

STAT 341 Midterm-1: Winter 2010

Useful facts

Feb 1, 2010

1. Permutations and combinations

There are $n! = \prod_{i=1}^n i = 1.2.3.4.\dots n$ permutations of n objects.

There are $\binom{n}{k} = n!/(k!(n-k)!)$ ways of choosing a given k objects from n .

2. Joint and conditional probabilities

If C and D are any events: $P(C \cup D) = P(C) + P(D) - P(C \cap D)$.

The conditional probability of C given D is $P(C | D) = P(C \cap D) / P(D)$.

C and D are independent if $P(C \cap D) = P(C).P(D)$.

3. Laws and theorems

Suppose E_1, \dots, E_k is a partition of Ω . That is $E_i \cap E_j$ is empty, and $E_1 \cup E_2 \cup \dots \cup E_k = \Omega$.

The law of total probability states that: $P(D) = \sum_{j=1}^k P(D \cap E_j) = \sum_{j=1}^k P(D | E_j) P(E_j)$

Bayes' Theorem states that: $P(E_i | D) = P(D | E_i) P(E_i)/P(D)$

4. Random variables and distributions

	discrete (mass)	continuous (density)
Probability mass/density function	pmf: $P(X = x) = p_X(x)$	pdf: $f_X(x)$
Cumulative dist. func. CDF, $P(X \leq x)$	$F_X(x) = \sum_{w \leq x} p_X(w)$	$F_X(x) = \int_{-\infty}^x f_X(w)dw$
Expectation:	$E(X) = \sum_x x P(X = x)$	$\int_{-\infty}^{\infty} x f_X(x)dx$
	$E(g(X)) = \sum_x g(x) P(X = x)$	$\int_{-\infty}^{\infty} g(x) f_X(x)dx$
provided the sum/integral converges absolutely.		

For any random variables X and Y :

Variance: $\text{var}(X) = E((X - E(X))^2) = E(X^2) - (E(X))^2$

Always: $E(aX + b) = aE(X) + b$, $E(X + Y) = E(X) + E(Y)$, $\text{var}(aX + b) = a^2 \text{var}(X)$.

If X and Y are independent: $\text{var}(X + Y) = \text{var}(X) + \text{var}(Y)$

If X_1, \dots, X_n are i.i.d, $\bar{X}_n \equiv (1/n) \sum_{i=1}^n X_i$ then $E(\bar{X}_n) = E(X_1)$, $\text{var}(\bar{X}_n) = \text{var}(X_1)/n$.

5. Basics of estimation of parameter θ

- (a) An n -sample is a set of n independent data random variables, Y_1, \dots, Y_n all from the same distribution (i.i.d), indexed by unknown parameter(s) θ .
- (b) A *statistic*, T , is any function of Y_1, \dots, Y_n .
- (c) An *estimator* of $g(\theta)$ is a statistic used to estimate $g(\theta)$.
- (d) The *estimate* of $g(\theta)$ is the value taken by the estimator in any particular instance.
- (e) The Method of Moments (MoM) estimator of one parameter θ is found by solving $\bar{Y}_n = (1/n) \sum_{i=1}^n Y_i = E_\theta(Y)$, giving say estimator W for θ . Then estimator of $h(\theta)$ is $h(W)$.

6. Properties of estimators

- (a) *Bias* of estimator T of θ is $b_T(\theta) = E_\theta(T) - \theta$.
- (b) *MSE* of estimator T of θ is $mse_\theta(T) = E((T - \theta)^2) = \text{var}_\theta(T) + (b_T(\theta))^2$.
- (c) An estimator T_n based on an n -sample is *asymptotically unbiased* if $b_{T_n}(\theta) \rightarrow 0$ as $n \rightarrow \infty$.
- (d) An estimator T_n based on an n -sample is *consistent* if, for all $\epsilon > 0$, $P(|T_n - \theta| > \epsilon) \rightarrow 0$ as $n \rightarrow \infty$.
- (e) Chebychev's inequality: consistency and MSE are related by the fact that, for all $\epsilon > 0$,

$$P(|T_n - \theta| > \epsilon) \leq E((T_n - \theta)^2)/\epsilon^2.$$

7. Standard distributions:

	pmf or pdf	mean	variance
(a) Binomial; $B(n, p)$ index n , parameter p	$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$ $k = 0, 1, 2, \dots, n$	np	$np(1-p)$
(b) Geometric; $Geo(p)$; parameter p	$P(X = k) = p(1-p)^{k-1}$ $k = 1, 2, 3, 4, \dots$	$1/p$	$(1-p)/p^2$
(c) Neg. Binomial; $NegB(r, p)$; index r , parameter p	$P(X = k) = \binom{k-1}{r-1} p^r (1-p)^{k-r}$ $k = r, r+1, r+2, \dots$	r/p	$r(1-p)/p^2$
(d) Poisson; $\mathcal{P}o(\mu)$	$P(X = k) = \exp(-\mu) \mu^k / k!$, $k = 0, 1, 2, \dots$	μ	μ
(e) Uniform on (a, b) ; $U(a, b)$;	$f_X(x) = 1/(b-a)$, $a < x < b$	$(b+a)/2$	$(b-a)^2/12$
(f) Normal, $N(\mu, \sigma^2)$	$f_X(x) = (1/\sqrt{2\pi\sigma^2}) \exp(-(x-\mu)^2/2\sigma^2)$	μ	σ^2
(g) Exponential, $\mathcal{E}(\lambda)$ rate parameter λ	$f_X(x) = \lambda \exp(-\lambda x)$ $0 \leq x < \infty$	$1/\lambda$	$1/\lambda^2$