1. (a) Intuitively, X and Y are symmetric in the bivariate norma distributionl, in the sense that (i) and (ii) in Tutorial 2 Question 5 remain true if X and Y are swapped. The swapped version of (i) gives the marginal distribution of Y.

[A complete argument uses the symmetry in the joint density function: not needed.]

- (b)  $cov(X,Y) = \rho \sigma_X \sigma_Y$ . Since  $\sigma_X \sigma_Y > 0$ , cov(X,Y) = 0 implies  $\rho = 0$ . From (ii), the conditional distribution of Y given X = x is  $N(\mu_Y, \sigma_Y^2)$ , for any real number x. Therefore, X and Y are independent.
- 2. (a) From (B), the standardised  $\bar{X}$ :

$$\frac{\bar{X} - \mu}{\sigma / \sqrt{n}} = \sqrt{n} \frac{\bar{X} - \mu}{\sigma}$$

has the N(0,1) distribution. Its square has the  $\chi^2_1$  distribution, by definition.

(b) (C) says that  $(n-1)S^2/\sigma^2 \sim \chi_{n-1}^2$  and by (A), it is independent of  $(\bar{X} - \mu)/(\sigma/\sqrt{n})$ . Therefore, by the definition of the t distribution,

$$\frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \div \frac{S}{\sigma} = \frac{\bar{X} - \mu}{S / \sqrt{n}} \sim t_{n-1}$$

(c) In view of (C), the idea is to calculate E and var of  $R=(n-1)S^2/\sigma^2$ , then move the constants. Since

$$E(R) = n - 1, \quad var(R) = 2(n - 1)$$

$$E(S^2) = \sigma^2, \, \text{var}(S^2) = 2\sigma^4/(n-1).$$

3. (a) From

$$\sum_{i=1}^{n} (X_i - \bar{X})^2 = (n-1)S^2$$

Tutorial 1 Question 6 gives

$$(n-1)S^{2} = \sum_{i=1}^{n} (X_{i} - \mu)^{2} - n(\bar{X} - \mu)^{2}$$

Since  $E\{(X_i - \mu)^2\} = \sigma^2$  and  $E\{(\bar{X} - \mu)^2\} = \sigma^2/n$ , by taking expectation we get

$$(n-1)E(S^2) = n\sigma^2 - n(\sigma^2/n) = (n-1)\sigma^2$$

Hence  $E(S^2) = \sigma^2$ .

If  $E(S) = \sigma$ , then  $var(S) = E(S^2) - \{E(S)\}^2 = 0$ , but this is wrong, since S is not a constant. Hence  $E(S) \neq \sigma$ ; in fact  $E(S) < \sigma$ .

(b) Since  $\hat{\sigma}^2 = (n-1)S^2/n$ ,

$$E(\hat{\sigma}^2) = \frac{n-1}{n}\sigma^2$$

Since  $\hat{\sigma} \leq S$ ,  $E(\hat{\sigma}) \leq E(S) < \sigma$ .

[You can also show that assuming  $E(\hat{\sigma}) = \sigma$  leads to a contradiction like in (a).]

4. The numbers of a's and b's are respectively Np and N(1-p). By definition,

$$\mu = \frac{1}{N} \{ Np \cdot a + N(1-p) \cdot b \} = pa + (1-p)b$$

$$\sigma^{2} = \frac{1}{N} \left\{ Np \cdot (a - \mu)^{2} + N(1 - p) \cdot (b - \mu)^{2} \right\}$$

Now  $a - \mu = (1 - p)(a - b)$ ,  $b - \mu = p(b - a)$ . Substitute these into the above to get the result.

- 5. (a) By exchangeability,  $(X_i, X_j, \ldots, X_N)$   $(X_i \text{ and } X_1 \text{ are swapped, and } X_j \text{ and } X_2 \text{ are swapped,})$  has the same distribution as  $(X_1, X_2, \ldots, X_N)$ . Hence,  $(X_i, X_j)$  has the same distribution as  $(X_1, X_2)$ , so  $\text{cov}(X_i, X_j) = \text{cov}(X_1, X_2)$ . This is true for any  $i \neq j$ .
  - (b) Notice that T is the sum of all population values, so is a constant. Let c be the covariance between  $X_i$  and  $X_j$ ,  $i \neq j$ . Hence  $0 = \text{var}(T) = N\sigma^2 + N(N-1)c$ , giving the answer.
  - (c) By Tutorial 1 Question 1(b),

$$\operatorname{var}\left(\sum_{i=1}^{n} X_{i}\right) = \sum_{1 \leq i, j \leq n} \operatorname{cov}(X_{i}, X_{j})$$

$$= \sum_{i=1}^{n} \operatorname{var}(X_{i}) + \sum_{i \neq j} \operatorname{cov}(X_{i}, X_{j})$$

$$= n\sigma^{2} + n(n-1)\left(-\frac{\sigma^{2}}{N-1}\right)$$

$$= n\sigma^{2} \frac{N-n}{N-1}$$

Dividing by  $n^2$  gives the result.