Package ‘bivpois’

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Title Bivariate Poisson Models Using The EM Algorithm

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Description Functions for fitting Bivariate Poisson Models using the EM algorithm. Details can be found in Karlis and Ntzoufras (2003, RSS D & 2004, AUEB Technical Report)

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bivpois.table  Probability of Bivariate Poisson Using Recursive relations

Description

Returns the probability of the bivariate Poisson distribution using recursive relations.

Usage

bivpois.table(x, y, lambda = c(1, 1, 1))

Arguments

x, y  single values containing which values should evaluated (x and y should be at least 1)
lambda Vector (of length 3) containing values of the parameters lambda1, lambda2 and lambda3 of the bivariate poisson distribution.

Details

In order to calculate bivpoison probability values we use recursive relationships. This function is much slower than pbivpois

Value

A matrix with dimension (x+1) X (y+1) is returned. Cell ij contains the probability P(X=i-1, Y=j-1).

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References


See Also

pbivpois.simple.bp.lm.bp.lm.dibp.
Description

The data has one pair \((x, y)\) of bivariate Poisson variables and five variables \((z_1, \ldots, z_5)\) generated from \(N(0,0.01)\) distribution. Hence
\[
X_i, Y_i \sim BP(\lambda_{1i}, \lambda_{2i}, \lambda_{3i}) \quad \text{with}
\]
\[
\log \lambda_{1i} = 1.8 + 2Z_{1i} + 3Z_{3i}
\]
\[
\log \lambda_{2i} = 0.7 - Z_{1i} - 3Z_{3i} + 3Z_{5i}
\]
\[
\log \lambda_{3i} = 1.7 + Z_{1i} - 2Z_{2i} + 2Z_{3i} - 2Z_{4i}.
\]

Usage

\[
data(ex1.sim)
\]

Format

A data frame with 100 observations on the following 7 variables.

\textbf{x, y}  \hspace{1cm} \text{Simulated Bivariate Poisson Variables used as response}

\textbf{z1, z2, z3, z4, z5}  \hspace{1cm} \text{Simulated N(0,0.01) explanatory variables}

Details

This data is used as example one in Karlis and Ntzoufras (2004).

Source


References


Examples

\#
\#
\# Double and Bivariate Poisson models can be fitted using the command
\# demo(exl, package='bivpois')
\#
\#
\# Here we present the same commands but iterations of the EM were restricted to 2 to save time

library(bivpois)  \hspace{1cm} \# load bivpois library
data(ex1.sim)  \hspace{1cm} \# load data of example 1
\#
\#
\# Simple Bivariate Poisson Model
ex1.simple<-simple.bp( ex1.sim$x, ex1.sim$y, maxit=2)  \# fit simple model of section 4.1.1
names(ex1.simple)  \hspace{1cm} \# monitor output variables
# Fit Double and Bivariate Poisson models ()

### Model 2: DblPoisson(l1, l2)

```r
ex1.m2<-lm.bp(x~1, y~1, data=ex1.sim, zeroL3=TRUE)
```

### Model 3: BivPoisson(l1, l2, l3); same as simple.bp(ex1.sim$x, ex1.sim$y)

```r
ex1.m3<-lm.bp(x~1, y~1, data=ex1.sim, maxit=2)
```

### Model 4: DblPoisson (l1=Full, l2=Full)

```r
ex1.m4<-lm.bp(x~., y~., data=ex1.sim, zeroL3=TRUE)
```

### Model 5: BivPoisson(l1=full, l2=full, l3=constant)

```r
ex1.m5<-lm.bp(x~., y~., data=ex1.sim, maxit=2)
```

### Model 6: DblPois(l1, l2)

```r
ex1.m6<-lm.bp(x~z1, y~z1+z5, l1l2=~z3, data=ex1.sim, zeroL3=TRUE)
```

### Model 7: BivPois(l1,l2,l3=constant)

```r
ex1.m7<-lm.bp(x~z1, y~z1+z5, l1l2=~z3, data=ex1.sim, maxit=2)
```

### Model 8: BivPoisson(l1=full, l2=full, l3=constant)

```r
ex1.m8<-lm.bp(x~., y~., l3=-., data=ex1.sim, maxit=2)
```

### Model 9: BivPoisson(l1=full, l2=full, l3=full)

```r
ex1.m9<-lm.bp(x~., y~., l3=-.z5, data=ex1.sim, maxit=2)
```

### Model 10: BivPoisson(l1, l2, l3=full)

```r
ex1.m10<-lm.bp(x~z1, y~z1+z5, l1l2=~z3, l3=~., data=ex1.sim, maxit=2)
```

### Model 11: BivPoisson(l1, l2, l3= z1+z2+z3+z4)

```r
ex1.m11<-lm.bp(x~z1, y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex1.sim, maxit=2)
```

---

### Description

The data has one pair \((x, y)\) of diagonal inflated bivariate Poisson variables and five variables \((z_1, \ldots, z_5)\) generated from \(N(0, 0.12)\) distribution. Hence

\[
X_i, Y_i \sim DIBP(\lambda_1, \lambda_2, \lambda_3, p = 0.30, Poisson(2))
\]

with

\[
\log \lambda_1 = 1.8 + 2Z_{1i} + 3Z_{3i}
\]

\[
\log \lambda_2 = 0.7 - Z_{1i} - 3Z_{3i} + 3Z_{5i}
\]

\[
\log \lambda_3 = 1.7 + Z_{1i} - 2Z_{2i} + 2Z_{3i} - 2Z_{4i}.
\]

### Usage

```r
data(ex2.sim)
```
**ex2.sim**

**Format**

A data frame with 100 observations on the following 7 variables.

- \( x,y \) Simulated Bivariate Poisson Variables used as response
- \( z1,z2,z3,z4,z5 \) Simulated \( N(0,0.01) \) explanatory variables

**Details**

This data is used as example one in Karlis and Ntzoufras (2004).

**Source**


**References**


**Examples**

```r
# Models of example 2 can be fitted using the command
# demo(ex2, package='bivpois')
#
# Here we present the same commands but iterations of the EM were restricted to 2 to save time

library(bivpois) # load bivpois library
data(ex2.sim) # load ex2.sim data from bivpois library
#
# Model 1: BivPois
ex2.m1<-lm.bp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim, maxit=2 )
# Model 2: Zero Inflated BivPois
ex2.m2<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=0, maxit=2 )
# Model 3: Diagonal Inflated BivPois with DISCRETE(1) diagonal distribution
ex2.m3<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=1, maxit=2 )
# Model 4: Diagonal Inflated BivPois with DISCRETE(2) diagonal distribution
ex2.m4<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=2, maxit=2 )
# Model 5: Diagonal Inflated BivPois with DISCRETE(3) diagonal distribution
ex2.m5<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=3, maxit=2 )
# Model 6: Diagonal Inflated BivPois with DISCRETE(4) diagonal distribution
ex2.m6<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=4, maxit=2 )
# Model 7: Diagonal Inflated BivPois with DISCRETE(5) diagonal distribution
ex2.m7<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=5, maxit=2 )
# Model 8: Diagonal Inflated BivPois with DISCRETE(6) diagonal distribution
ex2.m8<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=6, maxit=2 )
# Model 9: Diagonal Inflated BivPois with POISSON diagonal distribution
ex2.m9<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , distribution="poisson", maxit=2 )
# Model 10: Diagonal Inflated BivPois with GEOMETRIC diagonal distribution
ex2.m10<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , distribution="geometric", maxit=2 )
#
# printing parameters of model 7
ex2.m7$beta1
ex2.m7$beta2
```
ex2.m7$beta3
ex2.m7$p
ex2.m7$theta
#
# printing parameters of model 9
ex2.m9$beta1
ex2.m9$beta2
ex2.m9$beta3
ex2.m9$p
ex2.m9$theta

**Bivariate Example 3 Dataset: Health Care Data**

**Description**

Demand for health care in Australia data (Cameron and Trivedi, 1986). The data refer to the Australian Health survey for 1977-1978 with sample size equal to 5190.

**Usage**

```r
data(ex3.health)
```

**Format**

A data frame with 5190 observations on the following 20 variables.

- **doctorco** Number of consultations with a doctor or specialist in the past 2 weeks
- **prescrib** Total number of prescribed medications used in past 2 days
- **sex** 1 if female, 0 if male
- **age** Age in years divided by 100 (measured as mid-point of 10 age groups from 15-19 years to 65-69 with 70 or more coded treated as 72)
- **agesq** AGE squared
- **income** Annual income in Australian dollars divided by 1000 (measured as mid-point of coded ranges Nil, <200, 200-1000, 1001-, 2001-, 3001-, 4001-, 5001-, 6001-, 7001-, 8001-10000, 10001-12000, 12001-14000, with 14001- treated as 15000).
- **levyplus** 1 if covered by private health insurance fund for private patient in public hospital (with doctor of choice), 0 otherwise
- **freepoor** 1 if covered by government because low income, recent immigrant, unemployed, 0 otherwise
- **freepera** 1 if covered by government because low income, recent immigrant, unemployed, 0 otherwise
- **illness** Number of illnesses in past 2 weeks with 5 or more coded as 5
- **actdays** Number of days of reduced activity in past two weeks due to illness or injury
- **hscore** General health questionnaire score using Goldberg’s method. High score indicates bad health.
- **chcond1** 1 if chronic condition(s) but not limited in activity, 0 otherwise
- **chcond2** 1 if chronic condition(s) and limited in activity, 0 otherwise
nondocco  Number of consultations with non-doctor health professionals (chemist, optician, phys-
otherapist, social worker, district community nurse, chiropodist or chiropractor) in the past 2
weeks

hospadmi  Number of admissions to a hospital, psychiatric hospital, nursing or convalescent home
in the past 12 months (up to 5 or more admissions which is coded as 5)

hospdays  Number of nights in a hospital, etc. during most recent admission: taken, where appro-
priate, as the mid-point of the intervals 1, 2, 3, 4, 5, 6, 7, 8-14, 15-30, 31-60, 61-79 with 80 or
more admissions coded as 80. If no admission in past 12 months then equals zero.

medicine  Total number of prescribed and nonprescribed medications used in past 2 days

nonpresc  Total number of nonprescribed medications used in past 2 days

constant  Constant term

Details
Details can be found in Cameron and Trivedi (1986). This data is used as example three in Karlis and
Ntzoufras (2005). In this illustration two variables are used as response: the number of consultations
with a doctor or a specialist and the total number of prescribed medications used in past 2 days
(doctorco, prescrib). Three variables have been used as covariates: the gender (1 female, 0 male),
the age in years divided by 100 (measured as midpoints of age groups) and the annual income in
Australian dollars divided by 1000 (measured as midpoint of coded ranges) sex, age, income.

Source
Cameron, A.C. and Trivedi, P.K. (1986). Econometric Models Based on Count Data: Comparisons

References
the Demand for Health Care and Health Insurance in Australia, Review of Economic Studies, 55,
85 - 106.
Journal of the Royal Statistical Society, D, (Statistician), 52, 381 - 393.

Examples
# Models of example 3 can be fitted using the command
# demo(ex3, package='bivpois')
#
# Here we present the commands for the same models commented out in order to save time
#
#library(bivpois)
data(ex3.health)
# Bivariate Poisson models
#ex3.model.a<-lm.bp(doctorco~sex+age+income, prescrib~sex+age+income, 
data=ex3.health)
#ex3.model.b<-lm.bp(doctorco~sex+age+income, prescrib~sex+age+income, l3=~sex, 
data=ex3.health)
# Double Poisson model
#ex3.model.c<-lm.bp(doctorco~sex+age+income, prescrib~sex+age+income, 
#data=ex3.health, zeroL3=TRUE)

# diagonal inflated models
#ex3.dibp.a<-lm.dibp(doctorco~sex+age+income, prescrib~sex+age+income, 
#data=ex3.health, jmax=0) # model (a)
#ex3.dibp.b<-lm.dibp(doctorco~sex+age+income, prescrib~sex+age+income,l3=~sex, 
#data=ex3.health, jmax=0) # model (b)

<table>
<thead>
<tr>
<th>ex4.ita91</th>
<th>Bivpois Example 4 Dataset: Italian Series A Football Scores for Season 1991-92</th>
</tr>
</thead>
</table>

**Description**


**Usage**

data(ex4.ita91)

**Format**

A data frame with 306 observations on the following 4 variables.

- **g1** Goals scored by the home team
- **g2** Goals scored by the away team
- **team1** a factor indicating the home team with levels Ascoli Atalanta Bari Cagliari Cremonese Fiorentina Foggia Genoa Inter Juventus Lazio Milan Napoli Parma Roma Sampdoria Torino Verona
- **team2** a factor indicating the away team with levels Ascoli Atalanta Bari Cagliari Cremonese Fiorentina Foggia Genoa Inter Juventus Lazio Milan Napoli Parma Roma Sampdoria Torino Verona

**Details**

Data were originally used in Karlis and Ntzoufras (2003). The data consist of pairs of counts indicating the number of goals scored by each of the two competing teams. As covariates we have used dummy variables to model the team strength. In modelling outcomes of football games, it has been observed an excess of draws and small over-dispersion. Introducing diagonal inflated models we correct for both the over-dispersion and the excess of draws.

**Source**


**References**

Examples

# Models 1-12 of example 4 can be fully reproduced using the command
demo(ex4, package='bivpois')
#
# Here we present the same commands but iterations of the EM were restricted to 10 to save time
#
# Models 1-12 can be run using the demo command demo(ex4, package='bivpois')
#
library(bivpois) # loading of bivpois library
data(ex4.ita91) # loading ex4.ita91 data from bivpois library
#
# formula for modeling of lambda1 and lambda2
form1 <- ~c(team1,team2)+c(team2,team1)
#
# Model 1: Double Poisson
ex4.m1<-lm.bp( g1~1, g2~1, l1l2=form1, zeroL3=TRUE, data=ex4.ita91)
#
# Models 2-5: bivariate Poisson models
ex4.m2<-lm.bp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, maxit=2)
ex4.m3<-lm.bp(g1~1,g2~1, l1l2=form1, l3=~team1, data=ex4.ita91, maxit=2)
ex4.m4<-lm.bp(g1~1,g2~1, l1l2=form1, l3=~team2, data=ex4.ita91, maxit=2)
ex4.m5<-lm.bp(g1~1,g2~1, l1l2=form1, l3=~team1+team2, data=ex4.ita91, maxit=2)
#
# Model 6: Zero Inflated Model
ex4.m6 <-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, jmax=0, maxit=2)
#
# Models 7-11: Diagonal Inflated Bivariate Poisson Models
ex4.m7 <-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, distribution="geometric", maxit=2)
ex4.m8 <-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, jmax=1, maxit=2)
ex4.m9 <-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, jmax=2, maxit=2)
ex4.m10<-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, jmax=3, maxit=2)
ex4.m11<-lm.dibp(g1~1,g2~1, l1l2=form1, data=ex4.ita91, distribution="poisson", maxit=2)
#
# Models 12: Diagonal Inflated Double Poisson Model
ex4.m12 <- lm.dibp ( g1~1,g2~1, l1l2=form1, data=ex4.ita91, distribution="poisson", zeroL3=TRUE , maxit=2)
#
# monitoring parameters for model 1: Dbl Poisson
ex4.m1$coef # all parameters
ex4.m1$beta1 # model parameters for lambda1
ex4.m1$beta2 # model parameters for lambda2.
  # All are the same as in beta1 except the intercept
ex4.m1$beta2[1] # Intercept for lambda2.
ex4.m1$beta2[1]-ex4.m1$beta2[2] # estimated home effect

# estimating the effect for 18th level of attack (team1..team2) [Verona]
-sum(ex4.m1$coef[2:18])
#
# estimating the effect for 18th level of defence(team2..team1) [Verona]
-sum(ex4.m1$coef[19:35])

# ---------------------------------------------------------------
# monitoring parameters for model 2: BivPoisson(lambda1,lambda2,constant lambda3)
#
# monitoring parameters for model 1: Dbl Poisson
ex4.m2$beta1   # model parameters for lambda1
ex4.m2$beta2   # model parameters for lambda2.
  # All are the same as in betal except the intercept
ex4.m2$beta3   # model parameters for lambda3 (Here only the intercept)
ex4.m2$beta2[1]  # Intercept for lambda2.
ex4.m2$beta2[1]-ex4.m2$beta2[2]  # estimated home effect

# estimating the effect for 18th level of attack (team1..team2) [Verona]
-old(ex4.m2$coef[2:18])
# estimating the effect for 18th level of defence(team2..team1) [Verona]
-old(ex4.m2$coef[19:35])
#
# ---------------------------------------------------------------------------------
# ---------------------------------------------------------------------------------
# monitoring parameters for model 8: Biv.Poisson with Dis(1) diagonal distribution
#
# monitoring parameters for model 1: Dbl Poisson
ex4.m8$beta1   # model parameters for lambda1
ex4.m8$beta2   # model parameters for lambda2.
  # All are the same as in betal except the intercept
ex4.m8$beta3   # model parameters for lambda3. Here beta3 has only the intercept
ex4.m8$beta2[1]  # Intercept for lambda2.
ex4.m8$beta2[1]-ex4.m8$beta2[2]  # estimated home effect

# estimating the effect for 18th level of attack (team1..team2) [Verona]
-old(ex4.m8$coef[2:18])
# estimating the effect for 18th level of defence(team2..team1) [Verona]
-old(ex4.m8$coef[19:35])

ex4.m8$beta3     # parameters for lambda3 (here the intercept)
exp(ex4.m8$beta3)  # lambda3 (here constant)
ex4.m8$diagonal.distribution  # printing details for the diagonal distribution
ex4.m8$p        # mixing proportion
ex4.m8$theta   # printing theta parameters

---

**lm.bp**  

*General Bivariate Poisson Model*

**Description**

Produces a "list" object which gives details regarding the fit of a bivariate Poisson regression model of the form

\[ X_i, Y_i \sim BP(\lambda_{1i}, \lambda_{2i}, \lambda_{3i}) \]  

for \( i = 1, 2, \ldots, n \), with

\[
\log \lambda_{1i} = w_1 \beta_{1i}, \quad \log \lambda_{2i} = w_2 \beta_{2i}, \quad \text{and} \quad \log \lambda_{3i} = w_3 \beta_{3i};
\]

where

- \( n \) is the sample size.
\[ \lambda_k = (\lambda_{k1}, \lambda_{k2}, \ldots, \lambda_{kn})^T \] for \( k = 1, 2, 3 \) are vectors of length \( n \) with the estimated lambda for each observation.

- \( w_1, w_2 \) are \( n \times p \) data matrices containing explanatory variables for \( \lambda_1 \) and \( \lambda_2 \).
- \( w_3 \) is a \( n \times p_2 \) data matrix containing explanatory variables for \( \lambda_3 \).
- \( \beta_1, \beta_2, \beta_3 \) are parameter vectors used in the linear predictors of \( \lambda_1, \lambda_2 \) and \( \lambda_3 \).

Usage

```r
lm.bp( l1, l2, l1l2=NULL, l3=~1, data, common.intercept=FALSE, zeroL3=FALSE, maxit=300, pres=1e-8, verbose=getOption("verbose") )
```

Arguments

- **l1** Formula of the form "\( x \sim X_1 + \ldots + X_p \)" for parameters of \( \log \lambda_1 \).
- **l2** Formula of the form "\( y \sim X_1 + \ldots + X_p \)" for parameters of \( \log \lambda_2 \).
- **l1l2** Formula of the form "\( \sim X_1 + \ldots + X_p \)" for the common parameters of \( \log \lambda_1 \) and \( \log \lambda_2 \). If the explanatory variable is also found on \( l1 \) and/or \( l2 \) then a model using interaction type parameters is fitted (one parameter common for both predictors [main effect] and differences from this for the other predictor [interaction type effect]). Special terms of the form "\( c(X_1,X_2) \)" can be also used here. These terms imply common parameters of \( \lambda_1 \) and \( \lambda_2 \) on different variables. For example if \( c(x_1,x_2) \) is used then use the same beta for the effect of \( x_1 \) on \( \log \lambda_1 \) and the effect of \( x_2 \) on \( \log \lambda_2 \). For details see example 4 - dataset ex4.ita91.
- **l3** Formula of the form "\( \sim X_1 + \ldots + X_p \)" for the parameters of \( \log \lambda_3 \).
- **data** Data frame containing the variables in the model.
- **common.intercept** Logical function specifying whether a common intercept on \( \log \lambda_1 \) and \( \log \lambda_2 \) should be used. The default value is FALSE.
- **zeroL3** Logical argument controlling whether \( \lambda_3 \) should be set equal to zero (therefore fits a double Poisson model).
- **maxit** Maximum number of EM steps. Default value is 300 iterations.
- **pres** Precision used in stopping the EM algorithm. The algorithm stops when the relative log-likelihood difference is lower than the value of pres.
- **verbose** Logical argument controlling whether beta parameters will we printed while EM runs. Default value is taken equal to the value of options()$verbose. If verbose=FALSE then only the iteration number, the loglikelihood and its relative difference from the previous iteration are printed. If verbose=TRUE then the model parameters \( \beta_1, \beta_2 \) and \( \beta_3 \) are additionally printed.

Value

A list object returned with the following variables.

- **coefficients** Estimates of the model parameters for \( \beta_1, \beta_2 \) and \( \beta_3 \). When a factor is used then its default set of constraints is used.
- **fitted.values** Data frame with \( n \) lines and 2 columns containing the fitted values for \( x \) and \( y \). For the bivariate Poisson model the fitted values are given by \( \lambda_1 + \lambda_3 \) and \( \lambda_2 + \lambda_3 \) respectively.
residuals Data frame with \( n \) lines and 2 columns containing the residuals of the model for \( x \) and \( y \). For the bivariate Poisson model the residual values are given by \( x-E(x) \) and \( y-E(y) \) respectively; where \( E(x) = \lambda_1+\lambda_3 \) and \( E(y) = \lambda_2+\lambda_3 \).

\( \beta_1, \beta_2, \beta_3 \)
Vectors \( \beta_1, \beta_2 \) and \( \beta_3 \) containing the coefficients involved in the linear predictors of \( \lambda_1, \lambda_2 \) and \( \lambda_3 \) respectively. When \( \text{zeroL3}=\text{TRUE} \) then \( \beta_3 \) is not calculated.

\( \lambda_1, \lambda_2 \)
Vectors of length \( n \) containing the estimated \( \lambda_1 \) and \( \lambda_2 \) for each observation

\( \lambda_3 \)
vector containing the values of \( \lambda_3 \). If \( \text{zeroL3}=\text{TRUE} \) then \( \lambda_3 \) is equal to zero and is not provided.

loglikelihood
Maximized log-likelihood of the fitted model. This is given in a vector form (one value per iteration). Using this vector we can monitor the log-likelihood evolution in each EM step.

AIC, BIC
AIC and BIC of the model. Values are also provided for the double Poisson model and the saturated model.

parameters
Number of parameters.

iterations
Number of iterations.

call
Argument providing the exact calling details of the \text{lm.bp} function.

Author(s)
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References

See Also
\text{pbivpois}, \text{simple.bp}, \text{lm.dibp}.

Examples

data(ex1.sim)
# Fit Double and Bivariate Poisson models ()
#  
#  Model 2: DblPoisson(l1, l2)
ex1.m2<-lm.bp(x~1, y~1, data=ex1.sim, zeroL3=TRUE)
#  
#  Model 3: BivPoisson(l1, l2, l3); same as simple.bp(ex1.sim$x, ex1.sim$y)
ex1.m3<-lm.bp(x~1, y~1, data=ex1.sim)
#  
#  Model 4: DblPoisson (l1=Full, l2=Full)
ex1.m4<-lm.bp(x~., y~., data=ex1.sim, zeroL3=TRUE)
# for models 4–11 maximum number of iterations is set to 2
#
# Model 5: BivPoisson(l1=full, l2=full, l3=constant)
ex1.m5<-lm.bp(x~., y~., data=ex1.sim, maxit=2)
# Model 6: DblPois(l1,l2)
ex1.m6<-lm.bp(x~z1 , y~z1+z5 , l1l2=~z3, data=ex1.sim, zeroL3=TRUE)
# Model 7: BivPois(l1,l2,l3=constant)
ex1.m7<-lm.bp(x~z1 , y~z1+z5 , l1l2=~z3, data=ex1.sim, maxit=2)
# Model 8: BivPoisson(l1=full, l2=full, l3=full)
ex1.m8<-lm.bp(x~. , y~. , l3=~., data=ex1.sim, maxit=2)
# Model 9: BivPoisson(l1=full, l2=full, l3=z1+z2+z3+z4)
ex1.m9<-lm.bp(x~. , y~. , l3=~.-z5, data=ex1.sim, maxit=2)
# Model 10: BivPoisson(l1, l2, l3=full)
ex1.m10<-lm.bp(x~z1 , y~z1+z5 , l1l2=~z3, l3=~., data=ex1.sim, maxit=2)
# Model 11: BivPoisson(l1, l2, l3= z1+z2+z3+z4)
ex1.m11<-lm.bp(x~z1 , y~z1+z5 , l1l2=~z3, l3=~.-z5, data=ex1.sim, maxit=2)

lm.dibp

General Diagonal Inflated Bivariate Poisson Model

Description

Produces a "list" object which gives details regarding the fit of a bivariate diagonal inflated Poisson regression model of the form

\[
(X_i, Y_i) \sim DIBP(\lambda_{1i}, \lambda_{2i}, \lambda_{3i}, D(\theta))
\]

which is equivalent to

\[
(X_i, Y_i) \sim (1-p)BP(x_i, y_i | \lambda_{1i}, \lambda_{2i}) \text{ if } x_i \neq y_i
\]

\[
(X_i, Y_i) \sim (1-p)BP(x_i, y_i | \lambda_{1i}, \lambda_{2i}, \lambda_{3i}) + pD(x_i | \theta) \text{ if } x_i = y_i \text{ for } i = 1, 2, \ldots, n
\]

with

\[
\log \lambda_{ki} = w_{ki}^T \beta \quad \text{for } k = 1, 2, 3
\]

where

- \( n \) is the sample size.
- \( \lambda_k \) are vectors of length \( n \) containing the estimated lambda for each observation.
- \( w_1, w_2 \) are \( n \times p \) data matrices containing explanatory variables for \( \lambda_1 \) and \( \lambda_2 \).
- \( w_3 \) are \( n \times p_2 \) data matrix containing explanatory variables for \( \lambda_3 \).
- \( \beta \) is a vector of length \( p \) which is common for \( \lambda_1 \) and \( \lambda_2 \) in order to allow for common effects.
- \( \beta_3 \) vector of length \( p_2 \).
- \( D(\theta) \) is a discrete distribution with parameter vector \( \theta \) used to inflate the diagonal.
- \( p \) is the mixing proportion.

Usage

\[
\text{lm.dibp( } 11, 12, 1112=NULL, 13=-1, \text{ data, common.intercept=FALSE,}
\text{ zeroL3 = FALSE, distribution = "discrete", jmax = 2, maxit = 300,}
\text{ pres = 1e-08, verbose=getOption("verbose") )}
\]
Arguments

11 Formula of the form “$x \sim X_1 + \ldots + X_p$” for parameters of log $\lambda_1$.
12 Formula of the form “$y \sim X_1 + \ldots + X_p$” for parameters of log $\lambda_2$.
1112 Formula of the form “$\sim X_1 + \ldots + X_p$” for the common parameters of log $\lambda_1$ and log $\lambda_2$. If the explanatory variable is also found on 11 and/or 12 then a model using interaction type parameters is fitted (one parameter common for both predictors [main effect] and differences from this for the other predictor [interaction type effect]). Special terms of the form “c(X1, X2)” can be also used here. These terms imply common parameters of $\lambda_1$ and $\lambda_2$ on different variables. For example if c(x1, x2) is used then use the same beta for the effect of $x_1$ on log $\lambda_1$ and the effect of $x_2$ on log $\lambda_2$. For details see example 4 - dataset ex4.ita91.
13 Formula of the form “$\sim X_1 + \ldots + X_p$” for the parameters of log $\lambda_3$.

Data frame containing the variables in the model.

common.intercept Logical function specifying whether a common intercept on log $\lambda_1$ and log $\lambda_2$ should be used. The default value is FALSE.

zeroL3 Logical argument controlling whether $\lambda_3$ should be set equal to zero (therefore fits a double Poisson model).

distribution Specifies the type of inflated distribution; ="discrete": Discrete(J=jmax), ="poisson": Poisson($\theta$) ="geometric": Geometric($\theta$).

jmax Number of parameters used in Discrete distribution. This argument is not used for the Poisson or the Geometric distributions are used as for the inflation of the diagonal.

maxit Maximum number of EM steps. Default value is 300 iterations.

pres Precision used in stopping the EM algorithm. The algorithm stops when the relative log-likelihood difference is lower than the value of pres.

verbose Logical argument controlling whether beta parameters will we printed while EM runs. Default value is taken equal to the value of options() $\verb|verbose|$. If verbose=FALSE then only the iteration number, the loglikelihood and its relative difference from the previous iteration are printed. If verbose=TRUE then the model parameters $\beta_1$, $\beta_2$ and $\beta_3$ are additionally printed.

Value

A list object returned with the following variables.

coefficients Estimates of the model parameters for $\beta_1$, $\beta_2$ and $\beta_3$, $p$ and $\theta$.

fitted.values Data frame with $n$ lines and 2 columns containing the fitted values for $x$ and $y$.

residuals Data frame with $n$ lines and 2 columns containing the residuals of the model for $x$ and $y$ given by $x - E(x)$ and $y - E(y)$ respectively; where $E(x)$ and $E(y)$ are given by the fitted.values.

beta1,beta2, beta3 Vectors $\beta_1$, $\beta_2$ and $\beta_3$ containing the coefficients involved in the linear predictors of $\lambda_1$, $\lambda_2$ and $\lambda_3$ respectively. When zeroL3=TRUE then beta3 is not calculated.
lm.dibp

lambda1, lambda2

Vectors of length $n$ containing the estimated $\lambda_1$ and $\lambda_2$ for each observation.

lambda3

Vector containing the values of $\lambda_3$. If `zeroL3=TRUE` then `lambda3` is equal to zero and is not provided.

loglikelihood

Maximized log-likelihood of the fitted model. This is given in a vector form (one value per iteration). Using this vector we can monitor the log-likelihood evolution in each EM step.

AIC, BIC

AIC and BIC of the model. Values are also provided for the double Poisson model and the saturated model.

diagonal.distribution

label for the diagonal inflated distribution used.

p

mixing proportion.

theta

Parameter vector of the diagonal distribution. For discrete distribution theta has length equal to $j_{\text{max}}$ with $\theta_i = \theta[i]$ and $\theta_0 = 1 - \sum_{i=1}^{j_{\text{max}}} \theta_i$; for the Poisson distribution theta is the mean; for the Geometric distribution theta is the success probability.

parameters

Number of parameters.

iterations

Number of iterations.

call

Argument providing the exact calling details of the `lm.dibp` function.

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References


See Also

`pbivpois, simple.bp, lm.bp`

Examples

data(ex2.sim)

# Model 1: BivPois
ex2.m1<-lm.bp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim )

# Model 2: Zero Inflated BivPois
ex2.m2<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=0)

# for models 3-10, the maximum number of iterations is set to 2
#
# Model 3: Diagonal Inflated BivPois with DISCRETE(1) diagonal distribution
ex2.m3<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=1, maxit=2)
# Model 4: Diagonal Inflated BivPois with DISCRETE(2) diagonal distribution
ex2.m4<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=2, maxit=2)
# Model 5: Diagonal Inflated BivPois with DISCRETE(3) diagonal distribution
ex2.m5<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=3, maxit=2)
# Model 6: Diagonal Inflated BivPois with DISCRETE(4) diagonal distribution
ex2.m6<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=4, maxit=2)
# Model 7: Diagonal Inflated BivPois with DISCRETE(5) diagonal distribution
ex2.m7<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=5, maxit=2)
# Model 8: Diagonal Inflated BivPois with DISCRETE(6) diagonal distribution
ex2.m8<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , jmax=6, maxit=2)
# Model 9: Diagonal Inflated BivPois with POISSON diagonal distribution
ex2.m9<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , distribution="poisson", maxit=2)
# Model 10: Diagonal Inflated BivPois with GEOMETRIC diagonal distribution
ex2.m10<-lm.dibp( x~z1 , y~z1+z5, l1l2=~z3, l3=~.-z5, data=ex2.sim , distribution="geometric", maxit=2)
#
# printing parameters of model 7
ex2.m7$beta1
ex2.m7$beta2
ex2.m7$beta3
ex2.m7$p
ex2.m7$theta
#
# printing parameters of model 9
ex2.m9$beta1
ex2.m9$beta2
ex2.m9$beta3
ex2.m9$p
ex2.m9$theta

---

newnamesbeta

**Internal Function of BIVPOIS Package**

**Description**

This function was made only for internal use in Bivpois package and it should not be called separately

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Description

Returns the probability the probability (or the log) of the bivariate poisson distribution for values x and y.

Usage

```
pbivpois(x, y=NULL, lambda = c(1, 1, 1), log = FALSE)
```

Arguments

- `x`: Matrix or Vector containing the data. If `x` is a matrix then we consider as `x` the first column and `y` the second column. Additional columns and `y` are ignored.
- `y`: Vector containing the data of `y`. It is used only if `x` is also a vector. Vectors `x` and `y` should be of equal length.
- `lambda`: Vector (of length 3) containing values of the parameters $\lambda_1, \lambda_2$ and $\lambda_3$ of the bivariate Poisson distribution.
- `log`: Logical argument for calculating the log probability or the probability function. The default value is `FALSE`.

Details

This function evaluates the probability function (or the log) of the bivariate Poisson distribution with parameters $\lambda_1, \lambda_2$ and $\lambda_3$. Much faster than `bivpois.table` since it avoid ‘for-loops’ and does not use recursive relations.

Value

A vector of values of the probabilities of $PD(\lambda_1, \lambda_2, \lambda_3)$ evaluated at $(x, y)$ when `log=FALSE` or the log-probabilities of $PD(\lambda_1, \lambda_2, \lambda_3)$ evaluated at $(x, y)$ when `log=TRUE`.

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References


See Also

`bivpois.table, simple.bp, lm.bp, lm.dibp.`
Examples

```r
# probability function of (x,y)=(3,1) for lambda_1=1, lambda_2=1, lambda_3=1
pbivpois(3, 1)
# probability function of (x,y)=(3,1) for lambda_1=3, lambda_2=1, lambda_3=1
pbivpois(3, 1, lambda=c(3,1,1))
# log-probability function of (x,y)=(3,1) for lambda_1=1, lambda_2=1, lambda_3=1
pbivpois(3, 1, lambda=c(3,1,1), log=TRUE)
# evaluates f(1,1), f(1,3) and f(3,1) for PD(2,1,0.2)
pbivpois( c(1,3,1), c(1,1,3), c( 2,1,0.2 ) )
# same as above
pbivpois( cbind(c(1,3,1), c(1,1,3)), lambda=c(2,1,0.2) )
```

---

**simple.bp**

---

### Simple Bivariate Poisson Model

#### Description

Produces a "list" object which gives details regarding the fit of a simple bivariate Poisson model of the form \((X, Y) \sim BP(\lambda_1, \lambda_2, \lambda_3)\).

#### Usage

```r
simple.bp(x, y, ini3 = 1, maxit = 300, pres = 1e-08)
```

#### Arguments

- **x**: Matrix or Vector containing the data. If \(x\) is a matrix then we consider as \(x\) the first column and \(y\) the second column. Additional columns and \(y\) are ignored.
- **y**: Vector containing the data of \(y\). It is used only if \(x\) is also a vector. Vectors \(x\) and \(y\) should be of equal length.
- **ini3**: Initial value for \(\lambda_3\).
- **maxit**: Maximum number of EM steps.
- **pres**: Precision used in log-likelihood improvement.

#### Details

During the run of the algorithm the following details are printed: the iteration number, lambda1, lambda2, lambda3, the log-likelihood and the relative difference of the log-likelihood.

#### Value

A list object returned with the following variables.

- **lambda**: Vector with parameter values \(\lambda_1, \lambda_2, \lambda_3\)
- **loglikelihood**: Maximized log-likelihood of the fitted model. This is given in a vector form (one value per iteration). Using this we may monitor the log-likelihood improvement and how EM algorithm works.
AIC, BIC  AIC and BIC of the model. Values are also given for the double Poisson model and the saturated model.

parameters  Number of parameters.

iterations  Number of iterations.

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References

See Also

pbivpois, lm.bp, lm.dibp

Examples

# Generation of BP(1,2,3) data
x3<-rpois(100, 3)
x1<-rpois(100, 1)+x3
x2<-rpois(100, 2)+x3
#
# fits the model
x<-simple.bp(x1, x2)
#
# Monitors parameters
x$lambda1
x$lambda2
x$lambda3
#
# alternatively (for 10 iterations)
x<-simple.bp( cbind(x1, x2), maxit=2 )

splitbeta  Internal Function of BIVPOIS Package

This function was made only for internal use in Bivpois package and it should not be called separately.
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