

## Efficiently Identifying Working Sets in Block I/O Streams

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#### Key Ideas



- Grouping data is beneficial
- Even block I/O data can be grouped
  - Grouping block data can lead to high level insights
- The systems research world needs more trace data for modern systems







#### Why Group? - Power Efficiency



- Reduce the number of spin-ups
- Reduce on-disk seek time if grouping is done within a single disk
- Better pre-fetching while a drive is spinning, reducing further spin-ups







#### Why Group? - Reliability



- The domains affected by a given failure event are constrained to the domains that used the groups that failed
  - Better for one person to lose access to 80% of their data than for a hundred to lose 5%
  - A project often idles while restoring from backup even if it only lost a few scattered files
- Fewer spin-ups decrease probability of drive failure







#### Still Not Convinced?



- Priority: Working sets could be placed by desired performance, failure rate, etc
- Most files are still small
  - Median file size = 2475 bytes on a UNIX server
  - Moving small files around into working sets could yield huge results
  - Small files are frequently overwritten, but are they overwritten by the same programs?







#### What about Caching?



- Our system is designed to work on top of caching
  - Once a working set is identified, the system can choose to pull the entire set into cache once the set is accessed
- This makes working sets a meta-cache
- More work to be done in this intersection





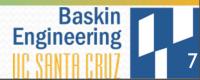
#### What about Clustering?



- Tried unsupervised learning methods
  - k-means
    - Number of clusters is getting easier to predict
  - Expectation maximization
  - Agglomerative clustering
- Useless for our data
  - Scattered, omnipresent writes to hot area distorted data
  - Number of clusters changes







#### Grouping is hard (but great!)



- For semantically labeled data, we can an average power savings of 20% by grouping data
- Data is expensive to label
- Rich meta-data costs performance to collect
- Privacy concerns
- What if we just collect block level data?







#### Data at the Block Level



- Block level data:
  - block offset location of block on physical disk
  - timestamp time of access
- Easy to collect
  - Low performance overhead
- No domain knowledge needed







#### MSR Cambridge Data: Characteristics

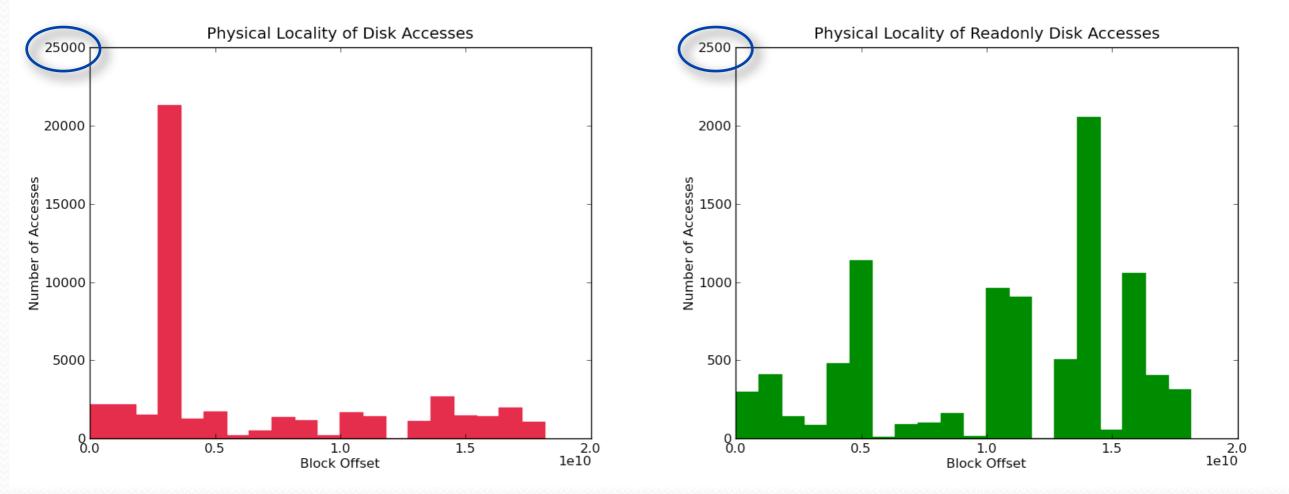


- Total number of accesses: 1433655
- Total number of "unique" block offsets: 46718
  - Unique offset-size pairs: 108793
- NTFS





#### MSR Cambridge Data: Access Src Locality



#### **Reads and Writes**



Workload is skewed by writes to a hot area







#### **MSR Cambridge Data:** Accesses



#### 0.0 1.0 1.5 0.5 Block Offset 1e10 **Reads and Writes**

Reads

Block Offset

0.5

1.0

- Read/Write ratio of 10/90
  - Many writes are to the same blocks



1e11

6

5

Access Times (s)

3

2





1e10

#### MSR Cambridge Data: Misc



- Available from SNIA
- Collected in 2007
- Comes from a multi-application research machine (rsrch\_0)
- Covers 7 days of machine operation
- Cases of consecutive writes to the same blocks

128166372454818843,rsrch,0,Write,3154137088,4096,1175 128166372454818856,rsrch,0,Write,3154137088,4096,1161 128166372472318823,rsrch,0,Write,3154137088,4096,1130 128166372507631099,rsrch,0,Write,3154137088,4096,1227 128166372524817728,rsrch,0,Write,3154137088,4096,2034 128166372524818590,rsrch,0,Write,3154137088,4096,1172







# Grouping at the Block Level



- All you have is offset, timestamp pairs
- Offsets are likely to be accessed repeatedly
- Calculate similarity across accesses







#### Similarity - Distance Matrices



- mxm matrix to calculate the distance between two offsets given all pairwise occurrences
- *m* = # unique block offsets
- $T_k = |t_{ik} t_{jk}|$
- $O_i$  = offset *i*

$$d(o_i, o_j) = \sqrt{\left(\frac{\sum_{i=1}^{|T|} T_i}{|T|}\right)^2 + oscale \times (o_i - o_j)^2}$$





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#### Similarity - Distance Lists



- Pick a threshold around an offset outside which similarities are not considered
- Combine lists of offset distances to get cumulative distance lists

$$[(o, o_i, d(o, o_i)_1 + \frac{d(o, o_i)_2}{|t_1 - t_2|}, (o, o_j, d(o, o_j)_1, (o, o_m, d(o, o_m)_2)]$$



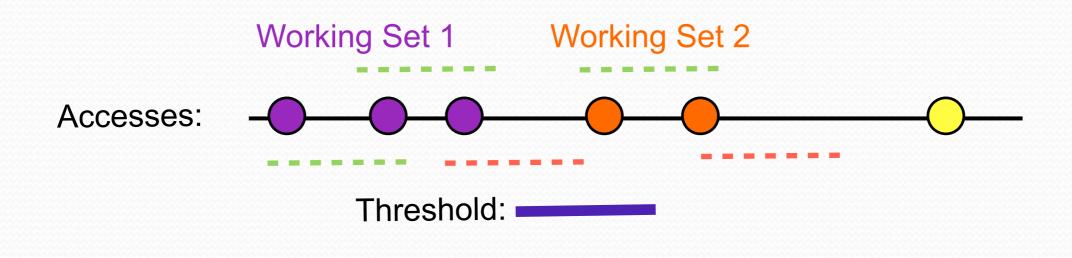




#### Comparison Technique: Neighborhood Partitioning



- Calculate global threshold based on mean and standard deviation between accesses
- Apply threshold to determine if adjacent accesses should be in the same working set



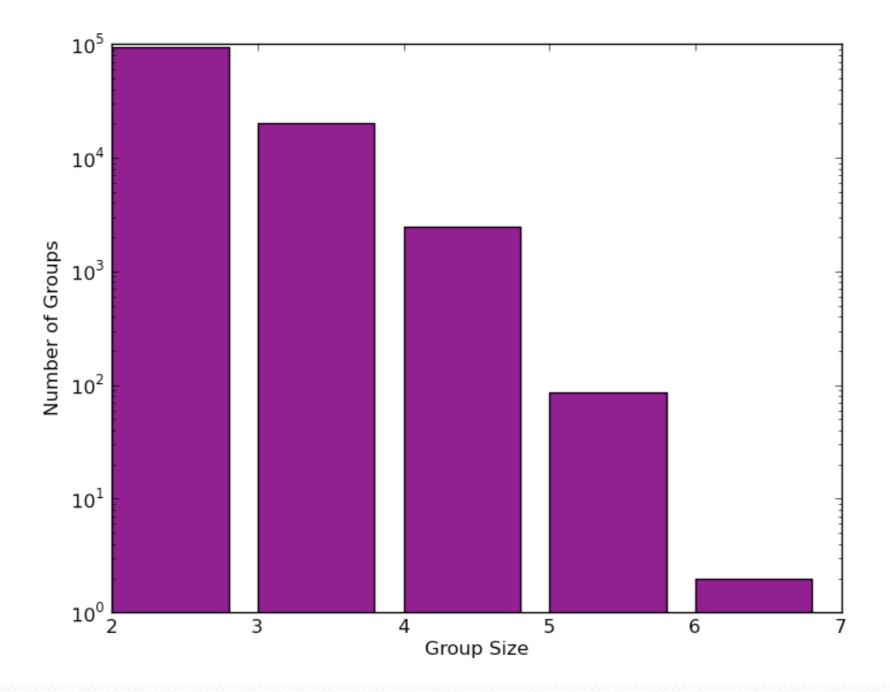






#### Results: Neighborhood Partitioning, Read-Write





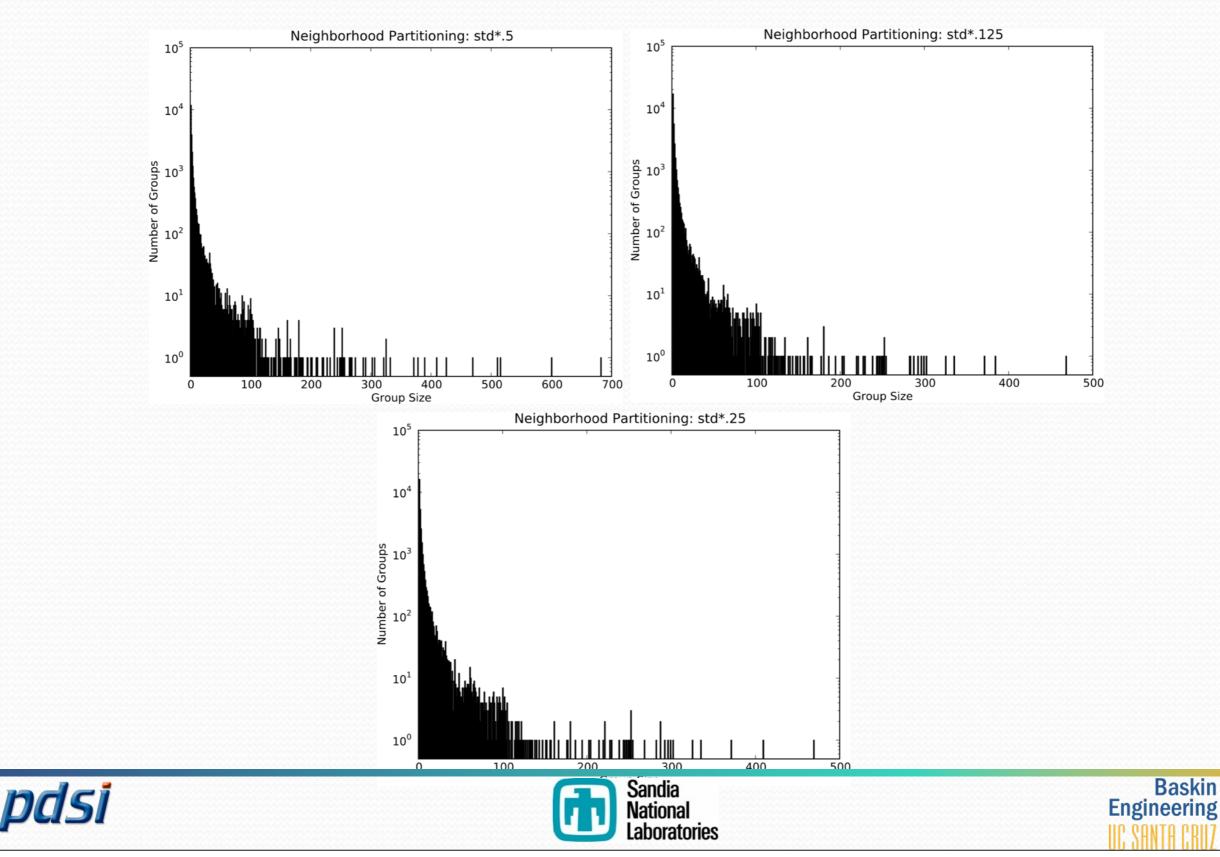






#### Results: Neighborhood Partitioning, Read-Only

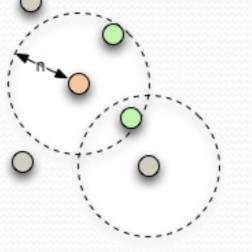




#### Comparison Technique: Nearest Neighbor (weighted)



- Calculate pairwise distances in spatial neighborhood n
- Calculate the average distance per pair
- Use average, scaled time/space distance to group files under different time/space thresholds.



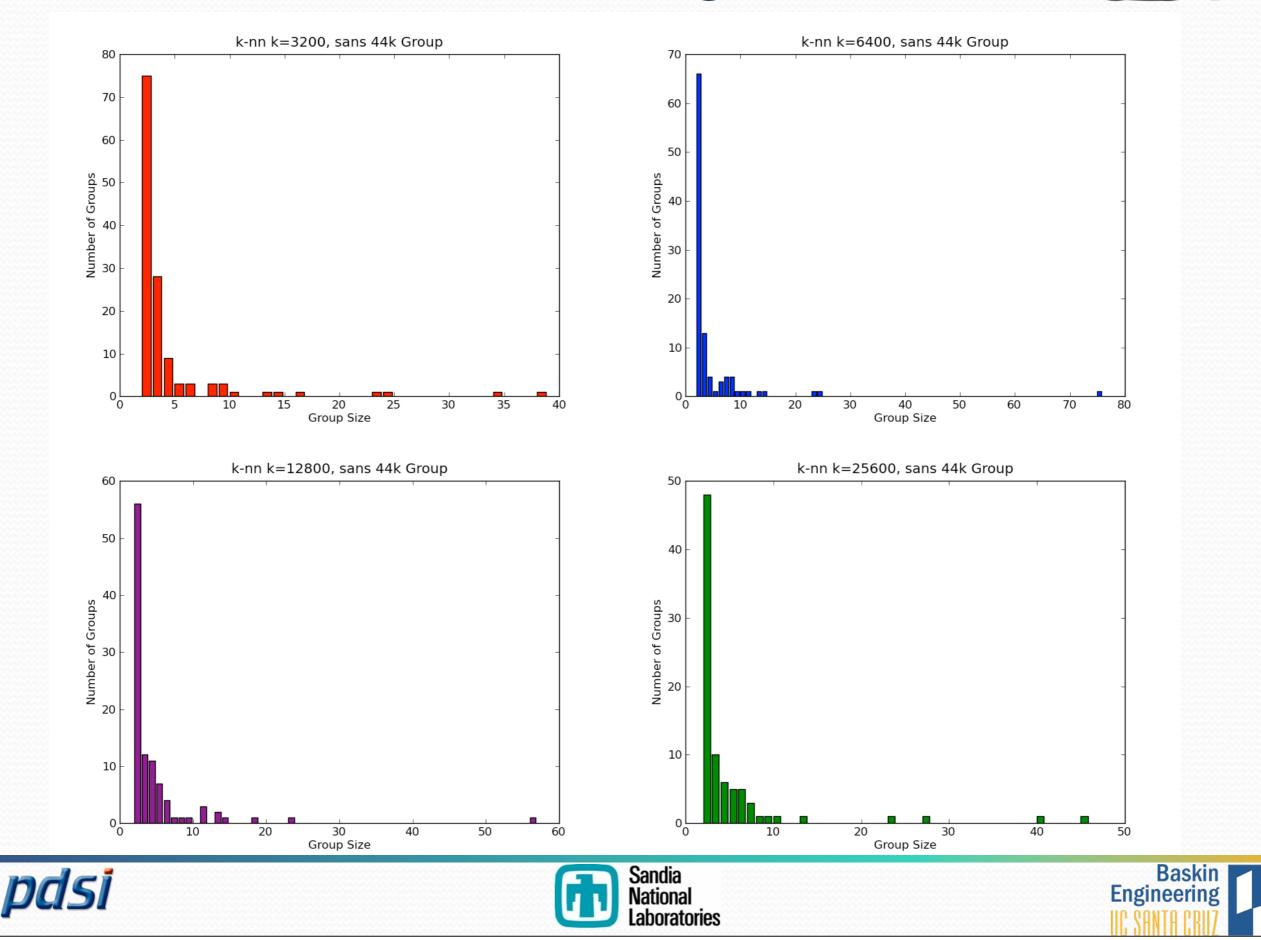
n = 3200 block offset





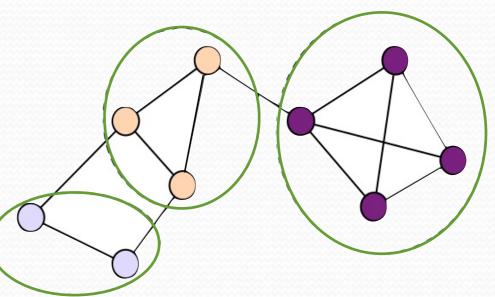


#### **Results: Nearest Neighbor**



#### Comparison Technique: Bagof-Edges

- Nodes = disk accesses
- Edge = two points have an acceptable distance between them (weight >= 0)



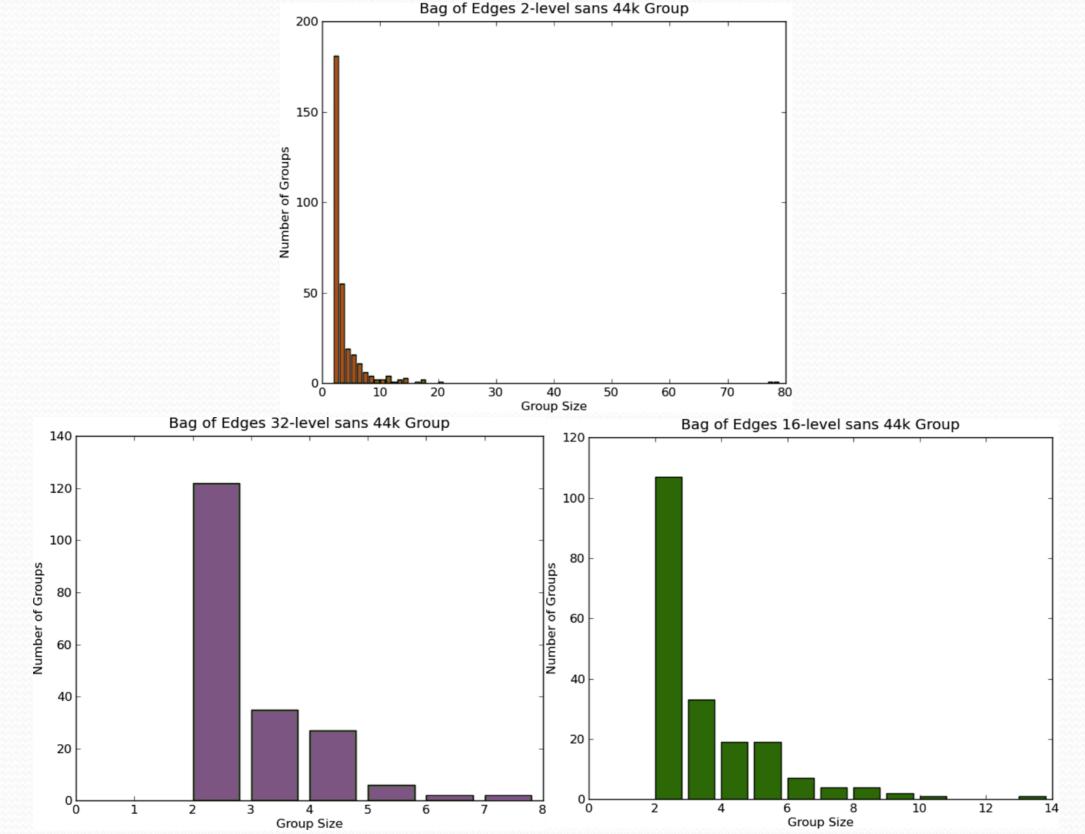
- Clique-cover seems right, but fails (and is NP-Complete)
- Less Restrictive: Longest path per connected component (Also NP-Complete)
  - Solution: Toss out weights; run shortest path over negated minimum spanning tree





#### **Results: Bag-of-Edges**











### Validity



- Do our groupings stay consistent over time?
  - Groups are resistant to most distance scaling factors
  - Large jumps for levels or neighborhood distances
  - Could be natural, correct, usage shift







#### Validity Methods



- Group overlap
  - Lots of methods to weight here
- Rand criterion
  - $\mathsf{R}(G_1, G_2) = \frac{(a+d)}{(a+b+c+d)}$ 
    - a = # pairs in  $G_1$  and  $G_2$
    - b = # pairs in  $G_1$  not in  $G_2$
    - c = # pairs in  $G_2$  not in  $G_1$
    - d = # pairs not in  $G_1$  and not in  $G_2$
  - 0 ≤ R ≤ 1
- Mutual entropy
  - Define probability with set intersection







#### Next Steps



- Protocol analyzer to collect more block I/O data.
  - Mixed-use educational storage systems
  - HPC Systems
- Implement working set detection real-time
  - Track power savings
  - Track reliability savings
  - Track bad working sets





#### Future Work



- Application Isolation
  - Working sets -> Application accesses
  - Goal: take a system and compartmentalize files that tend to be accessed by specific applications
    Duplicating files in storage is OK!
- Workload Characterization
  - Can anything about groupings be transferred to different workloads with similar characteristics?
    - What are these characteristics?
  - Classify based on separability
  - HPC vs. Enterprise vs. User-facing





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#### Please send all of your data to: (55)

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- Ethan: <u>elm@soe.ucsc.edu</u>
- Lee: <u>lee@sandia.gov</u>

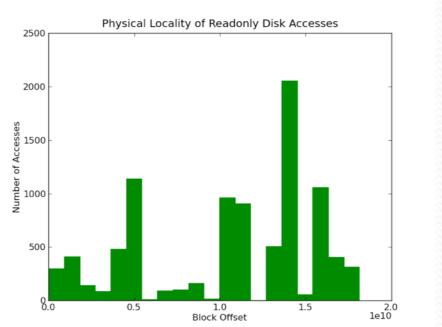
#### Thanks!

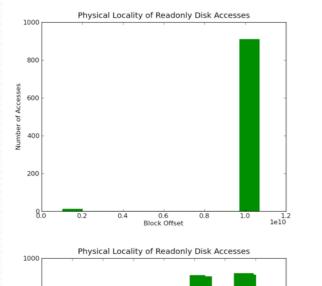


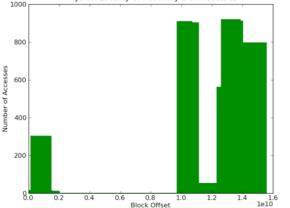


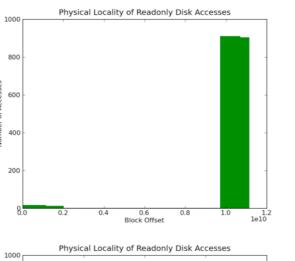


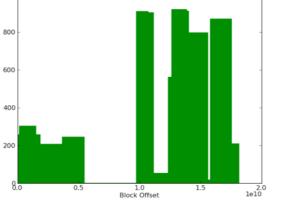
#### **BACKUP: Read Accesses**

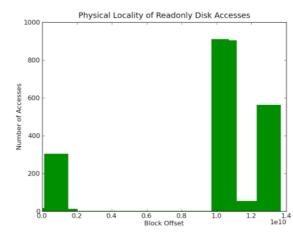


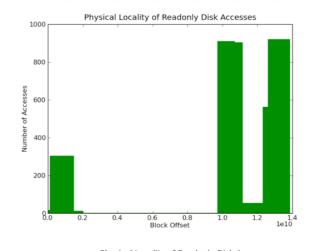


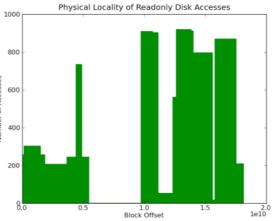


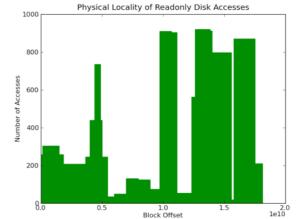


















Src

#### BACKUP: Comparison: Sliding Src Window

- Sliding window of
  - nxn pairwise 10<sup>5</sup> 10<sup>5</sup> 10<sup>5</sup> 9600.0 6400.0 3200.0 comparisons  $10^{4}$ 10<sup>4</sup> 10 10<sup>3</sup> 103 10 10<sup>2</sup> 10<sup>2</sup> 10 10<sup>1</sup> 10<sup>1</sup> 101 10<sup>0</sup> 10<sup>0</sup> 10<sup>0</sup> 20010-1 20010-1 10-1 50 100 150 50 100 150 150 200 50 100 0 0 0 10<sup>5</sup> 10<sup>5</sup> 105 25600.0 19200.0 12800.0  $10^{4}$  $10^{4}$ 10 103  $10^{3}$ 103 10<sup>2</sup> 10 102  $10^{1}$ 10<sup>1</sup> 101  $10^{0}$  $10^{0}$  $10^{0}$ 20010-1 10-1 20010 50 150 50 150 50 150 200 100 100 100 0 0





