## Scribbles on Gibbs distributions and Markov random fields

April 8, 2013

## 1 Markov random fields

Let  $y = (y_1, \ldots, y_n)$  be a random vector with elements  $y_i$ . Define  $NE(i) \subset \{1, \ldots, i-1, i+1, \ldots n\}$  to be the subset of indices such that, for all i, the conditional distribution for  $y_i$  may be written as

$$p(y_i \mid y_{(-i)} = p(y_i \mid y_j : j \neq i) = p(y_i \mid y_j : j \in NE(i)).$$
 (1)

Clearly specifying NE(i) for all i species a network or graph. The image here is of each element of the random vector as a node in this network, and NE(i) is the set of neighboring nodes. The neighborhood set NE(i) is often called the Markov blanket of node i.

A joint probability distribution specified in this manner is called a *Markov* random field. Clearly not all forms for the conditionals in (1) lead to a valid joint probability distribution. The interesting question is: which ones do?

## 2 Gibbs distributions

An important idea in understanding Gibbs distributions is that of a clique. A clique is a set C of nodes in a network such that every node in C is a neighbor of every other node in C. A potential function  $\phi_d$  of order d is a function of d arguments that is invariant to permutations of those arguments. For example,  $\phi_2(y_1, y_2) = y_1 y_2$  is a potential function. (Note: in some presentations of these ideas potential functions are defined as being strictly positive. I will not adopt that restriction.)

A Gibbs distribution is a probability distribution over y that depends on

the  $y_1, \ldots, y_n$  only through potentials on cliques. Specifically,

$$p(y) = p(y_1, \dots, y_n) \propto \exp \left\{ d \sum_{j=1}^n \sum_{a \in \mathcal{A}_j} \phi_k(y_{a_1}, \dots, y_{a_j}) \right\},$$

where  $A_j$  is the set of all subsets of  $\{1, \ldots, n\}$  of size j.

Loosely speaking, the Hammersley–Clifford theorem states that if Equation (1) defines a valid joint probability distribution, then this distribution must be a Gibbs distribution.