CIÊNCIA DE DADOS APLICADA A ANÁLISE ESPORTIVA UTILIZANDO PYTHON AVANÇADO

ALGORITMO GLICKO

DIEGO RODRIGUES DSC

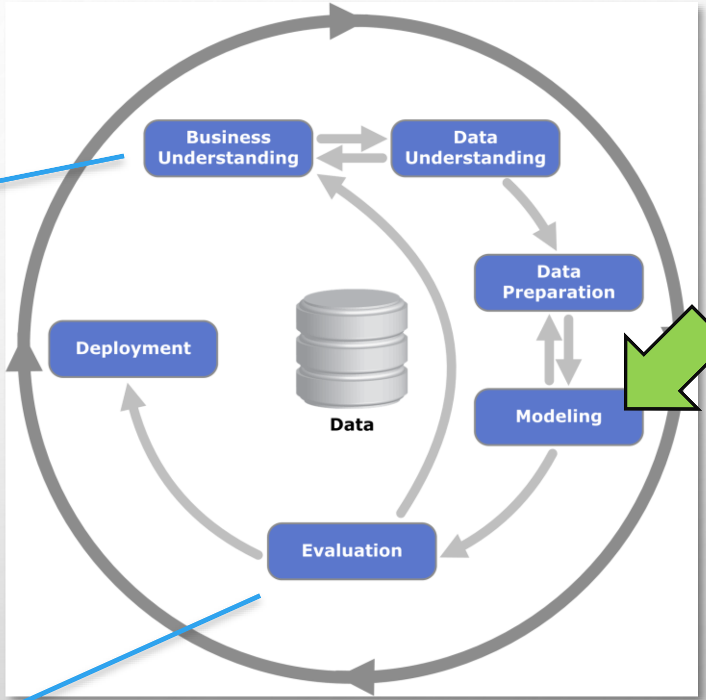
INFNET

AGENDA

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

CRONOGRAMA

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



CRISP-DM

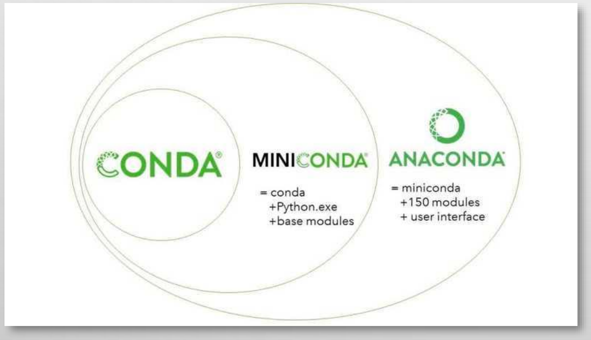
SETUP INICIAL DO AMBIENTE PYTHON

6. Estimação e Inferência

5. Visualização

4. Variáveis Aleatórias

1. Editor de Código



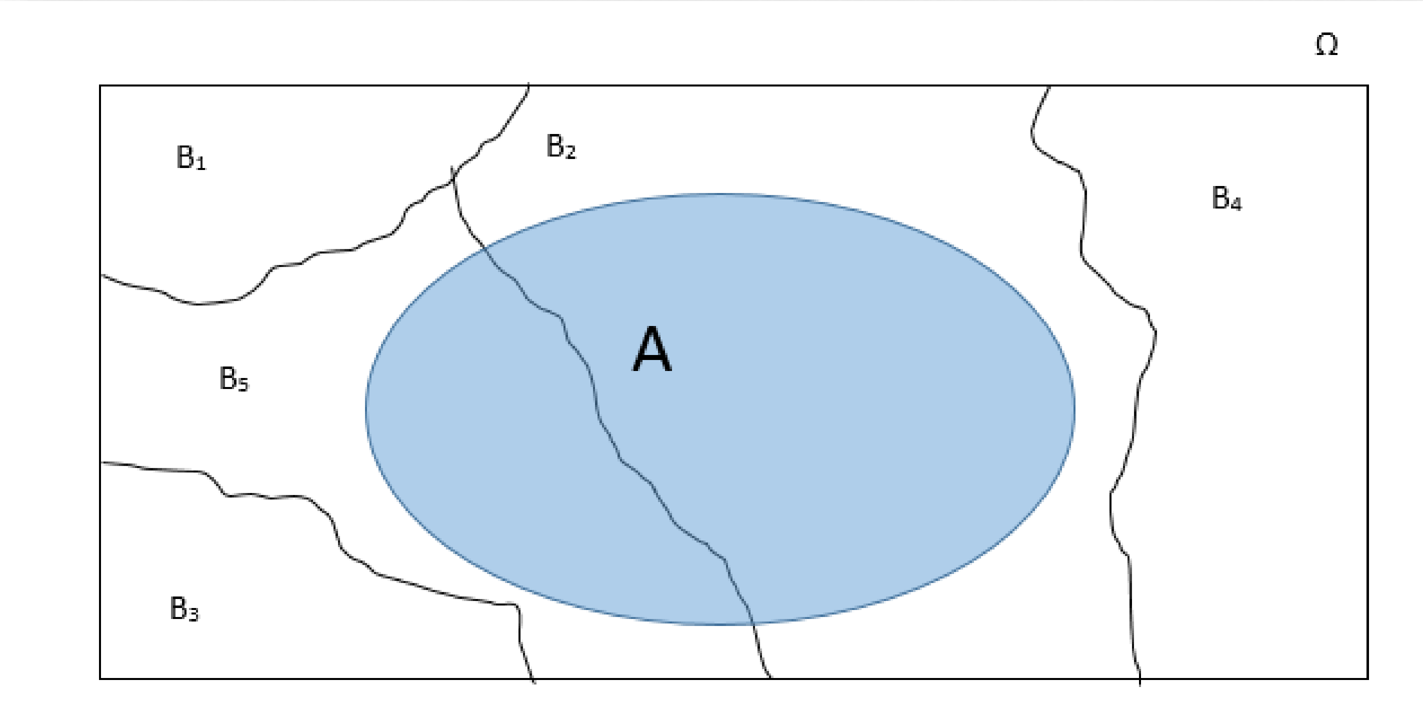
2. Gestor de Ambiente

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

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

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

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

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

$$p(y) = \int p(y \mid x)p(x)dx \tag{10.3}$$

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)

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

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

$$p(x) = N(x; \mu, \sigma^2) \tag{10.11}$$

If the prior is Gaussian

$$p(x) = N(x; x_0, 1/\beta_0) \tag{10.12}$$

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

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

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).

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

where the mean and precision are given by

$$\beta = \beta_0 + \beta_D \tag{10.15}$$

and

$$m = \frac{\beta_0}{\beta}x_0 + \frac{\beta_D}{\beta}y \tag{10.16}$$

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

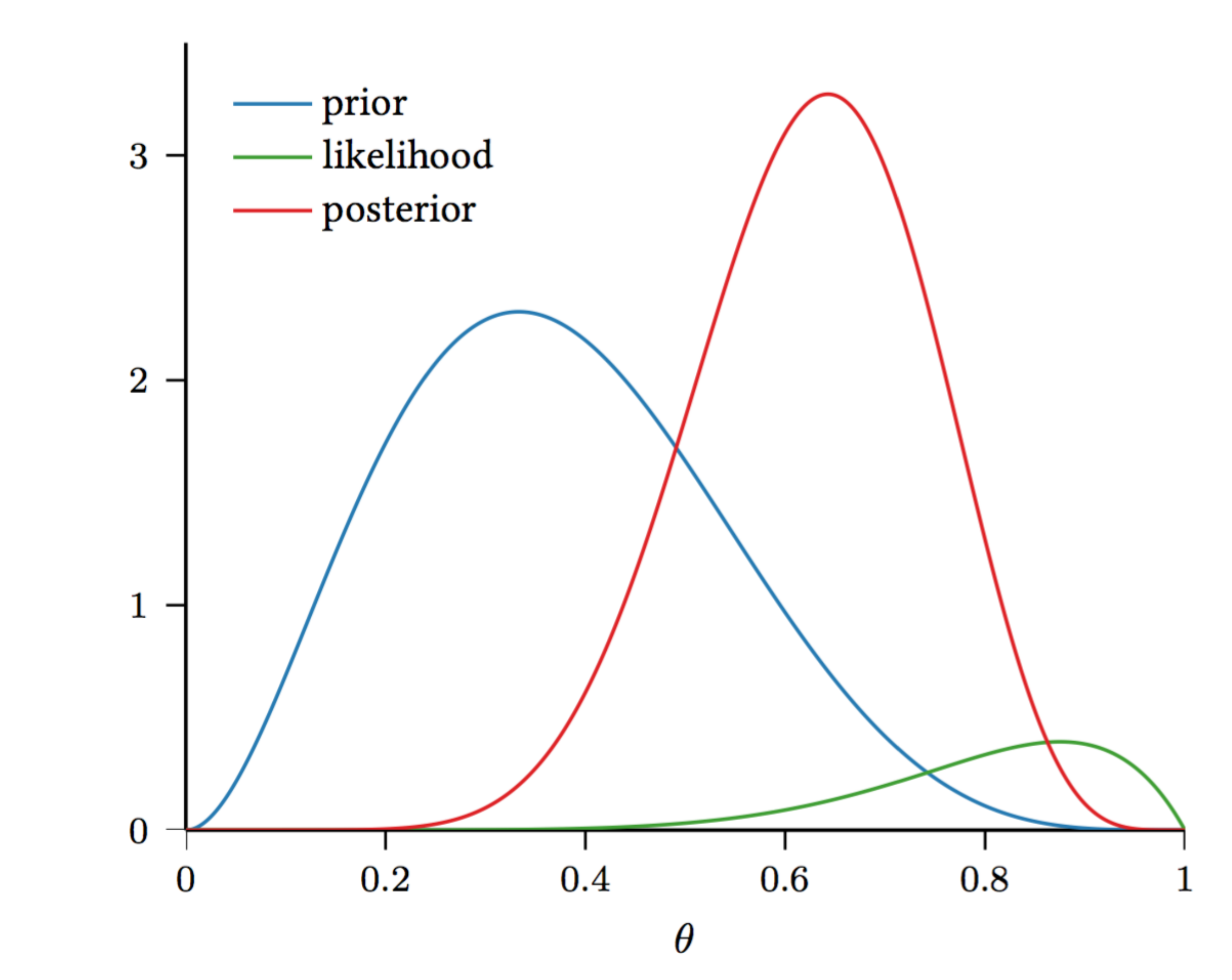
Suppose we have data $\mathcal{D} = \{x^{(i)}\}_{i=1}^{N}$

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