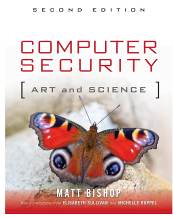
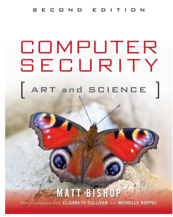


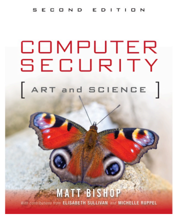
Entropy and Uncertainty

Appendix C



Outline

- Random variables
- Joint probability
- Conditional probability
- Entropy (or uncertainty in bits)
- Joint entropy
- Conditional entropy
- Applying it to secrecy of ciphers



Random Variable

- Variable that represents outcome of an event
  - X represents value from roll of a fair die; probability for rolling n: $p(=n) = 1/6$
  - If die is loaded so 2 appears twice as often as other numbers, $p(X=2) = 2/7$ and, for $n \neq 2$, $p(X=n) = 1/7$
- Note: $p(X)$ means specific value for X doesn't matter
  - Example: all values of X are equiprobable

Joint Probability

- Joint probability of X and Y, $p(X, Y)$, is probability that X and Y simultaneously assume particular values
  - If X, Y independent, $p(X, Y) = p(X)p(Y)$
- Roll die, toss coin
  - $p(X=3, Y=\text{heads}) = p(X=3)p(Y=\text{heads}) = 1/6 \times 1/2 = 1/12$

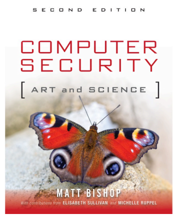
Two Dependent Events

- X = roll of red die, Y = sum of red, blue die rolls

$p(Y=2) = 1/36$	$p(Y=3) = 2/36$	$p(Y=4) = 3/36$	$p(Y=5) = 4/36$
$p(Y=6) = 5/36$	$p(Y=7) = 6/36$	$p(Y=8) = 5/36$	$p(Y=9) = 4/36$
$p(Y=10) = 3/36$	$p(Y=11) = 2/36$	$p(Y=12) = 1/36$	

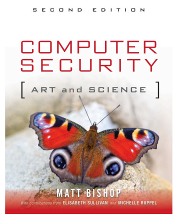
- Formula:

$$p(X=1, Y=11) = p(X=1)p(Y=11) = (1/6)(2/36) = 1/108$$



Conditional Probability

- Conditional probability of X given Y, $p(X \mid Y)$, is probability that X takes on a particular value given Y has a particular value
- Continuing example …
  - $p(Y=7 \mid X=1) = 1/6$
  - $\mathrm{p}(Y=7 \mid X=3) = 1/6$

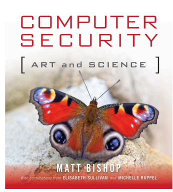


Relationship

- $p(X, Y) = p(X \mid Y)\, p(Y) = p(X)\, p(Y \mid X)$
- Example:

  $p(X{=}3, Y{=}8) = p(X{=}3 \mid Y{=}8)\, p(Y{=}8) = (1/5)(5/36) = 1/36$
- Note: if X, Y independent:

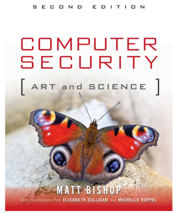
  $p(X \mid Y) = p(X)$



Entropy

- Uncertainty of a value, as measured in bits
- Example: *X* value of fair coin toss; *X* could be heads or tails, so 1 bit of uncertainty
  - Therefore entropy of *X* is $H(X) = 1$
- Formal definition: random variable *X*, values $x_1, \ldots, x_n$; so $\Sigma_i\, \mathrm{p}(X = x_i) = 1$; then entropy is:

$$H(X) = -\Sigma_i\, p(X{=}x_i) \lg p(X{=}x_i)$$



Heads or Tails?

- $H(X) = -\,p(X\text{=heads}) \lg p(X\text{=heads}) - \mathrm{p}(X\text{=tails}) \lg p(X\text{=tails})$
  $= -\,(1/2) \lg (1/2) - (1/2) \lg (1/2)$
  $= -\,(1/2)\,(-1) - (1/2)\,(-1) = 1$
- Confirms previous intuitive result

n-Sided Fair Die

$H(X) = -\Sigma_i \, p(X = x_i) \lg p(X = x_i)$

As $p(X = x_i) = 1/n$, this becomes

$H(X) = -\Sigma_i \, (1/n) \lg (1/n) = -n(1/n) (-\lg n)$

so

$H(X) = \lg n$

which is the number of bits in n, as expected

Ann, Pam, and Paul

Ann, Pam twice as likely to win as Paul

W represents the winner. What is its entropy?

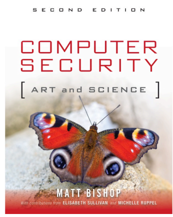
- w_1 = Ann, w_2 = Pam, w_3 = Paul
- $p(W{=}w_1) = p(W{=}w_2) = 2/5$, $p(W{=}w_3) = 1/5$

- So $H(W) = -\Sigma_i\, p(W{=}w_i) \lg p(W{=}w_i)$

  $= -\,(2/5) \lg (2/5) - (2/5) \lg (2/5) - (1/5) \lg (1/5)$

  $= -\,(4/5) + \lg 5 \approx -1.52$

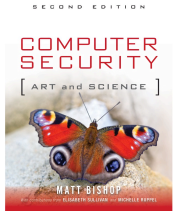
- If all equally likely to win, $H(W) = \lg 3 \approx 1.58$



Joint Entropy

- X takes values from $\{ x_1, \dots, x_n \}$, and $\Sigma_i\, p(X{=}x_i) = 1$
- Y takes values from $\{ y_1, \dots, y_m \}$, and $\Sigma_i\, p(Y{=}y_i) = 1$
- Joint entropy of X, Y is:

$$H(X, Y) = -\Sigma_j\, \Sigma_i\, p(X{=}x_i, Y{=}y_j) \lg p(X{=}x_i, Y{=}y_j)$$



Example

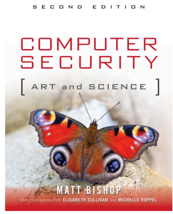
X: roll of fair die, Y: flip of coin

As X, Y are independent:

$p(X=1, Y=\text{heads}) = p(X=1)\, p(Y=\text{heads}) = 1/12$

and

$$H(X, Y) = -\Sigma_j \Sigma_i\, p(X=x_i, Y=y_j) \lg p(X=x_i, Y=y_j)$$
$$= -2 \,[\, 6 \,[\, (1/12) \lg (1/12) \,]\,] = \lg 12$$



Conditional Entropy

- X takes values from $\{ x_1, \ldots, x_n \}$ and $\Sigma_i\, p(X=x_i) = 1$
- Y takes values from $\{ y_1, \ldots, y_m \}$ and $\Sigma_i\, p(Y=y_i) = 1$
- Conditional entropy of X given $Y=y_j$ is:

$$H(X \mid Y=y_j) = -\Sigma_i\, p(X=x_i \mid Y=y_j) \lg p(X=x_i \mid Y=y_j)$$

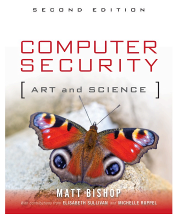
- Conditional entropy of X given Y is:

$$H(X \mid Y) = -\Sigma_j\, p(Y=y_j)\, \Sigma_i\, p(X=x_i \mid Y=y_j) \lg p(X=x_i \mid Y=y_j)$$

Example

- X roll of red die, Y sum of red, blue roll
- Note $p(X=1 \mid Y=2) = 1$, $p(X=i \mid Y=2) = 0$ for $i \neq 1$
  - If the sum of the rolls is 2, both dice were 1
- Thus

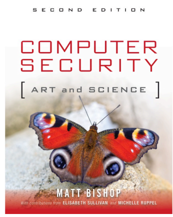
$$H(X \mid Y=2) = -\Sigma_i \, p(X=x_i \mid Y=2) \lg p(X=x_i \mid Y=2) = 0$$



Example (*con't*)

- Note $p(X=i, Y=7) = 1/6$
  - If the sum of the rolls is 7, the red die can be any of 1, …, 6 and the blue die must be 7–roll of red die
- $H(X | Y=7) = -\Sigma_i \, p(X=x_i | Y=7) \lg p(X=x_i | Y=7)$

$$= -6 \, (1/6) \lg (1/6) = \lg 6$$



Perfect Secrecy

- Cryptography: knowing the ciphertext does not decrease the uncertainty of the plaintext
- $M = \{ m_1, \ldots, m_n \}$ set of messages
- $C = \{ c_1, \ldots, c_n \}$ set of messages
- Cipher $c_i = E(m_i)$ achieves *perfect secrecy* if $H(M \mid C) = H(M)$