Fast Browsing of Archived Web Contents

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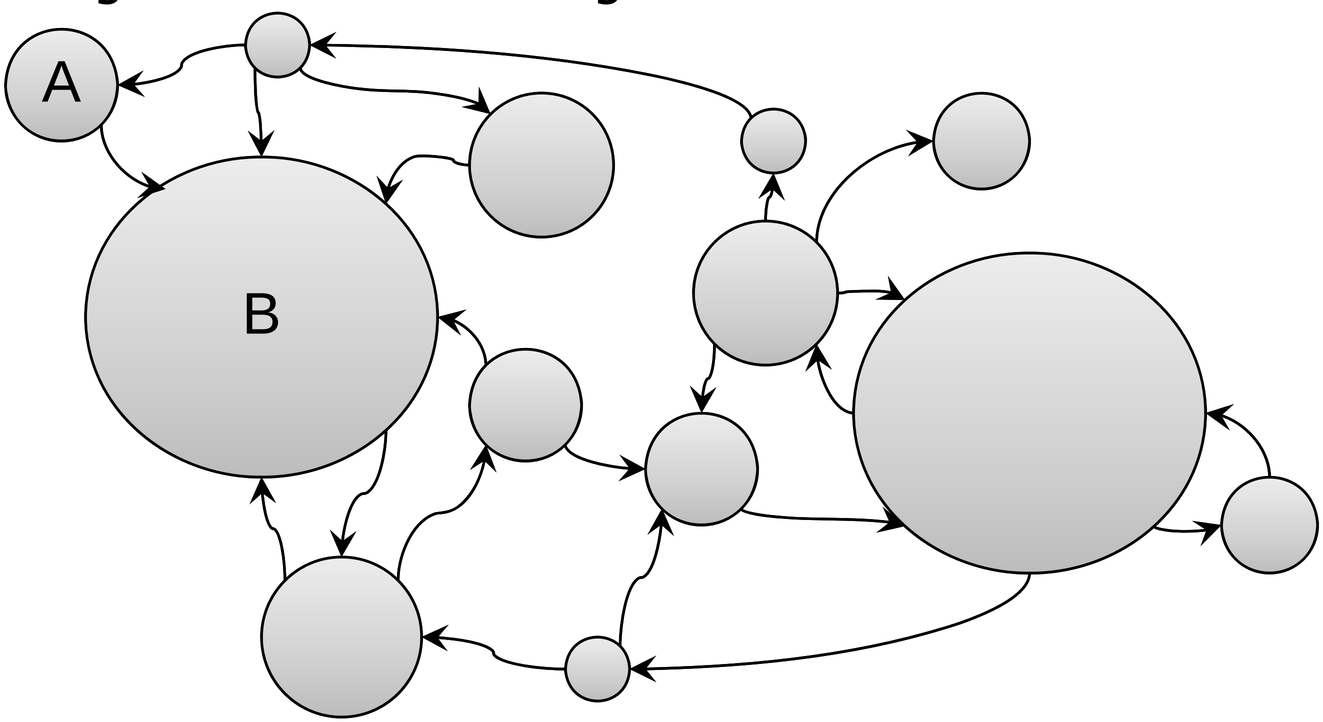
Motivation and Goal

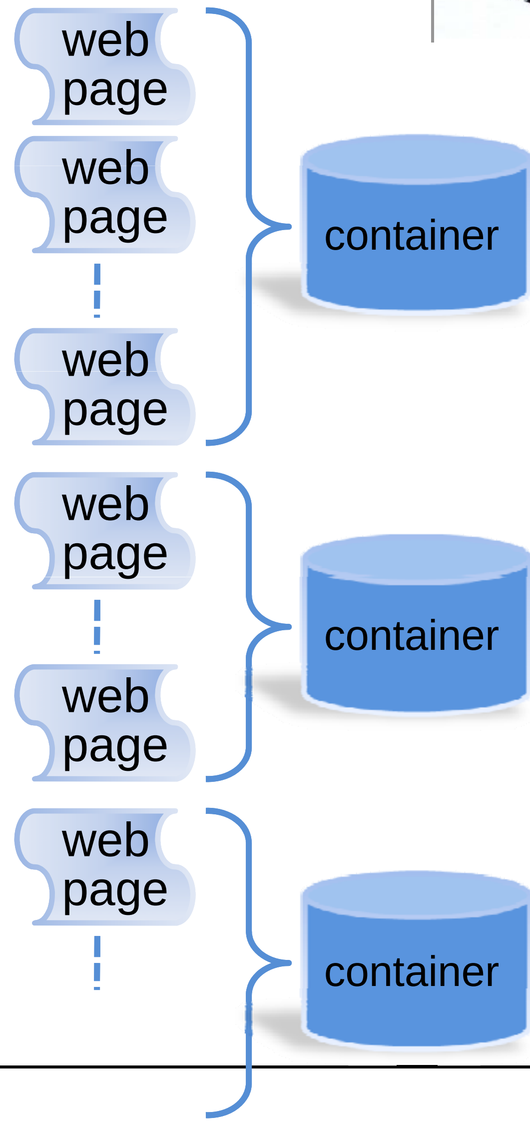
Web Graph

- Web as a weighted, directed graph.
  - Web page → Vertex
  - Hyperlink → Edge
  - Page size → Vertex weight



Web Containers

- A multitude of web pages are aggregated into a container (e.g. WARC)
- Each container serves as an archive object
- Currently adopted by the Internet Archive, and many other national archives, and libraries



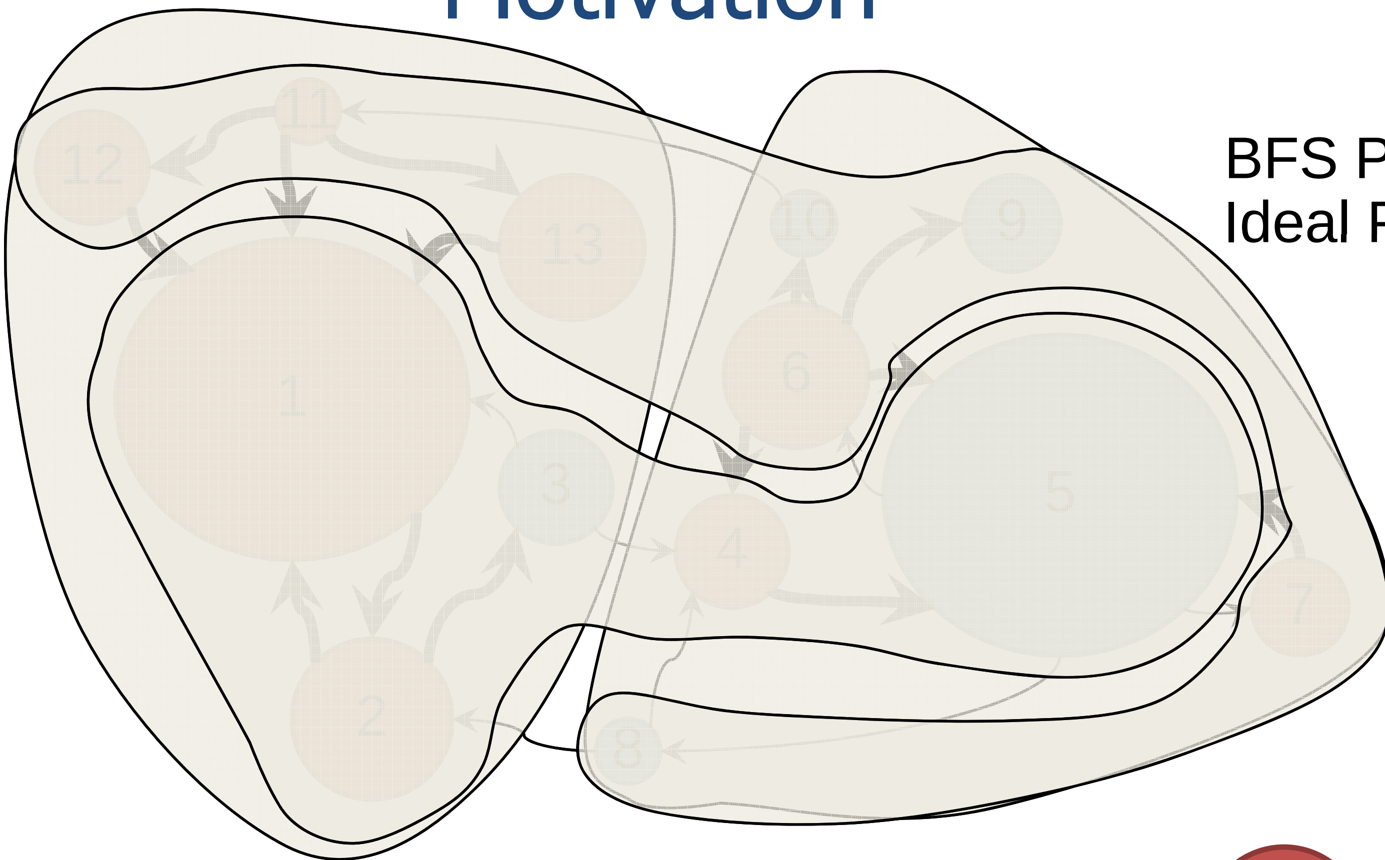
Current Container Packaging

- BFS or DFS based crawls
- First seen page → first put into a container
- When a container is full, a new container is created.

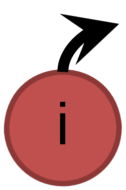
```
Input
Seed URLs : {url_1, url_2, … }
MAX_SIZE

Procedure
Enqueue(Q, Seed URLs)
i←1
visited[] ← FALSE
C_i ← new Container()
while (Q is non-empty)
        u ← Dequeue(Q)
        Fetch(u);
        visited[u] ← TRUE
        if (Size(C_i) + Size(u) > MAX_SIZE)
                i = i + 1
                C_i = new Container()
        C_i = C_i  U u
        for each v ∈ adjacent[u]
                if (visited[u] = FALSE)
                        Enqueue(Q, v)
```

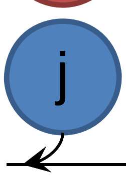
Motivation



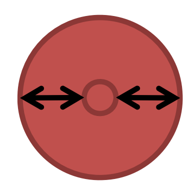
BFS Packaging
Ideal Packaging



Popular Page (visited i_{th} by BFS)



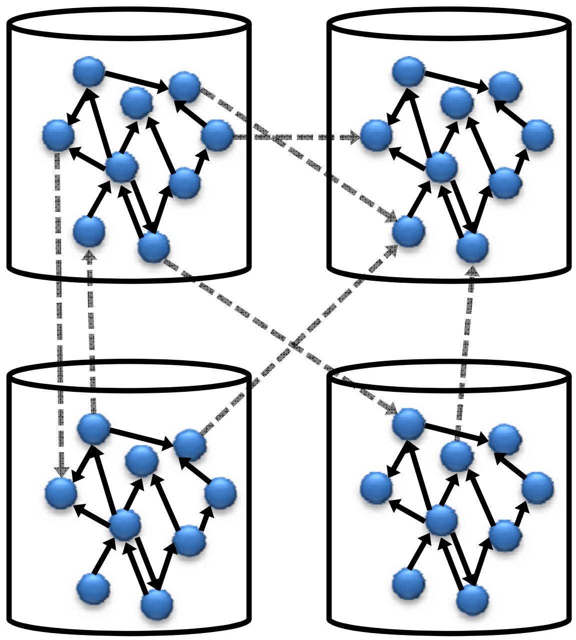
Unpopular Page (visited j_{th} by BFS)



Circle Size ≈ Page Size

Our Goal

- Minimize the probability that a user jumps often between containers.



Packaging Issues

Main Issue: How to minimize the number of containers necessary when accessing the archived web pages?

How to put together more relevant web pages in the same container?
→ Graph Partitioning

How to define 'relevancy'?
→ Graph Analysis

Our Approach

Our Approach

- Graph Analysis
  - Web graph is analyzed to obtain, for each edge, a global probability that the edge is taken.
- Graph Partitioning
  - Using edge weights from graph analysis, find the best partition where the sum of edge weights across different parts is minimized, and the size of each part is balanced.

```
Input
Seed URLs : {url_1, url_2, … }
MAX_SIZE

Procedure
G ← BuildWebGraph(Seed URLs)
n ← GetNumberOfContainers(G,MAX_SIZE)
G ← EdgeRank(G) /* Optional */
{UL_1,UL_2,…,UL_n} ← PartitionGraph(G, n)
for ( 1 ≤ i ≤ n)
    C_i ← new Container()
    for (v ∈ UL_n)
        fetch(v)
        C_i = C_i U v
```

Graph Analysis (1/2)

- PageRank [Brin, S. and Page, L, 1998]
  - Computes the importance of each web page.
  - Pages linked from important pages are considered important.
  - Ideal model: $PR(u) = \sum_{v \in I_u} p_{vu} PR(v)$
  - Two problems.
    - Dangling pages ➔ Solution: artificial out-links to all the other pages from dangling pages, w/ probability of *1/N*
    - Cyclic paths ➔ Solution: artificial out-links to all the other pages from each page, w/ probability of *1-d*
  - Modified model: $PR(u) = \frac{1-d}{N} + d \sum_{v \in I_u} p_{vu} PR(v)$

Graph Analysis (2/2)

- EdgeRank

$$ER(e) = \frac{PR(v)}{\text{outdegree}(v)}$$

- EdgeRank is used in our simulation

Graph Partitioning (1/2)

- Edge-Cut : The sum of the weights of the edges that connect any two different parts.
- *Web Graph Partitioning Problem*: Given a directed web graph $G:(V, E)$ with weighted nodes (weight of a node is the size of the corresponding page) and weighted edges, determine a partition $V = P_1 \cup P_2 \cup P_3 \cup \ldots \cup P_n$ such that,
  1. Edge-Cut is minimized.
  2. For all i's, $|P_i| \leq K$ for some fixed K, where $|P_i|$ is the sum of the weights of the vertices in P_i and K is an upper bound on the size of a container.
- This is an NP-Complete problem

Graph Partitioning (2/2)

- Scheme used in simulation: [Karypis and Kumar, 1998]
  - Fast multilevel graph partitioning algorithm
    1. First compute a maximal matching using a randomized algorithm
    2. Coarsen the graph by collapsing the matched vertices together
    3. Repeat 1~2 until a desired size of the coarsened graph is achieved
    4. Compute minimum edge-cut bisection
    5. Refine & uncoarsen the partitioned graph.

Experiments

Experiment Settings (1/2)

- Datasets
  - UMIACS : Web Graph built from our crawls of http://umiacs.umd.edu in 2007
  - Stanford : Web Graph built from a crawl of http://stanford.edu in 2002 by the Stanford WebBase project

- Dataset Properties

Datasets	# Vertices	# Edges	Total Vertex Weight
UMIACS Web Graph	4579	9732	2.49GB
Stanford Web Graph	281903	2312497	215.82GB

Experiment Settings (2/2)

- Three packaging methods
  - CONV: Pages are allocated to containers as they are fetched during the crawling process (BFS). Once a container is full, we use a new container.
  - GP: The graph partitioning technique is applied so as to minimize the number of edges connecting any two partitions. All the pages belonging to a partition are allocated to a single container.
  - ER+GP: EdgeRank is used to assign weights to edges, and the graph is partitioned using a minimum-weight partitioning algorithm.

Edge-Cut Result

$$EC_{scaled} = \frac{EC \times 100}{|E|},$$

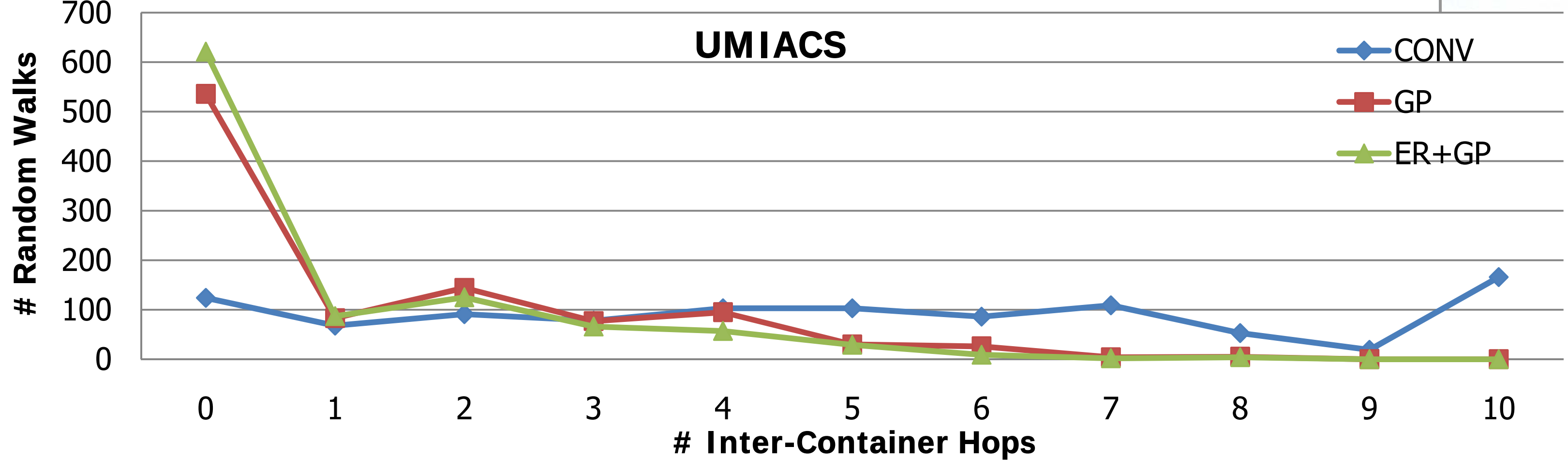
Edge-Cut	Unweighted Edges		Weighted Edges	
	CONV	**GP**	**ER+CONV**	**ER+GP**
UMIACS Web Graph	73.87	12.38	62.36	36.03
Stanford Web Graph	80.50	47.33	63.56	32.20

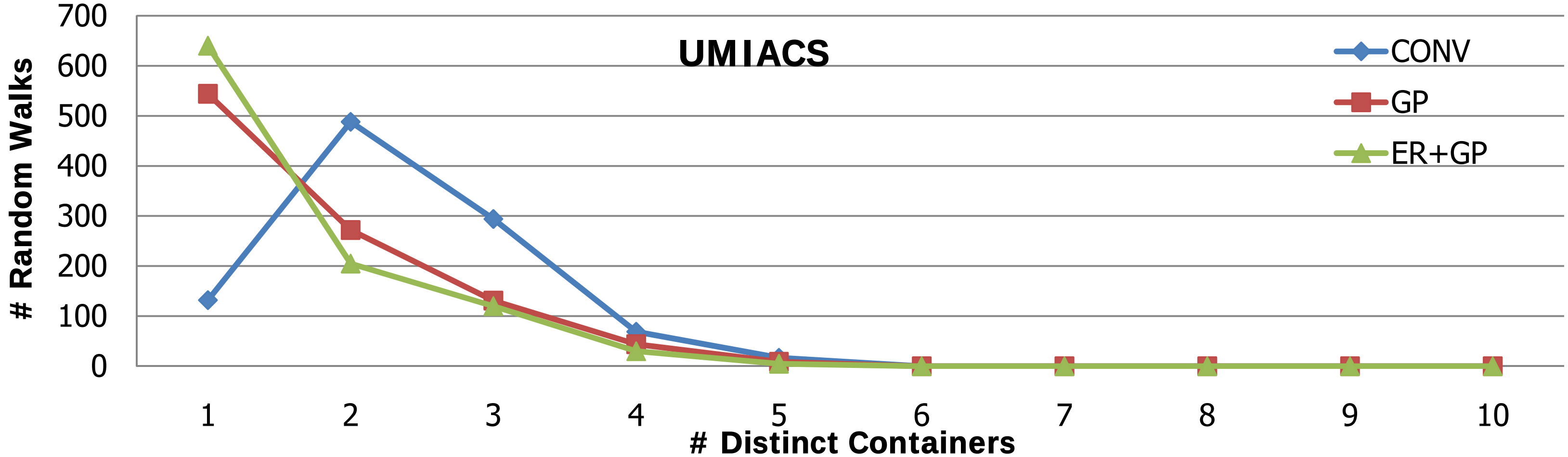
Simulation

- Simulation Parameters

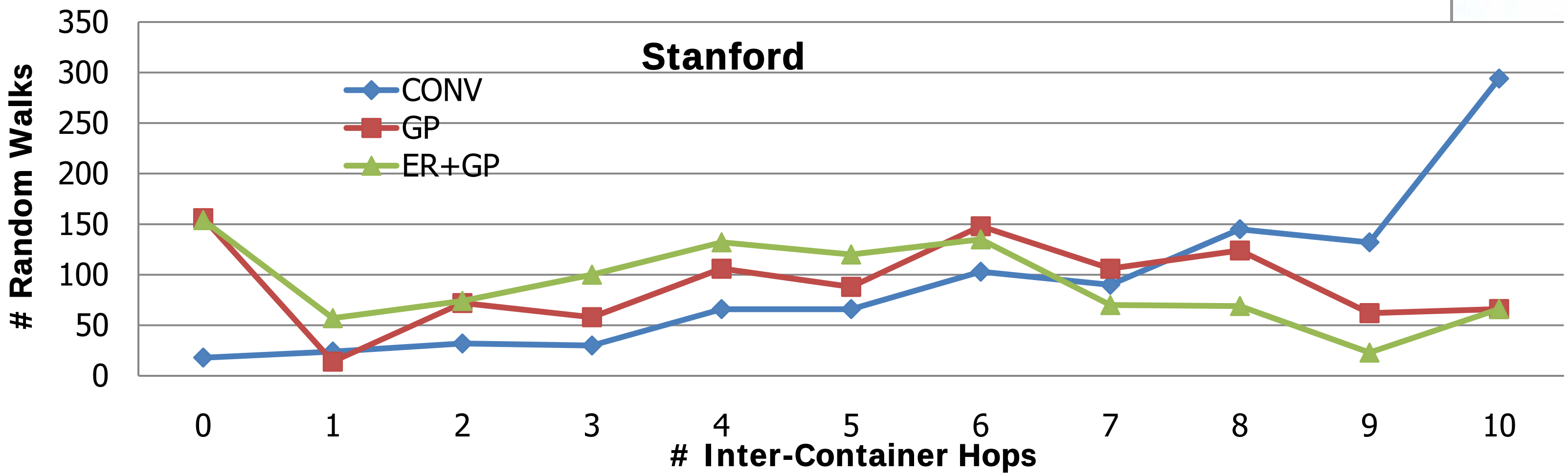
Parameter	Value
Number of Random Walks	1000
Number of Hops in Each Walk	10
Probability of Going Back	30%
Out-degree of Starting Vertex	> 5
Policy At Dangling Vertex	Go back

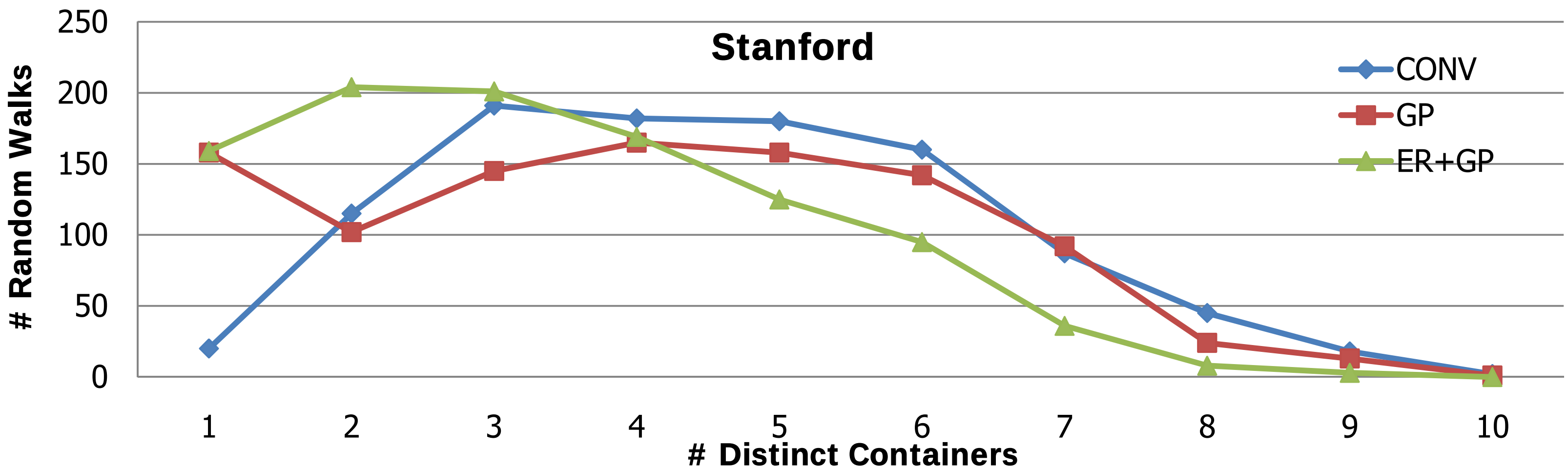
Simulation Results (UMIACS)



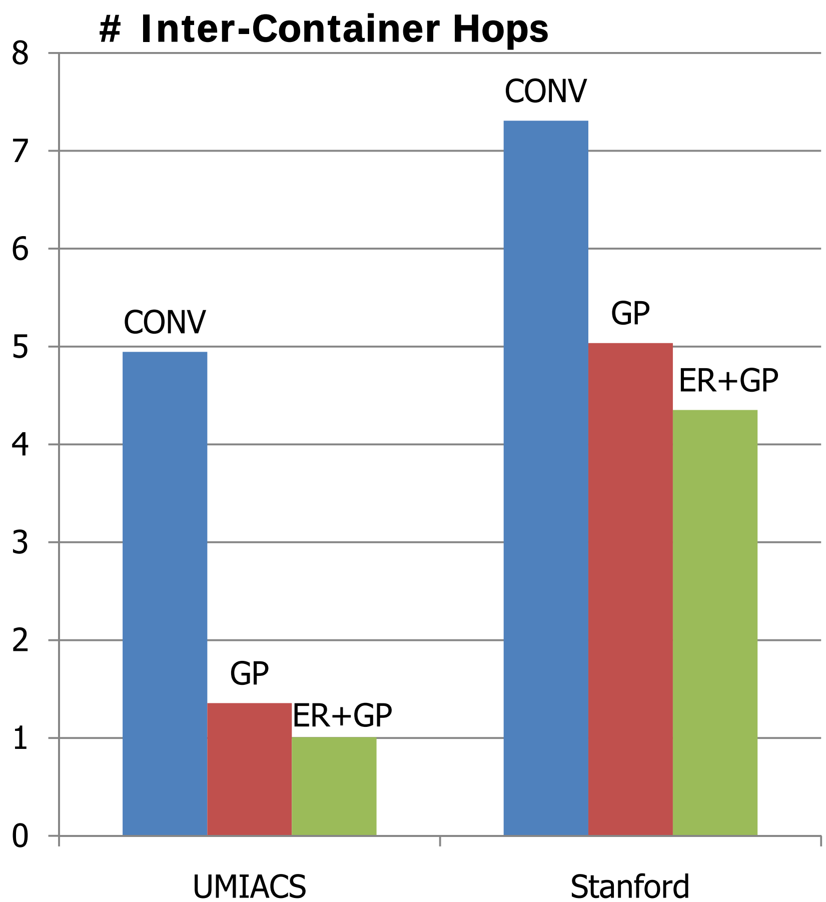


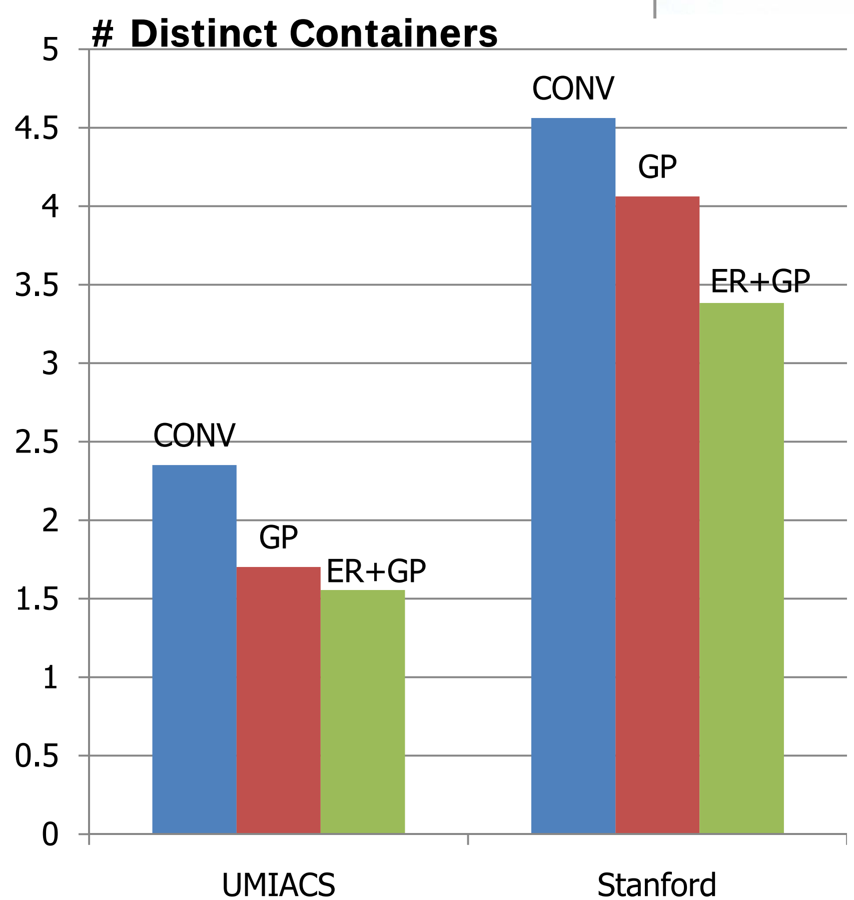
Simulation Results (Stanford)





Simulation Results





Conclusion

Conclusion

- We have shown that a graph partitioning scheme for organizing archive containers significantly reduces the number of containers that need to be accessed when a user browses through the archived web material.
- A graph analysis technique can improve this number even further.
- The overhead required by this technique is relatively small. On our 2 Ghz Intel Core 2 Duo processor, we could fully partition and compute EdgeRank of a large graph (the Stanford web graph that contains about 300,000 vertices, and 2.3 million edges) within minutes.
- Our simulation considers random access pattern on a single version of pages. However, the Web Graph model, and graph analysis technique can be extended to accommodate other access patterns on multiple versions.