

# Package ‘parglm’

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**Type** Package

**Title** Parallel GLM

**Version** 0.1.6

**Description** Provides a parallel estimation method for generalized linear models without compiling with a multithreaded LAPACK or BLAS.

**License** GPL-2

**Encoding** UTF-8

**LazyData** true

**LinkingTo** Rcpp, RcppArmadillo

**Imports** Rcpp, Matrix

**SystemRequirements** C++11

**Suggests** testthat, SuppDists, knitr, rmarkdown, speedglm, microbenchmark, R.rsp

**RoxygenNote** 6.1.1

**VignetteBuilder** R.rsp

**NeedsCompilation** yes

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parglm

*Fitting Generalized Linear Models in Parallel***Description**

Function like `glm` which can make the computation in parallel. The function supports most families listed in `family`. See `"vignette("parglm", "parglm")"` for run time examples.

**Usage**

```
parglm(formula, family = gaussian, data, weights, subset, na.action,
       start = NULL, offset, control = list(...), contrasts = NULL,
       model = TRUE, x = FALSE, y = TRUE, ...)
```

```
parglm.fit(x, y, weights = rep(1, NROW(x)), start = NULL,
          etastart = NULL, mustart = NULL, offset = rep(0, NROW(x)),
          family = gaussian(), control = list(), intercept = TRUE, ...)
```

**Arguments**

<code>formula</code>	an object of class <code>formula</code> .
<code>family</code>	a <code>family</code> object.
<code>data</code>	an optional data frame, list or environment containing the variables in the model.
<code>weights</code>	an optional vector of 'prior weights' to be used in the fitting process. Should be <code>NULL</code> or a numeric vector.
<code>subset</code>	an optional vector specifying a subset of observations to be used in the fitting process.
<code>na.action</code>	a function which indicates what should happen when the data contain NAs.
<code>start</code>	starting values for the parameters in the linear predictor.
<code>offset</code>	this can be used to specify an a priori known component to be included in the linear predictor during fitting.
<code>control</code>	a list of parameters for controlling the fitting process. For <code>parglm.fit</code> this is passed to <code>parglm.control</code> .
<code>contrasts</code>	an optional list. See the <code>contrasts.arg</code> of <code>model.matrix.default</code> .
<code>model</code>	a logical value indicating whether model frame should be included as a component of the returned value.
<code>x, y</code>	For <code>parglm</code> : logical values indicating whether the response vector and model matrix used in the fitting process should be returned as components of the returned value. For <code>parglm.fit</code> : <code>x</code> is a design matrix of dimension $n * p$ , and <code>y</code> is a vector of observations of length <code>n</code> .
<code>...</code>	For <code>parglm</code> : arguments to be used to form the default <code>control</code> argument if it is not supplied directly. For <code>parglm.fit</code> : unused.

etastart	starting values for the linear predictor. Not supported.
mustart	starting values for the vector of means. Not supported.
intercept	logical. Should an intercept be included in the null model?

### Details

The current implementation uses  $\min(\text{as.integer}(n / p), \text{nthreads})$  threads where  $n$  is the number observations,  $p$  is the number of covariates, and  $\text{nthreads}$  is the  $\text{nthreads}$  element of the list returned by `parglm.control`. Thus, there is likely little (if any) reduction in computation time if  $p$  is almost equal to  $n$ . The current implementation cannot handle  $p > n$ .

### Value

glm object as returned by `glm` but differs mainly by the `qr` element. The `qr` element in the object returned by `parglm(.fit)` only has the  $R$  matrix from the QR decomposition.

### Examples

```
# small example from `help('glm')`. Fitting this model in parallel does
# not matter as the data set is small
clotting <- data.frame(
  u = c(5,10,15,20,30,40,60,80,100),
  lot1 = c(118,58,42,35,27,25,21,19,18),
  lot2 = c(69,35,26,21,18,16,13,12,12))
f1 <- glm (lot1 ~ log(u), data = clotting, family = Gamma)
f2 <- parglm(lot1 ~ log(u), data = clotting, family = Gamma,
            control = parglm.control(nthreads = 2L))
all.equal(coef(f1), coef(f2))
```

---

parglm.control

*Auxiliary for Controlling GLM Fitting in Parallel*

---

### Description

Auxiliary function for `parglm` fitting.

### Usage

```
parglm.control(epsilon = 1e-08, maxit = 25, trace = FALSE,
              nthreads = 1L, block_size = NULL, method = "LINPACK")
```

### Arguments

epsilon	positive convergence tolerance.
maxit	integer giving the maximal number of IWLS iterations.
trace	logical indicating if output should be produced doing estimation.

<code>nthreads</code>	number of cores to use. You may get the best performance by using your number of physical cores if your data set is sufficiently large. Using the number of physical CPUs/cores may yield the best performance (check your number e.g., by calling <code>parallel::detectCores(logical = FALSE)</code> ).
<code>block_size</code>	number of observation to include in each parallel block.
<code>method</code>	string specifying which method to use. Either "LINPACK", "LAPACK", or "FAST".

### Details

The LINPACK method uses the same QR method as `glm.fit` for the final QR decomposition. This is the `dqrdc2` method described in `qr`. All other QR decompositions but the last are made with DGEQP3 from LAPACK. See Wood, Goude, and Shaw (2015) for details on the QR method.

The FAST method computes the Fisher information and then solves the normal equation. This is faster but less numerically stable.

### Value

A list with components named as the arguments.

### References

Wood, S.N., Goude, Y. & Shaw S. (2015) Generalized additive models for large datasets. *Journal of the Royal Statistical Society, Series C* 64(1): 139-155.

### Examples

```
# use one core
clotting <- data.frame(
  u = c(5,10,15,20,30,40,60,80,100),
  lot1 = c(118,58,42,35,27,25,21,19,18),
  lot2 = c(69,35,26,21,18,16,13,12,12))
f1 <- parglm(lot1 ~ log(u), data = clotting, family = Gamma,
             control = parglm.control(nthreads = 1L))

# use two cores
f2 <- parglm(lot1 ~ log(u), data = clotting, family = Gamma,
             control = parglm.control(nthreads = 2L))
all.equal(coef(f1), coef(f2))
```

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