

Template Model Builder

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$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

$$\int_a^b \epsilon \Theta + \Omega \int \delta e^{i\pi} = \{2.7182818284\}$$

$$\chi^2 \sum \gg$$

DTU Compute

Department of Applied Mathematics and Computer Science

- ▶ ADMB inspired R-package
- ▶ Combines external libraries: CppAD, Eigen, CHOLMOD
- ▶ Continuously developed since 2009, relatively few lines of code
- ▶ Implements Laplace approximation for random effects
- ▶ C++ Template based
- ▶ Automatic sparseness detection
- ▶ Parallelism through BLAS
- ▶ Parallel user templates
- ▶ Parallelism through `parallel` package

Example:

```
#include <TMB.hpp>
template<class Type>
Type objective_function<Type>::operator() () {
  DATA_VECTOR(Y);
  PARAMETER_VECTOR(X);
  PARAMETER_VECTOR(logtheta);
  vector<Type> th=exp(logtheta);
  Type ans=0, m;
  for(int i=1; i<Y.size(); i++){
    m = X[i-1]+th[0]*(1.0-pow(exp(X[i-1])/th[2],th[1]));
    ans -= dnorm(X[i],m,sqrt(th[3]),true);
  }
  for(int i=0; i<Y.size(); i++){
    ans -= dnorm(Y[i],X[i],sqrt(th[4]),true);
  }
  return ans;
}
```

```
Y<-scan("theta.dat", quiet=TRUE)
library(TMB)
compile("theta.cpp")
dyn.load(dynlib("theta"))
data <- list(Y=Y)
param <- list(X=data$Y * 0, logtheta=c(0,0,6,0,0))
obj <- MakeADFun(data,param,random="X")
opt <- nlminb(obj$par,obj$fn,obj$gr)
```

Optimizations

User's code goes through several phases of optimization:

1. Cpp file is at compile time optimized via the Eigen library.
2. Operations are put on a tape.
3. Tape is runtime optimized by CppAD.

Thereafter the user's cpp function is no longer used.

- ▶ User need not worry about optimizing the code (e.g Passing objects by const reference or eliminating temporaries etc)

Laplace and sparse Hessian

- ▶ Recall the Laplace approximation of the negative log-likelihood:

$$-\log L^*(\theta) = -n \log \sqrt{2\pi} + \frac{1}{2} \log \det(H(\hat{u}, \theta)) + f(\hat{u}, \theta). \quad (1)$$

$$\hat{u}(\theta) = \arg \min_u f(u, \theta). \quad (2)$$

We use $H(u, \theta)$ to denote the Hessian of $f(u, \theta)$ w.r.t. u

$$H(u, \theta) = f''_{uu}(u, \theta). \quad (3)$$

- ▶ Sparseness pattern of H: Which entries are zero for any choice of parameters (u, θ) ?
- ▶ For efficiency: utilizing 'sparseness pattern' of $H(\theta)$ greatly reduces the time to calculate the log-determinant.
- ▶ Key feature of TMB: Can detect the pattern automatically.
- ▶ How? Numerical test is not sufficient. A 'symbolic' analysis is required.

Example:

- ▶ Simple test function:

$$f(u_1, \dots, u_8) = u_1^2 + \sum_{i=2}^8 (u_i - u_{i-1})^2 .$$

- ▶ Implementation in TMB (examp.cpp):

```
#include <TMB.hpp>

template<class Type>
Type objective_function<Type>::operator() ()
{
    PARAMETER_VECTOR(u);
    Type ans=0;
    ans+=pow(u[0],2);
    for(int i=1;i<u.size();i++) ans+=pow(u[i]-u[i-1],2);
    return ans;
}
```

Run from R

- Compile and construct function object:

```
library(TMB)
compile("examp.cpp")
```

Note: Using Makevars in /home/kaskr/.R/Makevars

```
[1] 0
```

```
dyn.load(dynlib("examp"))
obj <- MakeADFun(data=list(),parameters=list(u=rep(0,8)),random="u")
```

- Get the Hessian:

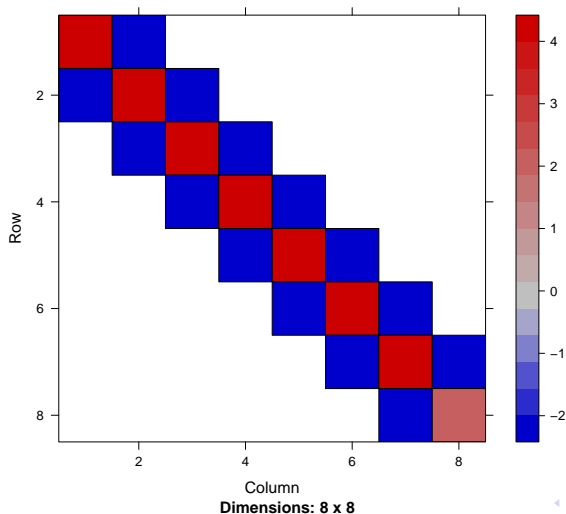
```
obj$env$spHess(random=TRUE)
```

8 x 8 sparse Matrix of class "dsCMatrix"

```
[1,]  4 -2  .  .  .  .  .  .
[2,] -2  4 -2  .  .  .  .  .
[3,]  . -2  4 -2  .  .  .  .
[4,]  .  . -2  4 -2  .  .  .
[5,]  .  .  . -2  4 -2  .  .
[6,]  .  .  .  . -2  4 -2  .
[7,]  .  .  .  .  . -2  4 -2
[8,]  .  .  .  .  .  . -2  2
```

Visualize from R

```
h <- obj$env$spHess(random=TRUE)
range <- c(0,nrow(h)) + .5
Matrix:::image(h,xlim=range,ylim=range)
```



- ▶ TMB detected the correct banded structure: Hessian entries outside the band are zero for any u .
- ▶ Works by analysing the internal representation of the computational graph.
- ▶ This is currently a modification of the AD tool (CppAD).
- ▶ Take a look at the computational graphs...

Tape of the test function

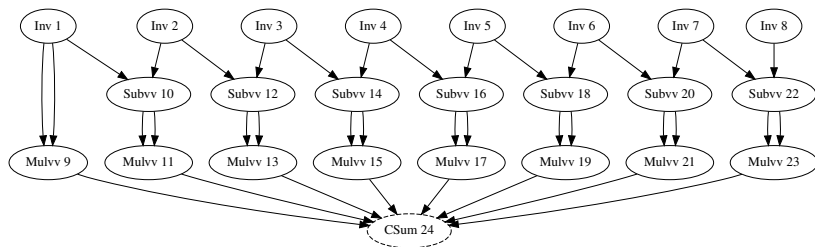


Figure: CppAD tape T1 for $f(u_1, \dots, u_8) = u_1^2 + \sum_{i=2}^8 (u_i - u_{i-1})^2$. Nodes "Inv 1"–"Inv 8" corresponds to u_1, \dots, u_8 and node "CSum 24" corresponds to $f(u_1, \dots, u_8)$.

Tape of the test function's gradient

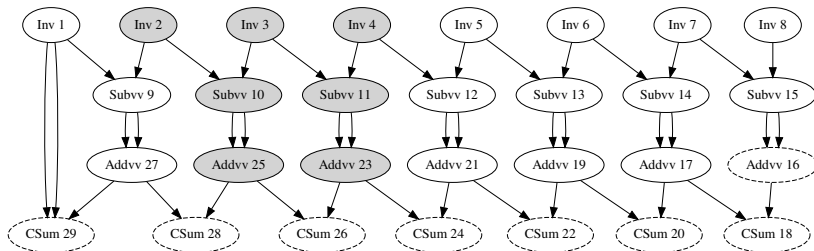


Figure: CppAD tape T2 for $f'(u)$, when $f(u)$ is defined as in previous figure. For example, node 26 corresponds to the partial of f w.r.t. u_3 ; i.e., $f'_3(u) = 2(u_3 - u_2) - 2(u_4 - u_3)$.

Summary sparsity detection

- ▶ Requiremnet: Fixed graph !
- ▶ Detection algorithm is a primitive dependency analysis: Never *false positives* but ther may be *false negatives* (e.g. $xy - xy$).
- ▶ Manual detection (like ADMB) does not have this problem !
- ▶ CONS: If statement flexibility.
- ▶ What happens to the sparsity pattern if an observation of the sum $\sum_i u_i$ is added:

$$x|u \sim N(\sum_i u_i, 1)$$

Atomic functions

- ▶ What is an atomic function?
- ▶ Example: 'ppois'

```
TMB_ATOMIC_VECTOR_FUNCTION(  
  // ATOMIC_NAME  
  ppois  
  ,  
  // OUTPUT_DIM  
  1  
  ,  
  // ATOMIC_DOUBLE  
  ty[0] = Rmath::Rf_ppois(  
      tx[0], tx[1], 1, 0);  
  ,  
  // ATOMIC_REVERSE  
  Type value = ty[0];  
  Type n = tx[0];  
  Type lambda = tx[1];  
  CppAD::vector<Type> arg(2);  
  arg[0] = n - Type(1);  
  arg[1] = lambda;  
  px[0] = Type(0);  
  px[1] = (-value + ppois(arg)[0])  
      * py[0];  
)
```

Definition

$$ppois(n, \lambda) = \sum_{k=0}^n \frac{\lambda^k}{k!} e^{-\lambda}$$

Partial derivatives:

$$\partial_n ppois(n, \lambda) = 0$$

$$\partial_\lambda ppois(n, \lambda) = -ppois(n, \lambda) + ppois(n-1, \lambda)$$

Overview of existing atomic functions

- ▶ Matrix multiply

```
atomic::matmul(x, y); // T(grad) < 3 * T(func)
```

- ▶ Matrix exponential

```
atomic::matexp(x); // T(grad) < 4 * T(func)
```

- ▶ Matrix inverse

```
atomic::matinv(x); // T(grad) < 2.5 * T(func)
```

NOTE

- ▶ Atomic functions have dense sparsity pattern in TMB !
- ▶ Cheap gradient preserved for these atomic operations (tested $10^3 \times 10^3$).

Checkpointing

- ▶ Purpose: reduce memory of AD when the same operation sequence is repeated multiple times.
- ▶ This technique is known as *checkpointing*.
- ▶ Given a function

```
template<class Type>
vector<Type> work(vector<Type> parms) {
    // Long computation
    return ans;
}
```

- ▶ Generate 'work' and its derivatives as native symbols:

```
REGISTER_ATOMIC(work);
```

Other new stuff

- ▶ ?precompile
- ▶ ?gdbsource
- ▶ ?config
- ▶ ?as.list.sdreport
- ▶ ?sdreport -> bias.correction
- ▶ ?oneStepPredict
- ▶ ?MakeADFun -> profile
- ▶ namespace autodiff