Highly Scalable Multi-Objective Test Suite Minimisation Using Graphics Card

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It is all good improving SBSE for practitioners, but...

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- GECCO 2011 GPGPU Competition
  - Full Implementation of an Estimation of Distribution Algorithm on a GPU, S. Poulding, J. Staunton, N. Burles
- Genetic Programming on GPU
  - A SIMT Interpreter for Genetic Programming, W. B. Langdon

Outline

- Motivation
- What is GPGPU?
- Reformulating Test Suite Minimisation/MOEA for GPU
- Empirical Results
- Lessons Learned

Motivation

- Computational Characteristics of Population-based EA
  - Single fitness function (most of the time)
  - Many individual to evaluate
  - Single Instruction Multiple Data (SIMD) Architecture
  - Can be expensive!

Motivation

- CPU-based Parallelism
- Multi-core CPUs do improve situation, but not much
- Clusters are expensive and difficult to manage
- Concurrent programming is hard

GPGPU

- General Purpose computation on Graphics Processing Units: uses graphics card to run massively parallel programs
- Modern graphics cards have hundreds of small cores, originally intended to be used to run shader algorithms
- Single algorithm, many different triangles: sounds familiar?

GPGPU

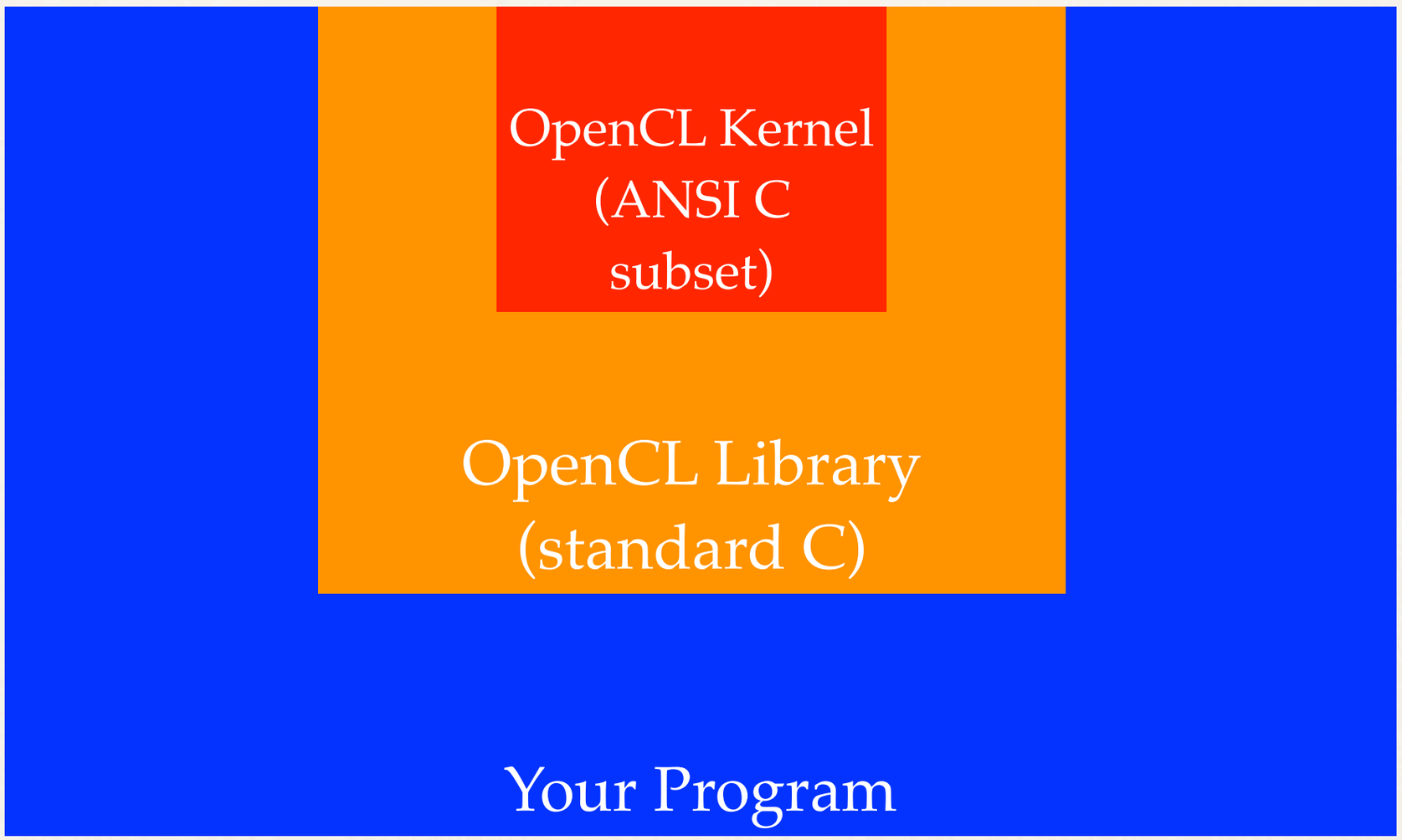
- Emerged during early 2000
  - Mapping Computational Concepts to GPUs, Mark Harris, ACM SIGGRAPH, 2005
- Now a must-have ingredient of any significant parallelisation

Tianhe, currently ranked at 2nd fastest supercomputer with 2.6 petaflops
14,337 Intel CPU + 7,168 NVidia GPU

GPGPU: Frameworks

- CUDA (Compute Unified Device Architecture) by NVidia
  - Works for NVidia Cards
  - Supports OpenCL too
- OpenCL (Open Computing Language) by Khronos
  - Device agnostic
  - Included in Mac OS X 10.6 and onwards

OpenCL: Language



OpenCL: Kernel Code

- Kernels are the smallest executable unit for OpenCL
- Compiled at runtime
- Many useful built-in functions and types, such as vector arithmetic. For example,
  - `float`*n*: float vector (*n* = 2, 4, 8, 16)
  - `float16 a = vload(0, ptr); float16 b = sqrt(a);`

OpenCL: Kernel Code

```
__kernel void multiply(__global float* C, __global
float* A, __global float* B, int wA, int wB)
{
    // Get the thread ids for this tile
    int tx = get_global_id(0);
    int ty = get_global_id(1);

    // value stores the element
    // that is computed by the thread
    float value = 0;
    for (int k = 0; k < wA; ++k)
    {
        value += A[ty * wA + k] * B[k * wB + tx];
    }

    // Write the matrix to device memory each
    // thread writes one element
    C[ty * wB + tx] = value;
}
```

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memory modifiers

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memory modifiers

built-in functions

OpenCL: Wrappers

- JavaCL: http://code.google.com/p/javacl/
  - Completely Object-oriented design
  - Nice integration with Java API
  - Thanks, Olivier :)
- PyOpenCL: http://mathema.tician.de/software/pyopencl

A Peek into JavaCL

```
CLContext context = JavaCL.createBestContext();
CLProgram program = context.createProgram(myKernelSource).build();
CLKernel multiplyKernel = program.createKernel(
        "myKernel",
        new float[] { u, v },
        context.createIntBuffer(Usage.Input, inputBuffer, true),
        context.createFloatBuffer(Usage.Output, resultsBuffer, false)
);
...
multiplyKernel.enqueueNDRange(queue, new int[]{bWidth, aHeight}, new
int[]{16, 16}, new CLEvent[]{});
queue.finish();
...
fitnessBuffer = fitnessMem.readBytes(queue, 0, aHeight * bWidth * 4,
new CLEvent[]{}).order(ByteOrder.LITTLE_ENDIAN);
coverageBuffer = coverageMem.readBytes(queue, 0, populationSize * 4,
new CLEvent[]{}).order(ByteOrder.LITTLE_ENDIAN);
scoreBuffer = scoreMem.readBytes(queue, 0, populationSize * 4, new
CLEvent[]{}).order(ByteOrder.LITTLE_ENDIAN);
queue.finish();
```

Test Suite Minimisation

- The Problem: Your regression test suite is too large.
- The Idea: There must be some redundant test cases.
- The Solution: Minimise (or reduce) your regression test suite by removing all the redundant tests.

Test Suite Minimisation

Things to tick off (branches, statements, DU-paths, etc)

	r0	r1	r2	r3	Time
t0	1	1	0	0	2
t1	0	1	0	1	3
t2	0	0	1	1	7
t3	0	0	1	0	3

Cost of ticking things off

Your tests

Now the problem becomes the following: what is the subset of rows (i.e. tests) that, when combined, will cover (i.e. put ‘1’ on) the most of the columns?

Reformulation

$$A' = \begin{pmatrix} a_{1,1} & \dots & a_{1,m} \\ a_{2,1} & \dots & a_{2,m} \\ & \dots & \\ a_{l,1} & \dots & a_{l,m} \\ cost(t_1) & \dots & cost(t_m) \end{pmatrix}$$

A: the test suite

a_{ij} = # element i has been executed by test case j

$$B = \begin{pmatrix} b_{1,1} & \dots & b_{1,n} \\ b_{2,1} & \dots & b_{2,n} \\ & \dots & \\ b_{m,1} & \dots & b_{m,n} \end{pmatrix}$$

B: the population

$b_{jk} = 1$ if test case j has been selected by individual k;

0 otherwise

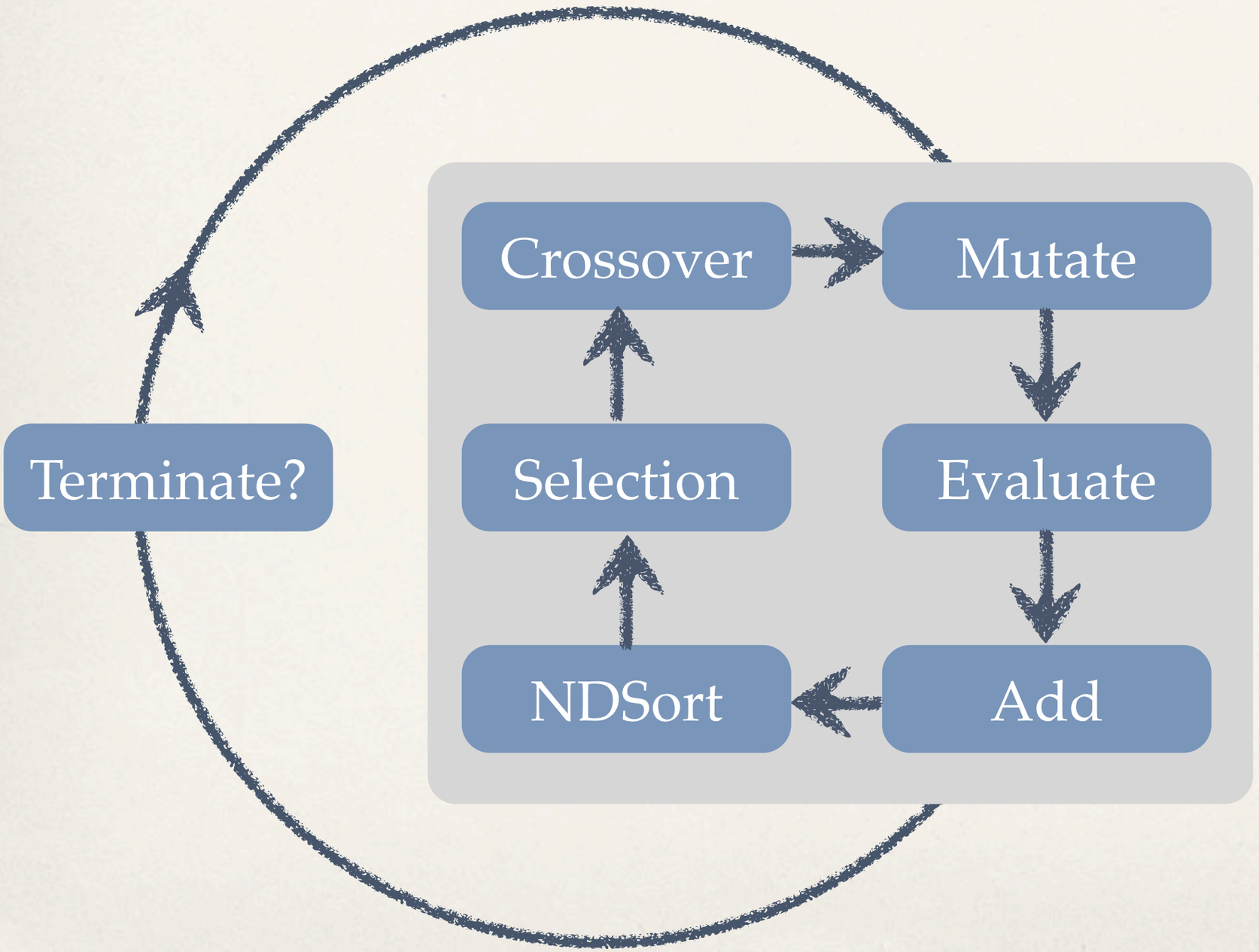
Reformulation

$$C' = AB = \begin{pmatrix} c_{1,1} & \dots & c_{1,n} \\ c_{2,1} & \dots & c_{2,n} \\ & \dots & \\ c_{l,1} & \dots & c_{l,n} \\ cost(p_1) & \dots & cost(p_n) \end{pmatrix}$$

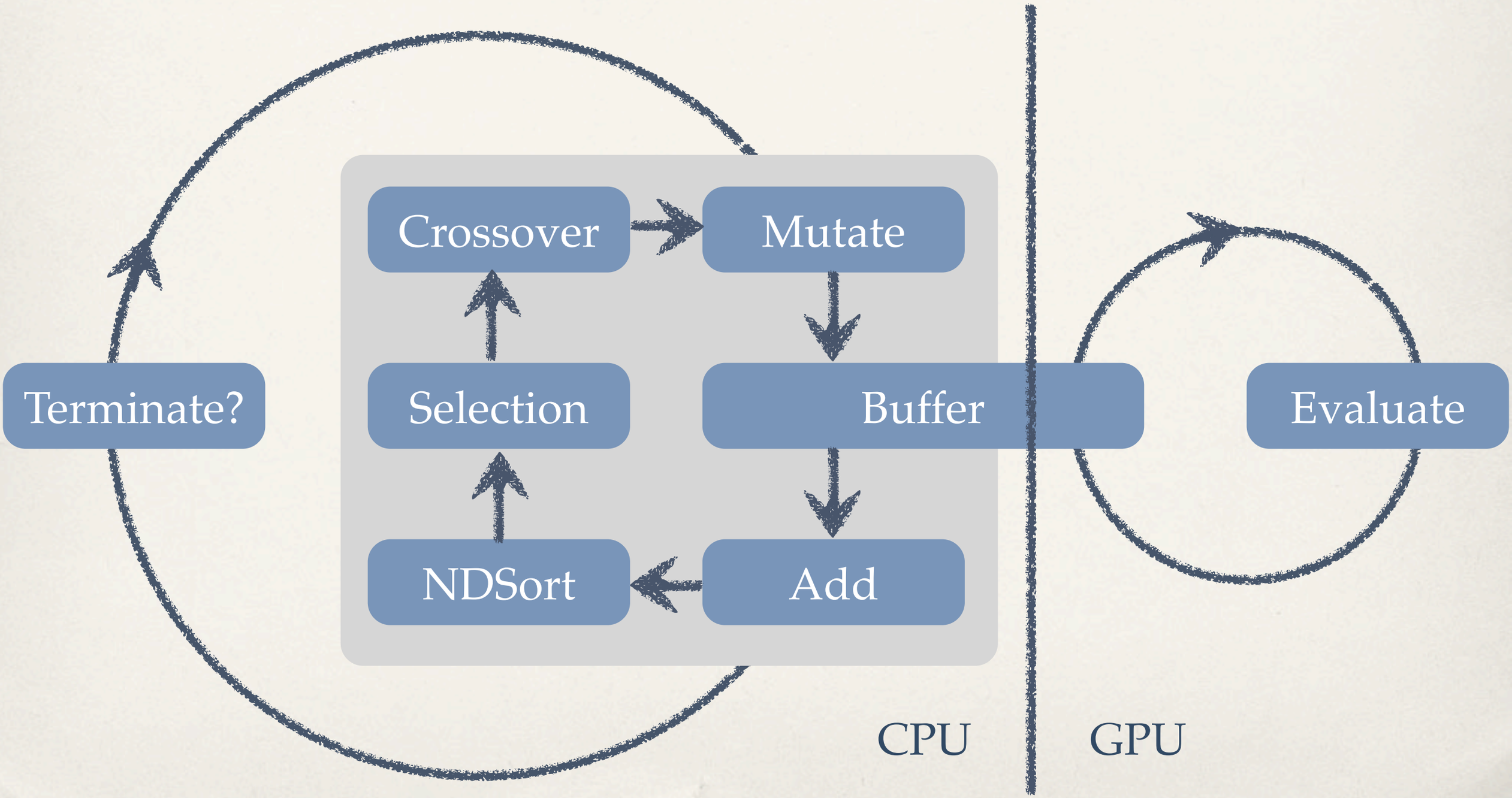
c_{ij} = # element *i* has been executed by test cases selected in individual *k*

$cost(p_k)$ = sum of execution cost of tests selected by individual k

Algorithm: NSGA-II



Algorithm: NSGA-II



Experimental Setup

- NSGA-II from jMetal, a Java MOEA library
- We have compared 5 different computational methods:
  - Baseline with OOP model: each individual is evaluated separately using a few method calls
  - JOMP with 1/2/4 threads: matrix-based approach on CPU with multi-threads
  - GPGPU: matrix-based approach on GPU, only fitness evaluation is performed on GPU

Experimental Setup

- Population size: 256 (1 individual per thread)
- Iteration: 250
- Single-point crossover with probability 0.9
- Single bit-flip mutation

Experimental Setup

- Hardware
  - Intel Core i7 2.8GHz (quad-core), 4GM RAM
  - ATI Radeon HD4850 (not the most powerful card right now, $100)
- Software
  - OS X 10.6.5 (Darwin Kernel 10.6.0 x64)
  - JRE 1.6.0_22

Subjects

Program	Program Size (LOC)	Test Suite Size
printtokens	188	315-319
		4,130
printtokens2	199	4,115
schedule	142	224-227
		2,650
schedule2	142	2,710
tcas	65	1,608
totinfo	124	1,052
replace	242	5,545
space	3,268	154-160
flex	3,956	103
gzip	2,007	213
sed	1,789	370
bash	6,167	1,061
ibm	61,770	181

- Both smaller test suites and the entire test input in SIR were considered for printtokens and schedule
- IBM middleware size represents functional checkpoints

Table 1: Speed–up results for NSGA-II

Subject	S_{JOMP1}	S_{JOMP2}	S_{JOMP4}	S_{GPU}
`printtokens-1`	0.83	1.21	1.54	2.14
`printtokens-2`	0.83	1.23	1.56	2.20
`printtokens-3`	0.82	1.21	1.53	2.13
`printtokens-4`	0.84	1.22	1.54	2.19
`schedule-1`	0.97	1.22	1.40	1.56
`schedule-2`	0.96	1.22	1.41	1.46
`schedule-3`	0.96	1.22	1.39	1.45
`schedule-4`	0.95	1.20	1.37	1.43
`printtokens`	0.76	1.24	1.44	4.52
`schedule`	0.69	1.08	1.26	3.38
`printtokens2`	0.72	1.18	1.37	4.38
`schedule2`	0.71	1.09	1.27	3.09
`tcas`	0.84	1.10	1.30	1.94
`totinfo`	0.90	1.28	1.61	2.50
`flex`	1.58	2.76	4.19	6.82
`gzip`	1.19	2.15	3.31	8.00
`sed`	1.02	1.87	3.04	10.28
`space-1`	1.77	3.22	5.10	10.51
`space-2`	1.86	3.34	5.19	10.88
`space-3`	1.80	3.27	5.16	10.63
`space-4`	1.76	3.25	5.12	10.54
`replace`	0.73	1.23	1.44	5.26
`bash`	1.54	2.90	4.87	25.09
`haifa`	3.01	5.55	9.04	24.85

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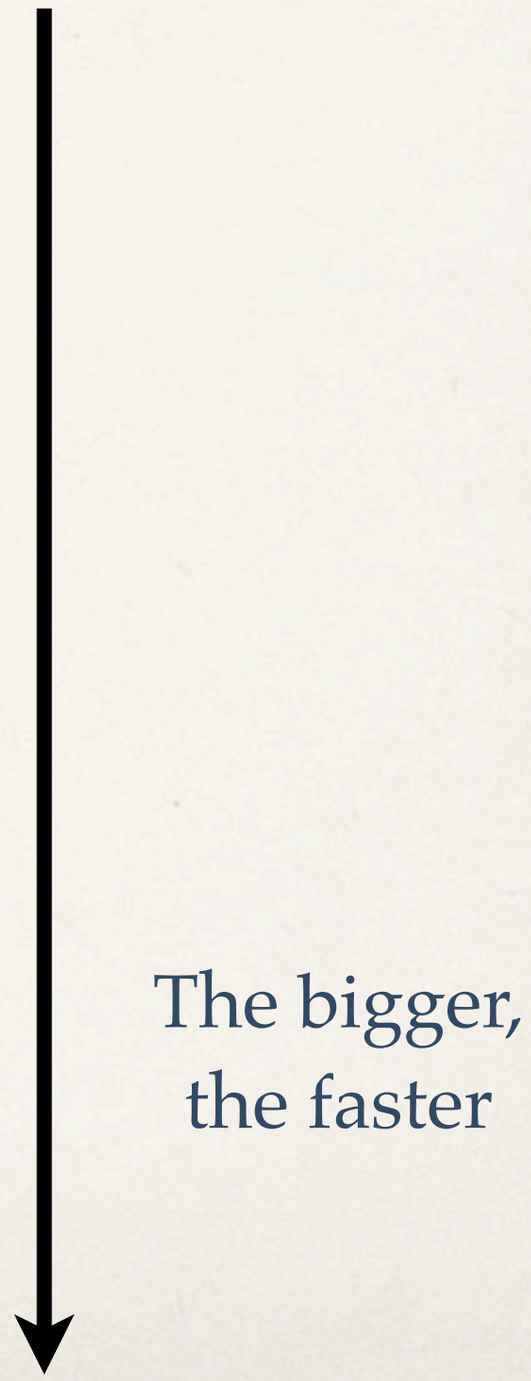


Table 1: Regression Analysis for NSGA-II

Config	Model	α	β	γ	R^2
JOMP1	$S_p \sim z$	1.56e-07	-	1.00e+00	0.4894
	$S_p \sim \log z$	2.01e-01	-	-1.34e+00	0.3423
	$S_p \sim l + m$	3.27e-05	-1.13e-04	1.17e+00	0.7060
	$S_p \sim \log l + m$	2.69e-01	-4.83e-05	-4.79e-01	0.8487
	$S_p \sim l + \log m$	3.12e-05	-1.78e-01	2.15e+00	0.7600
	$S_p \sim \log l + \log m$	2.62e-01	-6.83e-02	-6.15e-02	0.8509
JOMP2	$S_p \sim z$	3.24e-07	-	1.58e+00	0.5009
	$S_p \sim \log z$	4.78e-01	-	-4.05e+00	0.4606
	$S_p \sim l + m$	6.64e-05	-1.82e-04	1.87e+00	0.6367
	$S_p \sim \log l + m$	6.00e-01	-2.84e-05	-1.83e+00	0.9084
	$S_p \sim l + \log m$	6.35e-05	-3.07e-01	3.58e+00	0.6836
	$S_p \sim \log l + \log m$	5.96e-01	-4.04e-02	-1.59e+00	0.9086
JOMP4	$S_p \sim z$	5.80e-07	-	2.15e+00	0.5045
	$S_p \sim \log z$	8.72e-01	-	-8.13e+00	0.4814
	$S_p \sim l + m$	1.16e-04	-3.42e-04	2.70e+00	0.6199
	$S_p \sim \log l + m$	1.08e+00	-5.93e-05	-4.00e+00	0.9322
	$S_p \sim l + \log m$	1.11e-04	-5.49e-01	5.74e+00	0.6611
	$S_p \sim \log l + \log m$	1.08e+00	-5.50e-02	-3.72e+00	0.9313
GPU	$S_p \sim z$	2.25e-06	-	4.13e+00	0.7261
	$S_p \sim \log z$	3.45e+00	-	-3.66e+01	0.7178
	$S_p \sim l + m$	3.62e-04	-1.63e-04	5.33e+00	0.4685
	$S_p \sim \log l + m$	3.53e+00	7.79e-04	-1.66e+01	0.8219
	$S_p \sim l + \log m$	3.62e-04	-1.34e-01	5.98e+00	0.4676
	$S_p \sim \log l + \log m$	3.85e+00	1.69e+00	-2.82e+01	0.8713

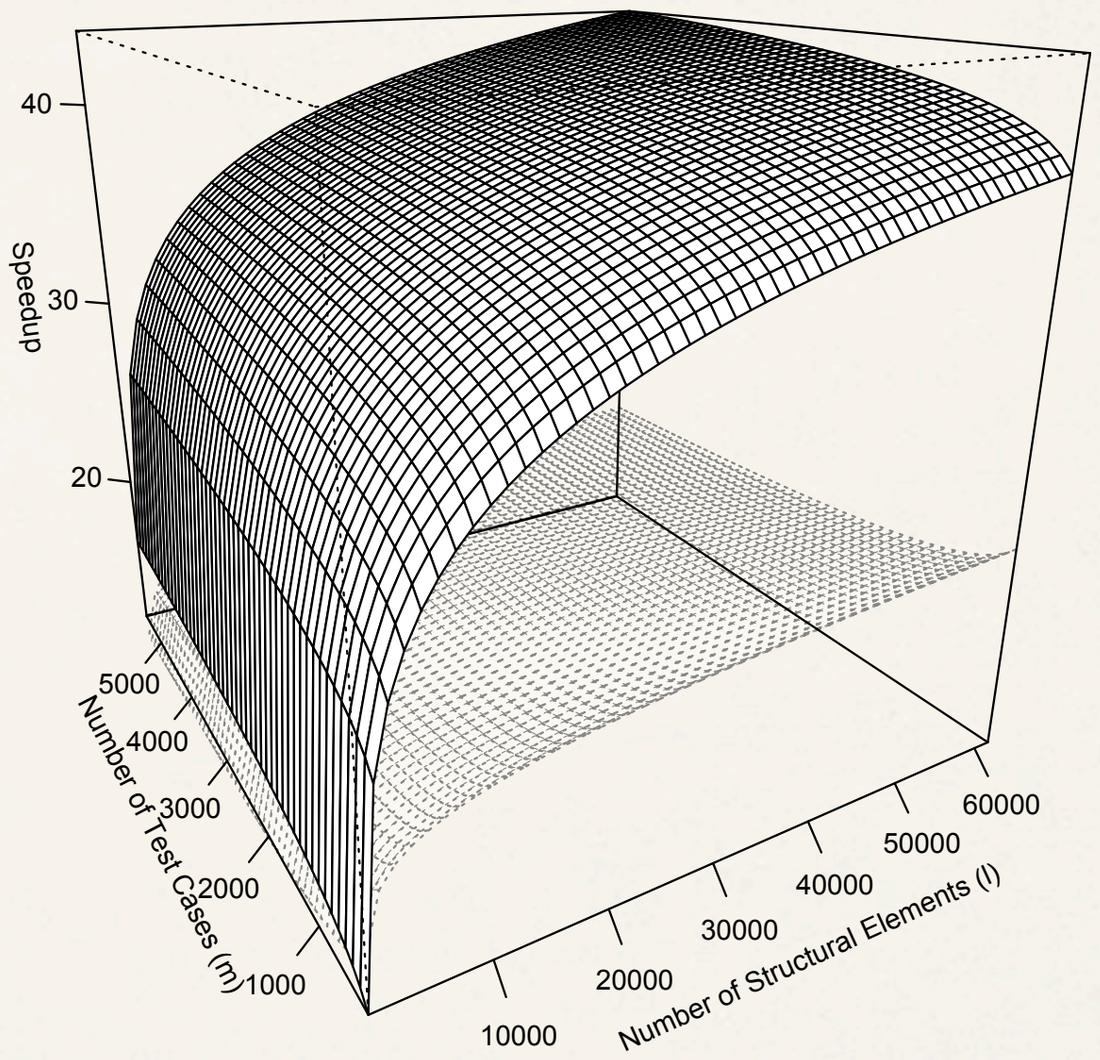
l: program size

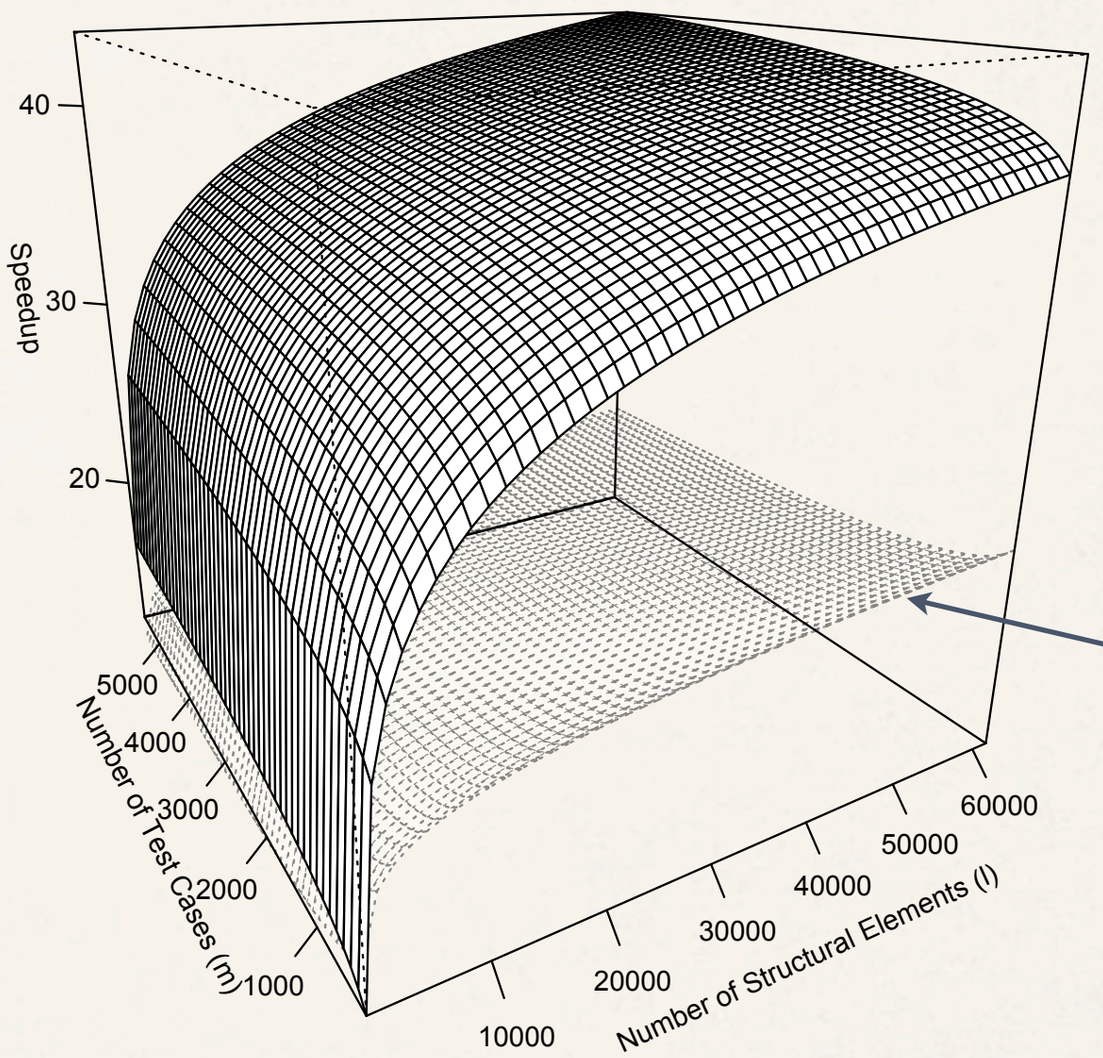
m: test suite size

z: l * m

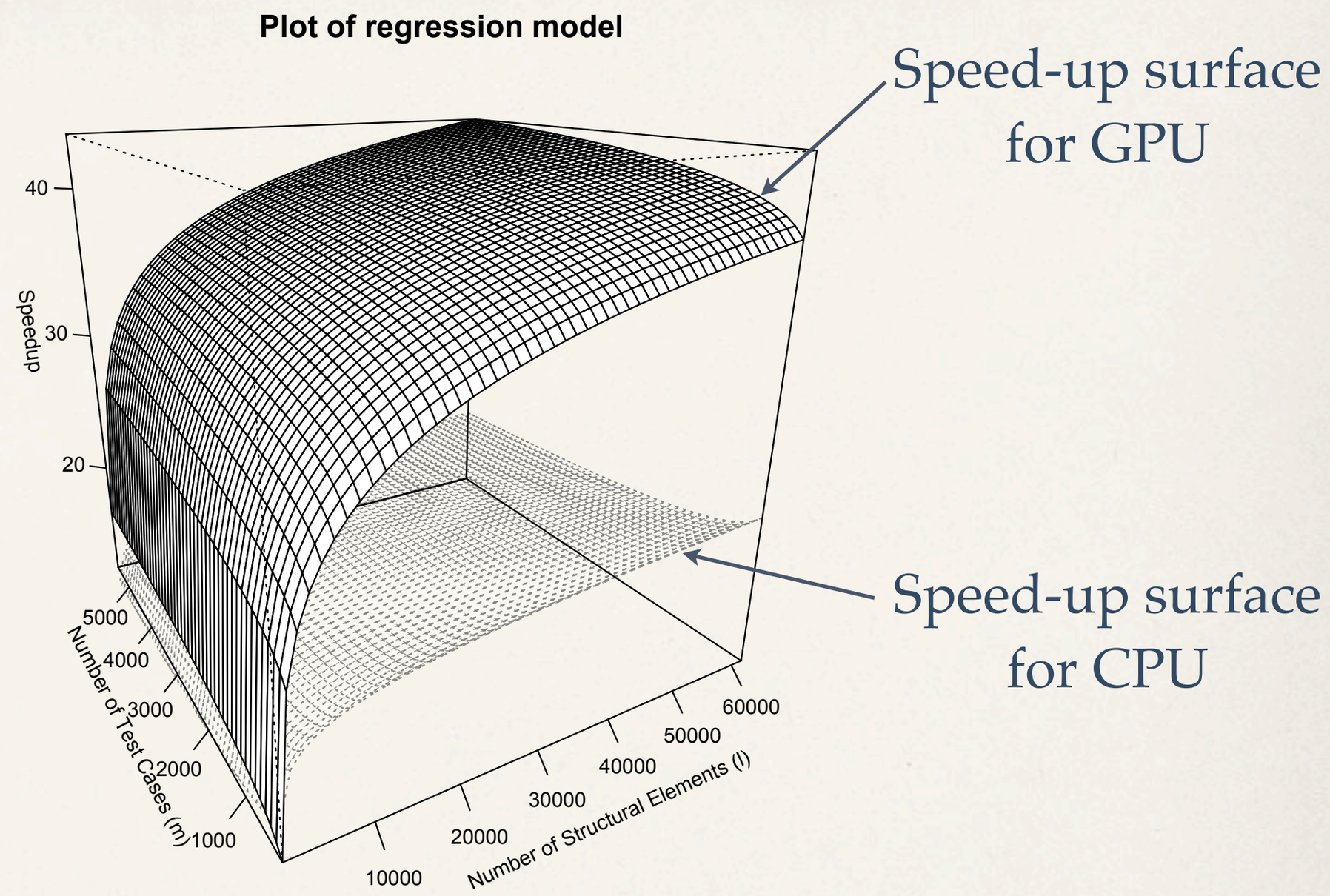
best fit: logarithmic

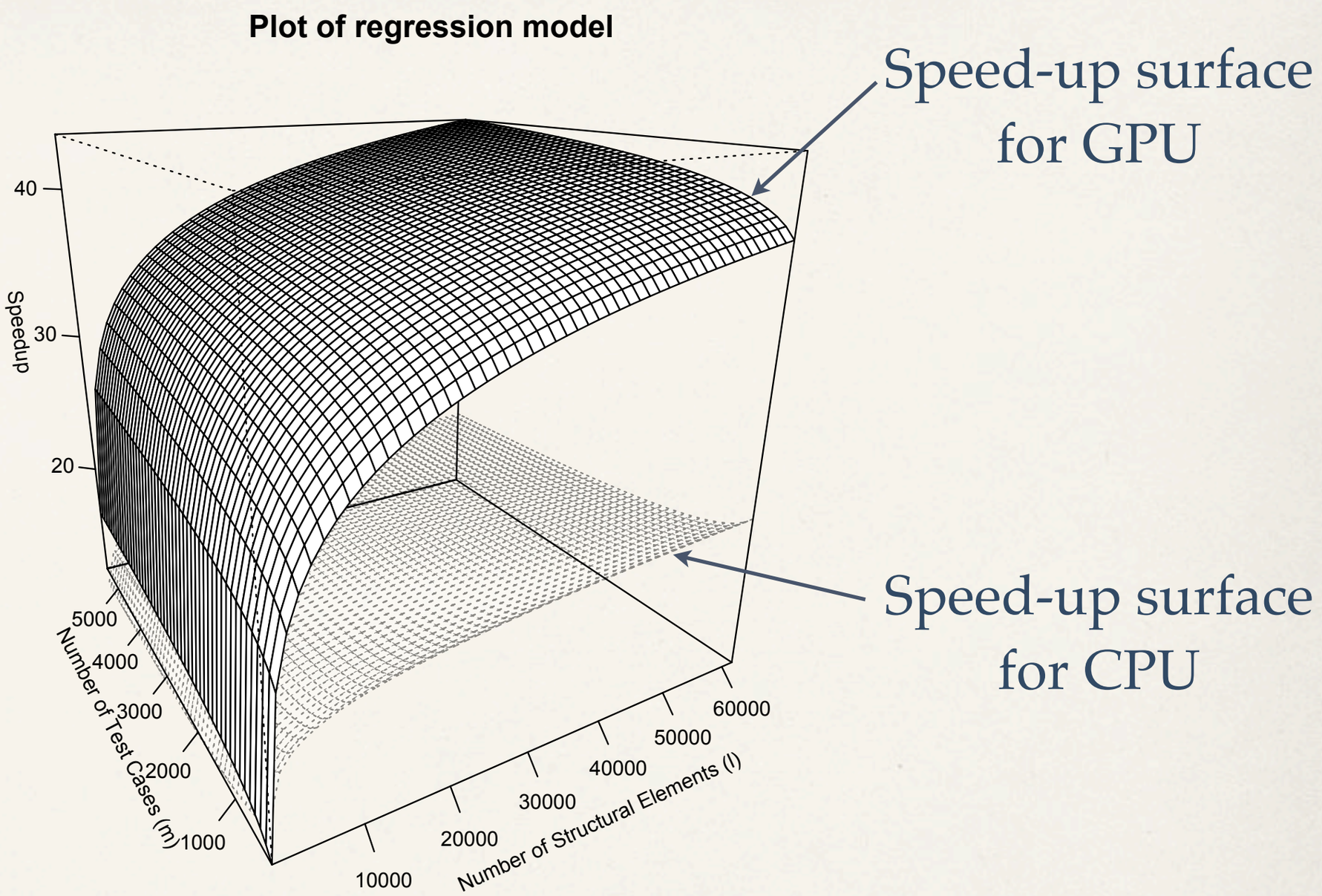
Plot of regression model





Speed-up surface for CPU


Plot of regression model
Speed-up surface for GPU
Speed-up surface for CPU
Speedup
40
30
20
Number of Test Cases (m)
5000
4000
3000
2000
1000
Number of Structural Elements (l)
10000
20000
30000
40000
50000
60000



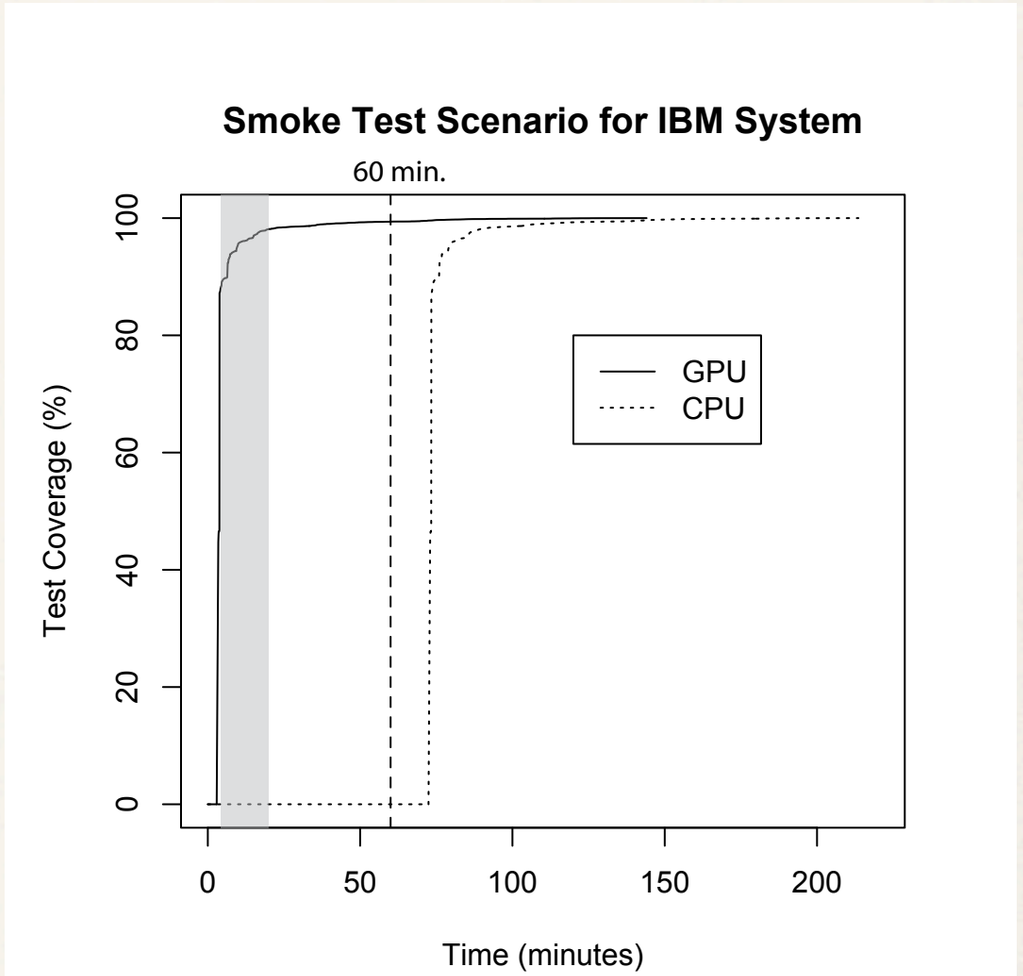
$$Speedup = 3.85 \log(l) + 1.69 \log(m) - 28.2$$

Benefits of Speed-up

- If optimisation itself takes too long, you may not meet the submission deadline

Benefits of Speed-up

- If optimisation itself takes too long, real world usage can be restricted.



Lessons Learned

- It is EASY: no need to switch languages, etc: many excellent wrappers out there.
- It is powerful: the language is fully expressive.
- It is available: most of you already have a machine that can achieve massive parallelism.

Lessons Learned

- You do need to care about a bit of low-level details: for example, endian-ness or hardware characteristics
- You need to be careful with memory
- Debugging can be hard: low observability
  - Maybe an interesting SBST problem?

- GPGPU is Easy
- GPGPU does Work
- GPGPU is Available
- http://www.macresearch.org/opencl