Illinois Informatics Initiative
Invent. Imagine. Innovate.

Opportunities for XXL Datamining

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Outline

- How a Supercomputer looks like in > 2010
- What it takes to run a DM code on such a platform
- How DM can help supercomputing

Large NSF Funded Supercomputers beyond 2010

- One Petascale platform -- Blue Waters at NCSA, U Illinois
  - Sustained performance: petaflop range
  - Memory: petabyte range
  - Disk: 10’s petabytes
  - Archival storage: exabyte range

- Multiple 1/4 scale platforms at various universities

- Available to NSF-funded “grand challenge” teams on a competitive basis

- **My talk**: What it takes to mine data at such scale
- **Your job**: Think big

The Uniprocessor Crisis

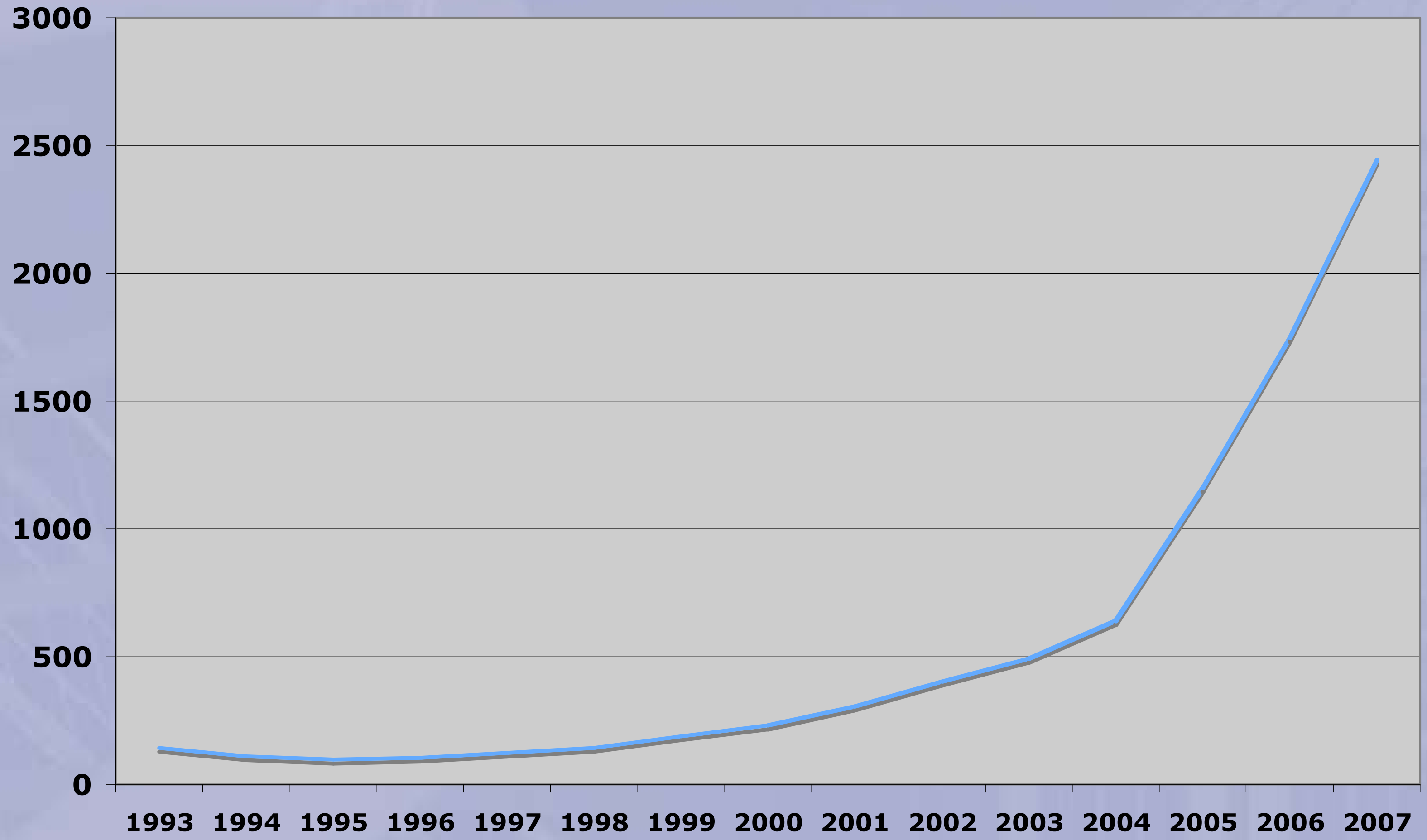
- Manufacturers cannot increase clock rate anymore (power problem)
- Computer architects have run out of productive ideas on how to use more transistors to increase single thread performance
  - Diminishing return on caches
  - Diminishing return on instruction-level parallelism

⇨ Increased processor performance will come **only** from the increase on number of cores per chip

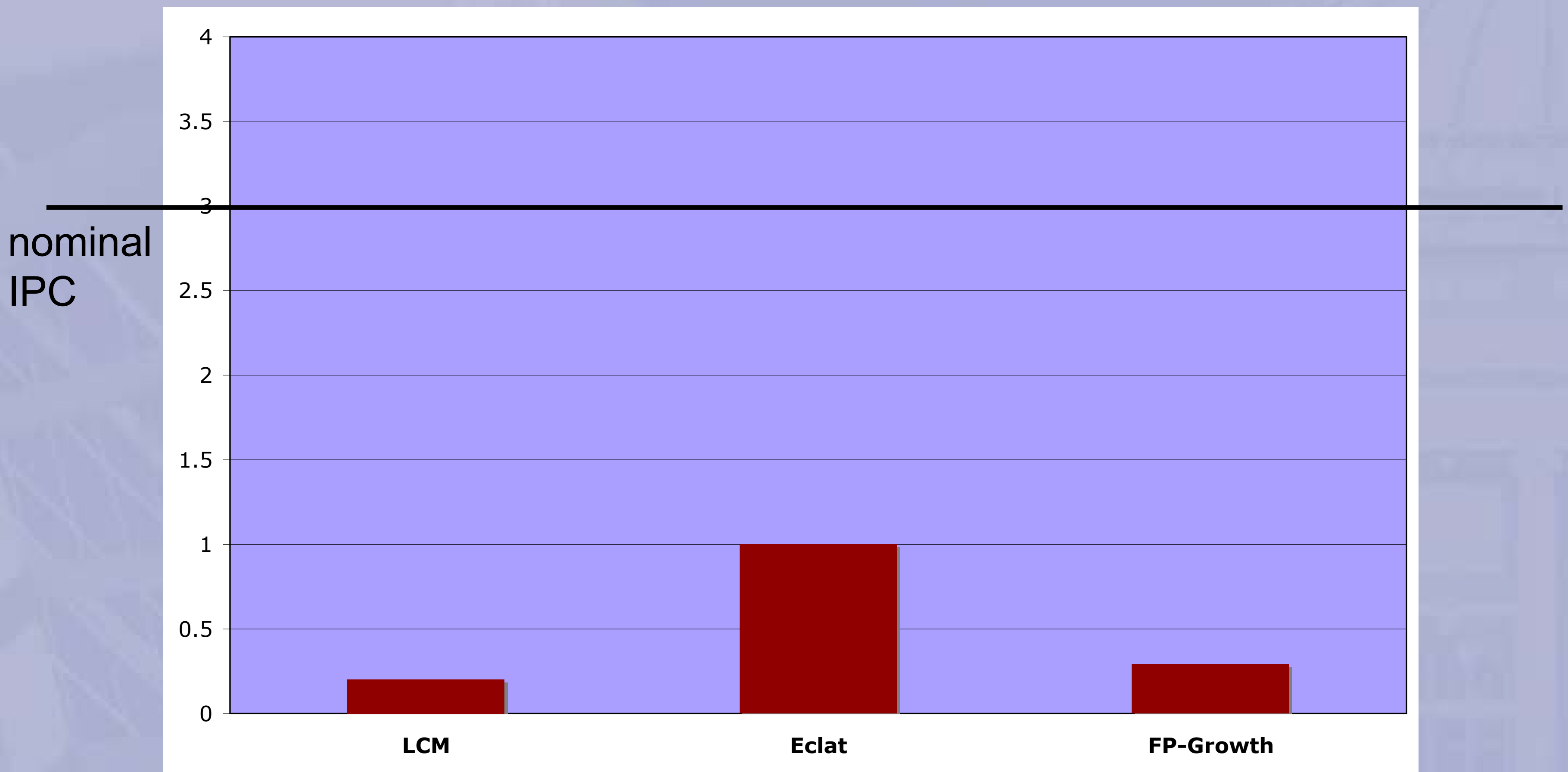
Petascale = 250K -- 1M threads

Need algorithms with massive levels of parallelism

Average # Processors Top 500 System



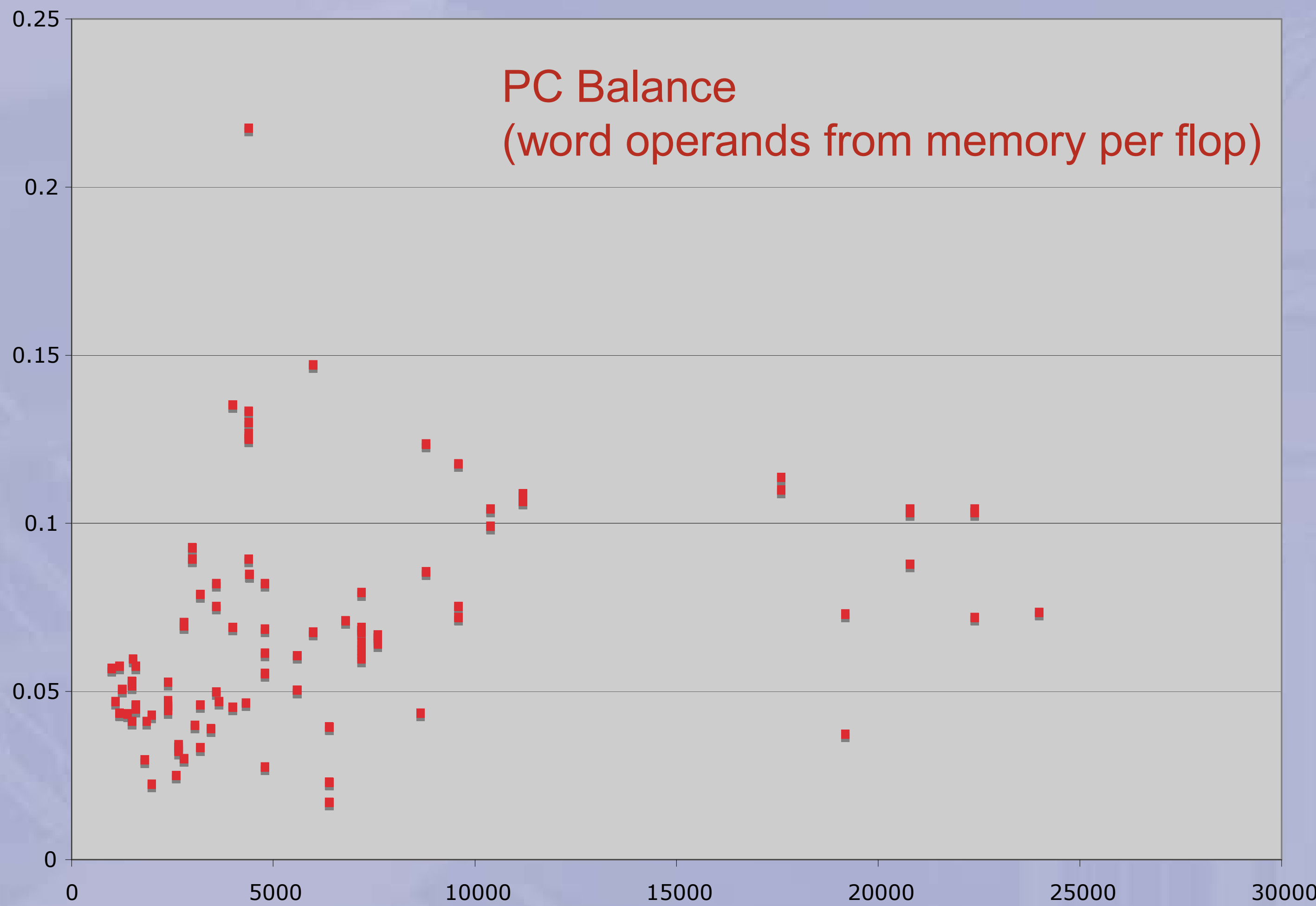
Mileage is Less than Advertised



Instruction per cycle, frequent item mining

(M Wei)

It’s the Memory, Stupid



Seem stuck at ~ 1:10 ratio

The Memory Wall and Palliatives

- The problem
  - Memory bandwidth is limited (cost)
  - Compilers cannot issue enough concurrent loads to fill the memory pipe
  - Compilers cannot issue loads early enough to avoid stalls
- Solutions
  - Multicore and vector operations -- to fill the pipe Simultaneous multithreading -- to tolerate latency
  - **Need even higher levels of parallelism!**

Solutions to the Memory Wall

- Caching and **locality**
  - **Need algorithms with good locality**
- Split communication
  - Memory prefetch (local memory)
  - Put/get (remote memory)
  - **Need programmed communication** (not necessarily message-passing)

- **N.B.:** Computer power is essentially free; you pay for storing and moving data
  - Accelerators (GPUs, FPGAs, Cell processors) enhance a non-critical resource, and will often have a negligible impact on overall performance

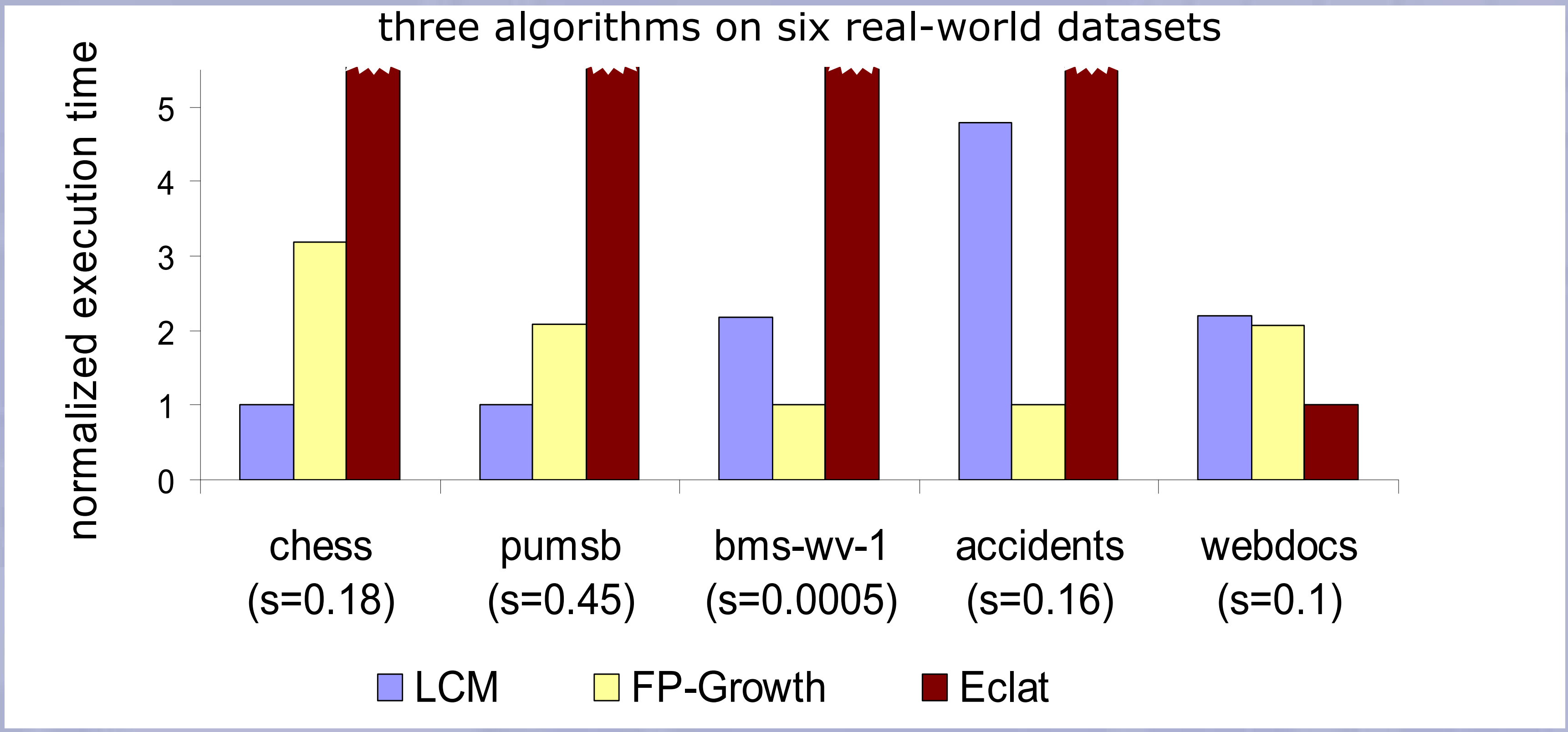
Load Balancing

- Problem: Amount of computation in DM kernels heavily data dependent -- work partitioning results in load imbalances
- Hard solution: develop good work predictors and do explicit, static load balancing
- Easy solution: use system with task virtualization and dynamic task migration
  - E.g., AMPI (Kale, http://charm.cs.uiuc.edu/) -- scalable, negligible (often negative) overheads
  - Overhead of task migration is few seconds, at worse
    - *Parallel file system is shared all*
  - **Task virtualization essential for modularity and ease of programming**

Code Tuning

- Is essential when using a Petascale system
  - 1 hour = $5K - $10K
- Is data dependent (more so with Datamining than with many applications)
- Is platform dependent

Relative Performance of Frequent Item Mining Codes is Input Dependent



FIMI workshop needs some thinking…

(C Jiang PhD thesis)

A Schematic View of Performance Tuning

All three should be platform and data dependent

1. Algorithm selection

(LCM, FP_Growth, Eclat,…)

2. Implementation selection

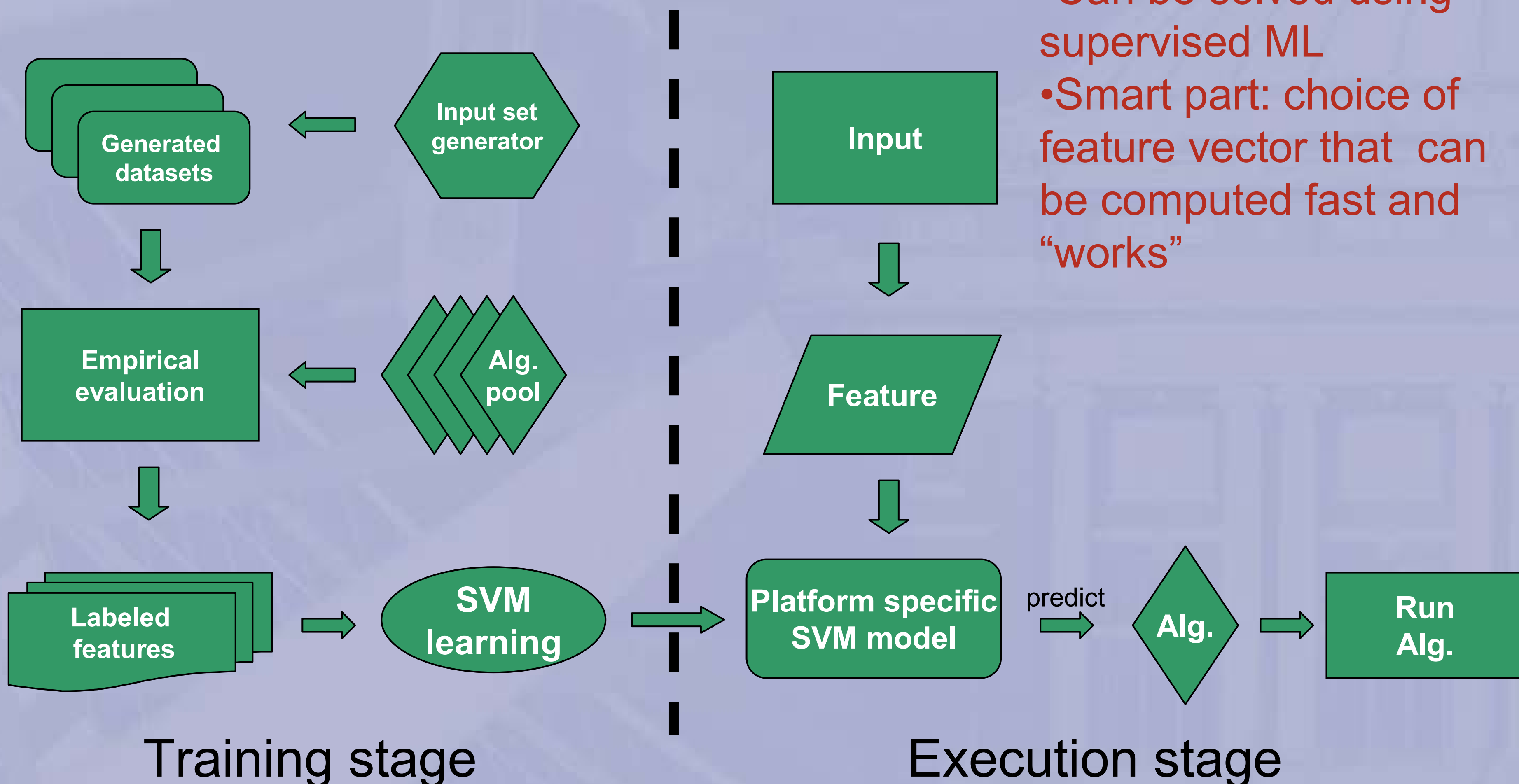
(choice of data structures…)

3. Automatic tuning

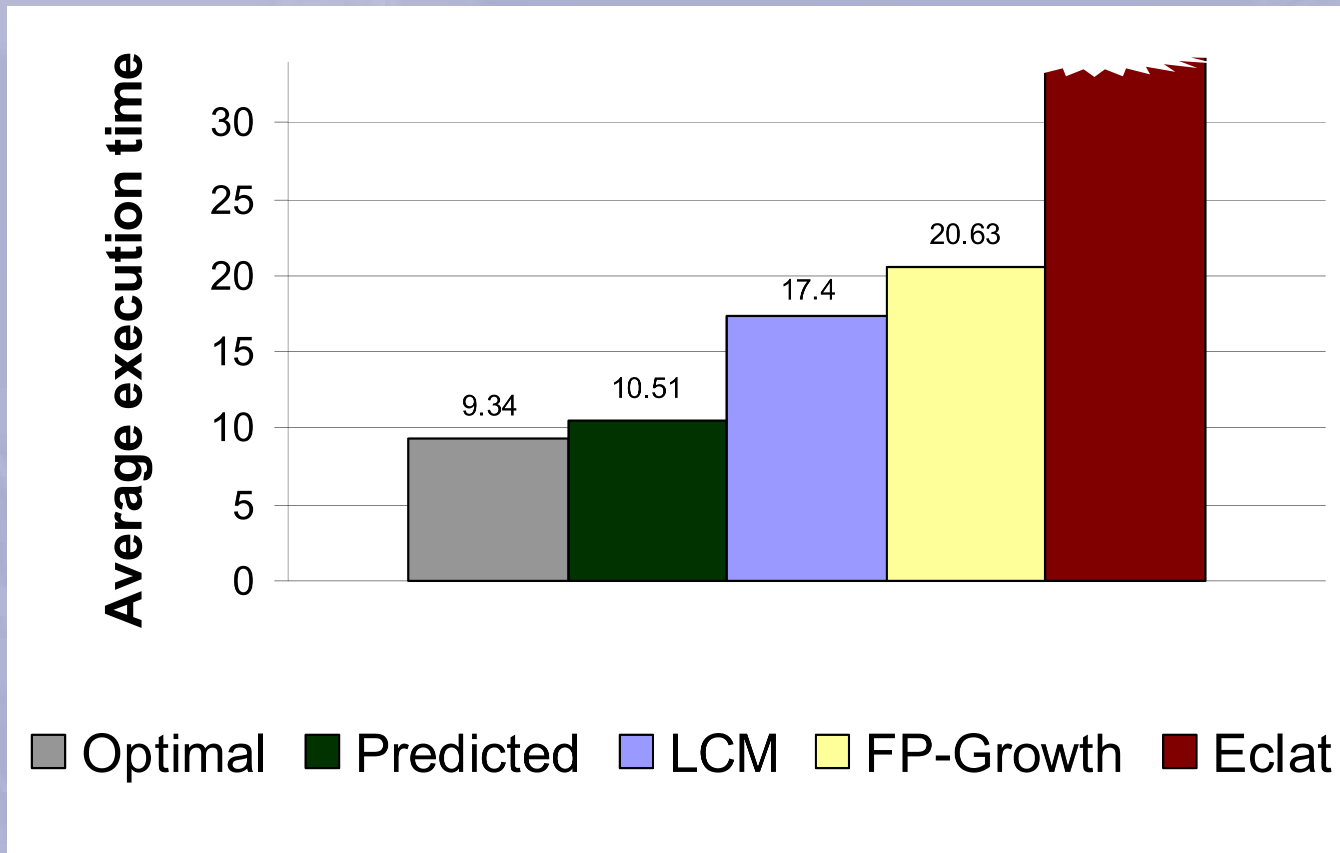
(compiler, runtime)

Algorithm Selection is a Classification Problem

- Can be solved using supervised ML
- Smart part: choice of feature vector that can be computed fast and "works"



Results: Average execution time



- The predicted algorithm is close to optimal (12.5% worse)
- The predicted algorithm is significantly better than LCM(65.3%)

Selected features

- **Size**
  - The number of '1's in the bit matrix
- **Density**
  - Number of '1's divided by number of cells
- **Height**:
  - 1 – support threshold / density
  - An estimate of how much room for the support to decrease to the threshold
- **Similarity**:
  - How similar transactions are to each other

Example:

1	1	1	0	0	1
1	1	1	0	0	1
1	1	0	1	0	1
1	1	0	1	0	0
0	1	0	0	1	1

Size=18

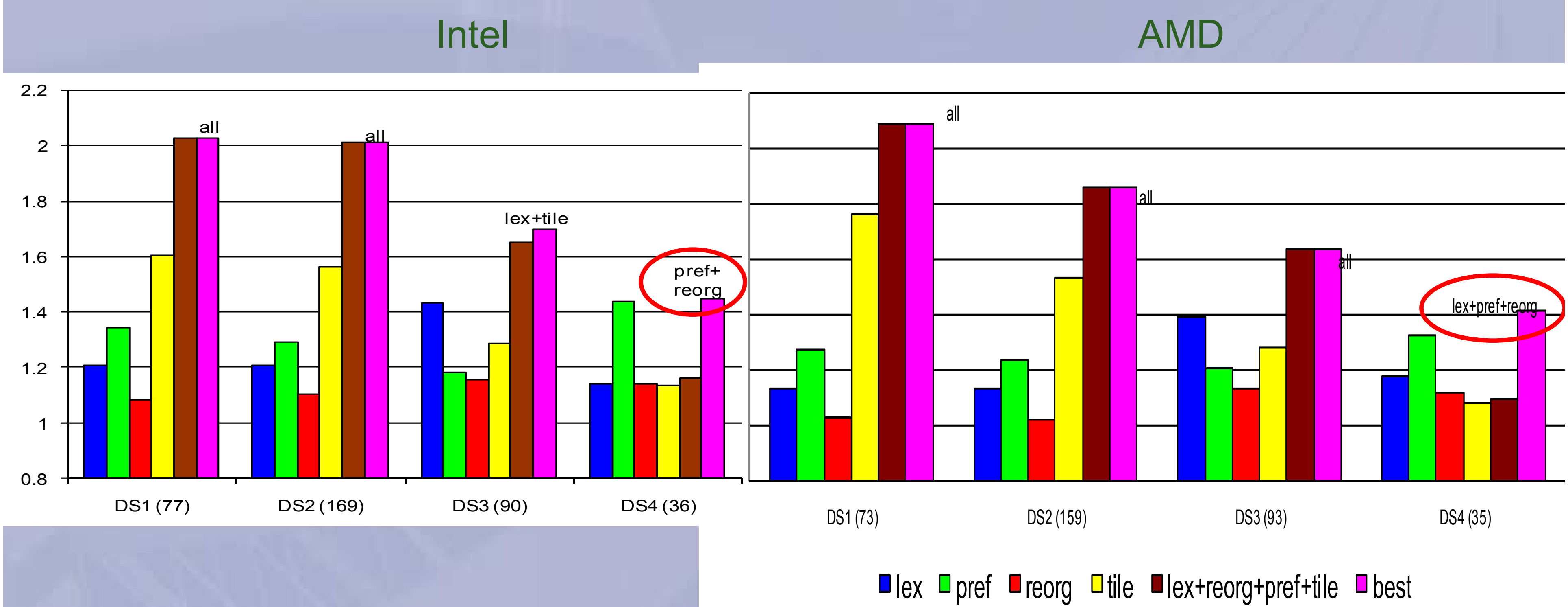
Density = 18/30 = 0.6

Height = 1-s/*density*
= 1 – 0.2/0.6 =2/3

Implementation Selection

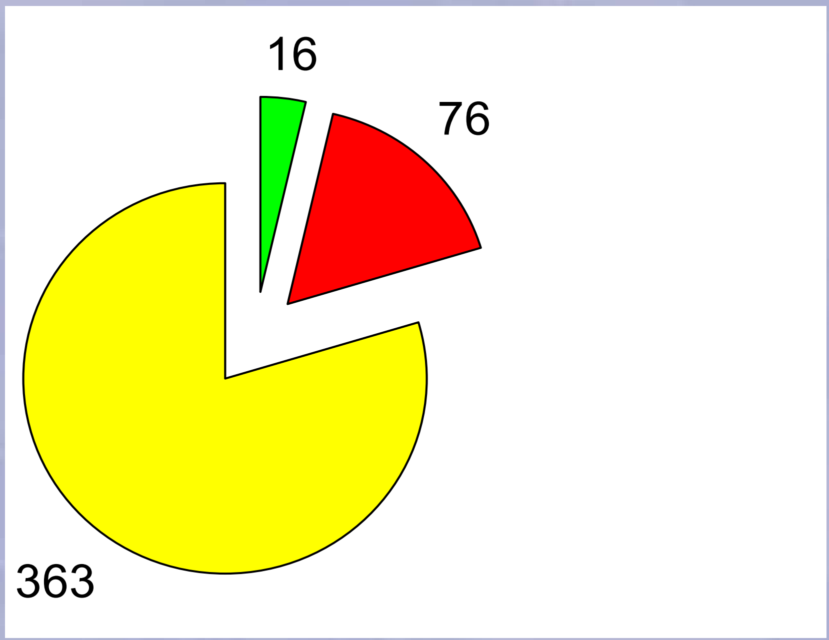
- We represent implementation choices via *tuning patterns* - descriptions of solutions to common software performance optimization problems that are applicable to multiple algorithms
  - Lexicographic ordering
  - Aggregation
  - Compaction
  - Wave-front prefetch
  - Tiling for sparse arrays
  - SIMDization
- Probably need richer ontology (relations, constraints, expert knowledge)
- Classification problem: select best set of tuning patterns
  - Used SVM; GA probably more appropriate

Speedups of LCM

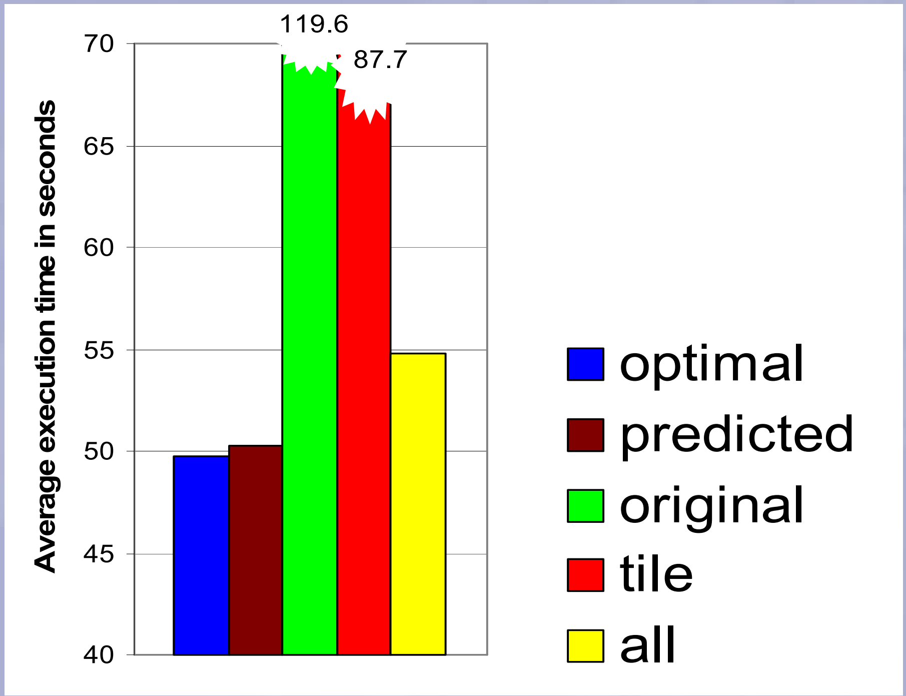


- Good speedup (up to 2.1)
- ALL does not always win!
- Optimal set of tuning patterns is machine and data dependent

Prediction results – LCM



Number of times that each code version is the fastest



Average execution time

- Prediction close to "optimal" (oracle)
- Prediction overhead is negligible

Summary

- Main obstacle to petascale datamining is dreaming of grand challenges that need it
- Petascale datamining requires tuned code
  – Node performance (locality) + scalability
- Should develop tunable code generators to adapt to platform and data
  – Need good training sets!
- Code tuning is a very interesting classification problem

Questions?

Similarity definition

- "Similarity": how similar transactions are to each other
- "***Normalized hamming distance***" (pair-wise similarity):
  - Given two transactions, their "*normalized hamming distance"* is the number of differences divided by the total number of unique ones.
  - Example:

T1	1	1	0	1	0	1
T2	0	1	0	0	1	1

Difference = 3,

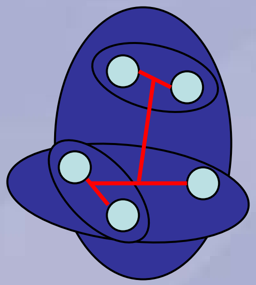
Therefore, distance(T1,T2) = 3/5 = 0.6

the number of unique ones is 5

Similarity feature definition

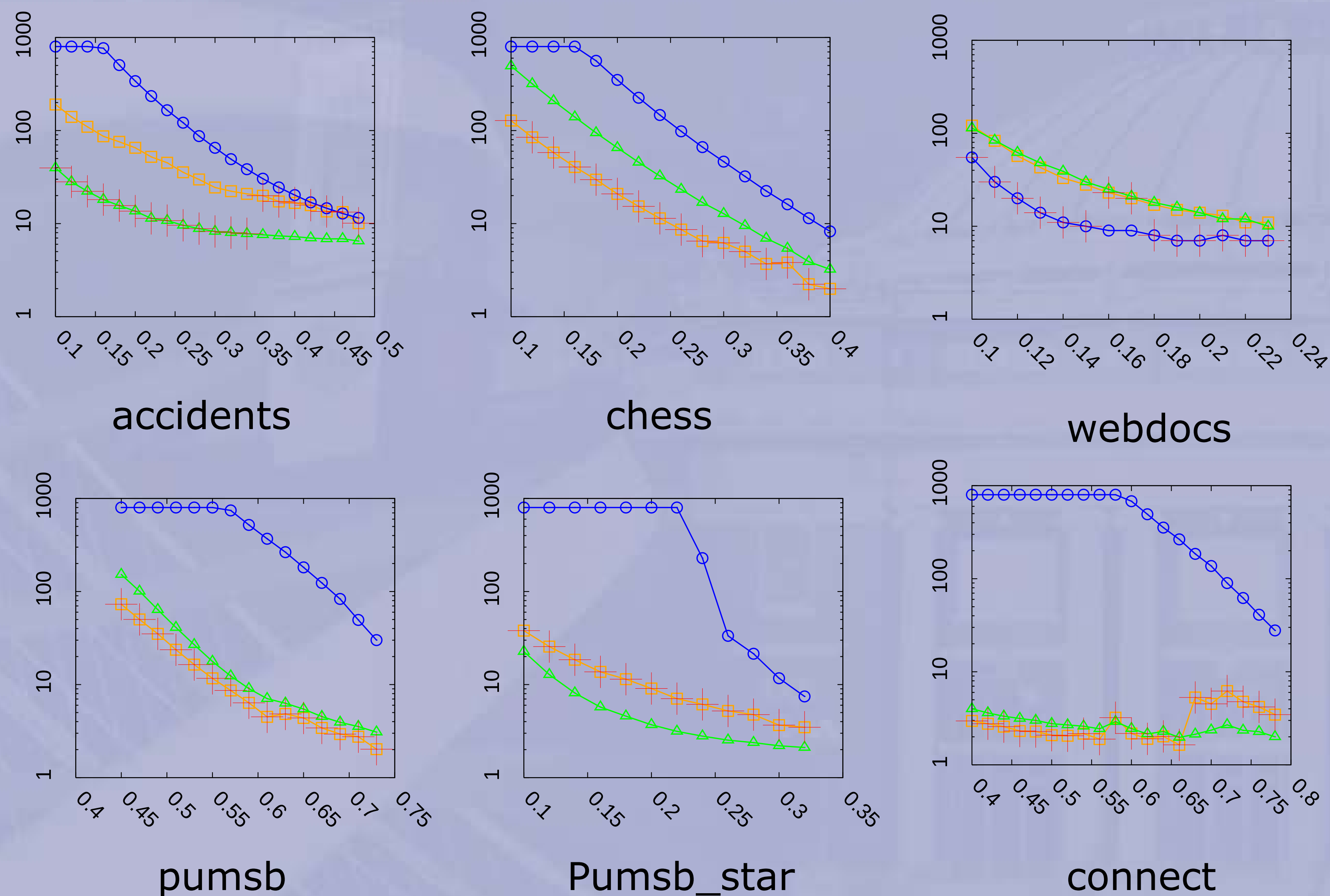
- Normalized hamming distance defines pair-wise distance, but we need a global measure of similarity among all transactions.

- Approach – "Average linkage clustering"
  - Start with *n* transactions, each as a cluster
  - Merge the two closest into one new cluster
  - Repeat merging until one cluster left.

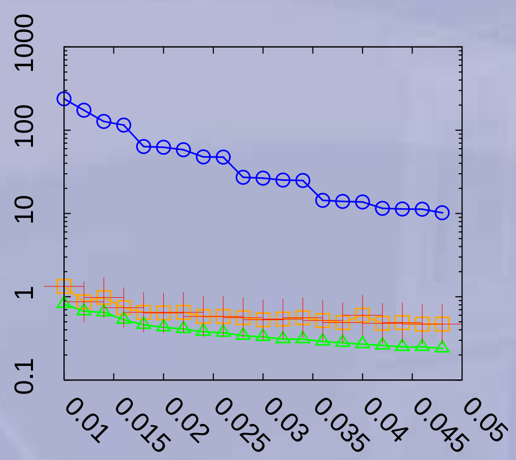


- "*Similarity*" = average value of the n-1 clustering distances

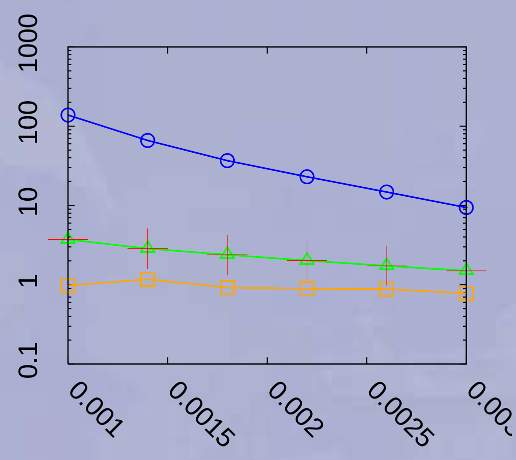
Prediction results on real-world datasets



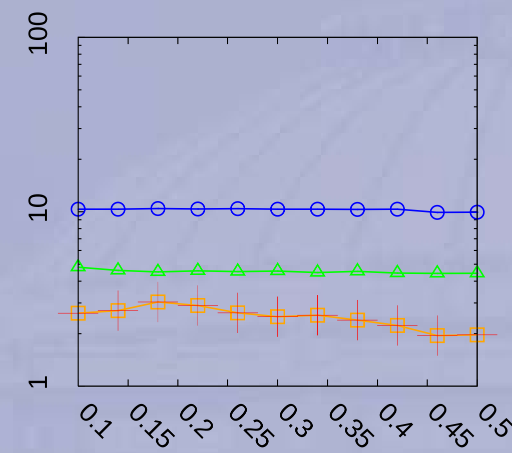
Prediction results on real-world datasets



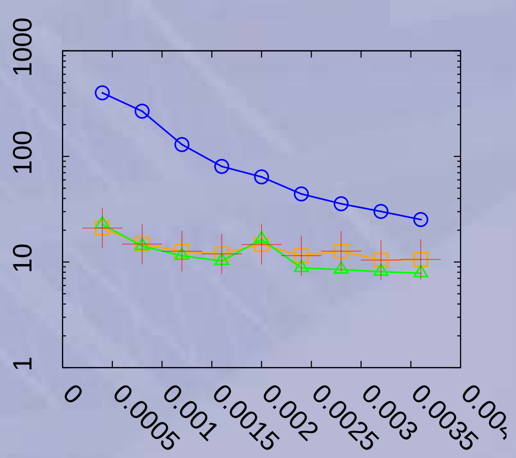
mushroom



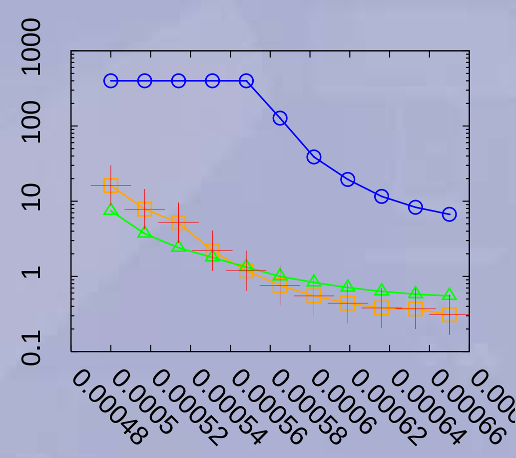
retail



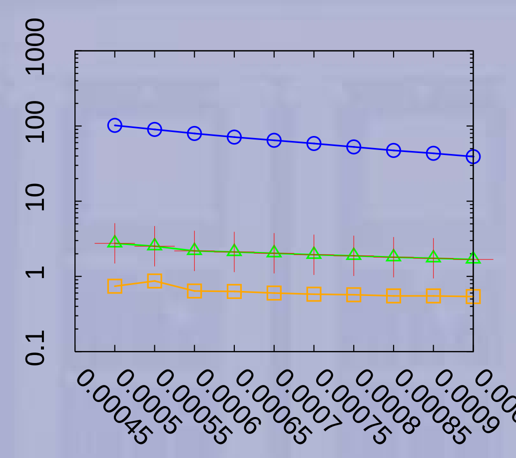
kosarak



BMS-POS



BMS-WebView1



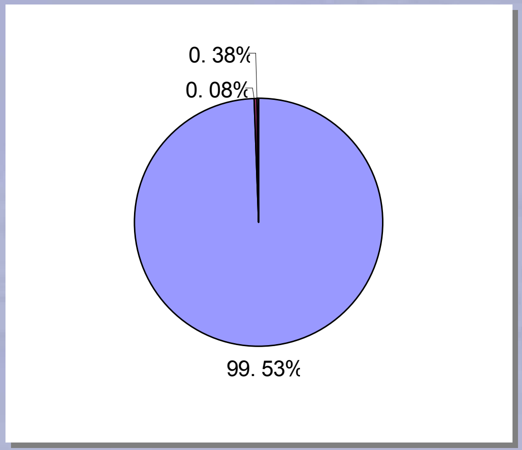
BMS-WebView2

Using synthetic data for training

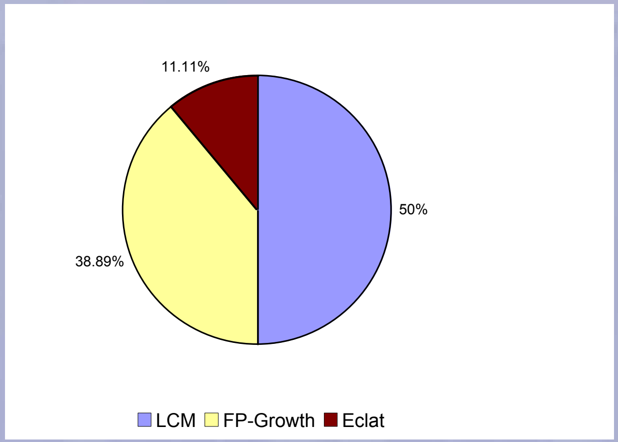
- IBM Quest dataset Generator
  - Widely used in data mining research

- Problem:
  - The generated dataset is not representative of real-world data

Best algorithm

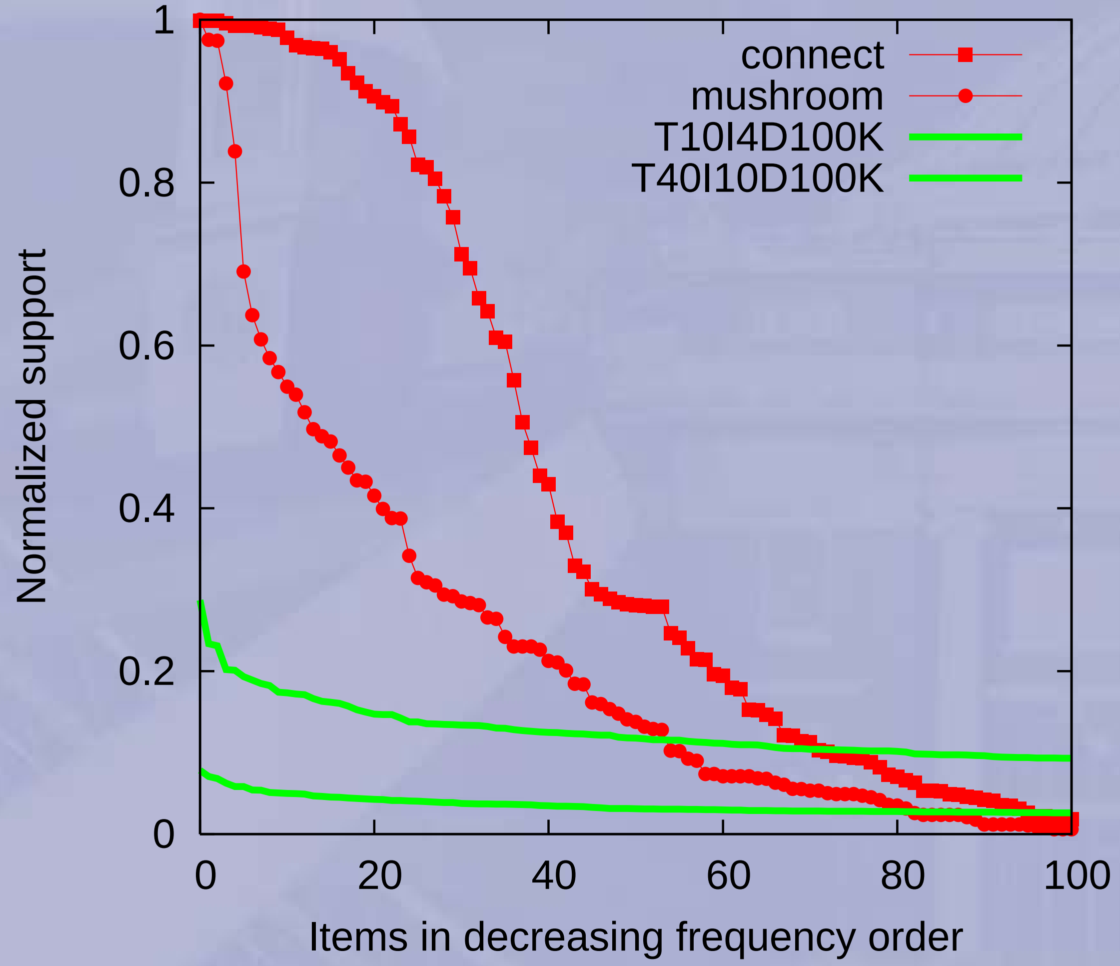


Synthetic datasets

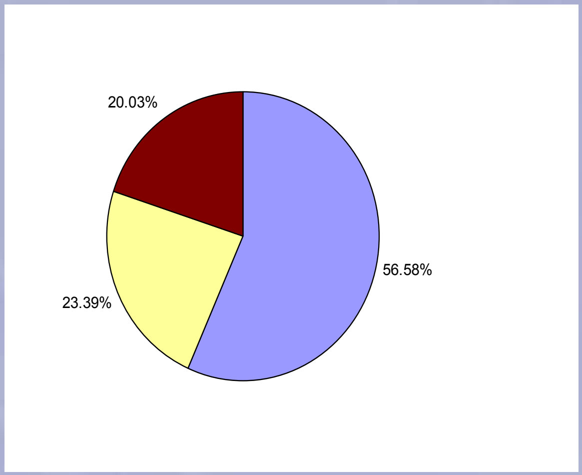


Real-world datasets

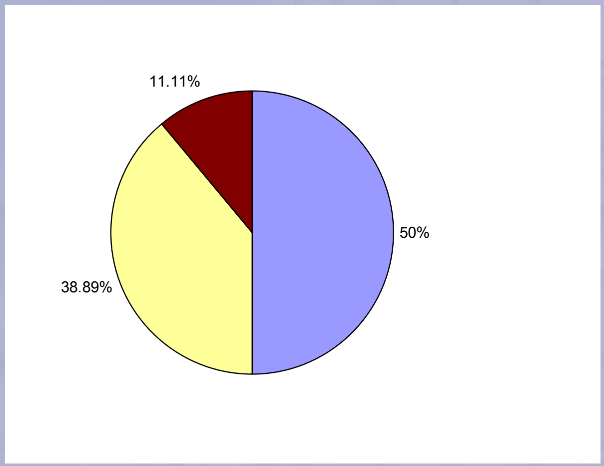
Item frequency curve



Using modified IBM generator to produce algorithm variability



Modified Synthetic datasets



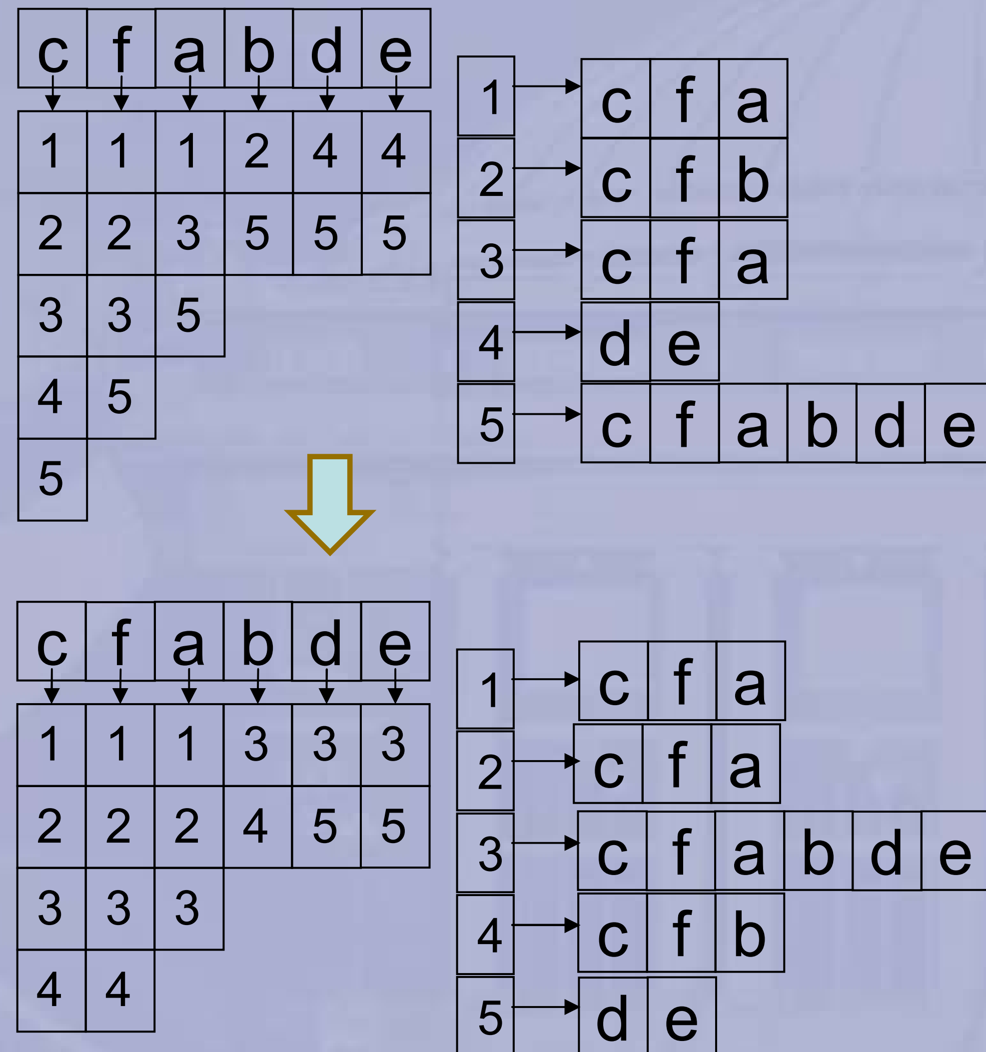
Real-world datasets

Lexicographic ordering of transactions

- **Preprocess** *original database* by reordering transactions in lexicographic order
  - Alphabet: items in descending frequency order
- ✓ Improves locality of accesses (LCM & FP_Growth); reduces computation (Eclat)
- × Overhead of lexicographic ordering

Lexicographic ordering in LCM

- Spatial locality of traversal is improved (fewer jumps)
  - Locality improved for most frequent items
  - Order mostly preserved for projected databases – ordering overhead amortized over multiple traversals



Lexicographic ordering in Eclat

- Range reduction reduces computation

	c	f	a	b	d	e
0	1	1	1	0	0	0
1	1	1	0	1	0	0
2	1	1	1	0	0	0
3	0	0	0	0	1	1
4	1	1	1	1	1	1

$\Rightarrow$

Mark first 1

1s becomes contiguous for c

1	1	1	0	0	0
1	1	1	0	0	0
1	1	1	1	1	1
1	1	0	1	0	0
0	0	0	0	1	1

Mark last 1

$\boxed{\{a\}} \cap \boxed{\{c\}}$ → Transactions for {a,c}

Rows are switched after lexicographic ordering

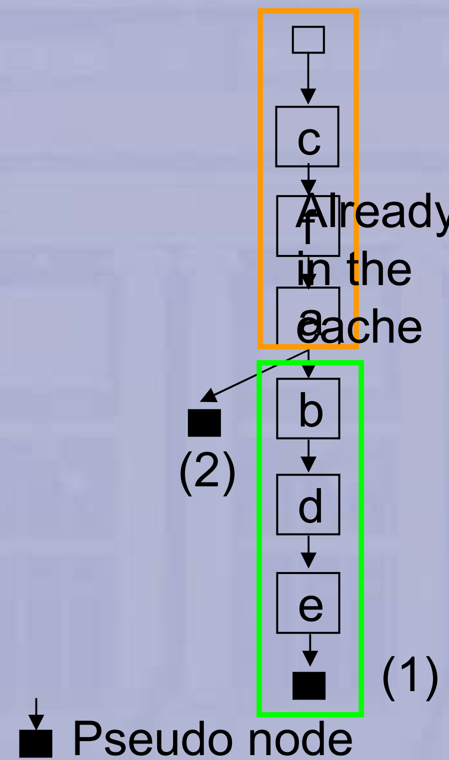
Lexicographic ordering – project() in FP-Growth

- Tree is constructed by inserting transactions from the original database one by one
- Lexicographic ordering improve the temporal locality for insertions.

tid	transaction
0	{c, f, a}
1	{c, f, b}
2	{c, f, a}
3	{d, e}
4	{c, f, a, b, d, e}

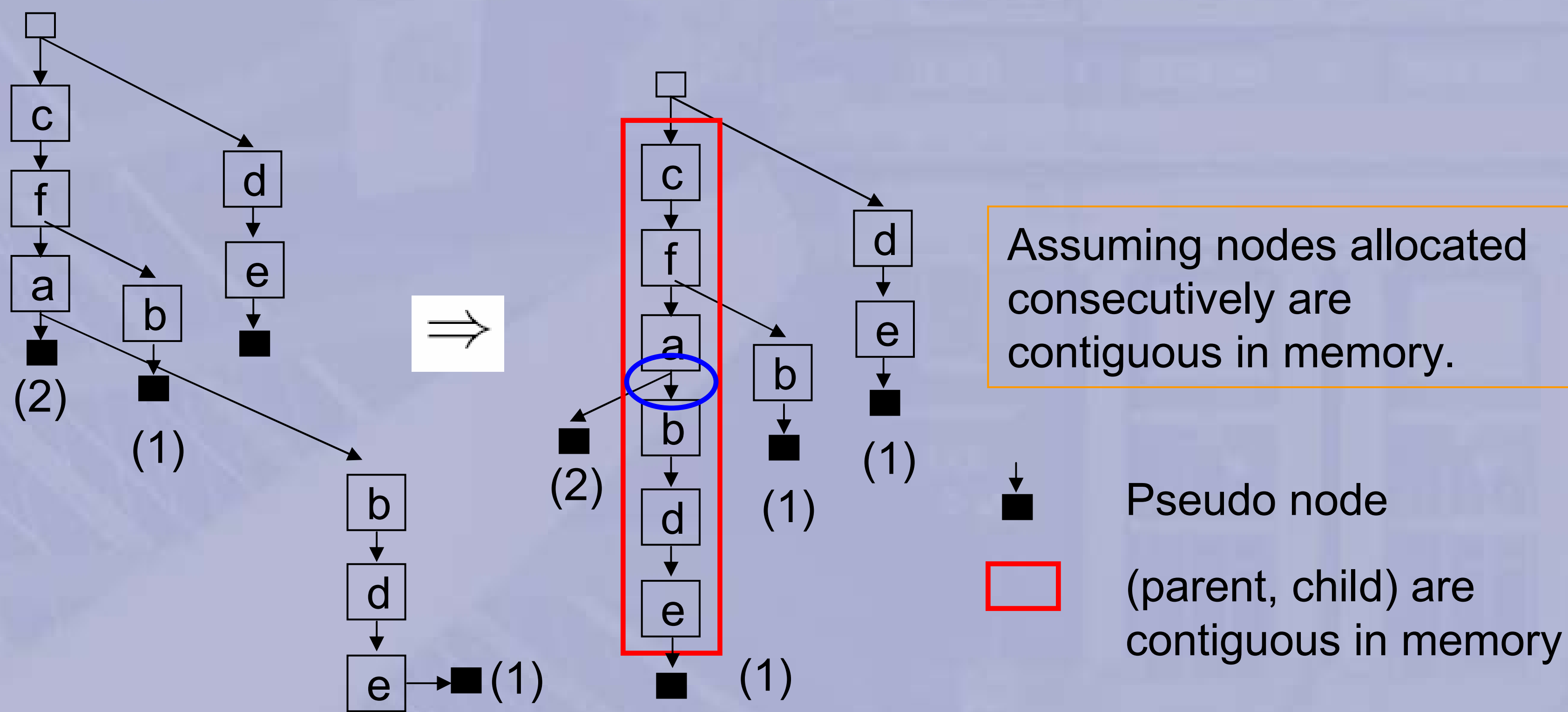
$\Rightarrow$

tid	transaction
0	{c, f, a}
1	{c, f, a}



Lexicographic ordering – project() in FP-Growth

- Access pattern: From an intermediate node to root
- More (parent, child) pairs are contiguous in the memory – better spatial locality

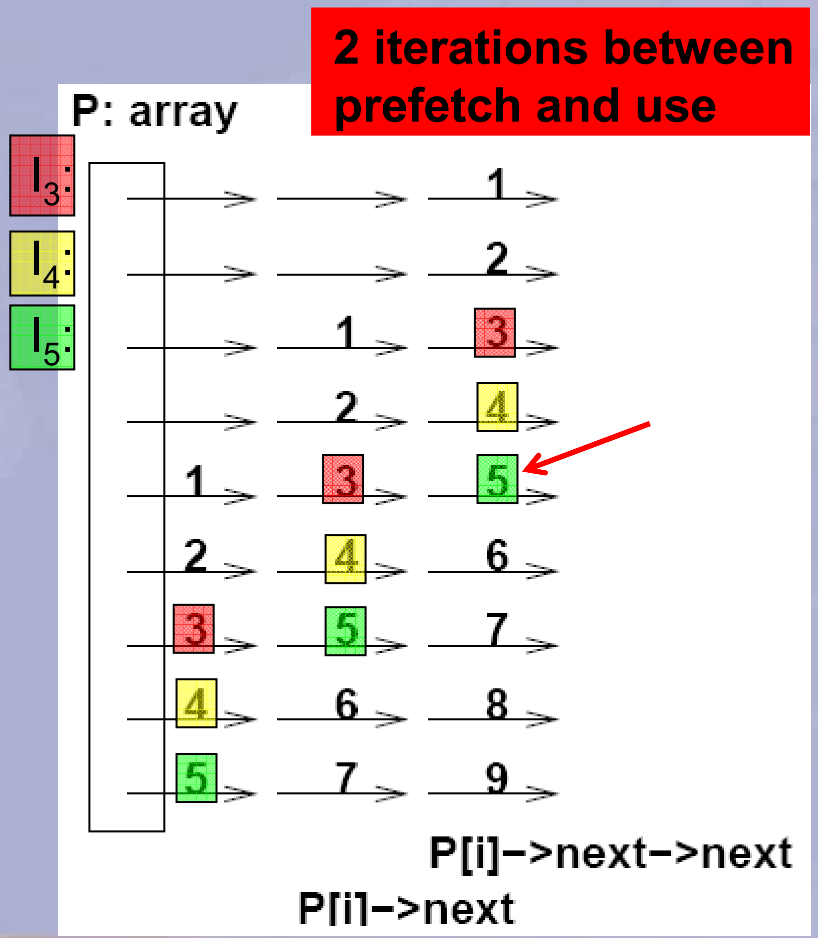


Wave-front prefetch

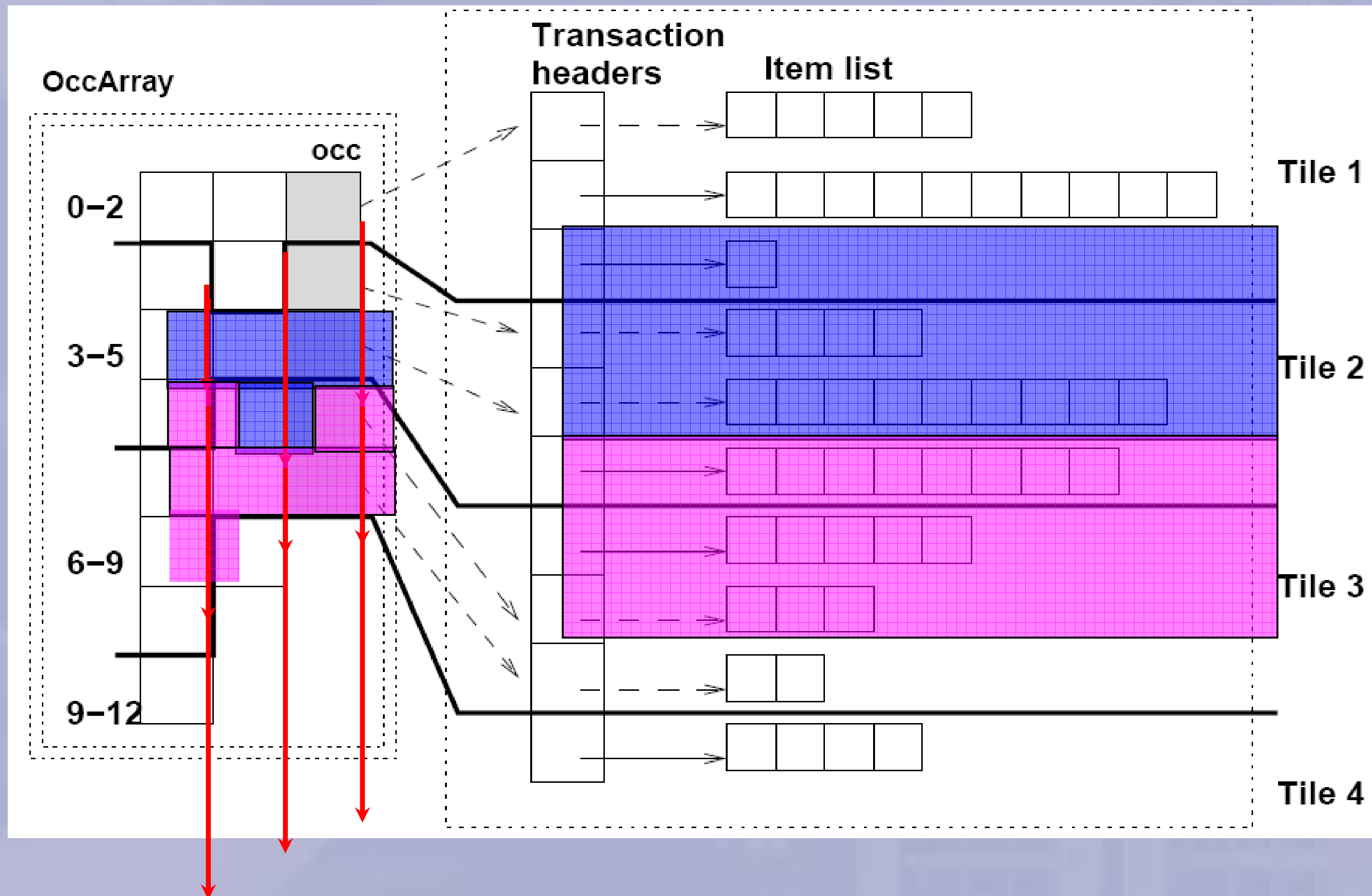
Array of short linked lists

- Prefetch pointers from different linked-lists in one iteration
- ✓ Hides memory latency
- × Increases register pressure

Can be used even if lists are of different length



Tiling (LCM)



- ✓ Improves temporal locality
- × Slightly increases instruction count and memory pressure

Programming patterns applied

Patterns	LCM	Eclat	FP-Growth
Lexicographic ordering	√	√	√
Aggregation	√	N/A	√
Compaction	√	N/A	√
Pointer prefetching	N/A	N/A	√
Tiling	√	N/A	○
Software prefetch	√	N/A	√
SIMDization	N/A	√	N/A