

10601 Machine Learning

September 21, 2011

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Announcements

- Fill in a survey at <http://www.surveymonkey.com/s/J7Q5JHL>
- Recitations
 - Wed 6 – 7pm (this time) or
 - Fri 4 – 5 pm
- Homework 1 is due on Monday, noon

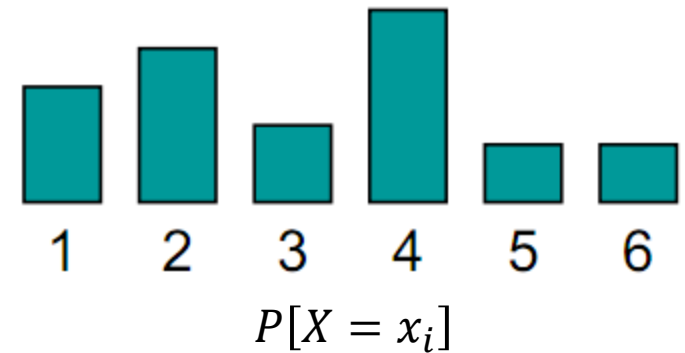
Outline

- Probability overview
- Maximum likelihood estimation

Probability review

X is discrete random variable (e.g. 6-sided die)

Probability mass function (pmf)



Cumulative distribution function (cdf)

$$P[X \leq a] = \sum_{x \leq a} P[X = x]$$

Example

Roll two fair 5-sided dice with labels $\{-2,-1,0,1,2\}$

- What is the pmf for the product of the two dice?
- What is the cdf for the product of the two dice?
- Let Y be 1 for a positive product, -1 for negative product and 0 for a zero product. What is the pmf for Y ?

Law of total probability

Given two discrete random variables X and Y

X takes values in $\{x_1, \dots, x_m\}$

Y takes values in $\{y_1, \dots, y_n\}$

$P(X = x_i)$

~~$P(Y = y_j) = \sum_j P(X = x_i, Y = y_j)$~~

??

~~$P(Y = y_j) = \sum_j P(X = x_i | Y = y_j) P(Y = y_j)$~~

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$P(X = x_i)$

Law of total probability

Given two discrete random variables X and Y

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$$P(X = x_i) = \sum_j P(X = x_i | Y = y_j)P(Y = y_j)$$



Law of total probability

Given two discrete random variables X and Y

$$P(X = x_i) = \sum_j \overbrace{P(X = x_i, Y = y_j)}^{\text{Joint probability of X,Y}}$$

$$= \sum_j \underbrace{P(X = x_i | Y = y_j)}_{\text{Conditional probability of X conditioned on Y}} \underbrace{P(Y = y_j)}_{\text{Marginal probability}}$$

Marginal probability

Conditional probability of X conditioned on Y

Marginal probability

Defining a probability distribution

Two discrete random variables X and Y take binary values

- How do we specify a probability distribution?

Joint probabilities

$$P(X = 0, Y = 1) = 0.2$$

Should sum up to 1

$$P(X = 0, Y = 0) = 0.2$$

$$P(X = 1, Y = 0) = 0.5$$

$$P(X = 1, Y = 1) = 0.5$$



Defining a probability distribution

Two discrete random variables X and Y take binary values

- How do we specify a probability distribution?

Joint probabilities

$$P(X = 0, Y = 1) = 0.2$$

$$P(X = 0, Y = 0) = 0.2$$

$$P(X = 1, Y = 0) = 0.3$$

$$P(X = 1, Y = 1) = 0.3$$



Defining a probability distribution

Two discrete random variables X and Y take binary values

- How do we specify a marginal distribution?

Joint probabilities

$$P(X = 0, Y = 1) = 0.2$$

$$P(X = 0, Y = 0) = 0.2$$

$$P(X = 1, Y = 0) = 0.3$$

$$P(X = 1, Y = 1) = 0.3$$

Marginal probabilities

~~$$P(X = 0) = 0.2$$~~

~~$$P(X = 1) = 0.8$$~~

$$P(Y = 0) = 0.5$$

$$P(Y = 1) = 0.5$$



Defining a probability distribution

Two discrete random variables X and Y take binary values

- How do we specify a marginal distribution?

Joint probabilities

$$P(X = 0, Y = 1) = 0.2$$

$$P(X = 0, Y = 0) = 0.2$$

$$P(X = 1, Y = 0) = 0.3$$

$$P(X = 1, Y = 1) = 0.3$$

Marginal probabilities

$$P(X = 0) = 0.4$$

$$P(X = 1) = 0.6$$

$$P(Y = 0) = 0.5$$

$$P(Y = 1) = 0.5$$



Conditional probabilities

What is the complementary event of $P(X=0 | Y=1)$?

$$P(X=1 | Y=1) \quad \text{OR} \quad P(X=0 | Y=0)$$

Expectation

X is a discrete random variable

$$E[X] = \sum_x xP[X = x]$$

Expectation of a function

$$E[f(X)] = \sum_x f(x)P[X = x]$$

Linearity of expectation

$$E[aX + bY] = aE[X] + bE[Y]$$

Expectation (examples)

Y = flip of a fair coin (1 = heads, 0 = tails)

$$E[Y] = 1 * P[Y = \text{heads}] + 0 * P[Y = \text{tails}] = 0.5$$

Z = outcome of a roll of a die

$$E[Z] = \sum_{z=1}^6 zP[Z = z] = \sum_{z=1}^6 \frac{z}{6} = 3.5$$

Variance

X is a discrete random variable

$$\text{Var}[X] = E[X - E[X]]^2 = E[X^2] - E[X]^2$$

X = flip of a fair coin (1 = heads, 0 = tails)

$$\text{Var}[X] = E[X^2] - E[X]^2 = \sum_{x \in \{0,1\}} x^2 P[X = x] - 0.5^2 = 0.25$$

Independence

Two random variables X and Y are independent if and only if

$$P[X = x, Y = y] = P[X = x]P[Y = y], \forall x, y.$$

Knowledge of one variable does not help us to make inference about the other variable.

Independence (cont.)

X and Y are independent.

Show that

$$- P[X | Y] = P[X]$$

$$- P[-X | Y] = P[-X]$$

$$- P[Y | X] = P[Y]$$

Independence (cont.)

Liked movie	Slept	raining	P
1	1	1	0.05
1	0	1	0.1
0	0	1	0.025
0	1	1	0.075
1	1	0	0.15
1	0	0	0.3
0	0	0	0.075
0	1	0	0.225

$$P[\text{slept}] = 0.5$$

$$P[\text{slept} | \text{rain} = 1] = 0.125 / 0.25 = 0.5$$

Slept and rain are independent

Conditional independence

Two random variables may become independent when conditioned on the third variable.

$$P[X, Y|Z] = P[X|Z]P[Y|Z]$$

X and Y are conditionally independent given Z

Number of parameters

Assume X and Y take Boolean values $\{0,1\}$

How many independent parameters do you need to fully specify:

- marginal probability of X ?

$P(X=0)$ 1 parameter only [because $P(X=1)+P(X=0)=1$]

- the joint probability of $P(X,Y)$?

$P(X=0,Y=0)$, $P(X=0,Y=1)$, $P(X=1, Y=1)$ 3 parameters

- the conditional probability of $P(X|Y)$?

$P(X=0|Y=0)$, $P(X=0|Y=1)$ 2 parameters

- the joint probability of $P(X,Y)$, X and Y are independent

$P(X=0)$, $P(Y=0)$ 2 parameters

KL divergence

The Kullback-Leibler (KL) divergence is a measure of distance between two probability distributions.

Let $p(x)$ and $q(x)$ be two pmfs.

$$KL(p, q) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

KL divergence (cont.)

Relationship to the mutual information

$$I[X; Y] = KL(P[X, Y], P[X]P[Y])$$

Can be used to measure independence of variables.

Maximum likelihood estimation

$$\hat{\theta} = \arg \max_{\theta} P(D|\theta)$$

$$\hat{\theta} = \arg \max_{\theta} \ln P(D|\theta)$$

Poisson distribution

$$P[X = x|\theta] = \frac{\theta^x e^{-\theta}}{x!}, \quad x = 0, 1, 2, \dots$$

Maximum likelihood estimation (cont.)

X_1, X_2, \dots, X_n are independent random variables with the Poisson distribution.

$$P[D|\theta] = \frac{\theta^{x_1} e^{-\theta}}{x_1!} \times \dots \times \frac{\theta^{x_n} e^{-\theta}}{x_n!}$$

$$P[D|\theta] = \frac{\theta^{\sum_i x_i} e^{-n\theta}}{x_1! x_2! \dots x_n!}$$

Joint distribution function (as a function of D)

Likelihood function (as a function of θ)

$$\ln P[D|\theta] = (\sum x_i) \log \theta - n\theta - \sum(\log x_i!)$$

Maximum likelihood estimation (cont.)

Log-likelihood function

$$l(\theta; D) = \ln P[D|\theta] = (\sum x_i) \log \theta - n\theta - \sum (\log x_i!)$$

$$\frac{dl}{d\theta} = \theta^{-1} \sum x_i - n = 0$$

$$\hat{\theta} = \frac{\sum x_i}{n} = \bar{x} \quad \text{————— Maximum likelihood estimate}$$

$$\frac{d^2l}{d\theta^2} = -\frac{\sum x_i}{\theta^2} < 0 \quad \text{Stationary point is the maximum}$$

Questions?