

# Bayesian statistics with R

## 7. Contrast scientific hypotheses with model selection

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## Model selection

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- The proportion of explained variance  $R^2$  is problematic, because the more variables you have, the bigger  $R^2$  is.
- Idea: **penalize models with too many parameters.**

## Akaike information criterion (AIC)

$$AIC = -2 \log(L(\hat{\theta}_1, \dots, \hat{\theta}_K)) + 2K$$

with  $L$  the likelihood and  $K$  the number of parameters  $\theta_i$ .

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A measure of goodness-of-fit of the model to the data: the more parameters you have, the smaller the deviance is (or the bigger the likelihood is).

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$$\text{AIC} = -2 \log(L(\hat{\theta}_1, \dots, \hat{\theta}_K)) + 2K$$

A **penalty**: twice the number of parameters  $K$



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- Two models are difficult to distinguish if  $\Delta AIC < 2$ .

## Bayesian version

- Deviance Information Criteria or DIC, a Bayesian method for model comparison that JAGS can calculate for (m)any models.

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- DIC is intended as a generalisation of AIC, and with little prior information,  $p_D$  should be approximately the true number of parameters.
- The model with the smallest DIC is estimated to be the model that would best predict a replicate dataset with same structure as that observed.



## DIC in Jags

storks

```
#> Inference for Bugs model at "code/logistic.txt", fit using jags,  
#> 2 chains, each with 2000 iterations (first 1000 discarded)  
#> n.sims = 2000 iterations saved  
#>      mu.vect sd.vect   2.5%   25%   50%   75%  97.5% Rhat n.eff  
#> a      1.550  0.085   1.431   1.515   1.553   1.594   1.667 1.161 2000  
#> b.rain  -0.148  0.062  -0.273  -0.188  -0.147  -0.106  -0.038 1.005 1500  
#> b.temp   0.028  0.064  -0.102  -0.014   0.031   0.071   0.147 1.065   30  
#> deviance 206.492 29.698 201.809 202.798 203.991 205.732 212.404 1.083 2000  
#>  
#> For each parameter, n.eff is a crude measure of effective sample size,  
#> and Rhat is the potential scale reduction factor (at convergence, Rhat=1).  
#>  
#> DIC info (using the rule,  $pD = \text{var}(\text{deviance})/2$ )  
#>  $pD = 441.0$  and  $DIC = 647.4$   
#> DIC is an estimate of expected predictive error (lower deviance is better).
```

## Further reading

- Hooten, M.B. and Hobbs, N.T. (2015), A guide to Bayesian model selection for ecologists. Ecological Monographs, 85: 3-28. <https://doi.org/10.1890/14-0661.1>
- Conn, P.B., Johnson, D.S., Williams, P.J., Melin, S.R. and Hooten, M.B. (2018), A guide to Bayesian model checking for ecologists. Ecol Monogr, 88: 526-542. <https://doi.org/10.1002/ecm.1314>