LECTURE 6: THE KALMAN FILTER

STAT 545: Introduction to computational statistics

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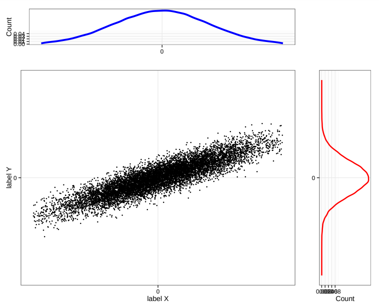
Marginalization:

$$\begin{bmatrix} X \\ Y \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \mu_X \\ \mu_Y \end{bmatrix}, \begin{bmatrix} \Sigma_{XX} & \Sigma_{XY} \\ \Sigma_{YX} & \Sigma_{YY} \end{bmatrix} \right), \quad X \sim ?$$



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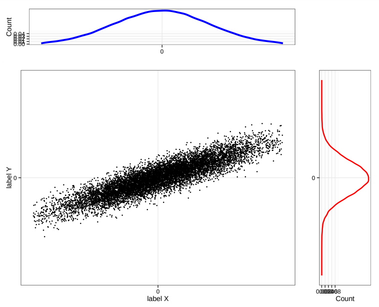

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$$X \sim \mathcal{N}\left(\mu_X, \Sigma_{XX}\right)$$

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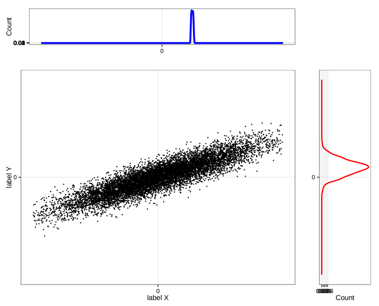

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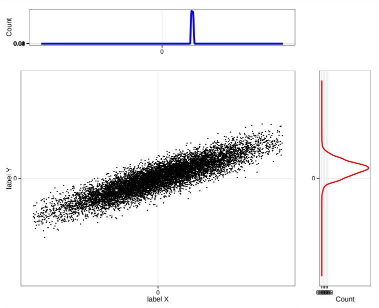

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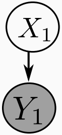
$$Y|X \sim \mathcal{N}\left(\mu_Y + \Sigma_{XY}\Sigma_{XX}^{-1}(a - \mu_X)\,,\ \Sigma_{YY} - \Sigma_{XY}\Sigma_{XX}^{-1}\Sigma_{YX} \right)$$

The Gaussian distribution, conjugacy and Bayes' rule

$$X_1 \sim \mathcal{N}(\mu, \Sigma)$$



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$$Y_1 = AX_1 + \epsilon$$

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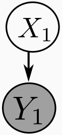

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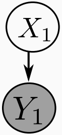

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X and Y jointly Gaussian: what is its mean and covariance?

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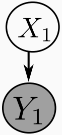

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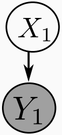

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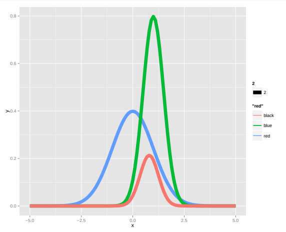
$X|Y$ is Gaussian: what is its mean and covariance?

Product of Gaussian densities:

Product of Gaussian densities is Gaussian a Gaussian density (upto a multiplication constant)



Intuition: sum of two quadratic functions is a quadratic

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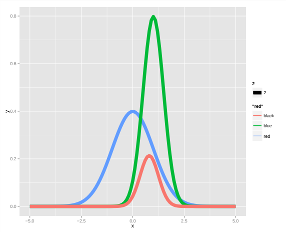
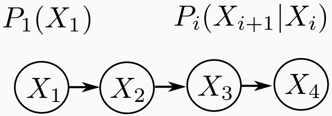


Intuition: sum of two quadratic functions is a quadratic

Aside: need only specify prob. distrib. to a constant

- $p(x)$ and $C \cdot p(x)$ represents the same, if C is independent of x
- Probabilities must integrate to 1

Markov chains



A sequence of random variables such that

$$P(X_{i+1}|X_i, X_{i-1}, \cdots, X_1) = P(X_{i+1}|X_i)$$

We'll stick to homogeneous chains:

$$P_1(X_1) \qquad P(X_{i+1}|X_i)$$

$$X_1 \to X_2 \to X_3 \to X_4$$

MARKOV CHAINS

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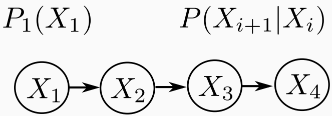

In fact, with $X_i \in \Re^D$, we will consider:

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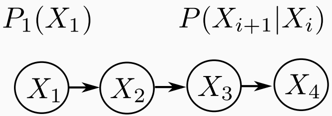

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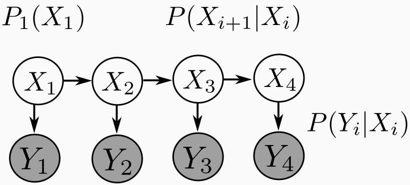
If our chain has T steps, a TD-dimensional Gaussian!
In the figure, $T = 4$. In practice: thousands to millions.

A hidden Markov model

We don't observe the chain directly:



$$Y_i = BX_i + \zeta_i, \quad \zeta \sim \mathcal{N}(0, \Sigma_z), \quad Y_i \in \Re^d$$

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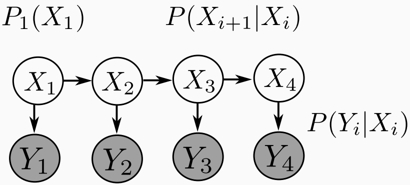

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We want to answer questions like: What is $p(X_i|Y_1, \cdots, Y_T)$?
$\{X_i, Y_i\}$ is a $(D+d)T$-dimensional Gaussian.

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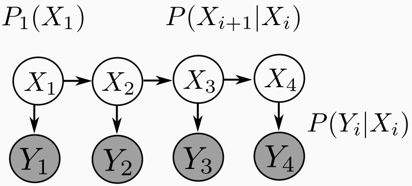

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We 'just' have to look at conditionals?

[board]