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Parallel computing (Parallel-Computing-With-R.html)

Strategies to Speedup R code (Strategies-To-Improve-And-Speedup-R-Code.html)

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Association Mining (Association-Mining-With-R.html)

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Optimization (Profiling.html)

InformationValue package (Information-Value-With-R.html)

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Contents

Dirichlet Regression

> Dirichlet regression can be used to model *compositional data*, when the dependent-Y variable is practically a sum total of contribution from multiple components.

Introduction

Dirichlet regression can be used to predict the ratio in which the sum total X (demand/forecast/estimate) can be distributed among the component *Ys*. It is practically a case where there are multiple dependent ‘Y’ variables and one predictor *X* variable, whose sum is distributed among the *Ys* .

A couple of possible real-world examples could be as follows:

1. Total demand of a product A in a multi-facility manufacturing organization is actually a sum of demand of product A from *n* individual factories of the organization. Given the total demand, we are interested to know in what proportions the *n* factories contributed.

2. The total car sales in the US is a sum of car sales from 50+ individual car brands. In case we know the total projected car sales in the US, the proportional contribution from the individual brands can be predicted using *Dirichlet regression*.
3. The demand of a product is actually the sum total of demand of 4 different models (variants) of the same product.

In either case, the dependent Y variables, which are the contributions from each component, should be converted to fractions summing up to 1. It is the job of `DirichReg()` to predict these fractions when the sum total `X` is known.

The code shown below can model, predict and visualize multiple Y Variables

1. Data Preparation

Prepare the test and training samples. Make the dirichlet Reg data on Y’s.

```
library (DirichletReg)
inputData <- ArcticLake  # plug-in your data here.
set.seed(100)
train <- sample (1:nrow (inputData), round (0.7*nrow (inputData)))  # 70% training sampl
e
inputData_train <- inputData [train, ] # training Data
inputData_test <- inputData [-train, ] # test Data
inputData$Y <- DR_data (inputData[,1:3])  # prepare the Y's
inputData_train$Y <- DR_data (inputData_train[,1:3])
inputData_test$Y <- DR_data (inputData_test[,1:3])
```

2. Train the model

```
# Train the model. Modify the predictors as such.
res1 <- DirichReg(Y ~ depth + I(depth^2), inputData_train)  # modify the predictors and
 input data here
res2 <- DirichReg(Y ~ depth + I(depth^2) | depth, inputData_train, model="alternative")
summary(res1)
#> Call:
#> DirichReg(formula = Y ~ depth + I(depth^2), data = inputData_train)
#>
#> Standardized Residuals:
#>           Min       1Q   Median      3Q     Max
#> sand  -1.6372  -0.8499  -0.4344  1.0560  2.2233
#> silt  -1.0645  -0.5042  -0.0898  0.1858  1.5665
#> clay  -1.5058  -0.6494   0.0081  0.5867  1.7450
#>
#> ------------------------------------------------------------------
#> Beta-Coefficients for variable no. 1: sand
#>              Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  1.8089738  1.0414098   1.737   0.0824 .
#> depth       -0.0220478  0.0458691  -0.481   0.6308
#> I(depth^2)   0.0002771  0.0004098   0.676   0.4988
#> ------------------------------------------------------------------
#> Beta-Coefficients for variable no. 2: silt
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept) 4.641e-01  1.124e+00   0.413    0.680
#> depth       4.355e-02  5.463e-02   0.797    0.425
#> I(depth^2)  2.064e-05  5.078e-04   0.041    0.968
#> ------------------------------------------------------------------
#> Beta-Coefficients for variable no. 3: clay
#>              Estimate Std. Error z value Pr(>|z|)
#> (Intercept) -1.5520413  1.1244396  -1.380    0.168
#> depth        0.0874478  0.0578113   1.513    0.130
#> I(depth^2)  -0.0002161  0.0005433  -0.398    0.691
#> ------------------------------------------------------------------
#> Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Log-likelihood: 80.66 on 9 df (183 BFGS + 2 NR Iterations)
#> AIC: -143.3, BIC: -131.7
```

```
#> Number of Observations: 27
#> Link: Log
#> Parametrization: common
```

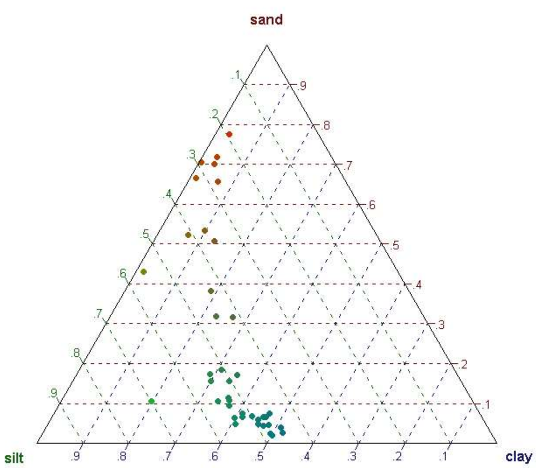
As you can see from the summary results, the β coefficients for the *Xs* are computed to predict each of the *Ys*.

3. Fitted and Forecasts

```
# Predict On Training Data: Fitted Values
predict(res1) # Model 1 fit
#>             sand      silt       clay
#>  [1,] 0.38244831 0.4564125 0.16113919
#>  [2,] 0.43736620 0.4285154 0.13411836
#>  [3,] 0.15978409 0.5177743 0.32244164
#>  [4,] 0.58529627 0.3386196 0.07608417
#>  [5,] 0.23630422 0.5094430 0.25425275
#>  .
#>  .
predict(res2) # Model 2 fit
resid(res1) # Residuals
# Predict On Test Data or Forecast
predicted_res1 <- predict(res1, inputData_test) # Model 1
predicted_res2 <- predict(res2, inputData_test) # Model 2
```

4. Visualize

```
# Plot
plot(DR_data(predicted_res2)) # plot test Data on model 2
# additional plots
plot(inputData$Y)
```



This page is based on the examples available in Dirichlet regression vignette (https://cran.r-project.org/web/packages/DirichletReg/vignettes/DirichletReg-vig.pdf) and details about the implementation are available in here (http://epub.wu.ac.at/4077/1/Report125.pdf).
