Automated scholarly paper review: Possibility and challenges

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Abstract

Peer review is a widely accepted mechanism for research evaluation, playing a pivotal role in scholarly publishing. However, criticisms have long been leveled on this mechanism, mostly because of its inefficiency and subjectivity. Recent years have seen the application of artificial intelligence (AI) in assisting the peer review process. Nonetheless, with the involvement of humans, such limitations remain inevitable. In this review paper, we propose the concept of automated scholarly paper review (ASPR) and review the relevant literature and technologies to discuss the possibility of achieving a full-scale computerized review process. We further look into the challenges in ASPR with the existing technologies. On the basis of the review and discussion, we conclude that there are already corresponding research and technologies at each stage of ASPR. This verifies that ASPR can be realized in the long term as the relevant technologies continue to develop. The major difficulties in its realization lie in imperfect document parsing and representation, inadequate data, defected human-computer interaction and flawed deep logical reasoning. In the foreseeable future, ASPR and peer review will coexist in a reinforcing manner before ASPR is able to fully undertake the reviewing workload from humans.

Keywords: Automated scholarly paper review, Peer review, Natural language processing, Artificial intelligence

1 Introduction

Scholarly peer review, also known as refereeing, has been defined as "the process of subjecting an author’s manuscript to the scrutiny of others who are experts in the same field, prior to publication in a journal". "This review process varies from journal to journal but it typically consists of two or three reviewers reporting back to a journal editor who takes the final decision." (Ware and Mabe, 2015) In the current academic journal publication cycle, peer review has become a common practice that plays an extremely important role. It helps editors decide whether academic work can be accepted for publishing in academic journals. Apart from journal papers, conference papers, patents, research proposals, etc. are also subject to peer review. They generally go through a peer review process similar to that of journal papers. In this paper, journal paper reviewing is our major focus.
The first record of peer review can be traced back to more than 300 years ago. It was performed by Henry Oldenburg (1619-1677) in 1665, who was the founder and the first editor of the world’s oldest scientific journal Philosophical Transactions of the Royal Society (Zuckerman and Merton, 1971). Before the 20th century, peer review was often conducted by editors-in-chief or editorial committees directly. At that time, editors of academic journals made publication decisions without seeking opinions from external reviewers. However, since the middle of the 20th century, in order to reduce the workload of the editorial board, some medical journals have begun to appoint external reviewers to carry out the review. This practice has later been widely adopted and major journals such as Nature and Science are increasingly relying on external reviewers. In several centuries, peer review evolves from a new thing to an industrial common practice in the academic publication cycle.

In peer review, whether or not an article can be accepted for publication depends on the review both by journal editors and experts in the certain field. The peer review panel makes a comprehensive assessment on the paper’s originality, quality, clarity and significance to maintain a consistent high standard in the published academic work to come. Therefore, peer review is regarded as the “gatekeeper, the final arbiter of what is valued in academia” (Marsh et al, 2008). Through peer review, flaws in academic manuscripts can be found and questionable manuscripts can be intercepted before publication. While at the same time, peer review also serves as the coach in academia as it gives valuable feedback to authors for revision. This helps authors improve the quality of their papers.

Although peer review is widely considered as the norm and its necessity is recognized by the majority of researchers, criticism from both academic and publishing circles has long been leveled at the peer review system (Smith, 2006; Brezis and Birukou, 2020). On the whole, it is subject to criticism surrounding the following issues.

• **Inefficiency.** According to data from Huisman and Smits (2017), the average review time, not included the revision time, for a manuscript is 17 weeks. To the author of the manuscript, this lengthy process is a profligate of academic time. In some cases, the research may even become outdated during the inappropriately long process. To scholars who dedicate to write reviews, with the ever-growing number of manuscripts, this reviewing work is an increasingly onerous burden. At the same time, reviewers usually receive little reward for their hard work. Even though some attempts have been made to record and credit peer reviewing, there still lack enough incentives for researcher to do the reviewing and rewards to justify such dedication. The time spent on reviewing could be spent alternatively on something more productive, like original research. That being the case, editors are scrambling to find qualified reviewers to even start the reviewing, making the originally time-costing process even more lengthy. Such a long-drawn process for sure discourages researchers from academic publication.

• **Subjectivity.** Biases, either intentional or unintentional, are always inevitable to human beings. Reviewers are no exception. Langford and Guzdial (2015) suggested the arbitrariness in paper reviewing, proving in an experiment that one-half to two-thirds of NIPS\(^2\) 2014 accepted manuscripts might have been rejected if another independent round of review was conducted. Worse still, it is more likely for groundbreaking research, especially with novelty involved, to induce more subjectivity. Conservatism in peer review can lead to bias against groundbreaking and innovative research (Wang et al, 2017). Reviewers tend to be particularly critical of conclusions that contradict their viewpoints, while they are more tolerant of views that conform to theirs (Grimaldo and Paolucci, 2013). Moreover, researchers have also proved the existence of gender bias (Wennerås and Wold, 1997; Budden et al, 2008) and nationality bias (Link, 1998) in peer review.

• **Knowledge limits.** Due to physical and cognitive limitations, an individual human being is certain to have knowledge limits. Peer review relies on the professional judgments of experts in a certain field. However, expert reviewers still have their knowledge scope within the field and

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1. https://publons.com/
2. Conference on Neural Information Processing Systems with its name later changed to NeurIPS in 2018.
hence the limits. Knowledge is becoming more specific with more emerging subdivisions within a knowledge field. What complicate the reviewing more are the ever-accelerating knowledge explosion and the growing trend of interdisciplinary research. It is more common that the content of the manuscripts goes beyond the scope of knowledge of experts from the same field but not the same subdivisions. The lack of knowledge will lead to the neglect of problems. A flawed manuscript might be wrongfully accepted for publication. This will bring harm to the prestige of the publisher and worst still the development of science.

• **Mismatching.** To any editor, finding suitable reviewers for a given manuscript is no easy task. Corresponding authors of previously published articles in the related domains from the same journal are often chosen as suitable reviewers. This practice, however, does not necessarily make sense because usually under the same domain, there are many different subfields. Experts of one subfield might not be knowledgeable enough to review and comment on works from another subfield. There have been some solutions proposed to tackle this issue (Anjum et al, 2019; Pradhan et al, 2021b), but the recommended researchers are not always available when invited for the reviewing, leaving the solution not very practical.

• **Conflicts of Interest.** Although the academic community has a rigorous system and strict academic regulations, conflicts of interest do occur from time to time. In the peer review system, reviewers are provided with extensive power and there are ways to abuse it. Reviewers could use missing citations as a rhetorical excuse to require authors to include the reviewers’ own works in the references while their works might not be strongly related to the current paper. Severe examples can also be found as there is loophole in this system that ideas can be stolen. A reviewer of Annals of Internal Medicine plagiarized a manuscript he reviewed and published it in another journal with data fraud at the same time (Laine, 2017). Plagiarism committed in peer review is an extreme example of reviewers abusing their power, but such examples do prove the possible damage the flawed system of peer review can cause.

Academic publishers use peer review to ensure the quality and integrity of science in publication. However, the problems above lead to flawed evaluation and hinder the development of science, which are running counter to the purpose of peer review. To young scientists, the defective system is especially harmful to their academic careers. The difficulty in publication can dampen their enthusiasm for doing research. Peer review is supposed to improve science, but it may now do exactly the opposite.

As we have discussed above, a human-led peer review is prone to making mistakes. With the development of artificial intelligence (AI), computers have been able to defeat the best human players in many fields, including Go game (Silver et al, 2017), Texas hold’em poker (Brown and Sandholm, 2019) and esport Dota 2 (OpenAI et al, 2019). A question should be asked: is AI already well developed enough to review scholarly papers independently?

To answer this question, we propose the concept of automated scholarly paper review (ASPR). In ASPR, manuscript review before publication is completed through computer technology. The review comments and the final editorial decision are generated without human involved. It should be noted that ASPR totally breaks away from the traditional concept of computers being an assistant for manuscript reviewing. Computers in ASPR are designed to complete the whole review process all on their own, playing the full roles of both editors and reviewers.

Shifting the current workload of peer review from human to computers comes with following advantages.

ASPR is capable of overcoming human limitations, both physically and psychologically. Physically, there is a limit to how much information a normal human being can handle. No matter how knowledgeable a person is, one can only grasp part of the total knowledge existing in this world. Psychologically, there is a limit to how objective a person can be. It is almost inhuman to expect a human to remain fair and objective completely and constantly in evaluation. These weaknesses to humans are exactly the strengths of computers. Theoretically, all the knowledge in the world can be gathered by computers to create a unified knowledge base, which can then be used for
information processing by themselves. Computers themselves can not be affected by emotions, hence the non-existence of conflicts of interest in reviewing.

ASPR can tackle the issue of the overwhelmingly increasing volume of submitted manuscripts. According to data from Dimensions, the number of scholarly publications has been increasing constantly from 2011 to 2020, with a total growth rate of 74.9% (Fig. 1). The number of manuscripts posted to preprint platforms such as arXiv is also on the rise year by year. As reported by Lin et al (2020), from 2008 to 2017, the preprints posted on arXiv in the category of Computing Research Repository (CoRR) total 141,961, 77.1% of which are published on peer-reviewed venues. The number of published papers itself is overwhelming enough and to add to this is the similarly enormous amount of those rejected papers which have also gone through the peer review process. To make it trickier, one manuscript generally needs at least two reviewers to counter subjectivity. All these circumstances together pose an overwhelming workload to the peer review system. To human, these figures might look daunting, but to a computer, they are not, because this is what computer is invented for. With proper architectural design and hardware support, computers can reach enormous computing power to review manuscripts in a very short period of time.

ASPR helps researchers improve their manuscripts in a highly efficient manner. In the traditional peer review system, researchers usually need to wait several months before the editorial decision is made. If a manuscript is returned for revision, it needs to be revised based on reviewers’ comments and then be resubmitted for another round of review. This process really takes time. ASPR is different. A manuscript submitted to an APRS system for reviewing can have the feedback given immediately. Such instant response provides researchers with more time to make improvements to their manuscripts. Also, ASPR has learned from the experience of countless human reviewers and is able to measure and evaluate manuscripts in a multi-dimensional way. As a result, apart from being used by the publishers for manuscript reviewing before publication, APRS can serve as an academic writing checker provided to individual researchers in their writing.

ASPR, as a highly integrated and demanding task, is beneficial to many related technologies. The introduction of a new integrated task often relies on related technologies and in turn this new task can drive the development of these related technologies. This is the same case with ASPR. The realization of ASPR can only be achieved with the most advanced technologies in several different fields. Examples include document parsing, document representation, text classification, information retrieval, text generation, etc. The development of these technologies will also drive the creation of more relevant datasets, creating a virtuous circle. At the same time, ASPR will in turn bring more studies into these fields. With the proposal of ASPR, we aim to bring overall progress to science and technology in different fields as a whole.

ASPR can significantly cut down the high cost of time and money in the current peer review. The research conducted by Houghton (2009) studied alternative reviewing models for scholarly publishing from the perspective of economic factors. The cost of time and money in the peer review process was quantified in their research and it was estimated that the average cost to every article was

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3https://app.dimensions.ai/discover/publication
4Data accessed in November, 2021.
5https://arxiv.org/
about 1400 euros.\textsuperscript{6} The majority of peer reviewers are serving as pro bono volunteers, but from this study we can see that the overall cost of peer reviewing is excessively high. Taking into consideration of the sheer volume of academic submission at present and the current price level, the cost of each peer-reviewed article must have increased a lot more. ASPR is a highly economical alternative to the costly peer review process both in terms of time and money. With the application of ASPR, human reviewers can be freed from the increasingly heavy workload to devote more time and energy to their own research; the publication cost can be reduced to a great extent both for the publishers and the authors.

The peer review system is a process with multiple parties involved, generally including an editor-in-chief, a review-editor, at least two reviewers and authors. The overall process of traditional peer review is shown in Fig. 2. Whereas ASPR is a one-stop solution with the computer functioning as the editor-in-chief, the review-editor and the reviewers at the same time. The computer can complete the whole review process independently, from manuscript receiving, parsing, screening, reviewing, commenting, scoring to the final editorial decision making. The pipeline for ASPR is shown in Fig. 3. Some previous studies (Ruan et al, 2018) conducted manuscript evaluation based on extra information. In a way that extra information like citations, altmetric scores and community response of the already published papers were not excluded in the testing of the model performance. ASPR is different. The process of ASPR in this paper is in comply with the reality of peer review. The computer has no less and no more information and metadata of a manuscript as well as the overall external knowledge existing during the peer review period.

In this paper, we review related technologies required at each stage of the ASPR pipeline. Some of them have already been incorporated into the scholarly reviewing process. Some are developed for other purposes and can be employed to achieve ASPR. Further, we discuss the challenges that these technologies have when used for ASPR and look into their future development. In our review, we mainly study English-related technologies. With some modifications, these technologies can be used to process multilingual manuscripts in ASPR.

\textsuperscript{6}This research is based on the price level in 2007.
2 Related work and datasets

Efforts have been made in previous studies to use computers in assisting peer review and improving the editorial work, but their focus only lies in computer assistance leaving a blank in automating the whole process of peer review. Price and Flach (2017) used computers to match manuscripts with suitable reviewers, assemble balanced peer review panels and calibrate review scores. Mrowinski et al (2017) used an evolutionary algorithm to optimize the editorial workflow, greatly reducing the peer review time by 30% without relying on more reviewers. Heaven (2018) demonstrated various AI tools that can help publishers improve the peer review process with computational support in choosing reviewers, validating data, summarizing key findings, etc. Checco et al (2021) explored the strengths, the weaknesses and the uncertainty in using AI to assist the reviewing of research results. Currently, most researchers hold the view that AI is an assistant to editors and reviewers but not a replacement. Table 1 shows the assisting tools for peer review.
Table 1  Existing tools of assisting peer review process

| Name         | Year | Official website                  | Applications                                                                 |
|--------------|------|-----------------------------------|-----------------------------------------------------------------------------|
| CrossCheck   | 2007 | https://www.ithenticate.com/      | Plagiarism checking, improper reference detection, writing scoring          |
| Penelope.ai  | 2015 | https://www.penelope.ai/          | Matching journal request detection, missing references checking, figure citations checking, standard format checking, risk warning |
| ScienceIE    | 2016 | https://scienceie.github.io/      | Key phrases identification and extraction, relationships between key phrases identification |
| Statcheck    | 2016 | http://statcheck.io/              | Statistical data extraction, $P$ values recomputation and consistency checking |
| StatReviewer | 2016 | http://statReviewer.com/         | Numerical errors checking, statistical tests, integrity and quality checking, methodological reporting |
| Recite       | 2018 | https://reciteworks.com/          | Citation match checking, reference format checking, reference stylistic errors checking |
| Scholarcy    | 2018 | https://www.scholarcy.com/        | Article summarization, reference extraction, tables and figures extraction, chapter breakdowns and highlighting |
| UNSILO       | 2018 | https://unsilo.ai/                | Key concept extraction, language quality assessment, journal match reviewing, reviewer finder, manuscript screening |
| SciScore     | 2020 | https://sciscore.com/             | Rigorous standard inspection, data reliability checking, paper scoring     |
| ReviewAdvisor| 2021 | http://review.nlpedia.ai/         | Review generation from eight aspects: originality, substance, replicability, clarity etc. |

This research falls under the general domain of automated evaluation of document quality. A highly similar task to ASPR is automated essay scoring (AES) (Ke and Ng, 2019; Ramesh and Sanampudi, 2021). In the 1960s, Page (1966) released the Project Essay Grade, which later becomes representative of AES system. In this system, the scoring is based on basic linguistic features. Another well-known system is Intelligent Essay Assessor (Foltz et al, 1999). This system grades an essay by making a comparison between this given essay and the outstanding essays stored in the system using Latent Semantic Analysis (LSA) (Deerwester et al, 1990). Educational Testing Service (ETS) developed e-rater (Attali and Burstein, 2004) for the scoring in the Test of English as a Foreign Language (TOEFL). This tool is based on continuously updated NLP techniques and is widely accepted by English language qualification community. An essay is defined as "a short piece of writing on a particular subject, especially one done by students as part of the work for a course" in the Cambridge Dictionary. Compared to an essay, a scholarly paper is normally longer in length and more complex in structure. The most different part is that scholarly papers, or at least those quality ones, should present new ideas or findings. Therefore, the standards in essay evaluation and scholarly paper evaluation should have different focuses. But the techniques used in AES can also work for ASPR. Other applications of automated document evaluation include content assessments on Wikipedia articles (Marrese-Taylor et al, 2019), evaluation of TED talks (Tanveer et al, 2019) and prediction of postgraduate program admission based on the Statement of Purpose (Kanojia et al, 2017). All these systems like AES have related techniques that can be used to achieve ASPR.

To AI research, data is especially crucial. The training and evaluation of research models can not go without data. The realization of ASPR
needs adequate annotation data, such as review comments, review scores, editorial decisions, etc.

NeurIPS is a prestigious conference in machine learning. This conference offers to the public their conference papers along with reviews, meta-reviews and discussion records between the reviewers and the authors. Apart from NeurIPS, reviewing information can also be found in some journals, such as eLife and PeerJ, and also platforms like OpenReview and F1000Research. However, the problem is that most rejected papers are not open to the public, which will lead to data imbalance between accepted manuscripts and the rejected ones.

In addition to using public raw data, some researchers have built structured datasets for research purposes. Kang et al (2018) created the first large peer review dataset PeerRead of scientific papers. This dataset contains 14.7k manuscripts and the corresponding accept/reject labels in top computer science conferences including ACL, NeurIPS and ICLR. It also collected 10.7k pieces of peer review texts written by experts, with 1.3k of them giving aspect scores. This dataset is widely used in automatic paper evaluation research. Plank and van Dalen (2019) constructed CiteTracked, which contains metadata, review texts and citations of 12.3k NeurIPS papers published from 2013 to 2018. Stappen et al (2020) conducted experiments with an undisclosed Interspeech 2019 Submission Corpus. This corpus is the largest single-blind peer review corpus containing over 2k submissions and around 6k textual reviews. However, the research data is kept confidential.

Besides comment generation, scoring and editorial decision making, ASPR also includes other tasks that rely on corresponding datasets. We present these relevant datasets and their corresponding applications in Table 2 with their properties given respectively. These datasets of various domains can be used at different stages of automated review, paving the foundation for the achievement of ASPR. In addition, these datasets also enable aspect performance comparison of tasks within ASPR.

3 Parsing and representation

In general, when submitting a manuscript to an academic venue, the manuscript is required to be formatted in LaTeX or PDF. In traditional peer review, the reviewers first need to use corresponding tools to open the files. In the cognitive process of reading the manuscripts, the content, including texts, tables, figures, mathematical expressions and related metadata, is first taken in by the eyes and then the information flows to the brain for further processing. Similar to the peer review process, the first step for ASPR is to conduct parsing and representation just like a human reviewer selecting a suitable tool to open the file and taking in the information with their eyes before the actual comprehension and evaluation of the content. In this prerequisite step, files of different formats need to be parsed and represented into proper data form before they can be processed by computers.

When it comes to LaTeX files, parsing is relatively easier. This is because LaTeX files is actually well-structured plain text and the files’ structure and content are required to be specified with symbols. Parsing a manuscript in the format of PDF file is more challenging, because a PDF file does not come with structural tags. It takes much more effort to extract data from PDF files while preserving the original layout. Currently, the most commonly used parser for PDF files is GROBID (Lopez, 2009), which is released in 2009, and has been constantly maintained and updated ever since. When it is first released, GROBID mainly performs the extraction of bibliographical data and is later updated for header extraction and parsing, in-text citation recognition and resolution, full-text extraction and structuring, etc. GROBID is a powerful tool in PDF parsing, nonetheless, it is not very good at figures, tables and mathematical expressions extracting, which are almost indispensable to scholarly papers. Efforts have been made to solve these problems. For figure extraction, Li et al (2019b) presented a tool using layout information to extract figures and their corresponding captions. This tool is available online.

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8https://neurips.cc/Conferences/2021/Reviewer-Guidelines
9https://reviewer.elifesciences.org/author-guide/editorial-process
10https://peerj.com/benefits/review-history-and-peer-review/
11https://openreview.net/about
12https://f1000research.com/about
13https://www.eecis.udel.edu/compbio/PDFigCapX
Table 2 ASPR related datasets

| Process               | Name                  | Scale                                      | Content                                                                 |
|-----------------------|-----------------------|--------------------------------------------|-------------------------------------------------------------------------|
| Citation              | S2ORC (Lo et al, 2020) | 81.1M papers with abstract information, 8.1M papers with full text and citations | Metadata, paper abstracts and resolved bibliographic references         |
|                       | unarXive (Saier and Färber, 2020) | 1M documents and 29.2M citation contexts | Full text, in-text citations and metadata                               |
| Generation checking   | SciXGen (Chen et al, 2021) | 205k papers in LaTeX format from arXiv 2012-2020 | Object such as tables and figures, highlighted texts and citation links |
| Language assessment   | LEDAT (Daudaravicius, 2014) | Around 4k papers from 48 journals and books | Paragraphs and tokens                                                   |
|                       | Sentence-level revisions (Tan and Lee, 2014) | 23k papers from arXiv and their different versions | Sentences comparison pair of different versions and strength difference annotation |
|                       | TOEFL-Spell (Flor et al, 2019) | Annotated around 6k spelling errors based on 883 essays | Annotated spelling errors in contexts                                  |
| Novelty detection     | TAP-DLND 1.0 (Ghosal et al, 2018) | 6k online version newspapers | Documents with non-novel or novel annotation                            |
| Review                | PeerRead (Kang et al, 2018) | 14.7k manuscript from ACL, NeurIPS or ICLR | Paper with decisions and pieces of peer review text                     |
|                       | ACL-2018 (Gao et al, 2019) | 4k reviews and 1.2k author responses from ACL 2018 | Review with responses texts and review scores                           |
|                       | CiteTracked (Plank and van Dalen, 2019) | Paper from NeurIPS 2013-2018 | Metadata, review texts and citations                                   |
|                       | Dataset of Hua et al (2019) | 14.2k reviews and 400 annotated reviews | Propositions and type annotation                                       |
|                       | Dataset of Stappen et al (2020) | 2k submissions and around 6k reviews text in Inter-speech 2019 | Metadata, review texts, decisions and scores                           |
|                       | ASAP-Review (Yuan et al, 2021) | ICLR 2017-2020 papers and NeurIPS 2016-2019 papers with reviews | Reference reviews, meta reviews, decisions and paper structure information |
|                       | COMPARE (Singh et al, 2021) | 39 papers with 117 reviews covering 1.8k sentences | Comparison or non-comparison sentences and annotation information       |
| Scoring               | AAPR (Yang et al, 2018) | 19k arXiv papers | Papers and acceptance labels                                           |
|                       | ACL-BiblioMetry (Dongen et al, 2020) | 30k papers from ACL Anthology database | Metadata, full text, citation scores and year-range uniformity          |
| SOTA checking         | TDMSci (Hou et al, 2021) | 2k sentences extracted from 30k ACL papers | Entity of task, dataset and metric                                      |
| Summarization         | Scisummnet (Yasunaga et al, 2019) | 1k scientific papers | Sentences, citation counts and manual summaries                       |
|                       | TalkSumm (Lev et al, 2019) | 1.7k papers with video talks from ACL, NAACL, EMNLP, SIGDIAL 2015-2018 and ICML 2017-2018 | Titles, URLs and the corresponding automatically-generated summaries |
|                       | SciTDLR (Cachola et al, 2020) | 5.4k TLDRs over 3.2k papers | Author-written and expert-derived TLDRs                                |
|                       | FacetSum (Meng et al, 2021) | 60k articles from Emerald journals | Paper and structured abstract                                           |

For table extraction, Zheng et al (2021) proposed Global Table Extractor (GTE) to detect tables and recognize cell structure jointly based on visual context. This framework delivers state-of-the-art (SOTA) performance. For mathematical expressions, Wang et al (2019) presented an unsupervised font analysis-based method to extract them from PDF files.

After parsing the submitted files, the next step in ASPR is to represent the structured data in...
suitable forms. For text, the common representation method is feature vector representation. In 2013, Mikolov et al (2013) published the technique word2vec, which converts words into vectors efficiently. There are two methods for learning representations of words in word2vec: the Continuous Bag-of-Words (CBOW) architecture and the Continuous Skip-gram architecture. CBOW predicts words based on the surrounding context, while in the Continuous Skip-gram architecture, the given words are used to predict the surrounding context words. Despite being a great technique of natural language processing (NLP), word2vec is not flexible enough to process polysemous words, i.e. words with multiple meanings, as it only generates a single embedding representation for each word or phrase. To produce more semantic-rich word embeddings, Peters et al (2018) proposed a bidirectional language model ELMo, which was pretrained on a large amount of text data. Unlike word2vec, when computing word representation for given words, this model takes into account the context, either at sentence or paragraph level, for each occurrence of the words. This way words are allowed to have separate embeddings for different meanings. Similar to ELMo, BERT (Devlin et al, 2019) is also a pretrained model, but it uses Transformer (Vaswani et al, 2017) to generate representations for words. BERT is then use as the base for many later-come pretrained language models (Qiu et al, 2020). This makes a significant change in the representation of words, sentences, paragraphs and documents and ushers in a new era for NLP.

For image representation, Convolutional Neural Network (CNN) (LeCun et al, 1989) is the classic and commonly used method. AlexNet is a typical deep architecture with 8 CNN layers. With its much deeper architecture and better performance, AlexNet proves that larger and deeper neural networks can better extract image features (Alex et al, 2012). However, as the number of layers increases, the risk of vanishing or exploding gradients also goes up. ResNet is designed by He et al (2016) for these problems and it is proved to be an effective solution. ResNet and other networks that based on it are popularly used for image feature extraction. Recently, inspired by the successful application of Transformer in NLP, Dosovitskiy et al (2021) used Transformer directly and achieved outstanding performance. With plentiful technologies for parsing and representation, the submitted files are prepared for the computers to process the content for further reviewing.

4 Screening

Editorial screening is the initial step of academic reviewing that decides whether the submitted manuscript should be sent for further reviewing. According to data from Nature, most of the manuscripts are desk-rejected without being sent out for external review with a desk-rejection rate of approximately 60%. Another report shows that around 80% of the manuscripts submitted to Nature Microbiology are already rejected after screening. In order to cope with the overwhelmingly large quantities of submissions, the top AI conference International Joint Conferences on Artificial Intelligence (IJCAI) also designs a similar mechanism called summary-rejects. At the screening stage, the detailed content of the manuscripts will not be put under close scrutiny. The manuscripts are mainly checked for their formats, topics and plagiarism, etc. to ensure conformity to the style guidelines and instructions as well as the aims and scope of the journal. Most work can be completed by AI sufficiently and many publishers have been using AI in assisting screening.

4.1 Format examination

It is the researchers’ responsibility to fulfill the requirements of the academic venues in their preparation for submission. This is the most basic skill of academic literacy that researchers should acquire. Therefore, format checking is also the basic step in screening to filter out unprofessional submissions with formatting issues. Most format checkers are based on document parsing tools. The PDF format is ubiquitous in academic submission. Format checking for PDF submissions is mainly targeted at the layers, fonts, length, etc., regardless of the content. One example is PDF eXpress from IEEE. For submissions in
unstructured document format, submissions can be parsed to check their differences in formatting with the standard template, for example the American Psychological Association 7th edition (Association, 2020). Lu and Liu (2014) used the XML format node template tree to detect formatting issues automatically. The model compares the format feature tree of a given paper with that of a template document and checks for the differences.

4.2 Plagiarism detection

Plagiarism is a serious academic offense, which should be detected at the earliest stage of reviewing as possible. Compared to other techniques involved in ASPR, plagiarism detection has yielded more mature methods, because of its early start in academic reviewing. Instead of solely relying on the surface string similarity, Osman et al (2012) used semantic role tagging (SRL) for plagiarism detection. Abdi et al (2015) combined both semantic and syntactic information to detect external plagiarism. External Plagiarism Detection System (EPDS) (Abdi et al, 2017) made further improvements by incorporating SRL technology, semantic, syntactic information and content word expansion approach into the model. This method can detect multiple kinds of plagiarism, such as paraphrasing, sentence transformation and word structure changing. Sahi and Gupta (2017) measured the semantic similarity between scholarly papers by computing the similarity of their corresponding topic events, which are the combination of multiple information profiles of the papers. This method can efficiently be used for plagiarism detection. Almja et al (2020) designed a more thorough plagiarism detection system, incorporating semantic knowledge like Dice measure, path similarity and depth estimation measure to compute the resemblance with different weights assigned.

Apart from monolingual plagiarism, cross-language plagiarism is becoming a growing threat to the academic integrity. This type of plagiarism occurs when a paper or fragment is translated from another paper or fragment written in a different language without proper citation. The detection of cross-language plagiarism is more complex and less explored. Elhsan and Shakery (2016) proposed a keyword-based approach to multilingual plagiarism detection. In this method, text is segmented based on different topics for the computing of local similarity. Roostae et al (2020) further proposed a method combining concept model with bag-of-words model to make use of both concept and keyword information with dynamic interpolation factor. This method achieved outstanding results in German-English and Spanish-English cross-language plagiarism detection. Gharavi et al (2020) introduced a two-step sentence-by-sentence comparison method to detect cross-lingual plagiarism. Firstly, a comparison is conducted between sentence representations with semantic and syntactic information to measure their similarity for candidate plagiarized documents. Secondly, parameter tunings both online and offline are employed to filter out actual plagiarized documents.

In addition to the plagiarism detection of text, it is equally important to check the images for plagiarism and forgery. Eisa et al (2019) identified similar semantics in graphics and detected structural changes with image technology for graphic plagiarism detection. Eisa et al (2020) studied the underlying features of graphics and proposed a more in-depth method, in which the graphic components are analyzed to obtain the meaning of the graphic. Meuschke (2021) conducted plagiarism detection by combining the detection of textual content and all other non-textual content for higher efficiency.

4.3 Machine generation detection

With the development of natural language generation (NLG), some programs are designed to generate research papers with figures, graphs and citations included. One famous example is SCIGen.\textsuperscript{18} There are cases of some researchers using these programs to generate papers for academic publishing. Labbé and Labbé (2013) detected that 89 papers generated by SCIGen have been published and indexed in several prestigious academic venues. Under these circumstances, identifying machine-generated submissions should become an indispensable part of screening. Amancio (2015) identified randomly generated nonsense in the form of research papers by creating a complex network through modeling on text. This network

\textsuperscript{18}https://pdos.csail.mit.edu/archive/scigen/
achieved at least 89% accuracy in machine generation detection. One of its contributions lies in that it proves that network features can be used to identify randomly generated meaningless papers. Nguyen-Son et al (2017) used statistical information to identify machine-generated text based on the differences in word frequency. Cabanac and Labbé (2021) designed a paper generation detector based on syntax rules, which achieved 83.6% detection precision in recognizing SCIGen-generated papers.

4.4 Article type recognition

Academic journals publish different types of articles, majorly including original research articles, review articles, commentaries, short reports or letters, etc. Some journals only accept original research articles, some might only accept review papers and some might publish multiple types of articles. Screening submissions for the right article types is basically a task of document classification. Conventional document classifiers are often based on traditional machine learning methods. Examples include Bayes classifier (Nigam et al, 2000) and Latent Dirichlet Allocation (LDA) (Hingmire et al, 2013). As deep learning models are proved to deliver better performance with the use of semantic information, neural network-based methods have become the mainstream way for document classification. The publishing of recurrent convolutional neural networks (Lai et al, 2015), hierarchical attention networks (Yang et al, 2016), GraphCNN (Peng et al, 2018) and BERT (Adhikari et al, 2019) has gradually improved the performance of document classification. These are all transferable frameworks and can be used for recognizing article types at the screening stage if corresponding labeled datasets are provided.

4.5 Scope evaluation

Every journal has its own aims and scope. At the screening stage, editors need to check the submissions to see whether they conform to the journals’ objectives and whether the content is what the journal wants to deliver to its audience. The survey conducted by (Froese and Bader, 2019) reveals that a significant cause for desk-rejection is the mismatching with the journal’s aims and scope. Researcher Dr. Tirthankar Ghosal has done a large number of studies on the mismatching between submissions and the journal’s aims and scope. He designed a binary classification model to help editors and authors to determine whether a manuscript matches with a journal (Ghosal et al, 2019b). He also used a multi-modal deep neural structure to identify mismatched submissions (Ghosal et al, 2019a). In 2020, he further found that titles and author profiles are more helpful in determining whether it is a good match between the manuscript and the journal. By doing so, mismatching of submissions and journals can be better identified (Ghosal et al, 2020). In addition, the technology proposed for a related task of academic venue recommendation can also be employed here. Wang et al (2018) was an early study into academic venue recommendation. In this study, abstracts of papers were crawled from web pages to train a chi-square feature selection and softmax regression hybrid model for recommendation. Content and Network-based Academic VEName Recommender system (CNAVER) (Pradhan and Pal, 2020) and Convolutional layer, LSTM with Attention mechanism-based scholarly VEName Recommender system (CLAVER) (Pradhan et al, 2021a) are two recently proposed network-based systems with the use of attention mechanism (Bahdanau et al, 2015). In these two similar systems, abstracts and titles are employed to recommend academic venues.

5 Main review

In the traditional peer review process, after clearing the initial screening, submissions will be sent out to external experts for review. Many publishers have developed peer review guidelines for the references of the reviewers. In ASPR, the main review is conducted instead with computers taking up the workload from external experts. The focuses of the main review stage are designed based on the thorough peer review guidelines provided by the top computer science conference NeurIPS 2021.19 In the guidelines, different aspects that the reviewers should focus on during the examination of the manuscripts are listed as follows: originality, quality, clarity and significance. In this section, we review the related

19https://neurips.cc/Conferences/2021/Reviewer-Guidelines
technologies that can enable ASPR based on the four aspects above.

5.1 Originality

Originality, or novelty is one of the most important criteria for scholarly publication. In the academic context, originality does not necessarily mean new inventions or discoveries. A study might not be able to reinvent the wheel in a certain field, but if it is a new idea that can move other ideas forward for incremental amount of advance in current knowledge, it should be considered a study with originality. From this aspect, originality is defined as recombining the components of pre-existing knowledge in an unprecedented way (Schumpeter, 1939; Nelson and Winter, 1982).

Based on this definition, reviewing a research paper for originality can be thought of as looking for the recombination of knowledge. Taking into consideration that the knowledge recombination is based on what can be found in the references section, the originality of a study can be evaluated based on the novel combinations of reference papers. Dahlin and Behrens (2005) proposed a definition of radical invention and designed a measurement method for an invention’s radicalness using backward citations. In this method, novelty was measured by quantified citation similarity. A radical invention should have a unique citation structure distinct from those of the existing inventions. Matsumoto et al (2021) later developed this measurement method towards a larger-scale novelty analysis. They only used bibliometric information for novelty measurement of papers in various research fields, countries and time periods. Uzzi et al (2013) examined 17.9 million scientific papers from the Web of Sciences (WOS) to study the relations between the combination of a paper’s references and its citation counts. Their findings suggest that an influential paper is highly likely to have one unusual citation that was not commonly cited in that certain field. This can be the basis of distinguishing papers with originality from those without. Shibayama et al (2021) designed a more integrated method, making use of both the citations and content of a paper. In this method, the semantic distance of references is quantified to determine the novelty of a given paper.

There are also methods to evaluate papers’ originality from other perspectives. Park and Simoff (2014) introduced a method of novelty identification based on a generative model. In this method, the novelty of a paper is rated according to the likelihood of a paper being machine-generated. This is enabled based on the proposition that if a paper have great similarity with any machine generated paper, then it is less likely to be a novel research paper. Amplayo et al (2018) introduced a graph-based novelty detection model. In this model, authors, documents, keywords, topics and words are used for feature representations to compose different graphs. Different papers added to the graphs will lead to different changes on the graphs. A paper that makes greater changes can be regarded as a paper with greater novelty.

5.2 Quality

Academic writing has its own established rigorous norms. In ASPR, quality of a paper is evaluated from three aspects: language, data and referencing. Language quality refers to linguistic issues including spelling, grammar and style. The assessment of data quality lies in its validity. For referencing, the manuscript will be checked to decide whether sources are cited properly.

In terms of language quality, spelling and grammar issues are the most fundamental parts. English is the most common language of academic publishing. Authors who speak English as their mother tongue can still make spelling or grammatical mistakes, let alone those authors that use English only as their working language. These are the most common mistakes and are also relatively easy to be pointed out and to be corrected. In addition to these two types of common mistakes, there are also sentences that might be grammatically correct but make no sense. Their existence in the published venues can cause confusion or distraction to readers in their reading and worst still can raise doubts in the rigor of the research as well as the publication.

The simplest way to check the spelling errors is to have the word looked up in the speller lexicon, which can be enabled by algorithms like n-gram or Levenshtein distance. In this way, the detected spelling errors can also be corrected with the right version in the lexicon. Examples include the research conducted by Zamora
et al (1981) and Hodge and Austin (2003). However, these dictionary-based methods are highly time-consuming and at the same time rely heavily on the size of dictionaries. In addition, they are not capable of more complex checking of word types. For this reason, Ahmad and Kondrak (2005) tried to use the expectation maximization algorithm (Dempster et al, 1977) to learn the edit distance weight directly from the correction log of the search without checking the lexicon. For a more advanced deep learning method, Whitelaw et al (2009) utilized big data in training to build seq2seq spelling error detection models to achieve more efficient detection and correction. Most of the tools for spelling detection are developed with datasets manually created and lacking context, so Flor et al (2019) constructed a real dataset with contextual spelling errors in papers and designed a minimally supervised context-aware approach for spelling error correction.

Grammar check is the foundation task for grammar correction. It was the focus of both the CoNLL-2013 (Ng et al, 2013) and CoNLL-2014 (Ng et al, 2014) shared tasks on grammatical error correction. Like the way spelling check develops, the early methods in grammar check are basically rule-based and data-driven. The limitation of these methods is that they can only detect certain types of grammatical errors, like erroneous prepositions (Chodorow et al, 2007; Felice and Pulman, 2013) and erroneous determiners. In order to bypass the dependence on annotation data, Liu and Liu (2017) trained a neural network-based model for grammatical error detection using unmarked error-free generated data. Their research showed that generated errors were also effective for automatic grammatical error detection. Deep learning is also applied to grammatical error detection. Rei and Yannakoudakis (2016) treated grammatical error detection as a sequence marking task and used Bi-LSTM (Graves and Schmidhuber, 2005) to predict the errors tagging. Bell et al (2019) made use of contextual word representations to represent words, learning semantic and component information in different contexts, and integrated the representation into the error detection model to improve the detection performance. Wang and Tan (2020) used the contextual information to represent words with pre-trained BERT-based word embeddings. A synthetic grammar error corpus was also employed. They further designed a positive and negative sample pair training mechanism to capture differences for more effective grammatical error detection. Hu et al (2021) constructed a neural network-based correction model for English grammatical errors. In their method, word vector features are used for feature representations instead of direct one-hot encoding to reduce semantic redundancy. In addition, they try to further compress article features for optimization using clustering methods.

Academic writing requires compliance with the formal and rigorous writing style, which is significantly different from other forms of writing. Papers written in overly casual style may come across as unprofessional or questionable. Daudaravicius (2015) proposed an Automated Evaluation of Scientific Writing Shared Task in 2016. Its goal was to access whether the style of a given sentence complied with the academic writing norms. For this shared task, the best performance was achieved by an attention-based encoder-decoder model developed by Schmaltz et al (2016). The second best results were delivered by a convolutional neural network model (Lee et al, 2016) that used both word2vec and GloVe (Pennington et al, 2014) embedding methods. Sanchez and Franco-Penya (2016) employed Tree Kernel-SVM (Cortes and Vapnik, 1995; Collins and Duffy, 2002) based methods and achieved the third best performance.

Data in scholarly papers speak greatly to its quality. As such, data validation is of great importance in the peer review process to uphold academic rigor. A common method for data validation in scientific research is the use of $P$ value. In academic disciplines like psychology, and econometrics, a considerable amount of data are usually involved in the research. Validating data for this kind of research through the calculation of $P$ values is formidably laborious for human reviewers. To automate the calculation for data validation, Nuijten and Polanin (2020) used statcheck to identify statistical inconsistency. Statcheck can be used as an R package or in a browser to automatically extract statistical research results from PDF or HTML files and recompute the $P$ values. In addition to the original use of statcheck for statistics in APA style, this study further explored the use of statcheck in meta-analyses. StatReviewer is an automated reviewing tool developed to examine whether statistical methods are appropriately used in scientific papers. This tool was
used in the biological field, to check whether papers in this field followed the reporting standards Consolidated Standards of Reporting Trials (CONSORT) (Heaven, 2018) for randomized controlled trials. This tool is now used in the Aries system for actual application in peer review.20

Proper referencing gives scholarly papers credibility and authority. Poor citation practices are a cause of concern to the authors’ academic ability and can even become a suggestion of potential plagiarism. One poor citation practice is that authors fail to provide citations to relevant major studies. For the checking of referencing quality, techniques used in citation recommendation (Ma et al, 2020; Ali et al, 2020) can be applied to detect poor citation practices. Anderson et al (2011) also proposed several methods to access whether a cited paper has its content properly presented in the citing paper.

5.3 Clarity

Clarity in the peer review process is checked based on the organization of the manuscript. It includes two aspects: textual clarity and visual clarity.

There are multiple methods proposed to quantify textual clarity for academic writing. Persing and Ng (2013) worked on the clarity scoring for student essays. They first build a dataset with student essays annotated with clarity score and clarity error type. Based on this dataset, they developed a clarity scoring model through a learning-based approach. Apart from assigning clarity scores, this model can also identify clarity error types. One important aspect of text clarity is text consistency, and a number of studies have been conducted to determine text consistency. Farag and Yannakoudakis (2019) designed a hierarchical deep learning framework to generate a coherence score. This framework was trained in a multi-task manner to measure coherence at a document level. Muangkammuen et al (2020) used local coherence between adjacent sentences to score text clarity.

One common way to achieve clarity in academic writing is to structure the paper in a certain layout. There are studies making efforts to evaluate the organizational clarity of scientific papers based on their writing layout. For most scientific papers, the IMRaD is a standard structure, which includes four main sections: Introduction, Methods, Results, and Discussion. Agarwal and Yu (2009) studied multiple approaches to the sentence-level classification of biomedical articles into those four IMRaD sections. In their study, a SVM classifier achieved the best results for automatic classification and annotation of sentences in biological articles.

Figures are an essential part of scholarly papers that visually provides clear and intelligible support to academic arguments. In peer review, figures also need to be checked for image-text consistency. Similar works can be found in the field of social media. Zhao et al (2019) proposed a multi-modal binary classification model based on sentiment analysis to predict whether the content of an image is consistent with the corresponding text. Then Springstein et al (2021) went further to quantify the image-text consistency by combining SOTA approaches from NLP and computer vision (CV).

5.4 Significance

As written in the Reviewer Guidelines of NeurIPS 2021, when evaluating a paper for its significance, the reviewer should base on the following questions, "Does the submission address a difficult task in a better way than previous work? Does it advance the state of the art in a demonstrable way?" Significance of an scholarly paper can be understood as the impact it makes. From this perspective, evaluating the significance of a paper can be achieved by evaluating its impact, which to a great extent is reflected in its citation counts. A paper with major impacts naturally and actually earns more citation counts. Therefore, in ASPR, citation count prediction can be used to automate the evaluation of significance. Apart from this, the impact of some studies is also decided by the performance of their proposed methods. In this sense, significance evaluation can also be achieved by comparing the method performance with the benchmarks to see whether the research method achieves SOTA results or not.

Despite of being a controversial measure for the impact of scholarly paper (Brody et al, 2006; Wang, 2016), citation count remains a popular method for this task. Fu and Aliferis (2008)
used titles, abstracts, keywords and bibliometric features like the citation counts of the authors’ previous works and authors’ academic background as feature representations. The task of citation count prediction is completed as a classification task using SVM. This method delivered outstanding results, but using bibliometric features for citation count predictions in ASPR can cause bias against scholars in their early career and in favor of scholars from prestigious institutions. In addition to this, the main body of the research paper will be left out using this method, which will fail to deliver a thorough and all-around review of scholarly papers in ASPR. The deep-learning model designed by Ma et al (2021) is one of the pioneering studies to incorporate the overall content. It extracted semantic information from the metadata text of papers first using doc2Vec (Le and Mikolov, 2014) and further using Bi-LSTM with attention mechanism for high-level features. This model achieved SOTA performance, outperforming the baseline models.

One of the important and more objective aspects of significance evaluation lies in the evaluation of research results. For scientific research papers that propose new ideas, this can be achieved by benchmarking, i.e. conducting performance comparison with alternative benchmark models. In ASPR, SOTA evaluation is the performance evaluation of a paper conducted through making a comparison with benchmark models. Authors often claim that their results reach the state of the art, but conducting SOTA evaluation to check their claims is no easy task. To enable SOTA evaluation in ASPR requires a thorough collection of all the existing benchmarks and this collection needs to be updated constantly to take in newly-made benchmarks.

Papers With Code is a prestigious platform gathering papers and source code in machine learning. This platform also collects benchmarks respectively for different tasks in different domains through crowdsourcing. This collection leads to the creation of the PWC Leaderboards dataset. This method, developing from natural language inference, learns the similarity patterns between labels and paper’s content at word level to automatically extract tasks, datasets, evaluation metrics and scores from published scientific papers. They then constructed a new corpus TDMSci composed of NLP papers manually annotated with the task, dataset and metric at document level. Based on this corpus and using the triples of the task, dataset and metric, they further designed a TDM tagger through data augmentation for automated extractions in the NLP domain (Hou et al, 2021). Kardas et al (2020) developed an machine learning tool AXCELL to extract results from research papers automatically. In AXCELL, the results extraction task is divided into three subtasks: table type classification, table semantic segmentation and linking results to baselines in leaderboards.

With these extraction methods, datasets of SOTA benchmarks in different domains can be built for a systematic SOTA comparison. Existing SOTA datasets can also be included to enrich these datasets. When ASPR receives a new submission, the system will extract the triple of core tasks, datasets and metrics of this study from the manuscript. This triple will then be compared to the triples of SOTA benchmarks to determine whether the method performance in this study matches or exceeds the SOTA benchmarks in the certain domain. The significance of a study is reviewed based on this comparison.

6 Review report generation

A review report is the end product of the peer review process. Constructive review reports provide valuable feedback to authors for them to improve their manuscripts. A comprehensive review report should contain a summary of the manuscript, comments highlighting its strength and weakness, reviewer scores to quantify the evaluation and the final editorial decision on accepting or rejecting the manuscript. Review report generation is of great importance in ASPR.

6.1 Summarization

According to the Reviewer Guidelines from NeurIPS that ASPR is based on, as well as the

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21 https://paperswithcode.com/sota
requirements of most other peer review guidelines, a review report should first include a summary section, briefly outlining the manuscript and its main contributions. This summary presents the basic knowledge and understanding of the reviewer on this manuscript. In ASPR, this is a task of automated text summarization, a common task in NLP. Mohamed and Oussalah (2019) innovatively adopted a Wikipedia graph-based approach to build a summary generation model. In this model, explicit semantic analysis (ESA) is used to label words and represent them as vectors with weighted Wikipedia concepts. Semantic role labeling (SRL) is adopted to identify semantic arguments based on the predicate verbs in the sentence. The summarization is achieved by the construction of a concept graph representation on semantic role-based multi-node vertices. A neural abstractive summarization framework newly proposed by Pilault et al (2020) is capable of producing abstractive summaries for long documents. The hybrid framework is composed of a hierarchical encoder-based extractive model and a Transformer language model. An initial extractive step is undertaken to reduce the context for the next abstractive step. The input to the Transformer language model is reordered to identify the introduction, the extracted sentences, the abstract or summary and the rest-of-the-article. This way the hybrid model is more focused for the summarization task and outperforms baseline methods on the arXiv, PubMed and bigPatent datasets. Gupta et al (2021) conducted a study to improve model performance on the task of scientific article summarization and proved in experiments the advantages of transfer learning via intermediate pretraining for this task.

6.2 Comment generation

The second section of a review report should present reviewer comments on the strength and weakness of the manuscript. Automatic comment generation for scholarly papers is a challenging task for ASPR. There exists already relevant research on this field, but it remains inadequate. Many existing studies have adopted an NLP approach in the generation of review text for scholarly papers using slot filling models. In NLP-enabled slot filling, the models generate review text by filling in a preset review format with extracted information. Bartoli et al (2016) proposed a corpus-based method to generate review based on the full text of a paper and a preset overall evaluation. Wang et al (2020) designed a knowledge-driven end-to-end framework ReviewRobot to automatically generate knowledgeable and explainable scores and comments. They achieved this by comparing the knowledge graphs built from the given paper and a large amount of other papers in the same domain. Yuan et al (2021) built a paper dataset and annotated the review comments for different aspects, so as to train a review generation summary model by using BART (Lewis et al, 2020). Experiments show that their model is capable of generating comprehensive comments, but they considered that more improvements were needed for this task.

In spite of the deficiency in the research into review generation for scholarly papers, some efforts have been made in relevant tasks, including recommender system, customer review generation and news article review generation, etc. With proper training corpora, neural network-based methods in these studies can be applied to generate review comments for scholarly papers. Baroni (2019) proved in experiments that syntactic rules can be captured through deep learning and further used to generate meaningful natural-language sentences. Apart from syntactic generation methods, topic and semantics are also used for review generation. Li et al (2019a) proposed an aspect-aware generation method and made full use of semantic, syntactic and contextual information. In this aspect-aware model, the reviewing of each aspect is set as a main task and this main task is assisted by auxiliary tasks. Two decoders are used in their model with one predicting a structural draft and another filling in words. Through this aspect-aware coarse-to-fine generation process, the model delivers a great performance in review generation in terms of overall generation quality, aspect coverage, and fluency.

6.3 Scoring

Scores to quantify the review comments are generally included in the review report. In ASPR, automated paper scoring is the second to last and also a crucial stage that can only be completed based on all the results from the previous stages.
There are relevant technologies that can be used to fulfill this task.

The task of automated paper scoring is considered by most researchers as a multiclass classification problem. Qiao et al (2018) designed an attention-based modularized recurrent convolutional network to produce scoring on various aspects of scholarly papers, including appropriateness, clarity, originality, etc. Experiments showed that this method outperformed two baseline methods on the average quadratic weighted kappa. In addition to scoring different aspects of a paper, there are also methods proposed to produce an overall score directly. Leng et al (2019) introduced an attention-based framework DeepReviewer that assigns scores for papers on OpenReview based on the semantic, grammatical and innovative features combined. This framework is composed of a hierarchical recurrent convolutional neural network, a customized unsupervised deep context grammar model, an unsupervised high-dimensional spatial density-based innovation model and an attention layer to generate the final review score. Experimental results showed that DeepReviewer outperformed many baseline models. Li et al (2020) presented a multi-tasking shared structure encoding method that can choose shared network structures and auxiliary resources in an automatic way. This method is especially helpful in the case of insufficient data.

6.4 Decision making

The prediction task of review decision on the acceptance or rejection of a manuscript can be recognized as a binary classification problem. Yang et al (2018) proposed a model of modularized hierarchical convolutional neural network to predict the acceptance result. This model was trained on positive samples of published arXiv papers and negative samples of unpublished arXiv papers. Experimental results showed that the model achieved 67.7% accuracy in its prediction. Additionally, In the paper, the influence of authors, abstract, conclusion and title on the prediction was also analyzed and authors were found to have greater impact on the results. Skorikov and Momen (2020) built a machine learning-based model to predict paper acceptance in prestigious AI conferences. In this study, a comparison was made between seven different machine learning algorithms. Random forest (Breiman, 2001), a classifier consisting of many decision trees delivered the best results. The model that used this classifier achieved an accuracy of 81% on the PeerRead dataset. Vincent-Lamarre and Larivière (2021) analyzed the full text of both accepted and rejected manuscripts to explore their semantic, lexical and psycholinguistic feature differences. They found that the readability of accepted manuscripts was lower than that of rejected manuscripts. By using a logistic regression of bag-of-words to predict the peer review outcome, they found that their model performed the best benchmark model when using the introduction text for prediction. Bao et al (2021) proposed an algorithm to build up decision sets for acceptance prediction of scholarly papers in a simple, effective and interpretable way.

Apart from the textual content of a scholarly paper, its structure and layout also make a difference in its quality (Sun and Linton, 2014). Huang (2018) treated paper review as image classification and trained a classifier that built on deep convolutional neural networks to predict the acceptance results for scholarly papers based solely on their visual features. They further provided tools that directly learned the mapping in the image space to provide authors with suggestions to enhance their papers visually. Moreover, visual features were also combined with text features to conduct document quality evaluation in the study of Shen et al (2019). They used Inception V3 to generate visual feature embedding of a manuscript’s snapshot and Bi-LSTM to produce textual feature embedding. The two embeddings were used to train a classification model that delivered the SOTA performance on the PeerRead dataset.

7 Current challenges

In the sections above, we explore the possibility of achieving ASPR with existing technologies. Through the reviewing, relevant technologies are found available at each stage of ASPR. Nonetheless, ASPR, as a high demanding task at its very early stage, is in the face of many challenges. In this section, we will discuss some of the major challenges.

- Imperfect document parsing and representation
As reviewed in Section 3, there are already related technologies available for document parsing and representation to achieve ASPR, but necessary improvements are still needed to be made. First of all, the accuracy in the parsing of PDF files needs to be improved. Currently, existing parsers are highly capable of extracting content and structure from PDF files, but they still fall short in the face of some special characters and unusual branches of typography. To live up to the rigor of academic reviewing, parsers used in ASPR should not be allowed to make even one punctuation error. However, this is still not realized at the very moment. A compromise solution will be requiring the writing on LaTeX and the submission of all related LaTeX files.

Second, the representation of long documents needs to be refined. Scholarly papers are generally of great length. However, with the current presentation methods, long documents can only be poorly represented because of their length. Available long document representation methods demand powerful hardware and are computationally ineffective. This task is greatly in need of further study. Last but not least, parsing of other types of resources, like videos, websites and source code, also needs to be developed. With the advancement of technology, the content of academic writing is extended to include more supplemental materials, such as demonstration videos, related websites and corresponding source code. To cope with the new changes, multi-model parsing has become a hot spot in recent studies (Zhang et al, 2020; Uppal et al, 2022). In ASPR, computers should be able to review all different types of data, which can only be enabled by multi-modal parsing technologies.

- **Inadequate data**

Through our review, we can see that there are indeed quite a few datasets available for ASPR. But it is still far from being enough and data insufficiency is still a major problem in ASPR. For one thing, existing datasets do not cover all the fields in academic studies. The vast majority of them only focus on computer science, since it is the field that is the most closely related. The ideal dataset to achieve the best performance in ASPR within the interdisciplinary trend should be a complete collection of all the papers from all different domains. Moreover, these data need to be structured in a predefined manner for machine learning. There are four main review dimensions in ASPR, which are originality, quality, clarity and significance. Each dimension shall be treated as a sub-task with corresponding datasets provided. This means that the review comments need to be labeled and segmented based on the content so as to build these corresponding datasets for the four review dimensions. Most of the available review comments, like those on OpenReview, are usually in plain text without content labels, therefore efforts are needed to create separate sub-datasets for each review dimension.

To add to the problem of data insufficiency is data imbalance between accepted papers and rejected papers. Existing datasets are mostly composed of peer-reviewed accepted papers. With these datasets, computers can learn to recognize papers of good quality. However, for those papers with insufficient quality, computers lack enough learning materials to identify what are bad scholarly papers. Some platforms, OpenReview for example, provide the public access to rejected papers and the review comments on them, but most rejected papers are not made public, especially those papers that are desk-rejected. Some datasets like PeerRead do claim to include rejected papers. But it is hard to be sure whether these papers are really peer-reviewed and rejected as it is not confirmed officially by the academic publishers.

"If you build a decision making system based on the articles which your journal has accepted in the past, it will have in-built biases" (Heaven, 2018). Data imbalance gives rise to even severer big data bias. The current ASPR is largely enabled by deep learning and big data, which usually means building models that are trained on certain datasets. For one thing, computers might not be able to identify papers with great novelty as these papers are in minority and deviate from the learned patterns of quality papers. Human reviewers with knowledge and experience might recognize these papers through logical reasoning, but computers will tend to reject such papers as they are off the beaten track. For another, computers trained
with imbalanced data are more capable of recognizing quality papers and are less sensitive to detect flaws in the manuscripts. This can lead to inappropriate acceptance of unqualified papers.

- **Defected human-computer interaction**
  The interactions between reviewers and authors are indeed at the core of the whole peer review process. A manuscript might be accepted, revised or rejected in traditional peer review. These decisions are made by the editors majorly based on the review comments and also in some cases the interactions between the reviewers and the authors. These interactions are especially important for those manuscripts that are revisions. In the case of those manuscripts that are revisions, usually after the first round of peer review, authors of these manuscripts will be provided with feedback from the reviewers, based on which they can make proper revisions to improve the manuscripts. In this review process, both the reviewers and the authors should communicate with each other in order to properly address all concerns about the manuscript. These interactions provide the editor with important information for the final editorial decision on whether a paper should be accepted for publication or not. In ASPR, technologies required for interactions between the ASPR system and the authors are still not mature enough. Therefore, in the early form of ASPR that we propose in this paper, interactions between the computer reviewers and the authors are not included. If a manuscript is rejected by the ASPR system, after making revisions based on the computer-generated comments, the author can submit the revised manuscript to ASPR for reviewing as a new manuscript.

- **Flawed deep logical reasoning**
  Peer review is a highly demanding task for reviewers’ reasoning ability. Reviewers need to read through the whole manuscript to scrutinize the consistency and soundness in the study and the writing. Some examples of the issues that need to be assessed by reviewers with strong reasoning ability include: are the methods used able to answer the research questions; do the conclusions match the research results and the research aims? To answer these questions, reviewers are required to be knowledgeable in a certain field and capable of logical reasoning. Induction, abduction and deduction are all closely involved in the peer review process, making it an error-prone process. Errors here mean that those logical flaws are hard to be spotted. For human reviewers, vilifying a study’s consistency and soundness through logical reasoning is no easy task. For computer reviewers, it is even more so. To achieve this part in ASPR relies on the full realization of automated reasoning. There are related studies (Antoniou et al, 2018; Chen et al, 2020; Storks et al, 2020), but there is still a certain period of development to be used for ASPR. Besides, academic studies are trending toward an interdisciplinary future. The integration of knowledge from multiple fields also poses greater difficulty to the knowledge-based logical reasoning of computers.

In summary, the major challenges hindering the full realization of ASPR are also the major issues in certain subfields in AI. From this, we can see that ASPR is an advanced integration of AI technologies. Its realization and the new era of strong AI will come hand in hand.

8 Conclusion
In this paper, we review the relevant literature and technologies in an attempt to answer the question that whether AI is already well developed enough to review scholarly papers independently. To answer this question, We propose the concept and pipeline of automated scholarly paper review (ASPR). Through our reviewing, we found that there are already corresponding technologies and resources that have been applied or can be applied to each stage of ASPR for its basic realization. Taking into consideration of the surging number of manuscripts and the steady development of relevant studies, ASPR is evaluated to be of great potential and feasibility. We further discuss the current challenges hindering the full realization of ASPR. The major challenges in its development lie in imperfect document parsing and representation, inadequate data, defected human-computer interaction and flawed deep logical reasoning. These challenges can be properly addressed with the development of AI, which will usher in the new era
of strong AI. In its full realization, computers will be able to carry the onerous reviewing workload for humans and both the research and publishing circles will benefit greatly from ASPR. Before its full enabling, ASPR will continue to coexist with peer review in a reinforcing way for scholarly publishing.

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