

# CMPSCI 240: “Reasoning Under Uncertainty”

## Lecture 8

Prof. Hanna Wallach  
wallach@cs.umass.edu

February 16, 2012

## Reminders

- ▶ Check the course website: `http://www.cs.umass.edu/~wallach/courses/s12/cmpsci240/`
- ▶ Second homework is due TOMORROW

Recap

## Last Time: Expectation

- ▶ **PMF:**  $p_X(x) = P(X=x) = P(\{X=x\})$

## Last Time: Expectation

- ▶ **PMF:**  $p_X(x) = P(X=x) = P(\{X=x\})$
- ▶ **Expectation:**  $\mathbb{E}[X] = \sum_x x p_X(x)$

## Last Time: Expectation

- ▶ **PMF:**  $p_X(x) = P(X=x) = P(\{X=x\})$
- ▶ **Expectation:**  $\mathbb{E}[X] = \sum_x x p_X(x)$
- ▶ If  $Y = g(X)$  then  $\mathbb{E}[Y] = \sum_x g(x) p_X(x)$

## Last Time: Expectation

- ▶ **PMF:**  $p_X(x) = P(X=x) = P(\{X=x\})$
- ▶ **Expectation:**  $\mathbb{E}[X] = \sum_x x p_X(x)$
- ▶ If  $Y = g(X)$  then  $\mathbb{E}[Y] = \sum_x g(x) p_X(x)$
- ▶ If  $Y = aX + b$  then  $\mathbb{E}[Y] = a\mathbb{E}[X] + b$

## Last Time: Variance

► **Variance:**  $\text{var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$



## Last Time: Variance

- ▶ **Variance:**  $\text{var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$
- ▶ If  $Y = aX + b$  then  $\text{var}(Y) = a^2 \text{var}(X)$

## Last Time: Variance

- ▶ **Variance:**  $\text{var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$
- ▶ If  $Y = aX + b$  then  $\text{var}(Y) = a^2 \text{var}(X)$
- ▶ **Standard deviation:**  $\sigma_X = \sqrt{\text{var}(X)}$

## Last Time: Variance

- ▶ **Variance:**  $\text{var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$
- ▶ If  $Y = aX + b$  then  $\text{var}(Y) = a^2 \text{var}(X)$
- ▶ **Standard deviation:**  $\sigma_X = \sqrt{\text{var}(X)}$
- ▶ If  $Y = aX + b$  then  $\sigma_Y = a \sigma_X$

## Last Time: Multiple Random Variables

- ▶ **Joint PMF:**  $p_{X,Y}(x,y) = P(\{X=x\} \cap \{Y=y\})$

## Last Time: Multiple Random Variables

- ▶ **Joint PMF:**  $p_{X,Y}(x,y) = P(\{X=x\} \cap \{Y=y\})$
- ▶  $p_X(x) = \sum_y p_{X,Y}(x,y)$  and  $p_Y(y) = \sum_x p_{X,Y}(x,y)$

## Last Time: Multiple Random Variables

- ▶ **Joint PMF:**  $p_{X,Y}(x, y) = P(\{X=x\} \cap \{Y=y\})$
- ▶  $p_X(x) = \sum_y p_{X,Y}(x, y)$  and  $p_Y(y) = \sum_x p_{X,Y}(x, y)$
- ▶ If  $Z = g(X, Y)$  then  $\mathbb{E}[Z] = \sum_x \sum_y g(x, y) p_{X,Y}(x, y)$

## Last Time: Multiple Random Variables

- ▶ **Joint PMF:**  $p_{X,Y}(x, y) = P(\{X=x\} \cap \{Y=y\})$
- ▶  $p_X(x) = \sum_y p_{X,Y}(x, y)$  and  $p_Y(y) = \sum_x p_{X,Y}(x, y)$
- ▶ If  $Z = g(X, Y)$  then  $\mathbb{E}[Z] = \sum_x \sum_y g(x, y) p_{X,Y}(x, y)$
- ▶ If  $Z = aX + bY + c$  then  $\mathbb{E}[Z] = a\mathbb{E}[X] + b\mathbb{E}[Y] + c$

## Multiple Random Variables (Cont.)



## Three or More Random Variables

- ▶ The joint PMF of  $X$ ,  $Y$ , and  $Z$  is denoted  $p_{X,Y,Z}$  where

$$p_{X,Y,Z}(x, y, z) = P(\{X=x\} \cap \{Y=y\} \cap \{Z=z\})$$

## Three or More Random Variables

- ▶ The joint PMF of  $X$ ,  $Y$ , and  $Z$  is denoted  $p_{X,Y,Z}$  where

$$p_{X,Y,Z}(x, y, z) = P(\{X=x\} \cap \{Y=y\} \cap \{Z=z\})$$

- ▶ The expected value of  $g(X, Y, Z)$  is

$$\mathbb{E}[g(X, Y, Z)] = \sum_x \sum_y \sum_z g(x, y, z) P_{X,Y,Z}(x, y, z)$$

## Three or More Random Variables

- ▶ The joint PMF of  $X$ ,  $Y$ , and  $Z$  is denoted  $p_{X,Y,Z}$  where

$$p_{X,Y,Z}(x, y, z) = P(\{X=x\} \cap \{Y=y\} \cap \{Z=z\})$$

- ▶ The expected value of  $g(X, Y, Z)$  is

$$\mathbb{E}[g(X, Y, Z)] = \sum_x \sum_y \sum_z g(x, y, z) P_{X,Y,Z}(x, y, z)$$

- ▶  $\mathbb{E}[aX + bY + cZ + d] = a\mathbb{E}[X] + b\mathbb{E}[Y] + c\mathbb{E}[Z] + d$

## Linearity of Expectation

- ▶ In general, the expectation of a **sum of random variables** is equal to the sum of their expectations, i.e.,

$$\mathbb{E}[X_1 + \dots + X_n] = \sum_{i=1}^n \mathbb{E}[X_i]$$

## Linearity of Expectation

- ▶ In general, the expectation of a **sum of random variables** is equal to the sum of their expectations, i.e.,

$$\mathbb{E}[X_1 + \dots + X_n] = \sum_{i=1}^n \mathbb{E}[X_i]$$

- ▶ If  $X_i$  has the same PMF as  $X_j$  they are **identically distributed**:

$$\mathbb{E}[X_i] = \sum_x x p_{X_i}(x) = \sum_x x p_{X_j}(x) = \mathbb{E}[X_j]$$

## Examples of Three or More Random Variables

- ▶ e.g., an office party decides to do a gift exchange for their annual holiday party. Everyone in the office purchases a gift and places it in a box. Each person is then given a random gift drawn from the box. What is the expected number of people who get back the gift that they purchased?

## Expectations of Standard Random Variables

- ▶ e.g., if  $X$  is a binomial random variable, what is  $\mathbb{E}[X]$ ?

# Conditioning



# Conditioning

- ▶ **Conditional PMF of  $X$  given  $Y$** : denoted by  $p_{X|Y}$ , where

$$p_{X|Y}(x|y) = P(X=x | Y=y) = P(\{X=x\} | \{Y=y\})$$

# Conditioning

- ▶ **Conditional PMF of  $X$  given  $Y$** : denoted by  $p_{X|Y}$ , where

$$p_{X|Y}(x|y) = P(X=x | Y=y) = P(\{X=x\} | \{Y=y\})$$

- ▶ Compute  $p_{X|Y}$  using the definition of conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \implies p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$$

## Conditioning and the Tabular Representation

	$y_1$	$y_2$	$y_3$	$y_4$
$x_1$	0.1	0.1	0	0.2
$x_2$	0.05	0.05	0.1	0
$x_3$	0	0.1	0.2	0.1

- ▶ Compute conditional PMF for  $Y$  given  $X=x$  by renormalizing the values in the row for  $x$  and conditional PMF for  $X$  given  $Y=y$  by renormalizing the values in the column for  $y$

## Conditioning and the Tabular Representation

	$y_1$	$y_2$	$y_3$	$y_4$
$x_1$	0.1	0.1	0	0.2
$x_2$	0.05	0.05	0.1	0
$x_3$	0	0.1	0.2	0.1

- ▶ e.g., to compute  $p_{X|Y}(x_1 | y_2)$ :

$$p_{X|Y}(x_1 | y_2) = \frac{p_{X,Y}(x_1, y_2)}{\sum_{i=1}^3 p_{X,Y}(x_i, y_2)} = \frac{p_{X,Y}(x_1, y_2)}{p_Y(y_2)}$$

## Calculating Joint and Marginal PMFs

- ▶ Apply the **multiplication rule** using the underlying events  $\{X=x\} \cap \{Y=y\}$ ,  $\{X=x\}$ , and  $\{Y=y\}$  to give

$$p_{X,Y}(x,y) = p_X(x) p_{Y|X}(y|x) = p_Y(y) p_{X|Y}(x|y)$$

## Calculating Joint and Marginal PMFs

- ▶ Apply the **multiplication rule** using the underlying events  $\{X=x\} \cap \{Y=y\}$ ,  $\{X=x\}$ , and  $\{Y=y\}$  to give

$$p_{X,Y}(x,y) = p_X(x) p_{Y|X}(y|x) = p_Y(y) p_{X|Y}(x|y)$$

- ▶ Divide-and-conquer approach to calculating marginal PMFs:

$$p_X(x) = \sum_y p_{X,Y}(x,y) = \sum_y p_Y(y) p_{X|Y}(x|y)$$

## Examples of Conditioning

- ▶ e.g., if my computer has a virus (which is true with probability 0.2) my antivirus program will detect this virus with probability 0.7. If my computer does not have a virus, my antivirus program will mistakenly detect a virus with probability 0.1. Let  $X$  and  $Y$  be binary random variables that are equal to 1 if my computer has a virus and the program detects a virus, respectively, and 0 otherwise. What is  $p_{X,Y}$ ?

# Conditioning on Events

- ▶ We can condition random variables on **events** too



## Conditioning on Events

- ▶ We can condition random variables on **events** too
- ▶ If  $X$  is associated with the same experiment as event  $A$  then

$$p_{X|A}(k) = P(X=k | A) = P(\{X=k\} | A)$$

## Conditioning on Events

- ▶ We can condition random variables on **events** too
- ▶ If  $X$  is associated with the same experiment as event  $A$  then

$$p_{X|A}(k) = P(X=k | A) = P(\{X=k\} | A)$$

- ▶ e.g.,  $X =$  “sum of two rolls”,  $A =$  “first roll is odd”

## Conditioning on Events

- ▶ We can condition random variables on **events** too
- ▶ If  $X$  is associated with the same experiment as event  $A$  then

$$p_{X|A}(k) = P(X=k | A) = P(\{X=k\} | A)$$

- ▶ e.g.,  $X =$  “sum of two rolls”,  $A =$  “first roll is odd”
- ▶ Nothing fancy here – this is just notation – when in doubt, **think about the underlying events and outcomes**

## Examples of Conditioning on Events

- ▶ e.g., a student will take a test repeatedly up to a maximum of  $n$  times, each time with a probability  $p$  of passing, independent of previous attempts. What is the PMF of the number of attempts, given that the student passes the test?

# Conditional Expectation

- ▶ Conditional version of expectation:

$$\mathbb{E}[X | Y=y] = \sum_x x p_{X|Y}(x|y)$$

# Conditional Expectation

- ▶ Conditional version of expectation:

$$\mathbb{E}[X | Y=y] = \sum_x x p_{X|Y}(x|y)$$

- ▶ For any function  $g(\cdot)$  of  $X$ , what is  $\mathbb{E}[g(X) | Y=y]$ ?

# Conditional Expectation

- ▶ Conditional version of expectation:

$$\mathbb{E}[X | Y=y] = \sum_x x p_{X|Y}(x|y)$$

- ▶ For any function  $g(\cdot)$  of  $X$ , what is  $\mathbb{E}[g(X) | Y=y]$ ?

$$\mathbb{E}[g(X) | Y=y] = \sum_x g(x) p_{X|Y}(x|y)$$

# Conditional Expectation

- ▶ Conditional version of expectation:

$$\mathbb{E}[X | Y=y] = \sum_x x p_{X|Y}(x|y)$$

- ▶ For any function  $g(\cdot)$  of  $X$ , what is  $\mathbb{E}[g(X) | Y=y]$ ?

$$\mathbb{E}[g(X) | Y=y] = \sum_x g(x) p_{X|Y}(x|y)$$

- ▶ Expectations can be conditioned on events too



## Conditional Variance and Standard Deviation

- ▶ Conditional variance of  $X$  given  $Y=y$ :

$$\text{var}(X | Y=y) = \mathbb{E}[X^2 | Y=y] - \mathbb{E}[X | Y=y]^2$$

## Conditional Variance and Standard Deviation

- ▶ Conditional variance of  $X$  given  $Y=y$ :

$$\text{var}(X | Y=y) = \mathbb{E}[X^2 | Y=y] - \mathbb{E}[X | Y=y]^2$$

- ▶ What is the conditional standard deviation of  $X$  given  $Y=y$ ?

# Conditional Variance and Standard Deviation

- ▶ Conditional variance of  $X$  given  $Y=y$ :

$$\text{var}(X | Y=y) = \mathbb{E}[X^2 | Y=y] - \mathbb{E}[X | Y=y]^2$$

- ▶ What is the conditional standard deviation of  $X$  given  $Y=y$ ?

$$\sigma_{X|Y=y} = \sqrt{\text{var}(X | Y=y)}$$

# Conditional Variance and Standard Deviation

- ▶ Conditional variance of  $X$  given  $Y=y$ :

$$\text{var}(X | Y=y) = \mathbb{E}[X^2 | Y=y] - \mathbb{E}[X | Y=y]^2$$

- ▶ What is the conditional standard deviation of  $X$  given  $Y=y$ ?

$$\sigma_{X|Y=y} = \sqrt{\text{var}(X | Y=y)}$$

- ▶ Both can be conditioned on events too

# Total Expectation Theorem

- ▶ **Total expectation theorem:** for any random variables  $X$  and  $Y$

$$\mathbb{E}[X] = \sum_y p_Y(y) \mathbb{E}[X | Y=y]$$

# Total Expectation Theorem

- ▶ **Total expectation theorem:** for any random variables  $X$  and  $Y$

$$\mathbb{E}[X] = \sum_y p_Y(y) \mathbb{E}[X | Y=y]$$

- ▶ For any disjoint events  $A_1, \dots, A_n$  that partition  $\Omega$ :

$$\mathbb{E}[X] = \sum_{i=1}^n P(A_i) \mathbb{E}[X | A_i]$$

## Expectations of Standard Random Variables

- ▶ e.g., if  $X$  is a geometric random variable, what is  $\mathbb{E}[X]$ ?

Independence



## Independence of Events

- ▶ Two events  $A$  and  $B$  are **independent** if and only if

$$P(A \cap B) = P(A) P(B)$$

## Independence of Events

- ▶ Two events  $A$  and  $B$  are **independent** if and only if

$$P(A \cap B) = P(A)P(B)$$

- ▶ If  $P(B) > 0$  this is equivalent to

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

## Independence of Events

- ▶ Two events  $A$  and  $B$  are **independent** if and only if

$$P(A \cap B) = P(A)P(B)$$

- ▶ If  $P(B) > 0$  this is equivalent to

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

- ▶ If  $P(A) > 0$  this is equivalent to  $P(B|A) = P(B)$

## Independence of Random Variables

- ▶  $X$  and  $Y$  are **independent** if and only if for all  $x$  and  $y$

$$p_{X,Y}(x,y) = p_X(x) p_Y(y)$$

## Independence of Random Variables

- ▶  $X$  and  $Y$  are **independent** if and only if for all  $x$  and  $y$

$$p_{X,Y}(x,y) = p_X(x) p_Y(y)$$

- ▶ Equivalently if for all  $x$  and  $y$  such that  $p_Y(y) > 0$

$$\frac{p_{X,Y}(x,y)}{p_Y(y)} = p_{X|Y}(x|y) = p_X(x)$$

## Independence of Random Variables

- ▶  $X$  and  $Y$  are **independent** if and only if for all  $x$  and  $y$

$$p_{X,Y}(x,y) = p_X(x) p_Y(y)$$

- ▶ Equivalently if for all  $x$  and  $y$  such that  $p_Y(y) > 0$

$$\frac{p_{X,Y}(x,y)}{p_Y(y)} = p_{X|Y}(x|y) = p_X(x)$$

- ▶ Or if  $p_{Y|X}(y|x) = p_Y(y)$  for all  $x$  and  $y$  such that  $p_X(x) > 0$

## Independence and the Tabular Representation

	$y_1$	$y_2$	$y_3$	$y_4$
$x_1$	0.05	0.15	0	0.2
$x_2$	0.025	0.075	0	0.1
$x_3$	0.05	0.15	0	0.2

- ▶ Are  $X$  and  $Y$  independent? How can we tell?

# Expectation and Independence

- ▶ If  $X$  and  $Y$  are independent then

$$\begin{aligned}\mathbb{E}[XY] &= \sum_x \sum_y x y p_{X,Y}(x, y) \\ &= \sum_x \sum_y x y p_X(x) p_Y(y) = \mathbb{E}[X] \mathbb{E}[Y]\end{aligned}$$



# Expectation and Independence

- ▶ If  $X$  and  $Y$  are independent then

$$\begin{aligned}\mathbb{E}[XY] &= \sum_x \sum_y x y p_{X,Y}(x,y) \\ &= \sum_x \sum_y x y p_X(x) p_Y(y) = \mathbb{E}[X] \mathbb{E}[Y]\end{aligned}$$

- ▶ This is **only true if  $X$  and  $Y$  are independent**

## Independence and Three or More Random Variables

- ▶  $X$ ,  $Y$ , and  $Z$  are independent if and only if for all  $x$ ,  $y$ , and  $z$

$$p_{X,Y,Z}(x,y,z) = p_X(x) p_Y(y) p_Z(z)$$

## Independence and Three or More Random Variables

- ▶  $X$ ,  $Y$ , and  $Z$  are independent if and only if for all  $x$ ,  $y$ , and  $z$

$$p_{X,Y,Z}(x,y,z) = p_X(x) p_Y(y) p_Z(z)$$

- ▶ If random variables  $X$ ,  $Y$ , and  $Z$  are independent then so are random variables of the form  $f(X)$ ,  $g(Y)$ , and  $h(Z)$

## Variance and Independence

- ▶ If  $X_1, X_2, \dots, X_n$  are **independent** then

$$\text{var}(X_1 + X_2 + \dots + X_n) = \sum_{i=1}^n \text{var}(X_i)$$

## Variance and Independence

- ▶ If  $X_1, X_2, \dots, X_n$  are **independent** then

$$\text{var}(X_1 + X_2 + \dots + X_n) = \sum_{i=1}^n \text{var}(X_i)$$

- ▶ If  $X_1, X_2, \dots, X_n$  are **independent and identically distributed**, then  $\text{var}(X_1) = \text{var}(X_2) = \dots = \text{var}(X_n)$  and

$$\text{var}(X_1 + X_2 + \dots + X_n) = n \text{var}(X_1)$$

## For Next Time

- ▶ Check the course website: `http://www.cs.umass.edu/~wallach/courses/s12/cmpsci240/`
- ▶ Second homework is due TOMORROW