

Enabling and Embedding ReverseCommunication Solvers

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Julia Computing, Inc. regularly assists clients in developing custom Julia functionality tailored to their specific application and operational needs

This presentation is a synopsis of one such engagement presented with client permission

Notebook and code: https://github.com/AndyGreenwell/JuliaCon2016

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Project Requirements



- Provide Julia alternative to existing optimization and root finding solvers
- Wrap client's existing solver with a Julia interface
- Integrate Julia in a large C/C++ batch processing workflow (call Julia from C)
- Add reverse communication to Julia solvers, including wrapped solvers
 - Client has many existing C/C++ based objective and derivative functions:
 - Must not be passed as arguments to Julia functions (do not require wrapping objective/derivative)
 - Must be evaluated directly in original C/C++ application
- Enable code migration between front and back office without full re-coding

Forward vs Reverse Communication Solvers



- Forward communication is utilized in most of Julia's optimization and root finding
 - Examples: Optim.jl, NLopt.jl, Roots.jl, NLsolve.jl
 - Objective/derivative function(s) are input arguments
 - Solver invokes the objective/derivative function(s) internally
 - Technique allows for powerful performance enhancements (e.g. Automatic Differentiation)
 - Requires objective/derivative function(s) to have a particular interface
 - For existing C code, this can involve creation of Julia wrappers
 - Not desired for this particular client's environment



Forward vs Reverse Communication Solvers



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 - For C code, this can involve creation of Julia wrappers

Reverse communication

- Classic technique where objective/derivative functions are not passed directly to the solver
- Solver returns to its calling environment when function evaluations are required
- Solver is then called repeatedly, each time resuming at its prior exit location



Example of Forward Communication



```
# Rosenbrock objective and derivative functions as used by Optim.jl
function f(x::Vector)
    (1.0 - x[1])^2 + 100.0 * (x[2] - x[1]^2)^2
end
function g! (x::Vector, storage::Vector)
    storage[1] = -2.0 * (1.0 - x[1]) - 400.0 * (x[2] - x[1]^2) * x[1]
    storage[2] = 200.0 * (x[2] - x[1]^2)
end
function h! (x::Vector, storage::Matrix)
    storage[1, 1] = 2.0 - 400.0 * x[2] + 1200.0 * x[1]^2
    storage[1, 2] = -400.0 * x[1]
    storage[2, 1] = -400.0 * x[1]
    storage[2, 2] = 200.0
end
@show results = Optim.optimize(f, [0.0, 0.0], LBFGS())
@show results = Optim.optimize(f, g!, [0.0, 0.0], LBFGS())
@show results = Optim.optimize(f, q!, h!, [0.0, 0.0], Newton())
```



Mechanical Transformation of FC to RC



Traditional transformation from forward to reverse communication solver:

- Trace execution of the forward solver
- Mark locations of each objective/derivative function evaluations
- Use a stateful object for storing position, objective, derivatives, and location
- Exit and resume solver at function call locations
- Calling the reverse communication solver repeatedly until hitting final condition
 - See notebook for an example mechanical transformation
 - Overall a tedious and error-prone development process





```
maintask = current task()
function f t(x::Vector)
    yieldto(maintask, x)
end
quess = [0.0; 0.0]
solver = @task Optim.optimize(f t, guess, NelderMead())
next x = copy(guess)
while !istaskdone(solver)
    fx = f(next x)
    next x = yieldto(solver, fx)
end
result = next x
@show result
```

Using Julia tasks, a forward communication solver can behave like a reverse communication solver.



```
# Define the main task
maintask = current task()
function f t(x::Vector)
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Define the main task
Define a redirection function that
yields control to the main task





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quess = [0.0; 0.0]
                                                         # Define an initial guess
solver = @task Optim.optimize(f t, guess, NelderMead())
next x = copy(guess)
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while !istaskdone(solver)
                                                         # Driver loop
    fx = f(next x)
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    fx = f(next x)
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    fx = f(next x)
    next x = yieldto(solver, fx)
                                                         # Yield back to the solver task
end
                                                         # On completion, next x contains
result = next x
                                                         # the solver output
@show result
```



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result = next x
                                                         # the solver output
@show result
```

Presentation notebook includes an example using both gradient and combined objective/gradient functions



Julia's C API can be used to embed general Julia code within C/C++

Used for calling Julia from other languages (e.g. Rjulia, pyjulia)

Tasks-based reverse communication solvers can be embedded within a C/C++ application that meets various client requirements:

- Provides Julian alternative to existing optimization and root finding solvers
- Integrates Julia in existing C/C++ batch processing workflow
- Provides reverse communication interface to Julia solvers
- Evaluates objective/derivative functions either as C/C++ functions or Julia functions
 - Enables easy migration of Julia code from front office to back office





```
setum ()
int r orth array t *w. th array t *tach
             double: xd = (double:)jl array_data(x);
double: jd = (double:)jl_array_data(jac);
               \begin{array}{lll} Sd(0) &= 2.0 + (1 - mig(0)) \\ Sd(1) &= -2.0 + (1 - mig(0)) \\ Sd(1) &= -00.0 + (mig(0) - pow(mig(0), 2.0)) + mig(0) //2.1 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) + mig(0) //2.2 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) //2.2 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) //2.2 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) //2.2 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) //2.2 + 24ment \\ Sd(2) &= -0.0 + (mig(0) - pow(mig(0), 2.0)) //2.2 + (mig(0) - pow(mig(0), 2.0))
  void r fq(jl array t *x, jl array t *f, jl array t *jac)
               double* nd = (double*)51 array data(x);

double* fd = (double*)51 array data(f);

double* fd = (double*)51 array data(f);

fd(0) = pow(1.0 - xd(0), 2.0);

fd(0) = pow(1.0 - xd(0), 2.0);

fd(1) = 100.0 * pow(pd(1) - pow(pd(0), 2.0), 2.0);
               5d[0] = -2.0 \cdot (1 - xd[0])_1

5d[1] = -600.0 \cdot (xd[1] - pow(xd[0], 2.0)) \cdot xd[0]_1 //2_1 \cdot element

5d[2] = 0.0_1

5d[3] = 200.0 \cdot (xd[1] - pow(xd[0], 2.0))_1 //2_2 \cdot element
                  jl_function t *taskdome = jl_get_function(jl_base_module, "istaskdome");
setum jl_call(taskdome, solven) == jl_true;
                                     ji value t* vala = ji calik((ji function t*) args[0], args[1], args[5], args[6]); // *vale* nuple
ji value t* solver = ji calik((ji function t*) args[0], args[0], args[0]); // solver task
```



```
#include <julia.h>
#include <stdio.h>
#include <math.h>

#ifdef _OS_WINDOWS_
    __declspec(dllexport) __cdecl
#endif
Include headers and definitions -
```





```
int r f(jl array t *x, jl array t *f)
   double^* \times d = (double^*) jl array data(x);
   double* fd = (double*)jl array data(f);
   fd[0] = pow(1.0 - xd[0], 2.0);
   fd[1] = 100.0 * pow(xd[1] - pow(xd[0], 2.0), 2.0);
                                      Define Objective and Gradient Functions -
   return 0;
int r g(jl array t *x, jl array t *jac)
   double* xd = (double*)jl array data(x);
   double* jd = (double*)jl array data(jac);
   jd[0] = -2.0 * (1 - xd[0]);
                                                      //1,1 element
   jd[1] = -400.0 * (xd[1] - pow(xd[0], 2.0)) * xd[0]; //2,1 element
                                                     //1,2 element
   jd[2] = 0.0;
                                                  //2,2 element
   jd[3] = 200.0 * (xd[1] - pow(xd[0], 2.0));
   return 0;
void r fg(jl array t *x, jl array t *f, jl array t *jac)
   double^* \times d = (double^*) jl array data(x);
   double* fd = (double*)jl array data(f);
   double* jd = (double*)jl array data(jac);
   fd[0] = pow(1.0 - xd[0], 2.0);
   fd[1] = 100.0 * pow(xd[1] - pow(xd[0], 2.0), 2.0);
   jd[0] = -2.0 * (1 - xd[0]);
                                                      //1,1 element
   jd[1] = -400.0 * (xd[1] - pow(xd[0], 2.0)) * xd[0]; //2,1 element
   jd[2] = 0.0;
                                                      //1,2 element
   jd[3] = 200.0 * (xd[1] - pow(xd[0], 2.0));
                                                  //2,2 element
```





```
jl value t* yieldto(jl value t *solver, jl value t *vals)
   jl function t *yieldto func = jl get function(jl base module, "yieldto");
   return jl call2(yieldto func, solver, vals);
                                                 Access functions from base Julia -
int istaskdone(jl value t *solver)
   jl function t *taskdone = jl get function(jl base module, "istaskdone");
   return jl call1(taskdone, solver) == jl true;
#define noinline attribute ((noinline))
void noinline real main()
   int n = 2;
   // Represent arrays that will be created and owned by C
   double *quess
                   = (double*) malloc (sizeof (double) *n);
   double *fval
                    = (double*) malloc (sizeof (double) *n);
   double *jacobian = (double*)calloc(n*n, sizeof(double));
   // Assign initial values into the above arrays
   quess[0] = -1.2;
   quess[1] = 1.0;
   fval[0] = 1.0/0.0;
    fval[1] = 1.0/0.0;
   // Body of real main here
    free (quess);
```

free(fval); free (jacobian);

```
Define "real_main" -
 Allocate C Arrays -
```

Free C Arrays -



```
jl value t **args;
// args[1] - :f
// args[2] - :g
// args[3] - :fg
```

```
// Root objects with the GC
// args[0] - NLsolve.DifferentiableMultivariateFunction(f!, q!, fq!)
                                                     Root variables with Julia's GC -
// args[4] - array type
// args[5] - guess::Vector{Float64}
                                     Load required Julia package (NLsolve.jl) -
// args[6] - fval::Vector{Float64}
// args[7] - jacobian::Matrix{Float64}
// args[8] - tuple function
// args[9] - solver task function
                                                      Define main and solver tasks -
JL GC PUSHARGS (args, 10);
jl eval string("using NLsolve");
                                                        Define redirection functions -
jl eval string("maintask = current task()");
jl eval string("f t!(x::Vector, fvec::Vector) = yieldto(maintask, (:f, x, fvec))");
jl eval string("g t!(x::Vector, fjac::Matrix) = yieldto(maintask, (:g, x, fjac))");
jl eval string("fg t!(x::Vector, fvec::Vector, fjac::Matrix) = yieldto(maintask, (:fq, x, fvec, fjac))");
args[0] = jl eval string("NLsolve.DifferentiableMultivariateFunction(f t!, g t!, fg t!)");
args[1] = (jl value t*) jl symbol("f");
args[2] = (jl value t*) jl symbol("g");
args[3] = (jl value t*) jl symbol("fg");
args[4] = (jl value t*) jl apply array type(jl float64 type, 1);
// Wrap the C arrays as Julia arrays. The final "0" argument means
// that Julia does not take ownership of the array data for GC purposes.
args[5] = (jl value t*) jl ptr to array 1d(args[4], guess, n, 0);
args[6] = (jl value t*) jl ptr to array 1d(args[4], fval, n, 0);
args[7] = (jl \ value \ t^*) \ jl \ ptr \ to \ array \ 1d(args[4], jacobian, n^*n, 0);
args[8] = (jl value t*) jl get function(jl base module, "tuple");
args[9] = jl eval string("solver task(df, quess) = @task nlsolve(df, quess)");
```



```
jl value t* vals = jl call3((jl function t*) args[8], args[1], args[5], args[6]); // "vals" tuple
   JL GC PUSH2(&vals, &solver);
                                            Implement the driver while loop -
   jl yield();
   while (!istaskdone(solver)){
       if (jl get nth field(vals, 0) == args[1]) {
                                                // :f case
          args[5] = jl get nth field(vals, 1);
          args[6] = jl get nth field(vals, 2);
          r f((jl array t*) args[5], (jl array t*) args[6]);
          vals = yieldto(solver, vals);
      } else if (jl get nth field(vals, 0) == args[2]) { // : g case
          args[5] = jl get nth field(vals, 1);
          args[7] = jl get nth field(vals, 2);
          r g((jl array t*) args[5], (jl array t*) args[7]);
          vals = yieldto(solver, vals);
      } else if (jl get nth field(vals, 0) == args[3]) { // :fg case
          args[5] = jl get nth field(vals, 1);
          args[6] = jl get nth field(vals, 2);
          args[7] = jl get nth field(vals, 3);
          r fg((jl array t*) args[5], (jl array t*) args[6], (jl array t*) args[7]);
          vals = yieldto(solver, vals);
                                                                 Print the results -
   jl show(jl stderr obj(), vals);
   jl eval string("println(\"\n\")");
   JL GC POP();
                                                   Pop variables from the GC -
JL GC POP();
```





Summary

- Most current Julia packages for root finding and optimization implement forward communication strategies (as they should!)
- Julia tasks can be utilized to transform forward communication solvers into reverse communication solvers without modifying the original forward solvers
- The reverse communication wrapper strategy can be embedded within a C/C++ application allowing for unmodified use of existing C/C++ objective/derivative functions





