Answers to 2009 STA 437/1005 mid-term test
1a) $\bar{x}=[100200]^{\prime}$.
1b)

| $x_{j 1}-\bar{x}_{1}$ | $\left(x_{j 1}-\bar{x}_{1}\right)^{2}$ | $x_{j 2}-\bar{x}_{2}$ | $]\left(x_{j 2}-\bar{x}_{2}\right)^{2}$ | $\left(x_{j 1}-\bar{x}_{j 1}\right)\left(x_{j 2}-\bar{x}_{2}\right)$ |
| :---: | :---: | :---: | :---: | :---: |
| -5 | 25 | 10 | 100 | -50 |
| 0 | 0 | 0 | 0 | 0 |
| 5 | 25 | -10 | 100 | -50 |
| -5 | 25 | -5 | 25 | 25 |
| 5 | 25 | 5 | 25 | 25 |

$$
\begin{aligned}
& s_{11}=(1 / 4) \sum_{j}\left(x_{j 1}-\bar{x}_{1}\right)^{2}=100 / 4 \\
& s_{22}=(1 / 4) \sum_{j}\left(x_{j 2}-\bar{x}_{j}\right)^{2}=250 / 4 \\
& s_{12}=s_{21}=(1 / 4) \sum_{j}\left(x_{j 1}-\bar{x}_{j 1}\right)\left(x_{j 2}-\bar{x}_{2}\right)=-50 / 4 \\
& S=\left[\begin{array}{rr}
100 / 4 & -50 / 4 \\
-50 / 4 & 250 / 4
\end{array}\right]=(50 / 4)\left[\begin{array}{rr}
2 & -1 \\
-1 & 5
\end{array}\right]
\end{aligned}
$$

1c) $S^{-1}=(4 / 50)\left[\begin{array}{ll}5 / 9 & 1 / 9 \\ 1 / 9 & 2 / 9\end{array}\right]=(4 / 450)\left[\begin{array}{ll}5 & 1 \\ 1 & 2\end{array}\right]$
$d_{1}^{2}=\left(x_{1}-\bar{x}\right)^{\prime} S^{-1}\left(x_{1}-\bar{x}\right)=\left[\begin{array}{ll}-5 & 10\end{array}\right](4 / 450)\left[\begin{array}{cc}5 & 1 \\ 1 & 2\end{array}\right]\left[\begin{array}{c}-5 \\ 10\end{array}\right]=2$

2a) By the spectral decomposition theorem, we can write any symmetric real matrix, $A$, as $A=\lambda_{1} e_{1} e_{1}^{\prime}+$ $\cdots+\lambda_{k} e_{k} e_{k}^{\prime}$. Since the $e_{i}$ are orthogonal (hence linearly independent), we can write any non-zero vector, $c$, as $c=c_{1} e_{1}+\cdots+c_{k} e_{k}$, for some scalars $c_{i}$, not all of which are zero. We can now write $c^{\prime} A c$ as follows:

$$
c^{\prime} A c=\left(c_{1} e_{1}+\cdots+c_{k} e_{k}\right)^{\prime}\left(\lambda_{1} e_{1} e_{1}^{\prime}+\cdots \lambda_{k} e_{k} e_{k}^{\prime}\right)\left(c_{1} e_{1}+\cdots+c_{k} e_{k}\right)
$$

Multiplying this out, and noting that $e_{i}^{\prime} e_{i}=1$, and also that $e_{i}^{\prime} e_{j}=0$ when $i \neq j$, we see that

$$
c^{\prime} A c=c_{1}^{2} \lambda_{1}+\cdots+c_{k}^{2} \lambda_{k}
$$

If all the $\lambda_{k}$ are positive, this must be greater than zero, since at least one of the $c_{i}$ is non-zero. The matrix $A$ is therefore positive definite.

2b) First, note that the converse of part (a) is true: if a matrix $A$ is positive definite, all its eigenvalues are positive. To see this, suppose $e$ is an eigenvalue of $A$ (which we can take to be of length one), with eigenvalue $\lambda$. Then $e^{\prime} A e>0$ by the definition of positive definiteness. But $e^{\prime} A e=e^{\prime} \lambda e=\lambda e^{\prime} e=\lambda$, so $\lambda>0$.
Next, write $A$ and $B$ as follows, using the spectral decomposition theorem:

$$
\begin{aligned}
A & =\alpha_{1} e_{1} e_{1}^{\prime}+\cdots+\alpha_{k} e_{k} e_{k}^{\prime} \\
B & =\beta_{1} e_{1} e_{1}^{\prime}+\cdots+\beta_{k} e_{k} e_{k}^{\prime}
\end{aligned}
$$

where $e_{1}, \ldots, e_{k}$ are the eigenvectors of both $A$ and $B, \alpha_{1}, \ldots, \alpha_{k}$ are the eigenvalues of $A$, and $\beta_{1}, \ldots, \beta_{k}$ are the eigenvalues of $B$.
When we now multiply $A$ and $B$, and note that $e_{i}^{\prime} e_{i}=1$, and also that $e_{i}^{\prime} e_{j}=0$ when $i \neq j$, we get

$$
A B=\alpha_{1} \beta_{1} e_{1} e_{1}^{\prime}+\cdots+\alpha_{k} \beta_{k} e_{k} e_{k}^{\prime}
$$

Since $\left(e_{i} e_{i}^{\prime}\right)^{\prime}=e_{i}^{\prime \prime} e_{i}^{\prime}=e_{i} e_{i}^{\prime}$, each term above is symmetric, so $A B$ is also symmetric. We can easily see that the eigenvectors of $A B$ are the same $e_{i}$, and that the eigenvalues are the $\alpha_{i} \beta_{i}$ - for instance

$$
A B e_{1}=\alpha_{1} \beta_{1} e_{1} e_{1}^{\prime} e_{1}+\alpha_{2} \beta_{2} e_{2} e_{2}^{\prime} e_{1}+\cdots=\alpha_{1} \beta_{1} e_{1}
$$

If $A$ and $B$ are positive definite, then all the $\alpha_{i}$ and $\beta_{i}$ are positive, and therefore all the eigenvalues of $A B$ are positive. By part (a), $A B$ is therefore positive definite.

3a) A
3b) B
3c) B
3d) C
The $T^{2}$ statistic for testing $H_{0}: \mu=0$ versus $H_{1}: \mu \neq 0$ is

$$
T^{2}=n \bar{x}^{\prime} S_{X}^{-1} \bar{x}
$$

Let $A$ be any non-singular $p \times p$ matrix. Transforming to $y=A x$, we will find that the sample mean is $\bar{y}=A \bar{x}$ and the sample covariance matrix is $S_{Y}=A S_{X} A^{\prime}$. The new $T^{2}$ statistic will then be

$$
\begin{aligned}
T^{2} & =n \bar{y}^{\prime} S_{Y}^{-1} \bar{y} \\
& =n(A \bar{x})^{\prime}\left(A S_{X} A^{\prime}\right)^{-1}(A \bar{x}) \\
& =n \bar{x}^{\prime} A^{\prime} A^{\prime-1} S_{X}^{-1} A^{-1} A \bar{x} \\
& =n \bar{x}^{\prime} S_{X}^{-1} \bar{x}
\end{aligned}
$$

which is the same as the old $T^{2}$ statistic.

4a) D, no outliers, not normal (heavy-tailed).
4b) E, no outliers, not normal (light-tailed).
4c) A, no outliers, no reason to think it's not normal (note the small sample size).
4d) B, one outlier (rightmost point, about 7), no reason to think it's not normal (after ignoring the outlier).

5a)

$$
\Sigma=\left[\begin{array}{llll}
5 & 1 & 1 & 1 \\
1 & 6 & 2 & 2 \\
1 & 2 & 7 & 3 \\
1 & 2 & 3 & 8
\end{array}\right]
$$

5b)

$$
\operatorname{Var}(\bar{Y})=\left[\begin{array}{llll}
1 / 4 & 1 / 4 & 1 / 4 & 1 / 4
\end{array}\right] \Sigma\left[\begin{array}{l}
1 / 4 \\
1 / 4 \\
1 / 4 \\
1 / 4
\end{array}\right]=23 / 8
$$

5c) Normal, with mean $0+1(8)^{-1}\left(y_{4}-0\right)=y_{4} / 8$ and variance $5-1(8)^{-1} 1=39 / 8$.

