

Suggesting Adjusted Impact Factor by using F min Search Algorithm.

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Abstract. Impact Factor has been widely used as a journal evaluation metric and it also has been used as an evaluation metric of researcher's research ability. However, Impact Factor does not provide a reliable metric when comparing journals in different subject categories. For instance, lower Impact Factors are given to traditional engineering and social sciences than those given to general sciences and biology. By using linearly combined 11 revised Impact Factor, we find the optimal combination to reduce the error rate and give a solution to weak point of current Impact Factor.

Key words Impact Factor, F min search, journal evaluation metric

1. Introduction

Impact Factor has been widely used as a journal evaluation metric for its efficiency. Evaluation of researcher's research ability is determined by this Impact Factor score.

Impact Factor is defined as the average number of citations of each journal in recent two years to the articles published in that journal. This Impact Factor data is provided by the database of Journal Citation Reports from Thomson Reuters. How competitive the report in particular field is shown in this report using Impact Factor score.

However Impact Factor cannot be a perfect indicator to evaluate journals. Firstly, Impact Factor could be manipulated considering review papers because review papers are more quoted than any other articles. The biggest problem is that it is hard to compare journals with different subject categories by Impact Factor. Because there are average difference in score of Impact Factor in different subject categories. It is the result of deviations between different research areas as a consequence of various natures of their academic environments. For instance, social science researchers mostly prefer to publish books rather than journals but computer scientists prefer to present their results in conference proceedings. (Chen and Konstan 2010). In particular, Impact Factor of articles in the field of "Medical Science," and "Biology" are higher than any other field because the quotation is common. Thus, Impact Factor of low level journals in the field of "Medical Science," and "Biology" are sometimes

higher than high level of those in the field of "Mathematics".

Despite this problem, we mostly evaluate researchers by using Impact Factor in Korea. As mentioned above, Impact Factor is not a perfect evaluation because some researchers can get disadvantages in peculiar fields of study.

Our study focus on introducing a new robust journal evaluation metrics that can normalize the differences in impact factor among various categories.

The rest of this paper is organized as follows. In Section 2, we introduce well-known journal evaluation metric. In Section 3, we will introduce the methodology of our research. In Sections 4 and 5, experimental result and conclusion is provided.

2. Review of well-known metric

To improve the problem of Impact Factor difference between subject categories, formal research used revised Impact Factor that divides Impact Factor with each representative (Pyo et al. 2016). They used representative as Impact Factor weighted (number of articles) mean, a higher 20% ranked average Impact Factor, a higher 30% ranked average Impact Factor, a higher 50% ranked average Impact Factor and total average Impact Factor.

However there is a problem when certain journal has more than two research fields. In this case, they could not decide what we use as study representative. Therefore, in the previous research they proposed two

methods that using Average Impact Factor and Maximum Adjusted Impact Factor.

The suggested method by Pyo et al. (2016) adjusted IF (A-IF), can reflect the information of each category and is defined by an average of impact factors divided by the AIFs of the included subject categories. Let $j^k \in J$ be the k th journal where $k \in \{1, 2, \dots, n\}$ in the alphabetical order and IF^k be the impact factor corresponding to journal j^k . Let $c_a \in C$ be the a th subject category where $a \in \{1, 2, \dots, m\}$ in the alphabetical order and AIF_{c_a} is an aggregate impact factor corresponding subject categories. j_{c_a, c_b}^k represents the k th journal included in subject categories c_a and c_b . C_k can be defined as a set of subject categories including the k th journal. A-IF of a journal j_{c_a, c_b, c_c}^k is the average value of the impact factor divided by each aggregate impact factor for a subject category included. $\text{card}(C_k)$ is the cardinality of C_k .

$$\begin{aligned} A - IF(j_{c_a, c_b, \dots, c_l}^k) &= \text{Average} \left(\frac{IF^k}{AIF_{c_a}}, \frac{IF^k}{AIF_{c_b}}, \dots, \frac{IF^k}{AIF_{c_l}} \right) \\ &= \frac{1}{\text{card}(C_k)} \left(\sum_{n=c_a, c_b, \dots, c_l \in C_k} \frac{IF_n^k}{AIF_n} \right) \end{aligned}$$

Pyo et al. also suggested using quantile of the impact factors of the journals listed in a subject category as a representative of journal's impact factor. The first new evaluation metric, namely, QAVG-IF, is a metric that corresponds to a quantile for each subject category included. Specifically, let $\text{Quan}_q(c_a)$ be a top q % quantile in the order of impact factors of the journals in category c_a and $\text{AVG}[\text{Quan}_q(c_a)]$ be the average impact factor for the journals included in top q % quantile in category c_a .

$$\begin{aligned} \text{QAVG} - IF(j_{c_a, c_b, \dots, c_l}^k) &= \text{Average} \left(\frac{IF^k}{\text{AVG}[\text{Quan}_q(c_a)]}, \frac{IF^k}{\text{AVG}[\text{Quan}_q(c_b)]}, \dots, \frac{IF^k}{\text{AVG}[\text{Quan}_q(c_l)]} \right) \\ &= \frac{1}{\text{card}(C_k)} \left(\sum_{n=c_a, c_b, \dots, c_l \in C_k} \frac{IF_n^k}{\text{AVG}[\text{Quan}_q(c_n)]} \right) \end{aligned}$$

The second evaluation metric, namely, QMAX-IF, is a maximum value instead of using the average value.

$$\begin{aligned} \text{QMAX} - IF(j_{c_a, c_b, \dots, c_l}^k) &= \text{MAX} \left(\frac{IF^k}{\text{AVG}[\text{Quan}_q(c_a)]}, \frac{IF^k}{\text{AVG}[\text{Quan}_q(c_b)]}, \dots, \frac{IF^k}{\text{AVG}[\text{Quan}_q(c_l)]} \right) \end{aligned}$$

<Numerical Formula 1> The Impact Factor Correction developed by existing research

However if we use those methods, existing research Impact Factor rank has reversed. In previous research, they regarded this problem as Error Rate. Each method has six percent to ten percent Error rate.

To solve this problem we use F min search to find minimal Error Rate by using linearly combined 11 revised Impact Factor.

3. Proposed Method

In this research, we focused on finding new measure that can replace original impact factor. So we tried to search the best linear combination of our features, which we made by manipulating original impact factor. So we define our new factor.

$$\begin{aligned} y(A) &= A^T X, \\ \{A = (a_1, a_2, \dots, a_m)^T, X = (x_1, x_2, \dots, x_m)^T\} \end{aligned}$$

a_i indicates weights of each factors, and x_i indicates impact factors. In our situation, we chose $m = 11$.

Then we defined new variable, which we have to minimize.

Initially: $r(A) = 0$,
 For f in every field:
 For all subsets containing two papers in field f :
 { If relative rank of published paper has changed, i.e. original impact factor and $y(A)$ show different results about which paper is better,
 $r(A) = r(A) + 1$ }

<Algorithm 1> Pseudo code for ranking check algorithm

Our goal is to find appropriate weight set A which minimizes $r(A)$. In this case, the objective function we should minimize is the number of changed ranks of journals, so it is difficult to use analytical or numerical methods related to gradients. So we used F min search method with different initial values to search for the best coefficients of our new factor.

3.1. F min search

F min search is a simplex search method (It is also called the Nelder-Mead method). Which means it is a direct search method, and it does not use numerical / analytical gradients to compute optimized solution. So this algorithm is applied to nonlinear optimization problems, that derivatives may not be known. In our case, the objective function is not differentiable, so we decided to use fminsearch algorithm.

If there's an n-dimensional vector x, the simplex will be a special polytope made by n+1 vertices in n dimensions. For example, the simplex will be a triangle on a plane, and will be a tetrahedron in 3 dimensional space. General idea of fminsearch is simple. In each search step, we pick new points around or inside the simplex. Then we evaluate the function values at those points and compare them to the function values at vertices. And if there's an improvement, we replace one of the vertices with one of our newly picked points. So new simplex is now generated. This iteration is repeated until the diameter of the simplex becomes smaller than specific tolerance we chose.

3.2. Algorithm of F min search

1. $x(i)$: List of points in the current simplex, $i = 1, \dots, n+1$.
2. Order the points in the simplex by function value, from the lowest $f(x(1))$ to the highest $f(x(n+1))$. Get rid of $x(n+1)$ which has the worst function value (because we are finding minimum values) and add new point to the simplex. [Or we can replace n points except $x(1)$, as we can see in Step 7.]

3. Generate the reflected point.

$$r = 2m - x(n+1),$$

where

$$m = \sum x(i)/n, i = 1 \dots n,$$

and then calculate $f(r)$.

4. If $f(x(1)) \leq f(r) < f(x(n))$, accept r and iteration is terminated. **Reflect**
5. If $f(r) < f(x(1))$, calculate s which is expansion point.

$$s = m + 2(m - x(n+1)),$$

and calculate $f(s)$.

- a. If $f(s) < f(r)$, accept s and iteration is terminated. **Expand**
 - b. Otherwise, accept r and iteration is terminated. **Reflect**
6. If $f(r) \geq f(x(n))$, contraction is performed between m and the better of $\{x(n+1), r\}$.

- a. If $f(r) < f(x(n+1))$ (i.e., r is better than $x(n+1)$), calculate the below.

$$c = m + (r - m)/2$$

and calculate $f(c)$. If $f(c) < f(r)$, accept c and iteration is terminated. **Contract outside**

Otherwise, continue with Step 7.

- b. If $f(r) \geq f(x(n+1))$, calculate the below.

$$cc = m + (x(n+1) - m)/2$$

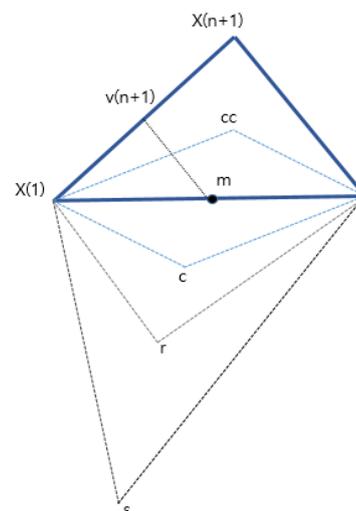
If $f(cc) < f(x(n+1))$, accept cc and iteration is terminated. **Contract inside** Otherwise, continue with Step 7.

7. Calculate the n points.

$$v(i) = x(1) + (x(i) - x(1))/2$$

and calculate $f(v(i))$ ($i = 2, \dots, n+1$). The simplex of next iteration is consisted of $x(1), v(2), \dots, v(n+1)$. **Shrink**

Figure 1 is an example of fminsearch procedure. Bold outline is the original simplex, and iteration continues until the simplex reaches the stopping criterion.



<Figure 1> Simple example of fminsearch

4. Experimental Results

We can identify that optimal value differs due to Initial value of our experiments. Since our optimization problem is not a convex optimization problem, it may have regarded local optimal value as global optimal value. In Table 1 we illustrated our results with various initial values.

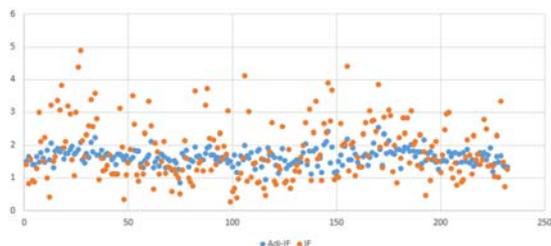
Initial value	Final value
0.3	1.187566
0.1	1.1425507
0.6	0.288932
0.7	-3.422044
0.8	-0.1674833
0.5	-1.5371737
0.6	-1.1111289
0.2	-0.1227432
0.6	-0.308715
0.5	3.4734253
0.4	0.559431

<Table 1> Best coefficient set

Adjusted IF	A-IF	QAVG-IF(20%)	QMAX-IF(20%)
Error Rate	6.24%	6.98%	8.17%
Adjusted IF	QMAX-IF(50%)	QAVG-IF(75%)	QMAX-IF(75%)
Error Rate	7.24%	5.94%	6.96%
Adjusted IF	QAVG-IF(30%)	QMAX-IF(30%)	QAVG-IF(50%)
Error Rate	6.56%	7.69%	6.14%
Adjusted IF	QAVG-IF(100%)	QMAX-IF(100%)	Adj-IF
Error Rate	5.88%	6.92%	5.32%

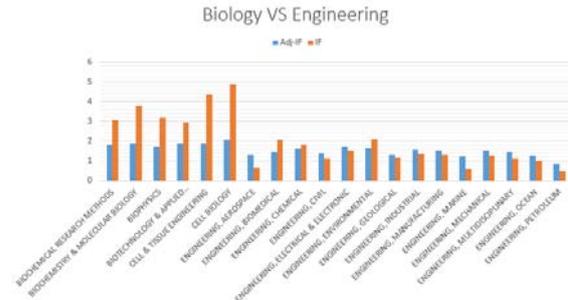
<Table 2> Error Rate from various adjusted impact factors

We can see the error rate from various adjusted impact factors in table 2. We found that our suggested adjusted Impact factor have lower error rate compared to previous adjusted impact factors.



<Figure 2> Average IF by categories

In Figure 2 we can compare average impact factor with average adjusted impact factor by categories' distribution. With Figure 2 we can identify that our suggested adjusted Impact factor has reduced Impact factor variance between different categories.



<Figure 3> Average Impact factor in Biology and Engineering

Figure 3 compared average Impact factor and average adjusted impact factor in categories related Biology and engineering. We found that our adjusted impact factor is more reasonable journal evaluation indicator in aspects of variance of categories.

5. Conclusions

By using F min search method to find optimal value, our model showed error rate of 5.3%, while previous model showed 6.8%. We need to apply various algorithms and object functions to find the optimal journal evaluation measure in future study.

References

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