods. Following their method, Gould\cite extended their method to a weighted lower linear envelope in binary Markov Random Fields (MRF) which can be solved with an efficient algorithm. They showed the energy function with auxiliary variables is submodular by transforming it into a quadratic pseudo-Boolean form and how “graph-cuts” like algorithm can be applied to do exact inference. They then optimized the model’s parameters under the max margin framework.

In their work they pointed out the potential relationship between their auxiliary representation and latent SVM. However, since removing of their fixed space constraint will result dependence between latent variable and parameters, further research still remains open.