

Package ‘unifiedml’

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Type Package

Title Unified Interface for Machine Learning Models

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Description Provides a unified R6-based interface for various machine learning models with automatic interface detection, consistent cross-validation, model interpretations via numerical derivatives, and visualization. Supports both regression and classification tasks with any model function that follows R's standard modeling conventions (formula or matrix interface).

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URL <https://github.com/Techtonique/unifiedml>

BugReports <https://github.com/Techtonique/unifiedml/issues>

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unifiedml-package	<i>Unified Interface for Machine Learning Models</i>
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Description

Provides a unified R6-based interface for various machine learning models with automatic interface detection, consistent cross-validation, model interpretations via numerical derivatives, and visualization. Supports both regression and classification tasks with any model function that follows R's standard modeling conventions (formula or matrix interface).

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cross_val_score *Cross-Validation for Model Objects*

Description

Perform k-fold cross-validation with consistent scoring metrics across different model types. The scoring metric is automatically selected based on the detected task type.

Usage

```
cross_val_score(
  model,
  X,
  y,
  cv = 5,
  scoring = NULL,
  show_progress = TRUE,
  cl = NULL,
  ...
)
```

Arguments

model	A Model object
X	Feature matrix or data.frame
y	Target vector (type determines regression vs classification)
cv	Number of cross-validation folds (default: 5)
scoring	Scoring metric: "rmse", "mae", "accuracy", or "f1" (default: auto-detected based on task)
show_progress	Whether to show progress bar (default: TRUE)
cl	Optional cluster for parallel processing (not yet implemented)
...	Additional arguments passed to model\$fit()

Value

Vector of cross-validation scores for each fold

Examples

```
library(glmnet)
X <- matrix(rnorm(100), ncol = 4)
y <- 2*X[,1] - 1.5*X[,2] + rnorm(25) # numeric -> regression

mod <- Model$new(glmnet::glmnet)
mod$fit(X, y, alpha = 0, lambda = 0.1)
cv_scores <- cross_val_score(mod, X, y, cv = 5) # auto-uses RMSE
```

```

mean(cv_scores) # Average RMSE

# Classification with accuracy scoring
data(iris)
X_class <- as.matrix(iris[, 1:4])
y_class <- iris$Species # factor -> classification

mod2 <- Model$new(e1071::svm)
cv_scores2 <- cross_val_score(mod2, X_class, y_class, cv = 5) # auto-uses accuracy
mean(cv_scores2) # Average accuracy

```

formula_to_matrix *Convert a formula-based model to a matrix interface*

Description

Wraps a model function that expects formula + data so it can be called with a plain X (data.frame or matrix) and y (vector). Factors in X are preserved; special column names are safely backtick-quoted in the generated formula so they survive the formula parser.

Usage

```
formula_to_matrix(fit_func, predict_func = stats::predict)
```

Arguments

fit_func	A model-fitting function whose first two arguments are formula and data (e.g. lm, glm).
predict_func	A prediction function with signature function(model, newdata, ...). Defaults to stats::predict.

Value

A named list with two elements:

fit(X, y, weights, ...) Fits the model. X is a data.frame (or coercible matrix), y is the response vector. Extra arguments are forwarded to fit_func.

predict(model, newdata, ...) Generates predictions. newdata must have the same columns as the X used in fit. Extra arguments are forwarded to predict_func.

Examples

```

lm_matrix <- formula_to_matrix(lm)
X <- data.frame(wt = mtcars$wt, hp = mtcars$hp, cyl = factor(mtcars$cyl))
y <- mtcars$mpg
model <- lm_matrix$fit(X, y)
lm_matrix$predict(model, X[1:5, ])

```

matrix_to_formula	<i>Convert a matrix-based model to a formula interface</i>
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Description

Wraps a model function that expects a numeric matrix X and a response vector y (like `glmnet::glmnet`) so it can be called with the familiar `formula + data` interface. The formula is expanded via `model.matrix`, which handles factor dummy-coding, interactions, and inline transformations automatically.

Usage

```
matrix_to_formula(
  fit_func,
  predict_func = function(model, newX, ...) stats::predict(model, newdata = newX, ...)
)
```

Arguments

<code>fit_func</code>	A model-fitting function whose first two positional arguments are x (numeric matrix) and y (response vector), e.g. <code>glmnet::glmnet</code> .
<code>predict_func</code>	A prediction function with signature <code>function(model, newX, ...)</code> where <code>newX</code> is a numeric matrix. Defaults to a thin wrapper around <code>stats::predict</code> that passes <code>newdata</code> as <code>newx</code> .

Value

A named list with two elements:

`fit(formula, data, ...)` Fits the model. The formula is expanded with `model.matrix`; the intercept column is dropped before passing to `fit_func` (add it back via `...` if your model needs it). Extra arguments are forwarded to `fit_func`.

`predict(model, newdata, ...)` Generates predictions. `newdata` is expanded with the same `model.matrix` terms captured at fit time. Extra arguments are forwarded to `predict_func`.

Examples

```
## Not run:
glmnet_formula <- matrix_to_formula(
  fit_func = glmnet::glmnet,
  predict_func = function(model, newX, ...) {
    glmnet::predict.glmnet(model, newx = newX, s = 0.01, ...)
  }
)
model <- glmnet_formula$fit(mpg ~ wt + hp + factor(cyl), data = mtcars)
glmnet_formula$predict(model, newdata = mtcars[1:5, ])

## End(Not run)
```

Description

Provides a consistent interface for various machine learning models in R, with automatic detection of formula vs matrix interfaces, built-in cross-validation, model interpretability, and visualization.

An R6 class that provides a unified interface for regression and classification models with automatic interface detection, cross-validation, and interpretability features. The task type (regression vs classification) is automatically detected from the response variable type.

Public fields

`model_fn` The modeling function (e.g., `glmnet::glmnet`, `randomForest::randomForest`)

`fitted` The fitted model object

`task` Type of task: "regression" or "classification" (automatically detected)

`X_train` Training features matrix

`y_train` Training target vector

Methods

Public methods:

- `Model$new()`
- `Model$fit()`
- `Model$predict()`
- `Model$print()`
- `Model$summary()`
- `Model$plot()`
- `Model$clone_model()`
- `Model$clone()`

Method `new()`: Initialize a new Model

Usage:

```
Model$new(model_fn)
```

Arguments:

`model_fn` A modeling function (e.g., `glmnet`, `randomForest`, `svm`)

Returns: A new Model object

Method `fit()`: Fit the model to training data

Automatically detects task type (regression vs classification) based on the type of the response variable `y`. Numeric `y` -> regression, factor `y` -> classification.

Usage:

```
Model$fit(X, y, ...)
```

Arguments:

X Feature matrix or data.frame

y Target vector (numeric for regression, factor for classification)

... Additional arguments passed to the model function

Returns: self (invisible) for method chaining

Method predict(): Generate predictions from fitted model

Usage:

```
Model$predict(X, ...)
```

Arguments:

X Feature matrix for prediction

... Additional arguments passed to predict function

Returns: Vector of predictions

Method print(): Print model information

Usage:

```
Model$print()
```

Returns: self (invisible) for method chaining

Method summary(): Compute numerical derivatives and statistical significance

Uses finite differences to compute approximate partial derivatives for each feature, providing model-agnostic interpretability.

Usage:

```
Model$summary(h = 0.01, alpha = 0.05)
```

Arguments:

h Step size for finite differences (default: 0.01)

alpha Significance level for p-values (default: 0.05)

Details: The method computes numerical derivatives using central differences.

Statistical significance is assessed using t-tests on the derivative estimates across samples.

Returns: A data.frame with derivative statistics (invisible)

Method plot(): Create partial dependence plot for a feature

Visualizes the relationship between a feature and the predicted outcome while holding other features at their mean values.

Usage:

```
Model$plot(feature = 1, n_points = 100)
```

Arguments:

feature Index or name of feature to plot

n_points Number of points for the grid (default: 100)

Returns: self (invisible) for method chaining

Method `clone_model()`: Create a deep copy of the model

Useful for cross-validation and parallel processing where multiple independent model instances are needed.

Usage:

```
Model$clone_model()
```

Returns: A new Model object with same configuration

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Model$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

Author(s)

Your Name

Examples

```
# Regression example with glmnet
library(glmnet)
X <- matrix(rnorm(100), ncol = 4)
y <- 2*X[,1] - 1.5*X[,2] + rnorm(25) # numeric -> regression

mod <- Model$new(glmnet::glmnet)
mod$fit(X, y, alpha = 0, lambda = 0.1)
mod$summary()
predictions <- mod$predict(X)

# Classification example
data(iris)
iris_binary <- iris[iris$Species %in% c("setosa", "versicolor"), ]
X_class <- as.matrix(iris_binary[, 1:4])
y_class <- iris_binary$Species # factor -> classification

mod2 <- Model$new(e1071::svm)
mod2$fit(X_class, y_class, kernel = "radial")
mod2$summary()

# Cross-validation
cv_scores <- cross_val_score(mod, X, y, cv = 5)
```

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