

# A Crowd-Powered Model for Identifying Negative Citations

Sujoy Chatterjee

I3S Laboratory

University of Nice Sophia-Antipolis

06903 Sophia Antipolis, France

Email: sujoy.2611@gmail.com

## ABSTRACT

In academics, the ranking of authors are usually done through the different quality metrics like h-index, i10-index, etc. and these metrics are basically based on the amount of citations received. Meanwhile, it is already established that all the citations received for a paper are not equal. Mainly, the distinction between sentiments of these citations occurs as these can be received from two perspectives i.e., endorsement or criticism of the papers. Recently, keywords based NLP techniques are proposed to track these sentiments, still, there are certain issues that require human perceptions to realize these sentiments. Therefore, the problem of identifying sentiments of citations (positive, negative and neutral), if outsourced to the crowd and feedback are received then it can be resolved in effective way. In this paper, we introduce a crowdsourcing based semi-supervised model that can be effective in finding negative citation and provide some insights to build an efficient research paper recommender system by utilizing this immense power of crowd.

## KEYWORDS

Crowdsourcing, Recommendation, Markov chain

## 1 INTRODUCTION

The count of citations in academics is considered to have a major impact in evaluating the credential of the proposed research. The amount of citation can play a major role in academic institution for securing better ranking, obtaining research grant, etc. In most of the situations, the citations coveted and received by the authors are in the form of a compliment. A current study may be consistent with the previous work but pointing out its flaws, limitations, etc can be serious that may be a critical issue in receiving future citation. As a consequence, criticism obtained through citation may cause falsification of citation [2]. A paper is needed to be observed for the next few years after the publication of it. As the technology and science incorporated in it are potentially brand new so it should be tested in the next few years. Therefore, understanding the sentiment (i.e., positive citation or negative citation) is crucial for those couple of years and thus are needed to be tracked for the further growth of science and research.

In recent studies, it is observed that the evolve of negative citation is low but it can not be neglected as mentioned by Alexander Oetl, an economist at Georgia Institute of Technology in Atlanta. This study was on checking 750,000 citations (mainly for 150000 papers) for a particular journal, namely, "Journal of immunology" [2]. In this experiment, the expertise of immunologist were taken into consideration to manually check the amount of negative citation of these papers. A line of research is already performed in finding the nature of citations with the effective use of NLP and manual expert annotation[1, 7, 8]. However, it is not always possible to retrieve the exact sentiment of citation by using NLP tool. For example, a research can have many limitations but it may be the pioneering work. So there should be a trade-off to judge the exact sentiment. On the other hand, expert manual annotations are very time and cost consuming. Therefore, this task of recognizing negative aspects on the papers can be outsourced to the general people with little expertise. As crowdsourcing can have a major role in solving a large task independently in distributed manner, therefore, leveraging the power of human resources to quantify the citation can be very much helpful in proper decision making in time and cost effective way [4–6]. Basically, the citations can be quantified as positive, negative and neutral. Therefore, the feedback set contains these three options and crowd opinions are collected from them based on their own perspectives. Finally, the decisions can be aggregated from multiple crowd opinions. Now as there are possibilities of involvement of malicious crowd workers, therefore, a 2-stage annotation process (independent and dependent manner) can be reliable to identify the efficient crowd workers.

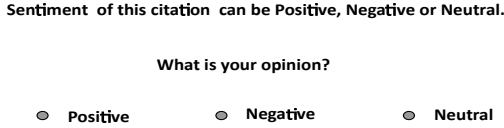
In this model, the research papers are segregated into various sections by keyword based NLP based tool and the different portions are outsourced to the crowd to obtain their feedback. In this situation, no one can observe others' opinions so these are independent opinions (as shown in Fig. 1. After collecting their opinions, all the opinions are revealed to them and again the opinions are collected from them (as demonstrated in Fig. 2). Thus the opinions collected in second phase are basically the dependent opinions of the crowd workers in a similar way as discussed [3]. So the challenges remain in obtaining the final sentiment of citation from these independent and dependent set of feedback. We propose a Markov chain based model that can be utilized for reaching a consensus sentiment from a set of independent and dependent opinions.

## 2 PROPOSED MODEL

Here we introduce a crowdsourcing model that outsources research papers to crowd and collects the sentiments of the citation from them. However, due to the existence of malicious crowd workers several measures are needed to be adopted in order to produce noise-free

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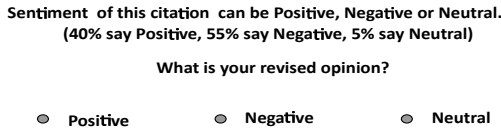
of questions asked. Using our theoretical framework, we analyze several strategies, and show that a strategy, claimed as “optimal” for this problem in a recent work, can perform arbitrarily bad in theory. We propose alternate strategies with theoretical guarantees. Using both public datasets as well as the production system at Facebook, we show that our techniques are effective in practice.



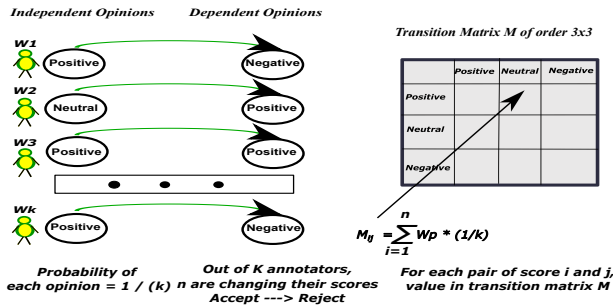
**Figure 1: Snapshot of collecting independent opinions.**

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**Figure 2: Snapshot of collecting dependent opinions.**



**Figure 3: Snapshot of the workflow to compute weighted transition matrix. Here, the options are ‘Positive’, ‘Negative’ and ‘Neutral’.**

decision. In this model, the opinions are basically of independent and dependent types. Observation over their opinions from independent to dependent situation are very crucial to quantify the better transition. Here the major challenges are how to define different quality metric criteria to identify the expert workers. We can take the effect of confidence gap (deviation from independent score to dependent score), reliability (closeness with majority opinions), accuracy (closeness with mean opinion) of the crowd workers. In addition to that, we measure the deviation of the worker’s opinion from the mean

of all the posterior opinions considering the question difficulty. Finally, these metric are used to compute a weighted transition matrix of the Markov chain. We start with any stationary distribution vector of the option set having options ‘Positive’, ‘Negative’, and ‘Neutral’. The final distribution of the option set is obtained by multiplying the stationary distribution vector with the transition matrix. Ultimately, the stationary distribution converges after a certain iteration of time. The option for which the distribution becomes maximum is treated as the final option. Thus this type of crowd powered system can be very helpful for preliminary understanding of the sentiment of the papers.

Along with this, an efficient user interface is needed to be designed to attract the crowd workers for soliciting their opinions. As the opinions are obtained in two phases, hence, effective mechanism should be designed so that curiosity can be evolved in crowd workers towards providing their best possible answer. Moreover, as the count of negative citation is too low so imbalanced property should also be taken into account. Again, the convergence property of Markov chain proves that the oscillation of the crowd workers’ opinions becomes stable after a certain iteration. On the other hand, this methodology can be easily integrated with the research papers recommender system.

Over the last decade, research papers recommender system has emerged as a mainstream research area to find the relevant research papers in an efficient way. However, most of the works in this area deal with different aspects like citation analysis, rating, author collaboration, recency, etc. A limited work concerning the negative citation of the papers is available in literature. Again, it is not feasible to continuous monitoring over the quality of citation while obtaining it. However, this can be easily done by voluntary crowdsourcing in a cost efficient manner. Due to the presence of non experts in crowd effective mechanism should be designed with an aim to extract better opinions from them. Thus this proposed model has a major impact not only in developing an efficient research paper recommender system but also it introduces various new avenues in this domain incorporating these vast human resources.

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