Understanding and Predicting Retractions of Published Work

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Abstract

Recent increases in the number of retractions of published papers reflect heightened attention and increased scrutiny in the scientific process motivated, in part, by the replication crisis. These trends motivate computational tools for understanding and assessment of the scholarly record. Here, we sketch the landscape of retracted papers in the Retraction Watch database, a collection of 19k records of published scholarly articles that have been retracted for various reasons (e.g., plagiarism, data error). Using metadata as well as features derived from full-text for a subset of retracted papers in the social and behavioral sciences, we develop a random forest classifier to predict retraction in new samples with 73% accuracy and F1-score of 71%. We believe this study to be the first of its kind to demonstrate the utility of machine learning as a tool for the assessment of retracted work.

1 Introduction

The last two decades have seen growing concern in the scientific community about the integrity of published work (Collaboration et al. 2015; Camerer et al. 2018; Klein et al. 2018) and an increase in the number of retractions of published articles (see Figure 1), in part due to increased scrutiny and improved oversight (Steen, Casadevall, and Fang 2013; Fanelli 2013; Brainard 2018). Focused studies of the primary reasons for retraction have suggested that research misconduct and fraud make up the majority, but also that a sizeable number of retractions are due to laboratory error, error in analyses, or inability to submit to reproduction or replication (Casadevall, Steen, and Fang 2014; Hesselmann et al. 2017).

Continued attention to and assessment of our confidence in published work is the cornerstone to efficient scientific progress, while the sheer volume of research papers published each year is overwhelming and increasing (Bornmann and Mutz 2015). Auditors and stakeholders, including reviewers, editors, other scientists, and the broader public, seek indicators and tools to contextualize and evaluate published findings, but these processes are still largely ad hoc. Proxies for credibility, such as citations and impact factors, while widespread, have also been shown to be biassed and flawed (Garfield et al. 1994; Seglen 1997; Bordons, Fernández, and Gómez 2002). Leading voices have argued for a re-imagining of scholarship itself (Stodden et al. 2016; Perkel 2018) in support of greater transparency and verifiability. While it is still unclear what form they must take, it is clear that computational tools will play a role in aggregating, sorting, querying, and evaluating scientific outputs in the future. Our work is motivated by this view, as we put forward a supervised approach to determine factors that best predict the retraction of scholarly work.

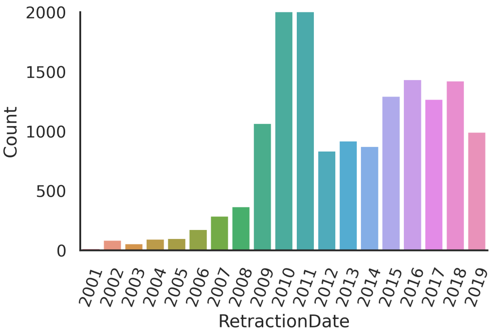


Figure 1: Uptrend in retractions over the past decade.

Here, we study retractions collected by The Center for Scientific Integrity and included in its Retraction Watch database (retractionwatch.com; (Oransky and Marcus 2012)). We extract a combination of metadata and full-text features that can separate retracted from non-retracted papers and develop a classifier to predict retraction in new samples with relatively high confidence. We focus on research publications in the social and behavioral sciences in this study, as it is not yet clear whether and how different research cultures and publishing norms differentially impact retraction across fields.

- Extract meaningful information from retracted papers in the social and behavioral sciences as well as from a complement set of non-retracted papers, from both metadata and full-text.
- Build a binary classifier to identify the likelihood of a paper's retraction given extracted information with 73% accuracy.
- Identify by ablation studies features and sets of features that best separate retracted from non-retracted papers.

These insights, we argue, can direct further research into automated tools for assigning confidence in publication claims.

The next section highlights related work in the area of understanding the retraction of scientific publications. Section 3 sketches our primary dataset and preprocessing pipeline. Section 4 outlines our features pulled from metadata and full-text documents. Sections 5 and 6 detail our classification approach and ablation studies. We conclude with a discussion of our findings and implications for ongoing and future work.

2 Related Work

Several studies have explored the retracted literature within a specific field of interest. (Bennett et al. 2020) analyses retracted papers in the obstetrics literature using the Retraction Watch database and PubMed. They present a breakdown of various metrics in that dataset, including journal impact factors, reasons for retractions, number of citations received, h-index of authors, and type of articles. Other authors have engaged in similar discussions across a variety of fields, including chemistry and material Science (Coudert 2019), biomedical sciences (Dal-Ré 2019), dentistry (Nogueira et al. 2017) and oncology (Pantziarka and Meheus 2019). One recent paper (Mistry, Grey, and Bolland 2019) surveys publication rates after the first retraction for biomedical researchers with multiple retracted publications. The study finds that publication rates of authors with multiple retractions, most of whom were associated with scientific misconduct, declined rapidly after their first retraction, but a small minority continued to publish regularly. Similarly, (Mott, Fairhurst, and Torgerson 2019; Suelzer et al. 2019) also found a decline in number of citations after retraction.

Other work supplements data-driven findings from the analysis of retracted papers in the literature with suggestions for the community. Authors of (Chan, Jones, and Albarracín 2017) highlight so-called continued influence effects, or the tendency of false beliefs to persist after correction and retraction, supporting their discussion through analysis of citations of retracted papers in downstream research articles. Their work puts forward a set of best practices for science communication scholars and practitioners. While, (Dal-Ré et al. 2020) analyses retractions due to conflict of interest and argues for greater transparency on the part of both journals and authors in disclosing financial interests.

More closely related to our work, two very recent papers have begun to suggest possible indicators of low credibility work. (Horton, Krishna Kumar, and Wood 2020) suggests that Benford's law can be used to differentiate retracted academic papers that have employed fraudulent/manipulated data from other academic papers that have not been retracted. Specifically, the authors construct several Benford conformity measures based on the first significant digits contained in the articles and show deviation for 37 papers containing known academic fraud. Supporting a broader conversation about open science and the role of transparency in scientific processes, (Lesk, Mattern, and Sandy 2019) study retraction rates in work with associated shared datasets. Authors found that published work with open data has fewer retractions, signaling higher credibility.

	China	United States	Japan	India	Germany
Count	3,211	1,462	460	392	314

Table 1: Top 5 number of retractions by country. Note that more than one country may be listed for a given record in the database.

Finally, with the recent outbreak of COVID-19 (SARS-CoV-2) and a flurry of scientific output related to the pandemic, the scientific community has also faced a surge in the number of retractions in publications related to COVID-19. Work done by Dinis-Oliveira (2020); Soltani and Patini (2020) studies retractions related to COVID-19 and highlight the need for better scrutiny of published papers.

3 Dataset

At the time of writing, the Retraction Watch database (Oransky and Marcus 2012) has 19,864 records of retracted papers. Our analysis considered 18,970 records in the dataset from the year 2001 to 2019. We further downselected 8,087 retractions in the social sciences for classification. Specifically, our classification task considered papers tagged by the Retraction Watch organization relating to the following subjects: Health Sciences (HSC, 5,396 papers), Social Sciences (SOC, 2,651 papers), and Humanities (HUM, 366 papers). More than one subject may be listed for a given paper.

Each record in the database includes a rich collection of metadata, including: *'Title', 'Subject', 'Institution', 'Journal', 'Publisher', 'Country', 'Author', 'URLS', 'ArticleType', 'RetractionDate', 'RetractionDOI', 'RetractionPubMedID', 'OriginalPaperDate', 'OriginalPaperDOI', 'OriginalPaperPubMedID', 'RetractionNature', 'Reason', 'Paywalled'*.

Approximately 72% of the 8,087 retractions in our dataset originate from one of five countries (see Table 1). China contributed 39.7% of the total retractions, followed by the United States at 18%.

For a majority of articles, limited to no information about the reason for retraction is available in the dataset. In cases where that information is given, investigation by external parties such as journals, institutions, companies, etc., contribute to 27.7% of retractions. Malpractices such as plagiarism, duplication, falsification, fabrication, manipulation of data represent 37.3% (most malpractice is determined as the result of an investigation). Other prevalent reasons for retractions include breach of policy by authors, withdrawals by authors, and author misconduct (see Table 2). Of 27,471 authors appearing in the dataset, 500 contribute to 3,863 (of 8,087) retractions. Eighty-five authors have ten or more than ten retractions. This trend echoes similar findings reported in (Brainard and You 2018).

The average time from date of publication to date of retraction in our dataset is 2 years. However, retraction time varies by subject. Average retraction time is 2.7 years for papers in HSC, as compared to 0.8 years in SOC and 1.7 years in HUM. We also observe a significant variation in the distribution of reasons for retractions across subjects. For example,

Reason for Retraction	Count
Limited or No Information	2,568
Investigation by Journal/Publisher	1,460
Investigation by Company/Institution	881
Duplication of Article	838
Withdrawal by author	673

Table 2: Top 5 reasons for retractions. Note that there may be more than one reason listed for a given record.

retractions due to limited or no information contributed to 69% of retractions in SOC; the same reason contributed to only 14% of retractions in HSC. Similar observations were drawn in a study of retractions in the surgical literature (King et al. 2018).

Dataset for Classification Of the 8,087 records, we further downsampled the records which have entries in PubMed. This choice to downsample to records available in PubMed is because abstracts and mesh terms available from PubMed can be used to search comparable negative samples. Of the records available in PubMed, we focus on records for which we can collect full-texts. Finally, we end up with 4,550 records of positive samples along with their full-texts for the classification task.

3.1 Negative Samples Collection

For classifier development and testing, a comparable set of non-retracted published articles (negative training samples) in a one-to-one mapping with retracted articles was collected such that:

- The negative sample was published within 3 years (before or after) the year of publication of the retracted sample.
- The negative sample most closely matches the retracted sample based on keywords (see below for details).

Keywords were retracted from papers using the TextRank algorithm proposed in (Mihalcea and Tarau 2004). TextRank uses a graph-based ranking model, which can be effectively used to extract keywords from text without the need for domain knowledge or annotated corpora. Extracted keywords were used to search for papers on similar topics around the same year of publication using the PubMed Entrez API[1]. The paper selected as the top match to each retracted paper, published within the three-year time window, was selected for inclusion in the negative training set. With collected negative samples and positive samples, our final dataset has $8,744$ records.

3.2 Preprocessing of full-texts

For both the records from Retraction Watch and the records selected from PubMed, we collected and preprocessed full-text PDFs. We experimented with several available conversion tools. While *pdftotext*[2] worked well for PDF to text conversion, it did not structure output in a usable way. Instead, to extract data from articles in a structured format, we used the GeneRation Of BIbliographic Data (Grobid) (Lopez 2009), which can segment PDF papers into TEI format, allowing programmatic access to various fields and sections of the paper. The GROBID output is further parsed using regular expression patterns (GROBID) and downstream feature extraction/development tasks.

4 Features

We use a comprehensive set of features, including publication metadata and features derived from the full-text of published papers. Metadata features are pulled through public scholarly APIs. While, we make use of various mining tools including GROBID and *pdftotext* to extract pertinent information from full-text PDFs of published articles.

4.1 Metadata features

We leverage the Scopus[3], Crossref[4] and Semantic Scholar[5] datasets and tools to collect key measures related to the papers in our dataset.

Lead author university rankings GROBID output includes the author's first and last names and institutional affiliations. We use this information when available. When missing, we search for authors' affiliation information through Elsevier API. We then augment the first author's affiliation with an affiliation score, calculated using institutional rankings from Times Higher Education[6] as follows:

$$\text{Affiliation Score} = \begin{cases} 1 - \frac{\text{Rank}}{100} & \text{if Rank} < 100 \\ 0 & \text{otherwise} \end{cases}$$

We retain numeric ranks only for the top 100 universities and set the others to a default score.

Journal impact score We use the SCImago Journal Rank (SJR) as the journal impact score, which is calculated as the average weighted citations per year divided by the total number of papers published in that journal over the past three years, where weight is determined by the prestige of the citing journal (see the SJR documentation for more details[7]).

Citation Next Citation Next (Aksnes, Langfeldt, and Wouters 2019) gives the average number of citations of a published work in the first three to five years after it has been published.

Citation Velocity The citation velocity represents the average rate at which a paper is cited in recent years, excluding self-citations (Kirkpatrick 2016). The value is retrieved from the Semantic Scholar API. A detailed explanation of how this metric is calculated can be found in the Semantic Scholar documentation[8] .

[1] https://www.ncbi.nlm.nih.gov/home/develop/api/

[2] https://www.xpdfreader.com/pdftotext-man.html

[3] https://www.scopus.com/

[4] https://www.crossref.org/

[5] https://www.semanticscholar.org/

[6] https://www.timeshighereducation.com/world-university-rankings

[7] https://www.scimagojr.com/SCImagoJournalRank.pdf

[8] https://www.semanticscholar.org/faq

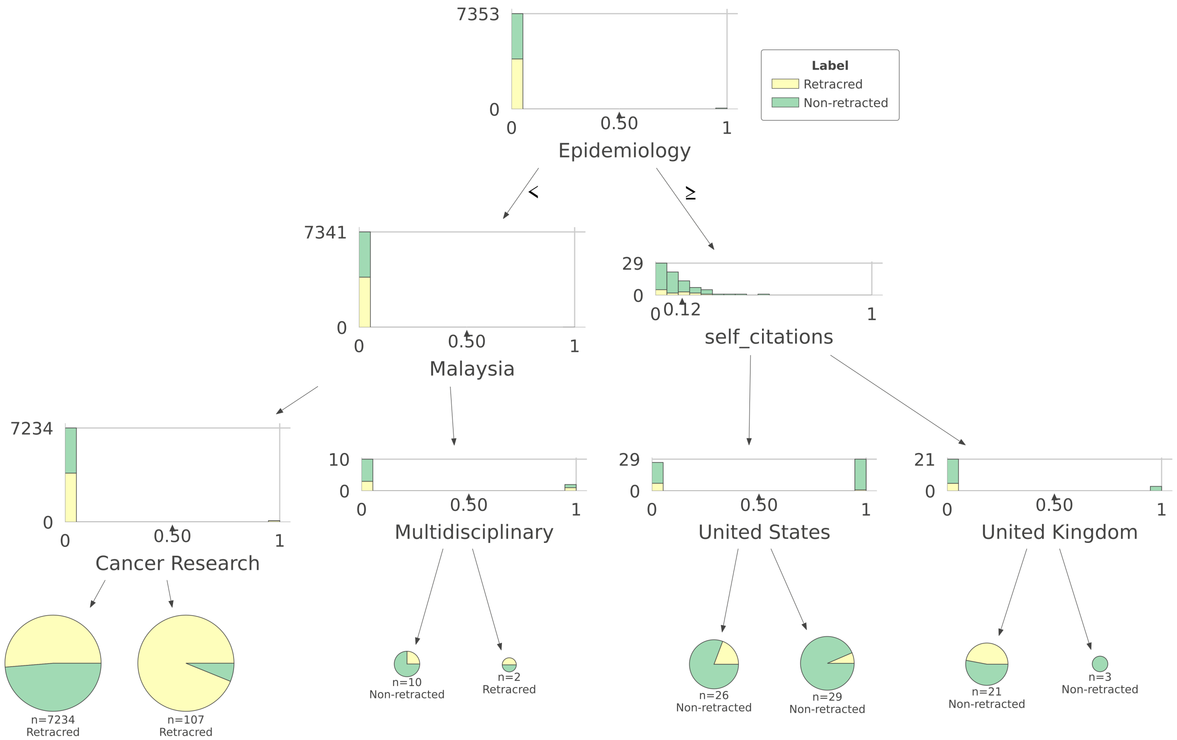


Figure 2: Decision Tree with depth=3, and country, subject, and self-citations as features.

Citation and Reference Intents Semantic Scholar also provides the intent behind each citation and reference. A paper can be cited as background, methodology, results, etc. For a given paper, we count the number of citing papers of certain intent(s) by querying the paper's identifiers (title or DOI) against the Semantic Scholar API. Similarly, we count the number of references for each intent of the given paper and use them as features.

Open access The open-access feature indicates whether the article can be accessed by any individual without a paywall. We collect this information from the Elsevier API and encode this flag as a binary feature.

Other Features In addition to the features outlined above, we use other readily available standard metadata including: (i) subject area in which paper is published; (ii) country of the primary authors' affiliations; (iii) the number of references; (iv) number of authors; and, (v) title (we concatenate title along with abstract).

4.2 Full-Text Features

While metadata features give an overview of the paper, full-text features represent features that are much more content-specific. Specifically, we extract test statistics of experiments from full-text. These features are extracted using PDF conversion tools followed by various downstream feature extraction tasks.

***p*-values** *p*-values signifies the confidence level of a null hypothesis based on experiments. Full-texts of published work can be mined to extract *p*-values and various other test statistics. For this, we use *pdftotext* to extract textual information present in full-texts PDFs. Most of the papers in SBS fields follow standard formats to report *p*-values. For example, *p*-values are reported as $p < 0.01$, or $p = 0.1$, or $p > 0.5$, etc. We follow methods similar to (Nuijten et al. 2016) to extract *p*-values using various regex patterns.

Furthermore, we extract other features from the *p*-values identified using the regex patterns such as number of *p*-values, real-*p*: defined as the lowest *p*-values among all the extracted *p*-values, sign-$p \in \{>, <, =\}$: defined as the sign of the real-*p*, *p*-value range: defined as the difference between the highest and lowest *p*-values extracted from text. Some scholarly works publish *p*-values along with test statistics such as ANOVA, Chi-squared, etc. We use a binary feature that indicates whether the *p*-value is reported along with a test statistic is extended-*p*. For example, $F(200) = 13.8, p = 0.1$.

We use the the number of *p*-values with test statistic and the number of *p*-values without test statistics as features. In the future sections, we refer all the above *p*-value related features as *p*-value features rather than referring them individually.

Sample Size Sample size is the number of observations made to determine the statistical significance of a hypothesis. Similar to *p*-value extraction, sample size can be extracted from a published article using regex patterns. In cases where test statistics are given, sample sizes can be calculated using various formulas based on the test statistic used. We use a combination of regex patterns and test statistic related formulas to extract sample sizes from a given paper.

Acknowledgements The acknowledgment section of a published paper may contain funding information. We use AckExtract to extract named entities using state-of-the-art Named Entity Recognition techniques, followed by a relation-based entity classifier to determine if the work was funded by an organization (Wu et al. 2020).

Self Citations Self-citation is common practice within the scientific community. Authors may cite their earlier works. The effects of self-citations and their significance for a paper's impact factor have been extensively studied (Renata 1977; Wolfgang, Bart, and Balázs 2004). Authors publishing in high-impact journals have more self-citations when compared with authors usually publishing in lower-impact journals (Anseel et al. 2004). However, when self-citation ratios are considered, they observe high-impact journals have lower self-citation ratios when compared with lower-impact journals. We extract self-citations from the references section of full-text by matching author names and calculate the self-citation ratio. For matching, we used author names in the title section to compare with the author names in the references section using a fuzzy string matcher.

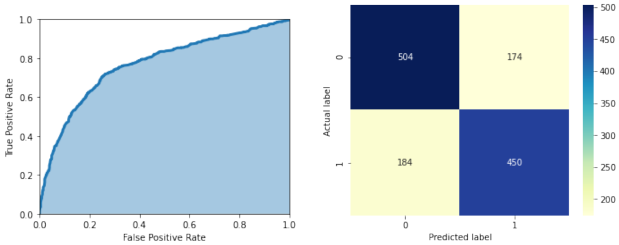
Abstract The abstract section provides an overview of what the article is about and its area of study. Capturing the abstract information in a meaningful and effective way as a feature can play an important role in the classification task. In this work, we have experimented with various word embeddings to represent abstracts.

Doc2Vec Embeddings: Sentence embeddings learned via distributed representations are proven to be effective in sentence classification tasks (Le and Mikolov 2014). Here, we experiment with these embeddings available as Doc2Vec in Gensim library (Řehůřek and Sojka 2010).

BioSentVec embeddings: Along with Doc2Vec embeddings, we also experiment with BioSentVec embeddings proposed by (Chen, Peng, and Lu 2019). BioSentVec is trained on large a large corpus of scholarly articles available in the PubMed database and clinical notes from MIMIC- III Clinical Database. The abstracts in our classification task are from a similar distribution on which BioSentVec is trained (Since all the records in our dataset are available in PubMed).

SciBERT embeddings: Bidirectional transformers have achieved state of the art results on most NLP tasks, including sentence classification. We experiment with sentence embeddings from SciBERT (Beltagy, Lo, and Cohan 2019) embeddings obtained via bidirectional transformers trained on a large corpus of scholarly articles from Semantic Scholar. In our experiments, we use *[CLS]* token embeddings from SciBERT's output. In cases where abstract exceeded 512 tokens, we omitted the extra tokens for embeddings.

TFIDF: Term Frequency-Inverse Document Frequency (TFIDF) is a popular technique in information retrieval and machine learning. In our experiments, we use TFIDF of abstracts with removed stop words removed along with words stemmed. We also use TFIDF with reduced dimensions using TruncatedSVD (Halko, Martinsson, and Tropp 2011).



(a) ROC Curve (b) Confusion Matrix

Figure 3: Classification Performance Using Random Forest Classifier.

5 Classification

We formulate the task of retraction classification as follows: given access to a labeled set of training samples, $\{(x_i, y_i)\}_{i=1}^{n} \in \mathcal{X}_{train} \times \mathcal{Y}_{train}$, such that $x_i \in \mathbb{R}^n$, $y_i \in \{0, 1\}$ we aim to train a classifier $f : \mathcal{X} \rightarrow \mathcal{Y}$ with minimum classification error on unseen data i.e, $\mathcal{X}_{test} \times \mathcal{Y}_{test}$.

$$y_i = \begin{cases} 0 & \text{if retracted,} \\ 1 & \text{if non retracted} \end{cases}$$

We use random forest classifier (Breiman 2001) to support interpretability of results and good performance. All of our experiments were done using 100 trees as we didn't see much performance improvements over 100 trees. For experiments in Table 3, we used TF-IDF for representing abstracts. Note that we concatenate the title of the paper along with the abstract as a single feature. To further simplify the model for interpretability, we decompose the TFIDF matrix using randomized SVD (Halko, Martinsson, and Tropp 2011) with 10 iterations to 15 dimensions. Randomized SVD is better suited for sparse matrices such as TFIDF. (We also experimented with PCA for dimensionality reduction, but dimensionality reduction using randomized SVD gave better results). For categorical variables in our dataset, i.e, *Subject, Country*, we use target encoding (Micci-Barreca 2001). Target encoder takes into account the posterior probability of the target, given a categorical value and the prior probability of the target on the entire training set to encode categorical variables. We report 10-fold cross-validation scores and scores on the train-test split (85% - 15%), see Table 3. For the train-test split, we report Area Under the Receiver Operating Characteristic (AUROC) of 78.1%. The ROC curve and a heat map of the confusion matrix are provided in Figure 3.

A closer look at individual decision trees of our random forests reveals several interesting insights. For example, certain combinations of countries and subjects combined with other underlying feature distributions of such as low *SJR* and *University Rank* are more prone to retractions. On the other hand, certain combinations of countries and subjects with a high self-citation ratio are less likely to be retracted. This can

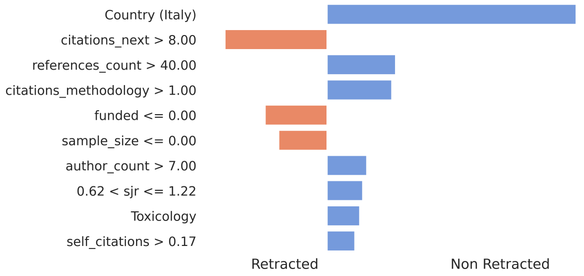


Figure 4: Plot showing features that contributed for Non-retraction classification of a sample

be observed in Figure 2. For the purpose of better visualization, we considered only three features: *Countries*, *Subjects* and *SJR*, and limited the depth of Decision Tree to 3. These three features together give an F1 score of 66%. Countries and Subjects are one-hot encoded for ease of understanding as opposed to target encoded for the scores in Table 3.

We further visualize a sample with actual and predicted label as non-retracted using Local Interpretable Model-Agnostic Explanations(LIME) (Ribeiro, Singh, and Guestrin 2016) to present the effectiveness of our classifier. LIME explains an individual prediction by perturbing a sample and observing how the prediction changes around the given sample's perturbations. From Figure 4, we can observe that the non-retracted sample has more than seven authors with the primary author's affiliation, located in Italy. The paper has more than 40 references, which was cited more than once as methodology and a self-citation ratio greater than 0.17. The SJR score of the journal where the paper is published falls in the interval $[0.62, 1.2]$. All these attributes contributed towards non-retracted classification confidence. While the overall prediction is non-retracted, having no funding agency acknowledged, no sample size information, and *citation_next* value greater than eight are seen as attributes that could lead to retraction. Note that this visual analysis is particular to a sample and does not represent the global feature importance, and is meant for a high-level intuition of how various features can meaningfully impact a published work's confidence.

	10-Fold Cross Valid.	**Train-test Split**
Accuracy	73.65	73.32
Precision	74.32	71.54
Recall	68.70	72.00
F1	71.37	71.77

Table 3: Random Forest Classifier performance for Accuracy, Precision, and Recall scores, averaged for 10-fold cross validation and train-test split

6 Ablation Studies

We completed an ablation study to identify features (or combinations of features) that are instrumental in identifying retracted papers. Table 4 shows the result of this investigation. Metadata features alone give an F1 score of 67%, while full-text features alone result in an F1 score of 63%. Combined together, metadata and full-text features help improve performance to an F1 score of 71%. The importance of full-text features can also be observed by excluding abstract, self-citations, and p-value features individually. Excluding abstract, self-citations ratio, and p-value separately doesn't lead to a significant drop in F1-score, but together they drop the F1-score to 67.7%.

	Accuracy	**Precision**	**Recall**	**F1**
Individual Features:				
Abstract$_{TF-IDF}$	67.14	64.71	69.01	66.76
Abstract$_{SciBERT}$	65.69	64.48	63.06	63.75
Abstract$_{SVD_{n=15}}$	65.05	63.51	63.30	63.39
Country	65.93	66.02	59.60	62.57
Abstract$_{BioSentVec}$	65.24	64.76	60.26	62.40
SJR	66.22	69.37	52.68	59.85
Subject	63.53	64.43	53.58	58.39
Cite. Next	57.07	56.02	48.59	51.95
Cite. Background	56.06	54.70	48.29	51.25
Cite. Results	56.06	54.70	48.29	51.25
Author Count	51.66	49.57	50.09	49.44
p**-value features**	53.61	51.84	44.09	47.62
Self-Cite.	53.29	51.62	38.57	44.14
Ref. Background	54.94	54.42	36.45	43.53
Abstract$_{DOC2VEC}$	50.69	48.12	37.18	41.89
Funded	54.87	54.58	34.00	41.87
Ref. Methodology	54.56	54.83	29.14	37.97
Cite. Methodology	54.09	54.14	25.87	34.98
Ref. Results	52.72	51.61	20.02	28.62
Uni. Rank	52.41	59.39	1.64	3.20
Open Access	52.14	0.00	0.00	0.00
Particular Feature Excluded:				
Cite. Next	73.42	74.25	68.08	71.00
Uni. Rank	73.36	74.22	67.99	70.94
Open Access	73.30	74.23	67.78	70.83
p**-Value features**	73.28	74.37	67.49	70.73
Author Cnt.	73.18	74.18	67.36	70.59
Self-Cite.	73.07	73.97	67.56	70.58
Abstract	72.72	72.95	68.37	70.58
Funded	73.01	74.07	67.13	70.41
Subject	72.64	73.55	66.97	70.07
Country	71.01	70.82	67.10	68.87
Overall Features:				
Metadata	71.73	74.74	61.96	67.70
Full-text	65.31	63.74	63.78	63.72
All Features	73.65	74.32	68.70	71.37

Table 4: Ablation study results. Ordered by individual feature performance, performance with particular feature excluded from all the features and overall performance results.

We examine the importance of each feature by excluding each from the overall features and also measuring the performance of each feature individually. In Table 4, the country of the primary author has the most predictive power. Excluding the country from the overall feature list hurts the F1-score significantly. Individually, *SJR, abstract, country* give the best performance out of all metadata features. Similarly, the

TFIDF of the abstracts gives the best performance of all the full-text features. We reduced the dimension of the TFIDF vector from 34,000 to 15 using Truncated SVD without a significant drop in performance. The best score is achieved by using all the features.

In regards to individual features, from Table 4 we note that features such as *self-citation* alone cannot achieve any separability. However, when combined with other features, they provide predictive power to the classifier Figure 2. University rank individually provides almost no separability. The university rank of $8,535$ records is set to default value 0; this suggests exploring better methods to encode affiliation information. $3,130$ records in our dataset have open access (open access flag set to 1), this feature exhibits almost zero correlation(-0.017) with *retracted vs. non-retracted* label. This suggests that open access of published articles is not an indicator of a scholarly work's confidence.

7 Conclusion

In this work, we present initial evidence for the utility of supervised approaches for the assessment of retracted scholarly work. Using metadata as well as features derived from the full-text for a subset of retracted papers in the social and behavioral sciences, we develop a random forest classifier to predict retraction in new samples. Looking ahead, we might assume that signals of credibility and concern will vary across scientific domains. And that further studies in ML-enabled understanding of retraction will, therefore, likely need to be undertaken by interdisciplinary teams. We suggest that yet more sophisticated features capturing argument structure, experimental conditions, and corroborations across the literature will be important steps for work in this direction.

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References

Aksnes, D.; Langfeldt, L.; and Wouters, P. 2019. Citations, Citation Indicators, and Research Quality: An Overview of Basic Concepts and Theories. *SAGE Open* 9: 215824401982957. doi:10.1177/2158244019829575.

Anseel, F.; Duyck, W.; De Baene, W.; and Brysbaert, M. 2004. Journal Impact Factors and Self-Citations: Implications for Psychology Journals. 59(1): 49–51. doi:10.1037/0003-066X.59.1.49.

Beltagy, I.; Lo, K.; and Cohan, A. 2019. SciBERT: A Pretrained Language Model for Scientific Text. 3615–3620. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/D19-1371. URL https://www.aclweb.org/anthology/D19-1371.

Bennett, C.; Chambers, L. M.; Al-Hafez, L.; Michener, C. M.; Falcone, T.; Yao, M.; and Berghella, V. 2020. Retracted articles in the obstetrics literature: lessons from the past to change the future. *American Journal of Obstetrics & Gynecology MFM* 2(4): 100201. ISSN 2589-9333. doi:10.1016/j.ajogmf.2020.100201. URL http://www.sciencedirect.com/science/article/pii/S2589933320301701.

Bordons, M.; Fernández, M. T.; and Gómez, I. 2002. Advantages and limitations in the use of impact factor measures for the assessment of research performance. *Scientometrics* 53(2): 195–206. ISSN 1588-2861. doi:10.1023/A:1014800407876. URL https://doi.org/10.1023/A:1014800407876.

Bornmann, L.; and Mutz, R. 2015. Growth rates of modern science: A bibliometric analysis based on the number of publications and cited references. *Journal of the Association for Information Science and Technology* 66(11): 2215–2222. doi:10.1002/asi.23329. URL https://asistdl.onlinelibrary.wiley.com/doi/abs/10.1002/asi.23329.

Brainard, J. 2018. Rethinking retractions. *Science* 362(6413): 390–393. ISSN 0036-8075. doi:10.1126/science.362.6413.390. URL https://science.sciencemag.org/content/362/6413/390.

Brainard, J.; and You, J. 2018. What a massive database of retracted papers reveals about science publishing's 'death penalty'. *Science* 25(1): 1–5.

Breiman, L. 2001. Random forests. *Machine Learning* 45(1): 5–32. ISSN 08856125. doi:10.1023/A:1010933404324. URL https://doi.org/10.1023/A:1010933404324.

Camerer, C. F.; Dreber, A.; Holzmeister, F.; Ho, T.-H.; Huber, J.; Johannesson, M.; Kirchler, M.; Nave, G.; Nosek, B. A.; Pfeiffer, T.; et al. 2018. Evaluating the replicability of social science experiments in Nature and Science between 2010 and 2015. *Nature Human Behaviour* 2(9): 637–644. doi:10.1038/s41562-018-0399-z.

Casadevall, A.; Steen, R. G.; and Fang, F. C. 2014. Sources of error in the retracted scientific literature. *The FASEB Journal* 28(9): 3847–3855. doi:10.1096/fj.14-256735.

Chan, M.; Jones, C.; and Albarracín, D. 2017. *Countering false beliefs: An analysis of the evidence and recommendations of best practices for the retraction and correction of scientific misinformation*, 341–350. Oxford University Press. doi:10.1093/oxfordhb/9780190497620.013.37.

Chen, Q.; Peng, Y.; and Lu, Z. 2019. BioSentVec: creating sentence embeddings for biomedical texts. *2019 IEEE International Conference on Healthcare Informatics (ICHI)* doi:10.1109/ichi.2019.8904728. URL http://dx.doi.org/10.1109/ICHI.2019.8904728.

Collaboration, O. S.; et al. 2015. Estimating the reproducibility of psychological science. *Science* 349(6251). ISSN 0036-8075. doi:10.1126/science.aac4716. URL https://science.sciencemag.org/content/349/6251/aac4716.

Coudert, F.-X. 2019. Correcting the Scientific Record: Retraction Practices in Chemistry and Materials Science. *Chemistry of Materials* 31: 3593–3598. doi:10.1021/acs.chemmater.9b00897.

Dal-Ré, R.; Bouter, L. M.; Moher, D.; and Marušić, A. 2020. Mandatory disclosure of financial interests of journals and editors. *BMJ* 370. doi:10.1136/bmj.m2872. URL https://www.bmj.com/content/370/bmj.m2872.

Dal-Ré, R. 2019. Analysis of retracted articles on medicines administered to humans. *British Journal of Clinical Pharmacology* 85(9): 2179–2181. doi:https://doi.org/10.1111/bcp.14021. URL https://bpspubs.onlinelibrary.wiley.com/doi/abs/10.1111/bcp.14021.

Dinis-Oliveira, R. J. 2020. COVID-19 research: pandemic versus "paperdemic", integrity, values and risks of the "speed science". *Forensic Sciences Research* 5(2): 174–187. doi:10.1080/20961790.2020.1767754. URL https://doi.org/10.1080/20961790.2020.1767754.

Fanelli, D. 2013. Why Growing Retractions Are (Mostly) a Good Sign. *PLoS Medicine* 10(12): e1001563. ISSN 1549-1676. doi:10.1371/journal.pmed.1001563. URL https://dx.plos.org/10.1371/journal.pmed.1001563.

Garfield, E.; et al. 1994. The impact factor. *Current contents* 25(20): 3–7.

Halko, N.; Martinsson, P. G.; and Tropp, J. A. 2011. Finding Structure with Randomness: Probabilistic Algorithms for Constructing Approximate Matrix Decompositions. *SIAM Rev.* 53(2): 217–288. ISSN 0036-1445. doi:10.1137/090771806. URL https://doi.org/10.1137/090771806.

Hesselmann, F.; Graf, V.; Schmidt, M.; and Reinhart, M. 2017. The visibility of scientific misconduct: A review of the literature on retracted journal articles. *Current sociology* 65(6): 814–845. doi:10.1177/0011392116663807.

Horton, J.; Krishna Kumar, D.; and Wood, A. 2020. Detecting academic fraud using Benford law: The case of Professor James Hunton. *Research Policy* 49(8): 104084. ISSN 0048-7333. doi: j.respol.2020.104084. URL http://www.sciencedirect.com/science/article/pii/S0048733320301621.

King, E. G.; Oransky, I.; Sachs, T. E.; Farber, A.; Flynn, D. B.; Abritis, A.; Kalish, J. A.; and Siracuse, J. J. 2018. Analysis of retracted articles in the surgical literature. *The American Journal of Surgery* 216(5): 851–855. doi:10.1016/j.amjsurg.2017.11.033.

Kirkpatrick, K. 2016. Search Engine's Author Profiles Now Driven By Influence Metrics. *Communications of ACM* URL https://cacm.acm.org/news/201387-search-engines-author-profiles-now-driven-by-influence-metrics/fulltext.

Klein, R. A.; Vianello, M.; Hasselman, F.; Adams, B. G.; Adams Jr, R. B.; Alper, S.; Aveyard, M.; Axt, J. R.; Babalola, M. T.; Bahník, Š.; et al. 2018. Many Labs 2: Investigating variation in replicability across samples and settings. *Advances in Methods and Practices in Psychological Science* 1(4): 443–490. doi: 10.1177/2515245918810225.

Le, Q. V.; and Mikolov, T. 2014. Distributed Representations of Sentences and Documents. In *International Conference on Machine Learning*. doi:10.5555/3044805.3045025.

Lesk, M.; Mattern, J. B.; and Sandy, H. M. 2019. Are papers with open data more credible? An analysis of open data availability in retracted PLoS articles. In *International Conference on Information*, 154–161. Springer. doi:10.1007/978-3-030-15742-5_14.

Lopez, P. 2009. GROBID: Combining Automatic Bibliographic Data Recognition and Term Extraction for Scholarship Publications. ECDL'09, 473–474. Berlin, Heidelberg: Springer-Verlag. ISBN 3-642-04345-3, 978-3-642-04345-1. doi:10.1007/978-3-642-04346-8_62. URL http://dl.acm.org/citation.cfm?id=1812799.1812875.

Micci-Barreca, D. 2001. A preprocessing scheme for high-cardinality categorical attributes in classification and prediction problems. *ACM SIGKDD Explorations Newsletter* 3(1): 27–32. doi:10.1145/507533.507538.

Mihalcea, R.; and Tarau, P. 2004. Textrank: Bringing order into text. In *Proceedings of the 2004 conference on empirical methods in natural language processing*, 404–411.

Mistry, V.; Grey, A.; and Bolland, M. J. 2019. Publication rates after the first retraction for biomedical researchers with multiple retracted publications. *Accountability in Research* 26(5): 277–287. doi:10.1080/08989621.2019.1612244. URL https://doi.org/10.1080/08989621.2019.1612244. PMID: 31025884.

Mott, A.; Fairhurst, C.; and Torgerson, D. 2019. Assessing the impact of retraction on the citation of randomized controlled trial reports: an interrupted time-series analysis. *Journal of Health Services Research & Policy* 24(1): 44–51. doi:10.1177/1355819618797965. URL https://doi.org/10.1177/1355819618797965. PMID: 30249142.

Nogueira, T. E.; Gonçalves, A. S.; Leles, C. R.; Batista, A. C.; and Costa, L. R. 2017. A survey of retracted articles in dentistry. *BMC Research Notes* 10(1): 253. ISSN 1756-0500. doi:10.1186/s13104-017-2576-y. URL https://doi.org/10.1186/s13104-017-2576-y.

Nuijten, M. B.; Hartgerink, C. H.; van Assen, M. A.; Epskamp, S.; and Wicherts, J. M. 2016. The prevalence of statistical reporting errors in psychology (1985–2013). *Behavior research methods* 48(4): 1205–1226. doi:10.3758/s13428-015-0664-2.

Oransky, I.; and Marcus, A. 2012. Retraction watch. URL http://retractiondatabase.org/RetractionSearch.aspx?

Pantziarka, P.; and Meheus, L. 2019. Journal retractions in oncology: a bibliometric study. *Future Oncology* 15(31): 3597–3608. doi: 10.2217/fon-2019-0233. URL https://doi.org/10.2217/fon-2019-0233. PMID: 31659916.

Perkel, J. M. 2018. A toolkit for data transparency takes shape. *Nature* 560(7718): 513–516. doi:10.1038/d41586-018-05990-5.

Řehůřek, R.; and Sojka, P. 2010. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, 45–50. Valletta, Malta: ELRA. http://is.muni.cz/publication/884893/en.

Renata, T. 1977. SELF-CITATIONS IN SCIENTIFIC LITERATURE. *Journal of Documentation* 33(4): 251–265. ISSN 0022-0418. doi:10.1108/eb026644. URL https://doi.org/10.1108/eb026644.

Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016*, 1135–1144. doi:10.18653/v1/N16-3020.

Seglen, P. O. 1997. Why the impact factor of journals should not be used for evaluating research. *Bmj* 314(7079): 497. doi: 10.1136/bmj.314.7079.497.

Soltani, P.; and Patini, R. 2020. Retracted COVID-19 articles: a side-effect of the hot race to publication. *Scientometrics* 125(1): 819–822. ISSN 1588-2861. doi:10.1007/s11192-020-03661-9. URL https://doi.org/10.1007/s11192-020-03661-9.

Steen, R. G.; Casadevall, A.; and Fang, F. C. 2013. Why has the number of scientific retractions increased? *PloS one* 8(7): e68397. doi:10.1371/journal.pone.0068397.

Stodden, V.; McNutt, M.; Bailey, D. H.; Deelman, E.; Gil, Y.; Hanson, B.; Heroux, M. A.; Ioannidis, J. P.; and Taufer, M. 2016. Enhancing reproducibility for computational methods. *Science* 354(6317): 1240–1241. doi:10.1126/science.aah6168.

Suelzer, E. M.; Deal, J.; Hanus, K. L.; Ruggeri, B.; Sieracki, R.; and Witkowski, E. 2019. Assessment of Citations of the Retracted Article by Wakefield et al With Fraudulent Claims of an Association Between Vaccination and Autism. *JAMA Network Open* 2(11): e1915552–e1915552. ISSN 2574-3805. doi: 10.1001/jamanetworkopen.2019.15552. URL https://doi.org/10.1001/jamanetworkopen.2019.15552.

Wolfgang, G.; Bart, T.; and Balázs, S. 2004. A bibliometric approach to the role of author self-citations in scientific communication. *Scientometrics Scientometrics* 59(1): 63–77. doi: 10.1023/B:SCIE.0000013299.38210.74. URL https://akjournals.com/view/journals/11192/59/1/article-p63.xml.

Wu, J.; Wang, P.; Wei, X.; Rajtmajer, S.; Giles, C. L.; and Griffin, C. 2020. Acknowledgement Entity Recognition in CORD-19 Papers. In *Proceedings of the First Workshop on Scholarly Document Processing*, 10–19. Online: Association for Computational Linguistics. URL https://www.aclweb.org/anthology/2020.sdp-1.3.