Practical Bayesian inference in trials is easier and more

- Since response-adaptive randomization in

the trial may lead to imbalances in baseline

covariates between treatment groups over

time, the models were adjusted for age,

- In order to investigate the variation at

different age, site and time-period level, we

put a hierarchical structure on these effects.

Time

JAGS

OSFD: Posterior Dist time with 10 categories

No_organ_support: Posterior Dist time

length_of_hospital_stay: Posterior Dist time

gender, site and enrollment period.

efficient when using the approximation method INLA.

Background & Aim

Bayesian inference has the capability to address various levels of uncertainty and naturally adapt to the data and to all relevant information at hand. However, the typical simulation methods used for Bayesian inference are hard to implement due to software complexity and high computational costs.

The approximation method INLA is a fast alternative to simulation-based MCMC methods. This has been proven in numerous simulation studies. However, the accuracy and efficiency of INLA method in real world clinical trial have not been investigated. Our study aimed to compare INLA with two MCMC methods (implemented in STAN and JAGS) on 1) posterior distribution estimation accuracy 2) ease of implementation of the software/package and 3) computation time using real Bayesian adaptive trial data.

Random Effects

OSFD: Posterior Dist age with 10 categories

No organ support: Posterior Dist age

length_of_hospital_stay: Posterior Dist age

Age

Site

JAGS 5

STAN

OSFD: Posterior Dist site with 10 categories

No_organ_support: Posterior Dist site

length_of_hospital_stay: Posterior Dist site

Methods

- Simulation-based Methods(MCMC): JAGS STAN Approximation-based Method: INLA
- Ordinal Logistic Regression(Proportional Odds Model)

Fixed Effects

treatment

No_organ_support: Posterior Dist trt

length_of_hospital_stay: Posterior Dist trt

Treatment

- $\circ \log \left(\frac{P(Y_i \le j | X_i = x)}{P(Y_i \ge j | X_i = x)} \right) = \alpha_j + \beta_1 gender_i + \beta_2 treatment_i + U_{site,i} + V_{age,i} + W_{time,i}$
- Binary Logistic Regression

Posterior Distributions

 $\circ \log \left(\frac{P(Y_i = 1 | X_i = x)}{P(Y_i = 0 | X_i = x)} \right) = \alpha + \beta_1 gender_i + \beta_2 treatment_i + U_{site,i} + V_{age,i} + W_{time,i}$

Gender

OSFD: Posterior Dist gender with 10 categories

No_organ_support: Posterior Dist gender

length_of_hospital_stay: Posterior Dist gender

Cox Survival Model

Results

Ordinal Logistic

Organ Support

Binary Logistic

without Organ

Cox Regression

Regression

Support(2)

Length of

Hospital

Stay(3)

Survival

Regression

Free Days(1)

Model

 $0 \quad \lambda_i(t) = \lambda_{0i}(t) \exp(\beta_1 gender_i + \beta_2 treatment_i + U_{site,i} + V_{age,i} + W_{time,i})$

INLA

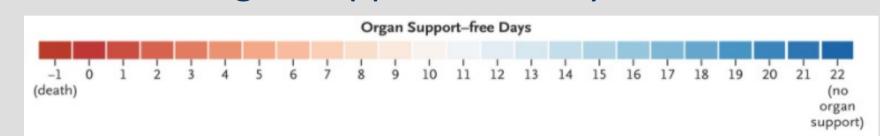
JAGS 5

Trial Information

International adaptive randomized controlled multiplatform trial to investigate the treatment effect of therapeutic anticoagulation with heparin in non-critically ill patients with covid-19 compared to usual care.

Key Outcomes of the Study

- Primary Outcome:
 - Ordinal Outcome
 - Organ Support Free Days



- Secondary Outcomes:
 - Binary Outcomes:
 - Survival until hospital discharge
 - Survival without receipt of organ support
 - Survival without receipt of invasive mechanical ventilation(IMV)
 - Survival without mechanical respiratory support
 - A major thrombotic event or death
 - Time to Event Outcome:
 - Length of hospital stay

Priors

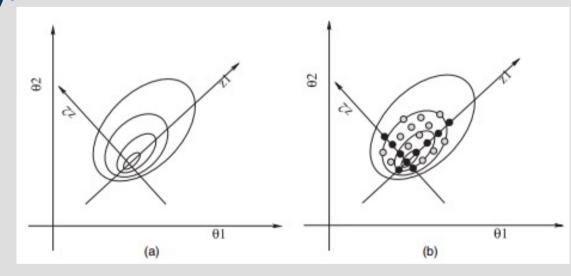
- Regression model coefficients
 - Intercept: Normal($\mu = 0, \tau = 0.1$)
 - Gender: Normal($\mu = 0, \tau = 0.1$)
 - Treatment: Normal($\mu = 0, \tau = 0.1$)
- Hierarchical model variance:

(Age, site, enrolment time-period)

- Normal($\mu = 0, \sigma^2$) • σ^2 ~ Half t distribution with
- df = 3, scale = 2.5

INLA:

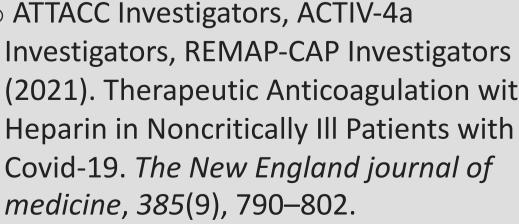
Starting at the mode of the joint posterior of the hyperparameters, INLA explores the probability space by performing a grid search after finding the search direction mathematically. The search stops when the search point is too far away from the mode, based on a pre-set threshold. The approximation can be improved by exploring the parameter space in finer search steps (smaller step lengths).



Reference

- Stan Version 2.29 User Manual
- JAGS Version 4.3.0 User Manual
- o Julian F, James W, Yue, Bayesian Regression Modeling with INLA
- Andrew Gelman. "Prior distributions for variance parameters in hierarchical" Bayesian Analysis, 1(3) 515-534 September
- o ATTACC Investigators, ACTIV-4a Investigators, REMAP-CAP Investigators (2021). Therapeutic Anticoagulation with Heparin in Noncritically III Patients with Covid-19. The New England journal of







Runtime

Model	INLA	JAGS	STAN	
(1)	31.28 seconds	1.5 hours	30.5 minutes	
(2)	4.74 seconds	7.2 minutes	7.35 minutes	
(3)	13.22 seconds	6.8 hours	59.23 minutes	

JAGS 2

Discussions

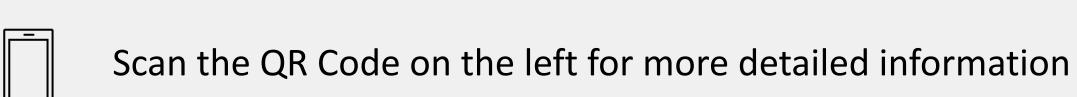
- Posterior density curves for the treatment and gender estimated with the INLA almost overlapped with the simulation methods.
- INLA does not estimate posterior of the hierarchical model variance well.
- INLA requires noticeably less computational time compared to STAN and JAGS (seconds) compared to hours)
- STAN and INLA have higher feasibility of implementation in statistical software R as there are well-established R packages.















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