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Data-Intensive Computing for Competent Genetic Algorithms: A Pilot Study using Meandre

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Outline

- Data-intensive computing and HPC?
- Is this related at all to evolutionary computation?
- Data-intensive computing with Meandre
- GAs and competent GAs
- Data-intensive computing for GAs





2 Minute HPC History

- The eighties and early nineties picture
 - Commodity hardware rare, slow, and costly
 - Supercomputers were extremely expensive
 - Most of them hand crafted and only few units
 - Two competing families
 - CISC (e.g. Cray C90 with up to 16 processors)
 - RISC (e.g. Connection Machine CM-5 with up 4,096 processors)
- Late nineties commodity hardware hit main stream
 - Start becoming popular, cheaper, and faster
 - Economy of scale
 - Massive parallel computers build from commodity components become a viable option





Two Visions

- C90 like supercomputers were like a comfy pair of trainers
 - Oriented to scientific computing
 - Complex vector oriented supercomputers
 - Shared memory (lots of them)
 - Multiprocessor enabled via some intercommunication networks
 - Single system image
- CM5 like computers did not get massive traction, but a bit
 - General purpose (as long as you can chop the work in simple units)
 - Lots of simple processors available
 - Distributed memory pushed new programming models (message passing)
 - Complex interconnection networks
- NCSA have shared memory, distributed memory, and gpgpu based





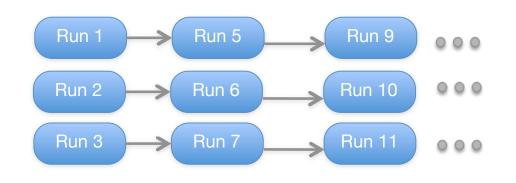
Miniaturization Building Bridges

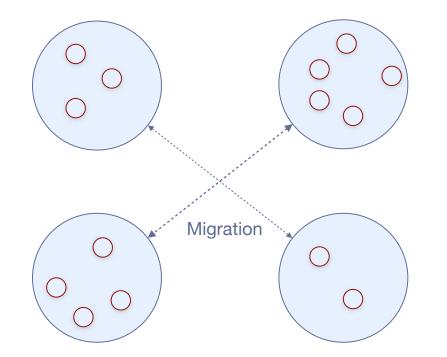
- Multicores and gpgpus are reviving the C90 flavor
- The CM-5 flavor now survives as distributed clusters of not so simple units

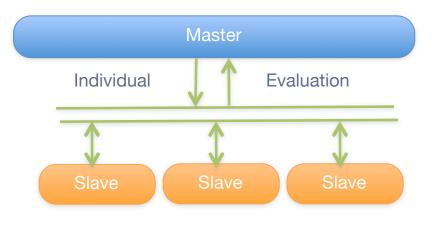


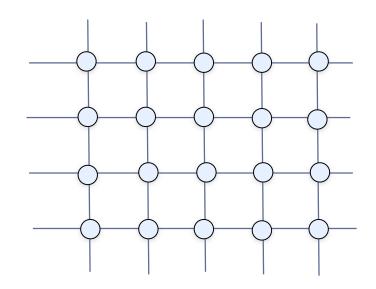


Control Models of Parallelization in EC













But Data is also Part of the Equation

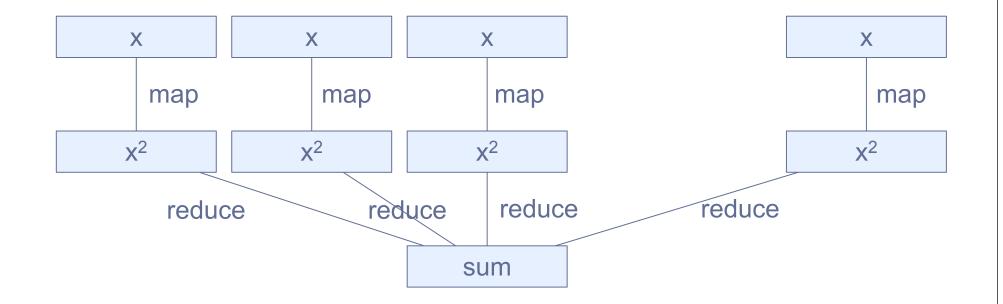
- Google and Yahoo! revived an old route
- Usually refers to:
 - Infrastructure
 - Programming techniques/paradigms
- Google made it main stream after their MapReduce model
- Yahoo! provides and open source implementation
 - Hadoop (MapReduce)
 - HDFS (Hadoop distributed filesystem)
- Store petabytes reliably on commodity hardware (fault tolerant)
- Programming model
 - Map: Equivalent to the map operation on functional programming
 - Reduce: The reduction phase after maps are computed





A Simple Example

n $\sum x^2 \rightarrow reduce(map(x, sqr), sum)$ i=0







Is This Related to EC?

- How can we easily benefit of the current core race painlessly?
- NCSA's Blue Waters estimated may top on 100K
- Yes on several facets
 - Large optimization problems need to deal with large population sizes (Sastry, Goldberg & Llorà, 2007)
 - Large-scale data mining using genetic-based machine learning (Llorà et al. 2007)
 - Competent GAs model building extremely costly and data rich (Pelikan et al. 2001)
- The goal?
 - Rethink parallelization as data flow processes
 - Show that traditional models can be map to data-intensive computing models
 - Foster you curiosity





Data-Intensive Computing with Meandre





The Meandre Infrastructure Challenges

- NCSA infrastructure effort on data-intensive computing
- Transparency
 - From a single laptop to a HPC cluster
 - Not bound to a particular computation fabric
 - Allow heterogeneous development
- Intuitive programming paradigm
 - Modular Components assembled into Flows
 - Foster Collaboration and Sharing
- Open Source
- Service Orientated Architecture (SOA)





Basic Infrastructure Philosophy

- Dataflow execution paradigm
- Semantic-web driven
- Web oriented
- Facilitate distributed computing
- Support publishing services
- Promote reuse, sharing, and collaboration
- More information at <u>http://seasr.org/meandre</u>





Data Flow Execution in Meandre

- A simple example $c \leftarrow a+b$
- A traditional control-driven language

a = 1 b = 2 c = a+b

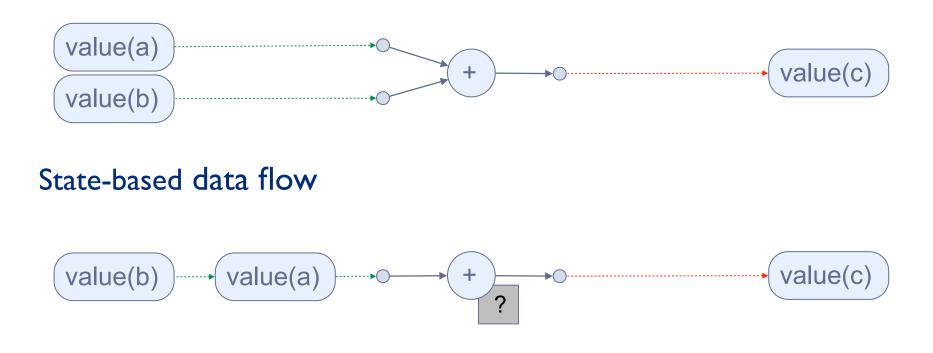
- Execution following the sequence of instructions
- One step at a time
 - a+b+c+d requires 3 steps
 - Could be easily parallelized





Data Flow Execution in Meandre

- Data flow execution is driven by data
- The previous example may have 2 possible data flow versions

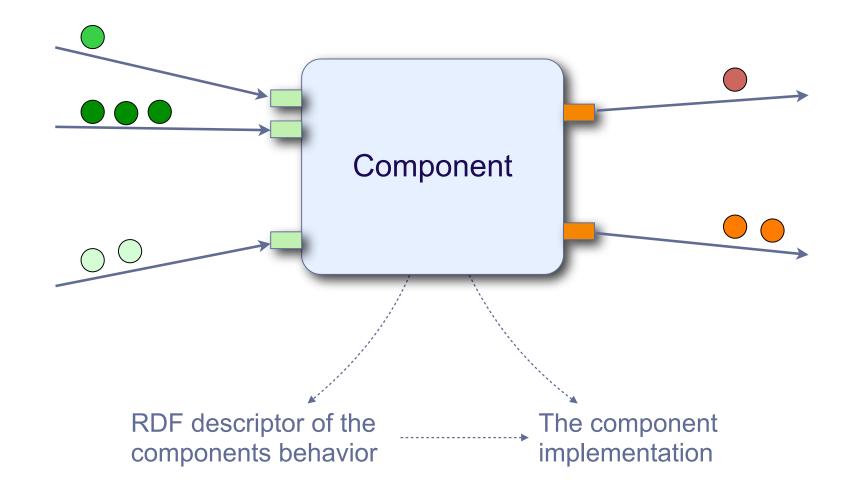








The Basic Building Blocks: Components







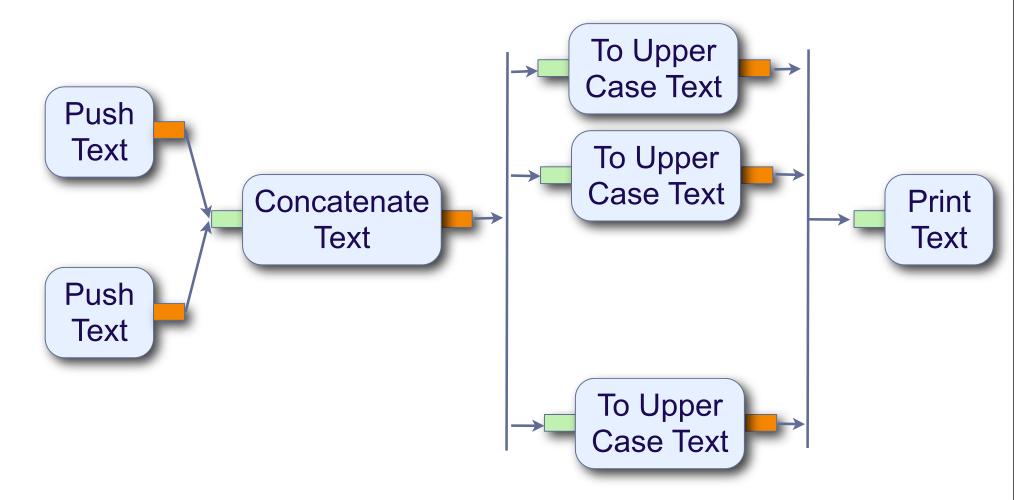
Go with the Flow: Creating Complex Tasks • Directed multigraph of components creates a flow Push Text To Upper Concatenate Print **Case Text** Text Text Push Text





Automatic Parallelization: Speed and Robustness

• Meandre ZigZag language allow automatic parallelization







GAs and Competent GAs





Selectorecombinative GAs

- I. Initialize the population with random individuals
- 2. Evaluate the fitness value of the individuals
- 3. Select good solutions by using s-wise tournament selection without replacement (Goldberg, Korb & Deb, 1989)
- 4. Create new individuals by recombining the selected population using uniform crossover (Sywerda, 1989)
- 5. Evaluate the fitness value of all offspring
- 6. Repeat steps 3-5 until convergence criteria are met





Extended Compact Genetic Algorithm

- Harik et al. 2006
- Initialize the population (usually random initialization)
- Evaluate the fitness of individuals
- Select promising solutions (e.g., tournament selection)
- Build the probabilistic model
 - Optimize structure & parameters to best fit selected individuals
 - Automatic identification of sub-structures
- Sample the model to create new candidate solutions
 - Effective exchange of building blocks
- Repeat steps 2–7 till some convergence criteria are met







- Use model-building procedure of extended compact GA
 - Partition genes into (mutually) independent groups
 - Start with the lowest complexity model
 - Search for a least-complex, most-accurate model

Model Structure	Metric
$[X_0] [X_1] [X_2] [X_3] [X_4] [X_5] [X_6] [X_7] [X_8] [X_9] [X_{10}] [X_{11}]$	1.0000
$[X_0] [X_1] [X_2] [X_3] [X_4X_5] [X_6] [X_7] [X_8] [X_9] [X_{10}] [X_{11}]$	0.9933
$[X_0] [X_1] [X_2] [X_3] [X_4 X_5 X_7] [X_6] [X_8] [X_9] [X_{10}] [X_{11}]$	0.9819
$[X_0] [X_1] [X_2] [X_3] [X_4 X_5 X_6 X_7] [X_8] [X_9] [X_{10}] [X_{11}]$	0.9644
•••	
$[X_{0}] [X_{1}] [X_{2}] [X_{3}] [X_{4}X_{5}X_{6}X_{7}] [X_{8}X_{9}X_{10}X_{11}]$	0.9273
$\begin{bmatrix} \mathbf{X}_{0} \mathbf{X}_{1} \mathbf{X}_{2} \mathbf{X}_{3} \end{bmatrix} \begin{bmatrix} \mathbf{X}_{4} \mathbf{X}_{5} \mathbf{X}_{6} \mathbf{X}_{7} \end{bmatrix} \begin{bmatrix} \mathbf{X}_{8} \mathbf{X}_{9} \mathbf{X}_{10} \mathbf{X}_{11} \end{bmatrix}$	0.8895



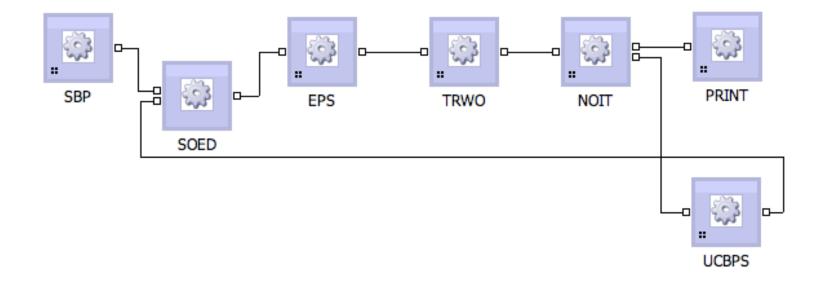


Data-Intensive Flows for Competent GAs





Selectorecombinative GA

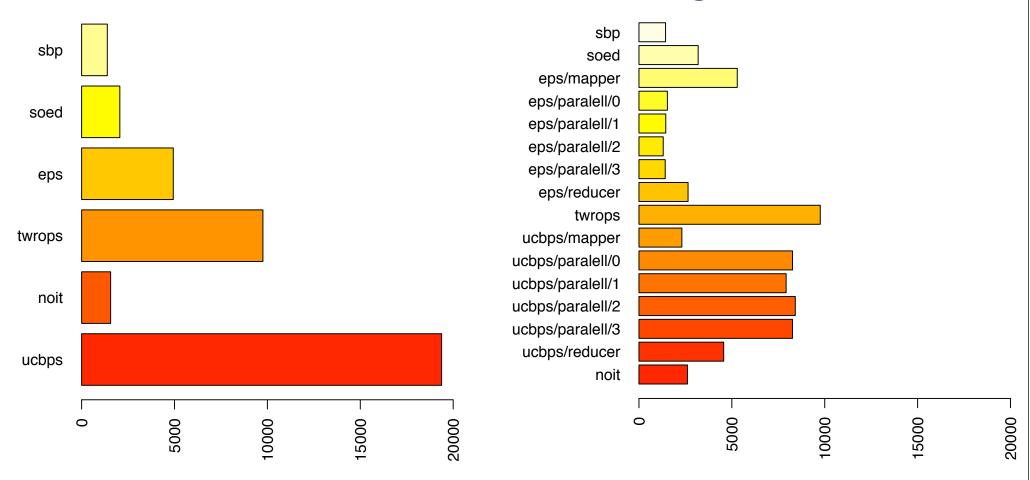






sGAs Execution Profile and Parallelization

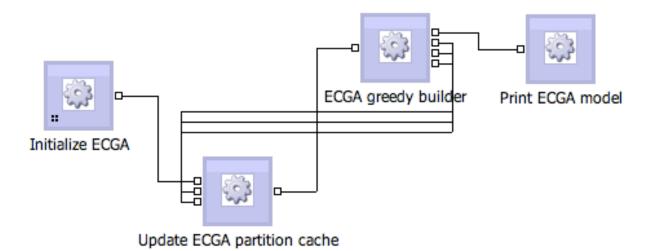
• Intel 2.8Ghz QuadCore, 4Gb RAM. Average of 20 runs.







eCGA Model Model building

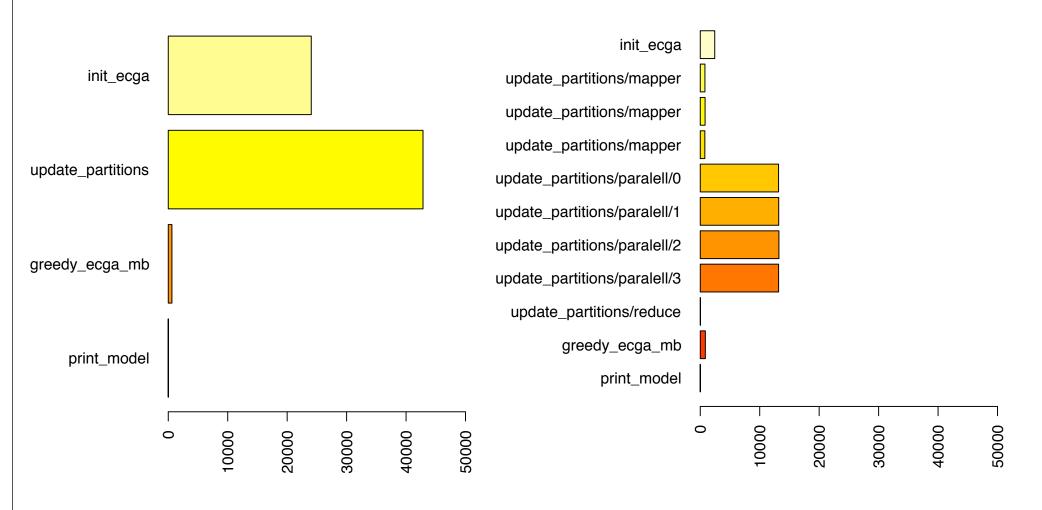






eCGA Execution Profile and Parallelization

• Intel 2.8Ghz QuadCore, 4Gb RAM. Average of 20 runs.

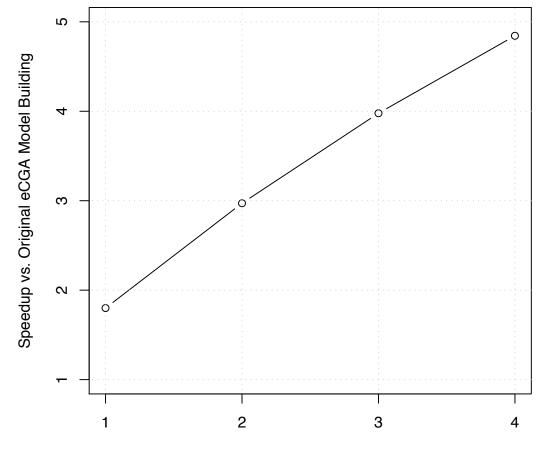






eCGA Model Building Speedup

- Intel 2.8Ghz QuadCore, 4Gb RAM. Average of 20 runs.
- Speedup against original eCGA model building



Number of cores





Scalability on NUMA Systems

- Run on NCSA's SGI Altix Cobalt
- 1,120 processors and up to 5 TB of RAM
- SGI NUMAlink
- NUMA architecture
- Test for speedup behavior
- Average of 20 independent runs
- Automatic parallelization of the partition evaluation
- Results still show the linear trend (despite the NUMA)
 - 16 processors, speedup = 14.01
 - 32 processors, speedup = 27.96





Wrapping Up





Summary

- Evolutionary computation is data rich
- Data-intensive computing can provide to EC:
 - Tap into parallelism quite painless
 - Provide a simple programming and modeling
 - Boost reusability
 - Tackle otherwise intractable problems
- Shown that equivalent data-intensive computing versions of traditional algorithms exist
- Linear parallelism can be tap transparently









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