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# **BNP.jl Documentation**

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**OFAI**

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The *BNP* package integrates a wide range of state-of-the-art Bayesian nonparametric models. In particular:

- Dirichlet Process Mixture Models
- Hierarchical Dirichlet Process Mixture Models
- Factor analysis Models (e.g. Variable Clustering Model)

**Contents:**



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## Getting Started

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### 1.1 Installation

The *BNP* package is currently not available through the Julia package system but can easily be installed by running `Pkg.clone("https://github.com/trappmartin/BNP.jl")`.

### 1.2 Clustering data using Dirichlet Process Mixture Model

In this example we start by drawing 100 observations from two bivariate Normal distributions.

```
julia> X = cat(2, rand(2, 50), rand(2, 50) + 10)
julia> Y = cat(2, zeros(50), ones(50))
```

Now we can initialize the package and construct a Gaussian data distribution using a Normal Inverse Wishart prior.

```
julia> using BNP
julia>  $\mu_0$  = vec( mean(X, 2) )
julia>  $\kappa_0$  = 1.0
julia>  $\nu_0$  = 4.0
julia>  $\Psi$  = eye(2) * 10
julia> G0 = GaussianWishart( $\mu_0$ ,  $\kappa_0$ ,  $\nu_0$ ,  $\Psi$ )
```

After constructing `G0` we can easily apply a Dirichlet Process Mixture Model using collapsed Gibbs sampling.

```
julia> models = train(DPM(G0), Gibbs(), KMeansInitialisation(), X)
```

Please note that this example can also be found in the demos folder, allowing interactive exploration of the model.





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## Initialization Methods

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In order to initialize the Bayesian nonparametric models we provide a set of initialization approaches. Currently not every initialization approach is available for all models.

### 2.1 Random Initialization

The Random Initialization randomly assigns the data to a predefined number of groups.

```
julia> init = RandomInitialisation() # Random Initialization with k = 2  
julia> init = RandomInitialisation(k = 5) # Random Initialization with k = 5
```

### 2.2 Incremental Initialization

The Incremental Initialization sequentially assigns the data to groups.

```
julia> init = IncrementalInitialisation() # Incremental Initialization k = 5
```

### 2.3 K-Means Initialization

The K-Means Initialization assigns the data using k-Means clustering to a predefined number of groups.

```
julia> init = KMeansInitialisation() # K-Means Initialisation with k = 2  
julia> init = KMeansInitialisation(k = 5) # K-Means Initialisation with k = 5
```



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## Distributions

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The following distributions are currently supported. We will add additional support for the Distributions package in near future.

### 3.1 Common Interface

A common interface to access the sufficient statistics and the log likelihood is provided for all distributions.

```
julia> add_data!(dist, X) # add datum to dist
julia> dist2 = add_data(dist, X) # add datum to copy of dist
```

```
julia> remove_data!(dist, X) # remove datum from dist
julia> dist2 = remove_data(dist, X) # remove datum from copy of dist
```

```
julia> logpred(dist, X) # log likelihood datum under dist
```

### 3.2 Beta-Binomial

The Binomial distribution with Beta prior of dimensionality  $D$  can be created using:

```
julia> dist = BinomialBeta(D) # with default  $\alpha = 1.0$  and  $\beta = 1.0$ 
julia> dist = BinomialBeta(D,  $\alpha = 3$ ,  $\beta = 4$ ) # specify  $\alpha$  and  $\beta$  parameter of Beta distribution
```

### 3.3 Dirichlet-Multinomial

The Multinomial distribution with Dirichlet prior of dimensionality  $D$  can be created using:

```
julia> dist = MultinomialDirichlet(D, 1.0) # with default  $\alpha = 1.0$ 
```

### 3.4 Wishart-Gaussian

The Gaussian distribution with Wishart prior of dimensionality  $D$  can be created using:

```
julia> dist = GaussianWishart( $\mu$ ,  $\kappa$ ,  $\nu$ ,  $\Psi$ ) # with specified  $\mu$  of dimensionality  $D$ ,  $\kappa$ ,  $\nu$  and  $\Psi$  of dimensionality  $D \times D$ 
```