1) Beta Drafavbustion:

(a) Litelihood function:

$$L(\theta) = p(x, \log x_2 ... x_n | \alpha, \beta)$$

$$= \prod_{i=1}^{N} \frac{\chi(\alpha+\beta)}{\chi(\alpha)\chi(\beta)} \chi^{(\alpha-1)} (1-\chi)^{\beta-1}$$

$$L(\theta) = \left( \begin{array}{c} Y(\alpha+\beta) \\ \overline{Y(\alpha)} & \overline{Y(\alpha-1)} \\ \overline{Y(\alpha)} & \overline{Y(\alpha-1)} \\ \overline{Y(\alpha)} & \overline{Y(\alpha-1)} \\ \overline{Y(\alpha-1)} & \overline{Y(\alpha-1)} \\ \overline{Y(\alpha-1)}$$

(b) Log Likelihood:

(b)  $l(B) = n \log k(x+B) - n \log k(x) - n \log k(B)$  $+ \log (x-1) \sum_{i=1}^{n} \log_{i} x_{i} + \log_{i} (B-1) \sum_{i=1}^{n} \log_{i} (1-x_{i})$ 

Negative log Likelihoodt

 $-l(\theta) = -n \log V(\alpha + \beta) + n \log V(\alpha) + n \log V(\beta)$   $- \ln (\alpha - 1) \log x - \ln (\beta - 1) \sum_{i=1}^{n} \log (1 - x_i)$   $= - \ln (\alpha - 1) \log x - \ln (\beta - 1) \sum_{i=1}^{n} \log (1 - x_i)$ 

() Computing partial Degiavations,

de 2 - n d 8 (x+B) + n 80

 $\frac{\partial l}{\partial x} = -n \frac{\partial \log(x(x+B))}{\partial (x(x+B))} + n \frac{\partial \log(x(x))}{\partial x}$ 

 $-\sum_{i=1}^{\infty}\log\left(x_{i}\right)=0$ 

Step 5+ (1xi - xi-1) (E)

if (1xi - xi-1) < E & R | Bi - Bi-1 | KE)

terminate; end; Step 67 and Jos.

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```
In [1]: using Distributions;
        using Gadfly, Cairo, Fontconfig
In [2]: function dl_by_da(samples, a, b)
            n = length(samples);
            result = - n*digamma(a+b)+n*digamma(a)-sum(log.(samples));
            return result;
        end
Out[2]: dl_by_da (generic function with 1 method)
In [3]: function dl by db(samples, a, b)
            n = length(samples);
            result = - n*digamma(a+b)+n*digamma(b)-sum(log.(1-samples));
             return result;
        end
Out[3]: dl by db (generic function with 1 method)
In [4]: function gradient_desent_beta(samples, learning_rate, max_iterations)
            n = length(samples);
            max_acc = 0.0001;
             a = rand()*10;
            b = rand()*10;
             for i=1:max_iterations
                 a_new = a - learning_rate * dl_by_da(samples, a, b);
                 b_new = b - learning_rate * dl_by_db(samples, a, b);
                 if ( abs(a new - a) < max acc && abs(b new - b) < max acc )</pre>
                     #print("Solution Converged");
                     break;
                 end
                 a = a_new;
                 b = b_new;
             end
             return a, b;
        end
Out[4]: gradient_desent_beta (generic function with 1 method)
In [5]: d = Beta(2,2);
        samples = rand(d, 1000);
        n = length(samples)
Out[5]: 1000
In [6]: | max_iterations = 10000000;
        learning_rate = 0.00001;
        a, b = gradient desent beta(samples, learning rate, max iterations)
Out[6]: (1.928375306495845, 1.987824660444101)
```

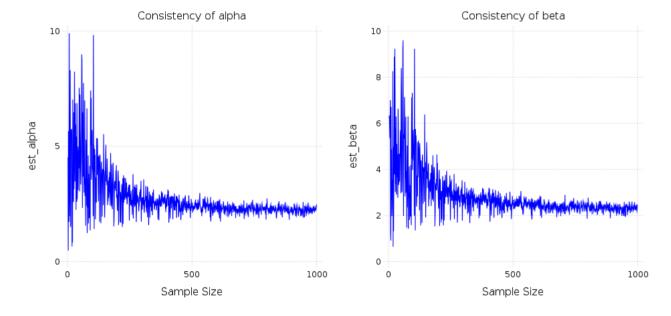
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```
In [7]: ### The estimated values of the Beta distribution Parameters are ###
alpha = 1.928
Beta = 1.987
```

WARNING: imported binding for Beta overwritten in module Main

Out[7]: 1.987

```
In [15]: d = Beta(a, b);
         samples_size = collect(2:1000);
         estimate a = zeros(length(samples size));
         estimate_b = zeros(length(samples_size));
         for i=1:length(samples_size)
             samples = rand(d,samples_size[i]);
             estimate_a[i], estimate_b[i] = gradient_desent_beta(samples, learning_rate, max_iterations)
         white_panel = Theme(panel_fill=colorant"white", default_color=colorant"blue", major_label_font_size =12r
         myplot1 = Gadfly.plot(x=samples_size,y=estimate_a,Geom.line,
                       Guide.xlabel("Sample Size"), Guide.ylabel("est_alpha"),
                       Guide.title("Consistency of alpha"),white_panel);
         myplot2 = Gadfly.plot(x=samples_size,y=estimate_b,Geom.line,
                       Guide.xlabel("Sample Size"), Guide.ylabel("est_beta"),
                       Guide.title("Consistency of beta"), white_panel);
         final_plot = hstack(myplot1,myplot2);
         draw(PNG(10inch, 5inch), final_plot);
```



In [ ]: ### The parameters are converging to the original values hence it is consistent ###