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Are Links Still A Powerful Google-Ranking Factor?

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INTRODUCTION

In this paper, we share new data on links as a Google-ranking factor. We will demonstrate the continuing importance that links play in rankings. It’s well known that links were a major ranking factor in the early days of Google (e.g., http://infolab.stanford.edu/~backrub/google.html), but many speculate that their importance is declining (e.g., http://www.searchmetrics.com/wp-content/uploads/Ranking-Factors-2015-Whitepaper-US.pdf) . However, we show that discussion of a decline in the importance of links as a ranking factor is grossly exaggerated. Indeed, links remain extremely powerful.

In March, 2016, Google Dublin’s Andrey Lippatsev and Ammon Johns engaged in a discussion; part of that discussion was (underlining added by authors):

“Ammon Johns: We heard that RankBrain is the third-most-important signal contributing to results now. Would it be beneficial to us to know what the first two are?

Andrey Lippatsev: Yes. Absolutely. I can tell you what they are. It’s content and links going into your site.”

MOZ AND SEARCHMETRICS STUDIES

Both Moz (Moz.com, 2015) and Searchmetrics (Searchmetrics.com, 2015) have run groundbreaking studies on ranking factors, and each includes a look at links. They can be found at

https://moz.com/search-ranking-factors/correlations and *http://www.searchmetrics.com/knowledge-base/ranking-factors/*

Key basic correlation results are displayed in Figure 1:

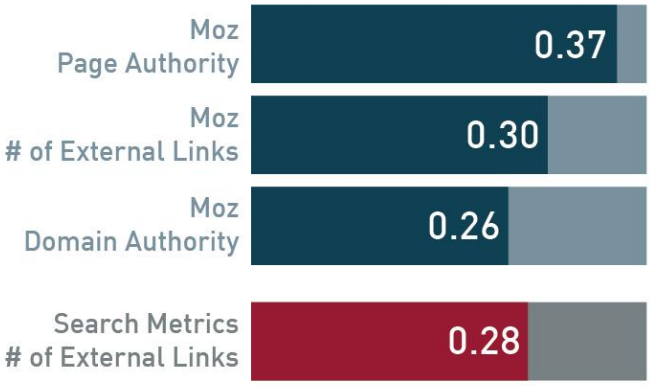

Figure 1: Correlations between higher rankings and the factor

Each of the bars in Figure 1 shows the correlation between that factor and (higher) rankings. In both the Moz and Searchmetrics studies, the correlation coefficient ("correlation") between ranking and the number of links was relatively high, but not especially higher than the correlation between higher rankings and the other factors they examined. That raises a question: If links are so important that a Googler would call them one of the two most important ranking factors, why aren't these correlations larger? The key to the Moz and Searchmetrics studies is understanding how the correlations were calculated. They considered each search-engine results-page (SERP) on an individual basis, and then took the mean of all the results (we'll call this the "Mean-of-the-Individual-Correlations" approach). Also, both of these studies focused solely on commercial search-terms.

We take a deeper look into the power of links, and took some new approaches to discern more about their impact. The bottom line is that the Mean-of-the-Individual-Correlations approach may not be providing a complete picture.

CURRENT STUDY

We performed a different type of calculation to determine the "average correlation." We based it on what might be called the "Quadratic Mean." This focuses on the square of the correlation (where the *Correlation Coefficient* is R, the quadratic mean uses R-squared values.) R-squared is named *The Coefficient of Determination*," although it seems that, most often, we hear it referred to simply as the "R-squared."

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It's actually the R-squared value that has a specific meaning in statistics. For example, if R is 0.8, then R squared is 0.64, and you can say that, based on the data, we estimate that about that 64% of the variability in Y (one of the two variables) is explained by variability in X (the other of the two variables), expressed in the linear relationship between Y and X. R-squared is "symmetric" (i.e., the same value) regardless of which variable is "labeled" the dependent variable and which is "labeled" the independent variable. What is key in our choice of focusing on the R-squared, is that *there is no meaningful sentence involving the magnitude of the correlation, R.* In other words, in our example of R = .8 and R-squared = .64, there is no meaningful sentence that begins, "[We estimate that] 80% of the..."

So, we determine the "average correlation" value by taking a *generalized sum* of the R-squared values, dividing by the number of values comprising the *generalized sum*, and then square-rooting the result. The *generalized sum* of n values is defined as taking the n values and computing a linear combination of the n values, where *each coefficient is either +1 or -1*, whichever is proscribed by the application. In our case of finding an "average correlation," our generalized sum is computed by putting a + (plus) sign in front of the R-squared value if $R > 0$, and a - (minus) sign in front of the R-squared value if $R < 0$. There are other applications that use the term: "generalized sum." For example, when adding/subtracting treatment combinations to find an effect in two-level factorial designs, it is common to refer to the "generalized sum of the 2^K treatment combinations" (e.g., Berger and Maurer, 2002); in that generalized-sum calculation, half of the signs are positive (+1) and half are negative (-1).

Figure 2 displays what this calculation process looks like (using the Spearman correlation in the example; the "Spearman" could also be the "Pearson."):

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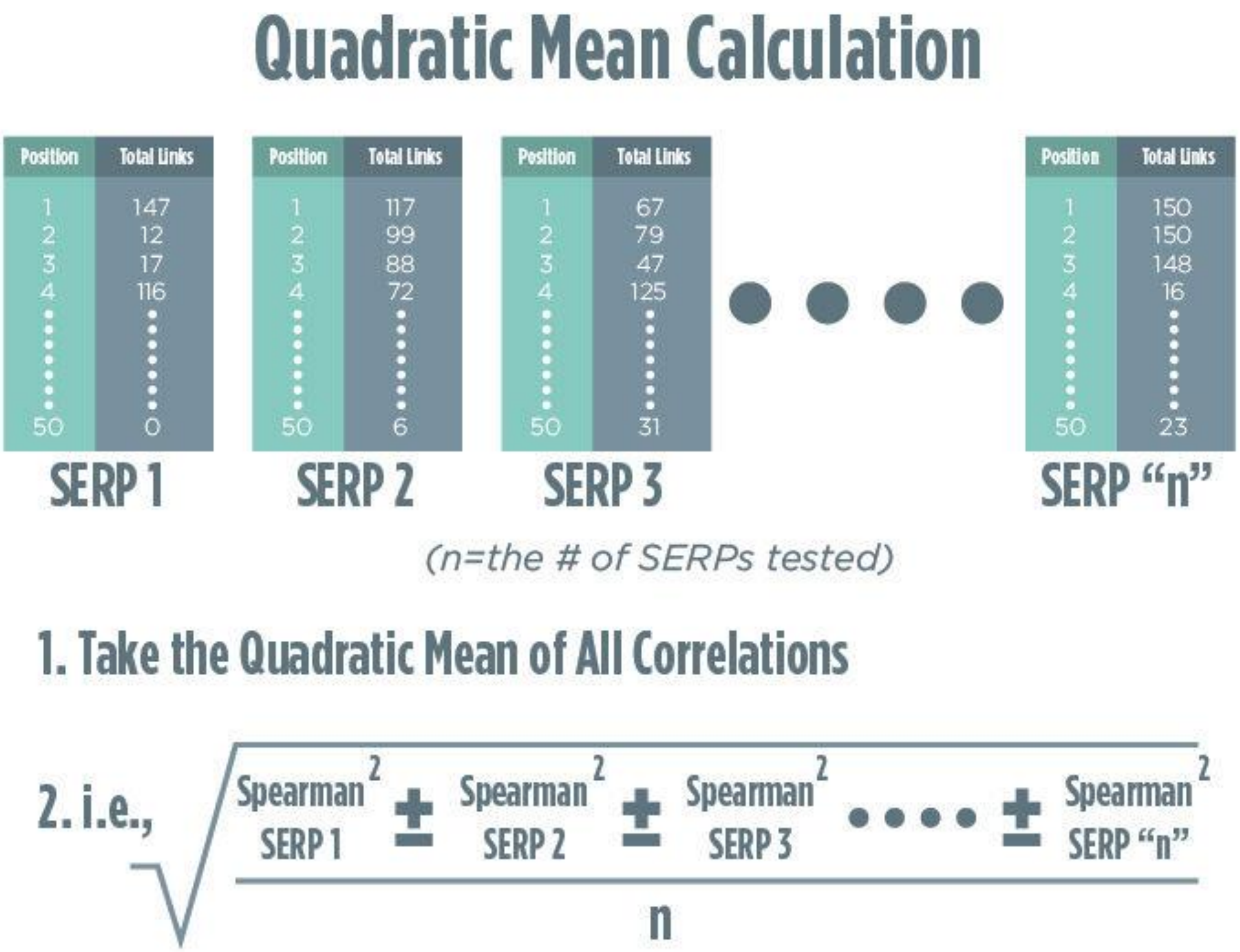

Figure 2: Illustration of our determination of the quadratic mean correlation

In addition to the different calculation approach exemplified in Figure 2, we also used a mix of different query types. We tested commercial head terms, commercial long tail terms, and also informational queries. Indeed, two-thirds of our queries were informational in nature. This may be one reason why we obtained somewhat different results from those of Moz and Searchmetrics, as displayed in Figure 3:

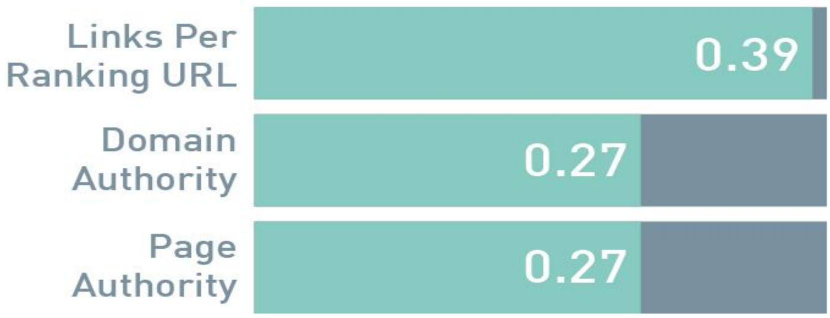

Figure 3: Correlation results in current study

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Our total links correlation value was higher than the Page Authority (PA) and Domain Authority (PA) values. Rand Fishkin of Moz commented on why that may be:

"We use a different, broader corpus of keywords to generate PA/DA algorithms, and thus, it makes sense that on different types of keyword queries, they'll have different levels of correlation. Very interesting to note that raw link counts tend to do better on these particular corpuses....."

Also of note is how high our link score correlation is, in comparison to Moz and Searchmetrics. The score shown above used a different methodology, but even when we use the exact same methodology as Moz and Searchmetrics (i.e., the *Mean-of-the-Individual-Correlations* approach), we still obtain a higher value. You can see the head-to-head comparison of all our link-score calculations using the *Mean of Individual Correlations* approach in Figure 4 (all of the StoneTemple Consulting data was obtained from the Moz API):

:

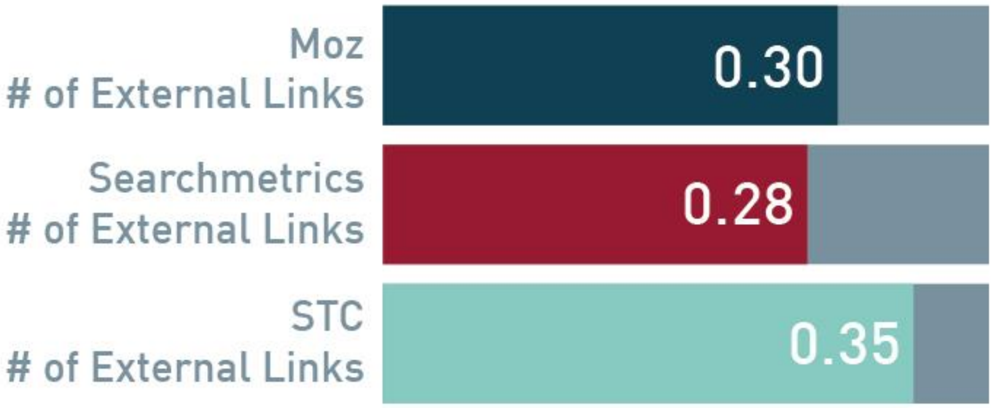

Figure 4: A direct comparison of the correlation between rank and # of external links, using the *Mean-of-the-Individual-Correlations* approach

OTHER APPROACHES

Given that we postulate that, in general/on average, there is a significant *positive* correlation, one would not expect that there would be a high number of large *negative* individual R values. Nevertheless, the *Mean of the Individual Correlations* and the *Quadratic Mean* approaches, while both valid, are very sensitive to even a small number of large *negative* individual R values; indeed, such occurrences can lower the resulting "mean correlation value" in a major way.

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For that reason, we decided to include some other approaches to our analysis. One of these was to measure the links in a more aggregated manner. To do this, we normalized the quantity of links. Then we took the total of all the search results by ranking position. The calculation equations for this approach are below in Figure 5:

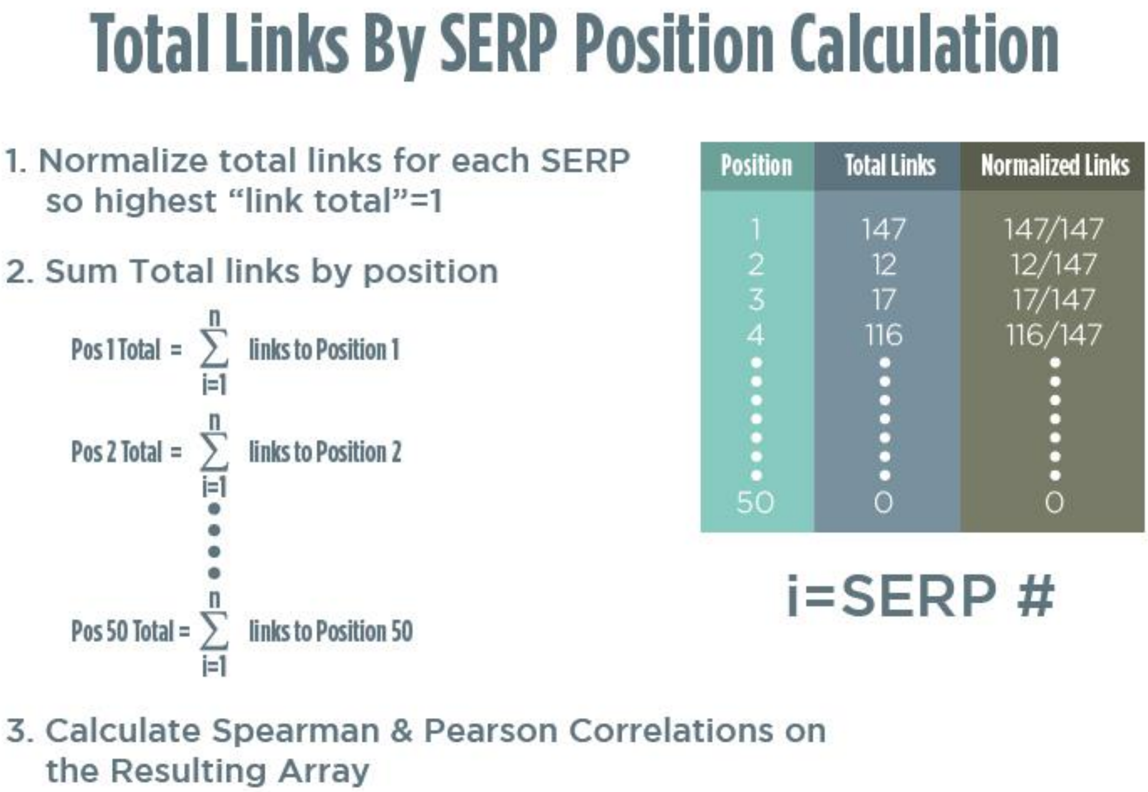

Figure 5: Another approach: total-links-by-SERP-position

The value of this approach is that it mitigates the impact of the negative correlations. When we determine the correlations in this manner, we find the results displayed in Figure 6:

Figure 6: Resulting correlations when using the total-links-by-SERP-position approach

We also considered another approach. We continued to use the normalized values of the links, but grouped them in ranking-groups of 10. That is, we summed the normalized-link totals for the top 10, then did the same for ranking positions 11 to 20, next 21 to 30, and so forth, resulting in 5 "data points." We then calculated the correlations (Pearson and Spearman), Those calculations are noted in Figure 7:

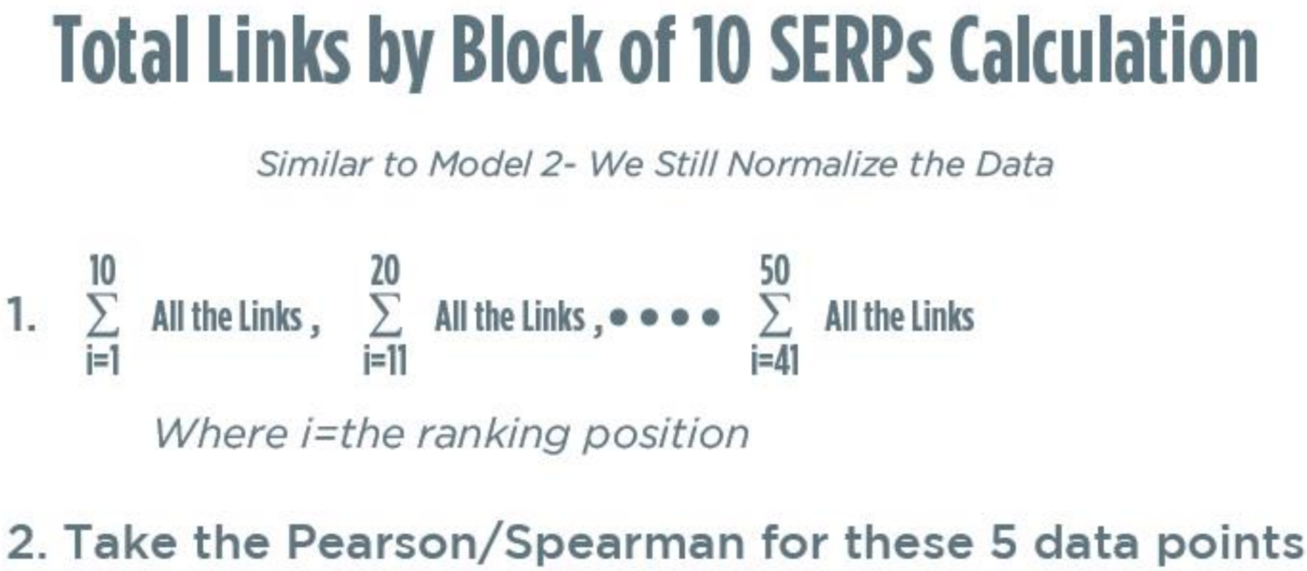

Figure 7: Yet another approach: total-links-by-blocks-of-10-SERPs

This provides a more granular approach than simply aggregating all the ranking positions into the SERP positions. Our results are shown in Figure 8:

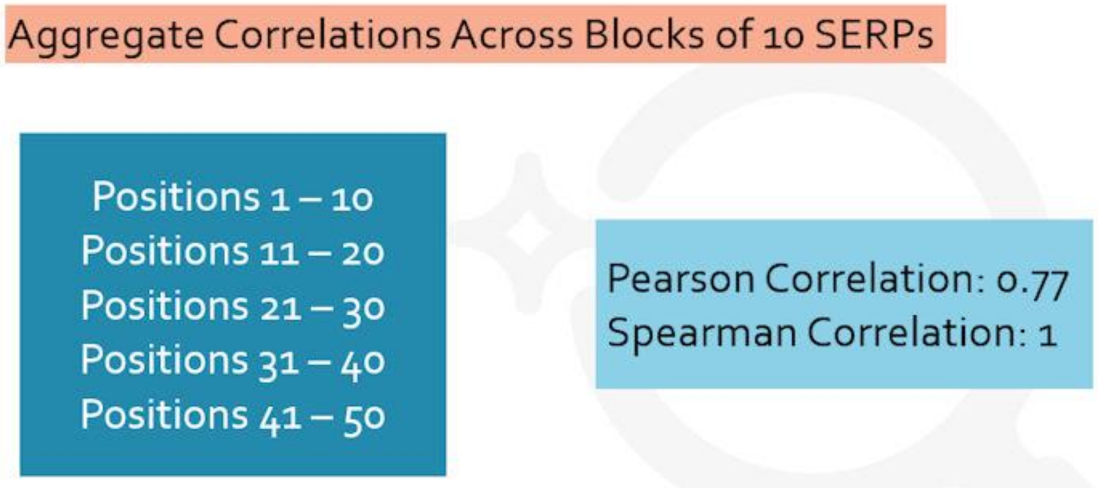

Figure 8: Resulting correlations when using the total-links-by-blocks-of-10-SERPs

We've now gone from values in the 0.39 range, to relatively high correlations (perfect for the Spearman!!) So, what do these numbers tell us? These aggregated approaches to the calculations tell us that links are far more important than the earlier-discussed "*Mean-of-the-Individual-Correlations* approach" or "*Quadratic-mean*"-based calculations reveal.

FURTHER ANALYSIS

To extend this analysis, we did manual examination of a few hundred results to inquire about what percentage of results were likely not materially influenced by links. And, we wanted to know what types of results these are. We found the following types:

1. Local results (not maps results, but results that are locally influenced)
2. Query deserves diversity
3. In Depth Articles

Our analysis indicated that about 6% of the outcomes came from these types of results. This is one factor, albeit, not one that explains the difference between the "mean" (individual or quadratic)-based calculations and the aggregate calculations.

However, the more important issue is understanding the role of content quality. Since Google has called content and links the two most important ranking factors, one can imagine a greatly simplified equation based on simply multiplying the "link score" times the "content score." This, of course, can be thought of as a classic "interaction" effect[1].

In this completely hypothetical discussion, we would argue that the content score likely counts for more than the link score. After all, if the content isn't relevant, it shouldn't rank. In addition, the level of relevance of a piece of content is highly variable.

Figure 9 illustrates, albeit in an oversimplified way, what the impact of this interaction effect might be:

[1] Consider a dependent variable, Y, which is a linear function of X1*X2 (in addition, perhaps, to other terms.) We can note that finding the change in Y per unit change in X1, by taking the first (partial derivative) of Y with respect to X1, yields a result that is a function of X2. So, this fits the classic definition of an *two-factor interaction* effect - namely that the effect of one factor (variable) on Y depends on the value of the other factor (variable.)

Figure 9: Illustration of the effect of the interaction between link score and content score

In Figure 9, it's actually scenario 2 that would rank higher (7200 to 7000), even though its "Link Score" is materially lower than that of scenario 1. Now imagine that the link score ranges from 1 to 100, and the content related scoring factors (relevance and quality) have an exponential decay (where minor variations in quality and relevance have a large impact on the "Content Score"), links will clearly not be able to overcome lower relevance or weaker content.

It is important to note that the above discussion was meant to illustrate the basic point about the significance of content scoring and its impact on ranking algorithms. It's all speculation based on the analysis of the data we've seen, and the case studies that we'll share in the next section).

CEMENTING THE POINT WITH CASE STUDIES

Figure 10 displays a sampling of the results across many clients of *Stone Temple Consulting*:

Keyword	Search Volume	Original Rank	Current Rank	# of New Links
keyword 1	135,000	7	1	11
keyword 2	165,000	18	1	7
keyword 3	49,500	6	1	3
keyword 4	450,000	20	1	25
keyword 5	201,000	15	3	12
keyword 6	159,500	3	2	15
keyword 7	27,100	6	1	5
keyword 8	110,000	5	1	13
keyword 9	68,600	7	1	4
keyword 10	165,000	12	2	4

Figure 10: A sampling of the results across many clients

Prototype sample results, such as those in Figure 10, have been repeated many, many times. However, we do not find that links can rescue poor quality content, or cause low relevance content to rank. Also, all of our efforts focus on the obtaining recognition from, or content published on, very high authority sites. Our data are not based on high-volume, low-quality link-building.

SUMMARY

The Google algorithm continues to evolve, and we see many things that are impacting overall organic search traffic. Some of the primary causes are:

1. More real estate allocated to paid search.
2. More content from other sources, such as image search, YouTube, and the other factors.
3. Some pages that have less than 10 web results.
4. Portions of the web results that are clearly less driven by links, such as local web, query deserves diversity, and in-depth article results.

As a result, there are fewer than ten results on the first page of the SERPs which are driven by factors other than links. That does not mean that links aren't involved at all in rankings for those pages, but rather, just that they matter *less*.

However, our study data strongly suggests that links continue to play a major role in rankings. In addition, our case study data overwhelmingly confirm this conclusion. When you are not facing page relevance or quality issues, links can, and do, continue to significantly impact rankings. It should be noted that, even though our data focused on showing the correlation based on the *quantity* of links, it does not mean that the *quality* of the links doesn't matter; indeed, quality *does matter*.

So what's the "quick and dirty" conclusion of these analysis? It's straightforward:

1. DO build great content and user experiences. In today's digital marketing world, that's just "table stakes."

   and

2. DO proactively market your business and do the types of things that cause people to write about you and link to you.

Note that the 1. and 2. above are connected by an "and;" you must do BOTH.

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