

Analysis of High-Throughput Biological Data Part I: Scalable High Performance Algorithms and Implementations

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21 February 2008









Sample Application

Tools and Technologies

Complexity Theory

Graph Algorithms

High Performance Computation

Reconfigurable Computation

Compute Engine

Problem Variants



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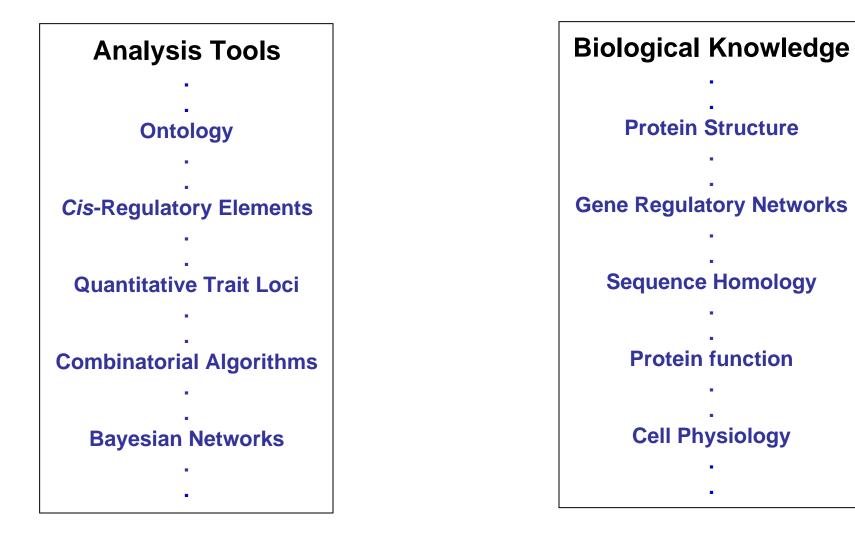




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Technology Mapping



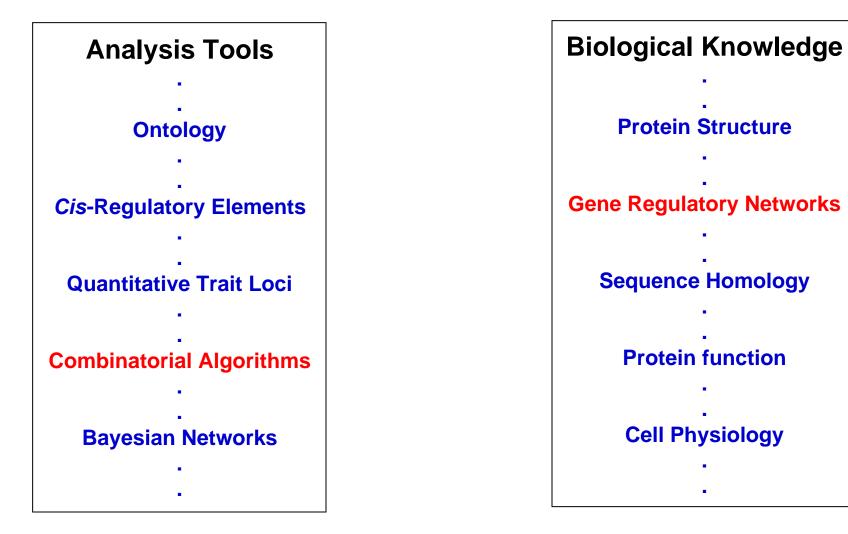




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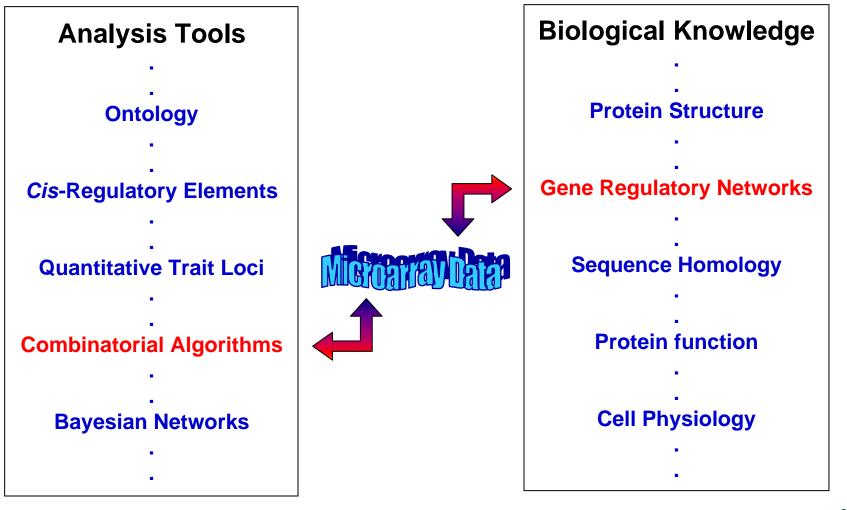
Technology Mapping







Technology Mapping





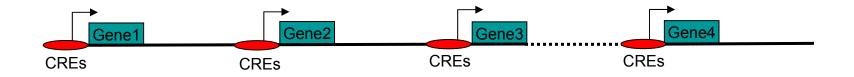




Gene Regulatory Networks

central dogma: one gene one protein

cis regulation



regulation via *cis* regulatory elements (CREs) promoter, TATA box, motifs, modules 8-15 bp in length, action often at the ends

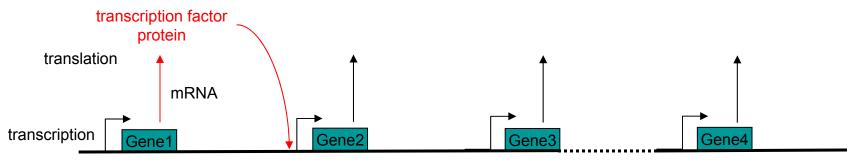






Gene Regulatory Networks

trans regulation (direct) via gene products



up or down regulate mRNA expression



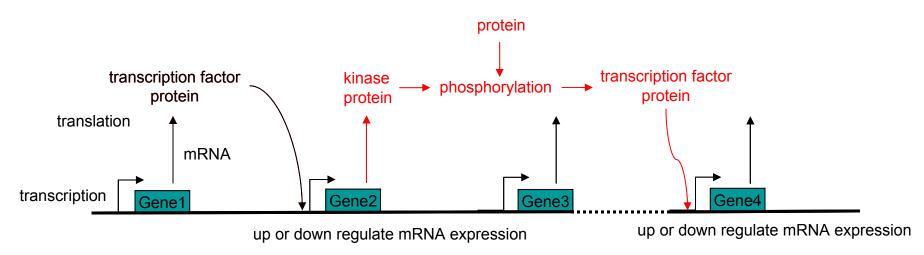


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Gene Regulatory Networks

trans regulation (indirect) via post-translational modification

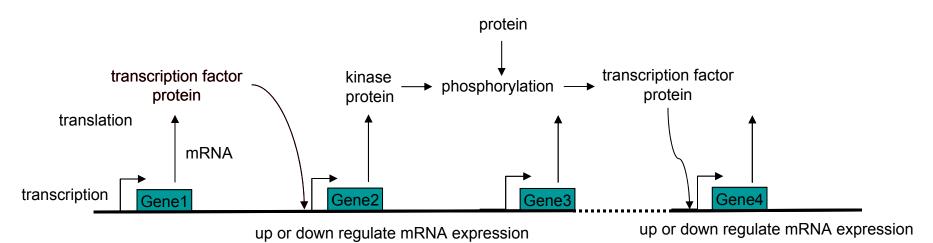






Gene Regulatory Networks

many other network actions



post-transcriptional regulation (e.g., alternate splicing) µRNA (e.g., functional RNA, RNAi and gene silencing) but all are forms of *co-regulation*

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Currently Awash in a Sea of Transcriptomic Data

An organism's mRNA transcripts:

- link between the genome, the proteome and the cellular phenotype
- data quality and richness increasing
 - noise reduction
 - more conditions
 - correlation, putative coregulation, regulatory networks
- cannot see post-translational modifications (e.g., phosphorylation)
- huge range of prokaryotic and eukaryotic data coming on line
- timely confluence of technologies
- proteomics, metabolomics data not far behind



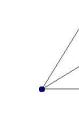




A Major Computational Bottleneck: Clique

Data transformation:

- representing biological networks with graphs is well understood
- genes (via transcripts, probesets) are denoted by vertices
- edges denote significant gene-gene correlations
- we seek genesets with common regulatory mechanisms
- thus we want to identify dense subgraphs, in particular *cliques*
 - complete subgraphs
 - special case of subgraph isomorphism
 - NP-complete to decide
 - NP-complete even to approximate



K_⊿







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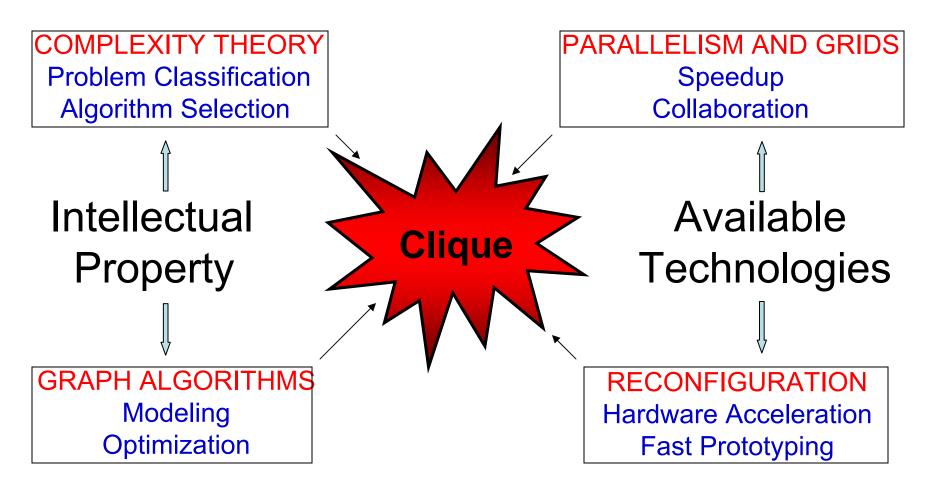
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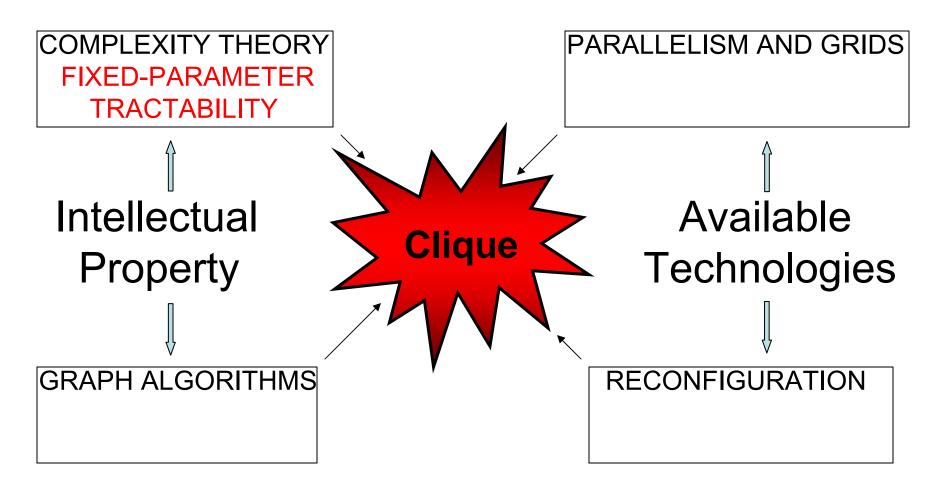


Tools and Technologies







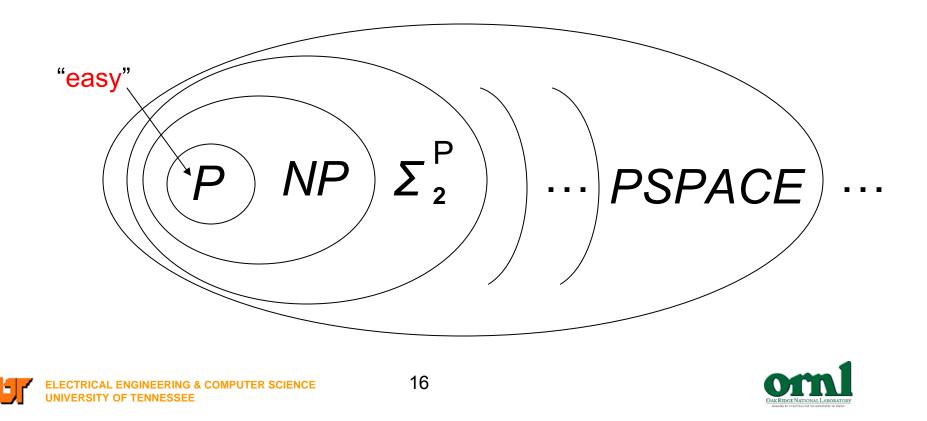






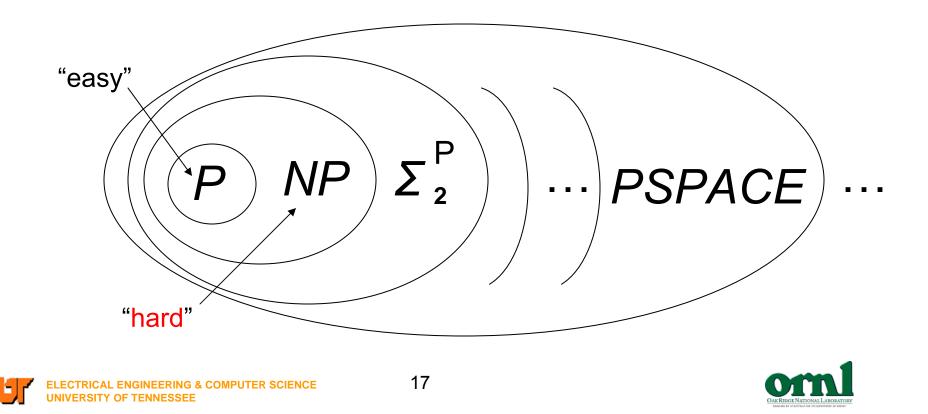


The Classic View:



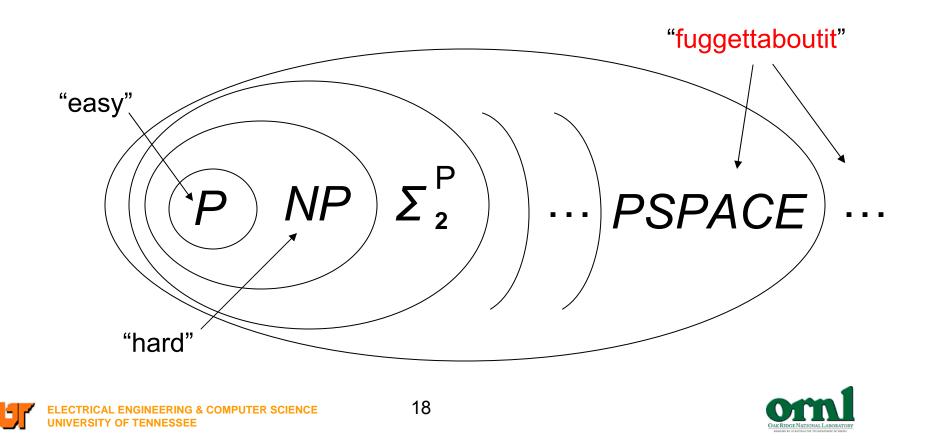


The Classic View:





The Classic View:





Fixed-Parameter Tractability

Pioneering approach going back twenty years

- Well-Quasi-Order theory
- nonuniform measure of complexity







Fixed-Parameter Tractability

Pioneering approach going back twenty years

- Well-Quasi-Order theory
- nonuniform measure of complexity

Exploit knowledge of the solution space

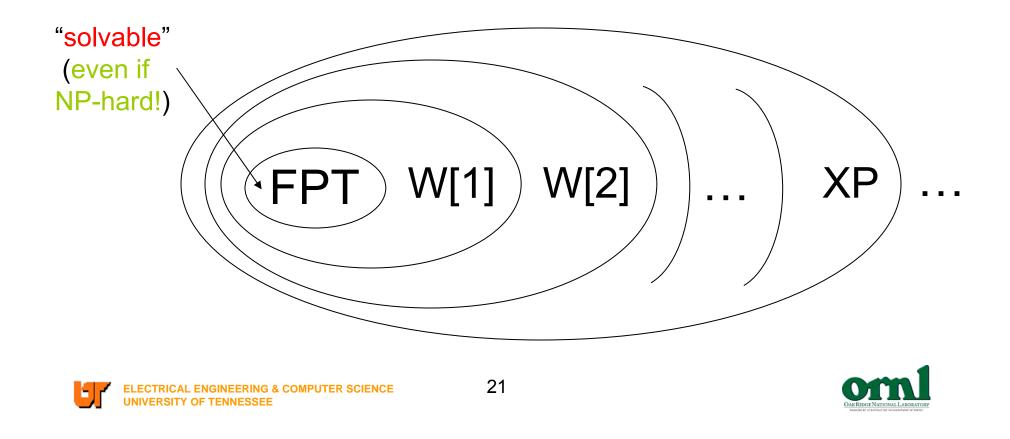
- Consider an algorithm with a time bound such as $O(2^{kn})$.
- And now one with a time bound more like $O(2^k n)$.
- Both are exponential in parameter value(s).
- But what happens when *k* is fixed?
- Fixed-Parameter Tractable (FPT) iff O(f(k)n^c)
- Confines superpolynomial behavior to the parameter





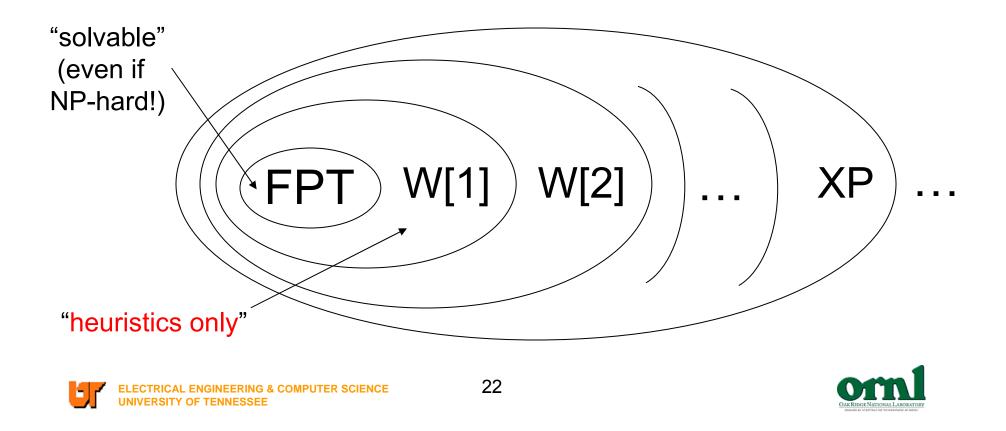


Hence, the Parameterized View:



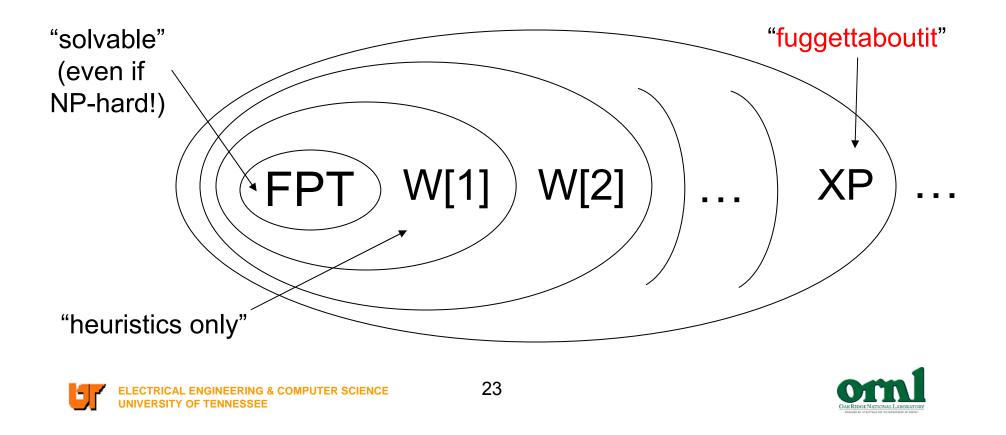


The Parameterized View:

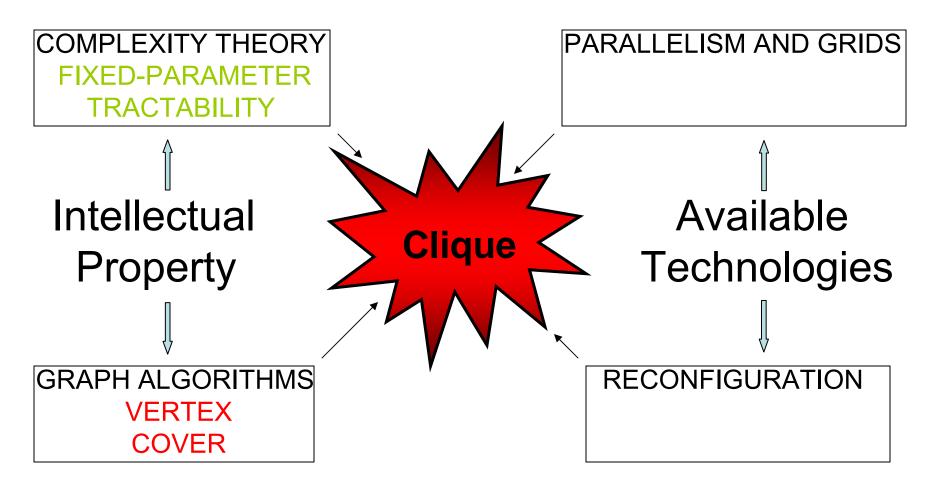




The Parameterized View:











Pioneering approach going back twenty years

- Well-Quasi-Order theory
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Duality

- We solve vertex cover, clique's complementary dual
- $O(1.2759^{k}k^{1.5}+kn)$ time

Key features

– Kernelization, branching and interleaving









- use preprocessing via degree structures
 - -Low degree rules
 - -High degree rule
 - –Resultant graph has size O(k²) [at most k(1+k/3) vertices]







- use preprocessing via degree structures
- then kernelize to reduce to a computational core
 –suite of codes







- use preprocessing via degree structures
- then kernelize to reduce to a computational core
 - -suite of codes
 - -LP variants

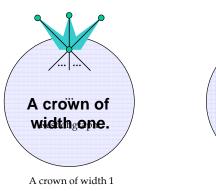
minimize: $\sum X_i$, *i* in V(G)subject to: $X_u + X_v >= 1$ for all *uv* in E(G)where: $X_i >= 0$ for all *i* in V(G)







- use preprocessing via degree structures
- then kernelize to reduce to a computational core
 - -suite of codes
 - -LP variants
 - -crown rule







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	CIMARepresentativeopierKernelization Results		
Algorithm	Run Time	Kernel (n')	Parameter (k')
LP	69.49	616	389
Network Flow	40.53	622	392
Crown Rule	0.07	630	392

Preprocessing completed first. All times in seconds.





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Preprocessing completed first. All times in seconds.

Some conclusions:

- Perform preprocessing, then the crown rule.
- If dense, stop trying to kernelize.
- If sparse, try LP or network flow before stopping.







- use preprocessing via degree structures
- then kernelize to reduce to a computational core
- employ branching to explore the core
 - –exhaustive search–highly parallel





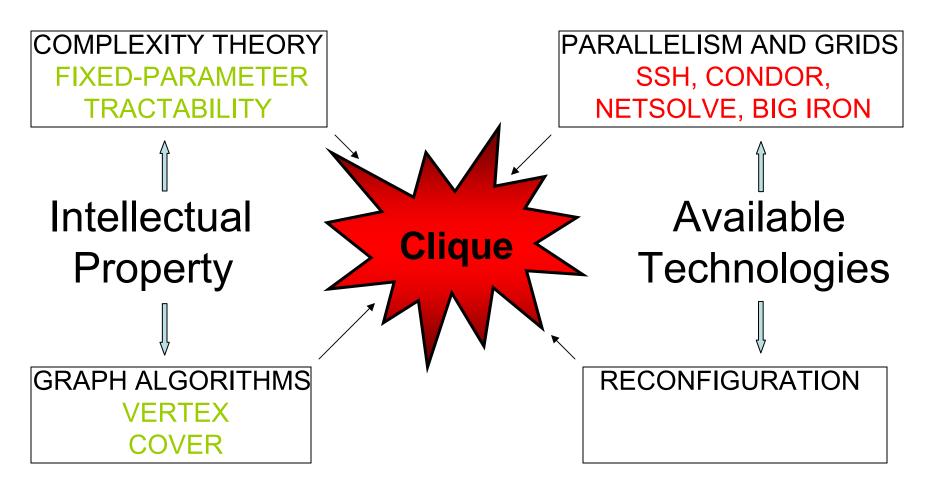
- use preprocessing via degree structures
- then kernelize to reduce to a computational core
- employ branching to explore the core
- finally, interleave all three







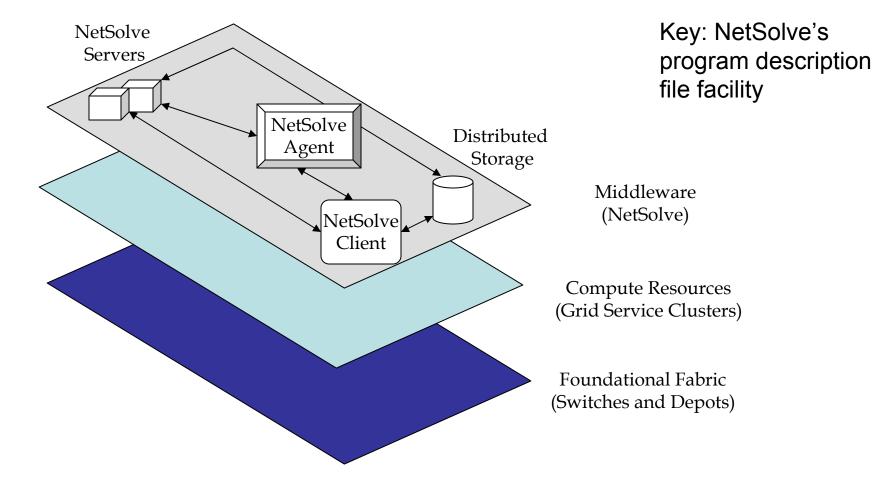
Tools and Technologies







Sample Grid Architecture







High Performance Implementations

- suites of maximum/maximal/bi/para clique methods
- have processed graphs with over 3M vertices
- memory often a limiting factor
- currently working on out-of-core methods



SGI Altix supercomputer at ORNL 256 dual-CPU processors, two terabytes of shared memory

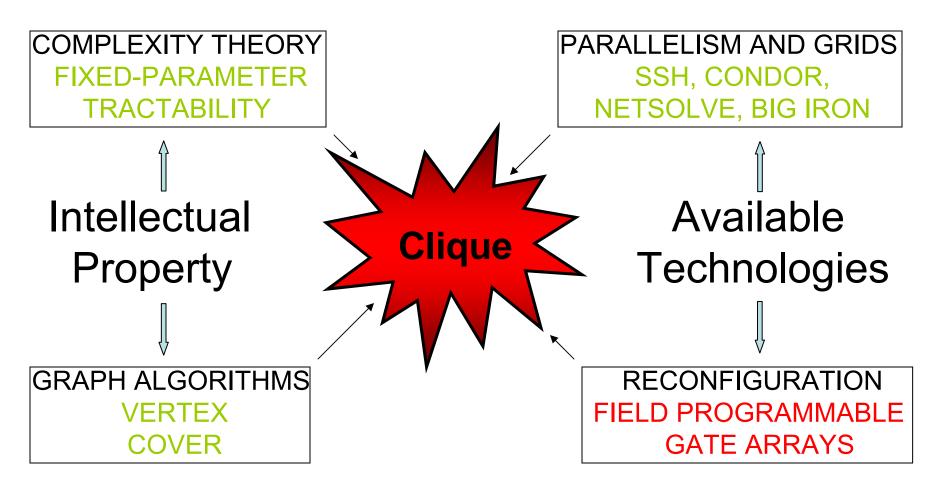


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Tools and Technologies









Hardware Acceleration

Algorithms are very different.

VHDL versus C.

I/O is often the most critical resource.



Sample FPGA

With current implementations, we are able to solve sub-instances:

- of size 512 or less,
- with speedups north of about 125.

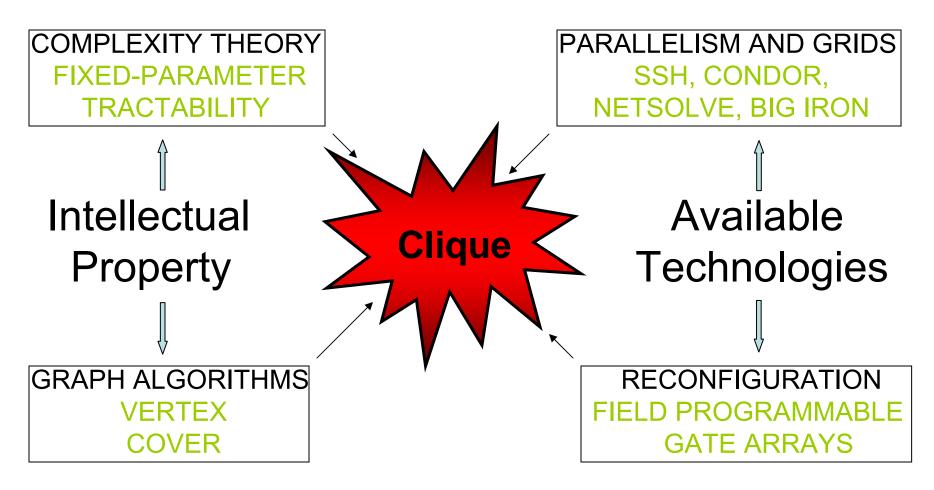






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Put the Pieces Together



39







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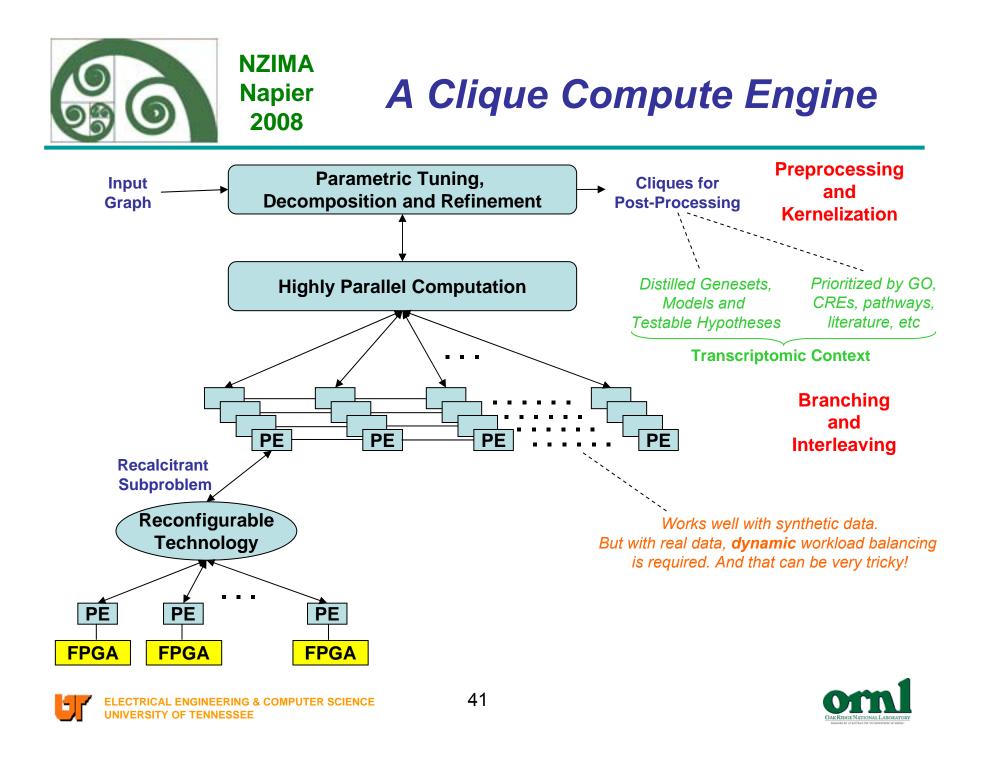
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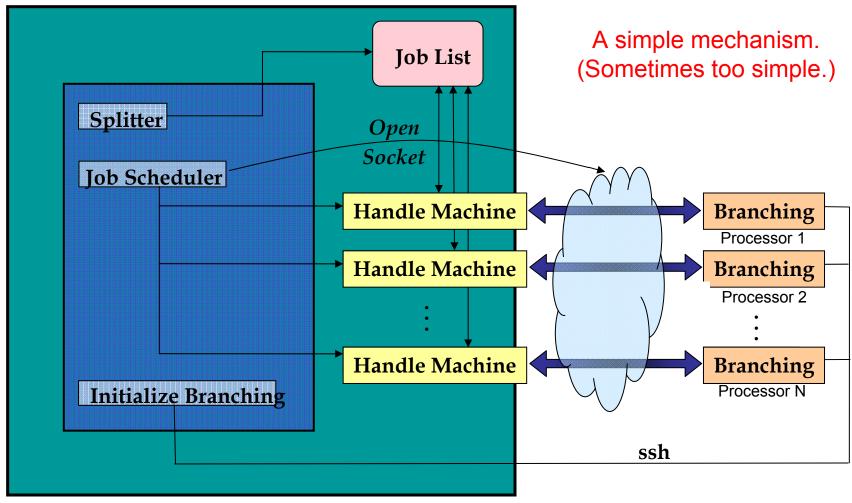








Workload Balancing: A Vertex Cover Driver

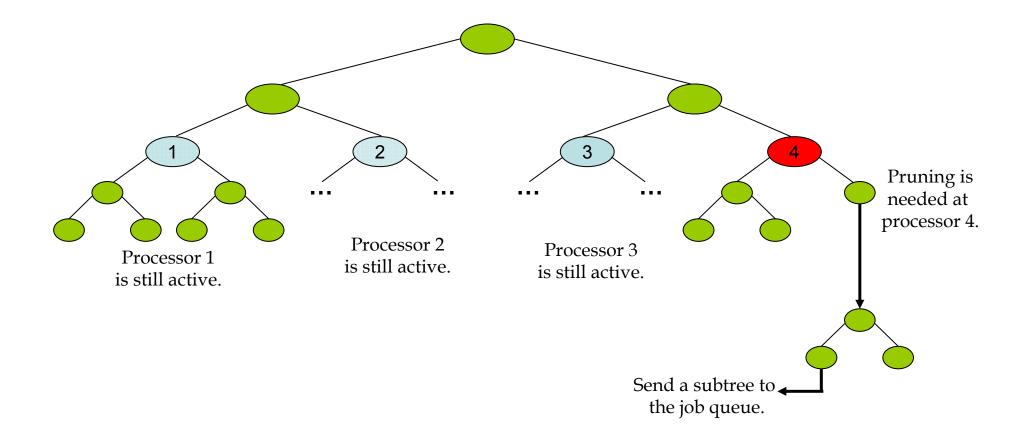








Workload Balancing: Distributed Subtree Splitting









Graph Name	Graph Size	Cover Size	Instance Type	Sequential Kernelization	Sequential Branching	Parallel Branching	Dynamic Decomposition
SH2-5	839	399	Yes	34 seconds	7 seconds	Not needed	Not needed
SH2-5	839	398	No	34 seconds	141 minutes	82 minutes	20 minutes
SH3-10	2466	2044 •					
SH3-10	2466	2043					

So clique size is 422.

A direct assault ~ 2466⁴²².







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32 PEs @ 500MHz.







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SH3-10	2466	2043	No	203 minutes	6+ days	6+ days	620 minutes

So clique size is 422.

The hardest computations.

32 PEs @ 500MHz.

Load balancing is critical. "No" is harder than "yes."







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We now routinely solve these sorts of instances in seconds. But these are not genome scale problems!







Guides our thinking, steering us to exploit parameters







Guides our thinking, steering us to exploit parameters

Kernelization sets the stage for efficiency







Guides our thinking, steering us to exploit parameters Kernelization sets the stage for efficiency Branching still requires serious computation







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Guides our thinking, steering us to exploit parameters Kernelization sets the stage for efficiency Branching still requires serious computation Interleaving is indispensible in practice Solve problems directly (clique not vertex cover) Better subtree pruning via iterated preprocessing **Examples:** Common Neighbor Preprocessing (CNP) **Color Preprocessing (CP)**







Common Neighbor Preprocessing versus Color Preprocessing

Mothod	Kernel Size	Time		
Method				
CNP				
СР				
CNP+CP				

Data Source: Gerling Affymetrix 430A read time 0:40, probe sets 22690, threshold edges 7,534,598, maximum clique size 248





Common Neighbor Preprocessing versus Color Preprocessing

Method	Kerne	l Size	Time
	Vertices	Edges	
CNP	5896	2785k	
СР	1700	585k	
CNP+CP	1692	576k	

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Common Neighbor Preprocessing versus Color Preprocessing

Mothod	Kerne	el Size	Time		
Method	Vertices	Edges	Preprocess		
CNP	5896	2785k	2:24		
СР	1700	585k	1:22		
CNP+CP	1692	576k	3:46		

Data Source: Gerling Affymetrix 430A read time 0:40, probe sets 22690, threshold edges 7,534,598, maximum clique size 248





Common Neighbor Preprocessing versus Color Preprocessing

Mathad	Kerne	el Size	Time		
Method	Vertices	Edges	Preprocess	Branch	
CNP	5896	2785k	2:24	51:54	
СР	1700	585k	1:22	4:04	
CNP+CP	1692	576k	3:46	3:46	

Data Source: Gerling Affymetrix 430A

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Common Neighbor Preprocessing versus Color Preprocessing

Method	Kerne	el Size	Time			
wethod	Vertices	Edges	Preprocess	Branch	Total	
CNP	5896	2785k	2:24	51:54	54:18	
СР	1700	585k	1:22	4:04	5:26	
CNP+CP	1692	576k	3:46	3:46	6:58	

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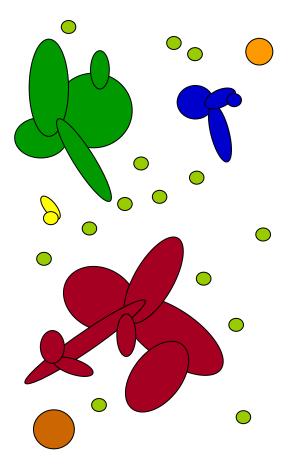




Biological Fidelity

Genes are Pleiotropic

Maximal Cliques May Overlap





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Biological Fidelity

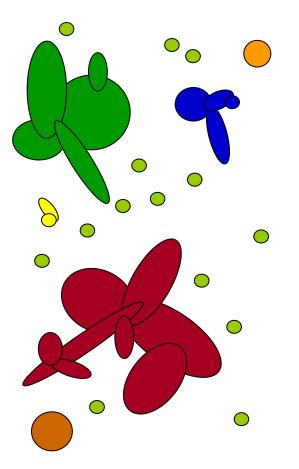
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Results

Efficiency

Predictable Range of Outputs









Maximal Clique

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Results

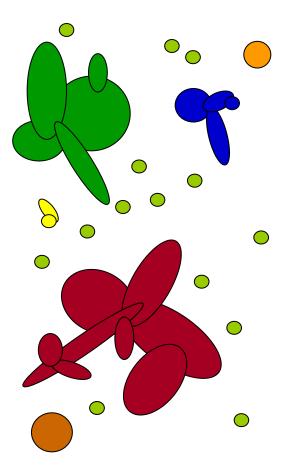
Efficiency

Predictable Range of Outputs

Keys

- **Global Shared Memory Map**
- **Bitmapped Implementations**
- **Synchronization and Load Balancing**

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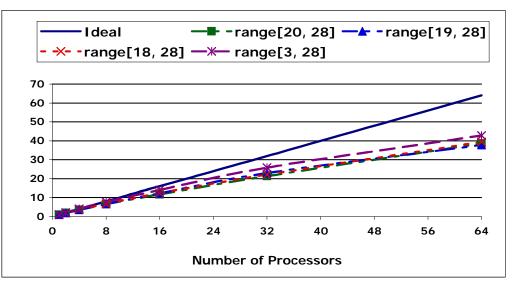


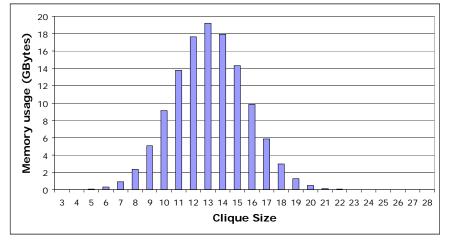


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Maximal Clique

Near Linear Speedup





Significant Memory Requirements









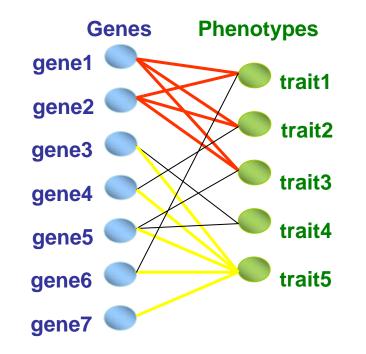
Concentrate on Bipartite Graphs

Previous Algorithms Make Unwarranted Assumptions

Bookkeeping

Branch & Bound

Ontological Discovery



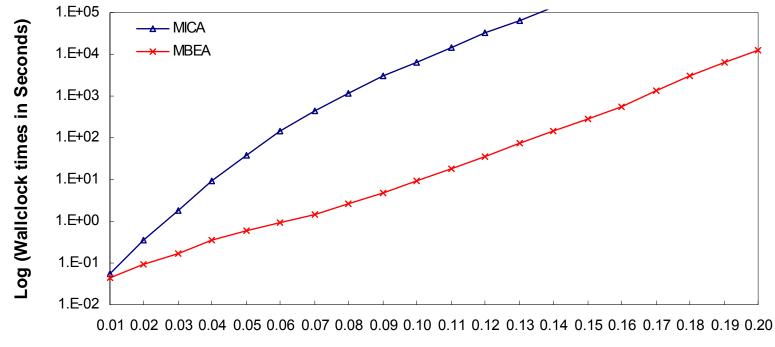






Observed Biclique Runtimes

2 ~ 3 orders of magnitude faster than the best previous alternative



p-value

Time Complexity: $O(dn^2B)$, where *d* is maximum degree and *B* is the number of maximal bicliques. Keys: preprocess and exploit structure. Sound familiar?

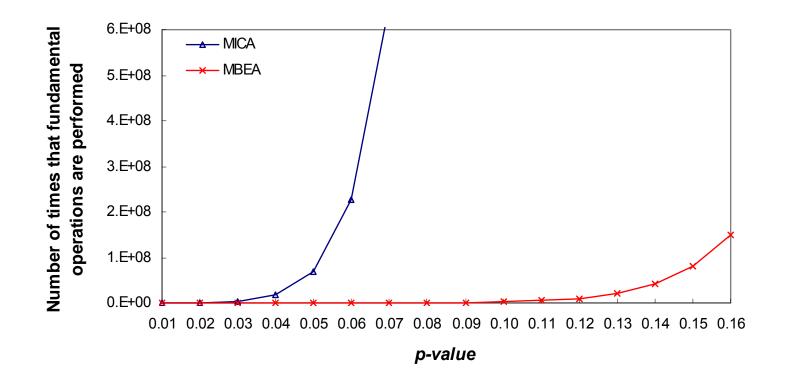






Discretionary Power

We can now explore much denser graphs, as shown by edge weights.

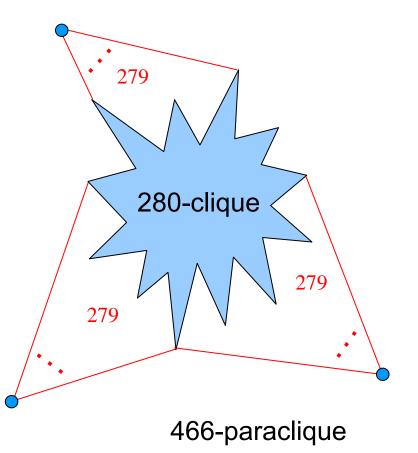








- Clique gloms onto highly connected vertices.
- Here a 280-clique is transformed into a 466-paraclique.
- Edge density remains north of about 95%.
- Lift and separate.







NZIMA Napier 2008

Collaborators

Research Scientists (Incomplete!):

Mikael Benson Elissa Chesler Frank Dehne **Mike Fellows Ivan Gerling** Dan Goldowitz Malak Kotb Mark Ragan Arnold Saxton Brynn Voy **Rob Williams Bing Zhang**

Current Students: Bhavesh Borate Patricia Carey John Eblen Jeremy Jay Zuopan Li Sudhir Naswa Andy Perkins Vivek Philip **Charles Phillips Gary Rogers** Jon Scharff Yun Zhang











