ABSTRACT
The deluge of new papers has significantly blocked the development of academics, which is mainly caused by author-level and publication-level evaluation metrics that only focus on quantity. Those metrics have resulted in several severe problems that trouble scholars focusing on the important research direction for a long time and even promote an impetuous academic atmosphere. To solve those problems, we propose Phocus, a novel academic evaluation mechanism for authors and papers. Phocus analyzes the sentence containing a citation and its contexts to predict the sentiment towards the corresponding reference. Combining others factors, Phocus classifies citations coarsely, ranks all references within a paper, and utilizes the results of the classifier and the ranking model to get the local influential factor of a reference to the citing paper. The global influential factor of the reference to the citing paper is the product of the local influential factor and the total influential factor of the citing paper. Consequently, an author’s academic influential factor is the sum of his contributions to each paper he co-authors.

KEYWORDS
citation classification, sentiment analysis, academic influential factor, data mining

1 INTRODUCTION
The number of papers published each year has grown greatly. For example, as shown in Figure 1, the number of new papers on IEEE Xplore1 increases sharply over the decade. Paper boom in academic fields results in many severe problems. Cortes et al. [10] examine 2014 NeurIPS and find that it is not able to pick out excellent researches, and could identify terrible papers. Chu et al. [8] reveals that too many papers published each year in a field hinder its development. They state this opinion in two aspects. First, researchers are busy coping with a lot of papers, but don’t have enough time to fully learn novel ideas; Second, the focused attention on a promising idea might be broken up by the deluge of new ideas.

Figure 1: the number of new publications on IEEE Xplore each year from 2000 to 2021.

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1https://ieeexplore.ieee.org/Xplore/home.jsp

Reference Format:
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The reason for sharp increase in papers is that evaluation metrics for researchers and scholars focus on the quantity of papers. From scientific output, research funding, to evaluation of professional rank, papers play an very important role, and the more papers, the better. However, It is time to make changes. Quantitative metrics could not evaluate the real academic impact of a scholar, or a paper. They ignore the essential differences between citations, which is a fatal error. Seglen expresses strong opposition to impact factors that measure the academic influence of journals for committees seldom have the specialist' insights to to assess primary researches[31].

We propose Phocus, a novel evaluation mechanism for scholars and publications. Phocus analyzes the sentence containing a citation and its contexts to predict the sentiment polarity towards the corresponding reference. Besides, Phocus also considers total number of citations, number of citations per sentence, author overlap, and number of references, similar to [35]. Given those factors above, Phocus uses Naive Bayesian Classifier to divide citations coarsely into 4 categories, and utilizes LambdaMART model to sort all references within a paper. Combining the categories and the ranking results, every reference gets its local influential factor within $[-1, 1]$, related to the citing paper. The global influential factor of the reference to the citing paper is the product of the local influential factor and the total influential factor of the citing paper. Consequently, an author’s academic influential factor is the sum of his contributions to each paper he co-authors.

2 RELATED WORK

Our work involves citation classification, aspect-based sentiment analysis, ranking model and evaluation metrics for academics, which will be introduced in subsections below respectively.

2.1 Citation Classification

In fact, there are already many researches have focused on citation classification. For example, Teufel et al. [33] classify citation intents into 12 classes, using simple regular match to extract features. Valenzuela et al. [35] divide citations into 4 classes: highly influential, background, method and results citations, using SVM with a RBF kernel and random forests, taking 13 features into consideration: total number of direct citations, number of direct citations per section, total number of indirect citations and number of indirect citations per section, author overlap, is considered helpful, citation appears in table and caption, 1/number of references, number of paper citations/all citations, similarity between abstracts, PageRank[28], number of total citing papers after transitive closure, and field of the cited paper. While Jurgens et al. [20] define 7 classes of citation intents: background, motivation, uses, extension, continuation, comparison or contrast, and future, with a Random Forest classifier trained using 4 types of features: structural features, lexical, morphological and grammatical features, field, and usage. Cohen et al. [9] propose a multitask model using BiLSTM and attention mechanism to classify citation intents that is the primary task, and predict the section where the citation occurs and where a sentence needs a citation that are auxiliary tasks and are used to assist the primary task6. They categorize intents into 3 classes: background information, method, and result comparison. Besides, Cohan builds a citation intent dataset SciCite. Those works simply classify citations according to intents, but ignore the sentiment citing paper towards references, which is vital.

 Butt et al. [6] utilize Naive-Bayes Classifier to predict the sentiment polarity of a sentence containing a citation and its contexts. Whereas Liu et al. [23] use averaged word embeddings to represent sentence vectors and to classify sentiment polarities. However, this method generates the overall sentiment of text, rather than the precise sentiment towards the cited paper, which is unable to apply directly.

2.2 Aspect-based Sentiment Analysis

Aspect-based sentiment analysis (ABSA) is proposed to define such task. Usually ABSA consists of two stages: locating aspects, and analyzing sentiment. Some works solve this problem also in two-stage way, while some jointly.

To detect citation span in Wikipedia, Fetahu et al. [13] propose a sequence classification method using a linear chain CRF to decide which text fragments are covered by a citation at sub-sentence level. Whereas Kaplan et al. [22] detect non-explicit citing sentences that surrounding an explicit citing sentence, utilizing relational, entity, lexical, and grammatical coherence between them. [25][39]even try to find the most relevant sentences in reference paper with the citing sentences. Qazvinian and Radev [29] proposed a method based on probabilistic inference to extract non-explicit citing sentences by modelling the sentences in an article and their lexical similarities as a Markov Random Field tuned to detect the patterns that context data create, and employ a Belief Propagation mechanism to detect likely context sentences. Abu-Jbara and Radev [1] determine the citation block by first segmenting the sentences and then classifying each word in the sentence as being inside or outside the citation block. Finally, they aggregate the labels of all the words contained in a segment to assign a label to the whole segment using with three different label aggregation rules(majority label of the words, at least one of the words, or all of them). Kaplan et al. [21] proposed a new method based on coreference-chains for extracting citation blocks from research papers.

Given aspects, Sun et al. [32] construct an auxiliary sentence from a aspect, and feed the sentence-pair into BERT-based model. Gao et al. [14] utilize three target-dependent variations of the $bert_{base}$ model. Bai et al. [2] propose a novel relational graph attention network3, which integrates typed syntactic dependency information.

As the errors are cumulated in the pipeline, some researchers explore solutions that detect aspects and classify sentiment jointly. Wang et al. [37] propose latent aspect rating analysis problem that aims at analyzing reviewers’ latent opinions on an entity from several aspects. For a certain entity, they define a set of keywords of aspects, and segment reviews into aspect level. Given aspect segmentation results, they use a novel latent rating regression model to calculate aspect ratings and corresponding weights. However, Wang et al. ignore the inter-dependencies between words and sentences, which causes great information loss. This class problem is also called aspect-based sentiment analysis (ABSA). Ruder et al. [30] proposes a hierarchical bidirectional LSTM to model the

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6https://github.com/allenai/scicite

3https://github.com/muyeby/RGAT-ABSA
inter-dependencies of sentences within a review. The aspect is represented by the average of its entity and attribute embeddings. Hoang et al. [18] propose to use a sentence pair classifier model from BERT[11] to solve ABSA at sentence and text levels. Hu et al. [19] propose a span-based extract-then-classify framework based on BERT[4]. Xu et al. [38] build a dataset, ReviewRC[5], and extend BERT with an extra tasking-specific layer to tune each task. Wallaert et al. [36] propose a two-stage algorithm to solve the ABSA for restaurant reviews: predicting the sentiment with a lexicalized domain ontology, and using a neural network with a rotatory attention mechanism (LCR-Rot) as a back-up algorithm. The order of rotatory attention mechanism operation is changed and the rotatory attention mechanism is iterated multiple times. Trusa et al. extend [36] with deep contextual word embeddings and adding an extra attention layer to its high-level representations[34]. To address imbalance issue and utilize the interaction between aspect terms, Luo et al. [24] propose a gradient harnomized and cascaded labeling model based on BERT. Chen et al. [7] utilize directional graph convolutional networks to perform end-to-end ABSA task.

2.3 Ranking Model
Ranking model is based on LambdaMART, which is the boosted tree version of LambdaRank[5]. This algorithm solves the gradients of non-smooth cost functions used in ranking models. Burges et al. [4] give a review on RankNet, LambdaRank, and LambdaMART.

To illustrate the ranking network, we use \( c_{ij} \) to denote the \( j \)-th citation of the \( i \)-th reference paper. Our ranking network receives an matrix of shape \((\sum_i n_{cit}, 4)\), where 4 stands for the feature quater-nion of \((au\_overlap, n\_cit, cit\_word, sen\_label)\). Among which cit_word is calculated as the total number of words in context_a + sentence + context_b. The network calculate a score \( s_{ij} \) on each time of citation \( c_{ij} \) individually, averaging on duplicate citations to get the score of each reference paper \( s_i = \frac{1}{n_{cit}} \sum_j s_{ij} \). Then \( s_i \) is used to rank all the reference paper, outputting \( r_i \).

2.4 Evaluation Metrics
In academic field, there are journal-level, author-level and paper-level metrics that measure their impacts.

The Impact Factor (IF)[26] and CiteScore[6] are used to measure the impact of a journal that based on the number of times articles cited during a fixed period published by the journal. Besides, Journal Citation Reports (JCR) give ranking for journals, Eigenfactor scores[3] measure how likely a journal is to be used, and SCimago Journal Rank (SJR)[15] regards the citations issued by more import journals as more important than those issued by less important ones. Whereas Source Normalized Impact per Paper (SNIP)[27] indicates that a single citation is much more important in subject areas where citations are less, and vice versa.

Author-level metrics include h-index, g-index, i10-index and so on. H-index, also called index \( h \), is proposed by Jorge E. Hirsch[17], and its definition is the number of papers with citation number higher or equal to \( h \). The g-index is defined as the largest number such that the top \( g \) articles received together at least \( g^2 \) citations[12]. Google Scholar proposes i10-index that is the number of a publication with at least 10 citations. Those metrics are derived from citations and do not reveal the truth among citations.

Paper-level metrics are usually the number of citations. Specially, Semantic Scholar makes the first step towards citation classification. It divided citations into 4 classes: highly influential, background, method and results citations[35], using SVM with a RBF kernel and random forests. The features Semantic Scholar use are total number of direct citations, number of direct citations per section, total number of indirect citations and number of indirect citations per section, author overlap, is considered helpful, citation appears in table and caption, 1/number of references, number of paper citations/all citations, similarity between abstracts, PageRank[28], number of total citing papers after transitive closure, and field of the cited paper.

3 METHODOLOGY
As shown in Figure 2, our algorithm consists of 4 stages: pre-processing, calculating factors, evaluating contribution, and propagating influential factors. In pre-processing stage, we clean raw data, and obtain simple factors. Complex factors, like sentiment polarity are calculated in second stage. When get all factors needed, we classify citations into four classes and rank all references, and figure out the local contribution factor of each reference. We initialize all new paper to the database with an academic influential factor 1.0, and propagate its impact on references iteratively. The factors extracted from papers are listed out in Table 1

3.1 Pre-processing
Given a paper of string format, a series steps process the raw data for next stage: parsing, segmentation, and matching. Paring is aimed at dividing the input text into title, authors, sections, and references. We utilize flair[8] to parse title, authors and publish year of the input paper and its references. We segment the input paper into two level: section level and sentence level. Section segmentation is based on keywords match, and classified into three categories: 0 representing

\[8https://pypi.org/project/flair/\]
Table 1: factor list

| Name     | Definition                                                                 | Ranges       |
|----------|---------------------------------------------------------------------------|--------------|
| cit_id   | reference number of a paper in the reference list                         | positive integer |
| cit_title| title of a reference                                                      | string       |
| cit_author| authors of cit_title                                                    | list of authors |
| cit_year | publish year of cit_title                                                | year         |
| au_overlap| overlap between authors of cit_title and citing paper                     | [0, 1]       |
| sent_id  | id of a sentence                                                         | natural number |
| sec_id   | section id of a sentence                                                 | 0: related work; 1: main body; 2: conclusion |
| n_cit    | time of cit_id cited in citing paper                                     | natural number |
| cit_text | text of the sentence that contains the cit_id                             | string       |
| context_a| related sentences previous to cit_text                                   | string       |
| context_b| related sentences behind to cit_text                                     | string       |
| sen_label| the sentiment citing paper towards cit_id                                | -1: negative; 0: neutral; 1: positive |

Table 2: the classifying standards of Phocus.

| Label | Description                                                                 |
|-------|-----------------------------------------------------------------------------|
| 3     | extending the work; highly influenced by the work                           |
| 2     | using the work                                                              |
| 1     | related work                                                                |
| 0     | negative sentiment towards the work                                         |

Figure 3: the propagation rules of influential factors

3.2 Calculating Factors

There are still three factors unsolved: context_a, context_b, and sen_label. We obtain context_a, context_b with BERT, and propose a novel aspect-based sentiment analysis algorithm to classify citation sentiment.

We fine-tune BERT on a manually annotated dataset containing over 1,000 sentence pairs labeled as ‘related’ or ‘irrelevant’. Each sentence pair is generated from single academic paper. We get an accuracy of 94.5% on the evaluation dataset. To obtain context of cit_context, we apply the above classifier iteratively on sentence pair $(S[sent_id - 1], S[sent_id])$ ($S$ representing the list of all sentences in the paper) where $i$ increase from 1. Once an ‘irrelevant’ pair is reported, the iteration is aborted and we take $S[sent_id - i : sent_id]$ as context_a. Another stopping criteria is that $S[sent_id - i]$ should always be in the same paragraph with $S[sent_id]$. A similar procedure is performed on $(S[sent_id + 1], S[sent_id])$ to get context_b.

3.3 Evaluating Contribution

After gathering all needed factors, we train a classifier to categorize citation into 4 classes: very important, important, neutral, and terrible. And we also train a ranking model to predict the related order of references in terms of their contributions to the paper. First, we classify citations into four categories with Naive Bayesian classifier. The classifying standards are shown in Table 2, and a larger the number of label represents more contributions.

Ranking model is based on LambdaMART, which is the boosted tree version of LambdaRank[5]. This algorithm solves the gradients of non-smooth cost functions used in ranking models. Burges et al. [4] give a review on RankNet, LambdaRank, and LambdaMART.

Based on the classes and order of references, we project them into $[0, 1]$ to get their influential factors.

3.4 Propagating Influential Factors

Given a list of references and their influential factors of the citing paper, we design some rules to propagate their influential. The main idea is shown in Figure 3.

$A$ denote a citing paper with academic influential factor $AF_A$ initialized as 1, set $R_A$, $IF_A$ denote all references of $A$, and their
corresponding local contribution to A, and \( IF_{jA}^i \in [-1, 1] \) is the local contribution of reference i to A. \( CA \) is the set of all papers that cite A, and for \( j \in CA, IF_{jA}^i \in [-1, 1] \) is A’s local contribution to j. Then, the academic influential factor of A is:

\[
AF_A = \sum_{j \in CA} AF_j IF_{jA}^i
\]

(2)

For author a who publishes a set of papers \( Pa \), and his contribution to paper \( i \in Pa \) is \( CIA \in [0, 1] \), his academic influential factor is:

\[
AF_a = \sum_{i \in Pa} CIAAF_i
\]

(3)

For paper A, and its N authors, \( \sum_{i=1}^{N} CIA \equiv 1 \). There are two problems to prove to ensure that our method is logical. The first one is margin effects. And the second one the propagation rules.

4 EXPERIMENTS

We conduct several experiments to demonstrate our new metrics that measure the influential factors of an individual scientist or scholar and the citation impact of the publications.

As the influential factor of a paper is the weighted sum of all papers that cite it and its corresponding contribution to them, the full and full publication of paper and network should be constructed. However, we cannot complete this job yet out of no access to some databases, no enough time or computational resources. We will select some scholars and their publications as targets, and utilize primary citation and secondary citation relationships. Besides, we also compare our modules to other state-of-art algorithm to show the improvement we achieve.

4.1 Peer Comparison

Scholar and their publications. Let Scholar Y denote some scholar. We will show the difference between Scholar Y and the Turing Award winner Pat. Hanrahan. As we emphasize, Pat. Hanrahan is much more influential than scholar Y is not only for he wins Turing Award, but also is based on solid statistics of citations. For example, He et al. [16] take one paper of scholar Y as a baseline that performs only better than one baseline among eleven. Table 4 shows evaluation results of scholar Y and Pat. Hanrahan on Aminer, Google Scholar, Semantic Scholar, and Phocus. Table 3 lists the number of publications and citations of scholar Y and Pat. Hanrahan. It’s obviously that scholar Y is more productive than Pat. Hanrahan. However, those numbers covers up some significant truths that not all papers are equal influential and not all citations mean agreement with the cited ones. where h represents h-index, g represents g-index, i10 means i10-index, and HIC is the number of highly influential citations. H-index, also called index h, is proposed by Jorge E. Hirsch[17], and its definition is the number of papers with citation number higher or equal to h. The g-index is defined as the largest number such that the top g articles received together at least \( g^2 \) citations[12]. Google Scholar proposes i10-index that is the number of a publication with at least 10 citations. Those metrics are derived from citations and do not reveal the truth among citations. Semantic Scholar makes the first step towards citation classification. It divided citations into 4 classes: highly influential, background, method and results citations[35], using SVM with a RBF kernel and random forests. The features Semantic Scholar use are total number of direct citations, number of direct citations per section, total number of indirect citations and number of indirect citations per section, author overlap, is considered helpful, citation appears in table and caption, 1/number of references, number of paper citations/all citations, similarity between abstracts, PageRank[28], number of total citing papers after transitive closure, and field of the cited paper. We collect XX papers that cite scholar Y from 78663, and XX papers that cite Patrick Hanrahan from 56383. Only utilizing primary citations, we get the global academic influential factors of scholar Y and Patrick Hanrahan are 0.40 and 0.52 respectively. Figure 4

4.2 Mathematical Invariance

To verify the model, we conduct a series experiments to prove it’s reasonable.
We conduct some experiments guided by [1] as our baseline. We show in Table 4, Phocus figures out that the global academic influential factors of scholar Y and Patrick Hanrahan are 0.40 and 0.52 respectively, and Patrick Hanrahan is 30% higher than scholar Y. It’s the results that only utilizing primary citation data. While the influential factors of scholar Y and Patrick Hanrahan are 0.40 and 0.52 respectively, and Patrick Hanrahan is 30% higher than scholar Y.

### 5 RESULTS

As show in Table 4, Phocus figures out that the global academic influential factors of scholar Y and Patrick Hanrahan are 0.40 and 0.52 respectively, and Patrick Hanrahan is 30% higher than scholar Y. It’s the results that only utilizing primary citation data. While the influential factors of scholar Y and Patrick Hanrahan are 0.40 and 0.52 respectively, and Patrick Hanrahan is 30% higher than scholar Y.

### 6 CONCLUSION

In this paper, we come up with Phocus, a novel set of academic evaluation metrics for authors and publication based on citation judgements that utilize aspect-based sentiment analysis. To verify our evaluation mechanism, peer comparison and ablation studies have been conducted. The results show that our metrics are able to identify truly worthiness of a paper or a scholar, which is difficult to citation times based metrics, like h-index, g-index and others.

Phocus still need improvements. As show in Section Experiment, we only use primary citation data, which is not enough to fully prove the reliability of Phocus. Besides, using more data such as secondary and tertiary citations, could further reflect the gaps between scholars and between metrics. There is still many problems unsolved, such as “citation circles” (groups of researchers who cite one another’s work), and self-citation.

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**Table 5: features used for citation span**

| Feature   | Description                                                                 |
|-----------|-----------------------------------------------------------------------------|
| distance  | The distance (in words) between the word and the target citation.            |
| position  | This feature takes the value 1 if the word comes before the target citation, and 0 otherwise. |
| segment   | After splitting the sentence into segments by punctuation and coordination conjunctions, this feature takes the value 1 if the word occurs in the same segment with the target reference, and 0 otherwise. |
| pos_tag   | The part of speech tag of the word, the word before, and the word after.     |
| dTreeDistance | Length of the shortest dependency path (in the dependency parse tree) that connects the word to the target reference or its representative. |
| lca       | The type of the node in the dependency parse tree that is the least common ancestor of the word and the target reference. |

**Table 6: results for three different models for citation span**

| Model     | Precision | Recall | F1  |
|-----------|-----------|--------|-----|
| SVM       | 0.78      | 0.56   | 0.65|
| LR        | 0.68      | 0.67   | 0.67|
| CRF       | 0.65      | 0.64   | 0.64|

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