Fast Browsing of Archived Web Contents

Sangchul Song and Josep JaJa

Institute for Advanced Computer Science Studies
Department of Electrical and Computer Engineering
University of Maryland, College Park, Maryland, USA
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Motivation and Goal
Web Graph

- Web as a weighted, directed graph.
  - Web page $\rightarrow$ Vertex
  - Hyperlink $\rightarrow$ Edge
  - Page size $\rightarrow$ 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, \ldots\}
MAX_SIZE

Procedure
1: \textbf{Enqueue}(Q, Seed URLs)
2: \texttt{i} \leftarrow 1
3: \texttt{visited[]} \leftarrow FALSE
4: \texttt{C}_i \leftarrow \text{new} \textbf{Container}()
5: \textbf{while} (Q is non-empty)
6: \texttt{u} \leftarrow \text{Dequeue}(Q)
7: \texttt{Fetch}(u);
8: \texttt{visited}[u] \leftarrow \text{TRUE}
9: \textbf{if} (\text{Size}(C_i) + \text{Size}(u) > \text{MAX}_\text{SIZE})
10: \texttt{i} = \texttt{i} + 1
11: \texttt{C}_i = \text{new} \textbf{Container}()
12: \texttt{C}_i = \texttt{C}_i \cup \texttt{u}
13: \textbf{for each} \texttt{v} \in \text{adjacent}[\texttt{u}]
14: \textbf{if} (\texttt{visited}[\texttt{u}] = \text{FALSE})
15: \textbf{Enqueue}(Q, \texttt{v})
Motivation

Popular Page (visited $i_{th}$ by BFS)

Unpopular Page (visited $j_{th}$ by BFS)

Circle Size $\approx$ 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 : {url₁, url₂, ... }
MAX_SIZE

Procedure
1:  G ← BuildWebGraph(Seed URLs)
2:  n ← GetNumberOfContainers(G, MAX_SIZE)
3:  G ← EdgeRank(G) /* Optional */
4:  {UL₁, UL₂, ..., ULₙ} ← PartitionGraph(G, n)
5:  for (1 ≤ i ≤ n)
6:      Cᵢ ← new Container()
7:      for (v ∈ ULₙ)
8:          fetch(v)
9:      Cᵢ = Cᵢ 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 \( \Rightarrow \) Solution: artificial out-links to all the other pages from dangling pages, w/ probability of \( 1/N \)
    • Cyclic paths \( \Rightarrow \) 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

<table>
<thead>
<tr>
<th>Datasets</th>
<th># Vertices</th>
<th># Edges</th>
<th>Total Vertex Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>UMIACS Web Graph</td>
<td>4579</td>
<td>9732</td>
<td>2.49GB</td>
</tr>
<tr>
<td>Stanford Web Graph</td>
<td>281903</td>
<td>2312497</td>
<td>215.82GB</td>
</tr>
</tbody>
</table>

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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

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

<table>
<thead>
<tr>
<th>Edge-Cut</th>
<th>Unweighted Edges</th>
<th>Weighted Edges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CONV</td>
<td>GP</td>
</tr>
<tr>
<td>UMIACS Web Graph</td>
<td>73.87</td>
<td>12.38</td>
</tr>
<tr>
<td>Stanford Web Graph</td>
<td>80.50</td>
<td>47.33</td>
</tr>
</tbody>
</table>
Simulation

- Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Random Walks</td>
<td>1000</td>
</tr>
<tr>
<td>Number of Hops in Each Walk</td>
<td>10</td>
</tr>
<tr>
<td>Probability of Going Back</td>
<td>30%</td>
</tr>
<tr>
<td>Out-degree of Starting Vertex</td>
<td>&gt; 5</td>
</tr>
<tr>
<td>Policy At Dangling Vertex</td>
<td>Go back</td>
</tr>
</tbody>
</table>
Simulation Results (UMIACS)

**Graph 1:**
- **Y-axis:** # Random Walks
- **X-axis:** # Inter-Container Hops
- Lines represent:
  - CONV
  - GP
  - ER+GP

**Graph 2:**
- **Y-axis:** # Random Walks
- **X-axis:** # Distinct Containers
- Lines represent:
  - CONV
  - GP
  - ER+GP
Simulation Results (Stanford)

Stanford

- CONV
- GP
- ER+GP

# Random Walks vs. # Inter-Container Hops

# Random Walks vs. # Distinct Containers

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Simulation Results

### # Inter-Container Hops

- **UMIACS**
  - CONV: ~5
  - GP: ~6
  - ER+GP: ~2

- **Stanford**
  - CONV: ~7
  - GP: ~5
  - ER+GP: ~5

### # Distinct Containers

- **UMIACS**
  - CONV: ~4
  - GP: ~4
  - ER+GP: ~1

- **Stanford**
  - CONV: ~5
  - GP: ~5
  - ER+GP: ~1.5

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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.