# Computational Numerical Statistics PROJECT 2

#### Group G1 – TP2

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### References

#### Random variable generation

Let  $X \sim Beta(\alpha, 1)$ , which has p.d.f.

$$f(x;\alpha) = \frac{x^{\alpha-1}}{B(\alpha,1)}, \alpha > 0, x \in [0,1]$$

#### Let

```
0.5409477 0.8184872 0.7848854 0.9850439 0.8963032 0.6089008 0.9549606 0.6795304 0.8451902 0.5613979 0.4029634 0.2741569 0.3996693 0.6371445 0.7521881
```

be an observed sample from X.

#### Likelihood, log-likelihood and score functions

Likelihood function:

$$L(\alpha) = \prod_{i=1}^{n} f(x_i | \alpha) = \alpha^n \prod_{i=1}^{n} x_i^{\alpha - 1}$$

Log-likelihood function:

$$I(\alpha) = logL(\alpha) = nlog(\alpha) + (\alpha - 1) \sum_{i=1}^{n} log(x_i)$$

Score function:

$$s(\alpha) = l'(\alpha) = \frac{n}{\alpha} - \sum_{i=1}^{n} log(x_i)$$

#### Maximum likelihood estimation of $\alpha$

The MLE of  $\alpha$  is obtained by maximizing L( $\alpha$ )

**1** Solve the equation  $s(\alpha) = 0$ 

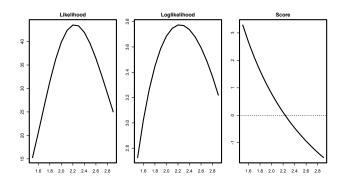
$$s(\alpha) = 0 \Leftrightarrow \frac{n}{\alpha} + \sum_{i=1}^{n} log(x_i) = 0 \Leftrightarrow$$
$$\Leftrightarrow \frac{n}{\alpha} = -\sum_{i=1}^{n} log(x_i) \Leftrightarrow \alpha = -\frac{n}{\sum_{i=1}^{n} log(x_i)}$$

② Confirm that  $s'(\alpha) < 0$ 

$$s'(\alpha; x) = l''(\alpha) = \left(\frac{n}{\alpha} - \sum_{i=1}^{n} log(x_i)\right)' = -\frac{n}{\alpha^2} < 0$$

- The maximum likelihood estimator of  $\alpha$  is  $\hat{\alpha} = -\frac{n}{\sum_{i=1}^{n} log(x_i)}$
- Calculate MLE for sample from ,  $\hat{\alpha} = 2.235083$

#### Maximum likelihood estimation of $\alpha$



#### Maximum likelihood estimation of $\alpha$

• Approximation of the ML estimate  $\alpha$  using the R function maxLik()

```
maxLik(logLik=loglik.b,start=mme.graph.b)

maxLik(logLik=loglik, start=mme.graphical)
#Maximum Likelihood estimation
#Newton-Raphson maximisation, 3 iterations
#Return code 1: gradient close to zero
#Log-Likelihood: 3.775335 (1 free parameter)
#Estimate(s): 2.235083
```

Bisection method

**INSERT GRAPHIC** 

Bisection method

#### Theorem (Bolzano theorem)

Let f be a continuous function in the limited interval [a, b]  $\in \mathbb{R}$  such that:

$$f(a)f(b) \leq 0$$

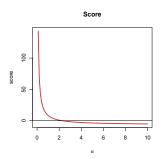
then f has at least one root  $x^* \in ]a, b[$ .

#### Bisection method

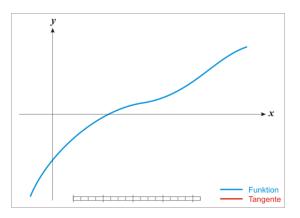
We can observe that s function is strictly descending, because

$$s'(\alpha;x)=-\frac{n}{\alpha^2}<0$$

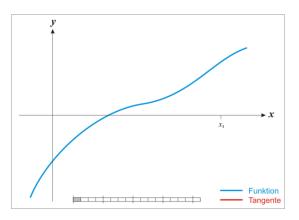
So, the function has one root in  $\mathbb{R}^+$ .



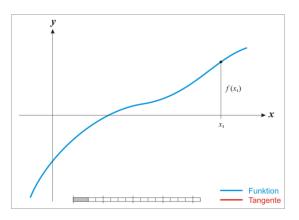
Therefore, we can conclude, whatever range that verifies the Bolzano theorem, this method will always converge.



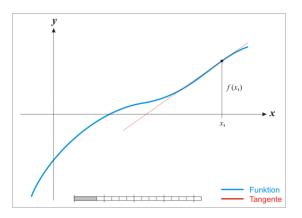
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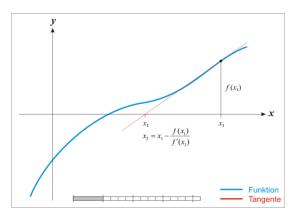
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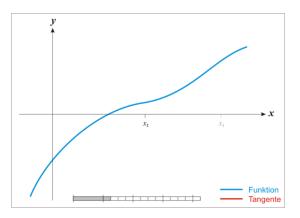
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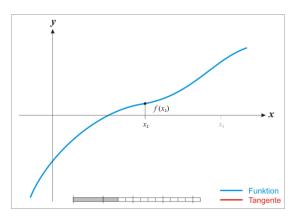
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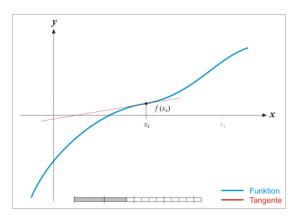
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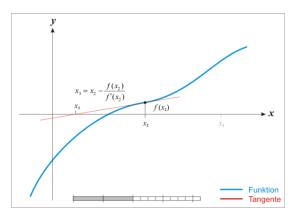
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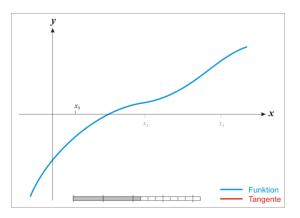
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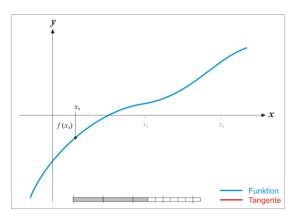
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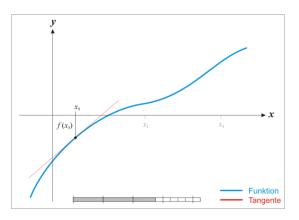
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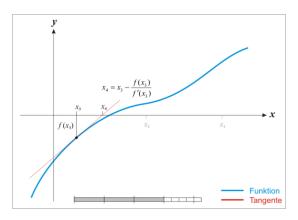
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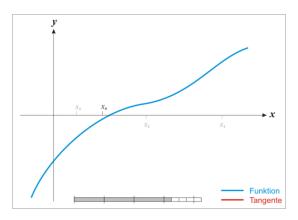
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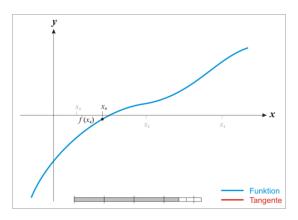
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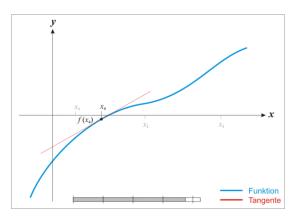
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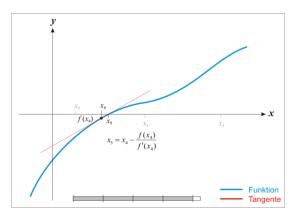
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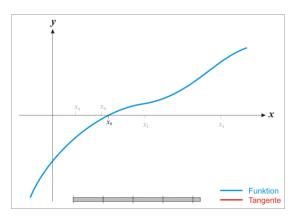
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#### Fisher Scoring Method

Fisher Scoring Algorithm:

$$x_{n+1} = x_n + \frac{s(x_n)}{\mathcal{I}_n} = x_n + \frac{s(x_n)}{\frac{n}{\alpha^2}}$$

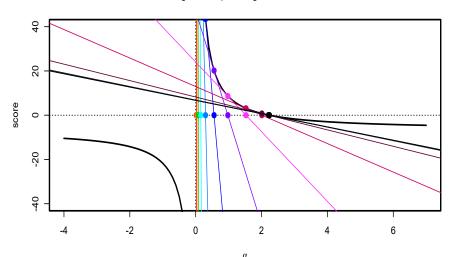
Where,

$$\mathcal{I}(\alpha) = -E\left[s'(\alpha;x)\right] = -E\left[-\frac{n}{\alpha^2}\right] = \frac{n}{\alpha^2}$$

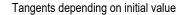
Newton Raphson Method:

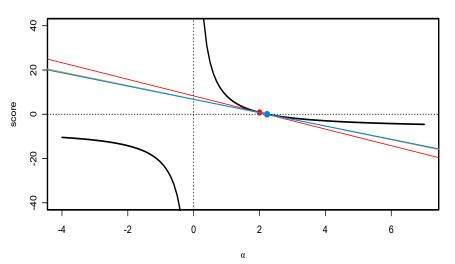
$$x_{n+1} = x_n - \frac{s(x_n)}{s'(x_n)} = x_n - \frac{s(x_n)}{-\frac{n}{\alpha^2}} = x_n + \frac{s(x_n)}{\frac{n}{\alpha^2}}$$
 (1)

Tangents depending on initial value



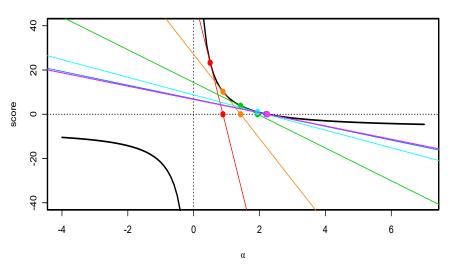
# alpha = 2





# alpha = 0.5





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- Let *X* be a discrete random variable with probability mass function (p.m.f.) f proportional to  $g(x) = 1 x + x^2$ , x = 0, 1, 2, 3, 4.
  - Identify the p.m.f. f
  - Derive the cumulative distribution function (c.d.f.) F of X.
  - Obscribe and implement the **inverse-transform** method in  $\mathbb R$  for generating a sample from f. Call your routine  $\mathtt{sim.itm}()$  and let it receive as input a generic sample size m. Provide both algorithm and  $\mathbf R$  code. Finally, use  $\mathtt{sim.itm}()$  to generate a sample of size m=10000 of f.
  - The same as in (c) but now using the acceptance-rejection method. Call you new simulation routine sim.arm(). Compute the rejection rate.
  - Plot the discrete histograms from (c) and (d) with the true p.m.f. superimposed.
  - Display the the hit-and-miss plot referring to sim.arm (10).

#### Random variable generation

#### present problem solving here

#### see template\_report.tex for other tips

include your plots centered in the slide

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