## Spring 2013

1. Consider an independent identically distributed sequence $X_{1}, X_{2}, \ldots, X_{n+1}$ taking values 0 or 1 with probability distribution

$$
P\left(X_{i}=1\right)=1-P\left(X_{i}=0\right)=p
$$

Uniformly choose $M$ fragments $F_{1}, F_{2}, \ldots, F_{M}$ of length 2 starting in the interval $[1, n]$, that is, $F_{i}=$ ( $\left.X_{j_{1}}, X_{j_{1}+1}\right)$ for some $1 \leq j_{i} \leq n$. Let $\boldsymbol{W}=(1,1)$.
a) Let $N_{\boldsymbol{W}}$ be the number of times the word $\boldsymbol{W}$ occurs among the $M$ fragments. Calculate $\mathbb{E}\left(N_{\boldsymbol{W}}\right)$.

Solution. We have

$$
\mathbb{E}\left(N_{\boldsymbol{W}}\right)=\sum_{i=1}^{M} \mathbf{1}\left(X_{j_{i}}=1, X_{j_{i}+1}=1\right)=M p^{2}
$$

b) Calculate the probability $P\left(F_{1}=\boldsymbol{W}, F_{2}=\boldsymbol{W}\right)$.

Solution. First, we note that there are three cases:
i. $\left|\left\{X_{j_{1}}, X_{j_{1}+1}\right\} \cap\left\{X_{j_{2}}, X_{j_{2}+1}\right\}\right|=2$ happens $n$ times with $P\left(F_{1}=\boldsymbol{W}, F_{2}=\boldsymbol{W}\right)=p^{2}$.
ii. $\left|\left\{X_{j_{1}}, X_{j_{1}+1}\right\} \cap\left\{X_{j_{2}}, X_{j_{2}+1}\right\}\right|=1$ happens $2 n-4$ times with $P\left(F_{1}=\boldsymbol{W}, F_{2}=\boldsymbol{W}\right)=p^{3}$.
iii. $\left|\left\{X_{j_{1}}, X_{j_{1}+1}\right\} \cap\left\{X_{j_{2}}, X_{j_{2}+1}\right\}\right|=0$ happens $n^{2}-3 n+4$ times with $P\left(F_{1}=\boldsymbol{W}, F_{2}=\boldsymbol{W}\right)=p^{4}$.

Hence, combining the three cases, we get

$$
P\left(F_{1}=\boldsymbol{W}, F_{2}=\boldsymbol{W}\right)=\frac{p^{2}\left(n+(2 n-4) p+\left(n^{2}-3 n+4\right) p^{2}\right)}{n^{2}}
$$

c) Calculate $\operatorname{Var}\left(N_{\boldsymbol{W}}\right)$.

Solution. We have

$$
\begin{aligned}
\operatorname{Var}\left(N_{\boldsymbol{W}}\right)= & \operatorname{Var}\left(\sum_{i=1}^{M} \mathbf{1}\left(X_{j_{i}}=1, X_{j_{i}+1}=1\right)\right) \\
= & \sum_{i=1}^{M} \operatorname{Var}\left(\mathbf{1}\left(X_{j_{i}}=1, X_{j_{i}+1}=1\right)\right) \\
& \quad+\sum_{i \neq k} \operatorname{Cov}\left(\mathbf{1}\left(X_{j_{i}}=1, X_{j_{i}+1}=1\right), \mathbf{1}\left(X_{j_{k}}=1, X_{j_{k}+1}=1\right)\right) \\
= & M\left(p^{2}-p^{4}\right)+2(M-1)\left(p^{3}-p^{4}\right) .
\end{aligned}
$$

NOTE: Due to time constraints, you can ignore the boundary effect.
2. Let $T$ and $C$ be independent Geometric random variables with succuess probability of $r$ and $s$, respectively. That is,

$$
\begin{array}{ll}
P[T=j]=r(1-r)^{j-1} ; & j=1,2, \ldots \\
P[C=j]=s(1-s)^{j-1} ; & j=1,2, \ldots
\end{array}
$$

Let $X=(\min (T, C), I(T \leq C))$. Denote $X_{1}=\min (T, C)$ and $X_{2}=I(T \leq C)$, where $I(\cdot)$ is the indicator function.
a) What is the joint distribution of $X$ ?

Solution. We have

$$
\begin{aligned}
P\left(X_{1}=k, X_{2}=1\right) & =P(\min (T, C)=k, T \leq C)=P(T=k, C \geq k)=P(T=k) P(C \geq k) \\
& =r(1-r)^{k-1} \sum_{j=k}^{\infty} s(1-s)^{j-1}=r(1-r)^{k-1} s(1-s)^{k-1} \sum_{j=0}^{\infty}(1-s)^{j} \\
& =r(1-r)^{k-1}(1-s)^{k-1},
\end{aligned}
$$

and

$$
\begin{aligned}
P\left(X_{1}=k, X_{2}=0\right) & =P(\min (T, C)=k, T>C)=P(C=k, T<k)=P(C=k) P(T>k) \\
& =s(1-s)^{k-1} \sum_{j=k+1}^{\infty} r(1-r)^{j-1}=s(1-s)^{k-1}(1-r)^{k} .
\end{aligned}
$$

Note that

$$
P\left(X_{1}=k\right)=P\left(X_{1}=k, X_{2}=1\right)+P\left(X_{1}=k, X_{2}=0\right)+(r+s-r s)(1-(r+s-r s))^{k-1}
$$

b) Calculate $\mathbb{E} X=\left(\mathbb{E} X_{1}, \mathbb{E} X_{2}\right)$ and the covariance matrix of $X=\left(X_{1}, X_{2}\right)$.

Solution. Since $X_{1} \sim \operatorname{Geom}(r+s-r s)$, we have

$$
\mathbb{E} X_{1}=\frac{1}{r+s-r s}, \text { and } \operatorname{Var}\left(X_{1}\right)=\frac{1-(r+s-r s)}{(r+s-r s)^{2}} .
$$

Also,

$$
\begin{aligned}
\mathbb{E} X_{2} & =P(T \leq C)=\sum_{k=1}^{\infty} P(T \leq k) P(C=k)=\sum_{k=1}^{\infty} s(1-s)^{k-1}\left(1-(1-r)^{k}\right) \\
& =\sum_{k=1}^{\infty} s(1-s)^{k-1}-\sum_{k=1}^{\infty} s(1-s)^{k-1}(1-r)^{k}=1-\frac{s(1-r)}{r+s-r s}=\frac{r}{r+s-r s}
\end{aligned}
$$

and so,

$$
\operatorname{Var}\left(X_{2}\right)=\mathbb{E} X_{2}^{2}-\left(\mathbb{E} X_{2}\right)^{2}=\frac{r}{r+s-r s}-\frac{r^{2}}{(r+s-r s)^{2}}=\frac{r s(1-r)}{(r+s-r s)^{2}}
$$

As for the covariance, we see that

$$
\begin{aligned}
\mathbb{E} X_{1} X_{2} & =\sum_{k=1}^{\infty} k P\left(X_{1}=k, X_{2}=1\right)=\sum_{k=1}^{\infty} k r(1-r)^{k-1}(1-s)^{k-1} \\
& =\frac{r}{r+s-r s} \sum_{k=1}^{\infty} k(r+s-r s)(1-r-s+r s)^{k-1}=\frac{r}{r+s-r s} \frac{1}{r+s-r s}=\frac{r^{2}}{r+s-r s}
\end{aligned}
$$

where the last summation identity comes from the fact that the EV of $\operatorname{Geom}(p)$ is $1 / p$. Hence,

$$
\operatorname{Cov}\left(X_{1}, X_{2}\right)=\mathbb{E} X_{1} X_{2}-\mathbb{E} X_{1}-\mathbb{E} X_{2}=0
$$

and so, the covariance matrix is
$\frac{1}{(r+s-r s)^{2}}\left[\begin{array}{cc}1-r-s+r s & 0 \\ 0 & r s(1-r)\end{array}\right]$.
c) Let $T_{1}, T_{2}, \ldots, T_{n}$ be a random sample from $T$, and $C_{1}, C_{2}, \ldots, C_{n}$ be a random sample from $C$. Define

$$
\begin{aligned}
& S_{1}=\sum_{i=1}^{n} \min \left(T_{i}, C_{i}\right) \\
& S_{2}=\sum_{i=1}^{n} I\left(T_{i} \leq C_{i}\right) .
\end{aligned}
$$

What is the maximum likelihood estimate ( $\hat{r}, \hat{s}$ ) of $(r, s)$, in terms of $S_{1}$ and $S_{2}$ ?
Solution. If $s_{2}$ is observed, without loss of generality, we may assume that it is the first $s_{2}$ such that $I\left(T_{i} \leq C_{i}\right)=1$. Then, the likelihood function is

$$
\begin{aligned}
\mathcal{L}(r, s ; \boldsymbol{T}, \boldsymbol{C}) & =\prod_{i=1}^{s_{2}} P\left(T_{i}=t_{i}, C_{i}=1\right) \prod_{i=s_{2}+1}^{n} P\left(T_{i}=t_{i}, C_{i}=0\right) \\
& =\prod_{i=1}^{s_{2}} r[(1-r)(1-s)]^{t_{i}-1} \prod_{i=s_{2}+1}^{n} s(1-r)[(1-r)(1-s)]^{t_{i}-1} \\
& =r^{s_{2}}(s(1-r))^{n-s_{2}}[(1-r)(1-s)]^{s_{1}-n},
\end{aligned}
$$

and so, the log-likelihood function is

$$
\log \mathcal{L}(r, s ; \boldsymbol{T}, \boldsymbol{C})=s_{2} \log r+\left(n-s_{2}\right) \log s(1-r)+\left(s_{1}-n\right) \log (1-r) \log (1-s) .
$$

The first partials are

$$
\frac{\partial}{\partial r} \log \mathcal{L}=\frac{s_{2}}{r}-\frac{s_{1}-s_{2}}{1-r}, \text { and } \frac{\partial}{\partial s} \log \mathcal{L}=\frac{n-s_{2}}{s}-\frac{s_{1}-n}{1-s},
$$

and setting them equal to zero gives

$$
\hat{r}=\frac{S_{2}}{S_{1}}, \text { and } \hat{s}=\frac{n-S_{2}}{S_{1}-S_{2}} .
$$

The second partials are

$$
\frac{\partial^{2}}{\partial r^{2}} \log \mathcal{L}=-\frac{s_{2}}{r^{2}}-\frac{s_{1}-s_{2}}{(1-r)^{2}}, \frac{\partial^{2}}{\partial s^{2}} \log \mathcal{L}=-\frac{n-s_{2}}{s^{2}}-\frac{s_{1}-n}{(1-s)^{2}}, \text { and } \frac{\partial^{2}}{\partial r \partial s} \log \mathcal{L}=0 .
$$

Evaluating these at $\hat{r}$ and $\hat{s}$ gives us that the maximum of the likelihood is achieved, and so, the MLE of $(r, s)$ is

$$
(\hat{r}, \hat{s})=\left(\frac{S_{2}}{S_{1}}, \frac{n-S_{2}}{S_{1}-S_{2}}\right)
$$

