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ACCELERATE R APPLICATIONS WITH CUDA

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AGENDA

- Background
- Deploy CUDA Libraries
- Apply DIRECTIVES
- Combine CUDA C/C++/Foratran
- Case study : kNN

Appendix: Build R with CUDA by Visual Studio on Windows

1.BACKGROUND

➢Advantages of R:

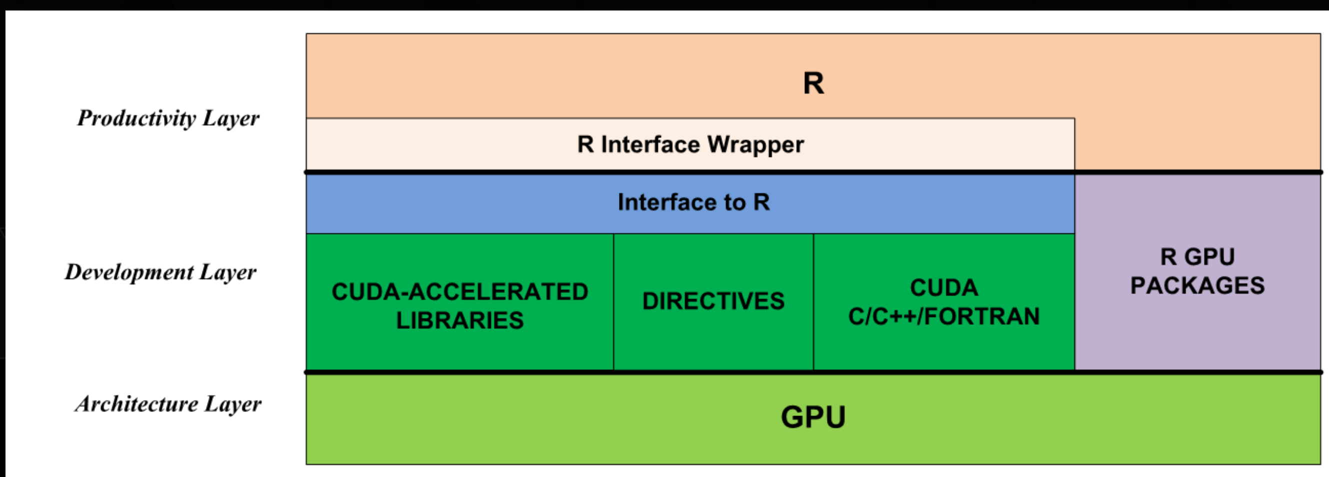
- Help to think with statistical methods
- Design for data orientation
- Interactive with other databases
- Integrate with other languages
- Provide high quality graphics

➢Drawbacks of R:

- speed : sometimes is very slow
- memory: requires all data to be loaded into major memory (RAM)

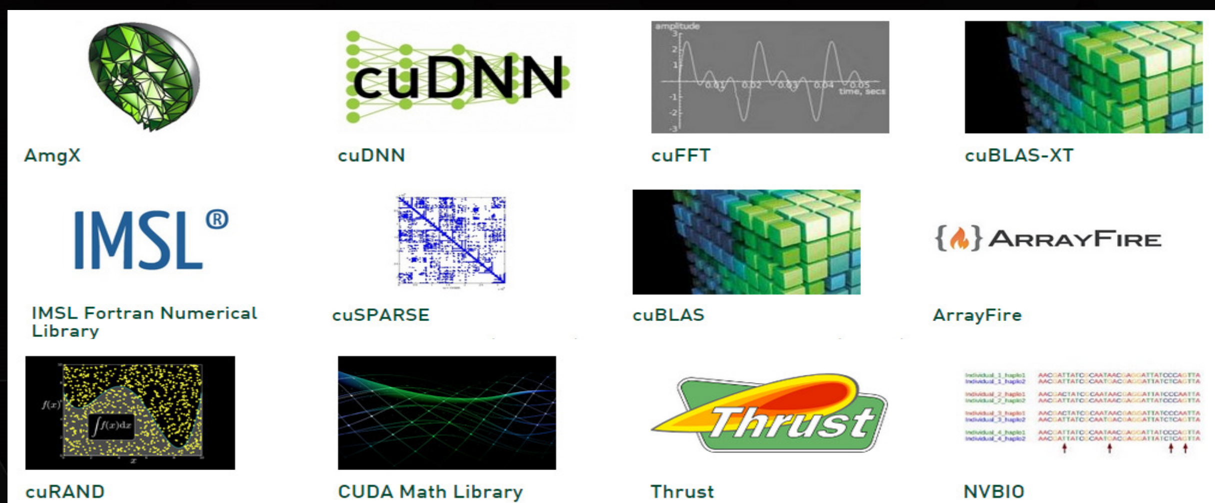
R SOFTWARE STACK WITH CUDA

- R GPU Packages : easy to use
- CUDA Libraries : high quality, usability, portability
- DIRECTIVES : both CPU and GPU
- CUDA C/C++/Fortran : high performance & flexibility



2.DEPLOY CUDA LIBRARIES TO R

- Excellent usability, portability and performance
- Less development efforts and risks



https://developer.nvidia.com/gpu-accelerated-libraries

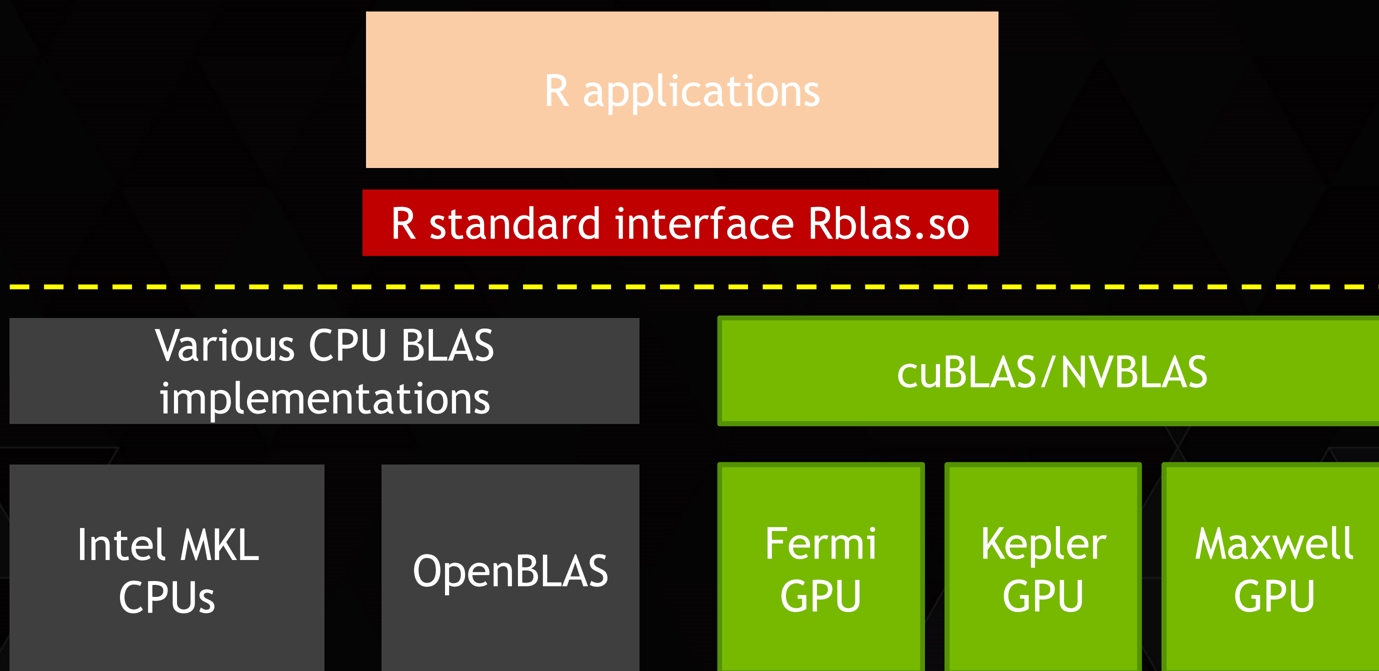
Two examples :

- Accelerate Basic Linear Algebra Subprograms (BLAS)
  - how to use drop in library with R (S5355, S5232)

- Accelerate Fast Fourier Transform (FFT)
  - how to deploy CUDA APIs
  - how to build, link and use CUDA shared objects (.so)

CASE 1. ACCELERATE BASIC LINEAR ALGEBRA SUBPROGRAMS (BLAS)

- Target : speedup R BLAS computation, such as %*%



Drop-in NVBLAS Library on Linux

- Wrapper of cuBLAS
- Includes Standard BLAS3 routines, such as SGEMM
- Supports Multiple-GPUs
- ZERO programming effort

Q: How to use it with R ?

A: Simple PRE-LOAD nvblas.so on Linux

Normally : ***R CMD BATCH <code>.R***

NVBLAS :

env LD_PRELOAD=libnvblas.so R CMD BATCH <code>.R

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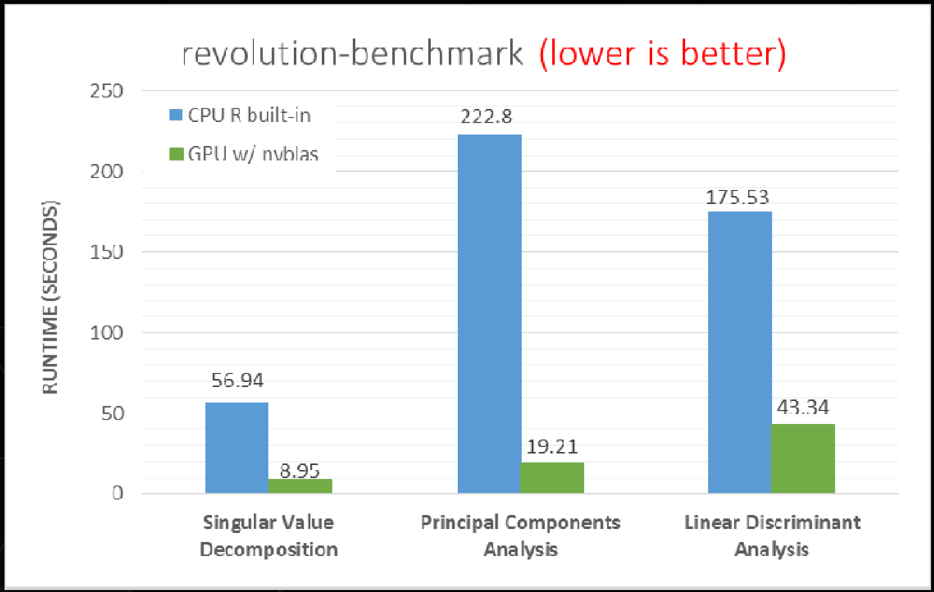
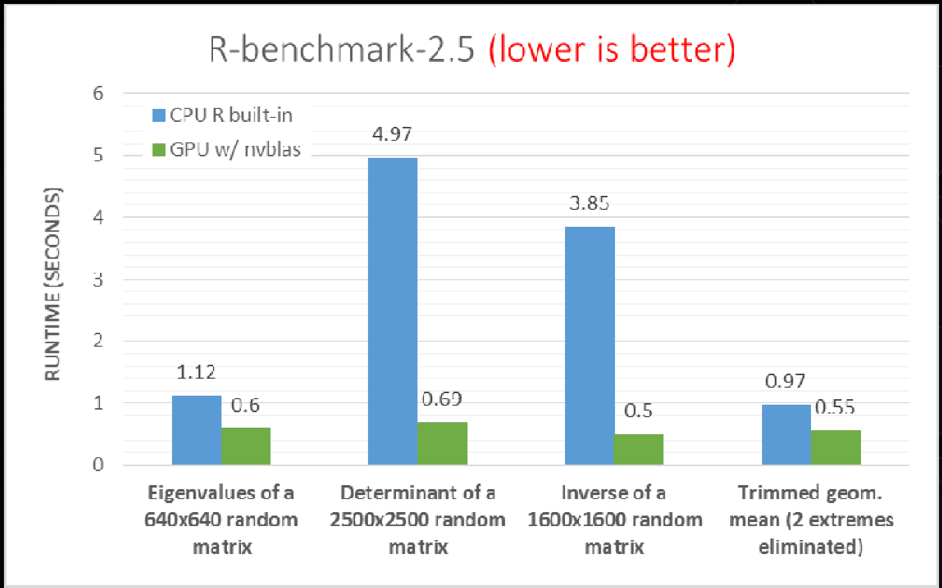
BENCHMARK RESULTS

- revolution-benchmark & R-benchmark-2.5





CPU : Intel, Sandy Bridge E5-2670, Dual socket 8-cores, @ 2.60GHz, 128 GB
GPU : NVIDIA, Tealsa, K40m, 6GB memory

CASE 2. ACCELERATE FAST FOURIER TRANSFORM (FFT)

How to link CUDA libraries to R, including

- Determine R target function
- Write an interface function
- Compile and link to shared object
- Load shared object in R wrapper
- Execute in R
- Test Performance

➢ Target Function in R

Basic compute pattern in finance, image processing, …

such as stats:convolve() function in R is implemented by fft()

Fast Discrete Fourier Transform
Description
Performs the Fast Fourier Transform of an array.
Usage
fft(z, inverse = FALSE)
Arguments
z : a real or complex array containing the values to be transformed.
inverse : if TRUE, the unnormalized inverse transform is computed (the inverse has a + in the exponent of e, but here, we do not divide by 1/length(x))

➢ CUDA library: cuFFT

Writing an interface function

Standard workflow for interface function

- declare for R
- allocate memory for CPU and GPU
- Copy memory from CPU to GPU
- Call CUDA API
- Copy memory back from GPU to CPU
- Free memory

```
#include  <cufft.h>
void cufft(int *n, int *inverse, double *h_idata_re,double *h_idata_im, double
*h_odata_re, double *h_odata_im)
{           cufftHandle plan;
            cufftDoubleComplex *d_data, *h_data;
            cudaMalloc((void**)&d_data, sizeof(cufftDoubleComplex)*(*n));
            h_data = (cufftDoubleComplex *) malloc(sizeof(cufftDoubleComplex) *
           (*n));

            // Covert data to cufftDoubleComplex type
            for(int i=0; i< *n; i++) {
              h_data[i].x = h_idata_re[i];
              h_data[i].y = h_idata_im[i];
            }
            cudaMemcpy(d_data, h_data, sizeof(cufftDoubleComplex) * (*n),
           cudaMemcpyHostToDevice);

            /* Use the CUFFT plan to transform the signal in place. */
            cufftPlan1d(&plan, *n, CUFFT_Z2Z, 1);

            if(!*inverse ) {
              cufftExecZ2Z(plan, d_data, d_data, CUFFT_FORWARD);
            } else {
              cufftExecZ2Z(plan, d_data, d_data, CUFFT_INVERSE);
            }
            cudaMemcpy(h_data, d_data, sizeof(cufftDoubleComplex) * (*n),
           cudaMemcpyDeviceToHost);

            // split cufftDoubleComplex to double array
            for(int i=0; i<*n; i++) {
              h_odata_re[i] = h_data[i].x;
              h_odata_im[i] = h_data[i].y;
            }
            /* Destroy the CUFFT plan. */
            cufftDestroy(plan);
            cudaFree(d_data);
            free(h_data);                         } //main
```

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➢ Compile and link to Shared Object (.so)

```
nvcc -O3 -arch=sm_35 -G -I/usr/local/cuda/r65/include \
     -I/home/patricz/tools/R-3.0.2/include/ \
     -L/home/patricz/tools/R/lib64/R/lib -lR \
     -L/usr/local/cuda/r65/lib64 -lcufft \
     --shared -Xcompiler -fPIC -o cufft.so cufft-R.cu
```

➢ Load Shared Object (.so) in Wrapper

```
cufft1D <- function(x, inverse=FALSE)
{
        dyn.load("cufft.so")
        n   <- length(x)
        rst <- .C("cufft",
                as.integer(n),
                as.integer(inverse),
                as.double(Re(z)),
                as.double(Im(z)),
                re=double(length=n),
                im=double(length=n))
    rst <- complex(real = rst[["re"]], imaginary = rst[["im"]])
    return(rst)
}
```

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Execute and Testing

```
> source("wrap.R")

> num <- 4
> z <-  complex(real = stats::rnorm(num), imaginary = stats::rnorm(num))

> cpu <- fft(z)
[1]  1.140821-1.352756i -3.782445-5.243686i  1.315927+1.712350i -0.249490+1.470354i

> gpu <- cufft1D(z)
[1]  1.140821-1.352756i -3.782445-5.243686i  1.315927+1.712350i -0.249490+1.470354i

> cpu <- fft(z, inverse=T)
[1]  1.140821-1.352756i -0.249490+1.470354i  1.315927+1.712350i -3.782445-5.243686i

> gpu <- cufft1D(z, inverse=T)
[1]  1.140821-1.352756i -0.249490+1.470354i  1.315927+1.712350i -3.782445-5.243686i
```

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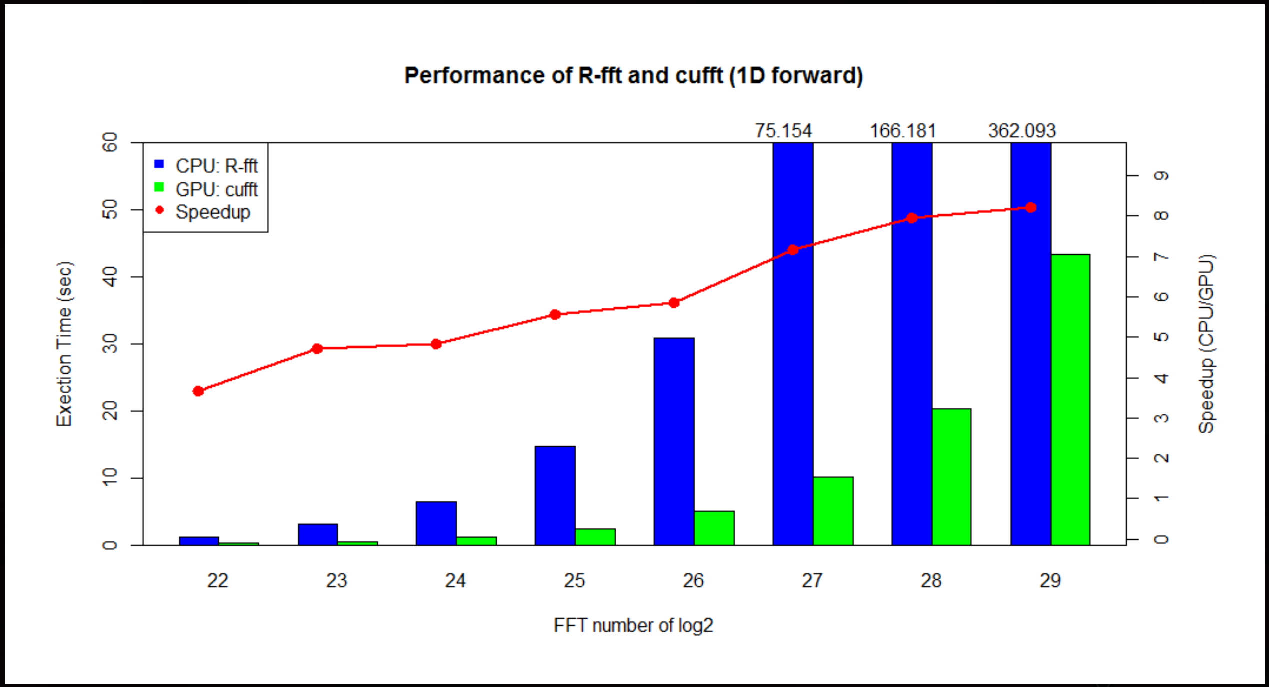

Intel Xeon CPU 8-cores (E5-2609 @ 2.40GHz / 64GB RAM)
NVIDIA GPU (Tesla K20Xm with 6GB device memory)

3. APPLY DIRECTIVES

- Directives is a common programming model now
  - Easy Programming : add several '#pragma' statements
  - Portability : compiler, devices, performance
  - Works for legacy code: less effort

- Implementations in C/C++/Fortran level
  - CPU : Coarse granularity, task/data parallel w/ OpenMP
  - GPU : Finer granularity, data parallel w/ OpenACC

Example: speedup legacy code in dist()

- Compute the distances between the rows of a data matrix
- Implemented by C function

```
> dist
function (x, method = "euclidean", diag = FALSE, upper = FALSE,
    p = 2)
{
    if (!is.na(pmatch(method, "euclidian")))
        method <- "euclidean"
    METHODS <- c("euclidean", "maximum", "manhattan", "canberra",
        "binary", "minkowski")
    method <- pmatch(method, METHODS)
    if (is.na(method))
        stop("invalid distance method")
    if (method == -1)
        stop("ambiguous distance method")
    x <- as.matrix(x)
    N <
    att
                                                = diag,
                                                = p, call = match.call(),

    else list                , Labels = dimnames(x)[[1L]], Diag = diag,
        Up       = upper, method = METHODS[method], call = match.call(),
        class = "dist")
    .Call(C_Cdist, x, method, attrs, p)
}
<bytecode: 0x0000000014068a90>
<environment: namespace:stats>
```

Call C function, C_Cdist

Tips: 1. Reorganize code structure for GPU friendly
2. Avoid much logical checks, such as isnan()
3. Notice data copy method/size between CPU and GPU
4. Use '-Mlarge_arrays' compiler option for big data

source code: <R source code path>/src/library/stats/src/distance.c

```
static double R_euclidean(double *x, int nr, int nc, int i1, int i2)
{
    double dev, dist;
    int count, j;

    count= 0;
    dist = 0;
    for(j = 0 ; j < nc ; j++) {
        if(both_non_NA(x[i1], x[i2])) {
            dev = (x[i1] - x[i2]);
            if(!ISNAN(dev)) {
                dist += dev * dev;
                count++;
            }
        }
        i1 += nr;
        i2 += nr;
    }
    if(count == 0) return NA_REAL;
    if(count != nc) dist /= ((double)count/nc);
    return sqrt(dist);
}
```

```
//Patric: Fine granularity parallel by openACC
//#include <cmath>
static double R_euclidean(double *x, int nr, int nc, int i1, int i2)
{
    double dev, dist;
    int    count, j;

    dist = 0;
    dev  = 0;
    count = 0;
//#pragma acc routine(std::isnan) seq
#pragma acc data copyin(x[0:nc*nr-1]) copy(dist)
#pragma acc parallel for                \
            firstprivate(nc, nr)      \
            private(j,dev,dist)      \
            reduction(+:dist)
    for(j = 0 ; j < nc ; j++) {
        dev   = (x[i1 + j*nr] - x[i2 + j*nr]);
        dist  += dev * dev;
    }
//    if(count == 0) return NA_REAL;
//    if(count != nc) dist /= ((double)count/nc);
     return sqrt(dist);
}
```

Compile with PGI

1. Do ‘make VERBOSE=1’ in stats/src

   this step will generate detail information for build

2. Compile distance.c by PGI

   original: gcc -std=gnu99 … -c distance.c -o distance.o

   changed: pgcc -acc -ta=nvidia -Minfo … -c distance.c -o distance.o

3. Link all .o file to .so by PGI

   original: gcc -std=gnu99 -shared -o stats.so init.o <all.o> ….

   changed: pgcc -acc -ta=nvidia –shared -o stats.so init.o <all.o> …

4. Updata stats.so

   cp stats.so <R-path>/lib64/R/library/stats/libs/

5. Launch R and Execution as normally

   use nvprof to confirm : nvprof R ….

Compile with PGI

1. Do ‘make VERBOSE=1’ in stats/src

   this step will generate detail information fo

2. Compile distance.c by PGI

   original: gcc -std=gnu99 … -c dist -o distance.o

   changed: **pgcc** -acc -ta=nvidia -Minfo … -c distance.c -o distance.o

3. Link all .o file to .so by PGI

   original: gcc -std=gnu99 -shared -o stats.so init.o <all.o> ….

   changed: **pgcc** -acc -ta=nvidia -shared -o stats.so init.o <all.o> …

4. Updata stats.so

   cp stats.so <R-path>/lib64/R/library/stats/libs/

5. Launch R and Execution as normally

   use nvprof to confirm : nvprof R ….

```
R_euclidean:
    53, Generating copyin(x[:nr*nc])
        Generating copy(dist)
    54, Accelerator kernel generated
    54, Sum reduction generated for dist
    55, #pragma acc loop gang, vector(256)
         /* blockIdx.x threadIdx.x */
    54, Generating Tesla code
```

Compile with PGI

1. Do ‘make VERBOSE=1’ in stats/src

   this step will generate detail information for build

2. Compile distance.c by PGI

   original: gcc -std=gnu99 … -c distance.c -o distance.o

   changed: pgcc -ac

3. Link all .o file to .so l

   original: gcc -std=g

   changed: pgcc -acc

4. Updata stats.so

   cp stats.so <R-path>/lib64/R/library/st[illegible]s/libs/

5. Launch R and Execution as norma[illegible]y

   use nvprof to confirm : nvprof R ….

```
> dist(z)
==30114== NVPROF is profiling process 30114, command: /home-2/patricz/tools/R-3.0.2-disable_openmp/lib64/R/bin/exec/R
          x
y 165550.3
> q()
Save workspace image? [y/n/c]: n
==30114== Profiling application: /home-2/patricz/tools/R-3.0.2-disable_openmp/lib64/R/bin/exec/R
==30114== Profiling result:
Time(%)      Time     Calls       Avg       Min       Max  Name
 77.80%  27.074ms        17  1.5926ms  3.6480us  1.7057ms  [CUDA memcpy HtoD]
 21.70%  7.5496ms         1  7.5496ms  7.5496ms  7.5496ms  R_euclidean_53_gpu
  0.49%  170.22us         1  170.22us  170.22us  170.22us  R_euclidean_53_gpu_red
  0.01%  3.8400us         1  3.8400    3.8400us  3.8400us  [CUDA memcpy DtoH]
```

RESULTS

Testing code from R:

```
a <- runif(2^24, 1, 5)
b <- runif(2^24, 1, 5)
x <- rbind(a,b)
system.time( dist(x) )
```

Vector (2^24)	Runtime (sec)	Speedup
R built-in dist()	0.207	
OpenACC	0.093	2.23X

CPU Intel Xeon E5-2609 @ 2.40GHz / 64 GB RAM

GPU Tesla K20Xm with 6GB device memory

3. COMBINE CUDA LANGUAGES TO R

- Existing libraries cant meet up function/performance target
- Write up your own functions by CUDA
- Same flow with calling CUDA library

    - Just change the CUDA API to your own kernel

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Step 1: write GPU kernel function for your algorithm

```
__global__ void  vectorAdd(const double *A,
                           const double *B,
                           double *C,
                           int numElements)
{
    int i = blockDim.x * blockIdx.x +  threadIdx.x;
    if(i < numElements)
    {
        C[i] = A[i] + B[i];
    }
}
```

Step 2: write wrapper function to call GPU kernel

```
extern "C“ void gvectorAdd(double *A, double *B, double *C, int *n)
{
  // Device Memory
  double *d_A, *d_B, *d_C;
  // Define the execution configuration
  dim3 blockSize(256,1,1);
  dim3 gridSize(1,1,1);
  gridSize.x = (*n + blockSize.x - 1) / blockSize.x;

  // Allocate output array
  cudaMalloc((void**)&d_A, *n * sizeof(double));
  cudaMalloc((void**)&d_B, *n * sizeof(double));
  cudaMalloc((void**)&d_C, *n * sizeof(double));

  // copy data to device
  cudaMemcpy(d_A, A, *n * sizeof(double), cudaMemcpyHostToDevice);
  cudaMemcpy(d_B, B, *n * sizeof(double), cudaMemcpyHostToDevice);
  // GPU vector add
  vectorAdd<<<gridsize,blocksize>>>(d_A, d_B, d_C, *n);

  // Copy output
  cudaMemcpy(C, d_C, *n * sizeof(double), cudaMemcpyDeviceToHost);
  cudaFree(d_A);
  cudaFree(d_B);
  cudaFree(d_C);
}
```

declare for R

allocate memory for CPU and GPU

Copy memory from CPU to GPU

Call CUDA kernel

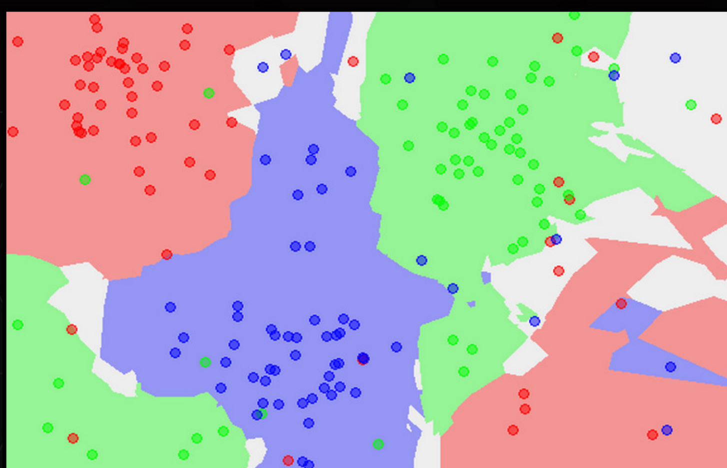
Copy memory back from GPU to CPU

Free memory

4.CASE STUDY: K NEAREST NEIGHBORS

- Common classify algorithm
- Find K nearest neighbors from the training data by distance
- O(MNP) time complexity for direct implementation
- Benchmark: handwritten digits data of MNIST

  Kaggle data size : test(~30k, ~2k), train(~40k, ~2k)



5-NN Classifier Map from Wikipedia

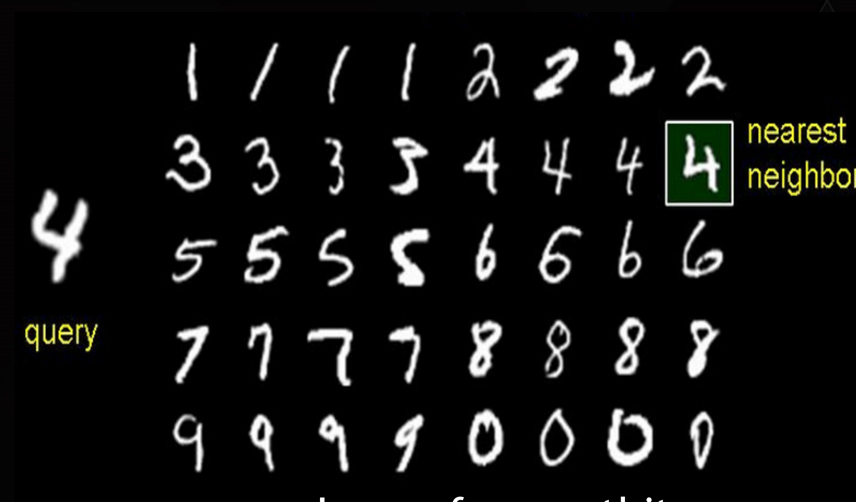
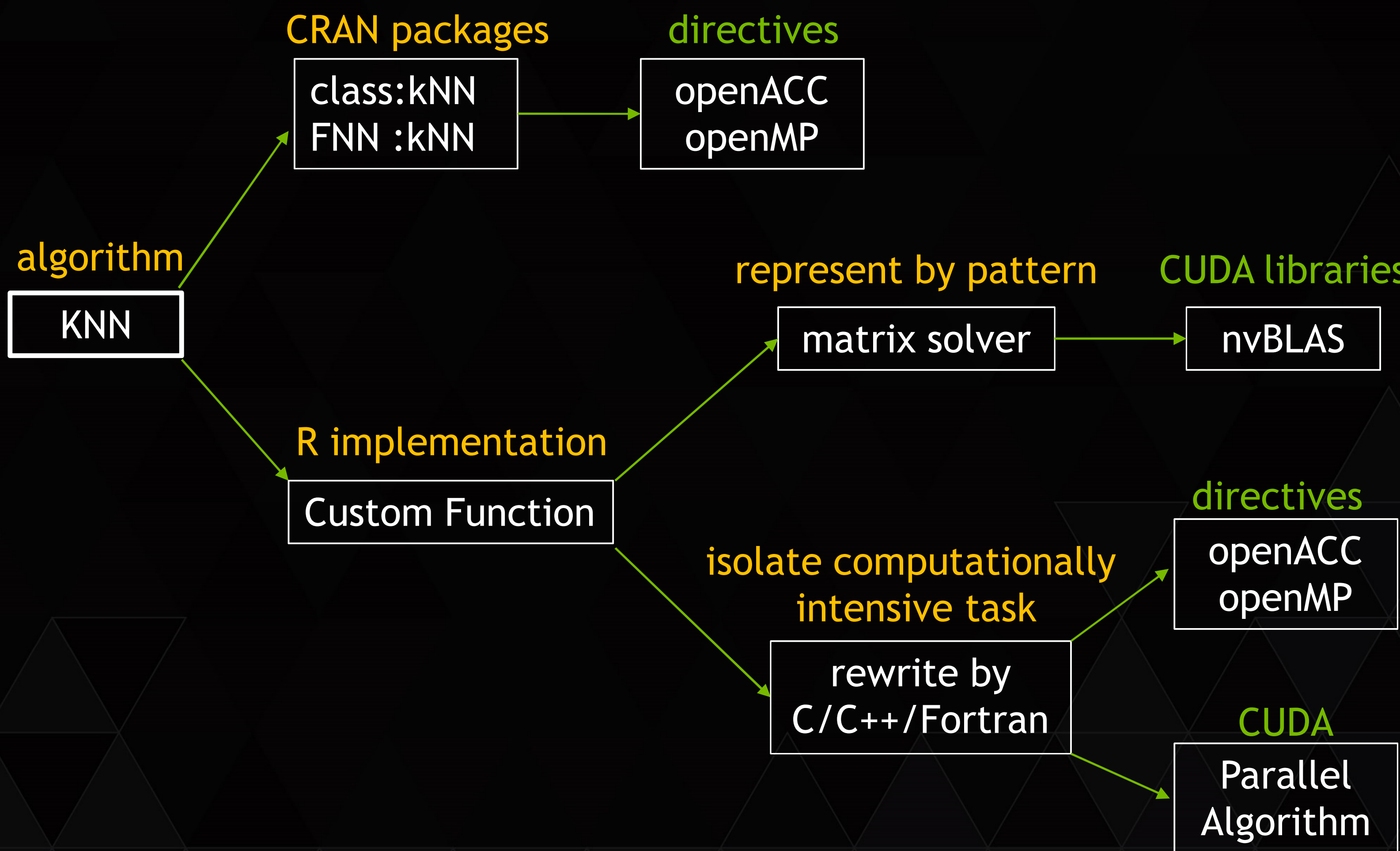


Image from ~athitsos

Parallel Strategies



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Basic Algorithm and Performance Baseline

Steps for kNN:

- Query a record : compute distance, sort, return most frequent labels

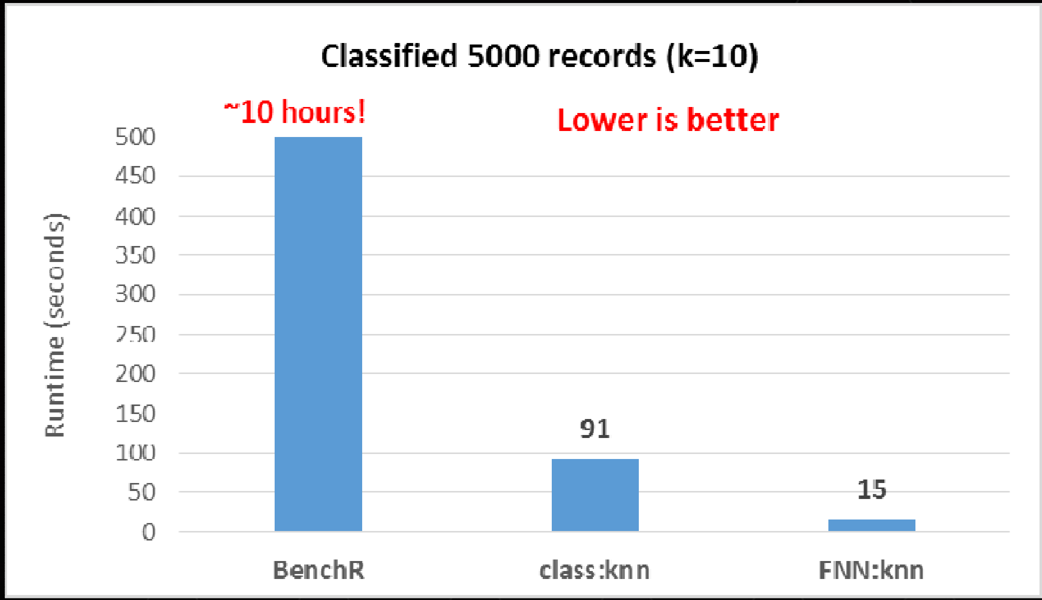
$$distance(j) = \sum_{k}^{P}(test_{jk} - train_{jk})^2$$

Implementations:

-Most common package
  class:KNN (C)

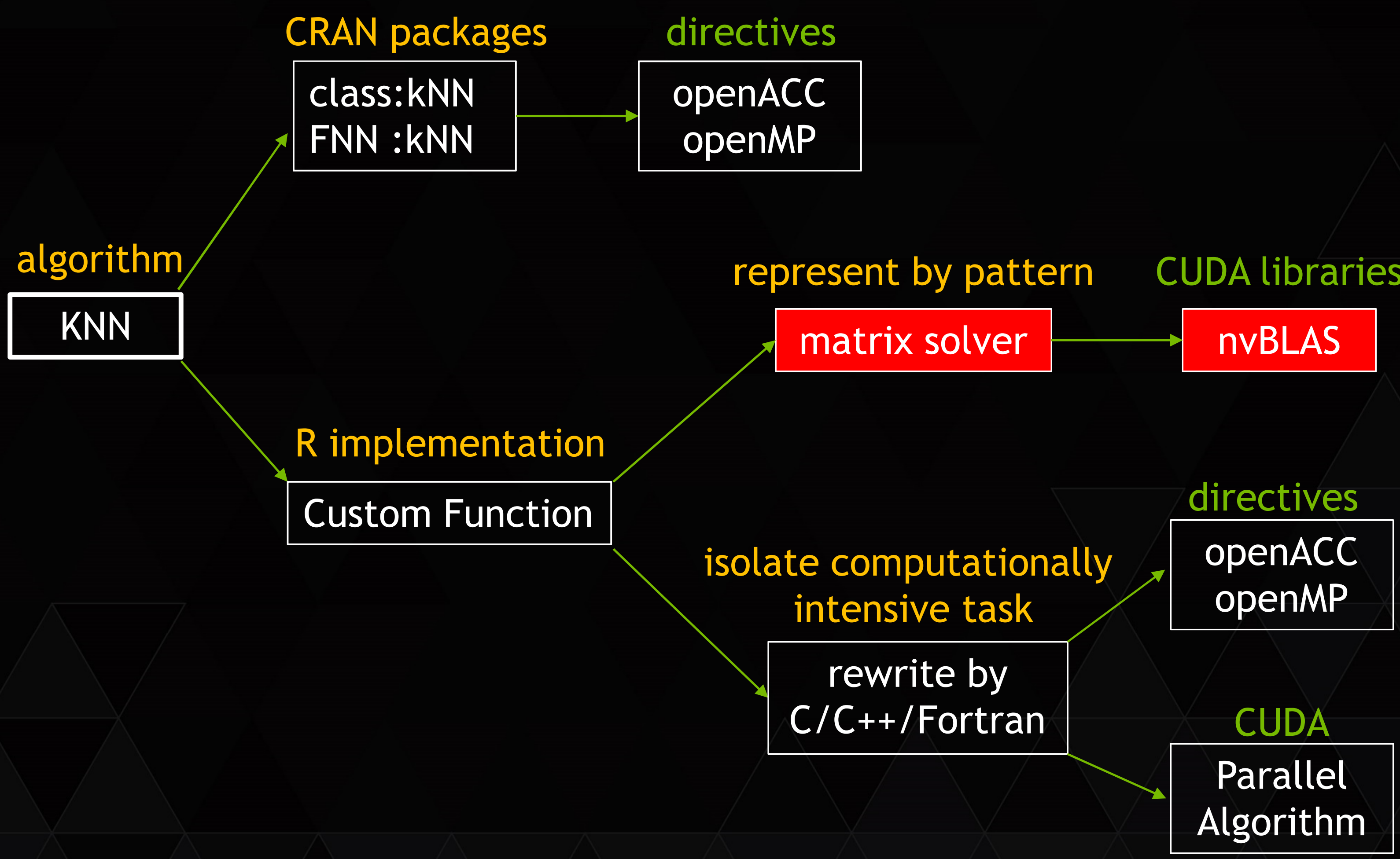
-Fast package
  FNN:KNN
  (C++, fast algorithm kd-tree)

-R implementation
  BenchR (R with 1 loop)



CPU: Ivy Bridge E5-2690 v2 @ 3.00GHz, dual socket 10-core, 128G
GPU: Nvidia Kepler, K40, 6G

Parallel Strategies



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Rewrite R implementation by pattern

$$\text{distance} = \sum_j^n \sum_i^p (\boldsymbol{test_i} - \boldsymbol{train_i})_j^2$$

$$= \sum_j^n \sum_i^p (\text{test}_i^2 \text{ - } 2^* \text{ test}_i{}^* \text{ train}_i + \text{test}_i^2)_j$$

$$= \sum_j^n \sum_i^p \text{test}_{ij}^2 \text{ -}2^* \sum_j^n \sum_i^p (test_i * train_i)_j + \sum_j^n \sum_i^p train_{ij}^2$$

rowSums(test*test)

test %*% t(train)

rowSums(train*train)

Now, we have represented KNN algorithm by matrix operations, and we can easily accelerate it by CUDA libraries as we mentioned previously.

Rewrite KNN by matrix pattern and vectorization

```
#Rewrite BenchR kNN by matrix operations and vectorization
knn.customer.vectorization <- function(traindata, testdata, cl, k)
 {

  n    <- nrow(testdata)
  pred <- rep(NA_character_, n)

  # (traindata[i,] - testdata[i, ])^2 --> (a^2 - 2ab + b^2)
  traindata2 <- rowSums(traindata*traindata)
  testdata2  <- rowSums(testdata*testdata)
  # nvBLAS can speedup this step
  testXtrain <- as.matrix(testdata) %*% t(traindata)

  # compute distance
  dist  <- sweep(testdata2 - 2 * testXtrain, 2, traindata2, '+')

  # get the k smallest neighbor
  nn <- t(apply(dist, 1, order))[,1:k]

  # get the most frequent labels in nearest K
  class.frequency <- apply(nn, 1, FUN=function(i) table(factor(cl[i], levels=unique(cl)))  )
  # find the max label and break ties
  pred <- apply(class.frequency, 2, FUN=function(i) sample(names(i)[i == max(i)],1))

  unname(factor(pred, levels=unique(cl)))

}
```

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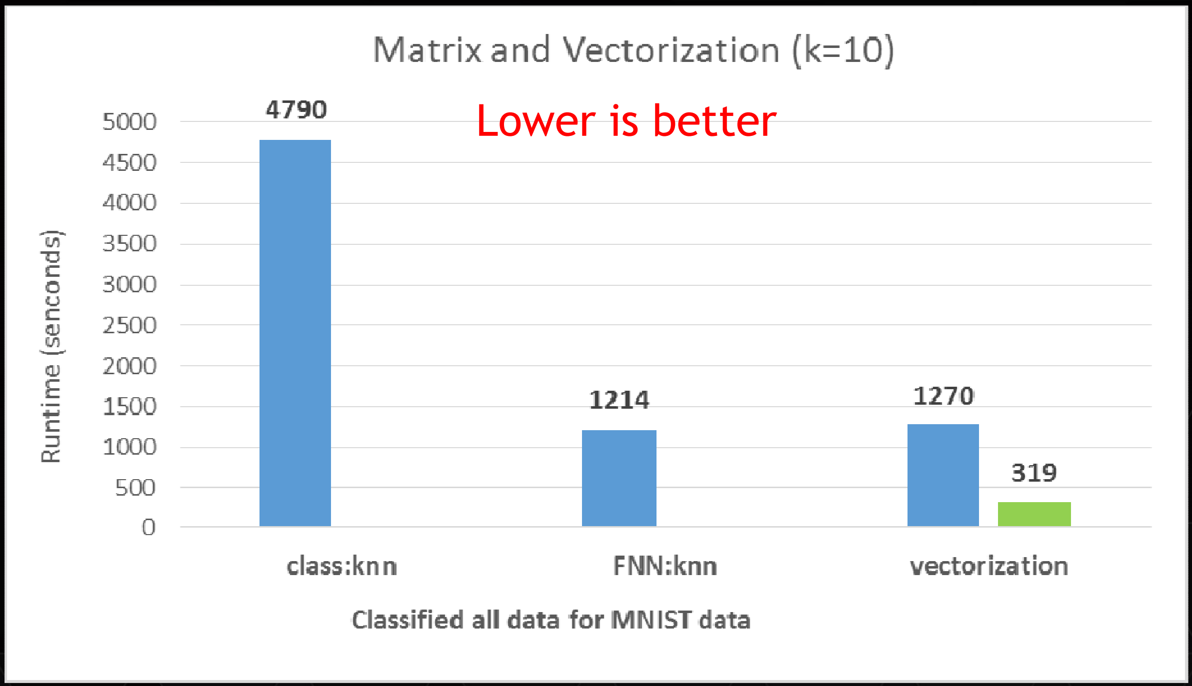
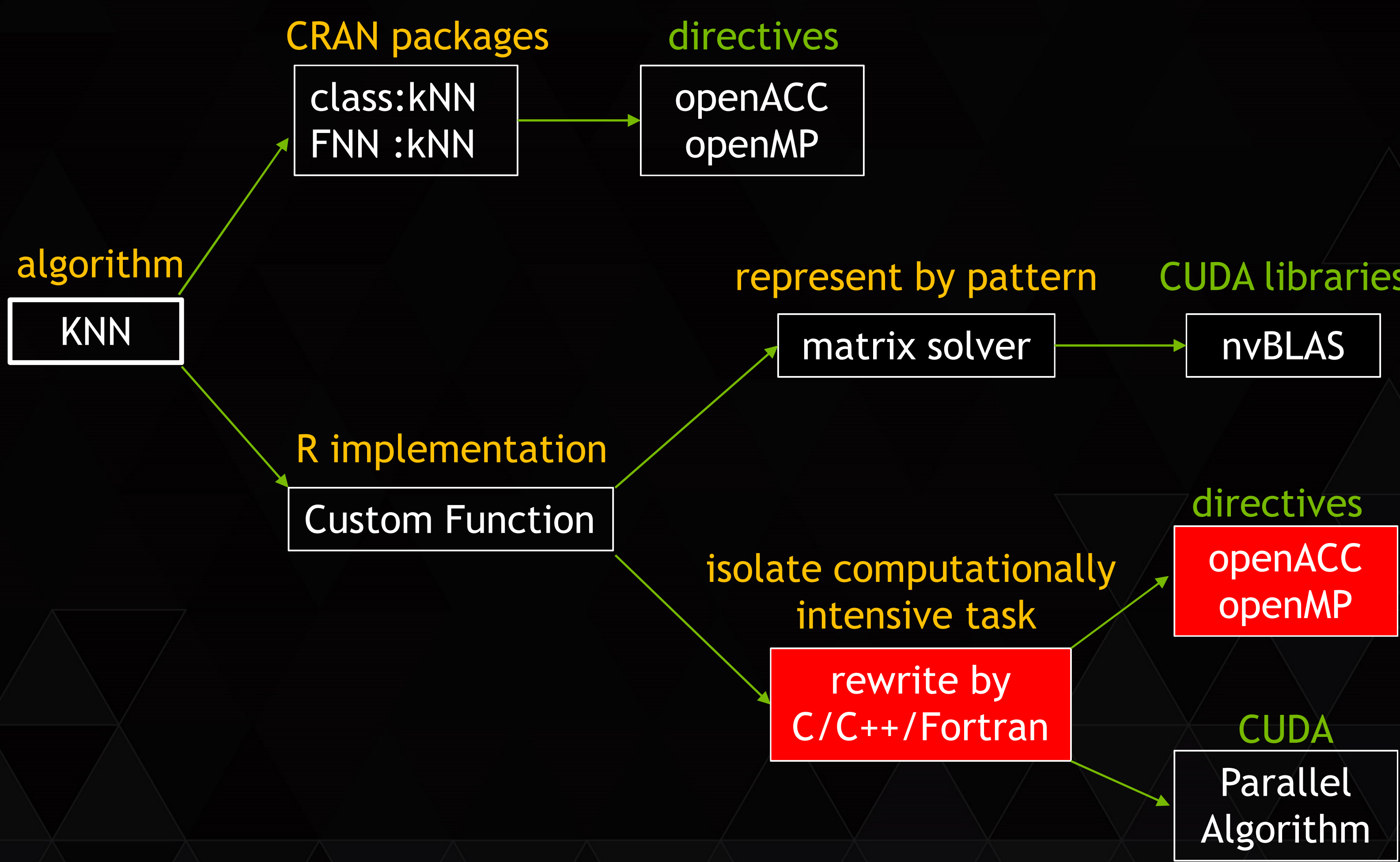
- Matrix version is as fast as FNN:knn
- Run with nvBLAS we got:

  15X faster than class:knn

  3.8X faster than FNN:knn



Parallel Strategies



Isolated computational task and rewrite by C

rewrite kNN by matrix operations and vectorization

```
knn.customer.vectorization <- function(traindata, testdata, cl, k)
 {

  n    <- nrow(testdata)
  pred <- rep(NA_character_, n)

  # (traindata[i,] - testdata[i, ])^2 --> (a^2 - 2ab + b^2)
  traindata2 <- rowSums(traindata*traindata)
  testdata2  <- rowSums(testdata*testdata)
  testXtrain <- as.matrix(testdata) %*% t(traindata)

  # compute distance
  dist  <- sweep(testdata2 - 2 * testXtrain, 2, traindata2, '+')

  # get the k smallest neighbor
  nn <- t(apply(dist, 1, order))[,1:k]

  # get the most frequent labels in nearest K
  class.frequency <- apply(nn, 1, FUN=function(i) table(factor(cl[i], levels=unique(cl)))
)
  # find the max label and break ties
  pred <- apply(class.frequency, 2, FUN=function(i) sample(names(i)[i == max(i)],1))

  unname(factor(pred, levels=unique(cl)))

}
```

```
dist.C <- function(tndata, ttdata)
{
  m <- nrow(ttdata)
  n <- nrow(tndata)
  p <- ncol(ttdata)
  rst <- .C("compute_dist",
  as.integer(n),
  as.integer(m),
  as.integer(p),
  as.double(ttdata),
  as.double(t(tndata)),
  mm = double(length=m*n))
  return(matrix(rst[["mm"]], nrow=m, ncol=n))
}
```

Write a C function

- don't need to transfer R to C line by line (use C style!)
- rethink KNN computations, which is really like GEMM

$$GEMM(i,j) = \sum_{k}^{P}(A_{ijk} * B_{ijk})$$

$$distance\ matrix(i,j) = \sum_{k}^{P}(test_{ijk} - train_{ijk})^2$$

So, we write C code by GEMM style for KNN

```
void compute_dist(int *m, int *n, int *p, double *traindata, double *testdata, double *result);

void compute_dist(int *m, int *n, int *p, double *traindata, double *testdata, double *result)
{

  int i = 0, j = 0, k = 0 ;

  // Compute Distance Matrix
  for(i = 0; i < (*m); i++)
  for(k = 0; k < (*p); k++)
  for(j = 0; j < (*n); j++)
  {
      // GEMM
      //  result[i* (*n) +j] += testdata[i* (*p) +k] *  traindata[k * (*n) +j];

      // KNN
      double dist = testdata[i* (*p) +k] -  traindata[k * (*n) +j];
      result[i* (*n) +j] += dist * dist  ;
  }
}
```

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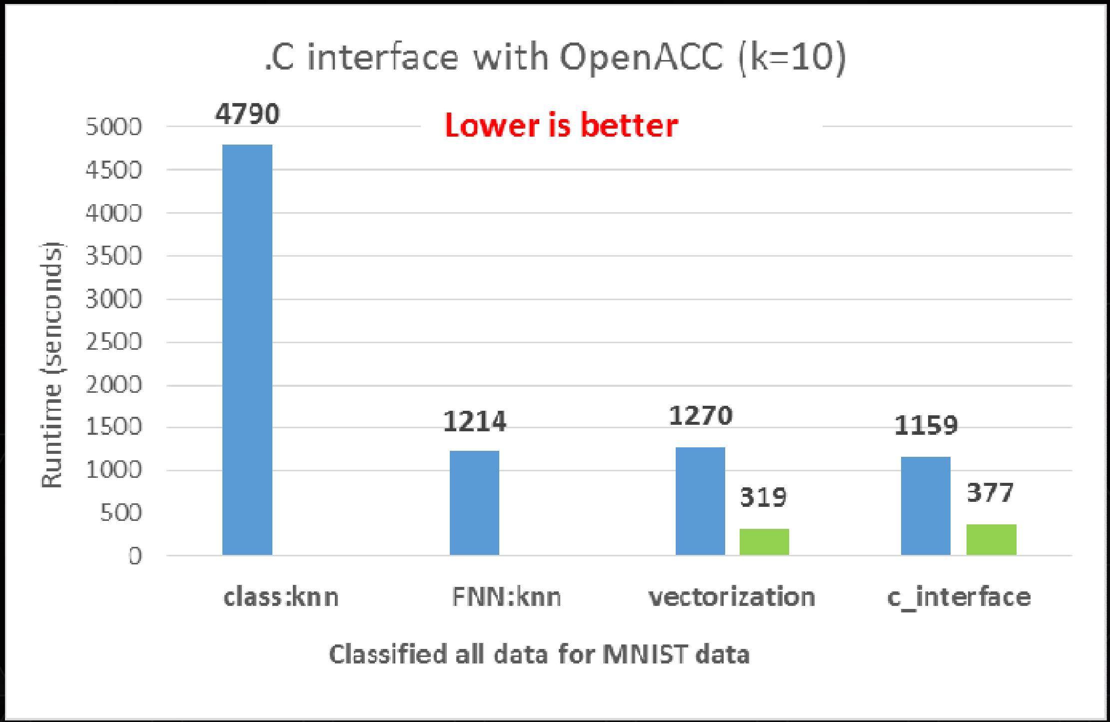
And then, accelerate by openACC

```
void compute_dist(int* m, int* n, int* p, double* restrict traindata, double* restrict testdata, double* restrict result);

void compute_dist(int* m, int* n, int* p, double* restrict traindata, double* restrict testdata, double* restrict result)
{

  int i = 0, j = 0, k = 0 ;
  int mm = *m, nn = *n, pp = *p;

  // Compute Distance Matrix
#pragma acc data copyout(result[0 : (mm * nn) -1]),  copyin(testdata[0 : (mm * pp) -1], traindata[0 : (pp * nn) -1])
  {
#pragma acc region for parallel, private(i), vector(8)
     for(i = 0; i < mm; i++)  {
#pragma acc for parallel,private(j,k),  vector(8)
     for(j = 0; j < nn; j++) {
#pragma acc for seq
     for(k = 0; k < pp; k++)  {
        double tmp = testdata[i* pp +k] -  traindata[k * nn +j];
        result[i* nn +j] += tmp * tmp ;
     }}}
  } // end openACC data region
}
```

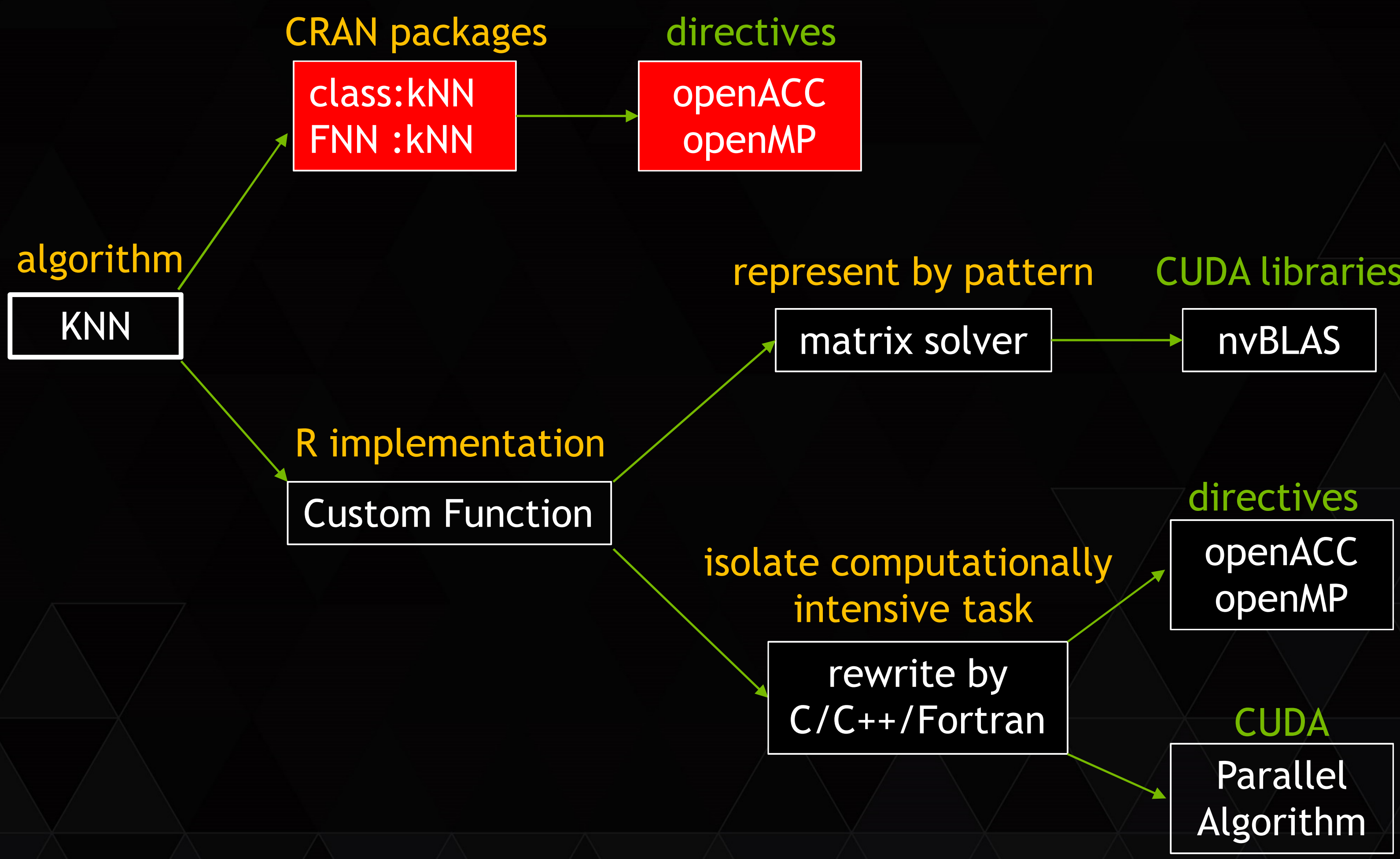
- C version is as fast as FNN:knn
- Compile with PGI (-Mlarge_arrays), we got:

13X faster than class:knn

3.2X faster than FNN:knn



Parallel Strategies



Accelerate CRAN packages by directive

- May be not easy since the package structure will be complex
- Need to fully understand algorithms and their implementations
- Select proper data decomposition method

  coarse granularity – openMP

  finer granularity - openACC

Class:KNN : source code is under:

<R source code path>/src/library/Recommended/class/src/class.c

knn function: *VR_knn(…)*

Coarse Granularity Decomposition

```
void
VR_knn(Sint *kin, Sint *lin, Sint *pntr, Sint *pnte, Sint *p,
       double *train, Sint *class, double *test, Sint *res, double *pr,
       Sint *votes, Sint *nc, Sint *cv, Sint *use_all)
{
            ……
 // Patric: Coarse Granularity Parallel by openMP
#pragma omp parallel for \
 private(npat, i, index, j, k, k1, kn, mm, ntie, extras, pos, nclass, j1, j2, needed, t, dist, tmp, nndist) \
 shared(pr, res, test, train, class, nte, ntr, nc)
   for (npat = 0; npat < nte; npat++) {
          …..

      // Patric : each thread malloc new buffer to resolve memory conflict of votes
      //            change all votes to __votes in below source code.
      //            Calloc is thread-safe function located in memory.c.
       Sint *__votes = Calloc(nc+1, Sint);
       …..

       Free(__votes);
   } // Patric: Top iteration and end of openMP
   RANDOUT;
}
```

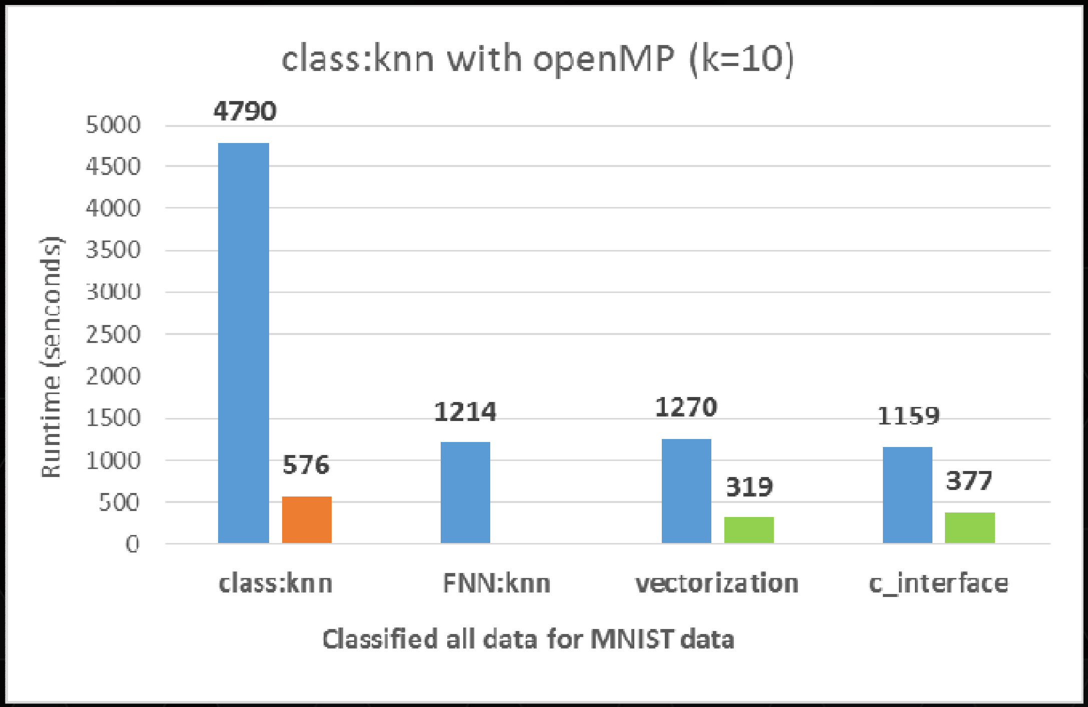
Finer Granularity Decomposition

```
void
VR_knn(Sint *kin, Sint *lin, Sint *pntr, Sint *pnte, Sint *p,
       double *train, Sint *class, double *test, Sint *res, double *pr,
       Sint *votes, Sint *nc, Sint *cv, Sint *use_all)
{
              ......
 // Patric: Finer Granularity Parallel by openACC
#pragma acc data copyin(test[0:nn*nte], train[0: nn*ntr])
    for (npat = 0; npat < nte; npat++) {
            .....

 // Only parallelize this loop  for Least Squares Model
#pragma acc parallel loop private(k), reduction(+:dist)
            for (k = 0; k < *p; k++) {
                tmp = test[npat + k * nte] - train[j + k * ntr];
                dist += tmp * tmp;
            }

......

}
RANDOUT;
}
```

- OpenACC version is not fast than original (only 2k features)
- OpenMP (1 CPU, 10 threads) is faster , we got:

  8.3X faster than class:knn

  2.3X faster than FNN:knn



Our post includes more details:

http://devblogs.nvidia.com/parallelforall/author/patricz/

Learn more on GTC 2015

CUDA General (tools, libraries)

S5820 - CUDA 7 and Beyond

CUDA Programming

S5651 - Hands-on Lab: Getting Started with CUDA C/C++

S5661 , S5662, S5663, S5664, CUDA Programming Series

Directives

S5192 - Introduction to Compiler Directives with OpenACC

Handwritten Digit Recognition

S5674 - Hands-on Lab: Introduction to Machine Learning with GPUs: Handwritten Digit Classification

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THANK YOU

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#GTC15

APPENDIX:

BUILD R WITH CUDA BY VISUAL STUDIO 2013 ON WINDOWS

1. Download and install Visual Studio 2013

   http://www.visualstudio.com/downloads/download-visual-studio-vs

2. Download and install CUDA toolkit

   https://developer.nvidia.com/cuda-toolkit

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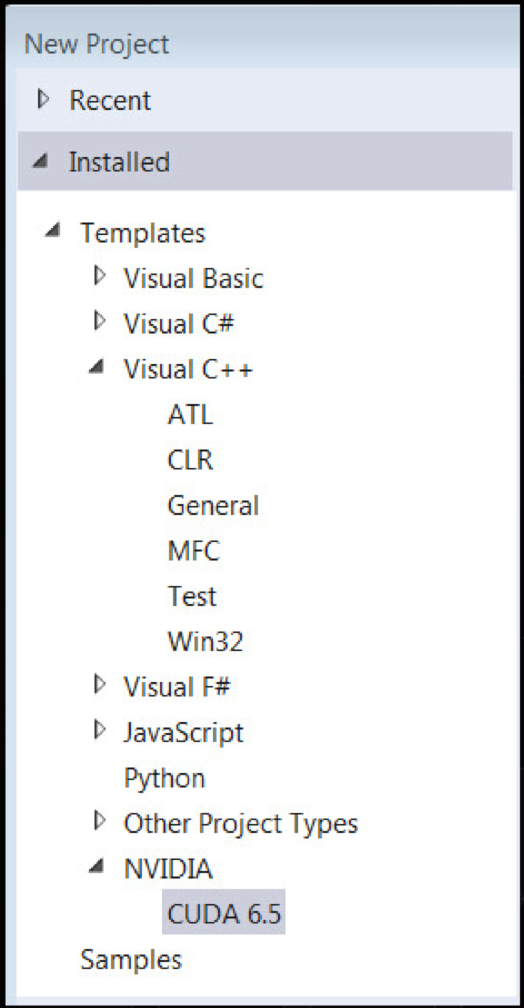
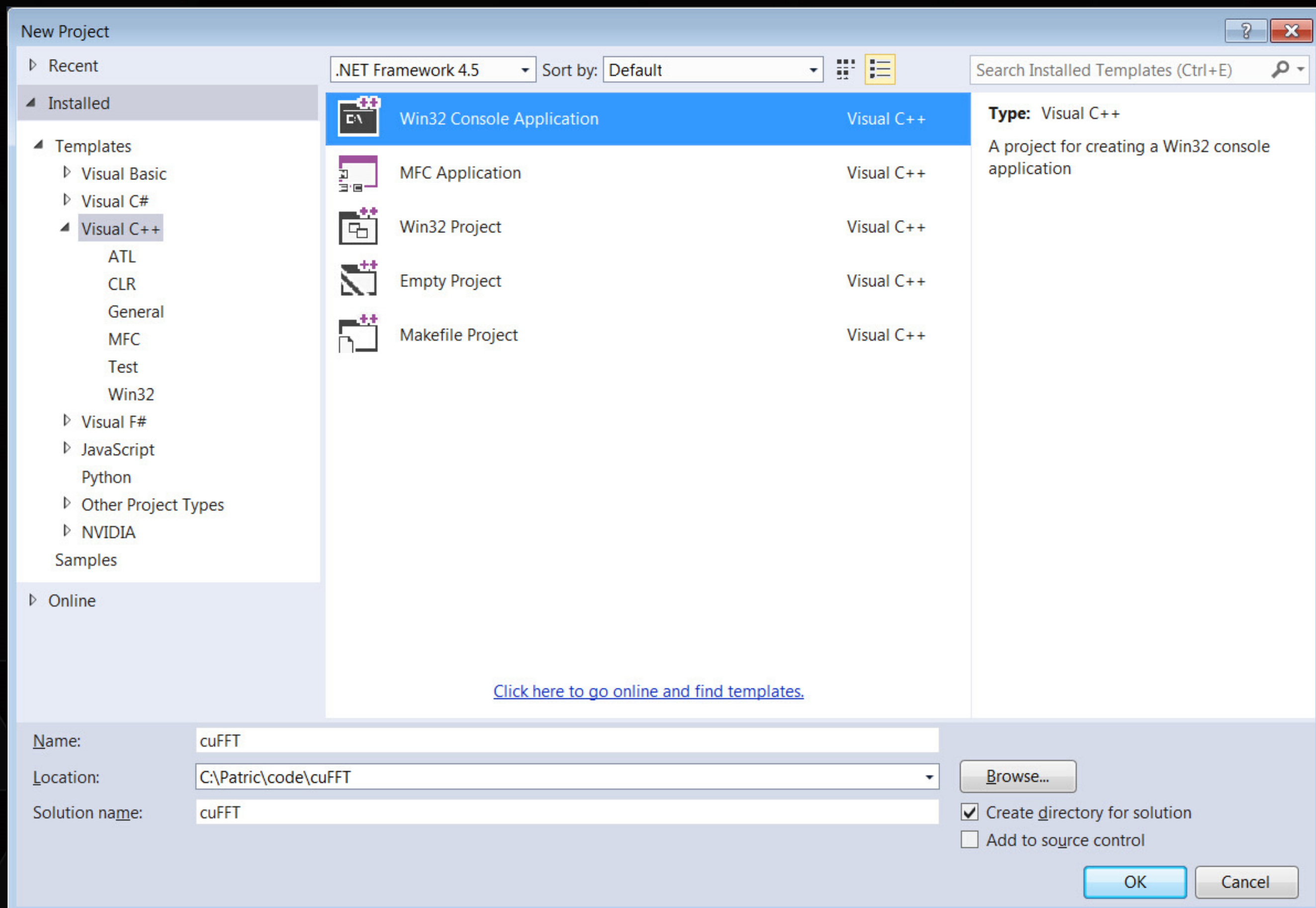
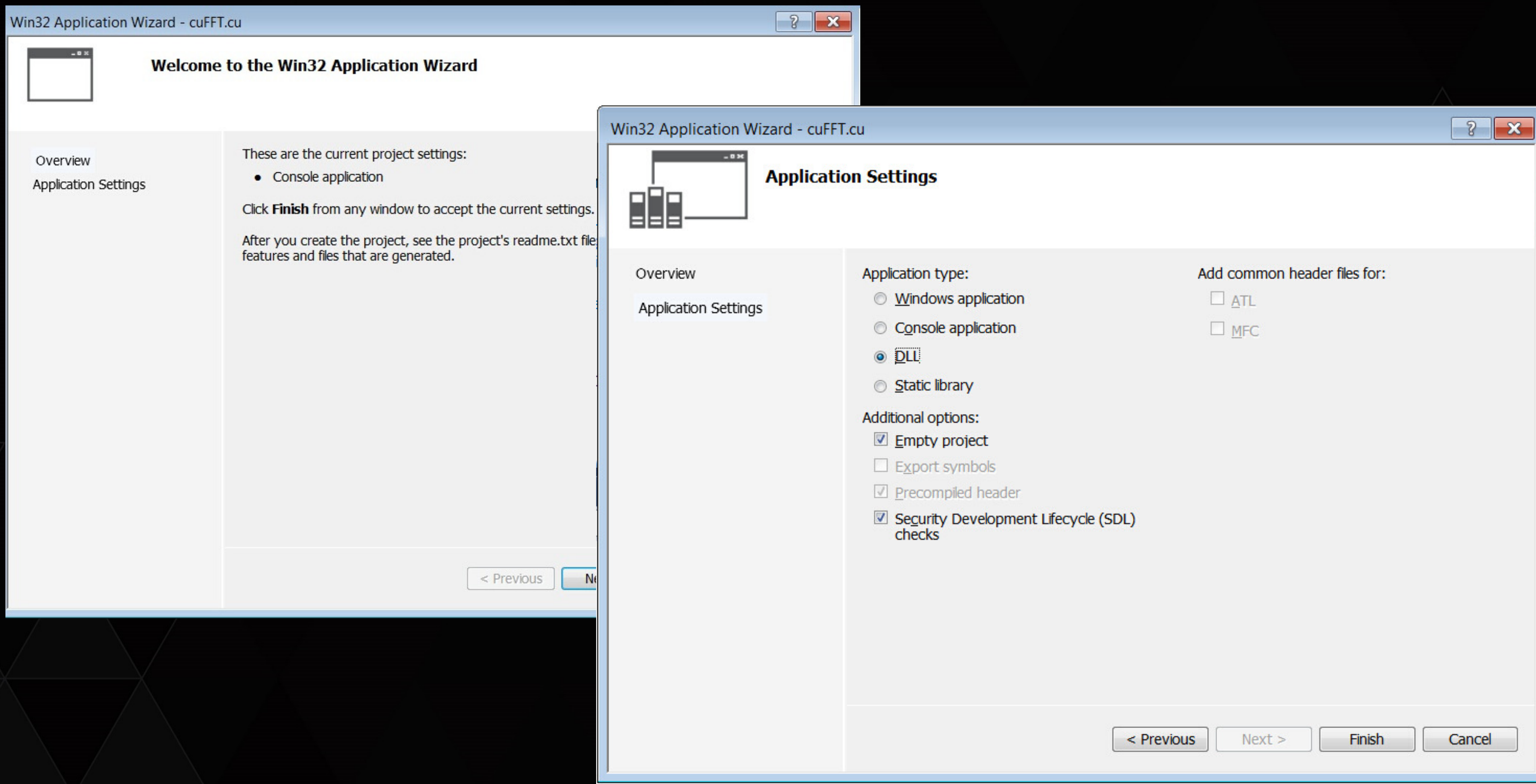
3. Open VS2013, and create 'New Project' then you will see NVIDIA/CUDA item.



4. Select ‘Visual C++’ → ‘Win32 Console Application’



5. Select ‘DLL’ for Application type to create a ‘Empty project’ in Wizard platform



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6. Changes Project type to CUDA

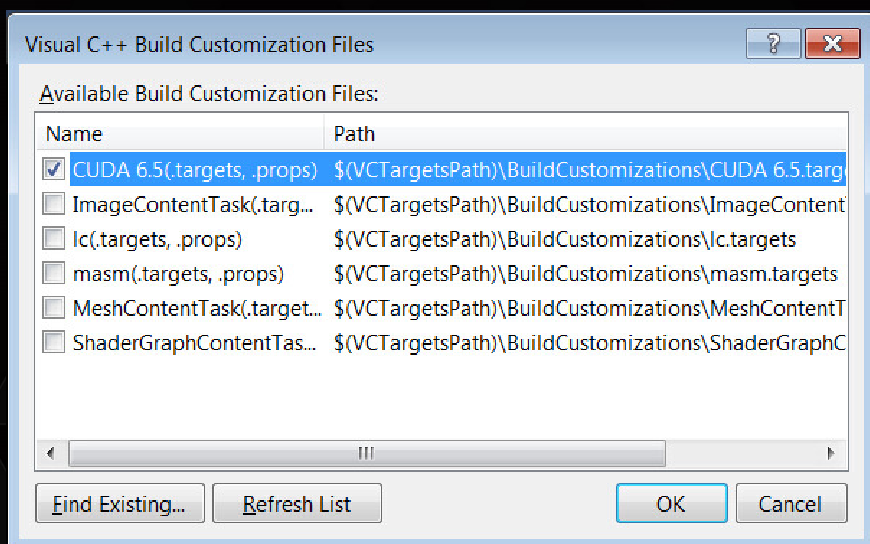
‘Solution Explorer’ →

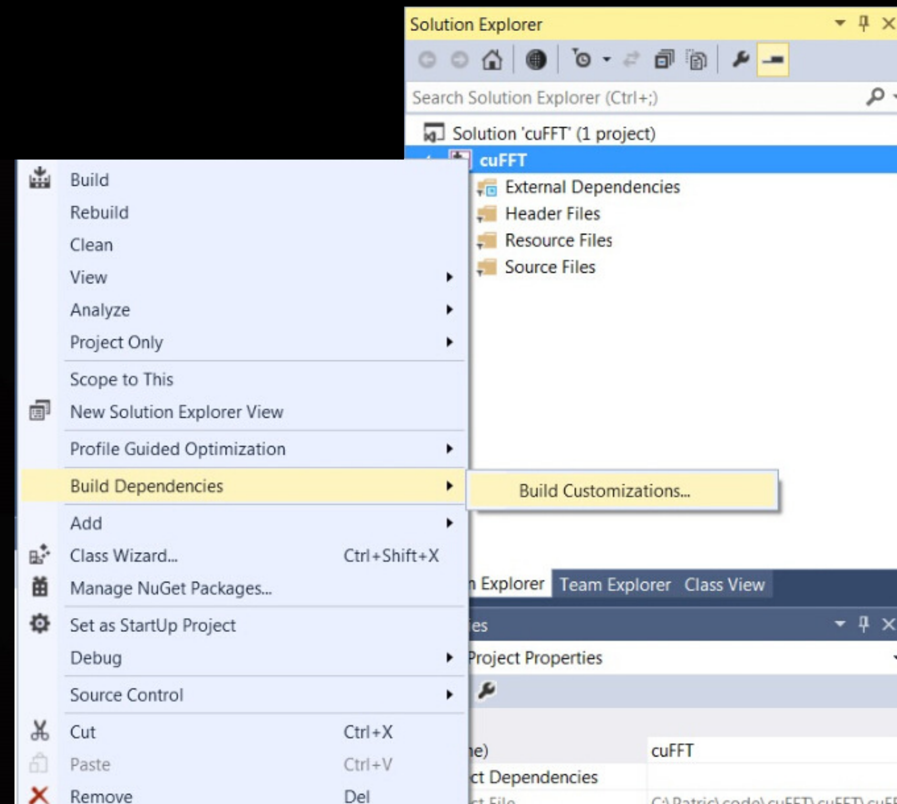
right click project name →

‘Build Dependencies’ →

‘Build Customizations…’ →

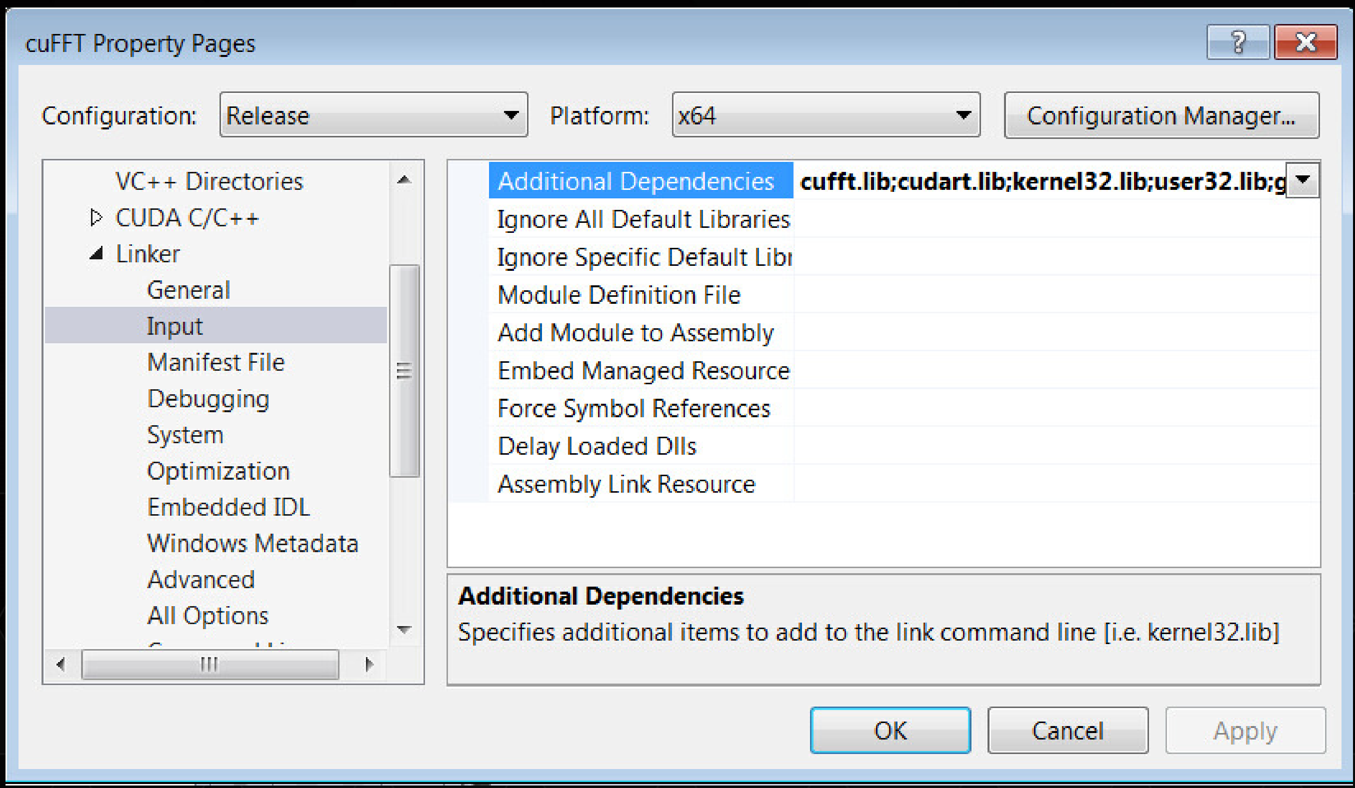
‘CUDA 6.5’





7. Add cuda and cuda accelerated libraries into Visual Studio

Right project name in ‘Solution Explorer’ →
‘Properties’ → ‘Linker’ → ‘Input’ → ’Additional Dependencies’
Add “cufft.lib” and “cudart.lib”



8. Add CUDA source code file with .cu suffix

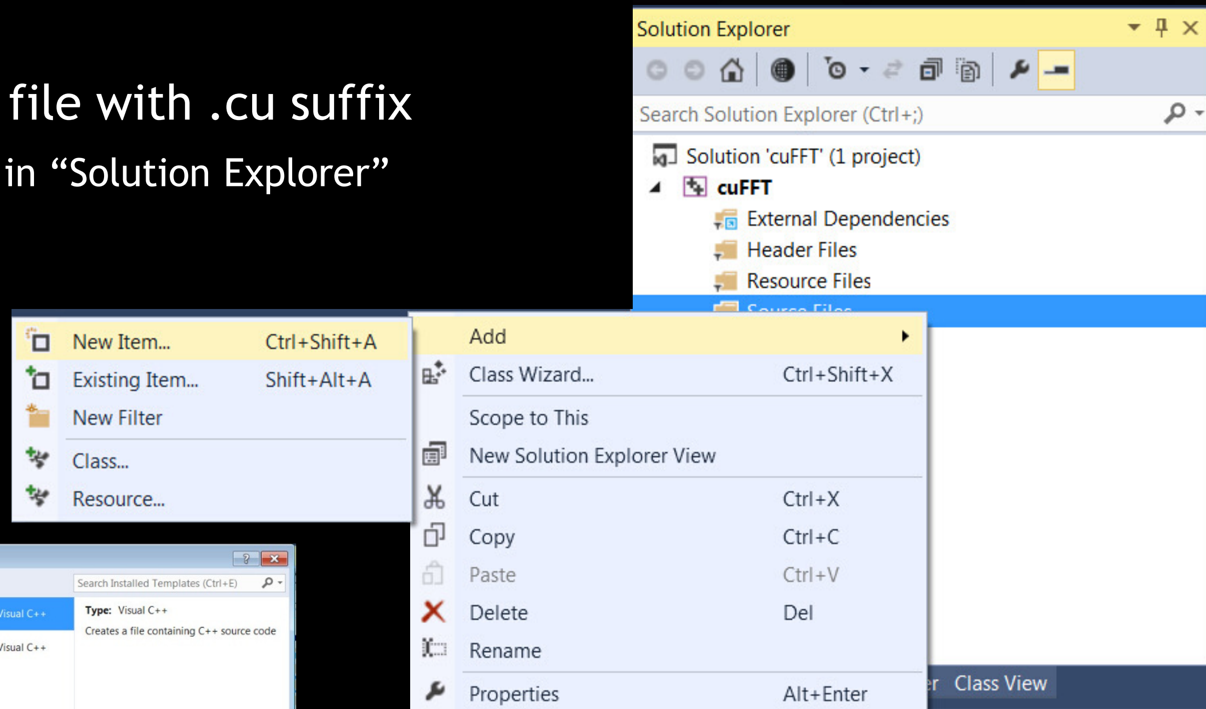
Right click “Source Files” in “Solution Explorer”

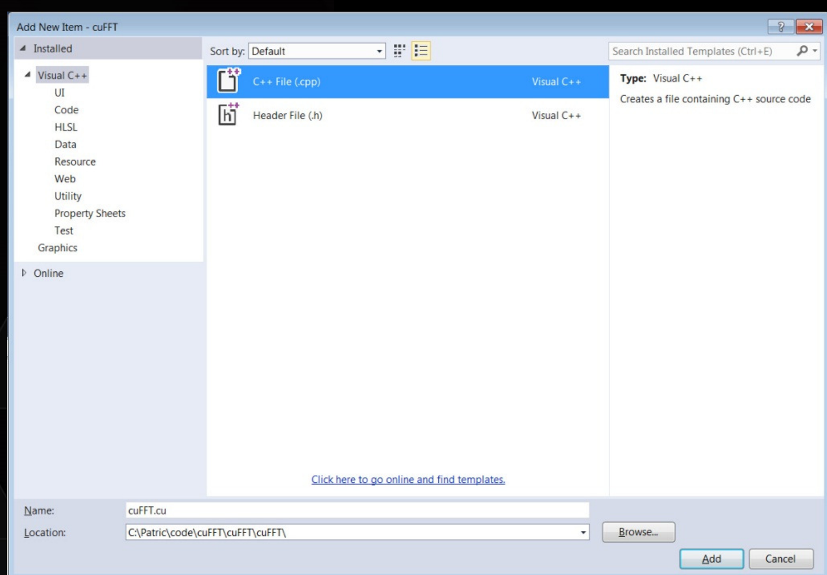
→ ‘Add’

→ ‘New Item’

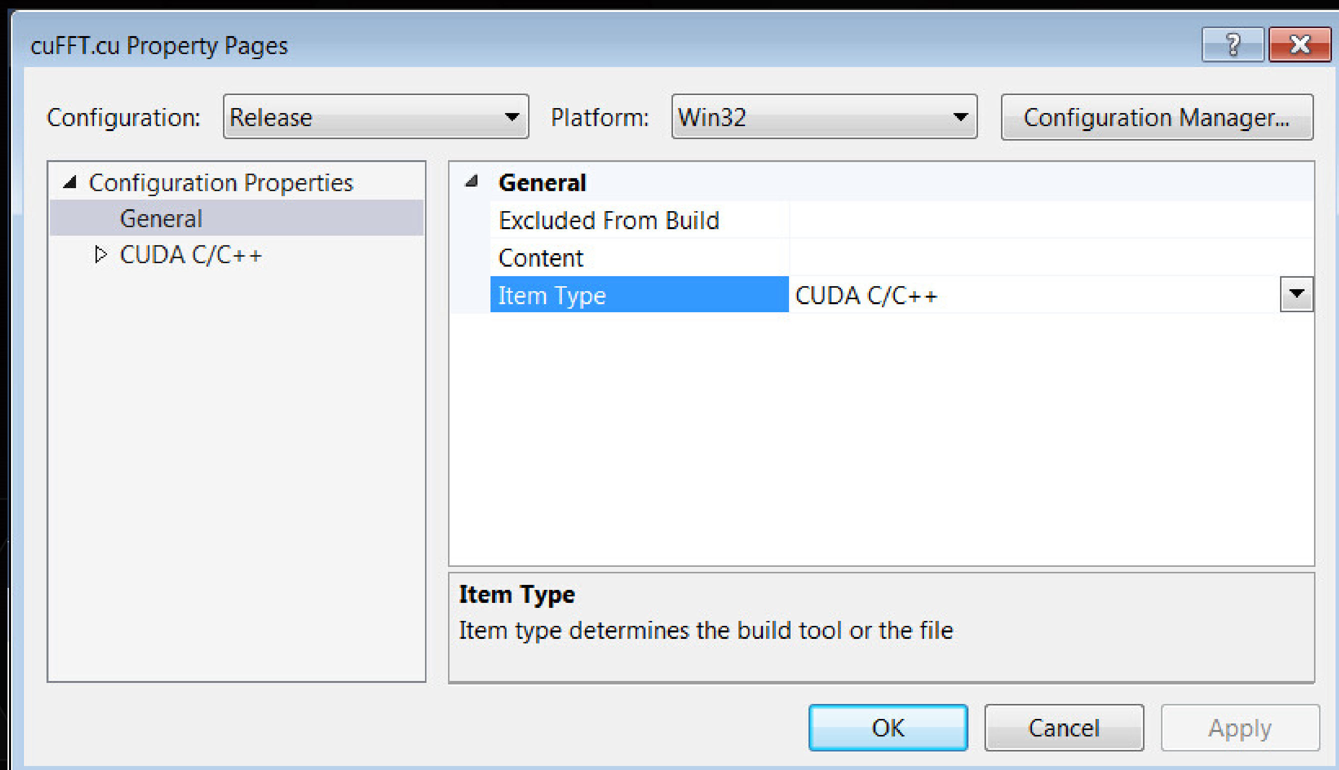
→ ‘C++ File(.cpp)’

→ type cuFFt.cu





- Check the ‘Item type’ of cuFFT.cu by right clicking filename (cuFFT.cu) and selecting ‘Properties’.
- The type should be ‘CUDA C/C++’; otherwise, change to CUDA type.



9. Change to 64bit in case you are using 64bit R and CUDA

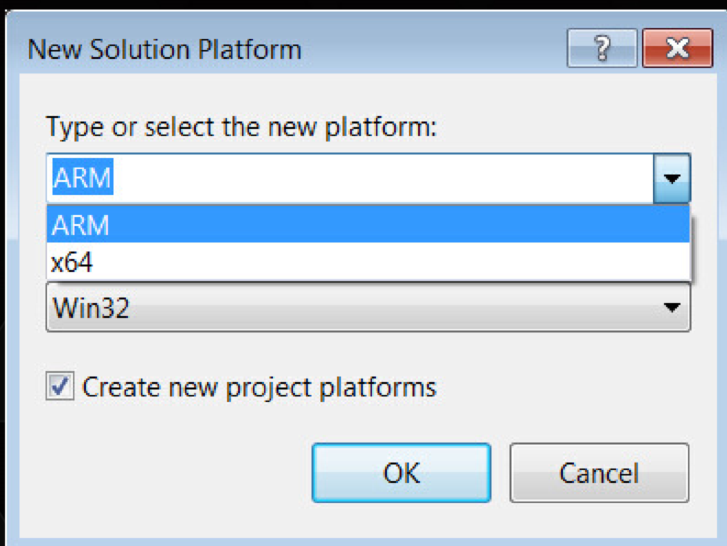
→ ‘Build’

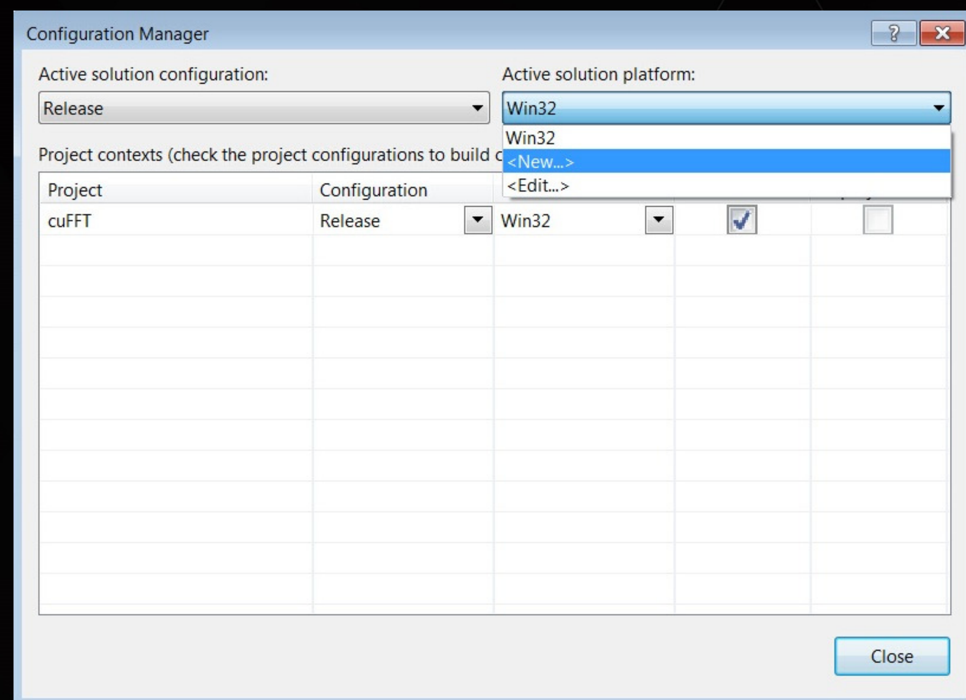
→ ‘Configuration Manager’

→ ‘Active solution platform:’

→ ‘New’

→ select ‘x64’





10. Select 64bit CUDA and shared runtime

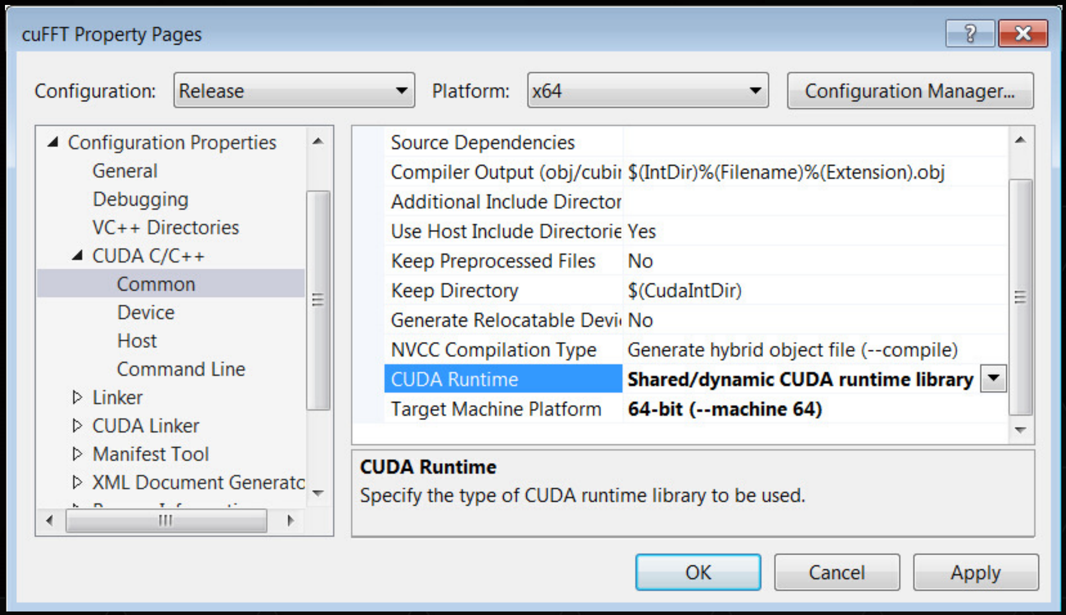
→ Right project name in 'Solution Explorer'

→ 'Properties' → 'CUDA C/C++' → 'Common'

Select :

'Shared/dynamic CDUA runtime library' in CUDA Runtime

'64-bit (--machine 64)' in Target Machine Platform



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11. Copy your CUDA code into this file

- Add necessary header files for CUDA

```
/* Basic API header files*/
#include <stdlib.h>

/* CUDA API header files*/
#include <cufft.h>
#include <cuda_runtime.h>
```

- Declare routines which need to call from R with
  extern “c” __declspec(dllexport)

```
extern "C" __declspec(dllexport)
void cufft(int *n, int *inverse, double *h_idata_re, double *h_idata_im, double *h_odata_re, double *h_odata_im)
```

12. Build Project and get cuFFT.dll

```
1>     Creating library C:\Patric\code\cuFFT\cuFFT\x64\Release\cuFFT.lib and object C:\Patric\code\cuFFT\cuFFT\x64\Release\cuFFT.exp
1>  LINK : /LTCG specified but no code generation required; remove /LTCG from the link command line to improve linker performance
1>  cuFFT.vcxproj -> C:\Patric\code\cuFFT\cuFFT\x64\Release\cuFFT.dll
========== Rebuild All: 1 succeeded, 0 failed, 0 skipped ==========
```

13. Load cuFFT.dll in R and check the dll path

```
> dyn.load("C:\\Patric\\code\\cuFFT\\cuFFT\\x64\\Release\\cuFFT.dll")
> getLoadedDLLs()
                                                                  Filename Dynamic.Lookup
base                                                                  base          FALSE
utils             C:/Program Files/R/R-3.0.2/library/utils/libs/x64/utils.dll          FALSE
methods       C:/Program Files/R/R-3.0.2/library/methods/libs/x64/methods.dll          FALSE
grDevices   C:/Program Files/R/R-3.0.2/library/grDevices/libs/x64/grDevices.dll          FALSE
graphics     C:/Program Files/R/R-3.0.2/library/graphics/libs/x64/graphics.dll          FALSE
stats             C:/Program Files/R/R-3.0.2/library/stats/libs/x64/stats.dll          FALSE
tools             C:/Program Files/R/R-3.0.2/library/tools/libs/x64/tools.dll          FALSE
internet                    C:/PROGRA~1/R/R-30~1.2/modules/x64/internet.dll           TRUE
(embedding)                                                        (embedding)          FALSE
cuFFT                         C:/Patric/code/cuFFT/cuFFT/x64/Release/cuFFT.dll           TRUE
```

14. Run cuFFT in R on Windows

```
> z <-  complex(real = stats::rnorm(num), imaginary = stats::rnorm(num))
> cufft1D(z)
[1] -3.375226-0.617570i  1.128137+3.148557i -0.781643+2.983633i -6.233749-0.037744i
> fft(z)
[1] -3.375226-0.617570i  1.128137+3.148557i -0.781643+2.983633i -6.233749-0.037744i
```

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Multi-GPUs Case : General Matrix Multiplication

- Just add more GPU index in nvblas.conf file

  NVBLAS_GPU_LIST 0 1

- GPU solution gains
  - higher speedup than multi-threads solutions