

Computer Lab 4 - Bayesian Model Inference

The labs are the only examination, so you should do the labs **individually**.

You can use any programming language you prefer, but do **submit the code**.

Submit a readable report in **PDF** (no Word documents!) or a **JuPyteR notebook**

1. **Robust regression modeling.** Consider the student- t regression model:

$$y_i = \mathbf{x}_i^T \beta + \varepsilon_i, \quad \varepsilon_i \stackrel{\text{iid}}{\sim} t_\nu(0, \sigma^2),$$

where $t_\nu(\mu, \sigma^2)$ is the student- t distribution with ν degrees of freedom, location μ and scale parameter σ^2 such that the variance is $\sigma^2\nu/(\nu - 2)$ whenever $\nu > 2$. Assume that ν is known, and use the prior $\beta \sim N(0, \tau^2 I_q)$ and non-informative prior for the scale: $p(\sigma) \propto 1/\sigma$. The file `StudentTRegression.R` contains the function `GibbsTReg` that implements a regression extension of the Gibbs sampler on Page 294 in the Bayesian Data Analysis book to simulate from the posterior $p(\beta, \sigma^2 | \mathbf{y}, \mathbf{X})$ for a given ν . The same file also contains the function `PredTReg` to simulate from the posterior predictive distribution.

- (a) Consider the dataset `regression.csv` (loaded from the code `StudentTRegression.R`). Let M_ν denote the above regression model with ν degrees of freedom, and let $\tau = 1$. Compare the models M_2 , M_5 , M_{10} and M_{30} using the following Bayesian model inference criteria:
- Posterior model probabilities using the BIC approximation of the marginal likelihood. Assume uniform prior over the set of models.
 - Posterior model probabilities using the Laplace approximation of the marginal likelihood. Assume uniform prior over the set of models.
 - WAIC
 - Bayesian leave-one-out cross-validation (no need to do code up importance sampling or the Pareto smoothed version since the data set is relatively small).
- (b) Repeat 1a) using $\tau = 10$ and $\tau = 100$.

Good luck! May the Bayes be with you.