Using the **sparseHessianFD** package

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The **sparseHessianFD** package is a tool to compute Hessians efficiently when the Hessian is sparse (that is, a large proportion of the cross-partial derivatives are zero). The user needs to supply the objective function, its gradient, and the sparsity pattern of the Hessian. The non-zero elements of the Hessian are computed through finite differencing of the gradients in a way that exploits the sparsity pattern. The Hessian is stored in a compressed format; specifically, an object of class `dgCMatrix`, as defined in the **Matrix** package(Bates and Maechler 2013). This allows sparse matrix algorithms to run more quickly, with a smaller memory footprint, than their dense-matrix counterparts. For example, the **trustOptim** package (Braun 2013b) includes an implementation of a trust region nonlinear optimizer that is designed to take advantage of the fact that a Hessian is sparse. The **sparseMVN** package (Braun 2013a) samples from, and computes the log density of, a multivariate normal distribution with a sparse covariance or precision matrix.

For dense Hessians, a standard way of approximating the Hessian involves taking the differences between the gradient at point $x \in \mathbb{R}^p$ and the gradient with a single element of x perturbed by a small amount ϵ. If $\nabla f(x)$ is the gradient of $f(x)$, then the i^{th}column of the Hessian is equal to $(\nabla(x + \epsilon e_i) - \nabla f(x))/\epsilon$, where e_i is a vector of zeros, with a 1 in the i^{th} element. This "forward differencing" method involves computing a gradient $p + 1$ times. More accurate approximations require even more evaluations of the gradient; central differencing requires $2p$ evaluations. This method

also requires the storage of p^2 elements, even if most of the elements of the Hessian are zero.

The **sparseHessianFD** package uses a graph coloring algorithm to partition the p variables into groups ("colors" in the graph theory literature), such that perturbing x_i will not affect the j^{th} element of the gradient for any j that is in the same group as i. This will happen when the cross-partial derivative with respect to x_i and x_j is zero, or, equivalently, that element (i, j) of the Hessian is zero. This means that we can perturb all of the x's in the same group in a single computation of the gradient. When the number of groups is small, we can estimate the Hessian much more quickly. Note that for a fully dense Hessian, the number of groups is equal to p, and there is no advantage to using this algorithm. Also, the number of groups depends crucially on exactly which elements of the Hessian are non-zero; sparsity does not guarantee that this method can be used. However, for many common sparsity patterns, the computational savings is dramatic.

As an example, suppose that we have, in a hierarchical model, N units, k heterogeneous parameters per unit, and r population-level parameters. Since the cross-partial derivative between an element in β_i and an element in β_j is zero, any element of β_i and β_j can be in the same group, but since the cross partials for elements with a single β_i are not zero, these elements cannot be in the same group. Furthermore, if we assume that any β_i could be correlated with the r population-level parameters, and that the r population-level parameters may be correlated amongst themselves, we can estimate the Hessian (with forward differences) with no more than $k + r + 1$ gradient evaluations. Note that this number *does not grow with N*. Thus, computing the Hessian for a log posterior density of a hierarchical model with, say, 100 heterogeneous units, is no more expensive than for a dataset with a million heterogeneous units, and the amount of storage required for the sparse Hessian grows only linearly in N.

Curtis et al. (1974) introduce the idea of reducing the number of evaluations to estimate sparse Jacobians, and Powell and Toint (1979) describe how to partition variables into appropriate groups, and how to recover Hessian information through back-substitution. Coleman and Moré (1983) show that the task of grouping the variables amounts to a classic graph-coloring problem. Gebremedhin et al. (2005) summarize more recent advances in this area. The actual computational "engine" for **sparseHessianFD** is ACM TOMS Algorithm 636 (Coleman et al. 1985). The original Fortran code is in

the file `inst/include/misc/FDHS-DSSM.f`. The file `src/FDHS-DSSM.c` is a translation of the originalFortran code into C. The copyright to both of these files is retained by the Association of Computational Machinery under terms that are included in the LICENSE file in the package source code. My contribution to the package is only the interface with R, and not the computational algorithm itself.

1 Using the package

Using **sparseHessianFD** involves constructing an object of class `sparseHessianObj`. The class `sparseHessianObj` contains only one slot: an external pointer to an instance of a C++ class that does all of the computation. This object stores all of the information needs to compute the objective function, gradient and Hessian for any argument vector x. The easiest way to compute this object is to use the `new.sparse.hessian.obj` function. Its signature is:

```
obj <- new.sparse.hessian.obj(x, fn, gr, hs, fd.method=0,
                              eps=sqrt(.machine$double.eps), ...)
```

The function `fn` returns $f(x)$, the value of the objective function to be minimized, `gr` that returns the gradient. Both functions can take additonal named arguments which are passed through the `...` argument in `get.new.sparse.hessian`. The argument `hs` is a list that represents the sparsity pattern of the Hessian. The `hs` list contains two integer vectors,`iRow` and `jCol`, that contain the row and column indices of the non-zero elements of the lower triangle of the Hessian. The length of each of these vectors is equal to the number of non-zeros in the lower triangle of the Hessian. Do *not* include any elements from the upper triangle. Entries must be in order, first by column, and then by row within each column. Indexing starts at 1. The package includes a convenience function, `Matrix.to.Coord`, that converts a matrix with the appropriate sparsity pattern to a list that can be used as the `hs` argument.

Coleman et al. (1985) provides two approaches for computing a sparse Hessian: indirect (`fd.method=0`) and direct (`fd.method=1`). We refer the reader to that source for an explanation of the difference. In short, the indirect method should be somewhat faster that the direct method, with comparable accuracy. The argument `eps` is the perturbation amount used in the finite differencing algorithm. Again, see Coleman

et al. (1985) for more details.

The algorithms in this package work best when the gradient is computed directly (i.e., derived analytically or symbolically), or otherwise computed exactly (say, by way of algorithmic differentiation). In general, we never recommend finite-differenced gradients. Finite differencing takes a long time to run, and is subject to numerical error, especially near the optimum when elements of the gradient are close to zero. Using **sparseHessianFD** with finite-differenced gradients means that the Hessian is "doubly differenced," and the resulting lack of numerical precision makes those Hessians nearly worthless.

Once the `sparseHessianObj` object is constructed at an initial value of x, we can then compute the function, gradient or Hessian for any other value of x. The **sparseHessianFD** includes the following methods:

```
get.fn(x, obj)
get.gr(x, obj)
get.hessian(x, obj)
get.fngr(x, obj)
```

These functions return `fn(x)`, `gr(x)`, the Hessian of `fn(x)`, and a list with both `fn(x)` and `gr(x)`, respectively. The Hessian is an object of class `dgCMatrix`. [1] These functions do not pass additional arguments to the original functions, since that information is stored in `obj`.

Alternatively, we can access the function, gradient, and Hessian functions directly from the object with:

```
obj$fn(x)
obj$gr(x)
obj$hessian(x)
obj$fngr(x)
```

[1] Even though the Hessian is symmetric, the `dgCMatrix` stores the entire matrix, and not just the lower triangle. This is because of a current limitation in the **RcppEigen** package. As **RcppEigen** functionality expands, we hope to return Hessians as `dsCMatrix` objects. This would effectively halve the storage requirements for the Hessian.

2 Sparsity pattern of the Hessian

In the following code, we construct a block diagonal matrix, and then use the `Matrix.to.Coord` function to generate a list of the row and column indices of the non-zero elements of the lower triangle.

```
require(Matrix)
M <- kronecker(Diagonal(4),Matrix(1,2,2))
print(M)
8 x 8 sparse Matrix of class "dgTMatrix"
[1,] 1 1 . . . . . .
[2,] 1 1 . . . . . .
[3,] . . 1 1 . . . .
[4,] . . 1 1 . . . .
[5,] . . . . 1 1 . .
[6,] . . . . 1 1 . .
[7,] . . . . . . 1 1
[8,] . . . . . . 1 1

H <- Matrix.to.Coord(M)
print(H)
$iRow
 [1] 1 2 2 3 4 4 5 6 6 7 8 8

$jCol
 [1] 1 1 2 3 3 4 5 5 6 7 7 8
```

To check that the indices do, in fact, represent the sparsity pattern of the lower triangular Hessian, you can convert the list back to a pattern `Matrix` using the `Coord.to.Matrix` function.

```
M2 <- Coord.to.Pattern.Matrix(H, 8,8)
print(M2)
8 x 8 sparse Matrix of class "ngCMatrix"

[1,] | . . . . . . .
[2,] | | . . . . . .
[3,] . . | . . . . .
[4,] . . | | . . . .
[5,] . . . . | . . .
[6,] . . . . | | . .
```

```
[7,] . . . . . | .
[8,] . . . . . | |
```

Notice that M2 is only lower-triangular. Even though M was symmetric, H contains only the indices of the non-zero elements in the lower triangle. To recover the pattern of the *symmetric* matrix, use the `Coord.to.Sym.Pattern.Matrix` function.

```
M3 <- Coord.to.Sym.Pattern.Matrix(H,8)
print(M3)
8 x 8 sparse Matrix of class "nsTMatrix"

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

3 An example

As an example,let's compute the Hessian of the log posterior density of a hierarchical model. Suppose we have a dataset of N households, each with T opportunities to purchase a particular product. Let y_i be the number of times household i purchases the product, out of the T purchase opportunities. Furthermore, let p_i be the probability of purchase; p_i is the same for all T opportunities, so we can treat y_i as a binomial random variable. The purchase probability p_i is heterogeneous, and depends on both k continuous covariates x_i, and a heterogeneous coefficient vector β_i, such that

$$p_i = \frac{\exp(x_i'\beta_i)}{1+\exp(x_i'\beta_i)},\ i = 1 \ldots N \tag{1}$$

The coefficients can be thought of as sensitivities to the covariates, and they are distributed across the population of households following a multivariate normal distribution with mean μ and covariance Σ. We assume that we know Σ, but we do not know μ. Instead, we place a multivariate normal prior on μ, with mean 0 and covariance Ω_0,

which is determined in advance. Thus, each β_i, and μ are $k-$dimensional vectors, and the total number of unknown variables in the model is $(N+1)k$.

The log posterior density, ignoring any normalization constants, is

$$\log \pi(\beta_{1:N}, \mu | Y, X, \Sigma_0, \Omega_0) = \sum_{i=1}^{N} p_i^{y_i} (1-p_i)^{T-y_i} - \frac{1}{2} (\beta_i - \mu)' \Sigma^{-1} (\beta_i - \mu) - \frac{1}{2} \mu' \Omega_0^{-1} \mu \tag{2}$$

Since the β_i are drawn iid from a multivariate normal, $\dfrac{\partial^2 \log \pi}{\partial \beta_i \beta_j} = 0$ for all $i \neq j$. We also know that all of the β_i are correlated with μ. Therefore, the Hessian will be sparse with a "block-arrow" structure. For example, if $N = 6$ and $k = 2$, then $p = 14$ and the Hessian will have the pattern as illustrated in Figure 1.

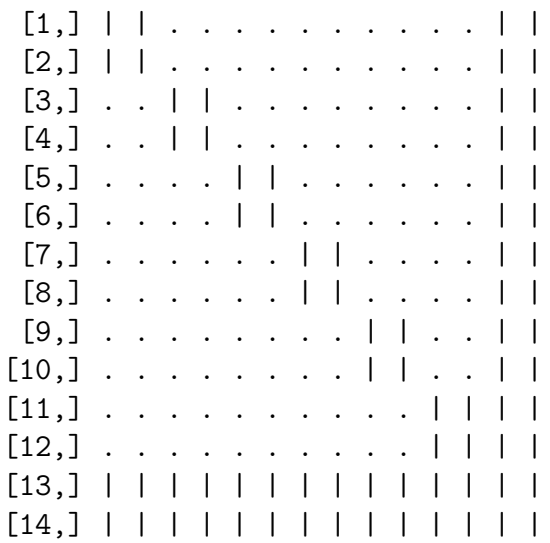

Figure 1: Sparsity pattern for hierarchical binary choice example.

There are 196 elements in this symmetric matrix, but only 169 are non-zero, and only 76 values are unique. Although the reduction in RAM from using a sparse matrix structure for the Hessian may be modest, consider what would happen if $N = 1000$ instead. In that case, there are 2,002 variables in the problem, and more than 4 million elements in the Hessian. However, only 12,004 of those elements are non-zero. If we work with only the lower triangle of the Hessian (e.g., through a Cholesky decomposition), we only need to work with only 7,003 values.

The file `inst/examples/example.R` demonstrates how to estimate the Hessian for this model. The function, gradient, and "true" Hessian are computed using functions in the file `inst/examples/ex_funcs.R`). In `example.R`, we first simulate some data. The `hess.struct` function returns the list than can be used for the `hs` argument in the `get.new.sparse.hessian` function.

We then create `obj` using the defaults for `fd.method` and `eps`. Finally, we compute the function, gradient and Hessian using the two different methods on `obj`.

The `get.hess` function (defined in `ex_funcs.R`) returns the exact Hessian, derived analytically. This Hessian is the same as the one that is computed by way of `get.hessian`.

4 Discussion points

For some functions, deriving and coding a gradient analytically is straightforward (either by hand, or using a symbolic computation tool like **Mathematica**). For many others, like log posterior densities, analytic Hessians can be messy to derive and code. Even then, storing and working with a $p \times p$ matrix is expensive when p is large. The **sparseHessianFD** package is useful when the Hessian is sparse and the sparsity pattern is known in advance, even when p is massively large. The speed at which **sparseHessianFD** computes the Hessian depends on the sparsity pattern. For block diagonal Hessians, as in the example above, computation time will grow with the size of each heterogeneous parameter, and the number of population-level parameters, but not with the number of heterogeneous units. As N grows, the number of non-zero elements in the Hessian grows linearly, and the number of gradient differences that need to be computed is constant.

We should note that finite differencing is not the current "state of the art" for estimating sparse Hessians. Algorithmic differentiation (AD) packages can be faster and more exact (and of course they can compute the gradient as well). A critical requirement of an AD package when we need to differentiate scalar-valued functions with large p is that it support "reverse-mode" differentiation. For C++, **CppAD** and **Adol-C** are popular choices, and others may be available for Matlab and Python. **AD Model Builder** is a scripting language for AD that can be called from R using the **R2admb** package (Bolker and Skaug 2012).

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