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[Next >](#)

## 5. Conditional Probability

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Exercises due May 19, 2021 19:59 EDT

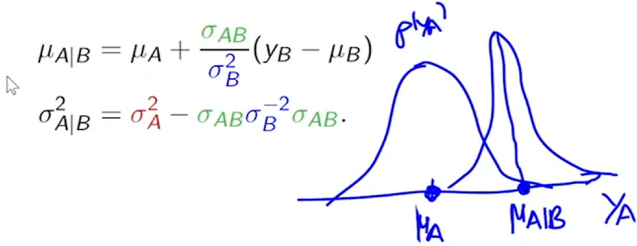
### Conditional Probability

Prediction: conditional probabilities

- $Y_A, Y_B$  Gaussian random variables. We observe  $Y_B = y_B$ .

$$\begin{bmatrix} Y_A \\ Y_B \end{bmatrix} \sim \mathcal{N} \left( \begin{bmatrix} \mu_A \\ \mu_B \end{bmatrix}, \begin{bmatrix} \sigma_A^2 & \sigma_{AB} \\ \sigma_{AB} & \sigma_B^2 \end{bmatrix} \right)$$

- **Conditioning:**  $p(Y_A|Y_B = y_B)$  is also Gaussian with mean and variance



Stefanie Jegelka (and Caroline Uhler) 31 / 35

So I actually get them always to be fairly close to each other if they are highly correlated. But all of this, essentially, is just **expressed in these two equations.** And they will be of central importance going forward when we start with more modeling. And, moreover, they will be very important also for the generalization to the matrix case that we'll look at next.

 10:00 / 10:16











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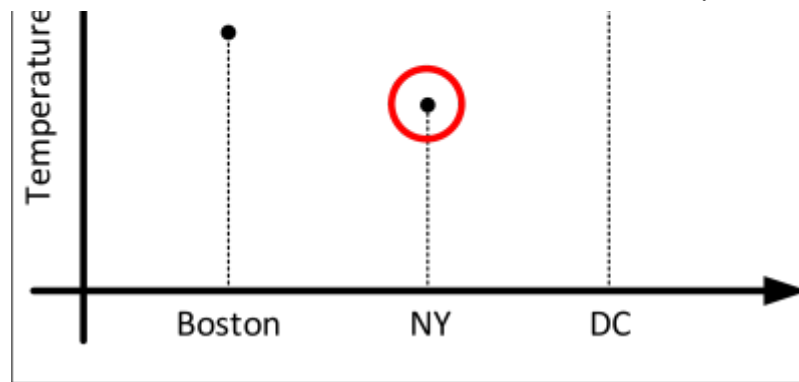
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**Definition 5.1** Two random variables are defined as jointly Gaussian if their joint distribution is a multivariate Gaussian random variable. For example, for two Gaussian random variables  $X_1$  and  $X_2$ , one can define a new two-dimensional random variable  $Y = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$ . The resulting probability density function for the joint distribution can be defined as

$$p \left( \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \mid \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \right) = \frac{1}{2\pi(\sigma_{11}\sigma_{22} - \sigma_{12}\sigma_{21})^{1/2}} \exp \left( -\frac{1}{2} \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right)^T \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}^{-1} \left( \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \right) \right)$$

### Conditional Distribution of Gaussian Random Variables





**31:** Temperature values at three different cities.

Recall the example shown in the above figure, and for simplicity consider only two random variables. Thus, assume there are two cities, *City 1* and *City 2*. Moreover, assume their respective temperatures behave like Normal random variables, denoted as  $X_1$  and  $X_2$ , and we have sufficient information to construct good estimates of their respective statistics, i.e.,  $(\mu_1, \mu_2)$  and their covariance matrix

$$\begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}$$

are known.

Now, assume we have access to a measurement of the temperature in the *City 2*, and we are interested in estimating the temperature in *City 1*. Let us denote the temperature in *City 2* as  $x_2$ .

Recall that we know that the temperature in *City 1* follows a Normal distribution with mean  $\mu_1$  and a standard deviation of  $\sigma_1$ . So, in the absence of any other information, one could expect that  $\mu_1$  is a reasonable estimate for the temperature in *City 1*. We also have additional information: we know  $X_1$  is correlated with  $X_2$ , and we have observed that  $X_2 = x_2$ . Can we get a better estimate for the temperature in *City 1*? A better estimate, in this case, refers to the reduction of the variance on the estimated value, which initially is denoted as  $\sigma_1$ .

In order to do so, we will need to compute the conditional probability of  $X_1$  given  $X_2 = x_2$ , under the assumption that  $X_1$  and  $X_2$  are correlated and jointly Gaussian.

Initially, recall that the conditional density function for  $X_1$  given  $X_2$  is defined as

$$\begin{aligned} p_{X_1|X_2=x_2}(x) &= \frac{p_{X_1, X_2}(x, x_2)}{p_{X_2}(x_2)} \\ &\propto \frac{\exp\left(-\frac{1}{2}\left(\begin{bmatrix} x - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}\right)^T \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}^{-1} \begin{bmatrix} x - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}\right)}{\exp\left(-\frac{1}{2}\left(\frac{x_2 - \mu_2}{\sigma_2}\right)^2\right)} \end{aligned}$$

Left as exercise...

$$\propto \exp\left(-\frac{1}{2}\left(\frac{\left[x - \left(\mu_1 + \frac{\sigma_{12}}{\sigma_2^2}(x_2 - \mu_2)\right)\right]^2}{\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}}\right)\right).$$

The result above implies that the conditional distribution  $P(X_1 | X_2 = x_2)$ , is still a Normal distribution with a new mean and a new standard deviation defined as

$$\mu_{X_1|X_2=x_2} = \mu_1 + \frac{\text{Cov}(X_1, X_2)}{\sigma_2^2}(x_2 - \mu_2) \quad (7.2)$$

$$\sigma_{X_1|X_2=x_2}^2 = \sigma_1^2 - \frac{\text{Cov}(X_1, X_2)^2}{\sigma_2^2}. \quad (7.3)$$

The result in these equations suggests a number of interesting interpretations.

- The conditional mean of  $X_1$  given  $X_2$  is the original mean estimate  $\mu_1$  shifted by a weighted version of the difference between the observation  $x_2$  and the mean  $\mu_2$ . Moreover, the weight is proportional to the ratio between the covariance  $\text{Cov}(X_1, X_2)$  between  $X_1$  and  $X_2$  and the variance of  $X_2$ .

- If  $X_1$  and  $X_2$  are independent, then  $\text{Cov}(X_1, X_2) = 0$ , therefore, observations of  $x_2$  will not affect the original statistics  $\mu_{X_1|X_2=x_2} = \mu_1$  and  $\sigma_{X_1|X_2=x_2}^2 = \sigma_1^2$ .
- The conditional variance of  $X_1$  given  $X_2$  is the original variance,  $\sigma_1^2$ , minus the ratio between the covariance squared,  $\text{Cov}(X_1, X_2)^2$ , and the variance,  $\sigma_2^2$ .

## Properties of Multivariate Gaussian Distribution

1 point possible (graded)

Is it possible that  $\sigma_1 < \frac{\text{Cov}(X_1, X_2)}{\sigma_2}$ ?

☐ Yes

☐ No

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You have used 0 of 1 attempt

## Conditional Probability

1 point possible (graded)

Assume the temperature in *City 1*  $X_1$  is a Gaussian random variable with mean  $\mu_1 = 60$  and  $\sigma_1 = 10$ , and that the temperature of *City 2*  $X_2$  is is a Gaussian random variable with mean  $\mu_2 = 90$  and  $\sigma_2 = 20$ . Moreover, we know that the covariance between  $X_1$  and  $X_2$  is 100. Today, we have observed that the temperature in *City 2* is 75. What is the probability that the new temperature in the *City 1* is bigger than 56.25?

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