

## Independence

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*Definition:* Two events  $A$  and  $B$  are independent if  $P(A \cap B) = P(A)P(B)$ .  
Alternatively, they are independent if  $P(A|B) = P(A)$  and  $P(B|A) = P(B)$ .

Informally, two events are independent if they don't influence each other; knowing that  $A$  happened doesn't give you any additional information about  $B$ .

$$\text{if } P(A \cap B) = P(A)P(B)$$

$$P(A) = \frac{P(A \cap B)}{P(B)} = P(A|B)$$

Conversely

$$\text{if } P(A|B) = \frac{P(A \cap B)}{P(B)} = P(A)$$

$$\text{Then } P(A \cap B) = P(A)P(B)$$

## Independence Example - Discrete

- Suppose that our sample space consists of  $N$  flips of a coin that has probability  $p$  of giving heads.
- The events corresponding to a  $H$  in position  $i$  and in position  $j$  are independent.
- The chance of getting  $k$  heads in  $N$  flips is

$$P(k, N) = \binom{N}{k} p^k (1-p)^{N-k}$$

The probability distribution on the set  $0, \dots, N$  given by this formula is called the *binomial distribution* for parameters  $p$  and  $N$ .

$$X = \text{Sequences of } H, T \text{ of length } N$$

$$= \{H, T\}^N$$

$$(H, T, H, H, \dots, H) \in X$$

$$P(\text{Head in position } i) = p$$

$$P(T \text{ " " "}) = 1-p$$

the positions are independent.

$$\text{If } E = (H, \dots, T, \dots, H)$$

$K$  heads  
 $N-K$  tails

$$P(E) = p^K (1-p)^{N-K}$$

Let  $P(k, N)$  be the chance of  $k$  heads in  $N$  flips.

Fix  $N$ :

$$P(k, N) = \binom{N}{k} p^k (1-p)^{N-k}$$

$P(k, N)$  = chance of  $k$  heads in  $N$  flips of a coin with  $P(H) = p$ .

$k = 0, 1, \dots, N$

Binomial Distribution  
with parameters  $p, N$ .

## Independence Example - Continuous

Suppose we have a thermometer that measures the temperature  $t$  within an error  $x = t - t_0$  from the true temperature, where  $x$  is normally distributed with standard deviation  $\sigma$ .

Suppose we make  $N$  independent measurements of the temperature. How are the errors distributed?

$$P(|x_1| < \delta, \dots, |x_N| < \delta) = \left( \frac{1}{\sigma\sqrt{2\pi}} \right)^N \int_{x_1=-\delta}^{\delta} \dots \int_{x_N=-\delta}^{\delta} e^{-(\sum_{i=1}^N x_i^2)/(2\sigma^2)} dx_1 \dots dx_N$$

This is the *multivariate gaussian* distribution.

$t_0$  true temp  
 $x = t - t_0$   $t$  = temp on thermometer.

$$P(|x| < \delta) = \left( \frac{1}{\sigma\sqrt{2\pi}} \right) \int_{x=-\delta}^{\delta} e^{-x^2/(2\sigma^2)} dx.$$

Make  $N$  independent measurements.  $t_1, \dots, t_N$   
 $x_i = t_i - t_0$ .

$$\begin{aligned} P(|x_1| < \delta, |x_2| < \delta, \dots, |x_N| < \delta) &= \left( \frac{1}{\sigma\sqrt{2\pi}} \right)^N \int_{x_1=-\delta}^{\delta} \int_{x_2=-\delta}^{\delta} \dots \int_{x_N=-\delta}^{\delta} e^{-x_1^2/(2\sigma^2) - x_2^2/(2\sigma^2) - \dots} dx_1 \dots dx_N \\ &= \left( \frac{1}{\sigma\sqrt{2\pi}} \right)^N \int_{x_i=-\delta}^{\delta} e^{-\|x\|^2/(2\sigma^2)} dx_1 \dots dx_N \end{aligned}$$

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$$P((x_1, \dots, x_N) \in U \subseteq \mathbb{R}^N) = \left( \frac{1}{\sigma\sqrt{2\pi}} \right)^N \int_U e^{-\|x\|^2/(2\sigma^2)} d\vec{x}$$

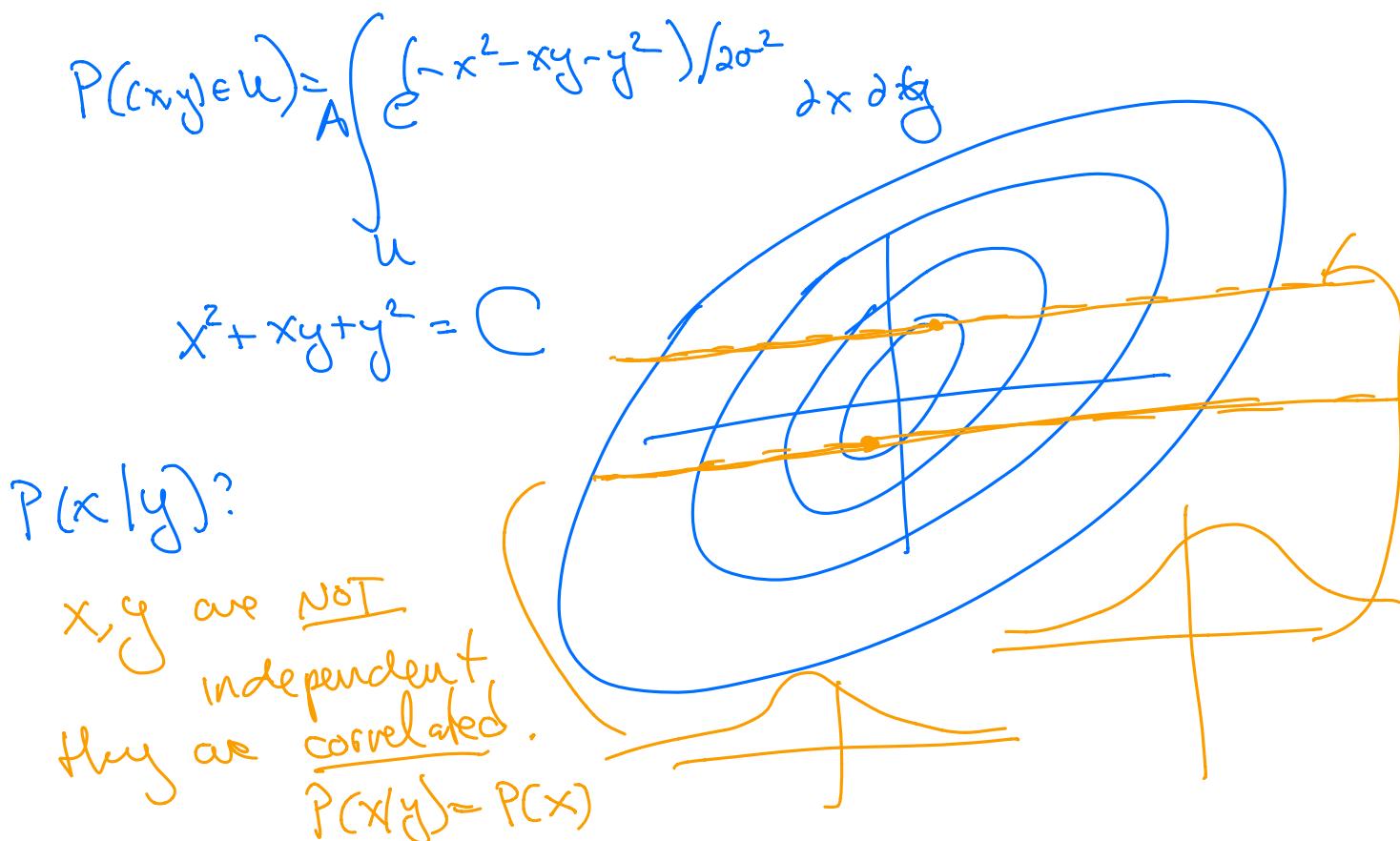
## Non-independent events

Suppose we draw a pair of real numbers  $(x, y)$  from the plane  $R^2$  controlled by the distribution

$$P((x, y) \in U) = A \int_U e^{(-x^2 - xy - y^2)/(2\sigma^2)} dx dy$$

This density function has a bump at the origin and its level curves are ellipses.

The two coordinates are not independent of each other.



## Non-independent events

Multivariate Gaussian

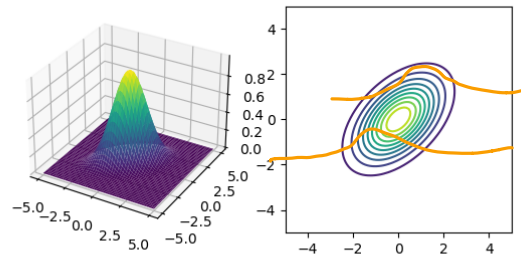


Figure 1: Multivariate Gaussian