

# Package ‘applicable’

February 24, 2026

**Title** A Compilation of Applicability Domain Methods

**Version** 0.2.1

**Description** A modeling package compiling applicability domain methods in R. It combines different methods to measure the amount of extrapolation new samples can have from the training set. See [doi:10.4018/IJQSPR.2016010102](https://doi.org/10.4018/IJQSPR.2016010102) for an overview of applicability domains.

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<https://applicable.tidymodels.org>

**BugReports** <https://github.com/tidymodels/applicable/issues>

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---

ames_new	<i>Recent Ames Iowa Houses</i>
----------	--------------------------------

---

### Description

More data related to the set described by De Cock (2011) where data were recorded for 2,930 properties in Ames IA.

### Details

This data sets includes three more properties added since the original reference. There are less fields in this data set; only those that could be transcribed from the assessor's office were included.

### Value

ames\_new      a tibble

### Source

De Cock, D. (2011). "Ames, Iowa: Alternative to the Boston Housing Data as an End of Semester Regression Project," *Journal of Statistics Education*, Volume 19, Number 3.

<https://www.cityofames.org/government/departments-divisions-a-h/city-assessor>

<https://jse.amstat.org/v19n3/decock/DataDocumentation.txt>

<https://jse.amstat.org/v19n3/decock.pdf>

---

apd_hat_values	<i>Fit a apd_hat_values</i>
----------------	-----------------------------

---

## Description

apd\_hat\_values() fits a model.

## Usage

```
apd_hat_values(x, ...)  
  
## Default S3 method:  
apd_hat_values(x, ...)  
  
## S3 method for class 'data.frame'  
apd_hat_values(x, ...)  
  
## S3 method for class 'matrix'  
apd_hat_values(x, ...)  
  
## S3 method for class 'formula'  
apd_hat_values(formula, data, ...)  
  
## S3 method for class 'recipe'  
apd_hat_values(x, data, ...)
```

## Arguments

x	Depending on the context: <ul style="list-style-type: none"><li>• A <b>data frame</b> of predictors.</li><li>• A <b>matrix</b> of predictors.</li><li>• A <b>recipe</b> specifying a set of preprocessing steps created from <code>recipes::recipe()</code>.</li></ul>
...	Not currently used, but required for extensibility.
formula	A formula specifying the predictor terms on the right-hand side. No outcome should be specified.
data	When a <b>recipe</b> or <b>formula</b> is used, data is specified as: <ul style="list-style-type: none"><li>• A <b>data frame</b> containing the predictors.</li></ul>

## Value

A `apd_hat_values` object.

## Examples

```
predictors <- mtcars[, -1]

# Data frame interface
mod <- apd_hat_values(predictors)

# Formula interface
mod2 <- apd_hat_values(mpg ~ ., mtcars)

# Recipes interface
library(recipes)
rec <- recipe(mpg ~ ., mtcars)
rec <- step_log(rec, disp)
mod3 <- apd_hat_values(rec, mtcars)
```

---

apd\_isolation

*Fit an isolation forest to estimate an applicability domain.*

---

## Description

apd\_isolation() fits an isolation forest model.

## Usage

```
apd_isolation(x, ...)

## Default S3 method:
apd_isolation(x, ...)

## S3 method for class 'data.frame'
apd_isolation(x, ...)

## S3 method for class 'matrix'
apd_isolation(x, ...)

## S3 method for class 'formula'
apd_isolation(formula, data, ...)

## S3 method for class 'recipe'
apd_isolation(x, data, ...)
```

## Arguments

x                    Depending on the context:

- A **data frame** of predictors.
- A **matrix** of predictors (see the `categ_cols` argument of `isotree::isolation_forest()`).
- A **recipe** specifying a set of preprocessing steps created from `recipes::recipe()`.

...	Options to pass to <code>isotree::isolation.forest()</code> . Options should not include data.
formula	A formula specifying the predictor terms on the right-hand side. No outcome should be specified.
data	When a <b>recipe</b> or <b>formula</b> is used, data is specified as: <ul style="list-style-type: none"><li>• A <b>data frame</b> containing the predictors.</li></ul>

## Details

In an isolation forest, splits are designed to isolate individual data points. The tree construction process takes random split locations on randomly selected predictors. As splits are made in the tree, the algorithm tracks when data points are isolated as more splits are made. The first points that are isolated are thought to be outliers or anomalous. From these results, an anomaly score can be constructed.

This function creates an isolation forest on the training set and measures the reference distribution of the scores when re-predicting the training set. When scoring new data, the raw anomaly score is produced along with the sample's corresponding percentile of the reference distribution.

## Value

A `apd_isolation` object.

## References

Liu, Fei Tony, Kai Ming Ting, and Zhi-Hua Zhou. "Isolation forest." 2008 *Eighth IEEE International Conference on Data Mining. IEEE*, 2008. Liu, Fei Tony, Kai Ming Ting, and Zhi-Hua Zhou. "Isolation-based anomaly detection." *ACM Transactions on Knowledge Discovery from Data (TKDD)* 6.1 (2012): 3.

## Examples

```
if (rlang::is_installed(c("isotree", "modeldata"))) {
  library(dplyr)

  data(cells, package = "modeldata")

  cells_tr <- cells |> filter(case == "Train") |> select(-case, -class)
  cells_te <- cells |> filter(case != "Train") |> select(-case, -class)

  if_mod <- apd_isolation(cells_tr, ntrees = 10, nthreads = 1)
  if_mod
}
```

---

apd\_pca

*Fit a apd\_pca*


---

### Description

apd\_pca() fits a model.

### Usage

```
apd_pca(x, ...)

## Default S3 method:
apd_pca(x, ...)

## S3 method for class 'data.frame'
apd_pca(x, threshold = 0.95, ...)

## S3 method for class 'matrix'
apd_pca(x, threshold = 0.95, ...)

## S3 method for class 'formula'
apd_pca(formula, data, threshold = 0.95, ...)

## S3 method for class 'recipe'
apd_pca(x, data, threshold = 0.95, ...)
```

### Arguments

x	Depending on the context: <ul style="list-style-type: none"> <li>• A <b>data frame</b> of predictors.</li> <li>• A <b>matrix</b> of predictors.</li> <li>• A <b>recipe</b> specifying a set of preprocessing steps created from <code>recipes::recipe()</code>.</li> </ul>
...	Not currently used, but required for extensibility.
threshold	A number indicating the percentage of variance desired from the principal components. It must be a number greater than 0 and less or equal than 1.
formula	A formula specifying the predictor terms on the right-hand side. No outcome should be specified.
data	When a <b>recipe</b> or <b>formula</b> is used, data is specified as: <ul style="list-style-type: none"> <li>• A <b>data frame</b> containing the predictors.</li> </ul>

### Details

The function computes the principal components that account for up to either 95% or the provided threshold of variability. It also computes the percentiles of the absolute value of the principal components. Additionally, it calculates the mean of each principal component.

**Value**

A apd\_pca object.

**Examples**

```
predictors <- mtcars[, -1]

# Data frame interface
mod <- apd_pca(predictors)

# Formula interface
mod2 <- apd_pca(mpg ~ ., mtcars)

# Recipes interface
library(recipes)
rec <- recipe(mpg ~ ., mtcars)
rec <- step_log(rec, disp)
mod3 <- apd_pca(rec, mtcars)
```

---

apd\_similarity

*Applicability domain methods using binary similarity analysis*

---

**Description**

apd\_similarity() is used to analyze samples in terms of similarity scores for binary data. All features in the data should be binary (i.e. zero or one).

**Usage**

```
apd_similarity(x, ...)
```

## Default S3 method:

```
apd_similarity(x, quantile = NA_real_, ...)
```

## S3 method for class 'data.frame'

```
apd_similarity(x, quantile = NA_real_, ...)
```

## S3 method for class 'matrix'

```
apd_similarity(x, quantile = NA_real_, ...)
```

## S3 method for class 'formula'

```
apd_similarity(formula, data, quantile = NA_real_, ...)
```

## S3 method for class 'recipe'

```
apd_similarity(x, data, quantile = NA_real_, ...)
```

## Arguments

x	Depending on the context: <ul style="list-style-type: none"> <li>• A <b>data frame</b> of binary predictors.</li> <li>• A <b>matrix</b> of binary predictors.</li> <li>• A <b>recipe</b> specifying a set of preprocessing steps created from <code>recipes::recipe()</code>.</li> </ul>
...	Options to pass to <code>proxyC::simil()</code> , such as <code>method</code> . If no options are specified, <code>method = "jaccard"</code> is used.
quantile	A real number between 0 and 1 or NA for how the similarity values for each sample versus the training set should be summarized. A value of NA specifies that the mean similarity is computed. Otherwise, the appropriate quantile is computed.
formula	A formula specifying the predictor terms on the right-hand side. No outcome should be specified.
data	When a <b>recipe</b> or <b>formula</b> is used, data is specified as: <ul style="list-style-type: none"> <li>• A <b>data frame</b> containing the binary predictors. Any predictors with no 1's will be removed (with a warning).</li> </ul>

## Details

The function computes measures of similarity for different samples points. For example, suppose samples A and B both contain  $p$  binary variables. First, a 2x2 table is constructed between A and B *across their elements*. The table will contain  $p$  entries across the four cells (see the example below). From this, different measures of likeness are computed.

For a training set of  $n$  samples, a new sample is compared to each, resulting in  $n$  similarity scores. These can be summarized into a single value; the median similarity is used by default by the scoring function.

For this method, the computational methods are fairly taxing for large data sets. The training set must be stored (albeit in a sparse matrix format) so object sizes may become large.

By default, the computations are run in parallel using *all possible cores*. To change this, call the `setThreadOptions` function in the `RcppParallel` package.

## Value

A `apd_similarity` object.

## References

Leach, A. and Gillet V. (2007). *An Introduction to Chemoinformatics*. Springer, New York

## Examples

```
data(qsar_binary)

jacc_sim <- apd_similarity(binary_tr)
jacc_sim
```

```

# plot the empirical cumulative distribution function (ECDF) for the training set:
library(ggplot2)
autoplot(jacc_sim)

# Example calculations for two samples:
A <- as.matrix(binary_tr[1, ])
B <- as.matrix(binary_tr[2, ])
xtab <- table(A, B)
xtab

# Jaccard statistic
xtab[2, 2] / (xtab[1, 2] + xtab[2, 1] + xtab[2, 2])

# Hamman statistic
((xtab[1, 1] + xtab[2, 2]) - (xtab[1, 2] + xtab[2, 1])) / sum(xtab)

# Faith statistic
(xtab[1, 1] + xtab[2, 2] / 2) / sum(xtab)

# Summarize across all training set similarities
mean_sim <- score(jacc_sim, new_data = binary_unk)
mean_sim

```

---

autoplot.apd\_pca

*Plot the distribution function for principal components*


---

## Description

Plot the distribution function for principal components

## Usage

```

## S3 method for class 'apd_pca'
autoplot(object, ...)

```

## Arguments

object	An object produced by apd_pca.
...	An optional set of dplyr selectors, such as <code>dplyr::matches()</code> or <code>dplyr::starts_with()</code> for selecting which variables should be shown in the plot.

## Value

A ggplot object that shows the distribution function for each principal component.

## Examples

```
library(ggplot2)
library(dplyr)
library(modeldata)
data(biomass)

biomass_ad <- apd_pca(biomass[, 3:8])

autoplot(biomass_ad)
# Using selectors in `...`
autoplot(biomass_ad, distance) + scale_x_log10()
autoplot(biomass_ad, matches("PC[1-2]"))
```

---

autoplot.apd\_similarity

*Plot the cumulative distribution function for similarity metrics*

---

## Description

Plot the cumulative distribution function for similarity metrics

## Usage

```
## S3 method for class 'apd_similarity'
autoplot(object, ...)
```

## Arguments

object	An object produced by apd_similarity.
...	Not currently used.

## Value

A ggplot object that shows the cumulative probability versus the unique similarity values in the training set. Not that for large samples, this is an approximation based on a random sample of 5,000 training set points.

## Examples

```
set.seed(535)
tr_x <- matrix(
  sample(0:1, size = 20 * 50, prob = rep(.5, 2), replace = TRUE),
  ncol = 20
)
model <- apd_similarity(tr_x)
```

---

binary	<i>Binary QSAR Data</i>
--------	-------------------------

---

**Description**

Binary QSAR Data

**Details**

These data are from two different sources on quantitative structure-activity relationship (QSAR) modeling and contain 67 predictors that are either 0 or 1. The training set contains 4,330 samples and there are five unknown samples (both from the Mutagen data in the QSARdata package).

**Value**

binary\_tr, binary\_ukn  
data frame frames with 67 columns

**Examples**

```
data(qsar_binary)
str(binary_tr)
```

---

okc_binary	<i>OkCupid Binary Predictors</i>
------------	----------------------------------

---

**Description**

OkCupid Binary Predictors

**Details**

Data originally from Kim (2015) includes a training and test set consistent with Kuhn and Johnson (2020). Predictors include ethnicity indicators and a set of keywords derived from text essay data.

**Value**

okc\_binary\_train, okc\_binary\_test  
data frame frames with 61 columns

**Source**

Kim (2015), "OkCupid Data for Introductory Statistics and Data Science Courses", *Journal of Statistics Education*, Volume 23, Number 2. doi:10.1080/10691898.2015.11889737

Kuhn and Johnson (2020), *Feature Engineering and Selection*, Chapman and Hall/CRC . <https://bookdown.org/max/FES/> and <https://github.com/topepo/FES>

**Examples**

```
data(okc_binary)
str(okc_binary_train)
```

---

```
print.apd_hat_values Print number of predictors and principal components used.
```

---

**Description**

Print number of predictors and principal components used.

**Usage**

```
## S3 method for class 'apd_hat_values'
print(x, ...)
```

**Arguments**

x	A apd_hat_values object.
...	Not currently used, but required for extensibility.

**Value**

None

**Examples**

```
model <- apd_hat_values(~ Sepal.Length + Sepal.Width, iris)
print(model)
```

---

```
print.apd_pca Print number of predictors and principal components used.
```

---

**Description**

Print number of predictors and principal components used.

**Usage**

```
## S3 method for class 'apd_pca'
print(x, ...)
```

**Arguments**

x	A apd_pca object.
...	Not currently used, but required for extensibility.

**Value**

None

**Examples**

```
model <- apd_pca(~ Sepal.Length + Sepal.Width, iris)
print(model)
```

---

`print.apd_similarity` *Print number of predictors and principal components used.*

---

**Description**

Print number of predictors and principal components used.

**Usage**

```
## S3 method for class 'apd_similarity'
print(x, ...)
```

**Arguments**

`x`                    A `apd_similarity` object.  
`...`                Not currently used, but required for extensibility.

**Value**

None

**Examples**

```
set.seed(535)
tr_x <- matrix(
  sample(0:1, size = 20 * 50, prob = rep(.5, 2), replace = TRUE),
  ncol = 20
)
model <- apd_similarity(tr_x)
print(model)
```

---

score	<i>A scoring function</i>
-------	---------------------------

---

**Description**

A scoring function

**Usage**

```
score(object, ...)
```

```
## Default S3 method:
score(object, ...)
```

**Arguments**

object	Depending on the context: <ul style="list-style-type: none"> <li>• A <b>data frame</b> of predictors.</li> <li>• A <b>matrix</b> of predictors.</li> <li>• A <b>recipe</b> specifying a set of preprocessing steps created from <code>recipes::recipe()</code>.</li> </ul>
...	Not currently used, but required for extensibility.

**Value**

A tibble of predictions.

---

score.apd_hat_values	<i>Score new samples using hat values</i>
----------------------	---

---

**Description**

Score new samples using hat values

**Usage**

```
## S3 method for class 'apd_hat_values'
score(object, new_data, type = "numeric", ...)
```

**Arguments**

object	A apd_hat_values object.
new_data	A data frame or matrix of new predictors.
type	A single character. The type of predictions to generate. Valid options are: <ul style="list-style-type: none"> <li>• "numeric" for a numeric value that summarizes the hat values for each sample across the training set.</li> </ul>
...	Not used, but required for extensibility.

**Value**

A tibble of predictions. The number of rows in the tibble is guaranteed to be the same as the number of rows in `new_data`. For `type = "numeric"`, the tibble contains two columns `hat_values` and `hat_values_pctl5`. The column `hat_values_pctl5` is in percent units so that a value of 11.5 indicates that, in the training set, 11.5 percent of the training set samples had smaller values than the sample being scored.

**Examples**

```
train_data <- mtcars[1:20, ]
test_data <- mtcars[21:32, ]

hat_values_model <- apd_hat_values(train_data)

hat_values_scoring <- score(hat_values_model, new_data = test_data)
hat_values_scoring
```

---

`score.apd_isolation`    *Predict from a `apd_isolation`*

---

**Description**

Predict from a `apd_isolation`

**Usage**

```
## S3 method for class 'apd_isolation'
score(object, new_data, type = "numeric", ...)
```

**Arguments**

<code>object</code>	A <code>apd_isolation</code> object.
<code>new_data</code>	A data frame or matrix of new samples.
<code>type</code>	A single character. The type of predictions to generate. Valid options are: <ul style="list-style-type: none"> <li>"numeric" for numeric predictions.</li> </ul>
<code>...</code>	Not used, but required for extensibility.

**Details**

About the score

**Value**

A tibble of predictions. The number of rows in the tibble is guaranteed to be the same as the number of rows in `new_data`. The score column is the raw prediction from `isotree::predict.isolation_forest()` while `score_pctl` compares this value to the reference distribution of the score created by predicting the training set. A value of  $X$  means that  $X$  percent of the training data have scores less than the predicted value.

**See Also**[apd\\_isolation\(\)](#)**Examples**

```
if (rlang::is_installed(c("isotree", "modeldata"))) {
  library(dplyr)

  data(cells, package = "modeldata")

  cells_tr <- cells |> filter(case == "Train") |> select(-case, -class)
  cells_te <- cells |> filter(case != "Train") |> select(-case, -class)

  if_mod <- apd_isolation(cells_tr, ntrees = 10, nthreads = 1)
  score(if_mod, cells_te)
}
```

---

`score.apd_pca`*Predict from a apd\_pca*

---

**Description**

Predict from a `apd_pca`

**Usage**

```
## S3 method for class 'apd_pca'
score(object, new_data, type = "numeric", ...)
```

**Arguments**

<code>object</code>	A <code>apd_pca</code> object.
<code>new_data</code>	A data frame or matrix of new samples.
<code>type</code>	A single character. The type of predictions to generate. Valid options are: <ul style="list-style-type: none"><li>• <code>"numeric"</code> for numeric predictions.</li></ul>
<code>...</code>	Not used, but required for extensibility.

**Details**

The function computes the principal components of the new data and their percentiles as compared to the training data. The number of principal components computed depends on the threshold given at fit time. It also computes the multivariate distance between each principal component and its mean.

**Value**

A tibble of predictions. The number of rows in the tibble is guaranteed to be the same as the number of rows in `new_data`.

**Examples**

```
train <- mtcars[1:20, ]
test <- mtcars[21:32, -1]

# Fit
mod <- apd_pca(mpg ~ cyl + log(drat), train)

# Predict, with preprocessing
score(mod, test)
```

---

score.apd\_similarity *Score new samples using similarity methods*

---

**Description**

Score new samples using similarity methods

**Usage**

```
## S3 method for class 'apd_similarity'
score(object, new_data, type = "numeric", add_percentile = TRUE, ...)
```

**Arguments**

<code>object</code>	A <code>apd_similarity</code> object.
<code>new_data</code>	A data frame or matrix of new predictors.
<code>type</code>	A single character. The type of predictions to generate. Valid options are: <ul style="list-style-type: none"> <li>"numeric" for a numeric value that summarizes the similarity values for each sample across the training set.</li> </ul>
<code>add_percentile</code>	A single logical; should the percentile of the similarity score <i>relative to the training set values</i> be computed?
<code>...</code>	Not used, but required for extensibility.

**Value**

A tibble of predictions. The number of rows in the tibble is guaranteed to be the same as the number of rows in `new_data`. For `type = "numeric"`, the tibble contains a column called "similarity". If `add_percentile = TRUE`, an additional column called `similarity_pct1` will be added. These values are in percent units so that a value of 11.5 indicates that, in the training set, 11.5 percent of the training set samples had smaller values than the sample being scored.

**Examples**

```
data(qsar_binary)

jacc_sim <- apd_similarity(binary_tr)

mean_sim <- score(jacc_sim, new_data = binary_unk)
mean_sim
```

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