BI documentation

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Table of contents

1

2 Introduction

2.1 1.1 Model set-up

We define a likelihood (e.g., a mathematical formula that specifies the plausibility of the data). The likelihood has parameters (e.g., adjustable inputs) for which we define priors (e.g., initial plausibility assignment for each possible value of the parameter). Considering a linear regression with an intercept (e.g., μ value when x is at zero, or at the mean if the data is centered), a slope (e.g., μ change value when x is incremented by one unit), and assuming the data is centered (as we will always concider in the next chapters):

* Toolpit available for each lines of equation

$$y \sim Normal(\mu, \sigma)$$

$$\mu \sim \alpha + \beta x$$

$$\alpha \sim Normal(0, 1)$$

$$\beta \sim Normal(0, 1)$$

$$\sigma \sim Uniform(0, 1)$$

2.2 1.2 Model fitting

By using probability distributions for parameters, we can better tune the model by describing parameters with '*subequations*' and accounting for *correlated varying effects*, *Gaussian processes*, *measurement error*, and *missing data*.

In addition, we can use *Bayesian updating* using the *Bayesian theorem* to 'reshape' the prior distributions by considering every possible combination of values for µ and and scoring each combination by its relative plausibility in light of the data. These relative plausibilities are the posterior probabilities of each combination of values µ and : the *posterior distributions*. Various techniques can be used to approximate the mathematics that follows from the definition of Bayes' theorem: grid approximation, quadratic approximation, and Markov chain Monte Carlo (*MCMC*).

$$\frac{likelihood * Priors}{averagelikelihood}$$

2.3 1.3 Model 'diagnostic'

The posterior distribution can be described using percentile intervals (*PI*), the highest posterior density interval (*HPDI*), and point estimates. We can also sample the posterior distribution and generate *dummy data*, which can help check the model through *observations and p uncertainty propagation on the samples*. In some aspects, it is the opposite of a null model as it represents an expected model.

2.4 1.4 Link functions

We will see different families of regreessions that have different distribtions. For the moment we just need to know that those different distribtions required _link function (for each specific family we will discuss the corresponding link function):

2.5 Vocabulary

This method evaluate if variable we want to predict -the dependent variable (Y)- and the variable(s) that may affect(s)-independent variables (Xs)- this dependent variable is

2.6 Conciderations

When implementing Bayesian linear regression with TensorFlow Probability, it's important to consider the following: - Specifying appropriate prior distributions for the model parameters. - Choosing an appropriate likelihood function that captures the relationship between the inputs and outputs. - Selecting an inference method to approximate the posterior distribution over parameters, such as Markov chain Monte Carlo (MCMC) or variational inference.