

# Package ‘acp’

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**Title** Autoregressive Conditional Poisson

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**Author** Siakoulis Vasileios

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**Maintainer** Siakoulis Vasilios <Siakoulis.Vasilios@atticabank.gr>

**Description** Package for time series analysis of count data

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acp

*Autoregressive Conditional Poisson (ACP) Regression***Description**

Fit an ACP(1,1) regression model.

**Usage**

```
acp(x, ...)
## Default S3 method:
acp(x, y, startval, varopt,...)
## S3 method for class 'formula'
acp(formula, data=list(), startval=NULL, varopt=T, family="acp",...)
## S3 method for class 'acp'
print(x, ...)
## S3 method for class 'acp'
summary(object, ...)
## S3 method for class 'acp'
predict(object, newxdata=NULL, newydata=NULL,...)
```

**Arguments**

x	a numeric design matrix for the model.
y	a numeric vector of responses.
startval	a numeric vector of starting values. If not provided the package will obtain starting values for the covariate parameters from a poisson regression and for the autoregressive parameters from an arma(1,1) regression.
family	A description of the specification to be used. If family="acp" or not provided an Autoregressive Poisson regression will be estimated whereas if family="poisson" a plain Poisson regression is provided.
formula	a symbolic description of the model to be fit.
data	an optional data frame containing the variables in the model.
varopt	an optional logical operator T (TRUE) or F (FALSE) determining whether the covariance matrix will be calculated (T) or not (F).
object	an object of class "acp", i.e., a fitted model.
newxdata	a data frame containing the covariates data upon which a static forecast will be performed.
newydata	a data frame containing the dependent variable upon which a static forecast will be performed.
...	not used.

## Details

This model has been proposed by Heinen (2003) for cases of count data exhibiting autoregressive behaviour. As pointed by Cameron and Trivedi (1998), when a count data set exhibits time dependence the plain Poisson regression is not adequate. Heinen (2003) proposed the ACP model in close analogy to the Autoregressive Conditional Duration model (ACD) of Engle and Russel (1998) and the GARCH model of Bollerslev (1986). The model can be also found in the international bibliography as Integer GARCH (Fokianos and Fried, 2010). The most commonly used variant of the model is the ACP(1,1) which is implemented in the package.

## Value

An object of class `logreg`, basically a list including elements

<code>coefficients</code>	a named vector of coefficients
<code>vcov</code>	covariance matrix of coefficients
<code>fitted.values</code>	fitted values
<code>residuals</code>	residuals

## Author(s)

Siakoulis Vasileios

## References

- Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307-327.
- Cameron, A., and Trivedi, P., 1998. *Regression Analysis of Count Data*. New York: Cambridge University Press.
- Engle, RF., Russell, JR., 1998. Autoregressive conditional duration: a new model for irregularly spaced transaction data. *Econometrica* 66, 1127-1162.
- Fokianos, K., Fried, R., 2010. Interventions in INGARCH processes. *Journal of Time Series Analysis* 31/3, 210-225.
- Heinen, A., 2003. *Modelling Time Series Count Data: An Autoregressive Conditional Poisson Model*. University Library of Munich.MPRA paper, 8113.

## Examples

```
data(polio)

#Create time trend and seasonality variables
trend=(1:168/168)
cos12=cos((2*pi*(1:168))/12)
sin12=sin((2*pi*(1:168))/12)
cos6=cos((2*pi*(1:168))/6)
sin6=sin((2*pi*(1:168))/6)

polio_data<-data.frame(polio, trend , cos12, sin12, cos6, sin6)
```

```

#Autoregressive Conditional Poisson Model with explaining covariates
mod1 <- acp(polio~-1+trend+cos12+sin12+cos6+sin6,data=polio_data)
summary(mod1)

##Static out-of-sample fit example
train<-data.frame(polio_data[c(1: 119),])
test<-data.frame(polio_data[c(120:nrow(polio_data)),])
vpolio<-polio_data[[1]]
yfor<-vpolio[120:nrow(polio_data)]
predict(mod1,test,yfor)

#Poisson Model with explaining covariates
mod2 <- acp(polio~trend+cos12+sin12+cos6+sin6,data=polio_data,family="poisson")
summary(mod2)

#Default method for ACP regression
X<-cbind(trend , cos12, sin12, cos6, sin6)
mod3<-acp(X,polio,startval=NULL,varopt=TRUE)
print(mod3)
summary(mod3)
residuals(mod3)
mod3$vcov

```

---

Berkowitz

*Berkowitz test*


---

## Description

Implements Berkowitz test (2001) for density evaluation.

## Usage

```
Berkowitz(ydata, yhatdata, rep, ...)
```

## Arguments

ydata	a data frame containing the real values of the dependent variable.
yhatdata	a data frame containing the fitted values of the dependent variable.
rep	number of uniform distribution drawings.
...	not used.

## Details

Diebold et al. (1998) proposed a density evaluation method which consists in computing the sequence of cumulative probability of the observed counts under the assumed forecast distribution (Probability Transform Integral-PIT). If the density fit is adequate this sequence will be uniformly distributed and will have no-autocorrelation left neither in level nor when raised to integer powers.

For this purpose intuitive graphical methods such as correlograms on the basis of the usual Bartlett confidence intervals, histograms and quantile-quantile (QQ) plots are used. In the case of discrete data Heinen et al. (2007) propose the use of a uniform zero-one continued extension as suggested by Denuit and Lambert (2005). Finally instead of using graphical tools for detecting uniformity and independence, Berkowitz (2001) applied a formal test for normality and independence of the inverse standard cumulative normal transform of the PIT sequence through the estimation of an AR(1) specification and the use of an LR test to the coefficients.

### Value

P-value of the Likelihood Ratio test statistic based on the chi-square distribution with 3 degrees of freedom.

### Author(s)

Siakoulis Vasileios

### References

- Berkowitz, J., 2001. Testing density forecasts with applications to risk management. American Statistical Association. Journal of Business and Economics Statistics, 19, 4.
- Denuit, M., and Lambert, P., 2005. Constraints on concordance measures in bivariate discrete data. Journal of Multivariate Analysis, 93, 40-57.
- Diebold, F., Gunther, T., and Tay, A., 1998. Evaluating density forecasts with applications financial to risk management. International Economic Review, 39, 4, 863-883.
- Heinen, A., Rengifo, E., 2007. Multivariate autoregressive modeling of time series count data using copulas. Journal of empirical finance 14 (2007) 564-583.

### Examples

```
data(polio)

#Create time trend and seasonality variables
trend=(1:168/168)
cos12=cos((2*pi*(1:168))/12)
sin12=sin((2*pi*(1:168))/12)
cos6=cos((2*pi*(1:168))/6)
sin6=sin((2*pi*(1:168))/6)

polio_data<-data.frame(polio, trend, cos12, sin12, cos6, sin6)
mod1 <- acp(polio~-1+trend+cos12+sin12+cos6+sin6,data=polio_data)
summary(mod1)
Berkowitz(polio_data[[1]],fitted(mod1),50)
```

---

evaluation

*acp Evaluation*

---

### Description

Evaluation of an acp regression model.

### Usage

```
evaluation(ydata, yhatdata, ...)
```

### Arguments

ydata	a data frame containing the real values of the dependent variable.
yhatdata	a data frame containing the fitted values of the dependent variable.
...	not used.

### Details

Diebold et al. (1998) proposed a density evaluation method which consists in computing the sequence of cumulative probability of the observed counts under the assumed forecast distribution (Probability Transform Integral-PIT). If the density fit is adequate this sequence will be uniformly distributed and will have no-autocorrelation left neither in level nor when raised to integer powers. For this purpose intuitive graphical methods such as correlograms on the basis of the usual Bartlett confidence intervals, histograms and quantile-quantile (QQ) plots are used. In the case of discrete data Heinen et al. (2007) propose the use of a uniform zero-one continued extension of the PIT as suggested by Denuit and Lambert (2005).

### Value

A group of scores for count model evaluation proposed by Czado et al (2009) along with a series of evaluation plots. More precisely the measures calculated are logarithmic score, quadratic score, spherical score, ranked probability score, Dawid-Sebastiani score, squared error score, mean absolute error score and root squared error score. Relatively to the graphical evaluation, sub-plot 1 depicts the predicted relatively to the real values, sub-plot 2 the non-randomized PIT histogram (Czado et al, 2009), sub-plots 3 and 4 the first two powers of the demeaned randomized PIT and sub-plots 5 to 7 the first three powers of the Pearson standardized residuals.

### Author(s)

Siakoulis Vasileios

## References

- Czado, C., Erhardt, V., Min, A., and Wagner, S., 2007. Zero-inflated generalized Poisson models with regression effects on the mean, dispersion and zero-inflation level applied to patent outsourcing rates. *Statistical Modelling*, 2007, 125.
- Denuit, M., and Lambert, P., 2005. Constraints on concordance measures in bivariate discrete data. *Journal of Multivariate Analysis*, 93, 40-57.
- Diebold, F., Gunther, T., and Tay, A., 1998. Evaluating density forecasts with applications financial to risk management. *International Economic Review*, 39, 4, 863-883.
- Heinen, A., Rengifo, E., 2007. Multivariate autoregressive modeling of time series count data using copulas. *Journal of empirical finance* 14 (2007) 564-583.

## Examples

```
data(polio)

#Create time trend and seasonality variables
trend=(1:168/168)
cos12=cos((2*pi*(1:168))/12)
sin12=sin((2*pi*(1:168))/12)
cos6=cos((2*pi*(1:168))/6)
sin6=sin((2*pi*(1:168))/6)
polio_data<-data.frame(polio, trend , cos12, sin12, cos6, sin6)

mod1 <- acp(polio~-1+trend+cos12+sin12+cos6+sin6,data=polio_data)
summary(mod1)
evaluation(polio_data[[1]],fitted(mod1))
```

---

forecast

*acp Forecast*

---

## Description

Recursive forecasting of an acp model.

## Usage

```
forecast(object, sample, ydata, ...)
```

## Arguments

object	an object of class "acp", i.e., a fitted model.
sample	the point of sample from which the recursive forecast process will begin.
ydata	a data frame containing the real values of the dependent variable.
...	not used.

**Value**

a series of forecasted values

**Author(s)**

Siakoulis Vasileios

**Examples**

```
data(polio)

#Create time trend and seasonality variables
trend=(1:168/168)
cos12=cos((2*pi*(1:168))/12)
sin12=sin((2*pi*(1:168))/12)
cos6=cos((2*pi*(1:168))/6)
sin6=sin((2*pi*(1:168))/6)
polio_data<-data.frame(polio, trend , cos12, sin12, cos6, sin6)

mod1 <- acp(polio~-1+trend+cos12+sin12+cos6+sin6,data=polio_data)
fitfor<-forecast(mod1,158,polio_data[[1]])
```

---

polio

*Polio cases in USA from Jan 1970 till Dec 1983*

---

**Description**

The data set contains the monthly number of cases of poliomyelitis in the United States between 1970 and 1983.

**Usage**

```
data(polio)
```

**Format**

The dataset consists of one variable of 168 monthly observations.

polio a numeric vector

**Source**

Zeger, S. A Regression Model for Time Series of Counts. *Biometrika*, Vol. 75, No 4 (Dec., 1988), pp. 621-629

**Examples**

```
data(polio)
```

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