Correlation of Expert and Search Engine Rankings

Michael L. Nelson
Department of Computer Science
Old Dominion University
Norfolk, VA, 23529
mln@cs.odu.edu

Martin Klein
Department of Computer Science
Old Dominion University
Norfolk, VA, 23529
mklein@cs.odu.edu

Manoranjan Magudamudi
Department of Computer Science
Old Dominion University
Norfolk, VA, 23529
maguds@gmail.com

ABSTRACT

In previous research it has been shown that link-based web page metrics can be used to predict experts' assessment of quality. We are interested in a related question: do expert rankings of real-world entities correlate with search engine rankings of corresponding web resources? For example, each year US News & World Report publishes a list of (among others) top 50 graduate business schools. Does their expert ranking correlate with the search engine ranking of the URLs of those business schools? To answer this question we conducted 9 experiments using 8 expert rankings on a range of topics including business schools, professional tennis players and cities in the United States. In 57 search engine vs. expert comparisons, only 1 strong and 4 moderate correlations were statistically significant. In 42 inter-search engine comparisons, only 2 strong and 4 moderate correlations were statistically significant. The correlations appeared to decrease with the size of the lists: the 3 strong correlations were for lists of 10, the 8 moderate correlations were for lists of 25, and no correlations were found for lists of 50.

1. INTRODUCTION

As a society, we enjoy lists, presumably compiled by "experts", that rank items, events, people, places, etc. At best, these lists are informative and help convey notions of quality in a compact manner. At worst, these lists can be misleading, biased, or overly simplified. Regardless, lists proclaiming the top 10, 25 or 50 of various resources are a persistent part of our culture.

At the same time, search engines now play a central role in society. The "big 3" search engines (SEs) - Google, Live (formerly MSN), and Yahoo - are the primary tool for discovering web resources for many people. Acquiring a high ranking in SEs is so important that an entire discipline and economy of search engine optimizers (SEO) has developed to help people raise the ranking of their web pages. Thus SEs move from a simple navigation and discovery aid to powerful cultural force. In some sense, if a web page does not appear in the first few pages of a SE's results for a particular query, it is as if it does not exist at all.

We found fewer correlations than we expected, and we also discovered that the correlations decreased as the size of the list increased.

The result is that although highly ranked pages are likely to be quality pages (cf. [1]), we cannot be sure that quality real-world resources (e.g., athletes, movies, universities) have highly ranked web pages. This has implications for digital libraries and other systems that build collections by using only search engine APIs [11] or use the APIs to augment focused crawling techniques [17, 23, 9]. Our findings also suggest there is future work in determining what are the additional factors of quality that are missed by conventional hyperlink derived metrics such as PageRank [5] and its many variations.

2. RELATED WORK

Although we are unaware of previous work that measures the correlation of expert rankings of "real-world" objects with their corresponding web resources, the quality of web search results has been the subject of many previous studies.

2.1 Quality and Authority in the Web

"Does 'Authority' mean 'Quality?'" is the question Amento et al. [1] asked when they evaluated the potential of link- and content-based algorithms to identify high quality web pages. Human experts rated web documents from the Yahoo directory related to five popular topics by their quality. Amento et al. found a high correlation between the rankings of the human experts leading to the conclusion that there is a common notion of quality. By computing link-based metrics as well as analyzing the link neighborhood of the web pages from their dataset, they were able to evaluate the performance of machine ranking methods. Here too they found a high correlation between in-degree, Kleinberg’s authority score [10] and PageRank. They isolated the documents that the human experts rated with good quality and evaluated the performance of algorithms on that list in terms of pre-
cision at 5 and at 10. In-degree e.g., has a precision at 5 of 0.76 which means on average almost 4 of the first 5 documents it returns would be rated good by the experts. In general they find that in-degree, authority score and PageRank are all highly correlated with rankings provided by experts. Thus, web document quality can be estimated with hyperlink based metrics.

Upstill, Craswell and Hawking [22] studied the PageRank and indegree of URLs for Fortune 500 and Fortune Most Admired companies. They found companies on those lists averaged 1 point more PageRank (via the Google toolbar’s self-reported 0-10 scale) than companies on the list. They also found that IT companies typically had higher PageRank than non-IT companies. Similar to [1], they found indegree highly correlated with PageRank.

Bharat and Mihaila [4] propose a ranking scheme based on authority where the most authoritative pages get the highest ranking. Their algorithm is based on a special set of “expert documents” which are defined as web pages about a certain topic with many links to non-affiliated web pages on that topic. Non-affiliated pages are pages from different domains and with sufficiently different IP address. These expert documents are not chosen manually but automatically picked as long as they meet certain requirements (sufficient out-degree, etc.). In response to a user query the most relevant expert documents are isolated. The proposed scheme locates relevant links within the expert documents and follows them to identify target pages. These pages are finally ranked according to the number and relevance of expert documents pointing to them and presented to the end user. Bharat and Mihaila evaluated their algorithm against three commercial search engines and found that it performs either just as good or in some cases even better than the top search engine when it comes to locating the home page of a specific topic. The same is true for discovering relevant pages to topic (where many good pages exist).

Rieh [18] conducted a study on user’s judgment of information quality and cognitive authority in the web by observing the user’s searching behavior. The idea was to understand the factors that influence user’s judgment of quality and authority in the web. In her work information quality on an operational level is defined as “the extend to which users think that the information is useful, good, current and accurate”. Cognitive authority is “the extend to which users think that they can trust the information”. Rieh found that users do predictive judgment (before opening the page) and evaluative judgment (after opening the page) when it comes to the choice what page and item on a page to look at. If the evaluative judgment does not correlate with the expectations made in the predictive judgment the user usually starts a new page or goes back to a previous one. If the two judgments match however the user stays on the page and uses its information. She also found in her experiments that users identify the facets characterizing cognitive authority in the web as: trustworthiness, reliability, scholarliness, credibility, officialness and authoritativeness. However for the subjects she conducted the study with authority was more important for some search tasks than for others. Looking for medicine e.g., authority was a major concern but did not affect the subjects much for the travel research task.

Rieh and Belkin [19] conducted a similar study about people’s decision making in respect to information quality and cognitive authority in the WWW. This study confirms the intuition that users of the web assess information quality based on source credibility and authority. Authority can be seen on a institutional level e.g., academic or governmental institutions and on a personal level e.g., professional experts. Another interesting finding of this work is that users believe that the web is less authoritative and also less credible than other, more conventional information systems.

2.2 Quality as a Factor in Web Page Ranking

Cho et al. [7] observe a “rich-get-richer” phenomenon where popular pages tend to get even more popular since search engines repeatedly return popular pages first. As other studies by Cho [6, 16] and Baeza-Yates [2] have shown, PageRank is significantly biased against new (and thus unpopular) pages which makes it problematic for these pages to draw the user’s attention even if they are potentially of high quality. That means the popularity of a page can be much lower than its actual quality. Cho et al. propose page quality as an alternative ranking method. By defining quality of a web page as the probability that a user likes the page when seeing it for the first time the authors claim to be able to alleviate the drawbacks of PageRank. With the intuition from PageRank that a user that likes the page will link to it the algorithm is able to identify new and high quality pages much faster than PageRank and thus shorten the time it takes for them to get noticed.

2.3 Quality of Web Documents

Lim et al. [12] introduce two models to measure the quality of articles from an online community like Wikipedia without interpreting their content. In the basic model quality is derived from the authority of the contributors of the article and the contributions from each of them (in number of words). The peer review model extends the basic model by a review aspect of the article content. It gives higher quality to words that “survive” reviews.

An approach to automatically predict information quality is given by Tang et al. [21]. Analyzing news documents they observe an association between users quality score and the occurrence and prevalence of certain textual features like readability and grammar.

3. EXPERIMENT DESIGN

The following sections details how the expert lists that were chosen, explains how we chose URLs to correspond with the entries in the expert lists, and discusses the searching and ranking algorithms and other operational details.

3.1 Choosing Expert Lists

We chose a variety of topics (2 academic, 2 financial, 2 athletic and 2 popular culture) as well as choose expert rankings that are well-known. The accuracy, criteria or bias of these rankings may be critiqued, but that is not the purpose of this investigation. We simply accept the rankings as given from the experts. They include (please note that the URLs are likely to change over time):

1. ARWU – The top 50 North & Latin American Universities as determined by the 2007 Academic Ranking of World Universities

http://www.arwu.org/rank/2007/ARWU2007_TopAmer.htm
2. **ATP** – The top 50 male tennis players (as of 2008-01-28) as ranked by the Association of Tennis Professionals ².

3. **Billboard** – The top 50 popular music songs as determined by Billboard Magazine (as of 2008-01-28) ³. This list is determined by a combination of sales and radio airplay. This list contained duplicates (artists with more than 1 song simultaneously on the chart). Since only the top 50 can be accessed without registration, this ranking produced lists of n=\{9,21,42\} when duplicates were removed.

4. **Fortune** – The 2007 top 50 American public corporations as measured by gross revenue. This list is published annually by Fortune Magazine ⁴.

5. **IMDB** – The top 250 movies as voted on by users of the Internet Movie Database (www.imdb.com)⁵. We used only the top 50 of 250 movies. We split this ranking into two lists: one that used only imdb.com URLs, and the other that used only en.wikipedia.org URLs for the same movie. For example, the URL for the 1990 movie “Goodfellas” was http://www.imdb.com/title/tt0099685/ in the first list and http://en.wikipedia.org/wiki/Goodfellas in the second list.

6. **Money** – The 2007 top 50 “best places to live” in the United States as determined by Money Magazine ⁶. The 2007 list was a departure from previous lists in that it only featured very small cities and towns (e.g., Milton, Massachusetts (population 27,500) instead of Boston, Massachusetts).

7. **US News** – The 2007 top 50 graduate business school programs as ranked by US News & World Report ⁷.

8. **WTA** – The top 50 female tennis players as ranked by the Women’s Tennis Association (as of 2008-01-29)⁸.

### 3.2 Mapping Resources to URLs

After the expert lists have been chosen, we began the process of mapping their real-world objects to single URLs. For some lists (ARWU, Fortune, US News) this was easily done because each real-world object has a canonical URL. For the IMDB lists, the URLs are not quite canonical, but they do come from two extremely well-known web sites: imdb.com and wikipedia.org. For the other lists (ATP, Billboard, Money, WTA), judgment calls were needed to determine the best URL.

The ARWU list was the easiest of all: each university had a unique URL that we could agree was the canonical URL for the university (e.g., www.harvard.edu for Harvard University). While there are many URLs available on the web that discuss Harvard University, it is our intuition that www.harvard.edu is the correct choice for representing all aspects of the university (as opposed to individual departments or the basketball team). Similarly, it was straightforward picking canonical URLs for the Fortune 500 companies, although when faced with multiple URLs, we chose the most general or public URL (e.g., www.aig.com over www.aigcorporate.com). The business schools generally had nicely structured URLs (e.g., mba.tamu.edu), but several had paths in their URLs that prove to be a limitation in some SEs (e.g., Yahoo’s site operator does not distinguish www.nd.edu/~mba from www.nd.edu see section 3.3.1 below). The IMDB URLs were directly taken from the IMDB web page. We used Google to locate their Wikipedia links to generate the second IMDB list.

For the ATP and WTA lists, it was less direct. Although many URLs were easy to discern (e.g., www.rogerfederer.com), we could not locate suitable home pages for 24 of the ATP members and 19 of the WTA members. In those situations we used a Wikipedia page (e.g., en.wikipedia.org/wiki/Alona_Bondarenko). This is because there are no large English-language fan bases.

For Money Magazine’s Best Places to Live list, we always chose the “official” government URL over commercial, real-estate or tourism related pages. This proved difficult in the case of Olney, Maryland (rank #17). Olney is an unincorporated area and a “census-designated place” in the larger region of Montgomery County, Maryland. We could not find an obvious government web page for Olney, and did not want to use a commercial page (ww.olsonmd.com). We ended up using the web page for Montgomery County, Maryland (ww.montgomerycountymd.gov), although a strong case can be made for former commercial page as well.

Mapping Billboard popular songs to URLs was the most problematic. Instead of trying to pick a URL to correspond to a song, we chose the home page of the artist that released the song. As noted above, several artists have more than one song on the Billboard list at one time, resulting in less than 50 URLs (acquiring data for the songs ranked 51-100 required registration). Furthermore, 9 of the songs were credited to more than one artist. For example, the number one song at the time of writing is “Flow” and is listed as “Flo Rida Featuring T-Pain”. In these cases, we chose the home page for the artist listed first (i.e., Flo Rida) and not the featured artist (i.e., T-Pain). The popular music artists also presented problems similar to the Olney, MD example described above. We used only “official” pages that appeared to be maintained by the artists themselves. We did not use unofficial “fan” pages, although we know fan pages are often of high quality. Even more challenging was that many artists had multiple candidate URLs: their official page, and their official myspace.com page. In all but one cases we chose the official page over the artists’ myspace.com pages; the group “Playaz Circle” (song #49 on the Billboard list) appeared to only have a myspace.com page.

---

²http://www.atptennis.com/3/en/rankings/entrysystem/default.asp
³http://www.billboard.com/bbcrom/charts/chart_display.jsp?g= Singles&f=The+Billboard+Hot+100
⁴http://money.cnn.com/galleries/2007/fortune/0704/gallery.500top50.fortune/
⁵http://www.imdb.com/chart/top
⁶http://money.cnn.com/galleries/2007/moneymag/0707/gallery.BFPT_top100.moneymag/
⁷http://www.usnews.com/usnews/edu/grad/rankings/mba/brief/smarrank_brief.php
⁸http://www.sonyericssonwttour.com/2/rankings/singles_numeric.asp
3.3 Creating an Ordinal Ranking of URLs from SE Queries

We developed a Perl program that takes a list of URLs and queries search engines to determine their relative ordering of those URLs. We do not determine a search engine’s absolute ranking for any particular URL. That is, we do not compute:

\[
\begin{align*}
\text{rank}(URL_A) &= 0.92 \\
\text{rank}(URL_B) &= 0.73 \\
\text{rank}(URL_C) &= 0.42 \\
&\vdots
\end{align*}
\]

We also are not interested in estimating the PageRank (or related metrics), independent of SEs, through link neighborhoods or other means: the SEs are the subject of our study, not the web graph itself. Instead, using a variation of strand sort (illustrated in section 3.3.2), we simply determine that a search engine ranks the URLs in order:

\[
\text{rank}(URL_A) \geq \text{rank}(URL_B) \geq \text{rank}(URL_C) \geq \ldots
\]

Note that the ranks of both the experts and search engines are ordinal variables, so generally:

\[
\text{distance}(URL_A, URL_B) \neq \text{distance}(URL_B, URL_C).
\]

We ran the program several times, but the results we report are from the machine tango.cs.odu.edu (IP 128.82.4.75) on February 8, 2008. The program queried the APIs of Google, Live and Yahoo. Although it has been shown that search engine APIs return different results than the public (human) interfaces [13] and possibly use a smaller index, we chose to use the APIs instead of “page-scraping” the results to avoid being denied access by the search engines.

Although the SE APIs can be queried for backlinks or ranking metrics, previous research has shown that these values are not always accurate, perhaps intentionally so to prevent reverse engineering of SE ranking algorithms [13]. Note that it is not our goal to compute the interval value of a particular URL in a given SE, but rather just to produce an ordinal ranking of URLs for a SE. We treat the SEs as a black box ranking system and do not try to reverse engineer its hyperlink-based methods.

With the exception of the rankings of international professional tennis players, all the expert lists and the SE APIs queried are biased toward the English language and lists of interest to the United States. We made no attempt to query non-English language SEs.

Ideally, we could submit all 50 URLs to a SE in a single query and record the resulting ordering. However, each SE has query length limitations for both characters and terms (discussed below) and queries that exceed these limitations are silently truncated. We must issue a series of overlapping queries to create an ordinal ranking of URLs relative to a specific SE. To this end, we used a variation of strand sort\(^9\). Strand sort is a sorting algorithm that uses multiple intermediate data structures to temporarily store a sorted subset of the data. These structures are eventually gathered together to sort the entire list of data. This behavior makes it part of the family of distribution algorithms.

\(^9\)http://en.wikipedia.org/wiki/Strand_sort

3.3.1 Querying Search Engine APIs

In order to determine the SE ranking of the URLs we must form unbiased queries. We do that by using the site: query modifier which is supported by all three search engines. It works as a filter by restricting the results to websites in the given domain only. We query for several URLs simultaneously (specified by q) and thus combine the URLs and the site: modifier with the boolean OR operator (also supported by all three search engines). This boolean operator returns results that match either side of the query string divided by the OR. Since our queries consist of URLs only, each with the same modifier and combined with the boolean operator and no keywords added, all search results have theoretically an equal opportunity to be returned as the top result and “only” the search engine’s ranking is dictating the ranking of the URLs now. We verified these searches were commutative: the order of the URLs in the queries did not change the final rankings. As an example, the query for Google and Live for the first five business schools in the US News ranking would be:

```
site:http://www.hbs.edu/ OR
site:http://www.gsb.stanford.edu/ OR
site:http://mba.wharton.upenn.edu/ OR
site:http://mitsloan.mit.edu/mba OR
site:http://www.kellogg.northwestern.edu/
```

There are restrictions to using the search engine’s APIs. Google allows only 1000 queries per day and the query length must not exceed 2048 bytes and 10 words. Yahoo searches were done slightly differently because their site: modifier requires a different syntax. It does not allow URI schemes like http in the query when using the modifier. It also allows only domain names without a specific path following the top level domain or country code e.g. site:mitsloan.mit.edu/ is legitimate but site:mitsloan.mit.edu/mba is not. Thus the Yahoo form of the above query is:

```
site:www.hbs.edu/ OR site:www.gsb.stanford.edu/ OR site:mba.wharton.upenn.edu/ OR site:mitsloan.mit.edu/ OR site:www.kellogg.northwestern.edu/
```

Besides the syntax Yahoo also limits the queries to 5000 per day. Due to Yahoo’s site: modifier syntax we can not include Wikipedia URLs in our comparison with the Yahoo search engine because all Wikipedia URLs follow the pattern http://en.wikipedia.org/wiki/certain_object where the path of the URL would be dismissed and only the ranking of the English Wikipedia site is compared to all other URLs, resulting in erroneously high score for the URL.

3.3.2 An Example Ordinal Ranking of URLs

We illustrate creating an ordinal ranking of URLs with an example. Assume an unordered list \(UL\) with eight URLs \((G, E, B, A, C, H, F, D)\). The expected outcome in the sorted list \(SL\) will be ranked in lexicographical order and we chose \(g = 3\). The first three URLs \((G, E, B)\) are queried against the search engine and the result is sorted \((B, E, G)\). The overlap URL \((g^{th}\) element), let us call it \(OL\), is the URL \(G\) since it is the result with the lowest rank in this subset of URLs. The other two URLs \((B, E)\) are stored in \(SL\).

In the next iteration we pull the next \(q-1\) elements from \(UL\) and together with \(OL = G\) form a new query \((G, A, C)\) for the search engine. The result is \((A, C, G)\) indicating that \(A\) and \(C\) can be ranked anywhere higher than \(OL\) and
thus need to be merged with the elements in $SL$. First we take $A$ and query it together with $(B, E)$ and get the result $(A, B, E)$. Since $SL$ contains just these three elements we are assured we found the correct rank for $A$. We know that $C$ was ranked lower than $A$ and thus only need to query $C$ together with all elements from $SL$ ranked below $A$. Thus we query $(C, B, E)$ and receive the result $(B, C, E)$ which we can append to the top ranked result $A$. $SL$ now consists of $(A, B, C, E)$. $G$ remains the OL since it was still the lowest ranked element in the subset and will now (in the third iteration) be queried together with the next $q-1$ elements from $UL$. The query $(G, H, F)$ returns $(F, G, H)$ which means $H$ as the lowest ranked URLs will become the new OL and $F$ and $G$ need to be merged with all elements of $SL$. First we query $F$ together with the first $q-1$ elements from $SL$ and get the result $(A, B, F)$. This may not be the final position of $F$ yet since $SL$ contains more than three elements. All we know at this stage is that $F$ is ranked below $A$ and $B$. Thus we need to also query $(F, C, E)$ and will get $(C, E, F)$. Now all elements in $SL$ are checked against $F$ and it turns out $F$ is the last element and thus can be appended to $SL$ which now holds the ranking $(A, B, C, E, F)$.

As the second part of this third iteration we need to find the final position of $G$. We again know its ranked lower than $F$ and since $F$ is the last element of $SL$ we can simply append $G$ to $SL$ which now contains the sorted list $(A, B, C, E, F, G)$. The new OL is queried together with the remaining element of $UL$, $D$ and the query returns $(D, H)$. This result tells us we need to treat $D$ the same way like we did with $F$ in the third iteration. We query $(D, A, B)$ and get $(A, B, D)$ then we query $(D, C, E)$ and get the result $(C, D, E)$. Now we have determined the final position of $URL_D$ and can place it accordingly in $SL$. Since the OL is still $H$ and $UL$ is empty we are assured $H$ is the lowest ranked URL in the entire set and can simply append $H$ to $SL$. This is the final step of the algorithm and $SL$ now holds the sorted list containing all URLs $(A, B, C, D, E, F, G)$.

4. RESULTS

4.1 Correlations

Our null hypothesis ($H_0$) was that there is no correlation between any of the rankings (experts and SEs as well as inter-SE). Tables 1 through 9 show the Kendall’s $\tau$ and 2-side p-value for each test. Statistically significant ($p < 0.05$) moderate and strong correlations are bolded. We compare each search engine with the expert ranking as well as inter-search engine comparisons.

We omit nearly all of the scatter plots because there is not enough of a correlation for them to be useful. For example, although there is a moderate correlation between ARWU and Yahoo ($n=10$), looking at figure 1 it is difficult to discern this correlation; the Yahoo data appears very similar to the Live and Google data. Furthermore, when there is no correlation at all, like $n=50$ for the ARWU data, the scatter plot is just noise (figure 2).

We could only reject $H_0$ in 11 of 99 cases. In 57 search engine vs. expert comparisons, only 1 strong (table 9 Live/WTA $n=10$) and 4 moderate correlations (table 1 Yahoo/ARWU $n=10$ and $n=25$, table 7 Google/Money $n=10$, table 8 Google/US News $n=25$) were statistically significant. Interestingly, the Google/Money $n=10$ correlation was negative. In 42 inter-search engine comparisons, only 2 strong (table 1 Yahoo/Google

---

**Algorithm 1 Ranking Algorithm**

1. **procedure** `INIT(Q)`
2. let $Q$ be the list of all URLs to be sorted and let $q$ be the number of URLs compared at a time
3. `FinalRankedList` = `undefined()`
4. take top $q$ URLs from $Q$
5. issue the $q$ URLs to SEs and store ranked result set in `TmpRankedList`
6. move top $q-1$ URLs from `TmpRankedList` to `FinalRankedList`
7. `OverlapURL` = $q^{th}$ ranked URL from `TmpRankedList`
8. **while** $Q$ is not empty **do**
9. take next top $q-1$ URLs from $Q$
10. issue the $q-1$ URLs plus `OverlapURL` to SEs and store ranked result set in `TmpRankedList`
11. `TmpList` = URLs ranked higher than `OverlapURL` in `TmpRankedList`
12. if `TmpList` is empty **then**
13. move `OverlapURL` to `FinalRankedList`
14. add top $q-1$ URLs of `TmpRankedList` to `FinalRankedList`
15. **else**
16. `FinalRankedList` = `Compare(TmpList, FinalRankedList)`
17. **end if**
18. append `TmpRankedList` to `FinalRankedList`
19. `OverlapURL` = $i^{th}$ ranked URL from `TmpRankedList`
20. **end while**
21. return `FinalRankedList`
22. **end procedure**
23. **procedure** `COMPARE(TmpList, FinalRankedList)`
24. `TmpFinalList` = `FinalRankedList`
25. `WorkList` = `undefined()`
26. for all URL i in `TmpList` **do**
27. take top $q-1$ URLs from `TmpFinalList`
28. issue the $q-1$ URLs plus the $i^{th}$ URL to SEs and store ranked result set in `TmpRankedList`
29. if i is the last element in `TmpRankedList` **then**
30. move the top $q-1$ URLs from `TmpRankedList` to `WorkList`
31. **else**
32. move all URLs ranked higher than i in `TmpRankedList` to `WorkList`
33. move i to `WorkList`
34. unshift the other URLs back to `TmpFinalList` **for** comparing to the remaining URLs in `TmpList`
35. **break** **if** (for comparing to the remaining URLs in `TmpList`)
36. **end if**
37. **end while**
38. **end for**
39. push all elements from `TmpFinalList` to `WorkList`
40. `FinalRankedList` = `WorkList`
41. **return** `FinalRankedList`
42. **end procedure**
n=10, table 4 Live/Yahoo n=10) and 4 moderate correlations (table 1 Live/Google n=10, table 4 Live/Yahoo n=25, table 7 Live/Yahoo n=10 and n=25) were statistically significant.

The correlations appeared to decrease with the size of the lists: the 3 strong correlations were for lists of 10 and the 8 moderate correlations were for lists of 25. No correlations were found for lists of 50. This is interestingly in contrast with [14], which warns of $\tau$ increasing as the size of the lists grows.

### 4.2 SE Errors

Of the 9 tests, we were able to complete only 3 in all configurations: for 3 list (n) sizes, 3 expert-SE comparisons and 3 inter-SE comparisons. These were ARWU (table 1), Billboard (table 3), and Money (table 7).

Limitations of the Yahoo site operator (see section 3.3.1) limited Yahoo’s inclusion in ATP (table 2), both IMDB tests (tables 5 and 6), US News (table 8), and WTA (table 9). There was a transient error with Yahoo in the Fortune list for n=50 (table 4) that we were unable to resolve on the day of the tests (15 URLs came back as not indexed). This

### Table 1: SE and ARWU Ranking of North and Latin American Universities.

| Comparison            | n  | $\tau$ | p    |
|-----------------------|----|--------|------|
| Live/ARWU             | 10 | -0.0222| 1    |
|                       | 25 | 0.0066 | 0.9813|
|                       | 50 | -0.1167| 0.2349|
| Yahoo/ARWU            | 10 | 0.5111 | 0.0490|
|                       | 25 | 0.4666 | 0.0011|
|                       | 50 | 0.3436 | 0.0004|
| Google/ARWU           | 10 | 0.1555 | 0.5915|
|                       | 25 | 0.0733 | 0.6288|
|                       | 50 | 0.0008 | 1     |
| Live/Yahoo            | 10 | 0.2000 | 0.4742|
|                       | 25 | 0.2599 | 0.0721|
|                       | 50 | 0.1183 | 0.2283|
| Live/Google           | 10 | 0.6444 | 0.0122|
|                       | 25 | 0.2666 | 0.0650|
|                       | 50 | 0.1151 | 0.2415|
| Yahoo/Google          | 10 | 0.5555 | 0.0318|
|                       | 25 | 0.2666 | 0.0650|
|                       | 50 | 0.1151 | 0.2415|

### Table 2: SE and ATP Ranking of Male Tennis Players.

| Comparison          | n  | $\tau$ | p    |
|---------------------|----|--------|------|
| Google/ATP          | 10 | 0.1111 | 0.7205|
|                     | 25 | 0.3933 | 0.0062|
|                     | 50 | -0.0987| 0.3154|
| Yahoo/Billboard     | 9  | -0.0555| 0.9169|
|                     | 21 | 0.0666 | 0.6946|
|                     | 42 | -0.1126| 0.2981|
| Google/Billboard    | 9  | -0.3333| 0.2514|
|                     | 21 | -0.1428| 0.3811|
|                     | 42 | -0.1010| 0.3513|
| Live/Yahoo          | 9  | -0.2222| 0.4655|
|                     | 21 | -0.1047| 0.5259|
|                     | 42 | 0.0894 | 0.4101|
| Live/Google         | 9  | 0.1666 | 0.6021|
|                     | 21 | 0.2761 | 0.0852|
|                     | 42 | 0.2497 | 0.0203|
| Yahoo/Google        | 9  | -0.2777| 0.3480|
|                     | 21 | -0.0857| 0.6077|
|                     | 42 | -0.0987| 0.36264|

### Table 3: SE and Billboard Ranking of Singles.

| Comparison          | n  | $\tau$ | p    |
|---------------------|----|--------|------|
| Live/Billboard      | 9  | 0.2777 | 0.3480|
|                     | 21 | -0.0666| 0.6946|
|                     | 42 | -0.1045| 0.3347|
| Yahoo/Billboard     | 9  | -0.0555| 0.9169|
|                     | 21 | 0.0666 | 0.6946|
|                     | 42 | -0.1126| 0.2981|
| Google/Billboard    | 9  | -0.3333| 0.2514|
|                     | 21 | -0.1428| 0.3811|
|                     | 42 | -0.1010| 0.3513|
| Live/Yahoo          | 9  | -0.2222| 0.4655|
|                     | 21 | -0.1047| 0.5259|
|                     | 42 | 0.0894 | 0.4101|
| Live/Google         | 9  | 0.1666 | 0.6021|
|                     | 21 | 0.2761 | 0.0852|
|                     | 42 | 0.2497 | 0.0203|
| Yahoo/Google        | 9  | -0.2777| 0.3480|
|                     | 21 | -0.0857| 0.6077|
|                     | 42 | -0.0987| 0.36264|
| Comparison         | n  | $\tau$  | p     |
|--------------------|----|---------|-------|
| Live/Fortune       | 10 | -0.0222 | 1     |
|                    | 25 | 0.1933  | 0.1831|
|                    | 50 | -0.0612 | 0.5359|
| Yahoo/Fortune      | 10 | -0.2444 | 1.0712|
|                    | 25 | 0.2066  | 0.1542|
|                    | 50 | 0.0481  | 0.6275|
| Google/Fortune     | 10 | 0.7333  | 0.0042|
|                    | 25 | 0.5133  | 0.0003|
| Live/Yahoo         | 10 | 0.4222  | 0.1074|
|                    | 25 | 0.3866  | 0.0072|
|                    | 50 | 0.3877  | 0.0001|
| Yahoo/Google       | 10 | 0.3333  | 0.2104|
|                    | 25 | 0.4199  | 0.0035|

Table 4: SE and Fortune Magazine Ranking of Companies.

| Comparison         | n  | $\tau$  | p     |
|--------------------|----|---------|-------|
| Live/IMDB          | 10 | -0.2888 | 0.2831|
|                    | 25 | 0.1799  | 0.2157|
|                    | 50 | 0.2702  | 0.0057|
| Google/IMDB        | 10 | 0.3000  | 0.4742|
|                    | 25 | 0.0999  | 0.4982|
|                    | 50 | 0.0253  | 0.8018|
| Live/Google        | 10 | 0.2000  | 0.4742|
|                    | 25 | 0.1066  | 0.4690|
|                    | 50 | -0.0775 | 0.4316|

Table 5: SE and IMDB Ranking of Movies.

| Comparison         | n  | $\tau$  | p     |
|--------------------|----|---------|-------|
| Live/Money         | 10 | 0.0666  | 0.8380|
|                    | 25 | 0.1933  | 0.1831|
|                    | 50 | 0.0432  | 0.6635|
| Yahoo/Money        | 10 | 0.2444  | 0.3710|
|                    | 25 | 0.1866  | 0.1989|
|                    | 50 | 0.0726  | 0.4616|
| Google/Money       | 10 | -0.5111 | 0.4909|
|                    | 25 | -0.0866 | 0.5593|
|                    | 50 | -0.0987 | 0.3154|
| Live/Yahoo         | 10 | 0.5555  | 0.0318|
|                    | 25 | 0.5266  | 0.0002|
|                    | 50 | 0.3665  | 0.0001|
| Yahoo/Google       | 10 | 0.0666  | 0.8580|
|                    | 25 | -0.0390 | 0.7972|
|                    | 50 | -0.0008 | 1.0000|
| Live/Google        | 10 | -0.3777 | 0.1524|
|                    | 25 | -0.2733 | 0.0585|
|                    | 50 | -0.2097 | 0.0322|

Table 7: SE and Money Magazine Ranking of Places to Live.

| Comparison         | n  | $\tau$  | p     |
|--------------------|----|---------|-------|
| Live/US News       | 10 | -0.2888 | 0.2831|
|                    | 25 | 0.1510  | 0.1237|
| Google/US News     | 10 | 0.2444  | 0.3710|
|                    | 25 | 0.4199  | 0.0035|
|                    | 50 | 0.3142  | 0.0013|
| Live/Google        | 10 | 0.4666  | 0.0369|
|                    | 25 | 0.1533  | 0.2932|
|                    | 50 | 0.3240  | 0.0009|

Table 8: SE and US News Ranking of Business Schools.

| Comparison         | n  | $\tau$  | p     |
|--------------------|----|---------|-------|
| Google/WTA         | 10 | -0.1555 | 0.5915|
|                    | 25 | 0.0634  | 0.6741|
|                    | 50 | 0.1796  | 0.0669|
| Live/Google        | 10 | -0.1555 | 0.5915|

Table 9: SE and WTA Ranking of Female Tennis Players.
problem disappeared on later runs, but rather than report data for the Fortune list for a date other than February 8, 2008, we simply dropped the Fortune n=50 data. This kind of transient error in using SE APIs is consistent with the experiences reported in [13].

Live produced unexpected results for all Wikipedia URLs. We have no explanation for why this is so, but it did result in Live being excluded from ATP (table 2), IMDB-Wiki (table 6), and WTA n=25 and n=50 (table 9). Interestingly, WTA n=10 did include 1 Wikipedia URL (which is returned as not indexed), but Live still showed a strong correlation. There were too many Wikipedia URLs in n=25 and n=50 for the data to be meaningful. Although we queried the API, this behavior was seen in the human interface as well. For example, Live indexes en.wikipedia.org/wiki/Pulp Fiction. But a query for site:http://en.wikipedia.org/wiki/Pulp Fiction returned did not return results about the movie, but instead provided only the location of a local movie theater. Also, queries for site:http://en.wikipedia.org/wiki/The_Godfather would produce only a single hit, http://en.wikipedia.org/wiki/The_Godfather/Sandbox, an invalid URL.

For example, figure 3 shows that Live indexes en.wikipedia.org/wiki/Pulp Fiction. But a query for site:http://en.wikipedia.org/wiki/Pulp Fiction shows that Live does not return the hits shown in figure 3, but is trying to provide location of a local movie theater (figure 4). Figure 5 shows a clearly incorrect result when searching for site: http://en.wikipedia.org/wiki/The_Godfather.

5. DISCUSSION

We found fewer correlations than we anticipated. We expected to find more of both expert-SE correlations and inter-SE correlations. The latter is especially surprising; we are aware that crawling and ranking strategies differ among the SEs, but they all are observing the same web graph (or at least have the opportunity to observe the same web graph). Although it is well known that SE results have little overlap (e.g., [20, 3, 8]), we were not interested in, for example, the rank of ATP players for the query “tennis”. Instead, we are interested only in the ordinal ranking of ATP players in a given SE.

One possible reason that we did not observe more correlations is that the methodology for mapping real-world objects to URLs (section 3.2) is limited. For some lists, not every entry has a clear canonical URL, and when forced to make a choice, we may have chosen poorly (although there is no such problem with the ARWU, Fortune and US News lists). The mapping of Billboard popular songs to the home pages of their respective artists is the most tenuous. Perhaps popular music lists of artists or their albums would have performed better. However, we did like the immedi-

Figure 3: Live Correctly Indexes the URL

Figure 4: Live Returns Incorrect Results for with the site operator

Figure 5: A Different Type of Incorrect Result from Live with the site operator
acy of the Billboard list, and we know that some SEs will boost the ranking of certain pages for current events and “hot topics” (cf. Google Trends\(^\text{10}\)).

It is possible that we have rediscovered the timeless discrepancy of “experts” vs. “popularity”. The SE rankings are constantly evolving to stay ahead of the spammers, but we believe they all have some form of hyperlink-based popularity metric at their core (i.e., variations on PageRank). In anticipation of this, we did try to include expert rankings that are closely aligned with general notions of popularity. For example, Billboard is determined by sales and radio airplay. The IMDB list is determined by popular vote of IMDB users (cf. the American Film Institute (AFI) Top 100 movies\(^\text{11}\)). Some expert lists, such as the US News ranking of MBA programs, are so widely accepted and quoted (for better or worse), they have the power to shape popularity.

Similarly, it is possible that the criteria used to create the expert rankings are not a good match to the popularity-based hyperlink metrics. For example, the Fortune 500 list is ranked according to gross sales—an obvious, impartial metric. However, we would expect companies such as Microsoft (Fortune rank #49) and Target (Fortune rank #33) to have a higher SE rank than companies such as Valero Energy (Fortune rank #16) and Cardinal Health (Fortune rank #19) based on the web nature (Microsoft) and online shopping potential (Target) of their sites. The WTA and ATP rank their players based on the obvious, quantifiable metrics of wins and monetary earnings. However, players’ web pages most likely accrue links based on additional characteristics such as charisma, endorsements and native language.

On the other hand, it is possible that Money Magazine’s choice to feature only small towns and cities in the 2007 more directly influenced their page ranking by the SEs. Prior to their appearance in this expert list, these places probably had little reason to acquire links and probably acquired hyperlinks as a mainly as a result of appearing in the Money expert list. Even though neither Live nor Yahoo was correlated with the expert list, they were moderately correlated with each other (and just missed a moderate correlation at \(n=50\)). This suggests that the hyperlinks they observed in the web graph were similar and insufficient for their respective algorithms to arrive at different rankings. However, we are at a loss as to why Google had a moderate negative correlation with the Money expert list.

We also suspect that there might be an optimal age for real-world objects to drive the popularity of their corresponding web pages. For example, the IMDB expert rankings only 9 of the 50 movies were released since 2000, most are much older. The #1 ranked movie according to the IMDB experts is “The Godfather”, released in 1972. While this movie’s place in various expert lists is assured, it is not clear that its corresponding URLs (either IMDB or Wikipedia) are acquiring hyperlinks at the same rate as contemporary movies. This is similar to “obliteration by incorporation” in citation indexing theory: some concepts become so accepted and pervasive that they no longer require citations\(^\text{15}\). In the other direction, it is possible that fast moving expert rankings such as Billboard might have real-world objects that outstrip their web page counterpart’s ability to acquire hyperlinks. For example, the Live API claimed to not have indexed the official home page of the artist with the number one song according to Billboard, “Flo Rida” (although it does show up in the web user interface).

Finally, it is possible that the SE rankings of web pages are significantly influenced by web-only phenomena that have no correspondence to their real-world objects. This could include things such as page update rate, MIME type, robots.txt files, etc.

### 6. CONCLUSIONS AND FUTURE WORK

Inspired by the question of Amento et al. [1] “Does Authority mean Quality?”, we have asked “Does Quality mean Authority?” We tested 57 expert-SE rankings and 42 inter-SE rankings. Of those 99 tests, only 11 had statistically significant moderate or high correlations. No SE stands out as more correlated than the others: Yahoo was correlated with Live 4 times, Live with Google once and Google with Yahoo once. Live, Google and Yahoo correlated with the experts once, twice and twice respectively. Mapping from real-world objects to corresponding web pages is difficult and this may have contributed to the low number of correlations. However, we were surprised to not find more inter-SE correlation. Although we cannot say we disproved correlation between expert rankings of real-world objects and the search engine rankings of their corresponding web pages, we have shown there are numerous scenarios where we believe it is reasonable to expect a correlation (especially in lists (e.g., IMDB, Billboard) where quality is a function of popularity), but this correlation is absent. Although highly ranked pages are likely to be considered quality pages by experts, we cannot be sure that real-world resources (e.g., athletes, movies, universities) considered to be quality by experts will have highly ranked corresponding web pages. To answer our question, although authority means quality, quality does not necessarily mean authority.

We consider these results to be baseline for future research. There are obvious areas to improve and extend the methodology and tests presented here. First, more and different expert lists could be used. For a particular topic, differing experts could be used (e.g., API vs. IMDB), and more topics could be explored (sports teams in addition to individual athletes, contemporary movies, consumer product reviews, etc.). In particular, more research should be done in profiling the optimum age for a real-world object / web page pair. We expect that as age increases, the ranking of the real-world object will continue to climb or hold its value, while the ranking of the web pages will likely give ground to newer web pages. The English language / United States bias should be removed.

Our immediate next step in our research is to expand the limitation of a single URL per real-world object. While this is less of a limitation for universities and businesses, artists and athletes are likely to have multiple candidate URLs. We are working on a refinement to our program to query a SE for a real-world object (e.g., “Roger Federer”) and record the top \(k\) resulting URLs. These URLs would then be aggregated to more accurately calculate the rank of a real-world object in a SE. This is a problem for all hyperlink derived metrics: multiple candidate URLs can compete for a limited number of links on web pages, thereby reducing their importance or popularity metric.

\(^{10}\)http://www.google.com/trends/hottrends

\(^{11}\)http://connects.afi.com/site/PageServer?pagename=micro_1001anding
7. REFERENCES

[1] B. Amento, L. Terveen, and W. Hill. Does “Authority” Mean Quality? Predicting Expert Quality Ratings of Web Documents. In Proceedings of SIGIR ’00, pages 296–303, 2000.

[2] R. A. Baeza-Yates, F. Saint-Jean, and C. Castillo. Web Structure, Dynamics and Page Quality. In Proceedings of SPIRE’02, pages 117–130, 2002.

[3] K. Bharat and A. Broder. A technique for measuring the relative size and overlap of public Web search engines. Computer Networks and ISDN Systems, 30(1-7):379–388, 1998.

[4] K. Bharat and G. A. Mihaila. When Experts Agree: Using Non-Affiliated Experts to Rank Popular Topics. ACM Transactions on Information Systems, 20(1):47–58, 2002.

[5] S. Brin and L. Page. The anatomy of a large-scale hypertextual Web search engine. Computer Networks and ISDN Systems, 30(1-7):107–117, 1998.

[6] J. Cho and S. Roy. Impact of Search Engines on Page Popularity. In Proceedings of WWW’04, pages 20–29, 2004.

[7] J. Cho, S. Roy, and R. E. Adams. Page Quality: In Search of an Unbiased Web Ranking. In Proceedings of SIGMOD’05, pages 551–562, 2005.

[8] A. Gulli and A. Signorini. The indexable web is more than 11.5 billion pages. In WWW ’05, pages 902–903, May 2005.

[9] T. G. Habing, T. W. Cole, and W. H. Mischo. Developing a technical registry of OAI data providers. In ECDL ’04, pages 400–410, 2004.

[10] J. M. Kleinberg. Authoritative sources in a hyperlinked environment. Journal of the ACM, 46(5):604–632, 1999.

[11] R. Kraft and R. Stata. Finding buying guides with a web carnivore. In Proceedings of LA-WEB, pages 84–92, 2003.

[12] E.-P. Lim, B.-Q. Vuong, H. W. Lauw, and A. Sun. Measuring Qualities of Articles Contributed by Online Communities. In Proceedings of WI ’06, pages 81–87, 2006.

[13] F. McCown and M. L. Nelson. Agreeing to disagree: search engines and their public interfaces. In JCDL ’07, pages 309–318, 2007.

[14] M. Melucci. On Rank Correlation in Information Retrieval Evaluation. SIGIR Forum, 41(1):18–33, 2007.

[15] R. K. Merton. Social Theory and Social Structure. Free Press, New York, 1968.

[16] S. Pandey, S. Roy, C. Olston, J. Cho, and S. Chakrabarti. Shuffling a stacked deck: the case for partially randomized ranking of search engine results. In VLDB ’05, pages 781–792, 2005.

[17] G. Pant, K. Tsioutsiouliklis, J. Johnson, and C. L. Giles. Panorama: extending digital libraries with topical crawlers. In JCDL ’04, pages 142–150, 2004.

[18] S. Y. Rieh. Judgement of Information Quality and Cognitive Authority in the Web. Journal of the American Society for Information Science and Technology, 53(2):145–161, 2002.

[19] S. Y. Rieh and N. J. Belkin. Understanding Judgment of Information Quality and Cognitive Authority in the WWW. In American Society for Information Science and Technology Annual Meeting, pages 24–29, 1998.

[20] A. Spink, B. Jansen, C. Blakely, and S. Koshman. A study of results overlap and uniqueness among major Web search engines. Information Processing and Management, 42(5):1379–1391, 2006.

[21] R. Tang, K. B. Ng, T. Strzalkowski, and P. B. Kantor. Automatically Predicting Information Quality in News Documents. In Proceedings of NAACL ’03, pages 97–99, 2003.

[22] T. Upstill, N. Craswell, and D. Hawking. Predicting fame and fortune: Pagerank or indegree? In Proceedings of the Australasian Document Computing Symposium, ADCS2003, pages 31–40, Canberra, Australia, December 2003.

[23] Z. Zhuang, R. Wagle, and C. L. Giles. What’s there and what’s not?: focused crawling for missing documents in digital libraries. In JCDL ’05, pages 301–310, 2005.