

# Package ‘KSD’

July 21, 2025

**Type** Package

**Title** Goodness-of-Fit Tests using Kernelized Stein Discrepancy

**Version** 1.0.1

**Date** 2021-01-11

**Description** An adaptation of Kernelized Stein Discrepancy, this package provides a goodness-of-fit test of whether a given i.i.d. sample is drawn from a given distribution. It works for any distribution once its score function (the derivative of log-density) can be provided. This method is based on ``A Kernelized Stein Discrepancy for Goodness-of-fit Tests and Model Evaluation'' by Liu, Lee, and Jordan, available at <[doi:10.48550/arXiv.1602.03253](https://doi.org/10.48550/arXiv.1602.03253)>.

**License** MIT + file LICENSE

**LazyData** TRUE

**RoxxygenNote** 7.1.1

**Imports** pryr, graphics, stats

**Suggests** datasets, ggplot2, gridExtra, mclust, mvtnorm

**NeedsCompilation** no

**Author** Min Hyung Kang [aut, cre],  
Qiang Liu [aut]

**Maintainer** Min Hyung Kang <Minhyung.Daniel.Kang@gmail.com>

**Repository** CRAN

**Date/Publication** 2021-01-11 08:50:16 UTC

## Contents

demo_gmm . . . . .	2
demo_gmm_multi . . . . .	2
demo_iris . . . . .	3
demo_normal_performance . . . . .	3
demo_simple_gamma . . . . .	4
demo_simple_gaussian . . . . .	4
gmm . . . . .	5

KSD . . . . .	5
likelihoodgmm . . . . .	7
perturbgmm . . . . .	7
plotgmm . . . . .	8
posteriorgmm . . . . .	9
rgmm . . . . .	9
scorefunctiongmm . . . . .	10

**Index****11**

---

**demo\_gmm***Tests 1-dimensional Gaussian Mixture Models.*

---

**Description**

Tests 1-dimensional Gaussian Mixture Models.

**Usage**

```
demo_gmm()
```

---

**demo\_gmm\_multi***Tests multidimensional Gaussian Mixture Models.*

---

**Description**

Tests multidimensional Gaussian Mixture Models.

**Usage**

```
demo_gmm_multi()
```

---

demo_iris	<i>Fits Gaussian Mixture model and computes the KSD value for the model</i>
-----------	---

---

## Description

We fit a Gaussian Mixture Model for a given dataset (Fisher's Iris), and we compute the KSD P-value on the hold-out test dataset. User may tune the parameters and observe the change in results. Reports average of p-values obtained during each k-fold. It also plots the contour for each k-fold iteration if only 2 dimensions of data are used. If a vector is specified for nClust, the code tries each element as the number of clusters and reports the optimal parameter by choosing one with highest p-value.

## Usage

```
demo_iris(cols = c(1, 2), nClust = 3, kfold = 5)
```

## Arguments

- cols : Columns of iris data set to use. If 2 dimensions, plots the contour for each k-fold.
- nClust : Number of clusters want to estimate with If vector, use each element as number of clusters and reports the optimal number.
- kfold : Number of k to use for k-fold
- 

---

demo_normal_performance	
	<i>Shows KSD p value change with respect variation in noise</i>

---

## Description

We generate a standard normal distribution, and add varying gaussian noise to this dataset and see the change in pvalues.

## Usage

```
demo_normal_performance()
```

`demo_simple_gamma`      *Tests 1-dimensional Gamma Distribution with customized parameters*

## Description

We generate a gamma distribution with given parameters, and add gaussian noise to this dataset. We then compute the score of each dataset for the original true distribution.

## Usage

```
demo_simple_gamma(
    trueshape = 10,
    truescale = 3,
    noisemu = 5,
    noisesd = 2,
    n = 100
)
```

## Arguments

<code>trueshape</code>	shape of true gamma distribution
<code>truescale</code>	scale of true gamma distribution
<code>noisemu</code>	mean of gaussian noise to add
<code>noisesd</code>	standard deviation of gaussian noise to add
<code>n</code>	number of samples to generate

`demo_simple_gaussian`      *Tests 1-dimensional Gaussian Distribution with customized parameters*

## Description

We generate a gaussian distribution with given parameters, and add noise to this dataset. We then compute the score of each dataset for the original true distribution.

## Usage

```
demo_simple_gaussian(truemu = 5, truesd = 1, noisemu = 0, noisesd = 2, n = 100)
```

## Arguments

<code>truemu</code>	mean of true distribution
<code>truesd</code>	standard deviation of true distribution
<code>noisemu</code>	mean of gaussian noise to add
<code>noisesd</code>	standard deviation of gaussian noise to add
<code>n</code>	number of samples to generate

gmm

*Returns a Gaussian Mixture Model***Description**

Returns a Gaussian Mixture Model

**Usage**

```
gmm(nComp = NULL, mu = NULL, sigma = NULL, weights = NULL, d = NULL)
```

**Arguments**

nComp	(scalar) : number of components
mu	(d by k): mean of each component
sigma	(d by d by k): covariance of each component
weights	(1 by k) : mixing weight of each proportion (optional)
d	: number of dimensions of vector (optional)

**Value**

model : A Gaussian Mixture Model generated from the given parameters

**Examples**

```
# Default 1-d gaussian mixture model
model <- gmm()

# 1-d Gaussian mixture model with 3 components
model <- gmm(nComp = 3)

# 3-d Gaussian mixture model with 3 components, with specified mu,sigma and weights
mu <- matrix(c(1,2,3,2,3,4,5,6,7),ncol=3)
sigma <- array(diag(3),c(3,3,3))
model <- gmm(nComp = 3, mu = mu, sigma=sigma, weights = c(0.2,0.4,0.4), d = 3)
```

KSD

*Estimate Kernelized Stein Discrepancy (KSD)***Description**

Estimate kernelized Stein discrepancy (KSD) using U-statistics, and use bootstrap to test H0:  $x_i$  is drawn from  $p(X)$  (via KSD=0).

## Usage

```
KSD(x, score_function, kernel = "rbf", width = -1, nboot = 1000)
```

## Arguments

x	Sample of size Num_Instance x Num_Dimension
score_function	( $\nabla_x \log p(x)$ ) Score function : takes x as input and output a column vector of size Num_Instance X Dimension. User may use pryr package to pass in a function that only takes in dataset as parameter, or user may also pass in computed score for a given dataset.
kernel	Type of kernel (default = 'rbf')
width	Bandwidth of the kernel (when width = -1 or 'median', set it to be the median distance between data points)
nboot	Bootstrap sample size

## Value

A list which includes the following variables :

- "ksd" : Estimated Kernelized Stein Discrepancy (KSD)
- "p" : p-Value for rejecting the null hypothesis that ksd = 0
- "bootstrapSamples" : the bootstrap sample
- "info": other information, including : bandwidth, M, nboot, ksd\_V

## Examples

```
# Pass in a dataset generated by Gaussian distribution,
# use pryr package to pass in score function
model <- gmm()
X <- rgmm(model, n=100)
score_function = pryr::partial(scorefunctiongmm, model=model)
result <- KSD(X, score_function=score_function)

# Pass in a dataset generated by Gaussian distribution,
# pass in computed score rather than score function
model <- gmm()
X <- rgmm(model, n=100)
score_function = scorefunctiongmm(model=model, X=X)
result <- KSD(X, score_function=score_function)

# Pass in a dataset generated by Gaussian distribution,
# pass in computed score rather than score function
# Use median_heuristic by specifying width to be -2.0
model <- gmm()
X <- rgmm(model, n=100)
score_function = pryr::partial(scorefunctiongmm, model=model)
result <- KSD(X, score_function=score_function, 'rbf', -2.0)

# Pass in a dataset generated by specific Gaussian distribution,
```

```
# pass in computed score rather than score function
# Use median_heuristic by specifying width to be -2.0
model <- gmm()
X <- rgmm(model, n=100)
score_function = pryr::partial(scorefunctiongmm, model=model)
result <- KSD(X, score_function=score_function, 'rbf', -2.0)
```

**likelihoodgmm***Calculates the likelihood for a given dataset for a GMM***Description**

Calculates the likelihood for a given dataset for a GMM

**Usage**

```
likelihoodgmm(model = NULL, X = NULL)
```

**Arguments**

model	: The Gaussian Mixture Model
X	(n by d): The dataset of interest, where n is the number of samples and d is the dimension

**Value**

P (n by k) : The likelihood of each dataset belonging to each of the k component

**Examples**

```
# compute likelihood for a default 1-d gaussian mixture model
# and dataset generated from it
model <- gmm()
X <- rgmm(model)
p <- likelihoodgmm(model=model, X=X)
```

**perturbgmm***Returns a perturbed model of given GMM***Description**

Returns a perturbed model of given GMM

**Usage**

```
perturbgmm(model = NULL)
```

**Arguments**

`model` : The base Gaussian Mixture Model

**Value**

`perturbedModel` : Perturbed model with added noise to the supplied GMM

**Examples**

```
#Add noise to default 1-d gaussian mixture model
model <- gmm()
noisymodel <- perturbgmm(model)
```

`plotgmm`

*Plots histogram for 1-d GMM given the dataset*

**Description**

Plots histogram for 1-d GMM given the dataset

**Usage**

```
plotgmm(data, mu = NULL)
```

**Arguments**

`data` (n by 1): The dataset of interest, where n is the number of samples.  
`mu` : True mean of the GMM (optional)

**Examples**

```
# Plot pdf histogram for a given dataset
model <- gmm()
X <- rgmm(model)
plotgmm(data=X)

# Plot pdf histogram for a given dataset, with lines that indicate the mean
model <- gmm()
mu <- model$mu
X <- rgmm(model)
plotgmm(data=X, mu=mu)
```

---

posteriorgmm	<i>Calculates the posterior probability for a given dataset for a GMM</i>
--------------	---

---

**Description**

Calculates the posterior probability for a given dataset for a GMM

**Usage**

```
posteriorgmm(model = NULL, X = NULL)
```

**Arguments**

- |       |  |
|-------|--|
| model | : The Gaussian Mixture Model   |
| X     | (n by d): The dataset of interest, where n is the number of samples and d is the dimension |

**Value**

P (n by k) : The posterior probability of each dataset belonging to each of the k component

**Examples**

```
# compute posterior probability for a default 1-d gaussian mixture model
# and dataset generated from it
model <- gmm()
X <- rgmm(model)
p <- posteriorgmm(model=model, X=X)
```

---

rgmm	<i>Generates dataset from Gaussian Mixture Model</i>
------	--

---

**Description**

Generates dataset from Gaussian Mixture Model

**Usage**

```
rgmm(model = NULL, n = 100)
```

**Arguments**

- |       |   |
|-------|---|
| model | : Gaussian Mixture Model defined by gmm() |
| n     | : number of samples desired               |

**Value**

data (n by d): Random dataset generated from given the Gaussian Mixture Model

**Note**

Requires library mvtnorm

**Examples**

```
#Generate 100 samples from default gaussian mixture model
model <- gmm()
X <- rgmm(model)

#Generate 300 samples from 3-d gaussian mixture model
model <- gmm(d=3)
X <- rgmm(model,n=300)
```

**scorefunctiongmm**

*Score function for given GMM : calculates score function  $d\log p(x)/dx$  for a given Gaussian Mixture Model*

**Description**

Score function for given GMM : calculates score function  $d\log p(x)/dx$  for a given Gaussian Mixture Model

**Usage**

```
scorefunctiongmm(model = NULL, X = NULL)
```

**Arguments**

model	: The Gaussian Mixture Model
X	(n by d): The dataset of interest, where n is the number of samples and d is the dimension

**Value**

y : The score computed by the given function

**Examples**

```
# Compute score for a given gaussianmixture model and dataset
model <- gmm()
X <- rgmm(model)
score <- scorefunctiongmm(model=model, X=X)
```

# Index

demo\_gmm, 2  
demo\_gmm\_multi, 2  
demo\_iris, 3  
demo\_normal\_performance, 3  
demo\_simple\_gamma, 4  
demo\_simple\_gaussian, 4  
  
gmm, 5  
  
KSD, 5  
  
likelihoodgmm, 7  
  
perturbgmm, 7  
plotgmm, 8  
posteriorgmm, 9  
  
rgmm, 9  
  
scorefunctiongmm, 10