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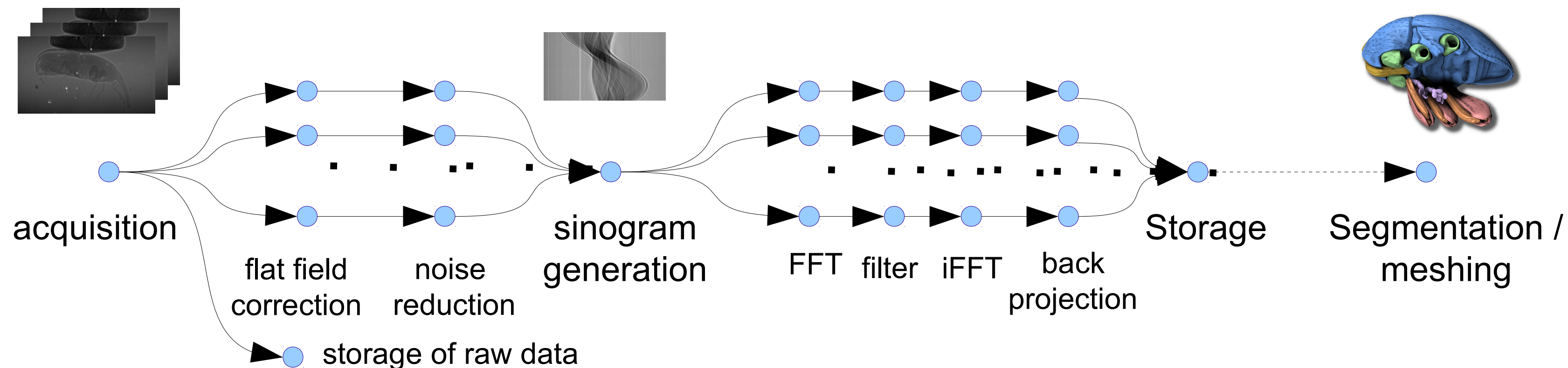
Adapting Filtered Back Projection algorithm for various parallel architectures

S. Chilingaryan



UFO *Ultra Fast X-ray Imaging of Scientific Processes with On-Line Assessment and Data-Driven Process Control*

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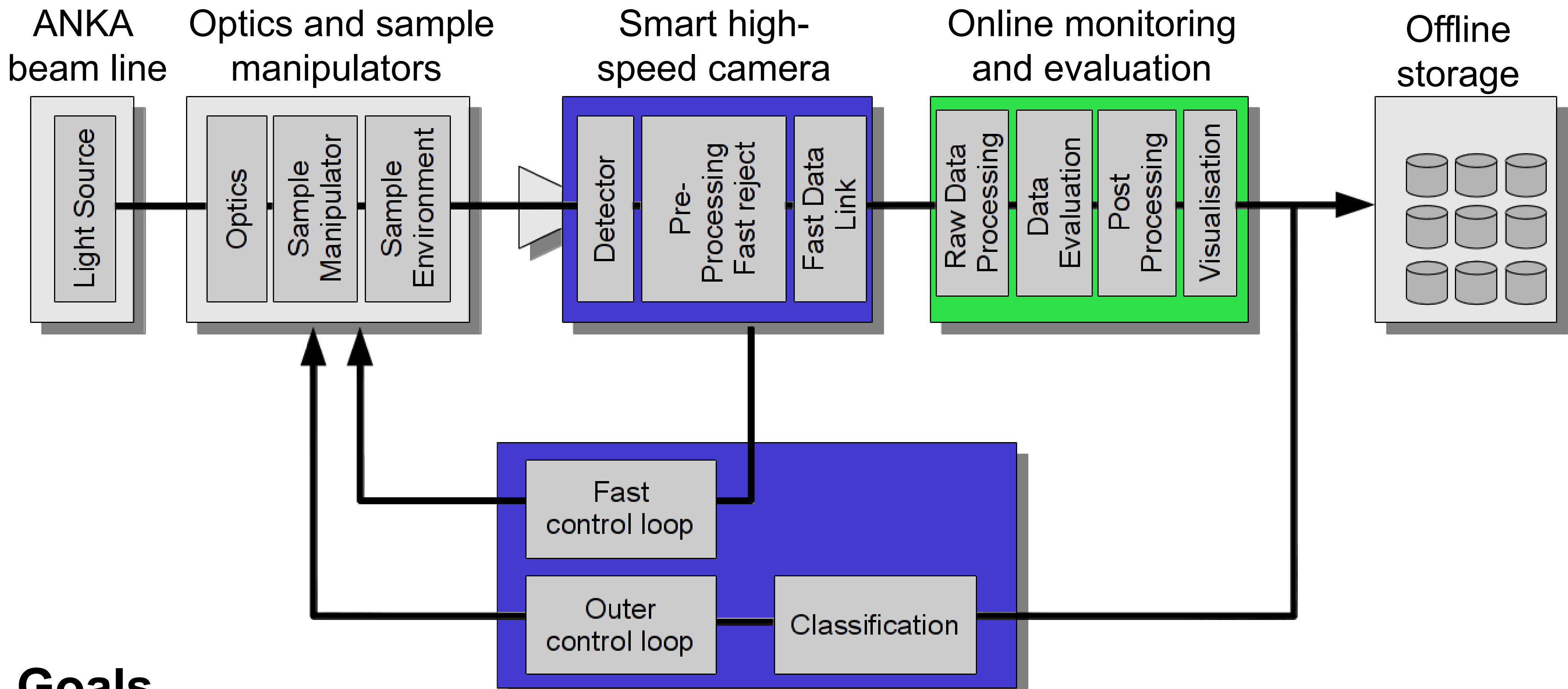

Goals

- High speed tomography
- Increase sample throughput
- Tomography of temporal processes
- Allow interactive quality assessment
- Enable data driven control
  - Auto-tunning optical system
  - Tracking dynamic processes
  - Finding area of interest

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Optimizing for parallel architectures

- **Consists of SIMD-type Compute Units (CU)**
  - One instruction is executed on many data items
  - Each CU able to execute several operation types
  - But only FP additions/multiplications are fast
- **Posses complex memory hierarchy**
  - Low Bandwidth-per-flop ratio and small caches
  - Up to four different types of memory
  - Optimal access pattern have to be followed
- **Architectures vary drastically**
  - Sizes, speed, and structure of memories / caches
  - Types and amount of provided processing units
  - Balance of operation throughput

Codes and algorithms have to be carefully optimized for the specific parallel architecture

Compute Unit on Fermi

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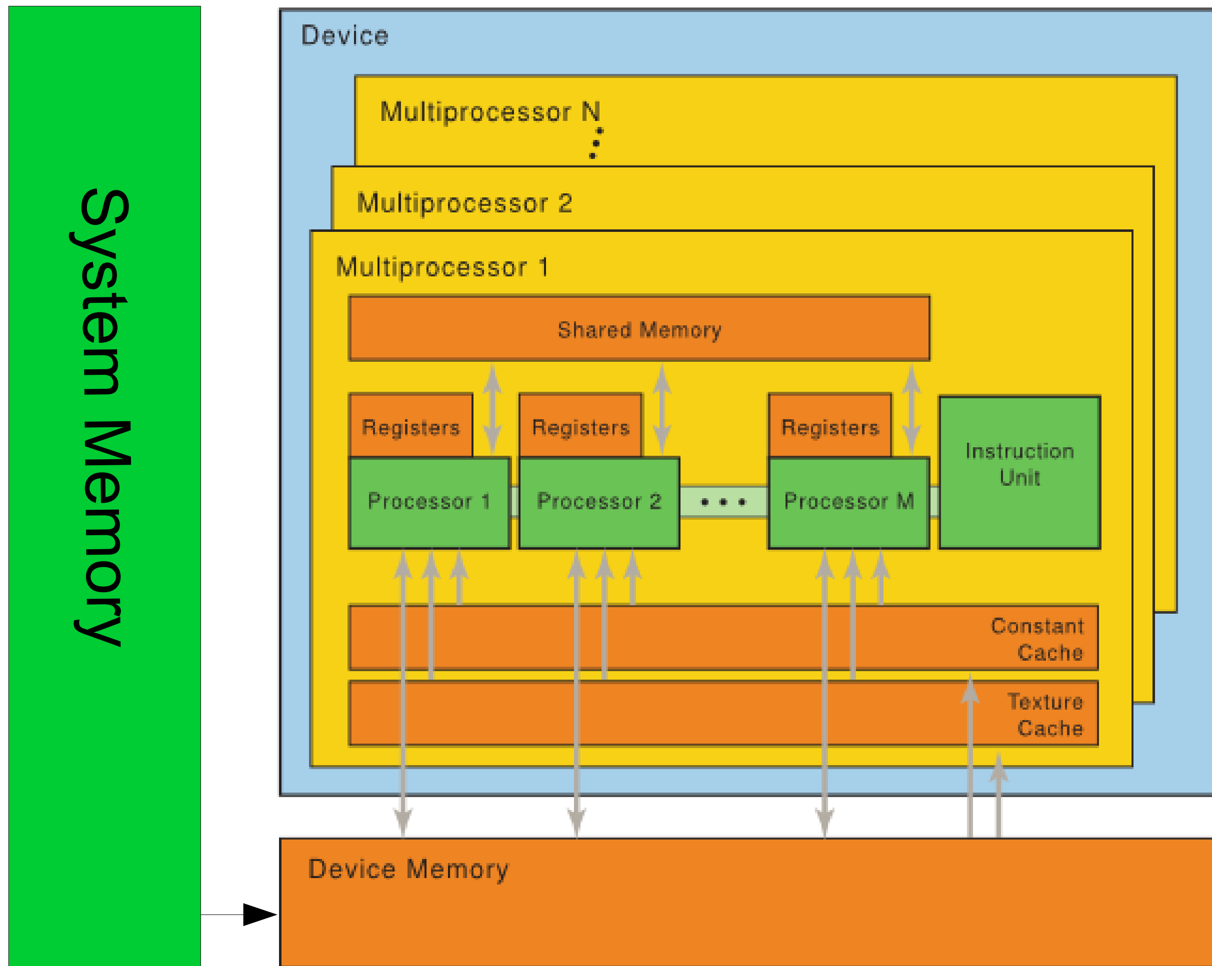
Memory model



- **Host Memory**
  - 6 GB/s (PCIe x16 gen2) to 12 GB/s (PCIe x16 gen3)
- **Global Memory**
  - 100 – 300 GB/s with latencies up to 1000 clocks
- **Local Memory**
  - 1 – 2 TB/s (total) with latencies below 100 clocks
- **Registers**
  - private to threads
- **Caches**
  - L1/L2 cache
  - Texture cache
  - Constant memory

Complex memory hierarchy consisting of 4 levels and with each level one order of magnitude faster when previous!

Programming Model

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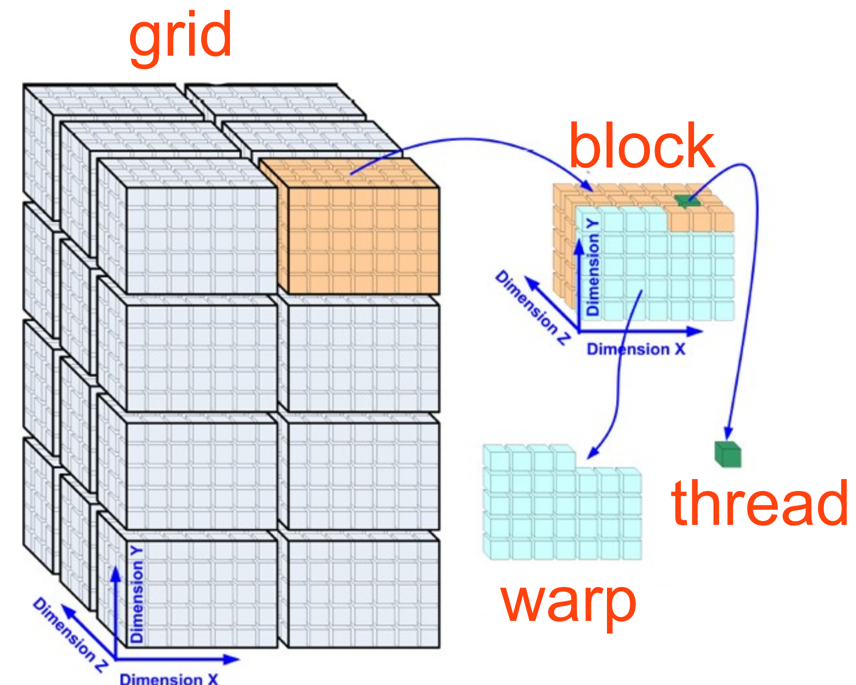
Thread abstraction is used to split the problem space into the independent GPU tasks

- All threads execute the same code (**kernel**)
- Task is defined by the linear or volumetric index of the thread
- GPU schedules threads in groups of fixed size (**warp**)
- A user-defined **block** of threads is assigned to a specific CU
- Threads of the block may exchange data using CU shared memory

e.g. resulting image is mapped to a 1-, 2-, or 3D grid of GPU threads and each pixel is computed by a thread with the index equal to pixel coordinates



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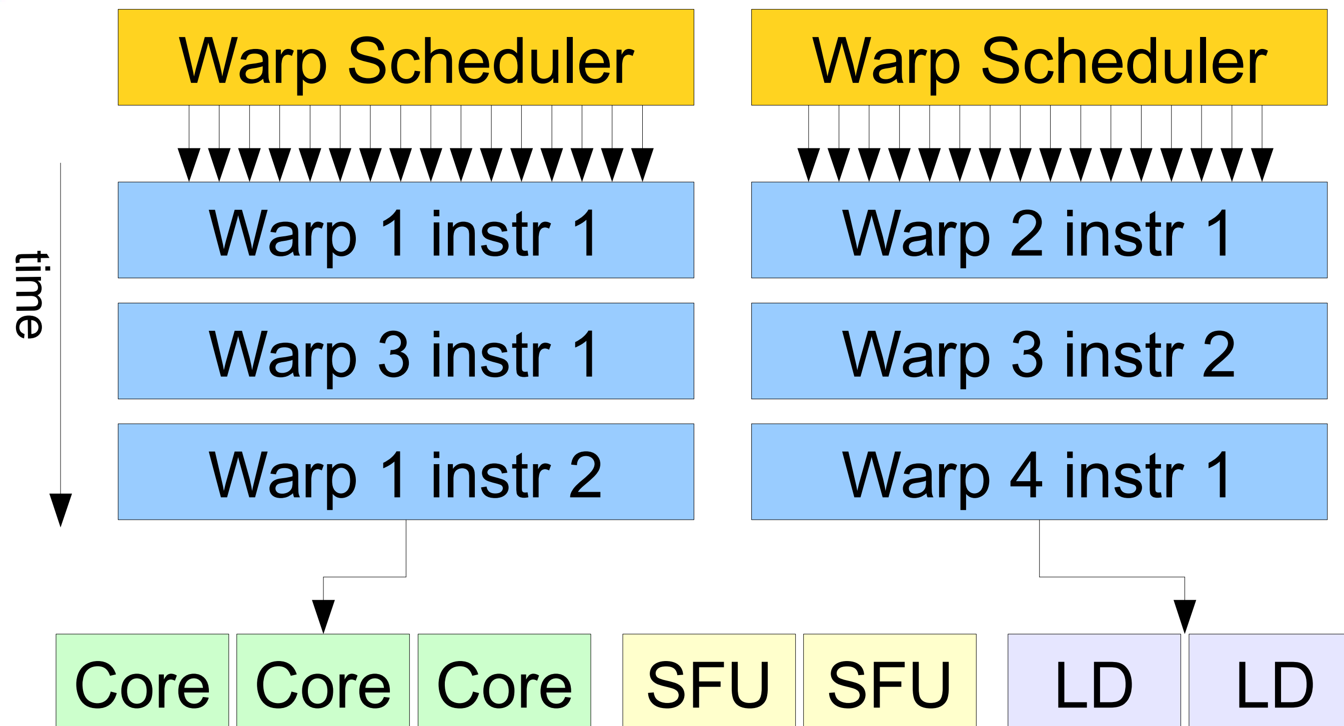
Scheduling



Multiple warps on CU executed in parallel

Independent instructions executed in parallel

Warp 4 will be blocked for a long time, but other warps on CU will execute and hide the latency

- Warps from several blocks are executed by CU in parallel
- The number of currently resident warps is called **occupancy**
- Occupancy is limited by available registers and shared memory
- Suboptimal occupancy limits the instruction bandwidth

For optimal performance we have to increase occupancy and number of independent instructions

FBP Reconstruction

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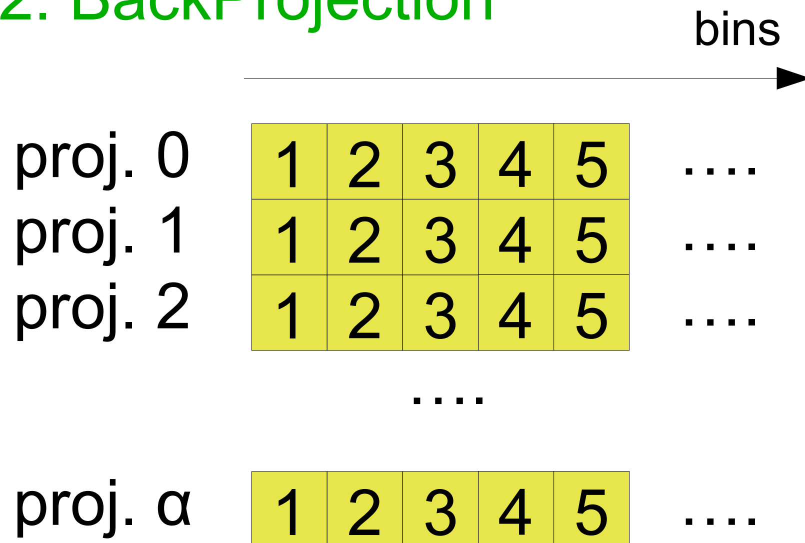
1. Filtering

Multiplication with the configured filter in the Fourier space

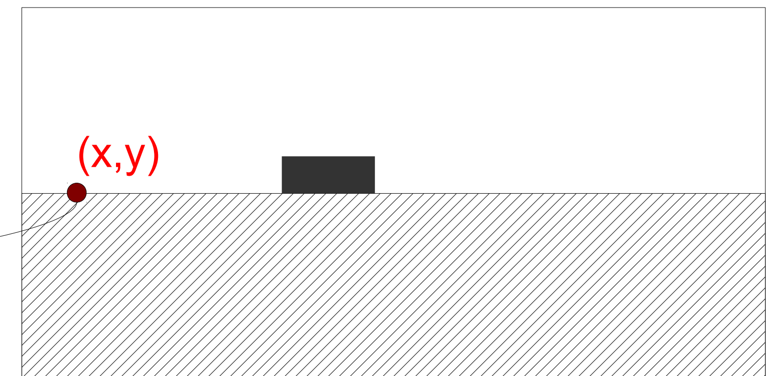
2. BackProjection



1. For each position we compute:
   $x \bullet \cos(\alpha) - y \bullet \sin(\alpha)$
2. Interpolate between neighboring bins
3. Sum over all projection
4. The sum is the value of (x,y)

$x \bullet \cos(\alpha) - y \bullet \sin(\alpha)$

For each texel of output volume and for each projection we perform a single linear interpolation



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Texture Engine

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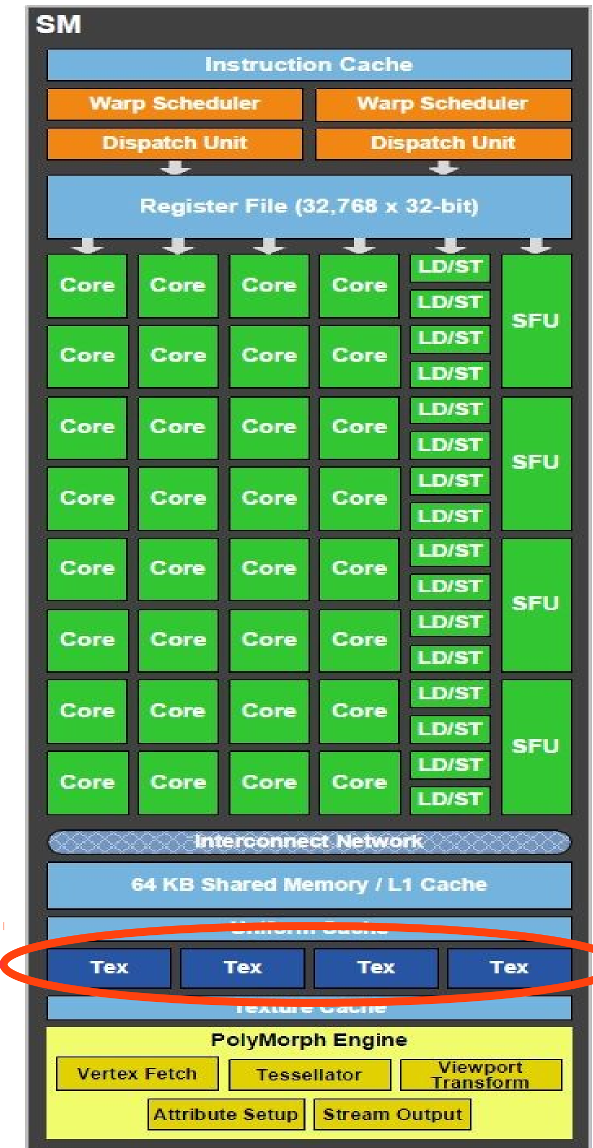
Features:

- Spatial-aware cache
- Bi/tri-linear interpolation
- Normalized coordinates
- Different clamping modes

Applications:

- Linear interpolation, i.e. image scaling
- Optimize random access to multidimensional arrays



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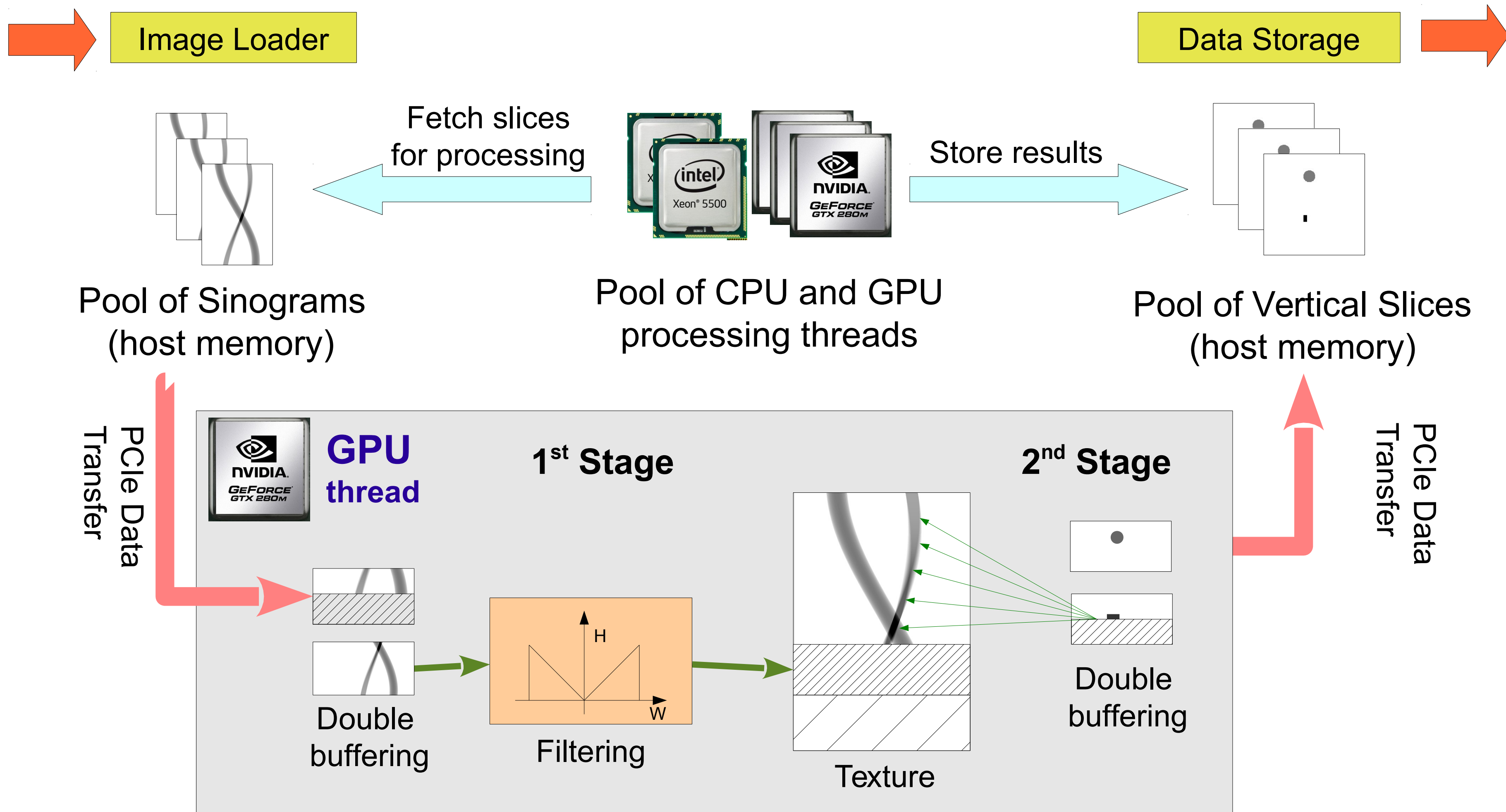
Filtered Back Projection



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Performance of Texture Engine

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	GT280	GTX580
Core Throughput	930 GF	1580 GF
Texture Fill Rate	48 GT/s	49 GT/s
Ratio	**19.3**	**31.6**

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Optimizing FBP for Fermi

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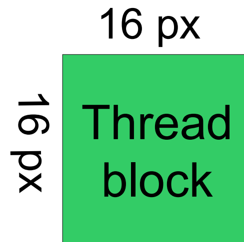
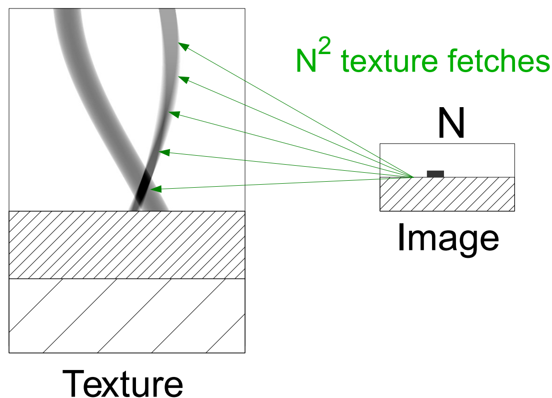


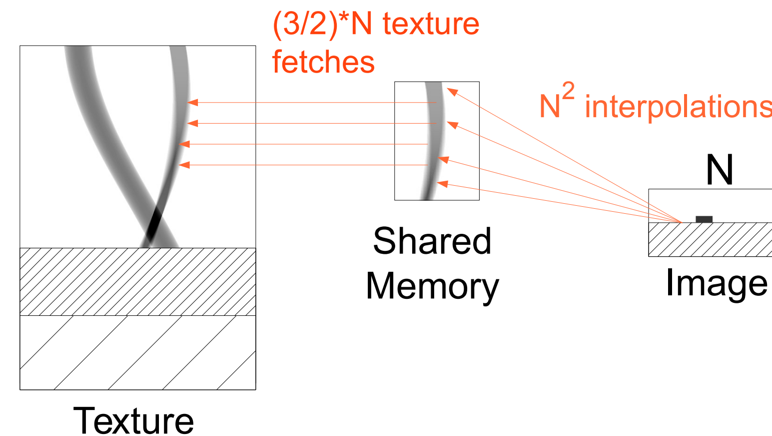
$v = x \bullet \cos(\alpha) - y \bullet \sin(\alpha)$

$\max_{x,y<N}(v) - \min_{x,y<N}(v) < N\sqrt{2}$

$N\sqrt{2} < 1.5\,N$

Each block of threads accesses actually only 3 ● N / 2 bins per projection





Standard Version

Texture engine is heavily loaded

Fermi-optimized Version

Both texture & computations engines are used

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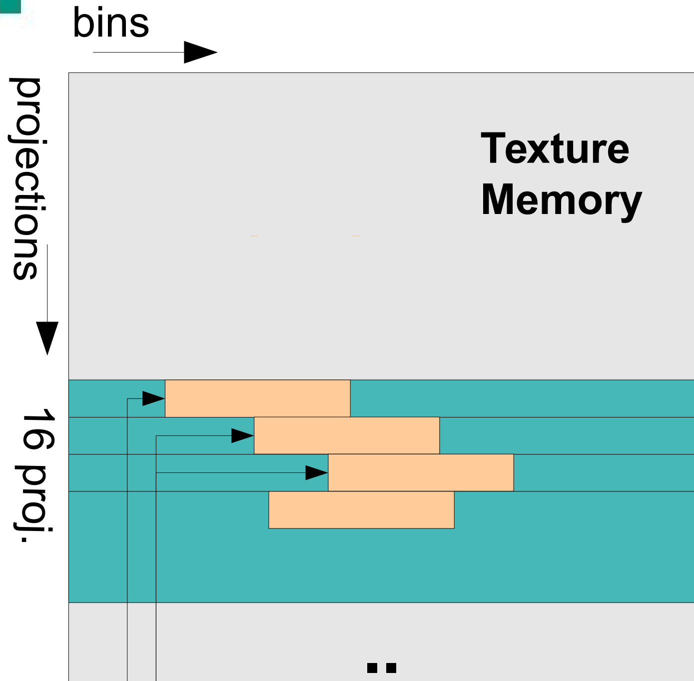
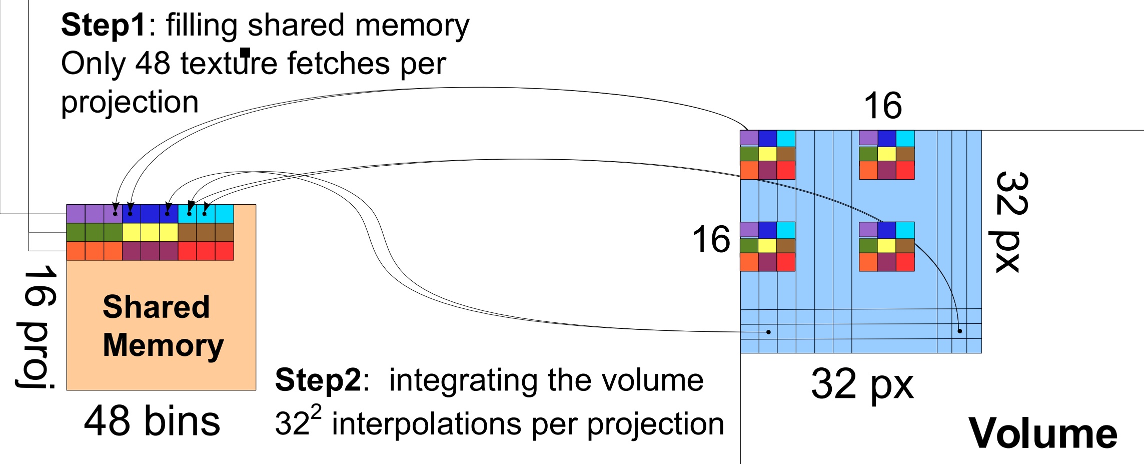
Pixel to thread mapping





Processing 4 pixels per thread reducing amount of texture fetches and hides operation latencies with multiple independent operations (instruction reordering).

Px.	Fetches/px.	Regs	ShMem	Occup.	ILP
1	0.09375	26	1536	66%	1
4	**0.046875**	32	3072	66%	**4**

Legend

- Processed by a single thread block (16x16)
- 48 bins of a projection required for current block
- 16 of the projections processed in a single pass

thr (1,1)	thr (2,1)	thr (3,1)
thr (1,2)	thr (2,2)	thr (3,2)
thr (1,3)	thr (2,3)	thr (3,3)

Processing in multiple passes, 16 projections each

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Oversampling

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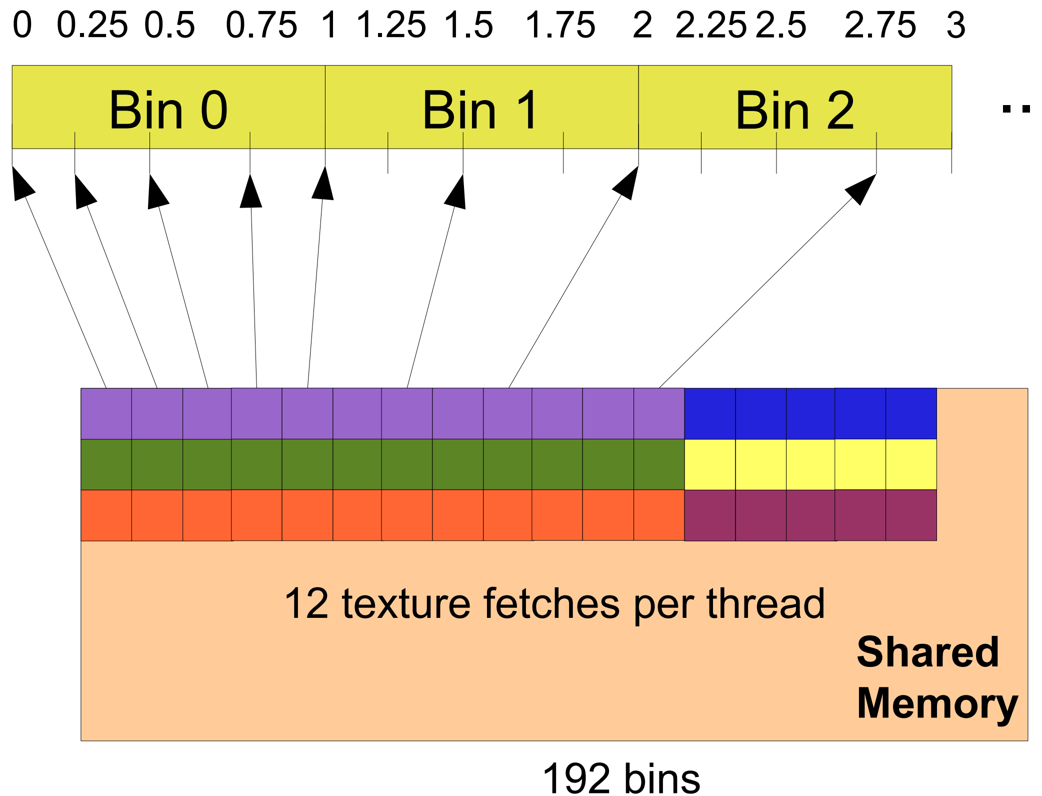

Linear interpolation is slow, and nearest neighbor is not precise enough

With oversampling the texture engine is used to interpolate 4 positions for each projection bin and near-neighbor interpolation is used then.

Method	Fetches/px	Regs	ShMem	Occup.	Reads/px	Flops/px
Linear	0.046875	32	3072	66%	2	7
Oversample	**0.1875**	42	12288	**50%**	**1**	**4**

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Kepler: Fast Texture Engine is Back

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	GT580	GTX680	Change
Texture Engine	49.4 GT/s	128.8 GT/s	**2.6 x**
Floating-point operations	16 x 32 x 1.55 GHz	8 x 192 x 1.006 GHz	**1.94 x**
Integer multiplication, bit operations, type conversions	16 x 16 x 1.55 GHz	8 x 32 x 1.006 GHz	**0.65 x**
Shared Memory	48 KB	48 KB	**1**
Blocks per SM	8	16	**2**
Registers	32K per SM, 63 per thr.	64K per SM, 63 per thr.	**1**

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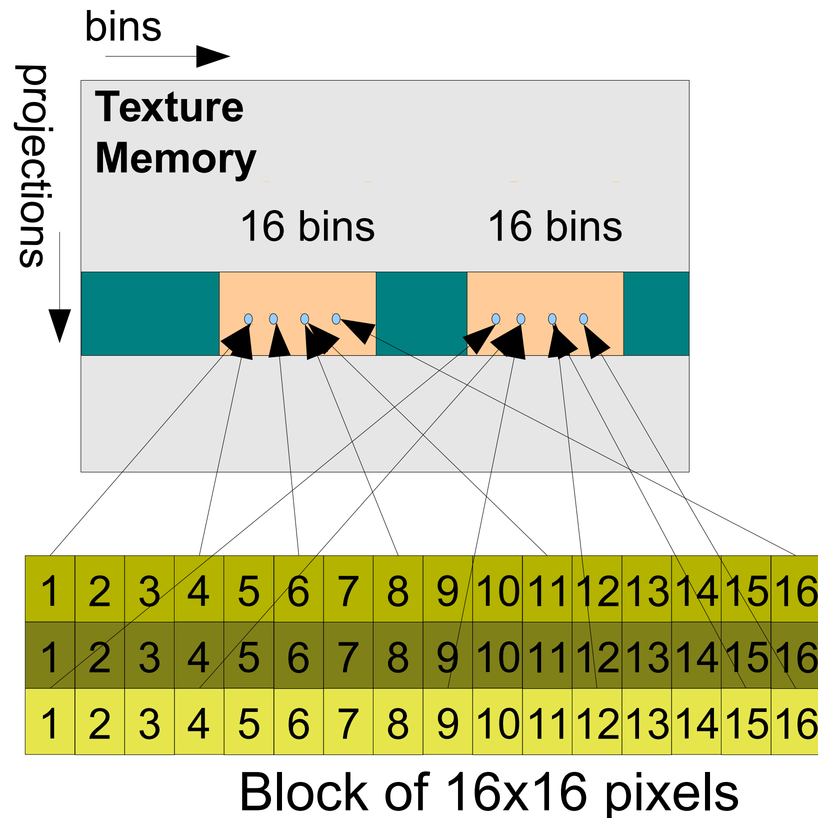
Default approach



Block of 16x16 pixels

Texture Cache Hit Rate	89 %
Texture Throughput	79.3 GT/s
Theoretical Throughput	128.8 GT/s

1. Up to 16 bins are accessed per warp
2. All threads are accessing a single texture row

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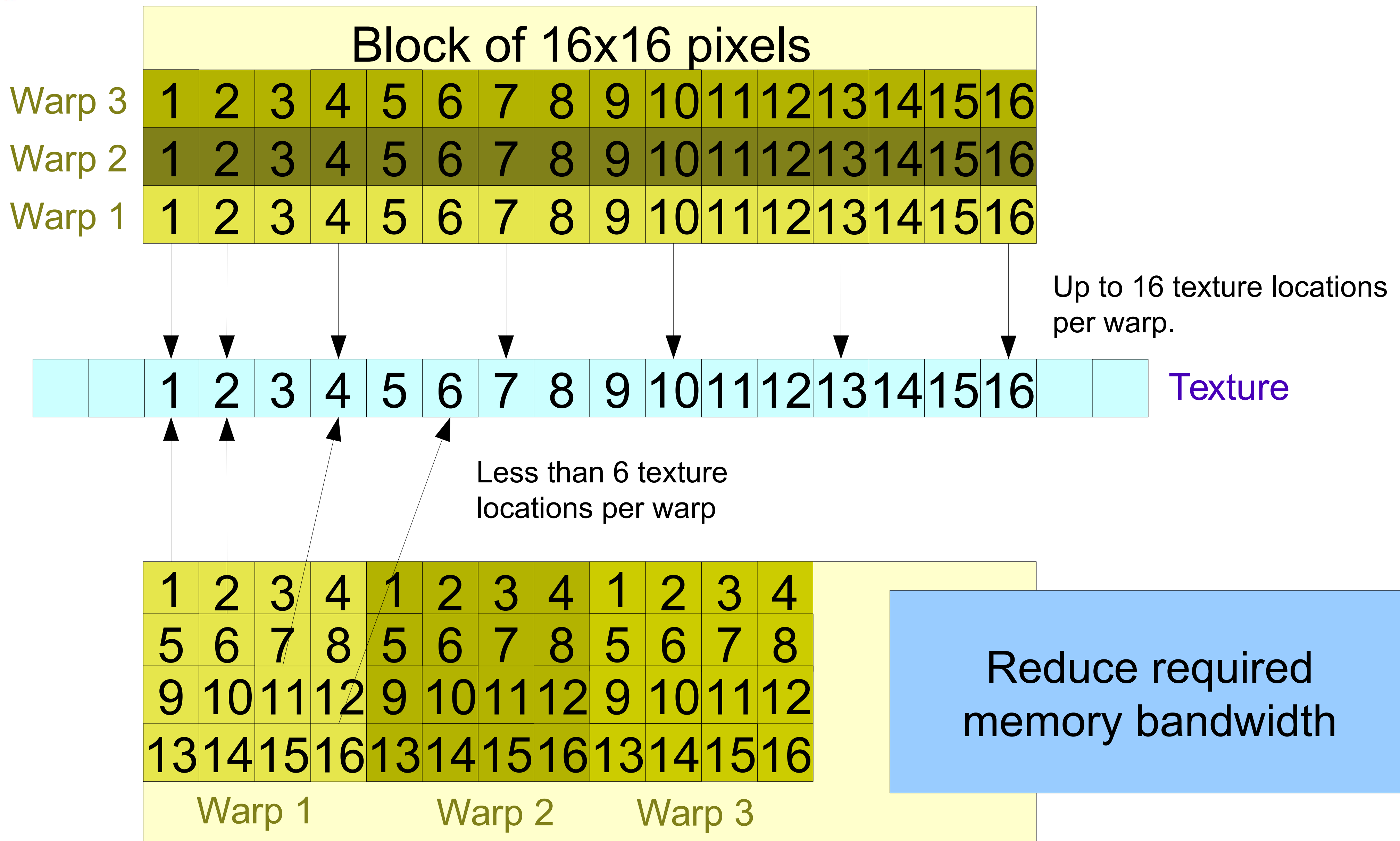
Optimizing the thread mapping



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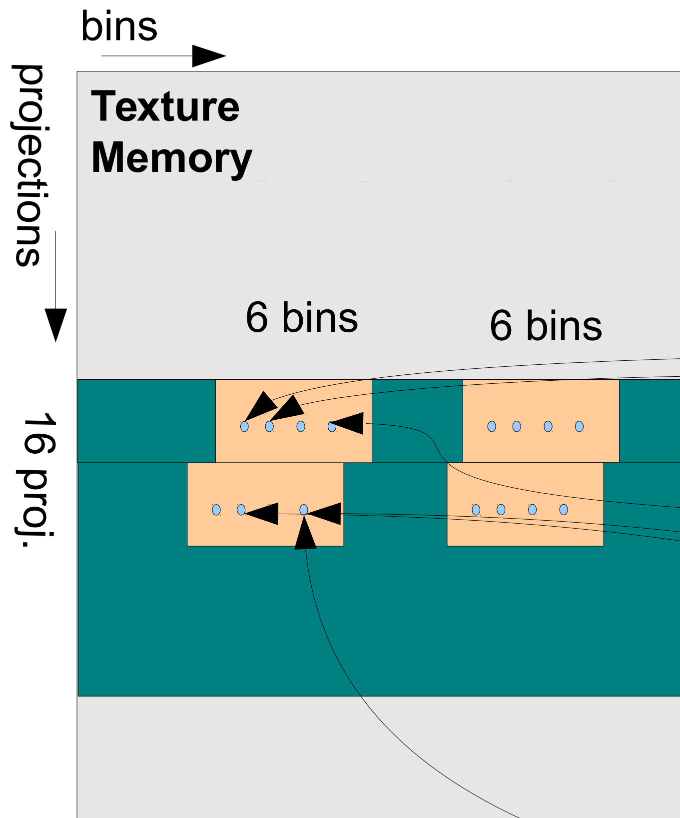
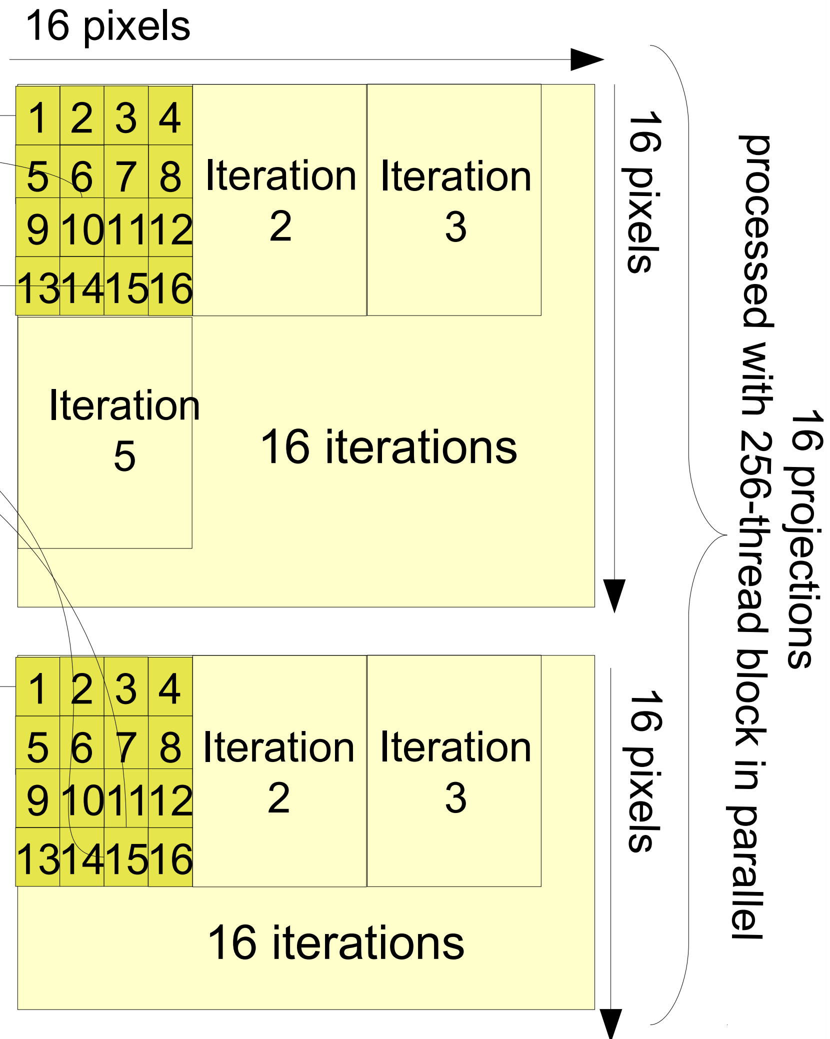
Using spatial locality

Layout	Regs	Occup.	Hit Rate	Bandwidth
Standard	32	100%	89	79.3 GT/s
Optimized	40	75%	96	**117.5 GT/s**





Better 2D texture cache locality with 16 projections computed in parallel

(16 sums are summed together after processing all projections)

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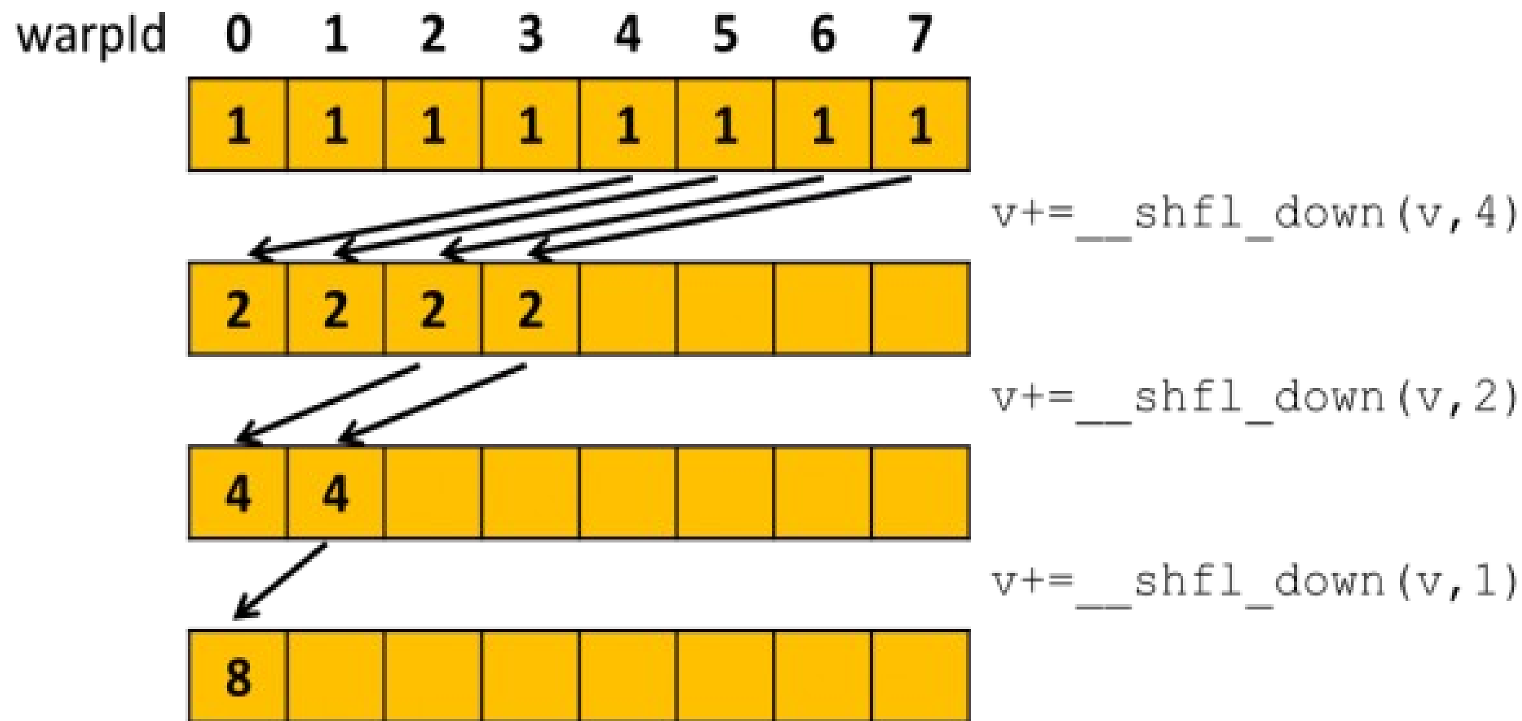
Faster reduction with shuffle instruction



Shuffle instruction introduced by Kepler architecture allows fast exchange of information between threads of the warp.

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Oversampling approach on Kepler

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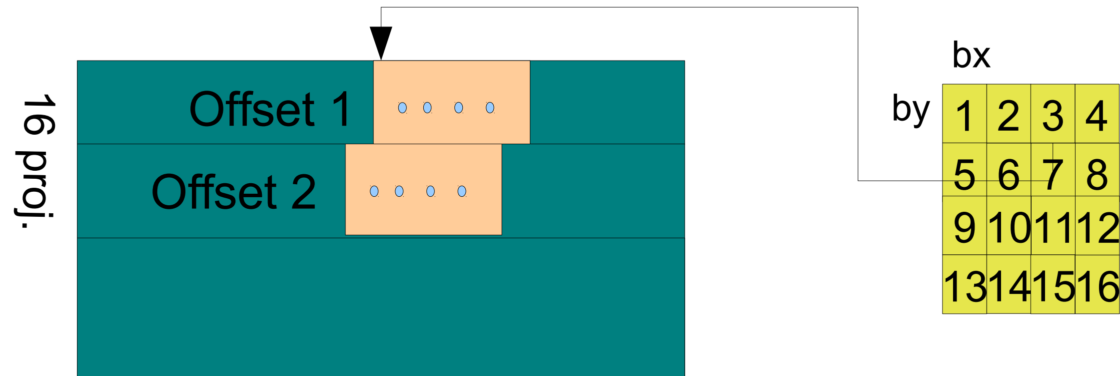
Slow performance of integer and rounding operations makes Fermi oversampling algorithm slow.



$$proj_offset = \lfloor bx \bullet \cos(\alpha) - by \bullet \sin(\alpha) + correction(\alpha) \rfloor$$

On Fermi, for each block and projection we compute smallest-bin offset on the fly by each thread. On Kepler instead we can:

- Optimize rounding routine
- Pre-calculate and cache offsets

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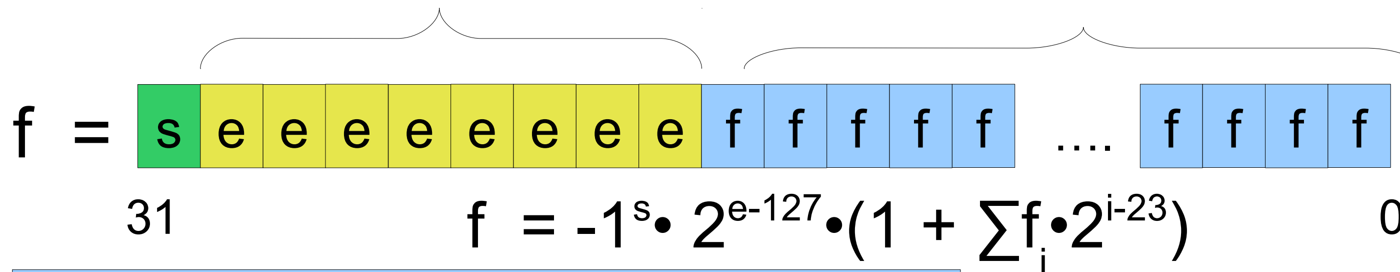
Looking for faster rounding on Kepler



$f = -1^s \cdot 2^{e-127} \cdot (1 + \sum f_i \cdot 2^{i-23})$

IEEE 754 single-precision floating point number

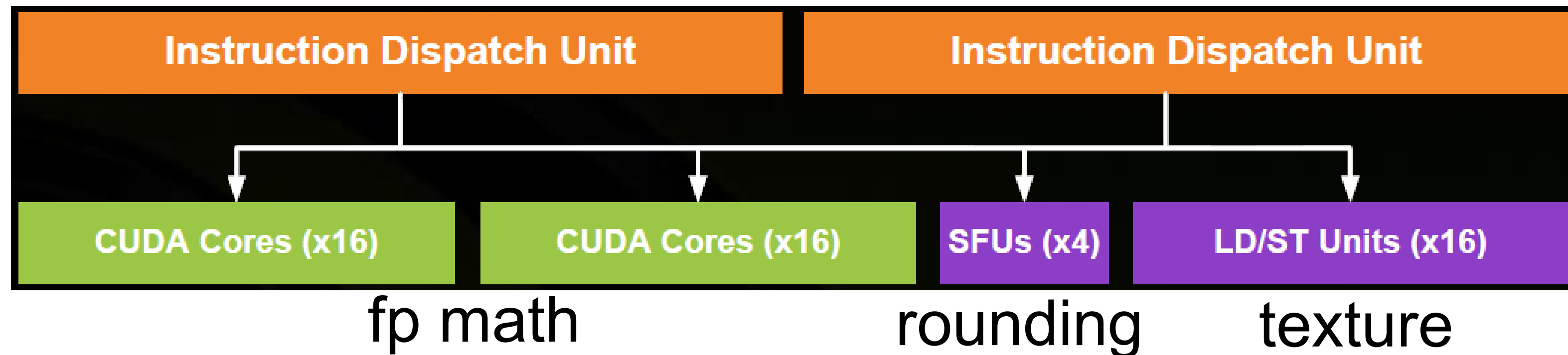
Only 23 significant positions, for small positive numbers:

$$f + 2^{23} = 2^{23} \cdot (1 + \sum f_i \cdot 2^{i-23})$$

i.e. no fractional part

$round(f) = f + 2^{23} - 2^{23}$

$(int)f = f + 2^{23} - 0x4B000000$



fp math rounding texture

We get faster rounding, but SFUs left unused and we got no speed up...

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Reducing number of rounding operations

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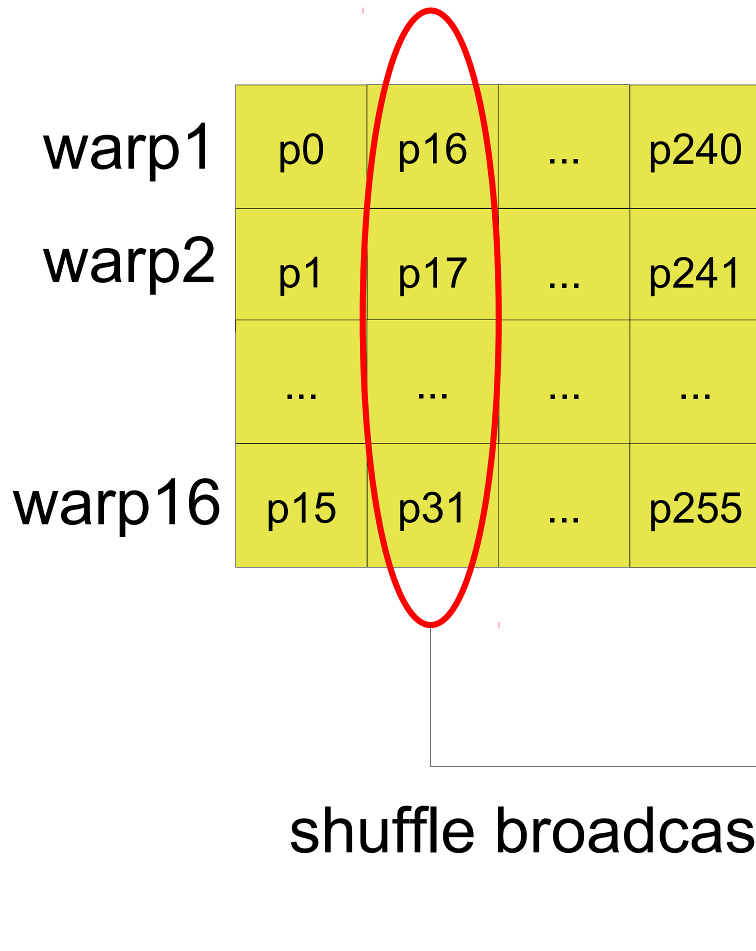
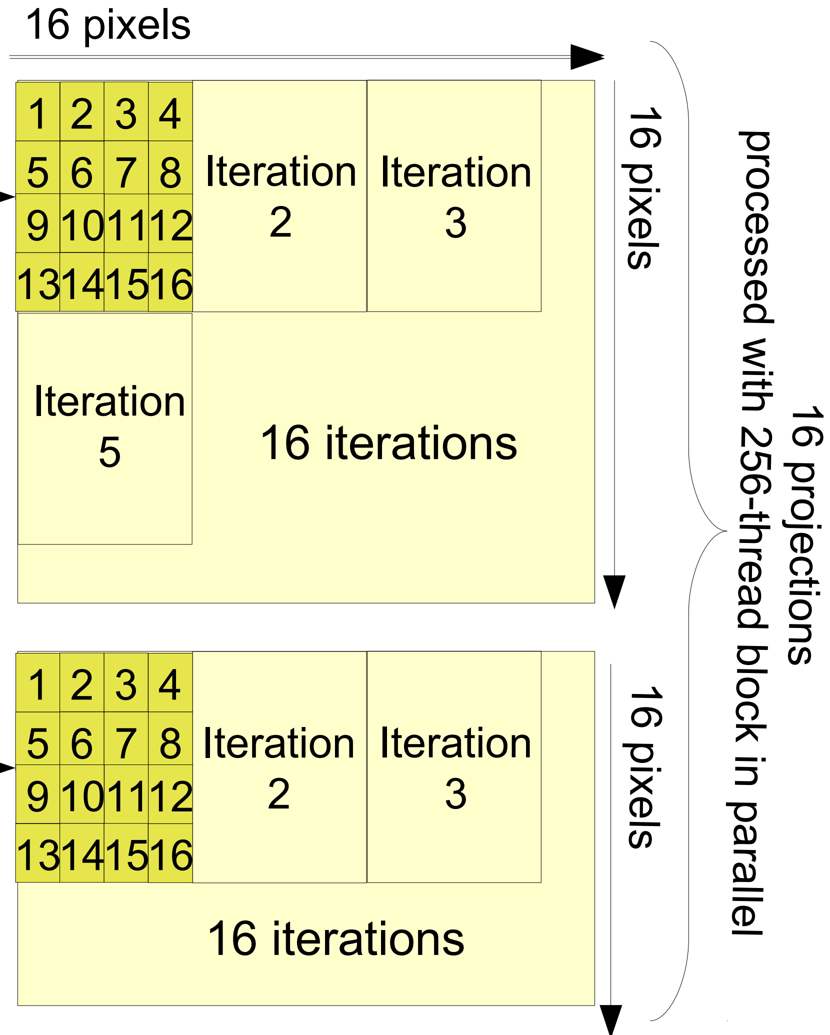


Get all 256 projection offsets at once and iterate 16 times over 16 projections.



On each iteration, the appropriate offsets are shuffled to all threads of the warp

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Summary: 3 stages of oversampling

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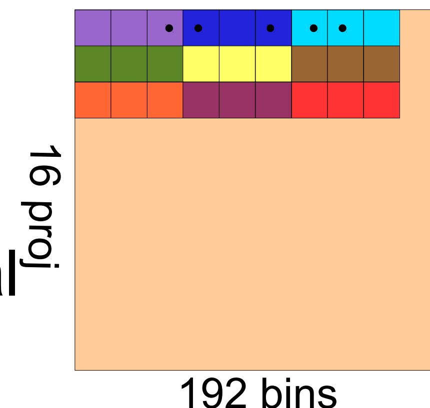
Work-group of 256 threads used to backproject area of 32x32 pixels from 256 projections

1

p0	p16	...	p240
p1	p17	...	p241
...	...	...	...
p15	p31	...	p255

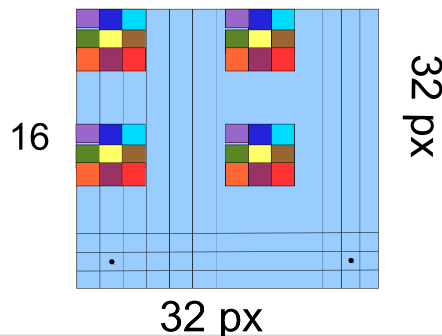
compute all offsets
work-items are mapped linearly to all projections.

2 *16 iterations (only 16 projections at once)*



cache data in shmem
warps are mapped to projections and individual work-items to its bins.

3 256 iterations each processing a single projection



interpolate pixels
work-items are mapped to area 16x16 pixels and proess 4 pixels at once

3 different mappings for optimal performance

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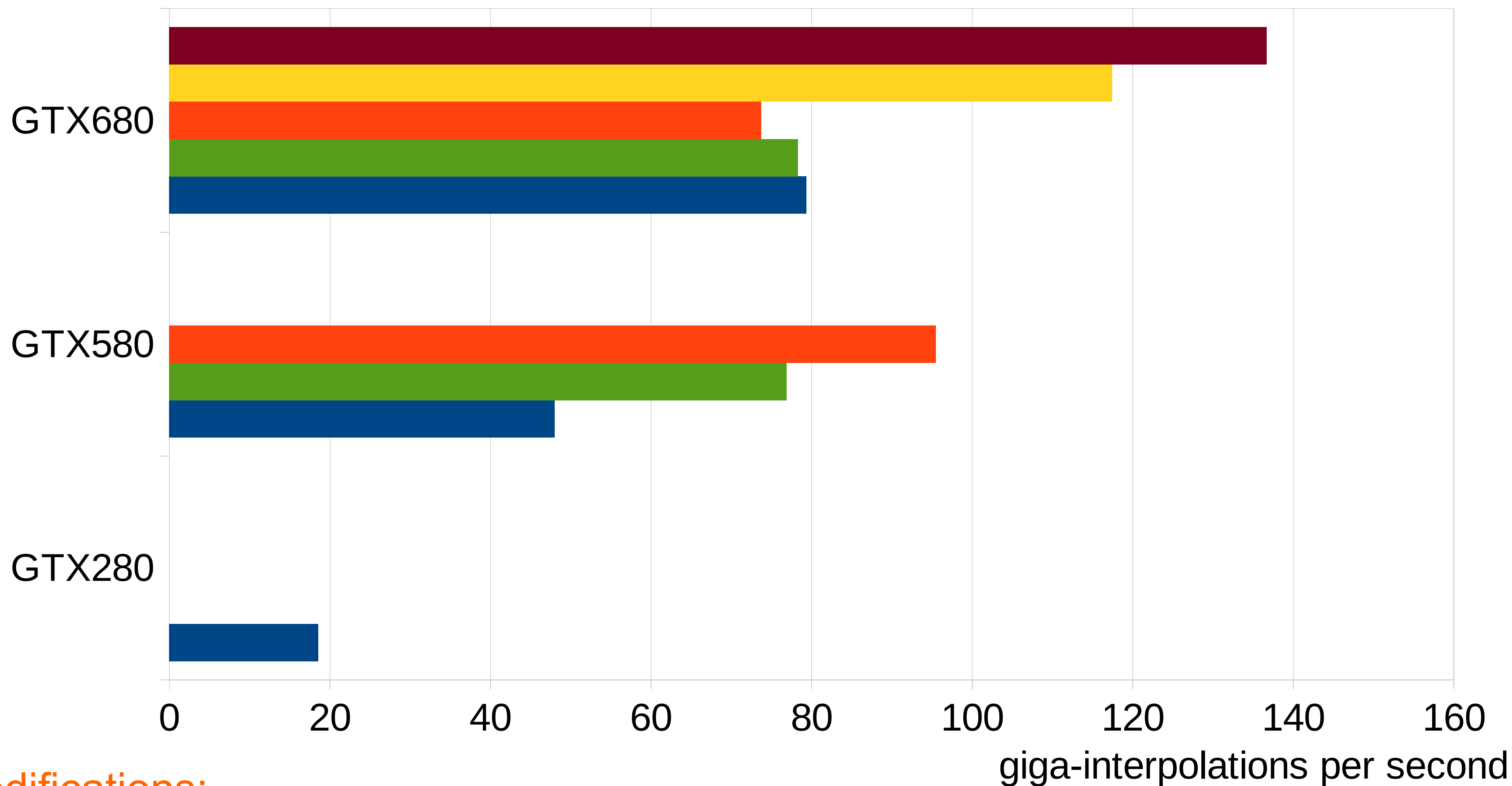
Performance of Back Projection



Modifications:

■ Standard ■ Linear ■ Oversample ■ Kepler ■ Kepler Oversample

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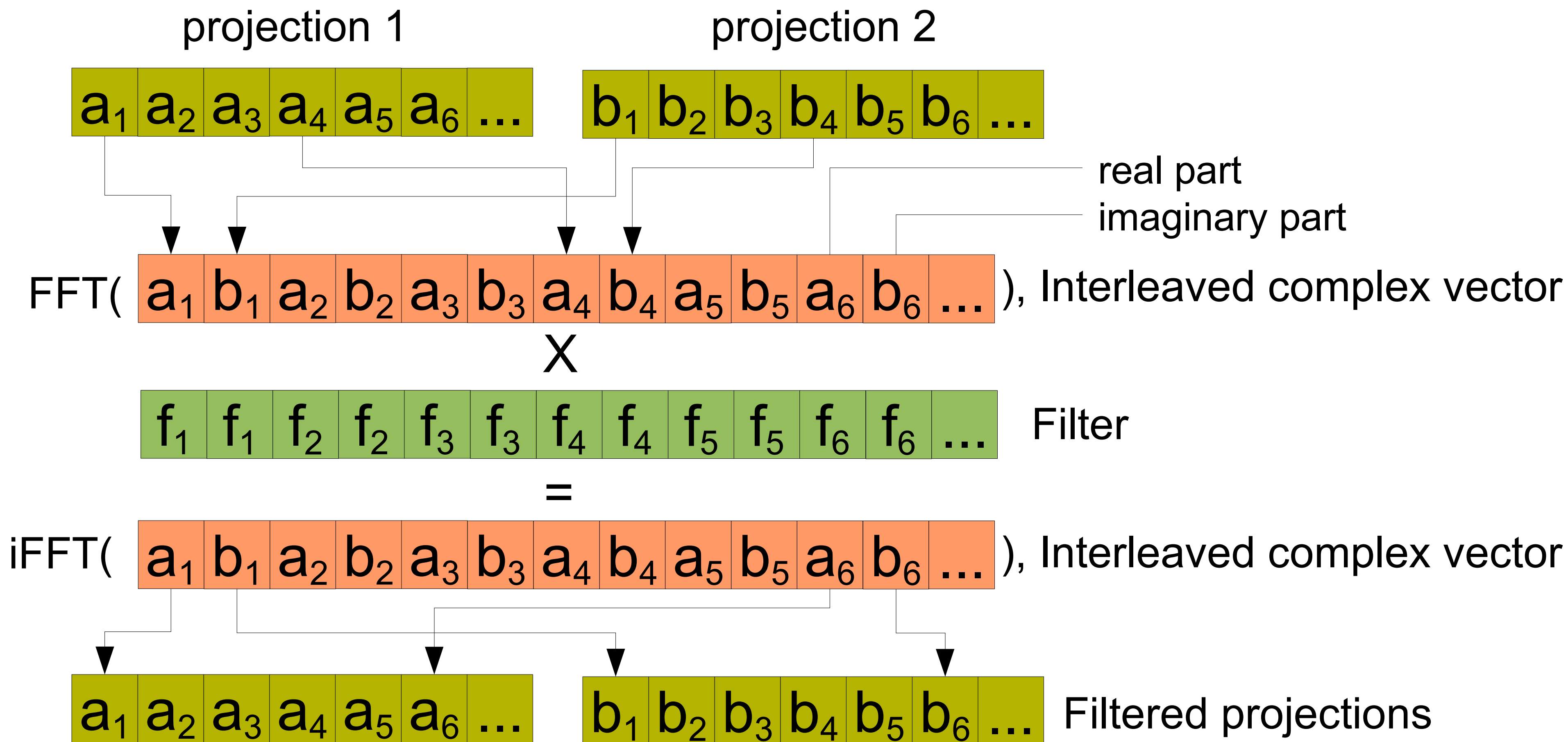
Optimizing Filtering Step

FFT library is optimized for complex-to-complex transforms while we are dealing with real numbers.



- **Also**
  - Pad data to a size equal to the closest power of 2
  - Batched processing

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Overall performance and scalability

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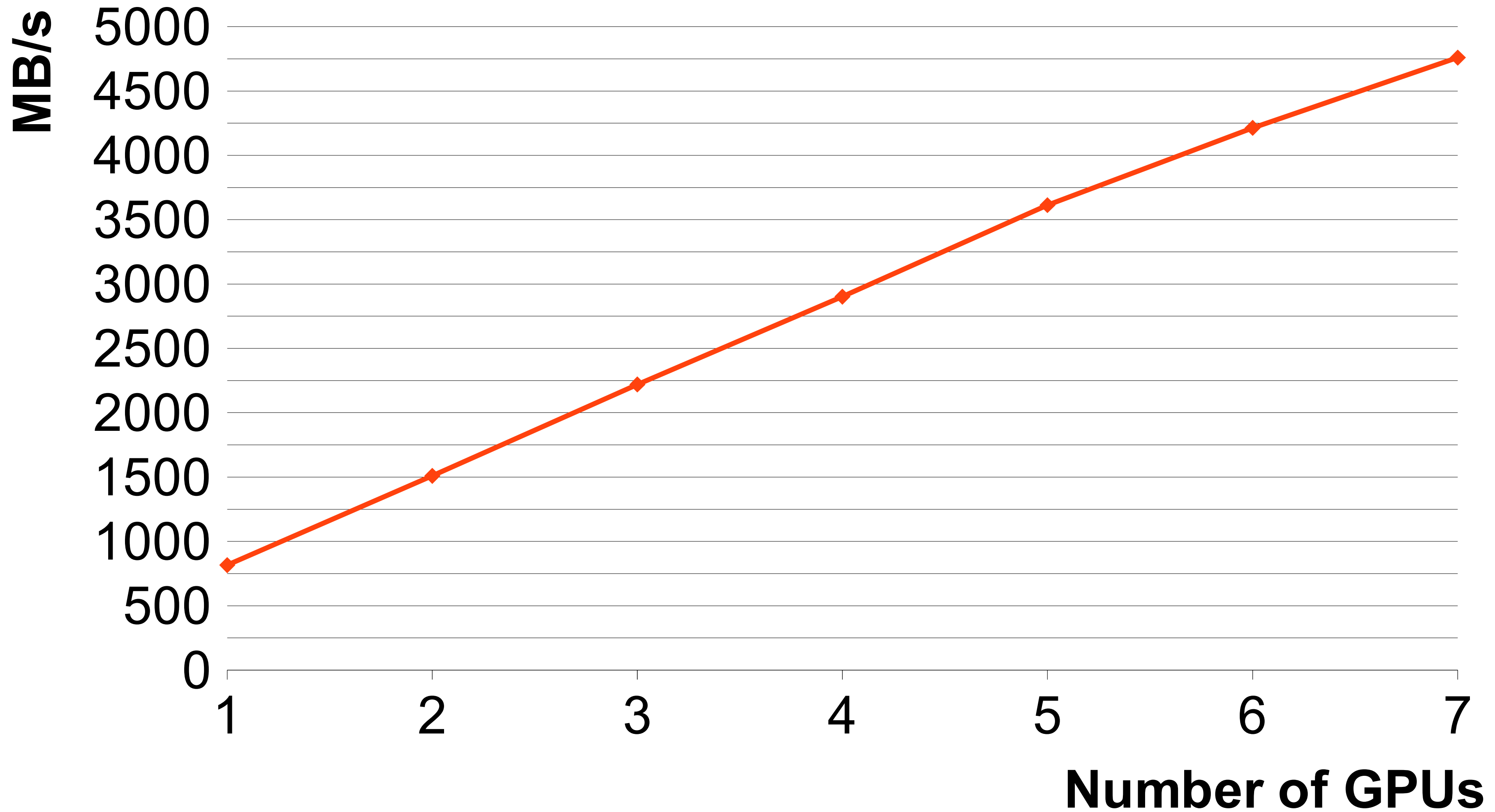

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Summary

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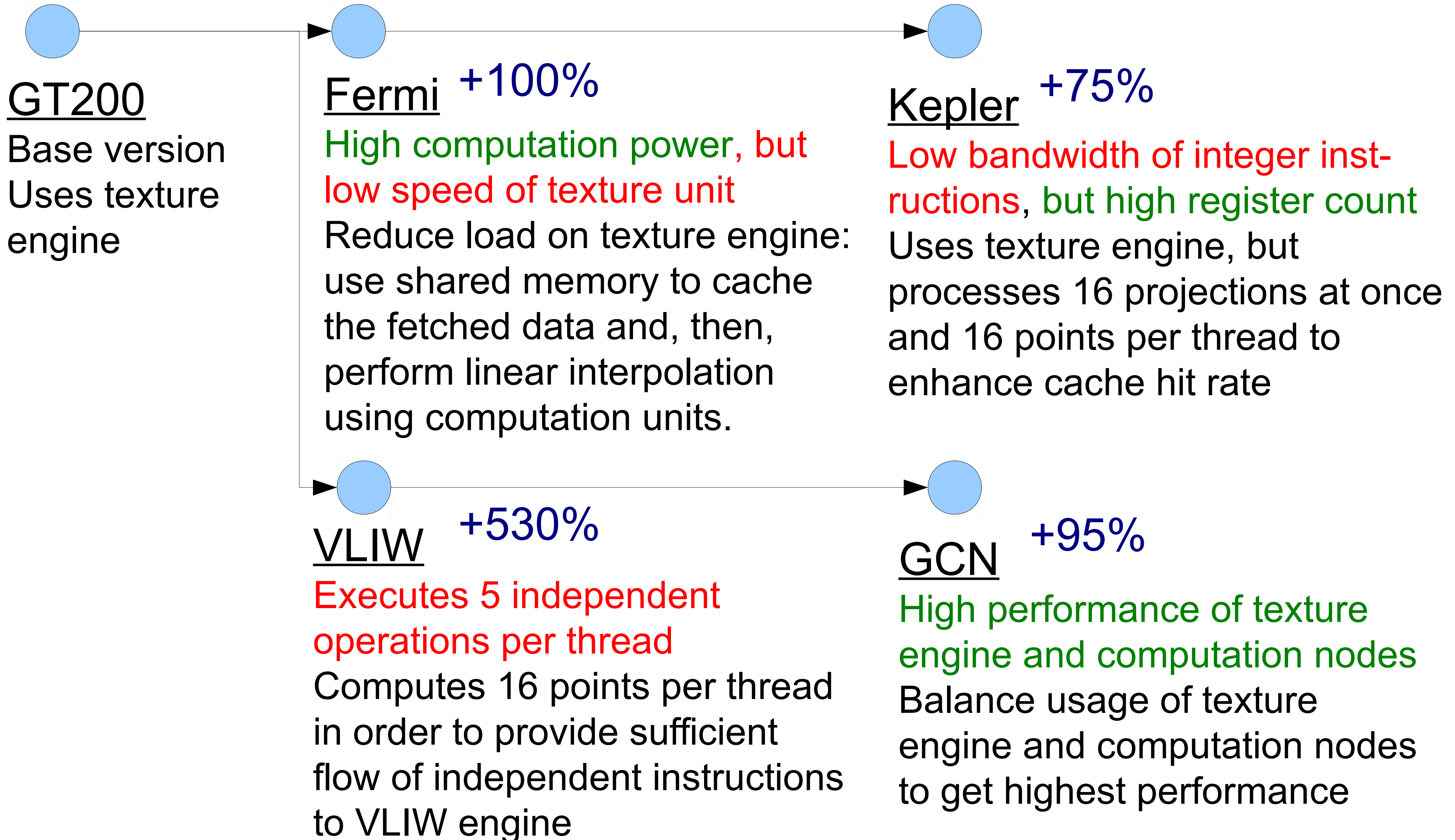

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