Exploiting auto-tuning to analyze and improve performance portability on many-core architectures

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Overview

- Performance portability is one of the key concerns for developers targeting many different architectures

- Current work in this area has provided mixed results

- Here we propose a method of rigorously analyzing performance portability by exploiting the black-box nature of auto-tuning

- We also present a simple technique that can improve performance portability when using auto-tuning

Devices

Vendor	Product	Architecture	Compute units
NVIDIA	GeForce GTX 580	Fermi (GF110)	16
	GeForce GTX 680	Kepler (GK104)	8
	GeForce GTX 780 Ti	Kepler (GK110)	15
	GeForce GTX 980 Ti	Maxwell (GM200)	22
	GeForce GTX 1080 Ti	Pascal (GP102)	28
AMD	Radeon HD 7970	Tahiti	32
	Radeon R9 290X	Hawaii	44
	Radeon R9 Furyx	Fiji	64
	Radeon RX 480	Ellesmere	36
Intel	Core i5-3550	Ivy Bridge	4
	Core i5-4590	Haswell	4
	Core i5-6600	Skylake	4

Benchmarks

- Using three benchmarks from different domains
- Implemented with OpenCL (using PyOpenCL)
  - Need portability but also explicit control over kernel implementation
- Expose large set of possible implementation decisions as tuning options
- Dynamically generate kernels to provide greater flexibility

Benchmark #1: Jacobi method

- Work-group size / parallel decomposition
- Memory layout / memory access pattern
- Loop unrolling
- *+ vs **mad** vs **fma**
- Branching vs masks
- Division by diagonal (inline or precompute)
- Address spaces of input vectors
- Embedding values into kernel as constants

Solve $A\boldsymbol{x} = \boldsymbol{b}$

↓

Split matrix **A** into diagonal **D** and remainder **R**

↓

$$\boldsymbol{x}_{i+1} = D^{-1}(\boldsymbol{b} - R\boldsymbol{x}_i)$$

Benchmark #2: Bilateral filter

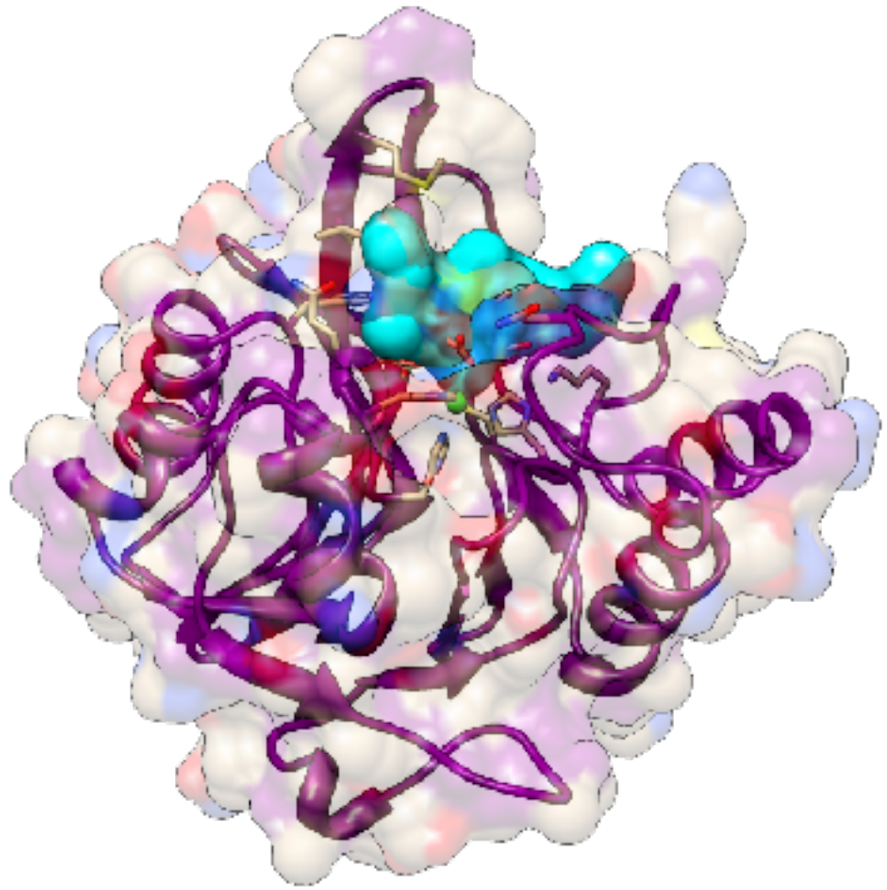
- Work-group size
- Tile size / tile layout
- Prefetch pixels into private/local memory
- Buffers vs images
- *+ vs **mad** vs **fma**
- Loop interchange
- Native math functions
- Embedding values into kernel as constants

$$O(x,y) = \frac{\sum_{i=-r}^{r}\sum_{j=-r}^{r} I(i,j)\cdot W(x,y,i,j)}{\sum_{i=-r}^{r}\sum_{j=-r}^{r} W(x,y,i,j)}$$

$$W(x,y,i,j) = e^{(-\frac{\sqrt{i^2+j^2}}{2\sigma_d} - \frac{||(I(x,y)-I(x+i,y+j)||}{2\sigma_r})}$$

Benchmark #3: BUDE

- Parallel decomposition / work-group size
- Data layout / memory access patterns
- Loop interchange
- Address space of molecules / forcefield
- Precomputing forcefield coefficients
- Native math functions
- Embedding values into kernel as constants



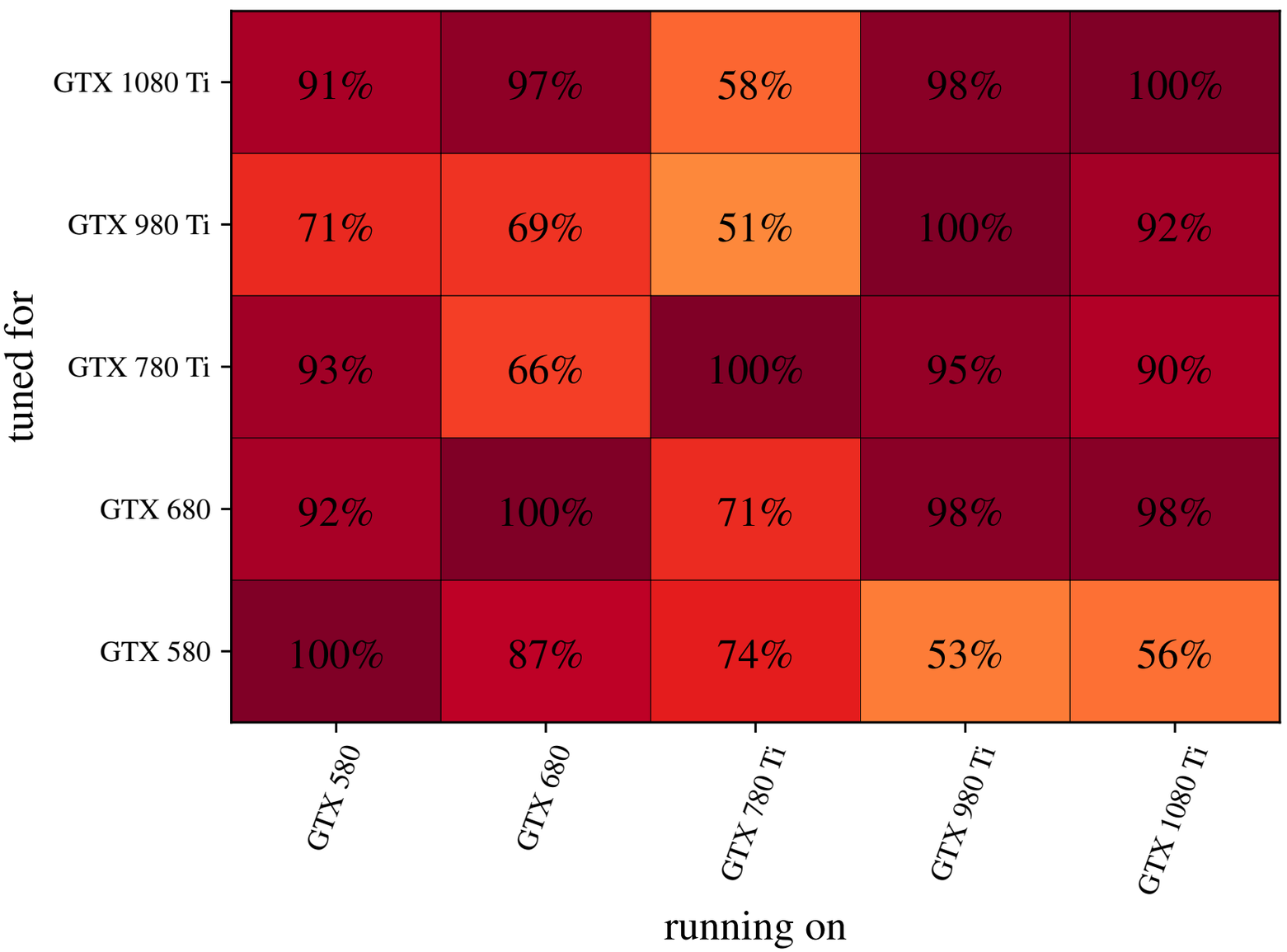
Analysis approach

- Run auto-tuner to optimize the kernel for each device individually
  - Genetic algorithm used for search
  - Tuned for 24 hours on each device (examines ~10K kernels)
- This produces a set of architecture-specific kernels
- We then run each architecture-specific kernel on every other device and measure efficiency
- Efficiency defined as fraction of best kernel observed on that device

Jacobi efficiencies

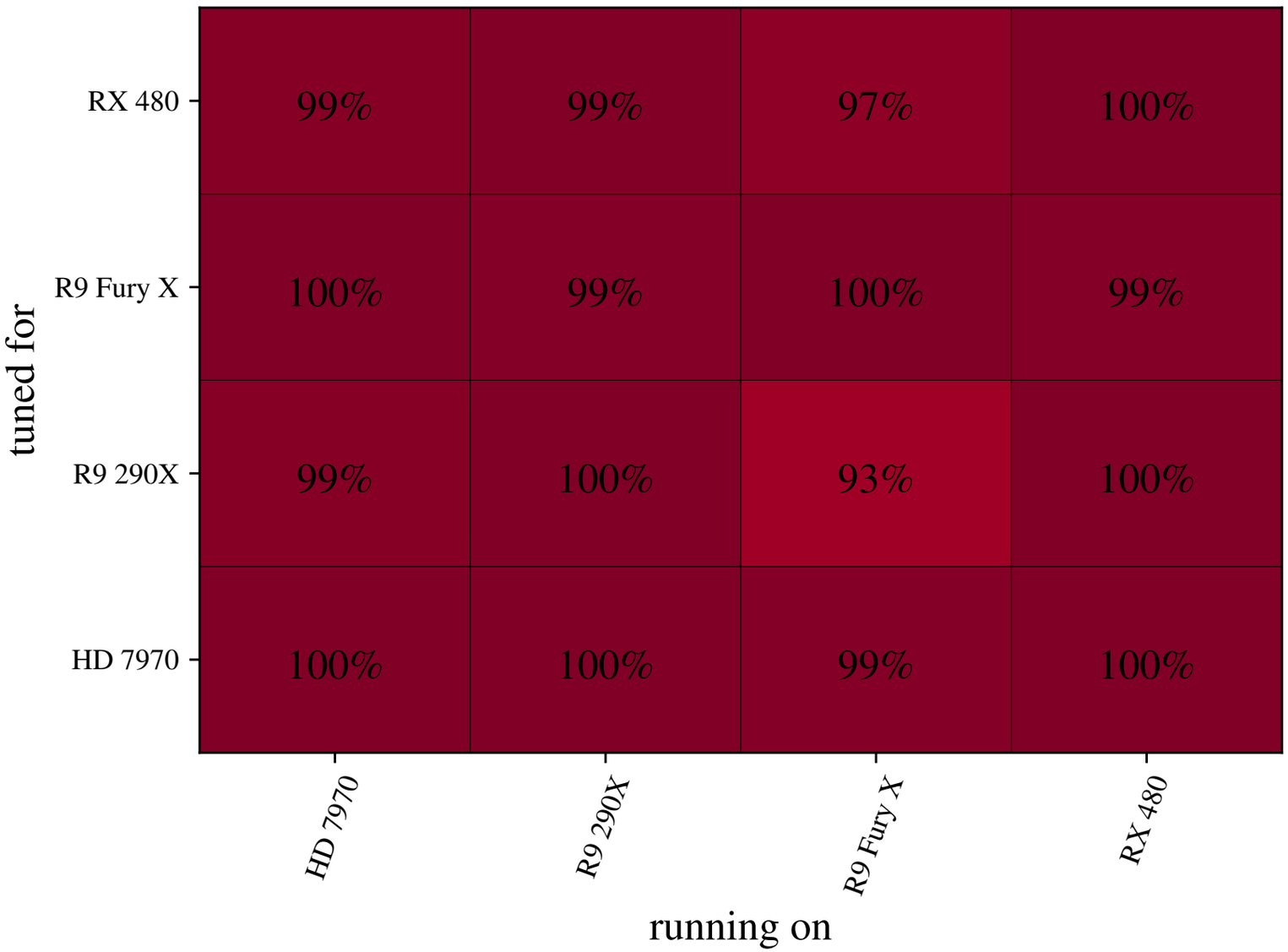
tuned for \ running on	GTX 580	GTX 680	GTX 780 Ti	GTX 980 Ti	GTX 1080 Ti	HD 7970	R9 290X	R9 Fury X	RX 480	Ivy Bridge CPU	Haswell CPU	Skylake CPU
Skylake CPU	90%	69%	93%	90%	90%	45%	28%	14%	21%	2%	99%	100%
Haswell CPU	12%	16%	16%	39%	43%	37%	20%	11%	17%	2%	100%	97%
Ivy Bridge CPU	21%	14%	18%	41%	40%	19%	14%	6%	13%	100%	53%	44%
RX 480	87%	74%	78%	95%	93%	99%	99%	97%	100%	2%	93%	81%
R9 Fury X	24%	20%	20%	23%	37%	100%	99%	100%	99%	62%	80%	65%
R9 290X	91%	79%	84%	97%	97%	99%	100%	93%	100%	2%	70%	57%
HD 7970	23%	19%	20%	21%	33%	100%	100%	99%	100%	73%	85%	71%
GTX 1080 Ti	91%	97%	58%	98%	100%	68%	38%	28%	62%	1%	5%	4%
GTX 980 Ti	71%	69%	51%	100%	92%	53%	33%	49%	36%	5%	5%	5%
GTX 780 Ti	93%	66%	100%	95%	90%	68%	33%	32%	62%	5%	5%	4%
GTX 680	92%	100%	71%	98%	98%	55%	38%	26%	57%	1%	5%	4%
GTX 580	100%	87%	74%	53%	56%	X	X	X	X	1%	5%	4%

Jacobi - NVIDIA



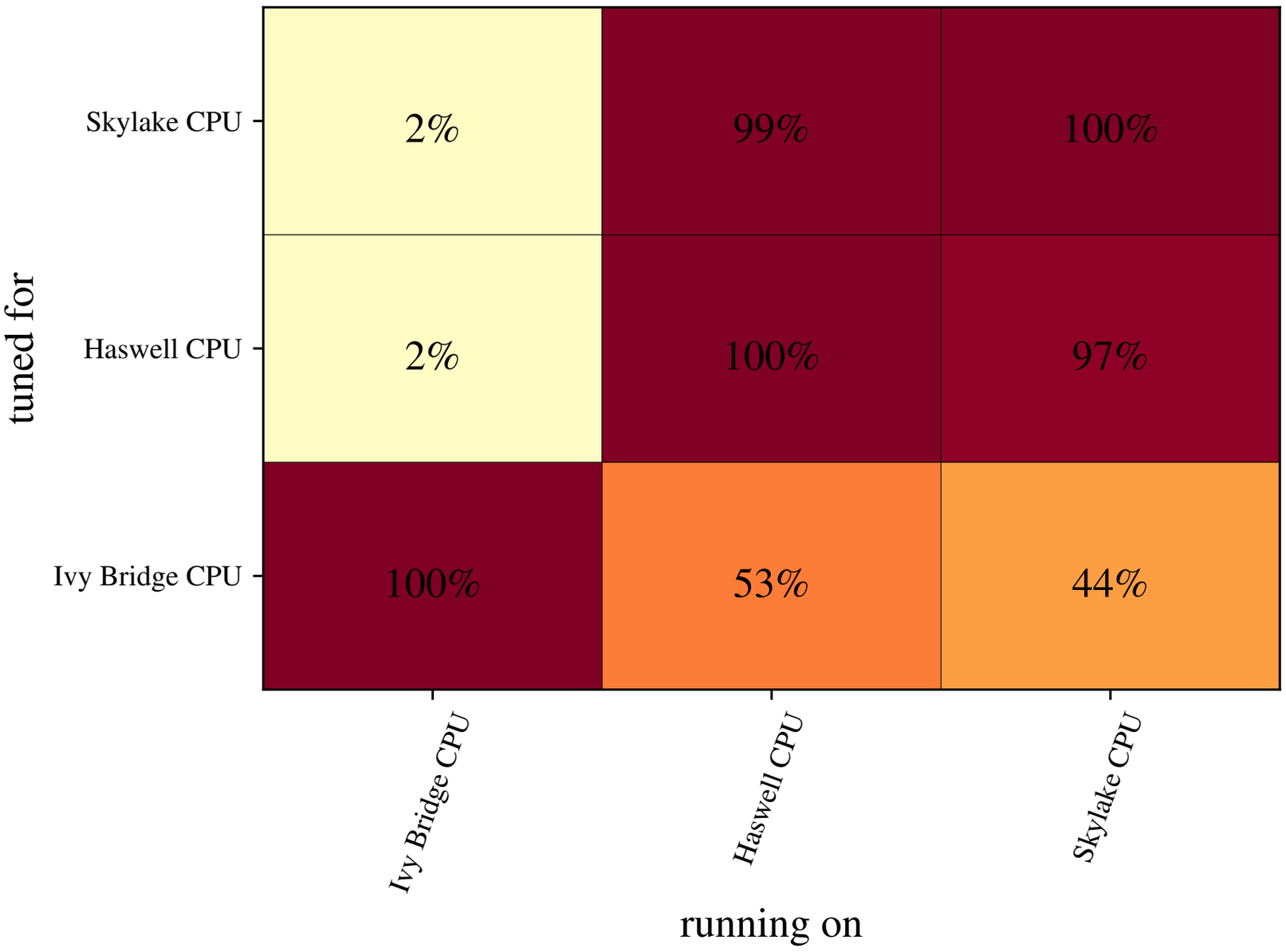
- Work-group size differs between devices
- Other drops due to address spaces and memory access pattern

Jacobi - AMD



- Most parameters uniform between all AMD devices
- FuryX suffers a little with expensive division

Jacobi - Intel



- Ivy Bridge performs poorly with **fma** builtin
- Vectorisation width differs

Jacobi efficiencies

tuned for \ running on	GTX 580	GTX 680	GTX 780 Ti	GTX 980 Ti	GTX 1080 Ti	HD 7970	R9 290X	R9 Fury X	RX 480	Ivy Bridge CPU	Haswell CPU	Skylake CPU	WCE
Skylake CPU	90%	69%	93%	90%	90%	45%	28%	14%	21%	2%	99%	100%	2%
Haswell CPU	12%	16%	16%	39%	43%	37%	20%	11%	17%	2%	100%	97%	2%
Ivy Bridge CPU	21%	14%	18%	41%	40%	19%	14%	6%	13%	100%	53%	44%	6%
RX 480	87%	74%	78%	95%	93%	99%	99%	97%	100%	2%	93%	81%	2%
R9 Fury X	24%	20%	20%	23%	37%	100%	99%	100%	99%	62%	80%	65%	20%
R9 290X	91%	79%	84%	97%	97%	99%	100%	93%	100%	2%	70%	57%	2%
HD 7970	23%	19%	20%	21%	33%	100%	100%	99%	100%	73%	85%	71%	19%
GTX 1080 Ti	91%	97%	58%	98%	100%	68%	38%	28%	62%	1%	5%	4%	1%
GTX 980 Ti	71%	69%	51%	100%	92%	53%	33%	49%	36%	5%	5%	5%	5%
GTX 780 Ti	93%	66%	100%	95%	90%	68%	33%	32%	62%	5%	5%	4%	4%
GTX 680	92%	100%	71%	98%	98%	55%	38%	26%	57%	1%	5%	4%	1%
GTX 580	100%	87%	74%	53%	56%	X	X	X	X	1%	5%	4%	-

Bilateral efficiencies

tuned for \ running on	GTX 580	GTX 680	GTX 780 Ti	GTX 980 Ti	GTX 1080 Ti	R9 290X	R9 Fury X	RX 480	Ivy Bridge CPU	Haswell CPU	Skylake CPU	WCE
Skylake CPU	19%	13%	18%	17%	12%	11%	8%	9%	98%	100%	100%	**8%**
Haswell CPU	19%	13%	18%	17%	12%	11%	8%	9%	98%	100%	100%	**8%**
Ivy Bridge CPU	8%	6%	7%	7%	7%	6%	5%	5%	100%	99%	99%	**5%**
RX 480	70%	70%	69%	84%	87%	100%	100%	100%	29%	27%	26%	**26%**
R9 Fury X	70%	71%	76%	85%	87%	100%	100%	100%	28%	27%	26%	**26%**
R9 290X	70%	68%	73%	85%	86%	100%	100%	100%	28%	27%	25%	**25%**
GTX 1080 Ti	93%	90%	97%	97%	100%	X	X	X	14%	72%	73%	**-**
GTX 980 Ti	100%	97%	99%	100%	98%	35%	31%	37%	14%	72%	71%	**14%**
GTX 780 Ti	95%	96%	100%	98%	98%	37%	37%	45%	74%	71%	73%	**37%**
GTX 680	96%	100%	99%	98%	97%	37%	38%	45%	74%	72%	74%	**37%**
GTX 580	100%	98%	99%	100%	99%	35%	31%	29%	14%	73%	74%	**14%**

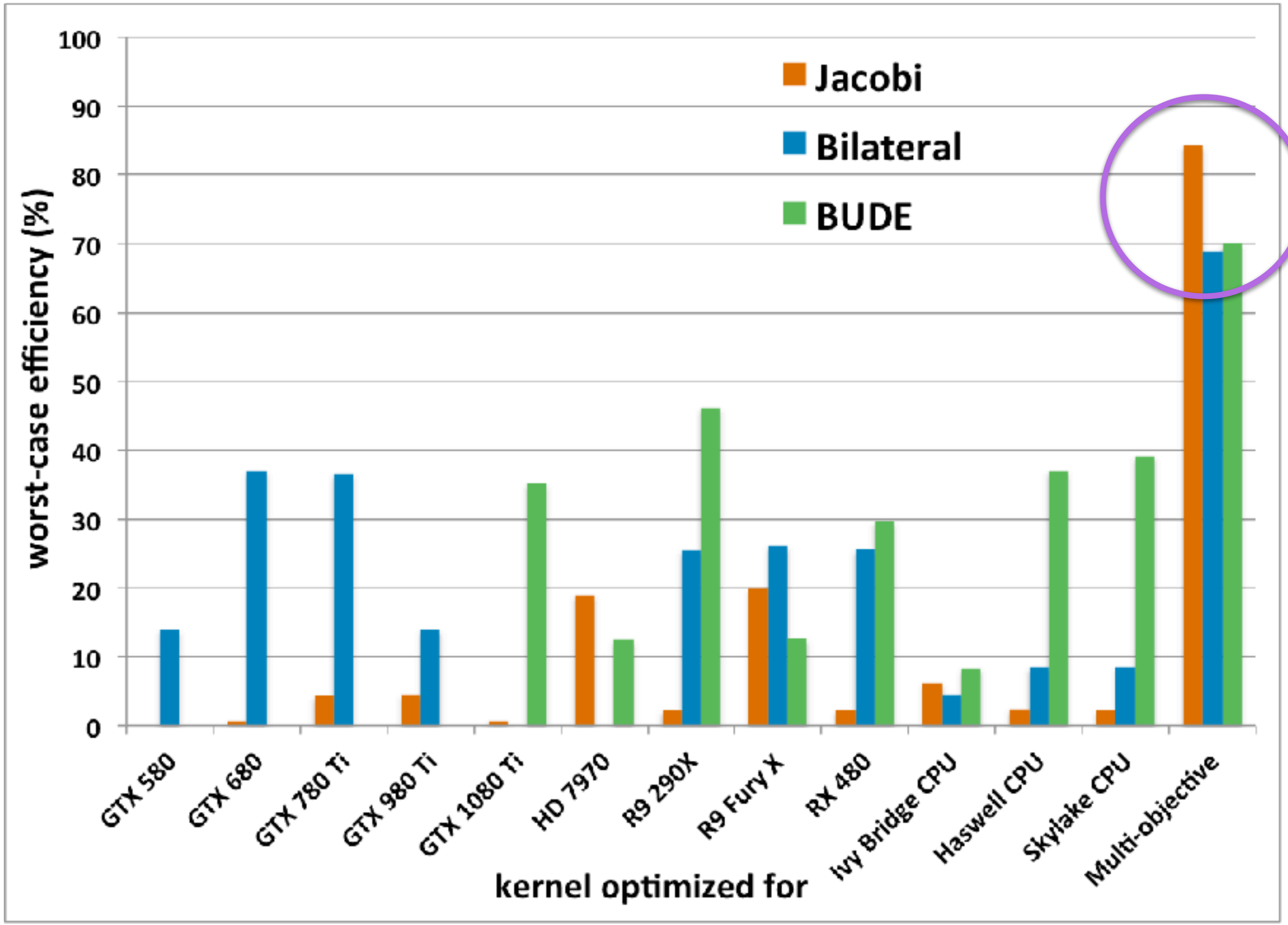
BUDE efficiencies

tuned for \ running on	GTX 580	GTX 680	GTX 780 Ti	GTX 980 Ti	GTX 1080 Ti	HD 7970	R9 290X	R9 Fury X	RX 480	Ivy Bridge CPU	Haswell CPU	Skylake CPU	WCE
Skylake CPU	74%	64%	39%	85%	87%	84%	61%	47%	92%	98%	98%	100%	39%
Haswell CPU	81%	81%	37%	90%	93%	78%	64%	48%	92%	98%	100%	98%	37%
Ivy Bridge CPU	15%	8%	13%	21%	29%	10%	10%	12%	12%	100%	98%	99%	8%
RX 480	68%	30%	32%	90%	96%	72%	67%	50%	100%	63%	61%	57%	30%
R9 Fury X	91%	52%	32%	79%	86%	72%	66%	100%	100%	16%	14%	13%	13%
R9 290X	84%	50%	46%	89%	97%	75%	100%	86%	98%	93%	93%	93%	46%
HD 7970	90%	78%	33%	66%	74%	100%	73%	86%	95%	15%	15%	12%	12%
GTX 1080 Ti	91%	48%	35%	77%	100%	71%	61%	71%	75%	62%	61%	57%	35%
GTX 980 Ti	91%	66%	83%	100%	100%	X	X	X	X	X	X	X	-
GTX 780 Ti	X	81%	100%	89%	83%	X	X	X	X	X	X	X	-
GTX 680	100%	100%	X	X	X	X	X	X	X	57%	51%	43%	-
GTX 580	100%	98%	X	X	X	X	X	X	X	57%	51%	43%	-

Multi-objective auto-tuning

- Extend tuning process to consider multiple devices at once
- Each time a kernel is generated, the auto-tuner evaluates it on every target device
- The performance values are then reduced into a single number representing the overall ‘fitness’
- We use worst-case efficiency for this fitness function

Multi-objective tuning results



Summary

- Over-optimisation hurts performance portability
- Auto-tuning can be a great way to expose these issues
- It can also help generate performance portable kernels
- Future work looking at tuning across different input/ problem configurations