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Improved Subgraph Estimation PageRank Algorithm for Web Page Rank

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ABSTRACT

The growth of Big Data has seen the increasing prevalence of interconnected graph datasets that reflect the variety and complexity of emerging data sources. Recent distributed graph processing platforms offer vertex-centric and sub graph centric abstractions to compose and execute graph analytics on commodity clusters and Clouds. Naıve translation of existing graph algorithms to these programming models can offer sub-optimal performance. We analyze the effectiveness of PageRank, a popular graph centrality measure, for a sub graph centric programming model, and propose variations based on the existing Block Rank algorithm to improve the performance. We evaluate these algorithms on real-world graphs using the PageRank on the subgraph, ranking vector, search engines, and is faster by 23 − 74% for most graphs we evaluated, while achieving an equivalent PageRank quality.

Keywords: PageRank on the sub graph, ranking vector, search engines.

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I. INTRODUCTION

At the same time, the introduction of these novel graph programming abstractions means that existing shared memory or parallel graph algorithms may not be a direct fit on these platforms. And a naıve translation of existing algorithms to these new abstractions may offer sub-optimal performance. It is well known that algorithmic innovations at design-time, that effectively use the underlying abstractions, can significantly improve the application performance compared to relying exclusively on runtime optimizations provided by the platform. As a result, there is a need to examine where existing algorithms fit directly, need to be adapted or new algorithms are required, to make the best use of such platforms. Graph centrality measures are a key analytic that is used in real-world networks, from understanding critical junctions in power grids to the spread of ideas (or diseases) in social (or human) networks. PageRank proposed by Google for web graphs is a special case of Eigenvalue Centrality, and is often used as a canonical algorithm for evaluating graph platforms. As graph structures and sizes have evolved over the past decade, research into PageRank has contributed more scalable algorithms that handle heterogeneous and distributed topologies. This paper continues in that spirit. There has been extensive work on improving the PageRank algorithm to fit different platforms, including MapReduce. As a result, it is useful to understand how 39 effectively the PageRank for a graph can be computed using such novel distributed graph processing frameworks – where existing PageRank algorithms work, and when new ones need to be developed.

II. LITERATURE SURVEY

In recent years, peer-to-peer (P2P) networks have received great attention. The advent of P2P techniques further boosts web information retrieval by leveraging distributed computing power, storage, and connectivity. In such architecture, the data and functionality are distributed through all the peers. Each peer is autonomous and can index its own fragment of the Web, so it is possible that the web fragments on different peers overlap with each other.

If the ranking is computed on each individual peer, it may lead to inconsistent and inaccurate scores for pages, as local web graphs are incomplete and overlap. The similar situation is presented in meta-searcher as well. A study shows that search engines are more different than people expected [1]. For 500 most popular search terms, Google and Yahoo! shared only 3.8 of their top 10 results on average. Part of the reasons behind this inconsistency is that the search engines fetch the web pages following different crawling algorithms.

According to a recent study [2],the major search engines including Google, Yahoo!, MSN, Ask/Teoma fetch different portions of the whole index able web. The percentage of the indexable web fetched by each search engine and their overlaps. It stands to reason that a meta-searcher helps to better aggregate relevant results, which may require ranking computation on multiple subgraphs.

To overcome the computation cost involved in centralized PageRank algorithm on large graph, there is past research on PageRank in distributed environment. Different algorithms have been designed to utilize the block structure of the Web [3]. In these papers, the entire web is considered to be cleanly partitioned into disjoint websites and domains. The strategy is usually first to compute the local ranking for each graph, only considering intra-site links, then to compute the site rankings considering inter-site links, and finally aggregate the local scores with rankings of web sites. [3] presents a ranking algebra to deal with ranking at different granularity levels.

In [8], a random walk used to determine the importance of web sites is defined by inter-site links, as well as the local PageRank scores for individual pages. Defines the random walk for web sites differently, while employing the same information. Then the local ranking scores are used as the start vector for true PageRank. [6] proposes a slightly improved algorithm to compute local PageRank. For each web site, an artificial page is added to represent all out-of-domain pages.

The stochastic transition matrix entries are defined by the sum of local PageRank values of all source pages from starting site. While these techniques examined ways to efficiently estimate PageRank scores, they are not applicable to arbitrarily overlapped web fragments, nor a subgraph. There also has been some work on a subgraph. That research estimates local PageRank values[10] by expanding a small subgraph surrounding the node of interest. The estimation is made based on this subgraph, usually for a few dozen to a few hundred nodes.

Alternatively, we target for an estimation of PageRank for a subgraph with possibly large sized graphs in this paper.

III. PROPOSED SYSTEM

We outlined the applications of subgraph based PageRank and overlap presented PageRank computation, which has not received much attention. We proposed an algorithm Subgraph Rank for this problem, that we expect to be considerably efficient than previous work as it only needs to be executed once on local peer. By assigning weights to the eternal node enriched graph and follows with a random walk, the Subgraph Rank converges to a unique stationary distribution. We discussed the possible improvement and customization of the algorithm.

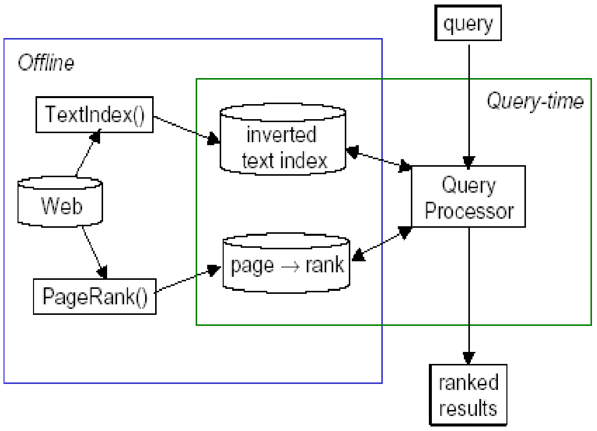

Fig 1. System architecture

The above diagram shows how we increase the scalability and optimized the searching of data according to the user convience. As the user enter our application the registration page is displayed and the user is asked to register, once th e user is registred he is automatically redirected to the login page where user login and Enters the application, the user data in the database is stored in the ecrypted Format to provide the security within the DB.

As the user enters our application the Search engine bar is displayed along with the number of links the user wants to select, as the user searches some data with minimum number of links, the data is given by fetching all the links about the related topic and matching the similarity of the data using similarity algorithm and hence increasing the easines for the user to find the exact data in one or two links to avoid time barrier increasing the User experience.

The server data is encrypted and is transmitted to Db and front end within secure Network Increasing the Data security and analyzing the Data mining.

IV. CONCLUSION

In this paper we outlined the applications of subgraph based PageRank and overlap presented PageRank computation, which has not received much attention. We proposed an algorithm SubgraphRank for this problem, that we expect to be considerably efficient than previous work as it only needs to be executed once on local peer. By assigning weights to the eternal node enriched graph and follows with a random walk, the SubgraphRank converges to a unique stationary distribution. We discussed the possible improvement and customization of the algorithm. The experiments evaluation are left as future work.

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