

Predator Preferences Model

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1 Generic Model

Strauss' statistic L_{st} [Str79] is the difference between r_{st} the proportion of prey species s found in the gut of a predator during occurrence t and p_{st} the proportion of prey species s found in the habitat of said predator during occurrence t . When the statistic $L_{st} := r_{st} - p_{st}$ is equal to zero we say the predator ate prey species s randomly during time t . A positive difference, $L_{st} > 0$, indicates preferential eating of prey species s , and negative values indicate aversion to prey species s at time t . We can replicate and add to the modeling considered by Strauss with the following set up.

Let $X_{jst} \sim \mathcal{P}(\lambda_{st})$ denote the number of prey species s found in the gut of predator j during occurrence t ; $j \in \{1, \dots, J\}, s \in \{1, \dots, S\}, t \in \{1, \dots, T\}$. For now we ignore the fact that we only observe a 1 if predator j ate prey species s during occurrence t or a zero if the predator did not. Further, $Y_{ist} \sim \mathcal{P}(\gamma_{st})$ will denote the number of prey species s found in trap i , $i \in \{1, \dots, I\}$, hypothesized to represent the habitat of predator j , during time occurrence t . Interest lies in the null hypothesis

$$H_0 : \boldsymbol{\lambda}_t = c\boldsymbol{\gamma}_t, \forall t \quad (1)$$

where $c \in \mathbb{R}$. This hypothesis suggests that the predator's eating preferences are independent of time, i.e. the ratio of the rate at which the predator eats prey species s to the rate at which prey species s is found in the habitat is constant across time. Strauss' L is a special case of this framework where only a particular combination of prey species s and time t is considered, and c is equal to the ratio of total number of prey found in the gut of the predator to the total number of prey found in the habitat.

We first consider the parameters of this model under the null hypothesis. Here, $S \cdot T + 1$ parameters will be estimated, γ_{st} for $(s, t) \in \{S \times T\}$ and c .

$$\hat{\gamma}_{st} = \frac{X_{\cdot st} + Y_{\cdot st}}{I \left(\frac{\sum_{st} X_{\cdot st}}{\sum_{st} Y_{\cdot st}} + 1 \right)} \text{ and } \hat{c} = \frac{I \sum_{s,t} X_{\cdot st}}{J \sum_{s,t} Y_{\cdot st}}.$$

The parameters under the general alternative hypothesis, $H_1 : \boldsymbol{\lambda}_t \neq c\boldsymbol{\gamma}_t, \forall t$, are simply the maximum likelihood estimates.

$$\hat{\lambda}_{st} = \frac{X_{\cdot st}}{J} \text{ and } \hat{\gamma}_{st} = \frac{Y_{\cdot st}}{I}$$

Null hypothesis (1) above is tested with the standard likelihood ratio statistic

$$\Lambda(X, Y) := -2 \log \frac{\sup L(\theta_0|X, Y)}{\sup L(\theta_1|X, Y)} \quad (2)$$

where $\theta_0 = \{\boldsymbol{\lambda}_t = c\boldsymbol{\gamma}_t, \forall t : (\gamma_{st}, c) \in \mathbb{R}^{ST+1}\}$ represents the likelihood under the null hypothesis, and $\theta_1 = \{\boldsymbol{\lambda}_{st} \neq c\boldsymbol{\gamma}_{st} : (\lambda_{st}, \gamma_{st}) \in \mathbb{R}^{2ST}\}$ represents the likelihood under the alternative hypothesis. Then $\Lambda \sim \chi_{ST-1}^2$ and null hypothesis (1) is rejected when $P(\chi_{ST-1}^2 > \Lambda) < \alpha$.

1.1 Non-Count Gut Data

With smaller animals it is not always possible to observe a count of prey species eaten by a predator species. Instead, a binary response of whether or not DNA of said prey species exists in the gut of the predator is observed. In this case, we can treat the count of eaten prey species as missing and maximize the likelihood via the EM algorithm.

We model what information we do observe. Denote this binary response by Z_{jst} , which takes on the value 1 if the j^{th} predator ate prey species s in time t and 0 otherwise. Hence, $\Lambda(X, Y)$ is still calculable via the EM algorithm as follows. Write out the complete data likelihood,

$$L_{comp}(X, Z, Y|\boldsymbol{\lambda}, \boldsymbol{\gamma}) = \prod_t \prod_s \prod_j f_{X,Z}(x, z|\boldsymbol{\lambda}) f_Y(y|\boldsymbol{\gamma}) \quad (3)$$

Take the expectation of $\log L_{comp}$ with respect to the distribution of the missing data given the observed data and parameters,

$$f_{X|Y,Z,\boldsymbol{\lambda},\boldsymbol{\gamma}}(x) = \frac{f_{X,Y,Z}(x, y, z|\boldsymbol{\gamma}, \boldsymbol{\lambda})}{f_{Y,Z}(y, z|\boldsymbol{\lambda}, \boldsymbol{\gamma})}.$$

Then maximize $\mathbb{E}_{X|Y,Z} l_{comp}$ with respect to the parameters $\gamma_{st}, \lambda_{st}, c$, just as above since here X_{jst} is simply replaced by its expectation.

1.2 Unequal Trap Schedules

Consider a situation where the traps (catching prey species) were left out for a differing length of time within each occurrence, e.g. trap i in month t was left out for 6 days, but trap i' in month t was left out for 3 days. We expect to catch an unequal number of prey in each trap simply because one trap was left out for a longer time within month t .

Put $I_t := \sum_i numDays_{it}$ to be the total number of days all traps were left out during month t . Then the complete data log-likelihood under this scenario is as follows.

$$l = -J \sum_{st} \lambda_{st} + \sum_{st} X_{st} \log \lambda_{st} - \sum_t I_t \sum_s \gamma_{st} + \sum_{st} Y_{st} \log \gamma_{st} + constant$$

If there exists a differing number of predators in each time period, we can similarly model this by indexing J by t , say J_t . The EM algorithm from above can be incorporated into this

scenario exactly as before, keeping in mind the M-step involves maximizing these functions, which I can't seem to do analytically.

2 Simulations

In order to simulate and test data, we need to install an R package named `spiders`. To install the package `spiders`, you can use `devtools`, or download the files from the [GitHub](#) webpage.

```
## library(devtools) install_github('spiders',  
## 'roualdes')  
library(spiders)
```

We can then simulate some data by using the function `spiders::simData`. Input to this function includes the number of predator species observed at each time point, the number of traps used at each time point, the number of prey species of interest, the number of time points for which measurements were taken, and rate parameters $\lambda_{st}, \gamma_{st}$ for which the predator ate and observed, respectively, prey species s at time t . For now, we assume that the number of predators and traps is fixed across time points. Below we specify rate parameters that will be proportional across time; we expect to fail to reject null hypothesis (1) here.

```
Predators <- 20  
Traps <- 15  
PreySpecies <- 3  
Times <- 5  
ST <- Times * PreySpecies  
l <- matrix(1, nrow = Times, ncol = PreySpecies)  
g <- matrix(2, nrow = Times, ncol = PreySpecies)
```

Simulate some data as follows.

```
fdata <- simPref(PreySpecies, Times, Predators, Traps, l,  
g)
```

Then we can fit the model and calculate a p-value from these data. The output of the model fit is below.

```
(prefs <- predPref(fdata$eaten, fdata$caught))  
  
$loglikH1  
[1] 1733  
  
$loglikH0  
[1] 1728
```

```

$`-2log(LRT)`
[1] 10.89

$df
[1] 14

$p.value
[1] 0.6949

```

An example where we reject the null hypothesis would have rate parameters that are differently proportional across time. Consider the following.

```

l <- matrix(1:ST, nrow = Times, ncol = PreySpecies)
g <- matrix(2 * (ST:1), nrow = Times, ncol = PreySpecies)
fdata <- simPref(PreySpecies, Times, Predators, Traps, l,
  g)
predPref(fdata$eaten, fdata$caught)$p.value

[1] 0

```

A Details

A.1 Complete, Balanced Data

With balanced, count data the log-likelihood is

$$l = -J \sum_{st} \lambda_{st} + \sum_{st} X_{.st} \log \lambda_{st} - I \sum_{st} \gamma_{st} + \sum_{st} Y_{.st} + \text{const.}$$

Under $H_0 : \lambda_{st} = c\gamma_{st}$ we find solutions of first derivatives of l with respect to $c, \gamma_{s't'}$ set equal to zero to be

$$c = \frac{\sum_{st} X_{.st}}{J \sum_{st} \gamma_{st}} \quad \text{and} \quad \gamma_{s't'} = \frac{X_{.s't'} + Y_{.s't'}}{Jc + I}.$$

Solving these equations simultaneously gives

$$\hat{c} = \frac{J^{-1} \sum_{st} X_{.st}}{I^{-1} \sum_{st} Y_{.st}} \quad \text{and} \quad \hat{\gamma}_{s't'} = \frac{X_{.s't'} + Y_{.s't'}}{I \left(\frac{\sum_{st} X_{.st}}{\sum_{st} Y_{.st}} + 1 \right)}.$$

Under $H_1 : \lambda_{st} \neq \gamma_{st}$ we find the maximum likelihood estimates to be

$$\hat{\lambda}_{s't'} = \frac{X_{.s't'}}{J} \quad \text{and} \quad \hat{\gamma}_{s't'} = \frac{Y_{.s't'}}{I}.$$

A.2 Complete, Unbalanced Data

With unbalanced, count data the log-likelihood is

$$l = - \sum_t J_t \sum_s \lambda_{st} + \sum_{st} X_{.st} \log J_t \lambda_{st} - \sum_t I_t \sum_s \gamma_{st} + \sum_{st} Y_{.st} \log I_t \gamma_{st}.$$

Under $H_0 : \lambda_{st} = c\gamma_{st}$ we find solutions of first derivatives of l with respect to $c, \gamma_{s't'}$ set equal to be

$$c = \frac{\sum_{st} X_{.st}}{\sum_t J_t \sum_s \gamma_{st}} \quad \text{and} \quad \gamma_{s't'} = \frac{X_{.s't'} + Y_{.s't'}}{cJ_{t'} + I_{t'}}.$$

Since we can't solve these equations simultaneously, we exploit the fact that the log-likelihood is concave; each term is concave and convexity is closed under addition. Hence, we can iteratively maximize the profile log-likelihood until convergence.

Under $H_1 : \lambda_{st} \neq \gamma_{st}$ we find the maximum likelihood estimates to be

$$\hat{\lambda}_{st} = \frac{X_{.s't'}}{J_{t'}} \quad \text{and} \quad \hat{\gamma}_{s't'} = \frac{Y_{.s't'}}{I_{t'}}.$$

A.3 Non-Count Data

When the count data are not observed we can fall back on treating the counts as missing, so long as we do observe indicators telling us when the predator species did eat prey species s .

E-Step

For this we need the conditional distribution of the missing data given the observed data

$$f_{X|Y,Z,\lambda,\gamma}(x) = \frac{\exp\{-\lambda_{st}\} \lambda_{st}^{X_{jst}}}{(1 - \exp\{-\lambda_{st}\}) X_{jst}!} \quad \text{where} \quad \mathbb{E}_{[X|Y,Z]} X_{jst} = \frac{\lambda_{st} \exp\{\lambda_{st}\}}{\exp\{\lambda_{st}\} - 1}.$$

Since the joint density of X_{jst}, Z_{jst} is

$$f_{X,Z|\lambda}(x, z) = \begin{cases} \exp\{-\lambda_{st}\}, & X_{jst} = 0 \text{ and } Z_{jst} = 0 \\ \frac{\exp\{-\lambda_{st}\} \lambda_{st}^{X_{jst}}}{X_{jst}!}, & X_{jst} > 0 \text{ and } Z_{jst} = 1 \\ 0 & \text{otherwise} \end{cases}$$

it is easy to calculate the complete data log-likelihood

$$\begin{aligned} l_{comp} &= \log f_{X,Z|\lambda}(x, z) + \log f_{Y|\gamma}(y) \\ &= \sum_{s=1}^S \sum_{t=1}^T \sum_{j=1}^{J_t} \log f_{X,Z|\lambda}(x_{jst}, z_{jst}) + \sum_{s=1}^S \sum_{t=1}^T \sum_{i=1}^{I_t} \log f_{Y|\gamma}(y). \end{aligned}$$

After we take the expectation of l_{comp} with respect to $f_{X|Y,Z,\lambda,\gamma}$ we get

$$\mathbb{E}l_{comp} = \sum_{s=1}^S \sum_{t=1}^T \sum_{j=1}^{J_t} \mathbb{E}[\log f_{X,Z|\lambda}(X_{jst}, z_{jst})] + \sum_{s=1}^S \sum_{t=1}^T \sum_{i=1}^{I_t} \log f_{Y|\gamma}(y)$$

where the expectation conditions on all of the remaining parameters. In this case we see

$$\log f_{X,Z|\lambda}(x_{jst}, z_{jst}) = \begin{cases} -\lambda_{st} & X_{jst} = 0 \text{ and } z_{jst} = 0 \\ -\lambda_{st} + X_{jst} \log(\lambda_{st}) - \log(X_{st}!) & X_{jst} > 0 \text{ and } z_{jst} = 1 \end{cases} ,$$

so that

$$\mathbb{E}[\log f_{X,Z|\lambda}(x_{jst}, z_{jst})] \equiv -\lambda_{st} + z_{jst} \left[\frac{\lambda_{st} \exp(\lambda_{st})}{\exp(\lambda_{st}) - 1} \log(\lambda_{st}) - \log(X_{st}!) \right] .$$

Substituting this value back into the expected log-likelihood we then get:

$$\mathbb{E}l_{comp} = \sum_{s=1}^S \sum_{t=1}^T \sum_{j=1}^{J_t} (-\lambda_{st} + z_{jst} \log(\lambda_{st}) \mathbb{E}X_{jst} - \text{const}) - \sum_t I_t \sum_s \gamma_{st} + \sum_{st} Y_{.st} \log I_t \gamma_{st} .$$

M-Step

We maximize $\mathbb{E}l_{comp}$ with respect to its parameters $\lambda_{st}, \gamma_{st}, c$, thus completing one step of the EM algorithm.

Hypotheses Under EM

Under $H_0 : \lambda_{st} = c\gamma_{st}$, we iteratively solve the following equations within on step of the EM algorithm

$$\hat{\gamma}_{st} = \frac{z_{.st} \mathbb{E}X_{jst} + Y_{.st}}{cJ_t + I_t} \quad \text{and} \quad \hat{c} = \frac{\sum_{st} z_{.st} \mathbb{E}X_{jst}}{\sum_t J_t \sum_s \gamma_{st}} .$$

Under H_1 we complete one step of the EM algorithm via

$$\hat{\lambda}_{st} = \frac{z_{.st} \mathbb{E}X_{jst}}{J_t} \quad \text{and} \quad \hat{\gamma}_{st} = \frac{Y_{.st}}{I_t} .$$

References

- [Str79] Richard E Strauss, *Reliability estimates for ivlev's electivity index, the forage ratio, and a proposed linear index of food selection*, Transactions of the American Fisheries Society **108** (1979), no. 4, 344–352.