Introduction to High Performance Computing

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SDS406 – Fall semester, 2024 - 2025

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L07: GPU programming, 11th November 2024

Outline

Matrix-vector multiplication on GPUs

Covering:

- Shared memory
- Details of GPU thread scheduling and warps
- Use of __syncthreads()
- Two-dimensional thread blocks

Matrix vector multiplication

y = Ax

- In the general case A is not square
- $A_{M \times N}, x_N, y_M$

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```
for(int i=0; i<m; i++) {
  y[i] = 0;
  for(int j=0; j<n; j++) {
    y[i] = y[i] + A[i][j] * x[j];
  }
}</pre>
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```
for(int i=0; i<m; i++) {
  y[i] = 0;
  for(int j=0; j<n; j++) {
    y[i] += A[i*n + j] * x[j];
  }
}</pre>
```

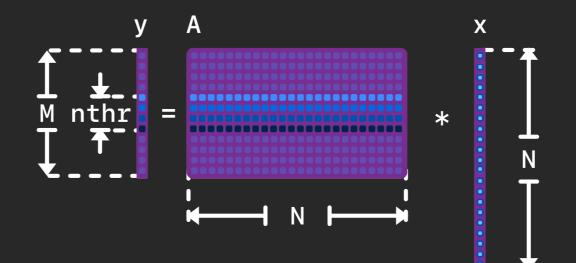
Take /onyx/data/sds406f24/l07/ex01/. for the CPU code¹:

```
[ikoutsou@front02 l07]$ cp -r /onyx/data/sds406f24/l07/ex01 .
[ikoutsou@front02 l07]$ cd ex01/.
[ikoutsou@front02 ex01]$ nvcc -arch=sm_60 -03 -Xcompiler -fopenmp -o matvec matvec.cu
[ikoutsou@front02 ex01]$ export OMP_PLACES="cores"
[ikoutsou@front02 ex01]$ export OMP_PROC_BIND="close"
[ikoutsou@front02 ex01]$ export OMP_NUM_THREADS=16
[ikoutsou@front02 ex01]$ srun -N 1 --cpus-per-task=16 -p p100 --gres=gpu:1 ./matvec 4096 8192
CPU: nthr = 16 t0 = 0.0036 sec P = 18.888 Gflop/s B = 37.791 GB/s
CPU: nthr = 16 t0 = 0.0030 sec P = 22.663 Gflop/s B = 45.343 GB/s
Diff = 0.000000e+00
```

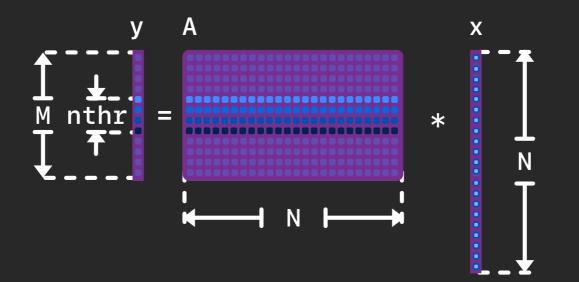
¹ Same as last week's: /onyx/data/sds406f24/l06/ex02/

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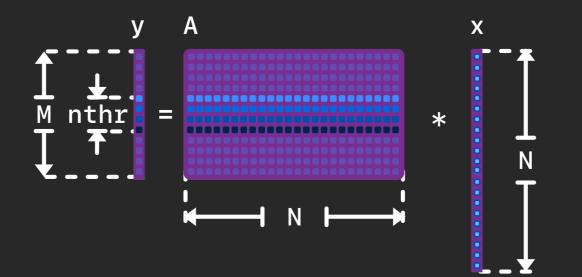
Our task is to modify the second call of the Ax() function to run on the GPU.



Straight-forward approach to begin with:

- Each block is responsible for one element of y[]
 - Each thread must read all elements of the corresponding row of A[]
 - Each thread must read all elements of x[]

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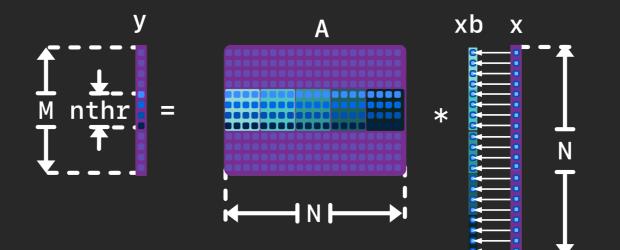
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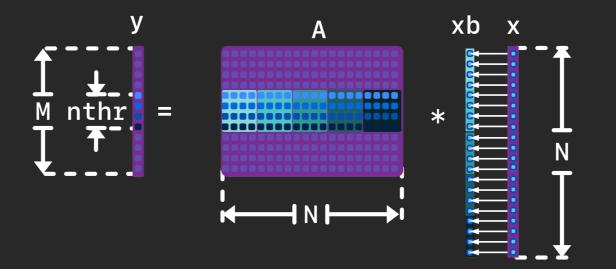
E.g., using 256 GPU threads:

```
[ikoutsou@front02 ex01]$ srun -N 1 --cpus-per-task=16 -p p100 --gres=gpu:1 ./matvec 4096 8192
CPU: nthr = 16 t0 = 0.0035 sec P = 19.108 Gflop/s B = 38.229 GB/s
GPU: nthr = 256 t0 = 0.0020 sec P = 32.994 Gflop/s B = 66.013 GB/s
Diff = 2.603650e-15
```

Now use a *shared array* to share the elements of x[]. Name the shared array xb[]:



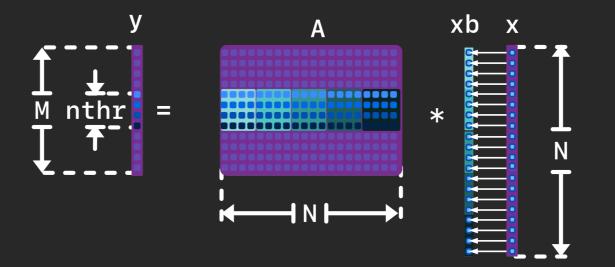
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- This requires splitting the matrix-vector multiplication of the block into steps

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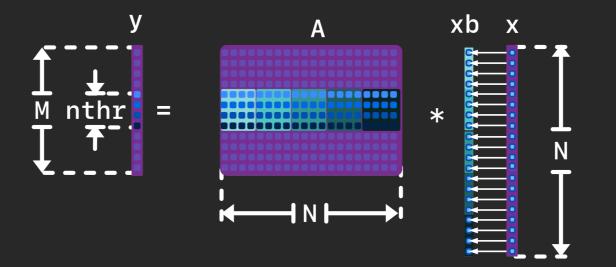
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[ikoutsou@front02 ex01]$ srun -N 1 --cpus-per-task=16 -p p100 --gres=gpu:1 ./matvec 4096 8192
CPU: nthr = 16 t0 = 0.0035 sec P = 19.384 Gflop/s B = 38.782 GB/s
GPU: nthr = 256 t0 = 0.0019 sec P = 35.375 Gflop/s B = 70.775 GB/s
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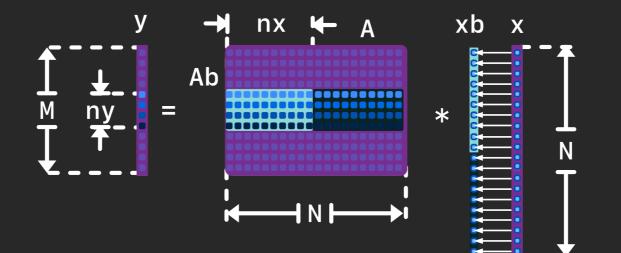
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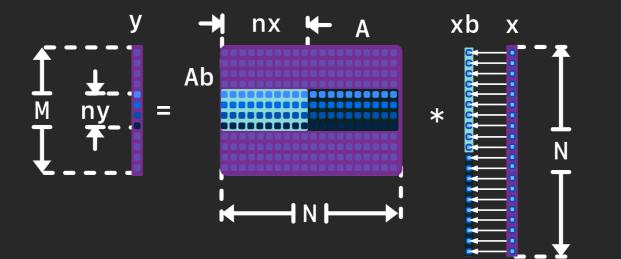
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Not much improvement compared to previous version

Now use a *shared array* for both A[] and x[]. Name them Ab[] and xb[]:



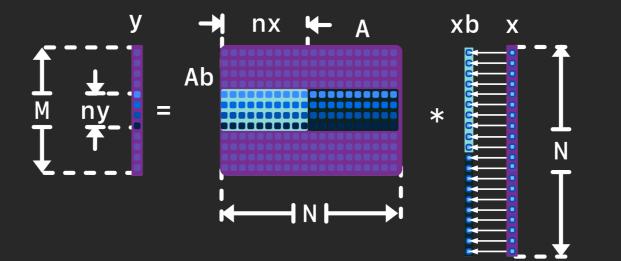
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Use a 2-dimensional thread block

- All threads are used to fill in Ab[]
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- Only some threads carry out the computation for y[]

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Using thread-blocks of, e.g. 8×64 :

```
[ikoutsou@front02 ex01]$ srun -N 1 --cpus-per-task=8 -p nehalem --gres=gpu:1 ./matvec 8 4 4096 8192
CPU: nthr = 16    t0 = 0.0035 sec  P = 19.278 Gflop/s  B = 38.570 GB/s
GPU: nthr = ( 8,  4) t0 = 0.0030 sec  P = 22.430 Gflop/s  B = 44.877 GB/s
Diff = 2.603650e-15
```

Scanning for the optimal parameters:

GPU: nthr = ((4,	4)	+0 =	0.0054	SAC	P	=	12 460	Gflop/s	В	=	24.928	GB/s
GPU: nthr = ((4 ,			0.0037			=		Gflop/s	B		36.576	
GPU: nthr = ((4,			0.0019		P	=		Gflop/s	B	=	70.668	
GPU: nthr = ((4,	32)		0.0018		P			Gflop/s	B		74.848	
GPU: nthr = ((4,	64)		0.0020		P			Gflop/s	B	=	66.371	
GPU: nthr = (128)		0.0020		Р	=		Gflop/s	В	=	65.751	
GPU: nthr = (256)		0.0035		P	=		Gflop/s	B	=	38.167	
GPU: nthr = ((8,			0.0030		P	=		Gflop/s	В	=	44.830	
GPU: nthr = (8,			0.0020		Р	=		Gflop/s	В	=	66.433	
GPU: nthr = ((8,			0.0011		Р	=		Gflop/s	В	=	123.418	
GPU: nthr = (8,	32)	t0 =	0.0013	sec	Р	=	53.139	Gflop/s	В	=	106.316	GB/s
GPU: nthr = ((8,	64)		0.0018		Р	=		Gflop/s	В	=		
GPU: nthr = ((8,	128)		0.0020		Р	=		Gflop/s	В	=		
GPU: nthr = ((16,	4)	t0 =	0.0015	sec	Р	=	43.351	Gflop/s	В	=	86.733	GB/s
GPU: nthr = ((16,	8)	t0 =	0.0013	sec	Р	=	53.179	Gflop/s	В	=	106.396	GB/s
GPU: nthr = ((16,	16)	t0 =	0.0010	sec	Р	=	67.793	Gflop/s	В	=	135.635	GB/s
GPU: nthr = ((16,	32)	t0 =	0.0013	sec	Р	=	52.475	Gflop/s	В	=	104.988	GB/s
GPU: nthr = ((16,	64)	t0 =	0.0017	sec	Р	=	39.566	Gflop/s	В	=	79.162	GB/s
GPU: nthr = ((32,	4)	t0 =	0.0014	sec	Р	=	47.530	Gflop/s	В	=	95.096	GB/s
GPU: nthr = ((32,	8)	t0 =	0.0015	sec	Р	=	44.707	Gflop/s	В	=	89.447	GB/s
GPU: nthr = ((32,	16)	t0 =	0.0016	sec	Р	=	42.150	Gflop/s	В	=	84.330	GB/s
GPU: nthr = ((32,	32)	t0 =	0.0019	sec	Р	=	35.967	Gflop/s	В	=	71.960	GB/s
GPU: nthr = ((64,	4)	t0 =	0.0013	sec	Р	=	52.426	Gflop/s	В	=	104.890	GB/s
GPU: nthr = ((64,	8)	t0 =	0.0015	sec	Р	=	45.561	Gflop/s	В	=	91.155	GB/s
GPU: nthr = ((64,	16)	t0 =	0.0017	sec	Р	=	38.771	Gflop/s	В	=	77.570	GB/s
GPU: nthr = ((128,	4)	t0 =	0.0013	sec	Р	=	52.260	Gflop/s	В	=	104.559	GB/s
	(128,	8)		0.0016		Р	=		Gflop/s	В		85.952	
GPU: nthr = ((256,	4)	t0 =	0.0015	sec	Р	=	45.502	Gflop/s	В	=	91.037	GB/s

~130 GB/s is about the maximum we can obtain

Now let's see what we get when using CUDA's implementation of the same kernel

• The matrix-vector multiplication is implemented as part of CUDA's BLAS implementation

#include <cublas_v2.h>

• The function to use is cublasSgemv() — see: <u>https://docs.nvidia.com/cuda/cublas/index.html#cublas-lt-t-gt-gemv</u>

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- This function is general and computes: $y = \alpha Ax + \beta y$, where α and β are scalars
- In our case, we need: $\alpha = 1$ and $\beta = 0$.

Call the CUBLAS function via:

cublasSgemv(handle, CUBLAS_OP_T, n, m, &alpha, d_A, n, d_x, 1, &beta, d_y, 1);

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• Add -lcublas to the compile command

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NVIDIA's version is not necessarily faster than our hand-tuned version