Summary of the discussion so far:

1) SVM → dual 2) Kernel 3) Kernel to capture complex relationships in input space [string, tree, convolution, graph, relational, KLOG] 4) Structure in output space (Struct SVM, MMMNs) Capturing complex relationships in output space [graphical models (directed & undirected)] 5) Dual of StructSVM ⇒ Kernelised Struct SVM (can capture complex relationships in i/p as well as o/p space) [Today: Briefly kernelised markov networks]

6) Special cases in Markov networks when inference can be solved efficiently
Maxproduct, Linear program with total unimodularity, submodularity 7) Constraints in linear program for inference in markov n/w to capture domain knowledge

(I) Max Margin Markov Networks can be kernelised (Slide 50 of http://www.cse.iitb.ac.in/~cs717/notes/classNotes/StructuredOutput/mmmn.ppt) (similar to dual of StructSVM)

1) H/W: Can the inference (MAP) problem in kernelised MMMN/StructSVM dual be also posed as (integer) linear programs.

2) Do total unimodularity conditions hold?

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2) Can we "lift" Markov networks to more complex/generalised representations such as first order logic (just as we studied KLOG as a kernel to capture first order relationships in i/p space)

Ans: Yes. Formalism called <u>Markov LOGIC Network</u>

Graphical / Probabilistic Models → "Lifted" versions (lifted to first order logic)

1) Markov N/ws → Markov Logic n/ws (MLN)

we will only discuss MLNs

2) Bayesian n/ws → Bayesian Logic Programs

3) Probabilistic context free grammar (similar in spirit to structsvm applied to learning parsing) → Stochastic Logic programs

We covered slide nos 1 to 30 of http://www.cse.iitb.ac.in/~cs717/notes/slides/other-slides/marklog.ppt and then slide nos 52 to 65

of http://www.cse.iitb.ac.in/~cs717/notes/slides/Slides-4-4-2010.ppt

and then slide nos 17 to 22

of http://www.cse.iitb.ac.in/~cs717/notes/classNotes/StructuredOutput/MaxMarginMarkovLogicNetworks.pdf