TÓPICOS EM CIÊNCIA DE DADOS PARA O ESPORTE

ALGORITMO GLICKO

DIEGO RODRIGUES DSC

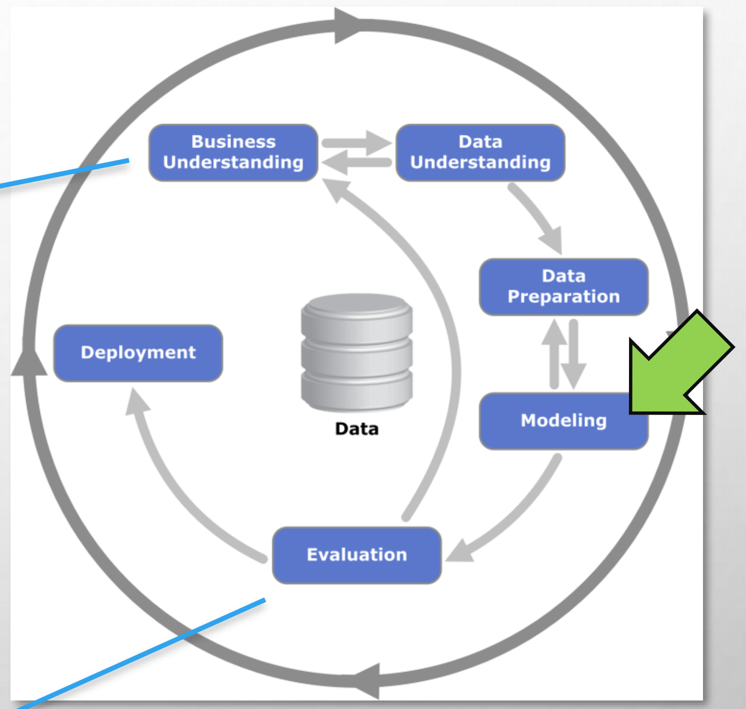
INFNET

AGENDA

- PARTE 1 : TEORIA
  - CONTEXTO
  - ALGORITMO GLICKO
- PARTE 2 : PRÁTICA
  - PROGRAMA PYTHON → RANQUEAMENTO ESTATÍSTICO DO BRASILEIRÃO (ELO VS GLICKO VS TRUESKILL)

CRONOGRAMA

DIA	NÚMERO	ÁREA	AULA	TRABALHOS
10/10/2023	1	Intro	Introdução a Disciplina e Organização do Ambiente	
17/10/2023	2	Dados	Coleta de Dados e Sensoriamento	
19/10/2023	3	Estatística	Variáveis Aleatórias	Grupos
24/10/2023	4		Análise Exploratória	
26/10/2023	5		Estatísticas para Ranqueamento	
31/10/2023	6		Ranqueamento Estatístico : ELO	Base de Dados
07/11/2023	7		Ranqueamento Estatístico : Glicko	
09/11/2023	8		Ranqueamento Estatístico : TrueSkill	
14/11/2023	9		Ranqueamento Estatístico : XELO	
16/11/2023	10	ML	Modelos de Aprendizado de Máquina	Pesquisa
21/11/2023	11		Machine Learning: Classificação	
23/11/2023	12		Machine Learning: Regressão	
28/11/2023	13		Machine Learning: Agrupamento	
30/11/2023	14		Machine Learning: Visão Computacional	Modelo
5/12/2023	15	Esportes	Aplicações & Artigos: Esportes Independentes	
7/12/2023	16		Aplicações & Artigos: Esportes de Combate	
12/12/2023	17		Aplicações & Artigos: Esportes de Objeto	
14/12/2023	18		Aplicações & Artigos : Betting	
19/12/2023	19	Workshop	Workshop	
21/12/2023	20		Apresentações de Trabalhos	Apresentação



CRISP-DM

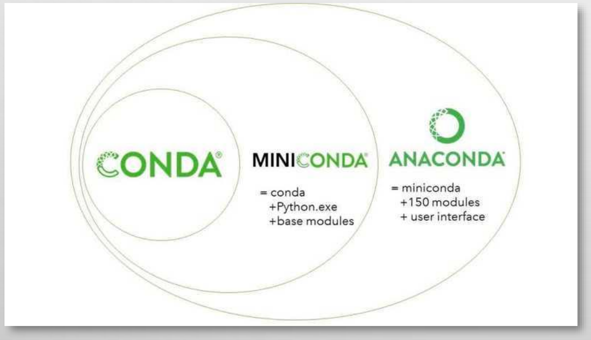
SETUP INICIAL DO AMBIENTE PYTHON

4. Variáveis Aleatórias

5. Visualização

6. Estimação e Inferência

1. Editor de Código



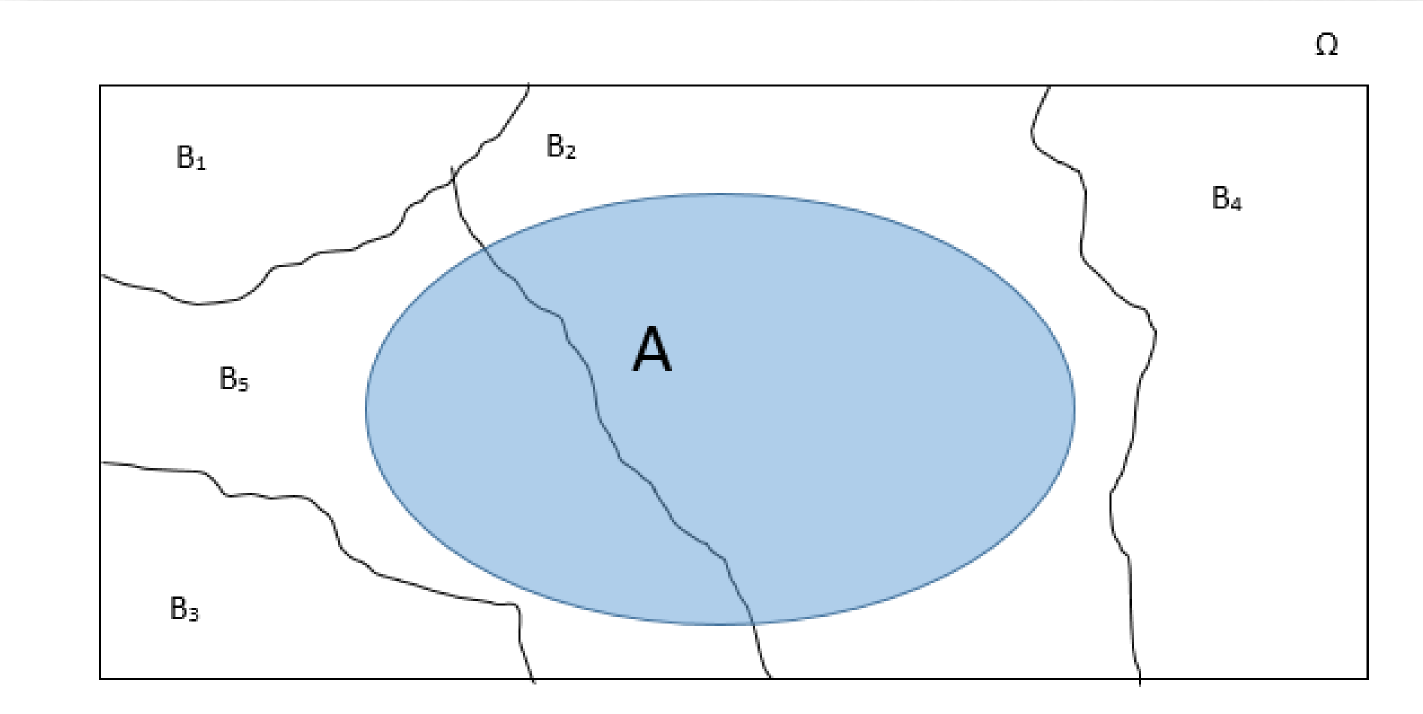
2. Gestor de Ambiente

3. Ambiente Python do Projeto

3. Notebook Dinâmico

CONTEXTO

TEOREMA DE BAYES



$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)}$$

INFERÊNCIA BAYESIANA

10.2 Bayes Rule

The distribution of a variable x conditioned on a variable y is

$$p(x \mid y) = \frac{p(x, y)}{p(y)} \quad (10.1)$$

Given that $p(y \mid x)$ can be expressed similarly we can write

$$p(x \mid y) = \frac{p(y \mid x)p(x)}{p(y)} \quad (10.2)$$

which is Baye's rule. The density $p(x)$ is known as the *prior*, $p(y \mid x)$ as the *likelihood* and $p(y)$ as the *evidence* or *marginal likelihood*. Baye's rule shows how a prior distribution can be turned into a posterior distribution ie. how we update our distribution in the light of new information. To do this it is necessary to calculate the normalising term; the evidence

$$p(y) = \int p(y \mid x)p(x)dx \quad (10.3)$$

which, being an integral, can sometimes be problematic to evaluate.

10.3 Gaussian Variables

A Gaussian random variable x has the probability density function (PDF)

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-(x-\mu)^2}{2\sigma^2}\right] \quad (10.10)$$

where the mean is μ and the variance is σ^2. The inverse of the variance is known as the precision $\beta = 1/\sigma^2$. The Gaussian PDF is written in shorthand as

$$p(x) = N(x; \mu, \sigma^2) \quad (10.11)$$

If the prior is Gaussian

$$p(x) = N(x; x_0, 1/\beta_0) \quad (10.12)$$

where x_0 is the prior mean and β_0 is the prior precision and the likelihood is also Gaussian

$$p(y \mid x) = N(y; x, 1/\beta_D) \quad (10.13)$$

where the variable x is the mean of the likelihood and β_D is the data precision then the posterior distribution is also Gaussian (see eg. [33],page 37).

$$p(x \mid y) = N(x; m, 1/\beta) \quad (10.14)$$

where the mean and precision are given by

$$\beta = \beta_0 + \beta_D \quad (10.15)$$

and

$$m = \frac{\beta_0}{\beta}x_0 + \frac{\beta_D}{\beta}y \quad (10.16)$$

Thus, the posterior precision is given by the sum of the prior precision and the data precision and the posterior mean is given by the sum of the prior data mean and the new data value each weighted by their relative precisions [1].

https://www.fil.ion.ucl.ac.uk/~wpenny/

MLE VS MAP

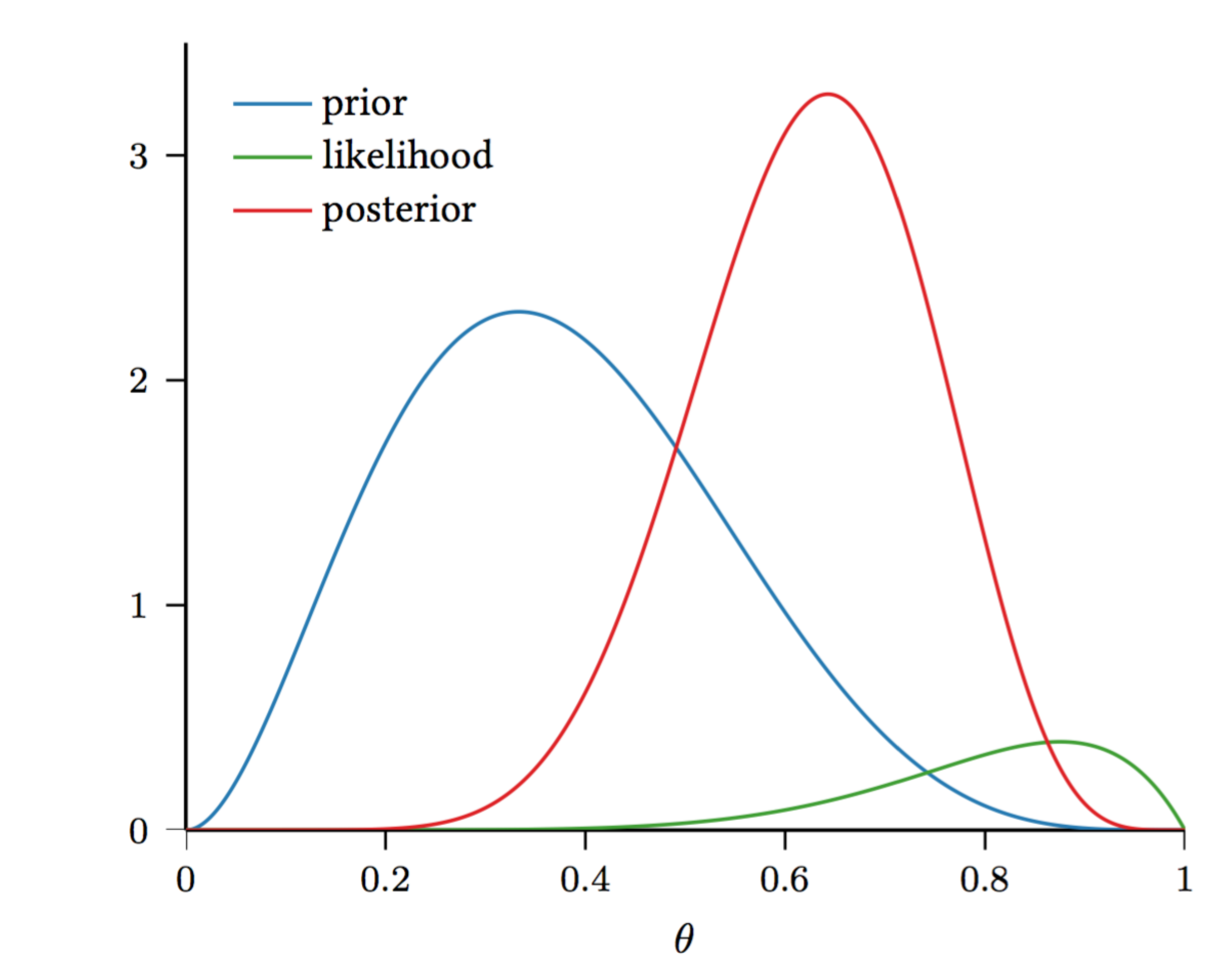
Suppose we have data $\mathcal{D} = \{x^{(i)}\}_{i=1}^{N}$

Maximum Likelihood Estimate (MLE)

$$\boldsymbol{\theta}^{\text{MLE}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i=1}^{N} p(\mathbf{x}^{(i)}|\boldsymbol{\theta})$$

Maximum *a posteriori* (MAP) estimate

$$\boldsymbol{\theta}^{\text{MAP}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \prod_{i=1}^{N} p(\mathbf{x}^{(i)}|\boldsymbol{\theta})\underbrace{p(\boldsymbol{\theta})}_{\text{Prior}}$$



https://datascience.stackexchange.com/questions/81811/what-is-the-difference-between-maximum-likelihood-hypothesis-and-maximum-a-poste

ALGORITMO GLICKO

PAPERS ORIGINAIS

DESAFIO: RODAR O BOOTELO NA MÁQUINA II

PRÓXIMA AULA
LEITURA: ALGORITMO TRUESKILL