

dent. In this case, equations (2.1, 2.2) specialize to

$$\hat{x} = PC^T (CPC^T + R)^{-1} y \quad (2.4)$$

$$\hat{P} = P - PC^T (CPC^T + R)^{-1} CP \quad (2.5)$$

where  $P \triangleq E [xx^T]$  is the prior covariance of the unobserved variables  $x$ . Assuming that  $P$  and  $R$  are both positive definite and hence invertible, we may use the matrix inversion lemma (see Appendix A.1) to rewrite equations (2.4, 2.5) as

$$(P^{-1} + C^T R^{-1} C) \hat{x} = C^T R^{-1} y \quad (2.6)$$

$$\hat{P} = (P^{-1} + C^T R^{-1} C)^{-1} \quad (2.7)$$

This information form of the normal equations plays a crucial role in computations involving the structured prior models considered later in this thesis.

Although the normal equations give an explicit formula for determining both  $\hat{x}$  and  $\hat{P}$ , directly solving them may require an intractable amount of computation for large-scale estimation problems. Let  $N_x$  be the dimension of  $x$ , and  $N_y$  be the dimension of  $y$ . If we assume that  $R$  is diagonal but all other matrices are full, then equations (2.4, 2.5) require  $\mathcal{O}(N_y^3 + N_x^2 N_y)$  operations, while equations (2.6, 2.7) require  $\mathcal{O}(N_x^3)$ . For practical problems arising in fields such as image processing and oceanography,  $N_x \approx N_y \approx 10^5$  and either formulation is intractable. Also, note that in the absence of special structure, simply storing  $P$  or  $\hat{P}$  requires  $\mathcal{O}(N_x^2)$  bytes, which is often unreasonably large. These costs motivate the development of structured statistical models which yield efficient estimation procedures.

## 2.2 Graphical Models

Graphical models provide a powerful general framework for encoding the probabilistic structure of a set of random variables [43, 48]. They are ideally suited to applications where the statistical behavior of a large, complex system may be specified in terms