# Randomized Selection on the GPU 

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## Top $k$ Selection on GPU

- Output the top $k$ keys and values from an unordered list of length $n$
- Top $k$ is in terms of key ordering
- Our motivating problem is from radio-astronomy
- Contributions of this work
- Speedups of 1.5-3x over best-known GPU selection, and $3-6 x$ over Thrust sort
- Selections on lists up to $4 x$ longer than Thrust sort
- New method of selecting pivots in this randomized select


## Motivating problem

- CLEAN on GPU
- Used in radio-astronomy to remove noise from images generated by multiple antennas
- Fast CLEAN algorithm (Clark)
- Chooses the $k$ brightest pixels in the
 image, and saves them to a clean image
- Convolves the $k$ pixels with the point-spread function via a Fast Fourier Transform (FFT), a convolution, and an inverse FFT
- Subtracts the result from the base image to get residual image
- This process iterates until all pixels in the residual image reach a threshold noise value. The clean image is then accepted.


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## CLEAN Constraints

- Choice of GPU for CLEAN
- Good FLOPS/watt ratio for remote telescope locations
- Have fast FFTs on GPU, need fast selection
- Choice of GPU for selection implementation
- Transfer of big images a performance killer
- Residual image changes at each of the many iterations in CLEAN
- If FFTs on GPU but selection on CPU, big image transfer each step
- CLEAN requirements for selection
- Requires very general version of select
- Need both keys and values
- Keys (pixel brightness) are what is ordered and selected upon
- Values (pixel locations) are what is needed for CLEAN
- Need all $k$ keys and values, not enough to grab just $k$ th


## Some Previous Work on Selection

Selection is a more general CS problem.

- Serial Lazy Select (Motwani and Raghavan 1995)
- Serial Quickselect (Bleloch 1996)
- Parallel Randomized Selection (Bader 2004)
- GPU Select via Explicit Construction (Govindaraju 2004)
- GPU Select via Minimization of a Complex Function (Beliakov 2011)
- Select via a Sort (e.g., Thrust)
- Does more than just the select
- Good if the list never changes
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## Randomized Selection Algorithm

- Choose two pivots for a partition so that:
- The $k$ th element is contained in the middle bin with probability $p_{k}$
- The middle bin is small relative to the list

|  |  |  |
| :---: | :---: | :---: |
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| Pivot 0 | Pivot 1 |  |

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| First Bin <br> keys < Pivot 0 | Middle Bin <br> PA-UR 11-04829 $0 \leq$ keys $\leq$ Pivot 1 |  |
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- Is $k$ th in middle bin?
- Yes, if number in first bin $<k$ and number in first and middle bins $\geq k$

| First Bin keys < Pivot 0 | Middle Bin Pivot $0 \leq$ keys $\leq$ Pivot 1 | $\begin{aligned} & \text { Last Bin } \\ & \text { keys }>\text { Pivot } 1 \end{aligned}$ |
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- Select on the middle bin (we used select-via-sort)

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## Algorithm observations

"Essentially a reduced selection
-Selection is on a smaller middle bin
-Pivot choice is heart of algorithm
-The action is in reads-to/writes-from shared memory
-The partition takes most of the time because of this
-Everything on the GPU except
-The overall control
-The probability sums in the pivot choice
-For convenience used GSL on CPU (validated, has numerical tricks)

## Guess and check

-This is a Las Vegas algorithm.
-Las Vegas algorithm = probabilistic, but gives correct result -An example of stochastic optimization
-Relatively slow to directly select but
-Fast to calculate the guess
-Fast to do the calculations, given the guess
-Fast and easy to check correctness of pivot guess
-Can guess pivots with arbitrary accuracy
-Guess + check faster than direct calculation

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## Parameters

- $n$, the list length
- This is limited by the amount of global memory
- We implemented only powers of 2, but can generalize
- $k$, the number of elements to be selected
- Varies between 1 and $n$
- Gives rise to the quantile $k / n$
- Quantile $k / n$ allows comparison between different $n$
- $p_{k}$, the desired probability that the middle bin contains the $k$ th element
- Larger $p_{k}$ implies fewer repetitions, but a larger final selection

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## Algorithm flow chart



## Pivot selection

- Randomly select some number (numSplitters) of elements from the list and call these splitters
- We empirically chose numSplitters $=8^{*} \sqrt{ } n$, to balance first and last sorts
- Sort the splitters
- Imagine that the list is partitioned into buckets defined by these splitters
- Each bucket has very roughly "more or less" the same number of elements
- This has the effect of flattening the distribution and allows one to reason probabilistically about the number of elements in each
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## Pivot selection

- The probability that the $k$ th is in the ith bucket is approximately

$$
\text { C(numSplitters, i) }(k / n)^{i}(1-(k / n))^{n u m S p l i t t e r s-i}
$$

- Binomial distribution approximation
- numSplitters random trials
- Success is defined as "the kth key < the splitter tried"
- Success has probability $k / n$
- Approximation may be weak for kth key outside splitters, but impact minimal if probabilities of end buckets small
- Starting at the bucket most likely to hold the $k$ th, $k /(n /($ numSplitters+1)), add probabilities, incrementing buckets on each side, until the desired probability is exceeded.
- Can do this as buckets are not overlapping
- Binomial distribution is approximated by normal


## Query and Partition kernels

- First pass -- counting loop
- Count thread contributions to first and middle bin
- Scan-add (prefix-sum) these for offsets
- Compare total elements falling into the first and into the first and middle to see if the $k$ th falls into the middle
- If not, then shift the pivots in the appropriate direction and repeat
- Second pass - partition
- Once you have good pivots, partition and write
- No atomics
- Closely coupled kernels account for most of the time spent
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## Coalesced vs. uncoalesced writes in partition-and-write kernel


_ coalesced topk $\longrightarrow$ coalesced kernel _ uncoalesced topk $\longrightarrow$ uncoalesced kernel

## GPU impact on algorithm

- Parallelism a great strength
- Ran on up to 64 million threads for the partition kernels
- Small amount of fast memory near processors
- Bandwidth gain in using coalesced writes
- But to do these coalesced writes also need to use more shared memory
- SIMD, divergent threads during partition
- Super-scalar technique in (Sanders and Winkel 2004) didn't help for our two-level tree
- Slow reads across PCIe bus
- If calculation is on GPU, best to select there too
- Limited global memory on GPU
- Limits size of list that can be processed

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## Verification

- This is an example of stochastic optimization
- If the wrong pivots are chosen, the answer will still be correct but the timing will be slower
- We verified the code statistically as part of our experimentation
- Did a series of experiments consisting of 10K runs each, and compared the observed number of times the $k$ th was in different buckets with the corresponding calculated bucket probabilities for different values of $k$
- Results were consistent with correct implementation of the algorithm

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## Experimental results

- Algorithms compared
- This randomized top $k$ selection
- Thrust-based select-via-sort
- Direct construction of $k t h$ element (Govindaraju 2004)
- Construction by minimization of a convex function (Beliakov 2011)
- Data compared
- Real radio-astronomy data
- Random data
- In-order and backward-order data
- Data with repetition
- All integer
- Platforms
- NVIDIA Quadro 6000 (mostly), Quadro 5000, GTX 285, 8800 GT


## 1.5-3x faster than best selections 3-6x faster than Thrust select-via-sort



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## Handles list lengths $n 2-4 x$ bigger than Thrust select-via-sort

| GPU | global <br> memory | $\max \boldsymbol{n}$ | max <br> $\boldsymbol{k} / \boldsymbol{n}$ | max $\boldsymbol{n}$, <br> no $\boldsymbol{k}$ <br> restriction | thrust <br> $\max \boldsymbol{n}$ |
| :--- | :--- | :---: | :---: | :---: | :---: |
| $\mathbf{6 0 0 0}$ | $\mathbf{6 G B}$ | $2^{29}$ | 0.34 | $2^{28}$ | $2^{28}$ |
| $\mathbf{5 0 0 0}$ | 2.5 GB | $2^{28}$ | 0.53 | $2^{27}$ | $2^{26}$ |
| $\mathbf{2 8 5}$ | 1 GB | $2^{27}$ | 0.13 | $2^{26}$ | $2^{25}$ |

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## Timings in terms of list length $n$



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## Real radio-astronomy data closely tracks random data



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## When is this algorithm slow?

- We identified one case when this is slower than select-via-sort
- Lots of repetition AND
- The $k$ th key occurs near the repetition
- In that case, the select-via-sort can be faster
- We found the break-even to be when between half and three-quarters of the elements repeat (and the $k$ th happens to be one of them)
- Because nearly a full sort is done in the final select, along with all of the other work


## Timings for different GPUs



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## Probabilities $p_{k}$ give similar timings when $\mathrm{p}_{\mathrm{k}}>30 \%$



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## Kernel timings, $n=2^{26}$



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## If you're on the GPU, select there too

 Same $n=2^{26}$ run as previous slide PCIe transfer time overwhelms the select time

## Conclusions

- We have shown a fast randomized selection on the GPU using a Las Vegas algorithm.
- Faster than other GPU-based selects we've examined
- Even those that do less (i.e., only grab the $k$ th, only grab keys)
- Select on the GPU when you're already there
- Use this randomized select if
- The list changes between calls to select
- You want longer lists than a sort handles on your GPU
- Use select-via-sort only if
- You are selecting on the same list many times
- That's the added value of doing a sort first
- You know the series of lists have more than half repeated keys and know that the $k$ th is one of them most of the time

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