Writing a domain-specific language (DSL) is a powerful and fairly common method for extending the R language. Both ggplot2 and dplyr, for example, are DSLs. In this post, I take a first look at NIMBLE (Numerical Inference for Statistical Models using Bayesian and Likelihood Estimation), a DSL for formulating and efficiently solving statistical models in general, and Bayesian hierarchical models in particular. The latter comprise a class of interpretable statistical models useful for both inference and prediction.

Most of what I describe here can be found in the comprehensive and the extensive [NIMBLE User Manual](https://r-nimble.org/manuals/NimbleUserManual.pdf).

At the risk of oversimplification, it seems to me that the essence of the NIMBLE is that it is a system for developing models designed around two dichotomies. The first dichotomy is that NIMBLE separates the specification of a model from the implementation of the algorithms that express it. A user can formulate a model, and then use different NIMBLE functions to solve the model. Or, looking at things the other way round, a user can write a NIMBLE function to implement some algorithm or another efficiently, and then use this function in different models.

The second dichotomy separates model setup from model execution. NIMBLE programming is done by writing nimbleFunctions, a subset of the R Language that is augmented with additional data structures and made compilable. nimbleFunctions come in two flavors. **Setup** functions run once for each model, node any model structure used to define the model. **Run** functions can be executed by R or compiled into C++ code.

NIMBLE is actually more complicated, or should I say “richer”, than this. There are many advanced programming concepts to wrap your head around. Nevertheless, it is pretty straightforward to start using NIMBLE for models that already have BUGS implementations. The best way to get started for anyone new to Bayesian statistics, or whose hierarchical model building skills may be a bit rusty, is to take the advice of the NIMBLE developers and work through the Pump Model example in Chapter 2 of the manual. In the rest of this post, I present an abbreviated and slightly reworked version of that model.

Before getting started, note that although NIMBLE is an R package listed on CRAN, and it installs like any other R package, you must have a C++ compiler and the standard make utility installed on your system before installing NIMBLE. (See Chapter 4 of the manual for platform-specific installation instructions.)

**Pump Failure Model**

The data driving the model are: x[i] the number of failures for pump, i in a time interval, t[i] where i goes from 1 to 10.

library(nimble)

library(igraph)

library(tidyverse)

pumpConsts <- list(N = 10,

t = c(94.3, 15.7, 62.9, 126, 5.24,31.4, 1.05, 1.05, 2.1, 10.5))

pumpData <- list(x = c(5, 1, 5, 14, 3, 19, 1, 1, 4, 22))

Arrival times are a Poisson distribution with parameter lambda, where lambda is itself modeled as a Gamma distribution with hyperparameters alpha and beta.

The model is expressed in the BUGS language wrapped inside the NIMBLE function nimbleCode(), which turns the BUGS code into a object that can be operated on by nimbleModel()

pumpCode <- nimbleCode(

{

for (i in 1:N){

theta[i] ~ dgamma(alpha,beta)

lambda[i] <- theta[i]\*t[i]

x[i] ~ dpois(lambda[i])

}

alpha ~ dexp(1.0)

beta ~ dgamma(0.1,1.0)

})

pumpInits <- list(alpha = 1, beta = 1,

theta = rep(0.1, pumpConsts$N))

nimbleModel() produces the model object that can be executed by R or compiled.

pump <- nimbleModel(code = pumpCode, name = "pump", constants = pumpConsts,

data = pumpData, inits = pumpInits)

The following command lets us look at the nodes that comprise the model’s directed graph, and plot it.

pump$getNodeNames()

[1] "alpha" "beta" "lifted\_d1\_over\_beta"

[4] "theta[1]" "theta[2]" "theta[3]"

[7] "theta[4]" "theta[5]" "theta[6]"

[10] "theta[7]" "theta[8]" "theta[9]"

[13] "theta[10]" "lambda[1]" "lambda[2]"

[16] "lambda[3]" "lambda[4]" "lambda[5]"

[19] "lambda[6]" "lambda[7]" "lambda[8]"

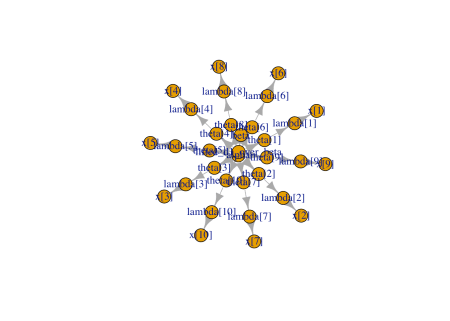
[22] "lambda[9]" "lambda[10]" "x[1]"

[25] "x[2]" "x[3]" "x[4]"

[28] "x[5]" "x[6]" "x[7]"

[31] "x[8]" "x[9]" "x[10]"

pump$plotGraph()



We can look at the values stored at each node. The node for x contains the initial values we entered into the model and the nodes for theta and lambda contain the initial calculated values

pump$x

[1] 5 1 5 14 3 19 1 1 4 22

pump$theta

[1] 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1

pump$lambda

[1] 9.430 1.570 6.290 12.600 0.524 3.140 0.105 0.105 0.210 1.050

We can also look at the log probabilities of the likelihoods.

pump$logProb\_x

[1] -2.998011 -1.118924 -1.882686 -2.319466 -4.254550 -20.739651

[7] -2.358795 -2.358795 -9.630645 -48.447798

Next, we use the model to simulate new values for theta and update the variables.

set.seed(1)

pump$simulate("theta")

pump$theta

[1] 0.15514136 1.88240160 1.80451250 0.83617765 1.22254365 1.15835525

[7] 0.99001994 0.30737332 0.09461909 0.15720154

These new values will, of course, lead to new values of lambda and the log probabilities.

pump$lambda

[1] 9.430 1.570 6.290 12.600 0.524 3.140 0.105 0.105 0.210 1.050

pump$logProb\_x

[1] -2.998011 -1.118924 -1.882686 -2.319466 -4.254550 -20.739651

[7] -2.358795 -2.358795 -9.630645 -48.447798

The model can also be compiled. The C++ code generated is loaded back into R with an object that can be examined like the uncompiled model.

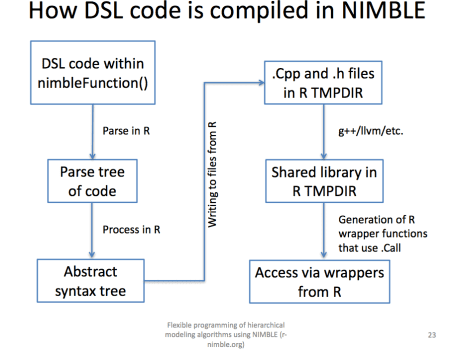
Cpump <- compileNimble(pump)

Cpump$theta

[1] 0.15514136 1.88240160 1.80451250 0.83617765 1.22254365 1.15835525

[7] 0.99001994 0.30737332 0.09461909 0.15720154

Note that since a wide variety of NIMBLE models can be compiled, NIMBLE should be generally useful for developing production R code.



Next, the default NIMBLE MCMC algorithm is used to generate posterior samples from the distributions for the model parameters alpha, beta, theta and lambda, along with summary statistics and the value of Wantanabi’s WAIC statistic.

mcmc.out <- nimbleMCMC(code = pumpCode, constants = pumpConsts,

data = pumpData, inits = pumpInits,

monitors=c("alpha","beta","theta","lambda"),

nchains = 2, niter = 10000,

summary = TRUE, WAIC = TRUE)

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names(mcmc.out)

[1] "samples" "summary" "WAIC"

The model object contains a summary of the model,

mcmc.out$summary

$chain1

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.69804352 0.65835063 0.27037676 0.287898244 1.3140461

beta 0.92862598 0.82156847 0.54969128 0.183699137 2.2872696

lambda[1] 5.67617535 5.35277649 2.39989346 1.986896247 11.3087435

lambda[2] 1.59476464 1.28802618 1.24109695 0.126649837 4.7635134

lambda[3] 5.58222072 5.28139948 2.36539331 1.961659802 11.1331869

lambda[4] 14.57540796 14.23984600 3.79587390 8.085538041 22.9890092

lambda[5] 3.16402849 2.87859865 1.63590766 0.836991007 7.1477641

lambda[6] 19.21831706 18.86685281 4.33423677 11.703168568 28.6847447

lambda[7] 0.94776605 0.74343559 0.77658191 0.077828283 2.8978174

lambda[8] 0.93472103 0.74313533 0.76301563 0.076199581 2.9598715

lambda[9] 3.31124086 3.03219017 1.61332897 0.955909813 7.2024472

lambda[10] 20.89018329 20.59798130 4.45302924 13.034529765 30.4628012

theta[1] 0.06019274 0.05676327 0.02544956 0.021069950 0.1199230

theta[2] 0.10157737 0.08203988 0.07905076 0.008066869 0.3034085

theta[3] 0.08874755 0.08396502 0.03760562 0.031186960 0.1769982

theta[4] 0.11567784 0.11301465 0.03012598 0.064170937 0.1824525

theta[5] 0.60382223 0.54935089 0.31219612 0.159731108 1.3640771

theta[6] 0.61204831 0.60085518 0.13803302 0.372712375 0.9135269

theta[7] 0.90263434 0.70803389 0.73960182 0.074122175 2.7598261

theta[8] 0.89021051 0.70774794 0.72668155 0.072571029 2.8189252

theta[9] 1.57678136 1.44390008 0.76825189 0.455195149 3.4297368

theta[10] 1.98954127 1.96171250 0.42409802 1.241383787 2.9012192

$chain2

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.69101961 0.65803654 0.26548378 0.277195564 1.2858148

beta 0.91627273 0.81434426 0.53750825 0.185772263 2.2702428

lambda[1] 5.59893463 5.29143956 2.32153991 1.976164994 10.9564380

lambda[2] 1.57278293 1.27425268 1.23323878 0.129781580 4.7262566

lambda[3] 5.60321125 5.27780200 2.32992322 1.970709123 10.9249502

lambda[4] 14.60674094 14.30971897 3.86145332 8.013012004 23.0526313

lambda[5] 3.13119513 2.84685917 1.67006926 0.782262325 7.2043337

lambda[6] 19.17917926 18.82326155 4.33456380 11.661139736 28.5655803

lambda[7] 0.94397897 0.74446578 0.76576887 0.080055678 2.8813517

lambda[8] 0.94452324 0.74263433 0.77013200 0.074813473 2.9457364

lambda[9] 3.30813061 3.04512049 1.58008544 0.986914665 7.0355869

lambda[10] 20.88570471 20.60384141 4.44130984 13.092562597 30.5574424

theta[1] 0.05937364 0.05611283 0.02461866 0.020956151 0.1161870

theta[2] 0.10017726 0.08116259 0.07855024 0.008266343 0.3010355

theta[3] 0.08908126 0.08390782 0.03704170 0.031330829 0.1736876

theta[4] 0.11592652 0.11356920 0.03064645 0.063595333 0.1829574

theta[5] 0.59755632 0.54329373 0.31871551 0.149286703 1.3748728

theta[6] 0.61080189 0.59946693 0.13804343 0.371373877 0.9097319

theta[7] 0.89902759 0.70901502 0.72930369 0.076243503 2.7441445

theta[8] 0.89954594 0.70727079 0.73345905 0.071250926 2.8054633

theta[9] 1.57530029 1.45005738 0.75242164 0.469959364 3.3502795

theta[10] 1.98911473 1.96227061 0.42298189 1.246910723 2.9102326

$all.chains

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.69453156 0.65803654 0.26795776 0.28329854 1.2999319

beta 0.92244935 0.81828160 0.54365539 0.18549077 2.2785444

lambda[1] 5.63755499 5.32462511 2.36129857 1.98294712 11.1597721

lambda[2] 1.58377379 1.28149065 1.23719199 0.12734396 4.7382079

lambda[3] 5.59271599 5.28024565 2.34769002 1.96451069 11.0072923

lambda[4] 14.59107445 14.27080924 3.82874035 8.04541916 23.0250158

lambda[5] 3.14761181 2.86460377 1.65311690 0.80506062 7.1718837

lambda[6] 19.19874816 18.84484055 4.33433610 11.68198222 28.6445471

lambda[7] 0.94587251 0.74395440 0.77117739 0.07927988 2.8911629

lambda[8] 0.93962214 0.74299160 0.76657858 0.07571751 2.9470742

lambda[9] 3.30968573 3.03910484 1.59675456 0.97386482 7.1120082

lambda[10] 20.88794400 20.60051118 4.44706278 13.05509616 30.5216406

theta[1] 0.05978319 0.05646474 0.02504028 0.02102807 0.1183433

theta[2] 0.10087731 0.08162361 0.07880204 0.00811108 0.3017967

theta[3] 0.08891440 0.08394667 0.03732417 0.03123228 0.1749967

theta[4] 0.11580218 0.11326039 0.03038683 0.06385253 0.1827382

theta[5] 0.60068928 0.54668011 0.31548032 0.15363752 1.3686801

theta[6] 0.61142510 0.60015416 0.13803618 0.37203765 0.9122467

theta[7] 0.90083096 0.70852800 0.73445465 0.07550465 2.7534885

theta[8] 0.89487822 0.70761105 0.73007484 0.07211191 2.8067373

theta[9] 1.57604083 1.44719278 0.76035931 0.46374515 3.3866706

theta[10] 1.98932800 1.96195345 0.42352979 1.24334249 2.9068229

and the value of the WAIC statistic.

mcmc.out$WAI

[1] 48.69896

Here, we select sample values for the parameters for pump 1 in the first chain, and put them into a data frame for plotting.

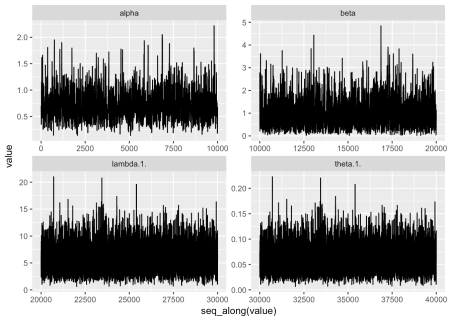
df <- data.frame(mcmc.out$samples$chain1)

df\_l <- df %>% select(alpha, beta, theta.1., lambda.1.) %>% gather(key="parameter", value="value")

We plot the sample values.

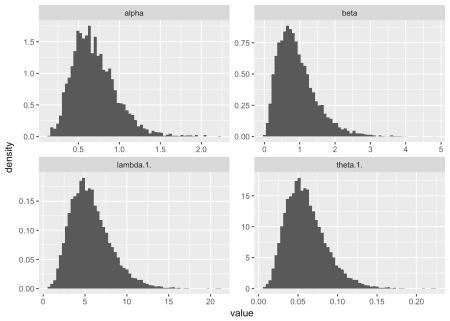
ps <- df\_l %>% ggplot(aes(x=seq\_along(value), y = value)) + geom\_line()

ps + facet\_wrap(~parameter, scales = "free")

And, we plot histograms.

p <- ggplot(df\_l,aes(value)) + geom\_histogram(aes( y= ..density..),bins = 60)

p + facet\_wrap(~parameter, scales = "free")



Note that it is also possible to perform the MCMC simulation using the compiled model.

mcmc.out\_c<- nimbleMCMC(model=Cpump,

monitors=c("alpha","beta","theta","lambda"),

nchains = 2, niter = 10000,

summary = TRUE, WAIC = TRUE)

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mcmc.out\_c$summary

$chain1

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.70269965 0.65474666 0.27690796 0.288871669 1.3525877

beta 0.92892181 0.82320341 0.54874194 0.186215812 2.2756643

lambda[1] 5.65646492 5.32568604 2.38108302 1.991839453 11.1329833

lambda[2] 1.58848917 1.28392445 1.25676948 0.133001650 4.7163618

lambda[3] 5.62720720 5.30681963 2.36776285 1.986194548 11.1264464

lambda[4] 14.61256770 14.29447077 3.75584085 8.106535985 22.8405075

lambda[5] 3.16521167 2.88771869 1.65132178 0.785161558 7.0181185

lambda[6] 19.12824948 18.77541823 4.27045427 11.733960316 28.4815908

lambda[7] 0.94353548 0.75312906 0.75111813 0.079570796 2.8410369

lambda[8] 0.93661525 0.74764821 0.75397145 0.078424425 2.8536890

lambda[9] 3.33178422 3.05974419 1.63035789 1.019006182 7.3163945

lambda[10] 20.90388784 20.58355995 4.45456152 12.997984788 30.2815949

theta[1] 0.05998372 0.05647599 0.02525009 0.021122370 0.1180592

theta[2] 0.10117765 0.08177863 0.08004901 0.008471443 0.3004052

theta[3] 0.08946275 0.08436915 0.03764329 0.031577020 0.1768910

theta[4] 0.11597276 0.11344818 0.02980826 0.064337587 0.1812739

theta[5] 0.60404803 0.55109135 0.31513774 0.149839992 1.3393356

theta[6] 0.60917992 0.59794326 0.13600173 0.373693004 0.9070570

theta[7] 0.89860522 0.71726577 0.71535060 0.075781711 2.7057495

theta[8] 0.89201452 0.71204591 0.71806805 0.074689928 2.7177991

theta[9] 1.58656391 1.45702104 0.77636090 0.485241039 3.4839974

theta[10] 1.99084646 1.96033904 0.42424395 1.237903313 2.8839614

$chain2

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.70184646 0.65773527 0.27237859 0.297108329 1.3420954

beta 0.92323539 0.82124257 0.53880496 0.194879601 2.2590201

lambda[1] 5.59702813 5.25201276 2.35832632 2.029382518 10.9327321

lambda[2] 1.62105397 1.31199418 1.26269004 0.137977536 4.8652461

lambda[3] 5.62874314 5.33611797 2.37576774 1.953756972 11.1296452

lambda[4] 14.53507135 14.22210300 3.84823087 8.042950272 22.9287741

lambda[5] 3.17647361 2.88816158 1.67257096 0.807468793 7.2500264

lambda[6] 19.13576117 18.82011366 4.34294395 11.646448559 28.4716352

lambda[7] 0.94656373 0.74705570 0.76192793 0.084445304 2.9245815

lambda[8] 0.94754678 0.75725106 0.75136514 0.083985118 2.8740656

lambda[9] 3.34514300 3.04989975 1.64818642 0.974288761 7.2961225

lambda[10] 20.97154230 20.61713159 4.45405753 13.260753885 30.5614115

theta[1] 0.05935343 0.05569473 0.02500876 0.021520493 0.1159357

theta[2] 0.10325185 0.08356651 0.08042612 0.008788378 0.3098883

theta[3] 0.08948717 0.08483494 0.03777055 0.031061319 0.1769419

theta[4] 0.11535771 0.11287383 0.03054151 0.063832939 0.1819744

theta[5] 0.60619725 0.55117587 0.31919293 0.154097098 1.3835928

theta[6] 0.60941915 0.59936668 0.13831032 0.370906005 0.9067400

theta[7] 0.90148927 0.71148162 0.72564565 0.080424099 2.7853158

theta[8] 0.90242550 0.72119149 0.71558585 0.079985826 2.7372053

theta[9] 1.59292524 1.45233321 0.78485068 0.463947029 3.4743440

theta[10] 1.99728974 1.96353634 0.42419596 1.262928941 2.9106106

$all.chains

Mean Median St.Dev. 95%CI\_low 95%CI\_upp

alpha 0.70227305 0.65580594 0.27464608 0.292312894 1.3489184

beta 0.92607860 0.82237274 0.54378998 0.191611561 2.2684771

lambda[1] 5.62674653 5.28611334 2.36985910 2.007150471 11.0415843

lambda[2] 1.60477157 1.29777398 1.25980697 0.135465213 4.8015059

lambda[3] 5.62797517 5.32327502 2.37170950 1.967656654 11.1291530

lambda[4] 14.57381952 14.26247905 3.80241886 8.071801955 22.9002186

lambda[5] 3.17084264 2.88801833 1.66194832 0.798927322 7.1492800

lambda[6] 19.13200533 18.78653361 4.30674559 11.682136284 28.4767857

lambda[7] 0.94504960 0.75003915 0.75652494 0.081865294 2.8859048

lambda[8] 0.94208101 0.75177975 0.75267045 0.080734142 2.8644982

lambda[9] 3.33846361 3.05488924 1.63926902 0.990402148 7.3041714

lambda[10] 20.93771507 20.60497943 4.45432662 13.116940079 30.4162660

theta[1] 0.05966857 0.05605635 0.02513106 0.021284735 0.1170900

theta[2] 0.10221475 0.08266076 0.08024248 0.008628358 0.3058284

theta[3] 0.08947496 0.08463076 0.03770603 0.031282300 0.1769341

theta[4] 0.11566523 0.11319428 0.03017793 0.064061920 0.1817478

theta[5] 0.60512264 0.55114854 0.31716571 0.152467046 1.3643664

theta[6] 0.60929953 0.59829725 0.13715750 0.372042557 0.9069040

theta[7] 0.90004724 0.71432300 0.72049994 0.077966947 2.7484808

theta[8] 0.89722001 0.71598072 0.71682900 0.076889659 2.7280935

theta[9] 1.58974458 1.45470916 0.78060429 0.471620071 3.4781768

theta[10] 1.99406810 1.96237899 0.42422158 1.249232389 2.8967872

**Monte Carlo Expectation Analysis**

To illustrate that NIMBLE is more than just an MCMC engine, the manual example uses NIMBLE’s built-in Monte Carlo Expectation algorithm to maximize the marginal likelihood for alpha and beta. The first step is to set up “box constraints” for the model. Then, the buildMCEM() function is used to construct an MCEM algorithm from a NIMBLE model.

pump2 <- pump$newModel()

box = list( list(c("alpha","beta"), c(0, Inf)))

pumpMCEM <- buildMCEM(model = pump2, latentNodes = "theta[1:10]", boxConstraints = box)

This is how to run the Monte Carlo Expectation model. Note that the authors of the NIMBLE manual point out that these results are within 0.01 of the values obtained by George et al.

pumpMLE <- pumpMCEM$run()

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Iteration Number: 1.

Current number of MCMC iterations: 1000.

Parameter Estimates:

alpha beta

0.8130146 1.1125783

Convergence Criterion: 1.001.

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Iteration Number: 2.

Current number of MCMC iterations: 1000.

Parameter Estimates:

alpha beta

0.8148887 1.2323211

Convergence Criterion: 0.02959269.

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Iteration Number: 3.

Current number of MCMC iterations: 1000.

Parameter Estimates:

alpha beta

0.8244363 1.2797908

Convergence Criterion: 0.005418668.

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Monte Carlo error too big: increasing MCMC sample size.

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Iteration Number: 4.

Current number of MCMC iterations: 1250.

Parameter Estimates:

alpha beta

0.8280353 1.2700022

Convergence Criterion: 0.001180319.

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Monte Carlo error too big: increasing MCMC sample size.

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Monte Carlo error too big: increasing MCMC sample size.

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Iteration Number: 5.

Current number of MCMC iterations: 2188.

Parameter Estimates:

alpha beta

0.8268224 1.2794244

Convergence Criterion: 0.000745466.

Like the tidyverse, NIBMLE is an ecosystem of DSLs. The BUGS language is extended and used as a DSL for formulation models. nimbleFunctions is a language for writing algorithms that may be used with both BUGS and R. But, unlike the tidyverse, the NIMBLE DSLs are not distributed across multiple packages, but instead wrapped up into the NIMBLE package code.