

Fast approximate Bayesian inference of HIV indicators

PhD Student Presentations & Networking Event, Alan Turing Institute

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Fast-Track Targets

by 2020

90-90-90

Treatment

500 000

New infections among adults

ZERO

Discrimination

by 2030

95-95-95

Treatment

200 000

New infections among adults

ZERO

Discrimination

Figure 1: Ambitious targets required to end the AIDS epidemic as a public health threat by 2030.

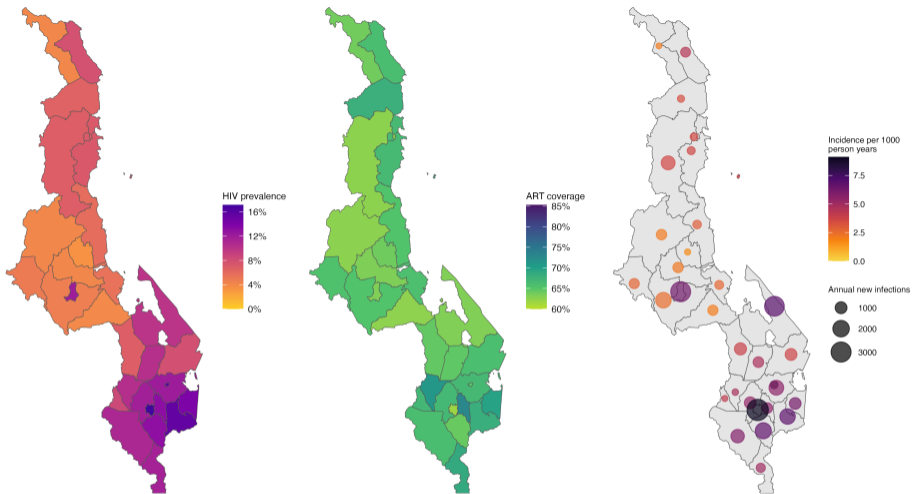


Figure 2: More effective intervention based on granular estimates of HIV indicators. One size does not fit all!

1 2 3 4 5 6 7

Upload inputs Review inputs Model options Fit model Calibrate model Review output Save results

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Spectrum file (required)

Select new file

Area boundary file (required)

Select new file

Population (required)

Select new file

Household Survey (required)

Select new file

ART

Select new file

ANC Testing

Select new file

BACK / CONTINUE

Figure 3: Generation of estimates by country teams strengthens data quality, use and ownership. User interface from <https://naomi.unaids.org/>.

Want

Fast approximate Bayesian inference for a complex, spatiotemporal, evidence synthesis model

Strategy

1. Marginal Laplace approximation
2. Adaptive Gauss-Hermite quadrature
3. Principal components analysis

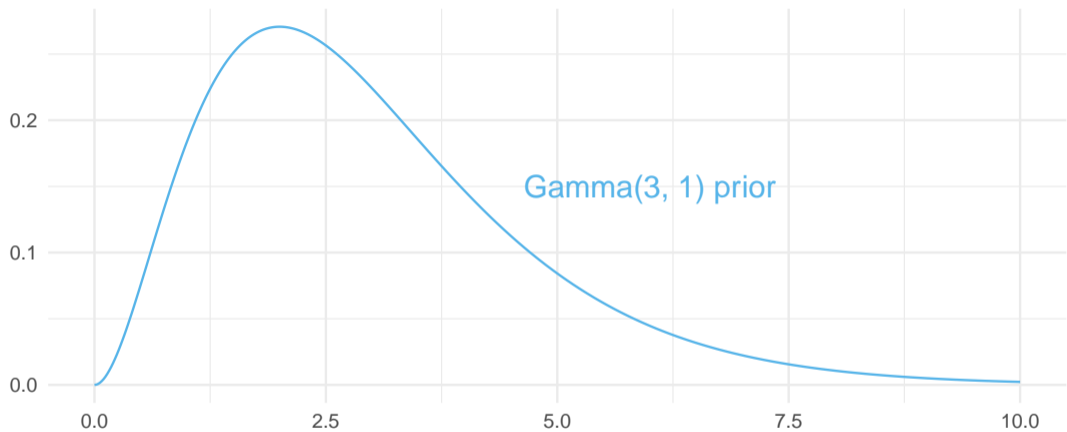


Figure 4: A Gamma prior with $a = 3$ and $b = 1$.

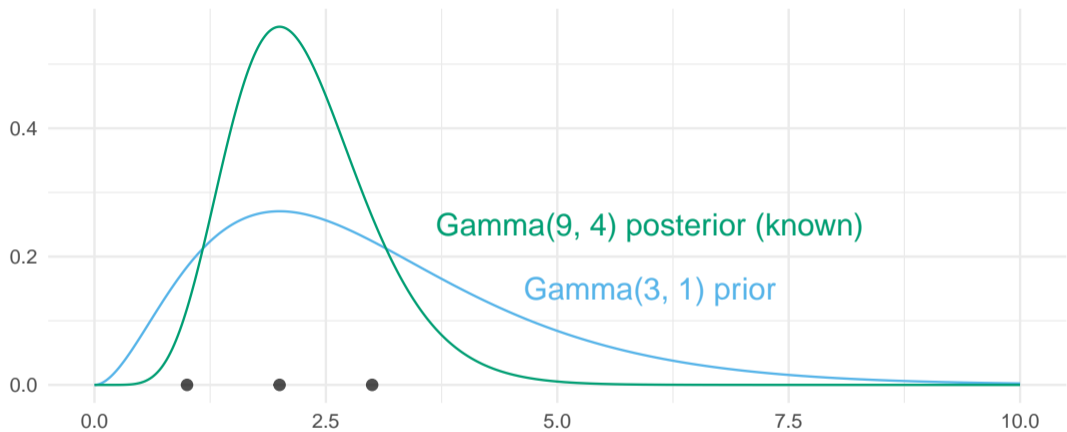


Figure 5: Draw 3 points from $\text{Poisson}(3)$, then compute the posterior.

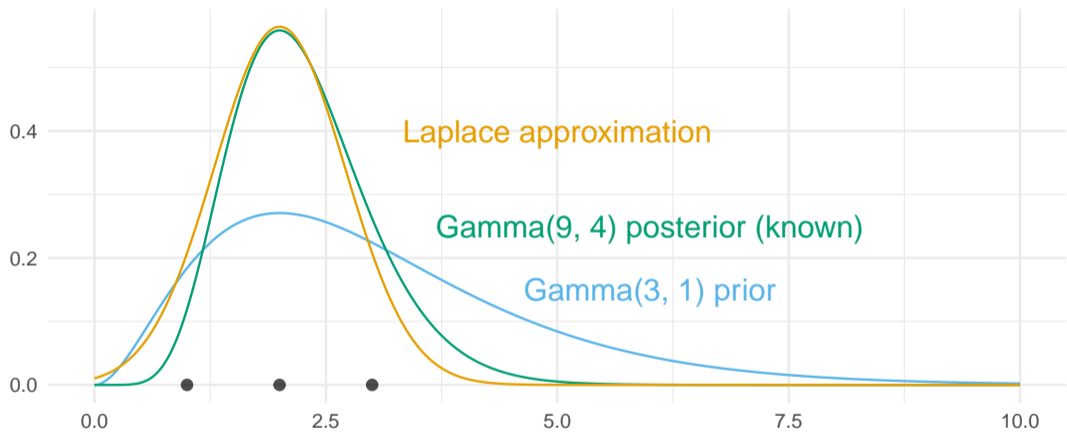


Figure 6: The Laplace approximation in this case is good near the mode but not in the tails.

- For Malawi, the model has 491 parameters
- 467 have a joint Gaussian prior: call them the latent field x
- 24 are not Gaussian: call them hyperparameters θ
- Use the Laplace approximation only for the latent field marginal posterior!

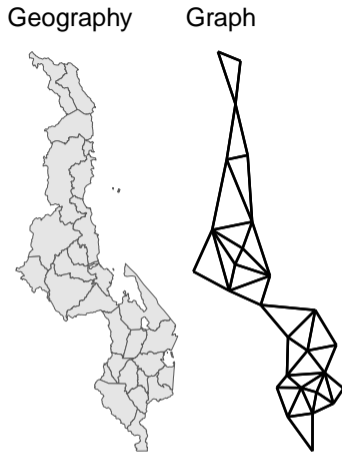


Figure 7: Spatial random effects $\phi_i | \phi_{-i} \sim \mathcal{N}\left(\frac{1}{n_{\delta i}} \sum_{j:j \sim i} \phi_j, \frac{1}{n_{\delta i} \tau_\phi}\right)$ are included in the latent field. We assume that neighbouring districts are similar: first law of geography.

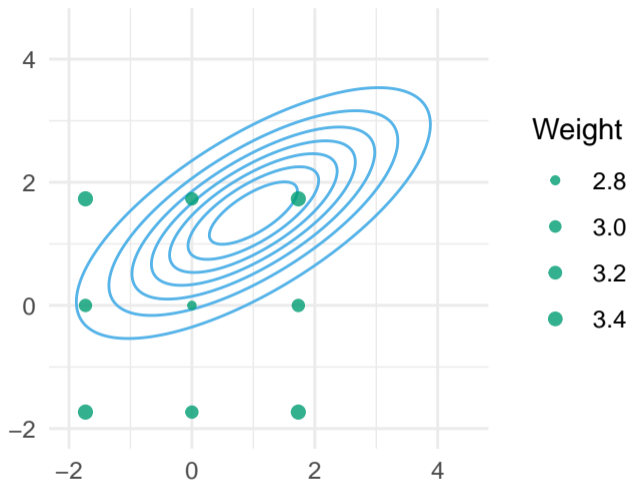


Figure 8: Unadapted Gauss-Hermite points in two dimensions with $k = 3$.

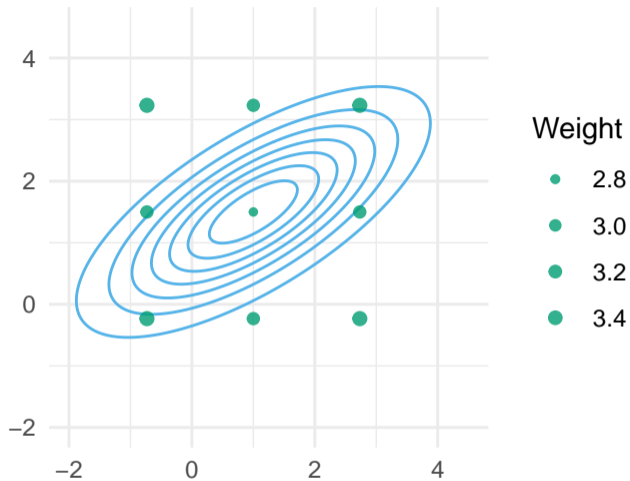


Figure 9: Add the mean $z + \hat{\theta}$.

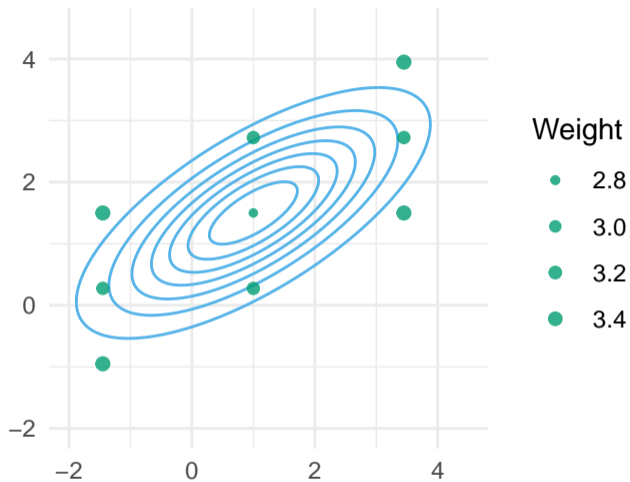


Figure 10: First option: rotate by the lower Cholesky $Lz + \hat{\theta}$.

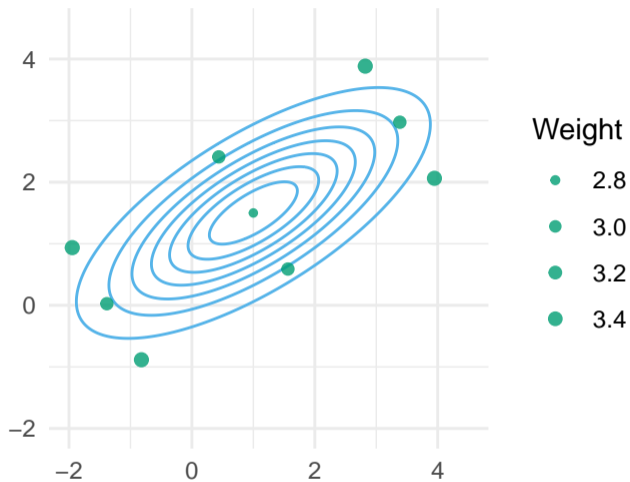


Figure 11: Second option: rotate using the eigendecomposition $E\Lambda^{1/2}z + \hat{\theta}$.

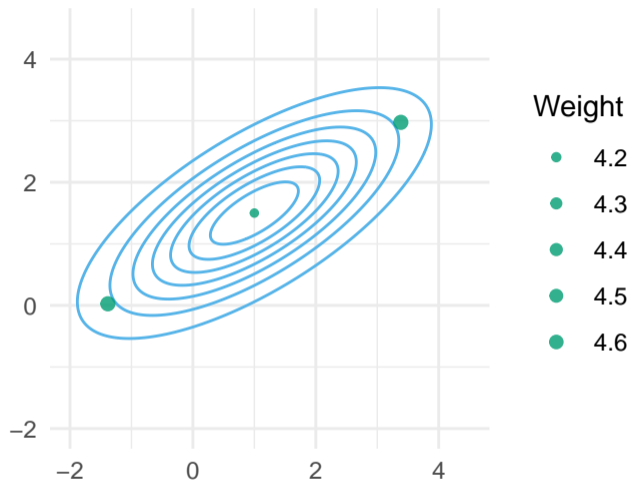


Figure 12: Now keeping only the first principal component, $s = 1$.

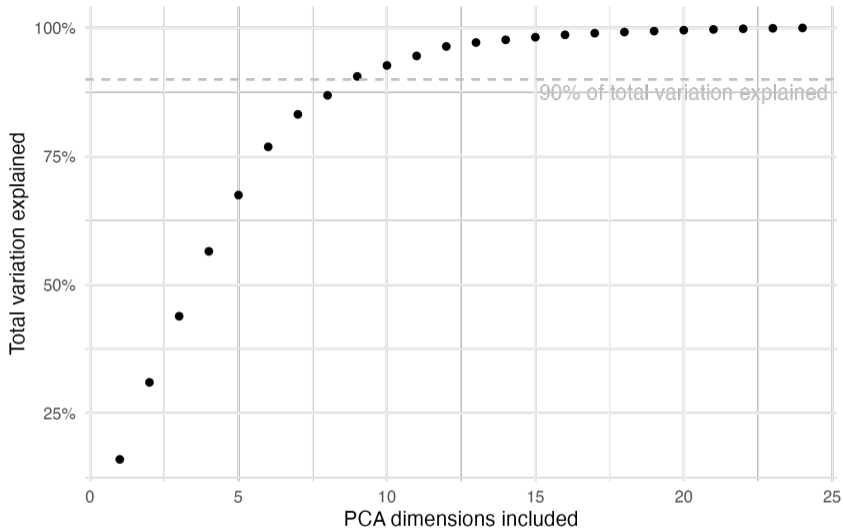


Figure 13: Scree plot suggests 10 or so dimensions is enough. We use $s = 8$ to avoid long computation times.

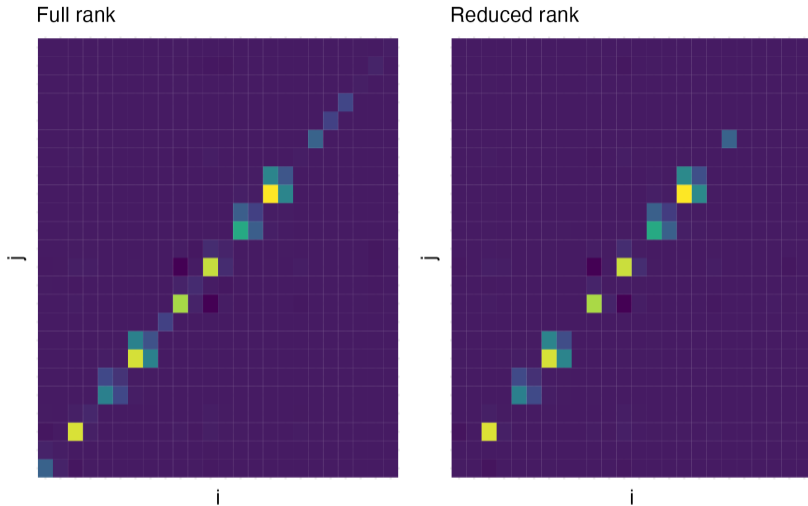


Figure 14: With 8 dimensions, the hyperparameter covariance matrix is accurately reproduced.

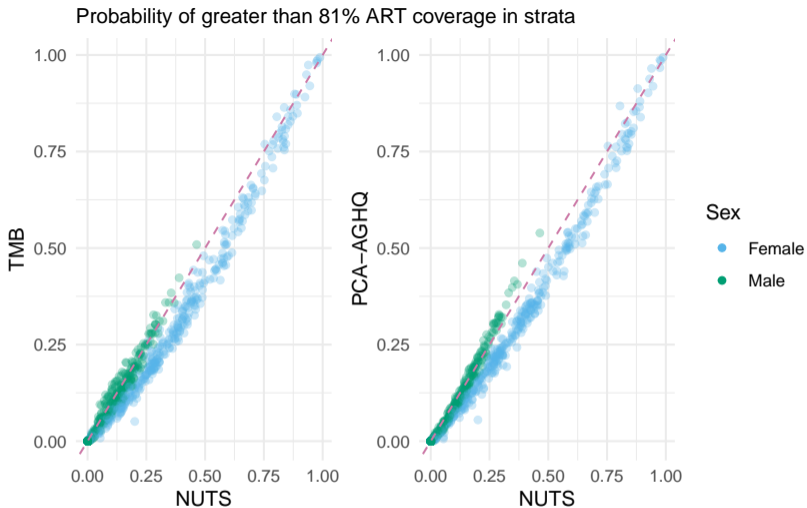


Figure 15: Reduced RMSE by 10 percent, but still a work in progress! Also seeing small improvements using Kolmogorov-Smirnov tests, Pareto-smoothed importance sampling, maximum mean discrepancy.

Thanks for listening!

- For more about Naomi, see Eaton et al. (2021)
- Joint work with Alex Stringer (Waterloo), Seth Flaxman (Oxford), and Jeff Eaton (Harvard, Imperial)
- For more about me, see athowes.github.io/about



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MACHINE LEARNING
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References I

Eaton, Jeffrey W., Laura Dwyer-Lindgren, Steve Gutreuter, Megan O'Driscoll, Oliver Stevens, Sumali Bajaj, Rob Ashton, et al. 2021. "Naomi: A New Modelling Tool for Estimating HIV Epidemic Indicators at the District Level in Sub-Saharan Africa." *Journal of the International AIDS Society* 24 (S5): e25788.