Linguistic Analysis of the bioRxiv Preprint Landscape

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Abstract

Preprints allow researchers to make their findings available to the scientific community before they have undergone peer review. Studies on preprints within bioRxiv have been largely focused on article metadata and how often these preprints are downloaded, cited, published, and discussed online. A missing element that has yet to be examined is the language contained within the bioRxiv preprint repository. We sought to compare and contrast linguistic features within bioRxiv preprints to published biomedical text as a whole as this is an excellent opportunity to examine how peer review changes these documents. The most prevalent features that changed appear to be associated with typesetting and mentions of supplementary sections or additional files. In addition to text comparison, we created document embeddings derived from a preprint-trained word2vec model. We found that these embeddings are able to parse out different scientific approaches and concepts, link unannotated preprint-peer reviewed article pairs, and identify journals that publish linguistically similar papers to a given preprint. We also used these embeddings to examine factors associated with the time elapsed between the posting of a first preprint and the appearance of a peer reviewed publication. We found that preprints with more versions posted and more textual changes took longer to publish. Lastly, we constructed a web application that allows users to identify which journals and articles that are most linguistically similar to a bioRxiv or medRxiv preprint as well as observe where the preprint would be positioned within a published article landscape.

Introduction

The dissemination of research findings is key to science, and initially much of this communication happened orally [1]. During the 17th century, the predominate form of communication shifted to personal letters that were shared from one scientist to another [1]. Scientific journals didn't become a predominant mode of communication until the 19th and 20th centuries when the first journal abstract was created [1,2,3]. Although scientific journals became the primary method of communication, they added high maintenance costs and long publication times to scientific discourse [2,3]. Scientists' solution to some of these issues was to communicate through preprints, which are scholarly works that have yet to undergo peer review process [4,5].

Preprints are commonly hosted on online repositories, where users have open and easy access to these works. Notable repositories include arXiv [6], bioRxiv [7] and medRxiv [8]; however, there are over 60 different repositories available [9]. The burgeoning uptake of preprints in life sciences has been examined through research focused on metadata from the bioRxiv repository. For example, scientists found that life science preprints are being posted at an increasingly high rate [10]. Furthermore, these preprints are being rapidly shared on social media, routinely downloaded, and cited [11]. Certain preprint categories are read and shared by both scientists and non-scientists alike [12]. Overall, about two-thirds to three-quarters of preprints are eventually published [13,14] and life science articles that have a corresponding preprint version are cited and discussed more often than articles without them [15,16,17]. Preprints take an average of 160 days to become published [18], and those with multiple versions take longer to publish [18].

In spite of the success and excitement of preprints, there are number of issues that arose from their constant use. Preprint repositories receive a growing number of submissions, which pose challenges for this mode of communication [19]. For example, repositories have a hard time searching and linking preprints with their published counterparts [16,20], which results in missing links and consequently erroneous metadata. Furthermore, these repositories lack tools to show how textual content of preprints are altered due to the peer review process [19]. These repositories are open access for all to view preprints, which results in concern from scientists that they could be scooped by competitors [19,21]. Plus, preprint repositories do not have in-depth peer review which can result in

posted preprints containing inconsistent results or conclusions [17,20,22,23]. Despite a growing emphasis on using the study of preprints to examine the publishing process in the life sciences, how these findings relate to the text of documents within bioRxiv has not been examined.

Textual analysis is a methodology that uses linguistic, statistical and machine learning techniques to analyze and extract information from text [24]. This set of techniques have made a sizable impact within the life science community by providing valuable insight on biomedical text. For instance, scientists analyzed linguistic similarities and differences of biomedical corpora [25,26]. Scientists have provided the community with a number of tools that aide future text mining systems [27,28,29] as well as advice on how to train and test future text processing systems [30,31,32]. We use textual analysis to examine the bioRxiv repository, placing a particular emphasis on understanding the extent to which full text analysis can address hypotheses derived from the analysis of metadata alone.

Preprints are still an emerging method of scientific communication in the life sciences. To understand how they relate to the traditional publishing ecosystem, we examine the linguistic similarities and differences between preprints and peer reviewed text and observe how linguistic features change during the peer review and publishing process. We theorize that preprints and biomedical text would be quite similar, especially when controlling for the differential uptake of preprints across fields. In other contexts, neural networks trained in certain ways can produce a representation of words and documents that has useful properties for many tasks - termed word or document embeddings [33,34]. Here, we hypothesize that using these networks to embedded preprints provides a versatile way to disentangle linguistic features along with serving as a practical medium for improving preprint repository functionality. We test this hypothesis by producing a linguistic landscape of bioRxiv preprints, detecting preprints that change substantially during publication, and identify journals that publish manuscripts that are linguistically similar to a target preprint. We encapsulate our findings through a web-app that projects a user-selected preprint onto this landscape and suggests journals and articles that are linguistically similar. Taken together, our work reveals how linguistically similar and dissimilar preprints are to peer reviewed text, quantifies linguistic changes that occur during the peer review process and highlights the feasibility of document embeddings in respect to preprint repository functionality and peer review's affect on publication time.

Materials and Methods

Corpora Examined

BioRxiv Corpus

BioRxiv [7] is a repository for life sciences preprints. We downloaded an xml snapshot of this repository on February 3, 2020 from bioRxiv's Amazon S3 bucket [35]. This snapshot contained the full text and image content of 98,023 preprints. Preprints on bioRxiv are versioned, and in our snapshot 26,905 out of 98,023 contained more than one version. When preprints had multiple versions, we used the latest one unless otherwise noted. Authors submitting preprints to bioRxiv can select one of twenty-nine different categories. Furthermore, researchers can also select the type of article: a new result, confirmatory finding, or contradictory finding. Some preprints in this snapshot were withdrawn from bioRxiv and when this happens their content is replaced with the reason for withdrawal. As there were very few withdrawn preprints, we did not treat these as a special case.

PubMed Central Open Access Corpus

PubMed Central (PMC) is a digital archive for the United States National Institute of Health's Library of Medicine (NIH/NLM) that contains full text biomedical and life science articles [36]. PMC articles can be closed access ones from research funded by the NIH appearing after an embargo period or be

published under Gold Open Access [37] publishing schemes. Paper availability within PMC is largely dependent on the journal's participation level [38]. Individual journals have the option to fully participate in submitting articles to PMC, selectively participate sending only a few papers to PMC, only submit papers according to NIH's public access policy [39], or not participate at all. As of September 2019, PMC had 5,725,819 articles available [40]. Out of these 5 million articles, about 3 million were open access (PMCOA) and available for text processing systems [28,41]. PMC also contains a resource that holds author manuscripts that have already passed the peer review process [42]. Since these manuscripts have already been peer reviewed, we kept them out of our analysis as the scope of our work is solely focused on examining the beginning and end of a preprint's lifecycle. We downloaded a snapshot of the PMCOA corpus on January 31, 2020. This snapshot contained many types of articles: literature reviews, book reviews, editorials, case reports, research articles and more. We used only research articles, which aligns with the intended role of bioRxiv, and we refer to these articles as the PMCOA corpus.

The New York Times Annotated Corpus

The New York Times Annotated Corpus (NYTAC) is [43] is collection of newspaper articles from the New York Times dating from January 1, 1987 to June 19, 2007. This collection contains over 1.8 million articles where 1.5 million of those articles have undergone manual entity tagged by library scientists [43]. We downloaded this collection on August 3rd, 2020 from the Linguistic Data Consortium (see Software and Data Availability section) and used the entire collection as a negative control for our corpora comparison analysis.

Mapping bioRxiv preprints to their published counterparts

We used CrossRef [44] to identify bioRxiv preprints that were linked to a corresponding published article. We accessed CrossRef on July 7th, 2020 and were able to successfully link 23,271 preprints to their published counterparts. Out of those 23,271 preprint-published pairs only 17,952 pairs had a published version present within the PMCOA corpus. For our analyses that involved published links we only focused on this subset of preprints-published pairs.

Comparing Corpora

We compared the bioRxiv, PMCOA, and NYTAC corpora to assess the similarities and differences between them. We used the NYTAC corpus as a negative control to assess the similarity between two life sciences repositories when compared with non-life sciences text. All corpora contain both words and non-word symbols (e.g., $\pm$), which we refer to together as tokens to avoid confusion. We calculated the following characteristic metrics for each corpus: the number of documents, the number of sentences, the total number of tokens, the number of stopwords, the average length of a document, the average length of a sentence, the number of negations, the number of coordinating conjunctions, the number of pronouns and the number of past tense verbs. Spacy is a lightweight and easy to use python package designed to preprocess and filter out text [45]. Due to its processing power, we used spaCy's "en_core_web_sm" model [45] (version 2.2.3) to preprocess all corpora and filtered out 326 spaCy-provided stopwords.

Following our cleaning process, we calculated the frequency of every token across all corpora. Because many tokens were unique to one set or the other and observed at low frequency, we focused on the union of the top 0.05% (~100) most frequently occurring tokens within each individual corpus. For each token in this union, we generated a contingency table and calculated the odds ratio along with the 95% confidence interval [46]. Along with token enrichment analysis, we measured corpora similarity by calculating the Kullback–Leibler (KL) divergence across all corpora. This metric measures the extent to which two distributions, but not the specific entities that comprise those distributions,

differ. A low value of KL divergence implicates that two distributions are similar and vice versa for high values. The optimal number of tokens used to calculate the KL divergence is unknown, so we calculated this metric using a spectrum of 100 most frequently occurring tokens between two corpora to 5000 most frequently occurring tokens.

Constructing a Document Representation for Life Sciences Text

We sought to build a model that would capture the linguistic similarities of biomedical preprint and articles. Word2vec is a suite of neural networks designed to model linguistic features of words based on their appearance in text. These models are trained to either predict a word based on its sentence context, called a continuous bag of words (CBOW) model, or predict the context based on a given word, called a skipgram model [33]. Through these prediction tasks both networks learn latent linguistic features that can be used for downstream tasks such as identifying similar words. We used gensim [47] (version 3.8.1) to train a CBOW [33] model over all the main text within each preprint in the bioRxiv corpus. Determining the best number of dimensions for word embeddings can be a non-trivial task; however, it has been shown that optimal performance is between 100-1000 dimensions [48]. Based on this finding, we chose to train the CBOW model using 300 hidden nodes, batch size of 10000 words and for 20 epochs. We set a fixed random seed and used gensim's default settings for all other hyperparameters. Once trained, every token present within the CBOW model is associated with a dense vector that represents latent features captured by the network. We used these word vectors to generate a document representation for every article within the bioRxiv and PMCOA corpora. Each document vector is generated by taking the average of every token present within the CBOW model as well as the individual article [34]. Any token present within the article but not in the CBOW model is ignored during this calculation process.

Visualizing and Characterizing Preprint Representations

We sought to visualize the landscape of preprints and determine the extent to which their representation as document vectors corresponded to author-supplied document labels. We used principal component analysis (PCA) [49] to project bioRxiv document vectors into a low dimensional space. We trained this model using scikit-learn's [50] implementation of a randomized solver [51] with a random seed of 100, output of 50 principal components (PCs), and default settings for all other hyperparameters. After training the model, every preprint within the bioRxiv corpus is assigned a score for each generated PC. We sought to uncover concepts captured the generated PCs and used the cosine similarity metric to examine these concepts. This metric takes two vectors as input and outputs a score between -1 (most dissimilar) and 1 (most similar). For our use case we used this metric to score the similarity between all generated PCs and every token within our CBOW model. We report the top 100 positive and negative scoring tokens in the form of word clouds, where the size of each word corresponds to the magnitude of similarity and color represents positive (orange) or negative (blue) association.

Discovering Unannotated Preprint-Publication Relationships

The bioRxiv maintainers have automated procedures to link preprints to peer reviewed versions and many journals require authors to update preprints with a link to the published version. However, this automation is largely based on exact matching of certain preprint attributes. If authors change the title between a preprint and published version (e.g., [52] and [53]), then this change will prevent bioRxiv from automatically establishing a link. Furthermore, if the authors do not report the publication to bioRxiv, the preprint and its corresponding published version are treated as distinct entities despite representing the same underlying research. We hypothesize that close proximity in the document embedding space could match preprints with their corresponding published version. If this finding holds, then we could use this embedding space to fill in links that were missed by existing

automated processes. We used the subset of paper-preprint pairs annotated in CrossRef as described above to calculate the distribution of known preprint to published distances. This distribution was calculated by taking the Euclidean distance between the preprint's embedding coordinates and the coordinates of its corresponding published version. We also calculated a background distribution, which consisted of the distance between each preprint with an annotated publication and a randomly selected article from the same journal. We compared both distributions to determine if there was difference between both groups as a large difference would indicate that this embedding method can parse preprint-published pairs apart. Following the comparison of the two distributions, we calculated distances between preprints without a published version link with PMCOA articles that weren't matched with a corresponding preprint. We filtered any potential links with distances that were greater than the minimum value of the background distribution as we considered these pairs to be true negatives. Lastly, we binned the remaining pairs based on percentiles from the annotated pairs distribution at the [0,25th percentile), [25th percentile, 50th percentile), [50th percentile, 75th percentile), and [75th percentile, minimum background distance). We randomly sampled 50 articles from each bin and shuffled these four sets to produce a list of 200 potential preprint-published pairs with a randomized order. We supplied these pairs to two co-authors to manually determine if each link between a preprint and a putative matched version was correct or incorrect. After the curation process, we encountered eight disagreements between the reviewers. We supplied these pairs to a third scientist, who carefully reviewed each case and made a final determination. Using this curated set, we evaluated the extent to which distance in the embedding space revealed true but unannotated links between preprints and their published versions.

Measuring Time Duration for Preprint Publication Process

Preprints can take varying amount of time to become published. We sought to measure the time required for preprints to be published in the peer reviewed literature and compared this time measurement across author selected preprint categories as well as individual preprints. First, we queried bioRxiv's application programming interface (API) to obtain the date a preprint was posted onto bioRxiv as well as the date a preprint was accepted for publication. We measured time elapsed as the difference between the date at which a preprint was first posted on bioRxiv and its publication date. Along with calculating the amount of time elapsed, we also recorded the number of different preprint versions posted onto bioRxiv.

Using this captured data, we used the Kaplan-Meier estimator [54] via the KaplanMeierFitter function from the lifelines [55] (version 0.25.6) python package to calculate the halflife of preprints across all preprint categories within bioRxiv. We considered survival events as preprints that have yet to be published. There were a limited number of cases in which authors appeared to post preprints after the date of publication, which results in preprints receiving a negative time difference, as previously reported [56]. We removed these preprints for this analysis as they were incompatible with our analytical approach.

Following our halflife calculation, we measured the textual difference between preprints and their corresponding published version by calculating the Euclidean distance for their respective embedding representation. This metric can be difficult to understand within the context of textual differences, so we sought to contextualize the meaning of a distance unit. We accomplish this by first randomly sampled with replacement a pair of preprints from the Bioinformatics topic area as this was well represented within bioRxiv and contains a diverse set of research articles. Next, we calculated the distance between two preprints 1000 times and reported the mean. We repeated the above procedure using every preprint within bioRxiv as a whole. The percent change between these two means represents the amount of textual changes a single Euclidean distance unit represents. Following our contextualization approach, we performed linear regression to model the relationship between preprint version count with a preprint's time to publication. We also performed linear regression to measure the relationship between document embedding distance and a preprint's time

to publication. For this part of our analysis, we retained preprints with negative time within our linear regression model as these preprints had minimal impact on results. We visualize our version count regression model as a violin plot and our document embeddings regression model as a square bin plot.

Building Classifiers to Detect Lingusitcally Similar Journal Venues and Published Articles

Preprints are more likely to be published in journals that contained similar content to the work in question. We assess this claim by building classifiers based on document and journal representations. First, we removed all journals that had fewer than 100 papers in the PMC corpus. We held our preprint-published subset (see Mapping bioRxiv preprints to their published counterparts) and treated it as a gold standard test set. We used the remainder of the PMCOA corpus for training and initial evaluation for our models.

Certain journals publish articles in a focused topic area, while others publish articles that cover many topics. Likewise, some journals have a publication rate of at most hundreds of papers per year while others publish at a rate of at least ten-thousand papers per year. Accounting for these characteristics, we designed two approaches - one centered on manuscripts and another centered on journals.

For the manuscript-based approach, we identified manuscripts that were most similar to the preprint query and evaluated where these documents were published. We embedded each query article into the space defined by the word2vec model (see Constructing a Document Representation for Life Sciences Text). We selected manuscripts in close proximity of the query via Euclidean distance in the embedding space. Once identified we return the journal in which these articles were published. We also return the articles that led to each journal being reported as this approach allows for journals that frequently publish papers to engulf our results.

We constructed a journal-based approach to accompany the manuscript-based approach to account for overrepresentation of theses high publishing frequency journals. For this approach, we identified the most similar journals by constructing a journal representation in the same embedding space. We computed this representation by taking the average embedding of all published papers within a given journal. We then projected a query article into the same space and returned journals that were in close proximity to the query.

Both models were constructed using the scikit-learn k-Nearest Neighbors implementation [57] with the number of neighbors set to 10 as this is an appropriate number for our use case. We consider a prediction to be a true positive if the correct journal appears within our reported list of neighbors and evaluate our performance using 10-fold cross validation on the training set along with test set evaluation.

Web Application for Discovering Similar Preprints and Journals

We developed a web application that identifies similar papers and journals for any bioRxiv and medRxiv preprint and that places the preprint into the overall document landscape. Our web application downloads a pdf version of a preprint hosted on the bioRxiv or medRxiv server. We use pdfminer [58] to extract text from the downloaded pdf. The extracted text is then fed into our CBOW model to construct a document embedding representation. We pass this representation onto our journal and manuscript search to identify journals based on the ten closest neighbors of individual papers as well as journal centroids. We implemented this search using the scikit-learn implementation of k-d trees. To run it more cost effectively on cloud computing environment, we sharded the k-d trees into four trees.

Accompanying these recommendations, we also provided a neural network derived visualization of our training set and the article's position within it. We used SAUCIE [59], an autoencoder designed to cluster single cell RNA-seq data, to build a two-dimensional embedding space that could be applied to newly generated preprints without retraining, a limitation of other approaches that we explored for visualizing entities expected to lie on a nonlinear manifold. We trained this model on document embeddings of PMC articles that did not contain a matching preprint version. We used the following parameters to train the model: a hidden size of 2, a learning rate of 0.001, lambda_b of 0, lambda_c of 0.001, and lambda_d of 0.001 for 2000 iterations. When a user requests a new document, we can then project that document onto our generated two-dimensional space; thereby, allowing the user to see where their preprint falls along the landscape. We illustrate our recommendations as a short list and provide access to our network visualization at our website (see Software and Data Availability).

Results

Comparing bioRxiv to other corpora

bioRxiv Metadata Statistics

The preprint landscape is rapidly changing, and the number of bioRxiv preprints in our data download (71,118) was nearly double that of a recent study that reported on a snapshot with 37,648 preprints [60]. Because the rate of change is rapid, we first analyzed category data and compared our results with previous findings. As in previous reports [60], neuroscience remains the most common category of preprint followed by bioinformatics (Supplemental Figure S1). Microbiology, which was fifth in the most recent report [60], has now surpassed evolutionary biology and genomics to move into third. When authors upload their preprints, they select from three result category types: new results, confirmatory results or contradictory results. We found that nearly all preprints (97.5%) were categorized as new results, which is consistent with reports on a smaller set [61]. Taken together, the results suggest that while bioRxiv has experienced dramatic growth, the way in which it is being used appears to have remained consistent in recent years.

Global analysis reveals similarities and differences between bioRxiv and PMC

Table 1: Summary statistics for the bioRxiv, PMC, and NYTAC corpora.

Metric	bioRxiv	PMC	NYTAC
document count	71,118	1,977,647	1,855,658
sentence count	22,195,739	480,489,811	72,171,037
token count	420,969,930	8,597,101,167	1,218,673,384
stopword count	158,429,441	3,153,077,263	559,391,073
avg. document length	312.10	242.96	38.89
avg. sentence length	22.71	21.46	19.89
negatives	1,148,382	24,928,801	7,272,401
coordinating conjunctions	14,295,736	307,082,313	38,730,053
coordinating conjunctions%	3.40%	3.57%	3.18%
pronouns	4,604,432	74,994,125	46,712,553
pronouns%	1.09%	0.87%	3.83%

Metric	bioRxiv	PMC	NYTAC
passives	15,012,441	342,407,363	19,472,053
passive%	3.57%	3.98%	1.60%
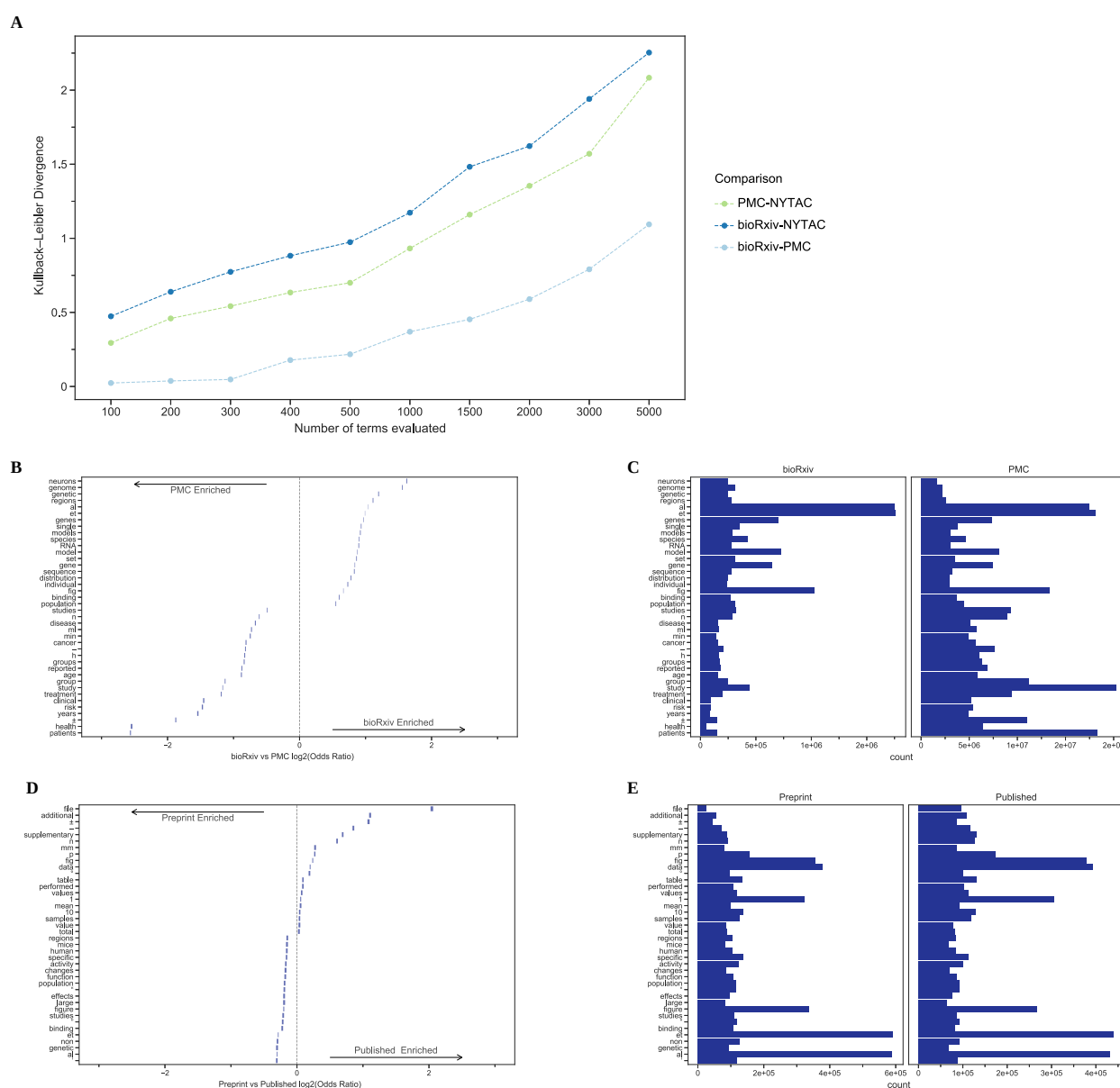
Figure 1: A. The Kullback–Leibler divergence measures the extent to which the distributions, not specific tokens, differ from each other. The token distribution of bioRxiv and PMC corpora is more similar than these biomedical corpora are to the NYTAC one. **B.** The major differences in token frequencies for the corpora appear to be driven by the fields that have had the highest uptake of bioRxiv, as terms from neuroscience and genomics are relatively more abundant in bioRxiv. We plotted the 95% confidence interval for each reported token. **C.** Of the terms that differ between bioRxiv and PMC, the most abundant in bioRxiv are "et" and "al" while the most abundant in PMC is "study." **D.** The major differences in token frequencies for preprints and their corresponding published version often appear to be associated with typesetting and supplementary or additional materials. We plotted the 95% confidence interval for each reported token. **E.** The tokens with the largest absolute differences in abundance appear to be stylistic.

Documents within bioRxiv were slightly longer than those within PMCOA, but both were much longer than those from our control (NYTAC) (Table 1). The average sentence length, fraction of pronouns, and the use of the passive voice were all more similar between bioRxiv and PMC than they were to NYTAC(Table 1). The Kullback–Leibler (KL) divergence of term frequency distributions between bioRxiv and PMCOA were low, especially among the top few hundred tokens (Figure 1A). As more tokens were incorporated the KL divergence started to increase, but remained much lower than the biomedical

corpora compared against NYTAC. These findings support our notion that bioRxiv is linguistically similar to the PMCOA repository.

Terms like "neurons" "genome" and "genetic", which are common in genomics and neuroscience, were more common in bioRxiv than PMCOA while others associated with clinical research, such as "clinical" "patients" and "treatment" were more common in PMCOA (Figure [1]B and [1]C). When controlling for the differences in the body of documents to identify textual changes associated with the publication process, we found that tokens such as "et" "al" were enriched for biorxiv while "$\pm$", "–" were enriched for PMCOA (Figure [1]D and [1]E). Furthermore, we found that certain changes appeared to be related to journal styles: "figure" was more common in bioRxiv while "fig" was relatively more common in PMCOA. Other changes appeared to be associated with an increasing reference to content external to the manuscript itself: the tokens "supplementary", "additional" and "file" were all more common in PMCOA than bioRxiv suggesting that journals are not simply replacing one token with another but that there are more mentions of such content after peer review.

Taken together these results suggest that the structure of the text within preprints on bioRxiv are similar to published articles within PMCOA. The differences in uptake across fields is supported not only by differences in authors' categorization of their articles but also in the text of the articles themselves. At the level of individual manuscripts, the terms that change the most appear to be associated with typesetting, journal style, and an increasing reliance on additional materials after peer review.

Document embeddings derived from bioRxiv reveal fields and subfields
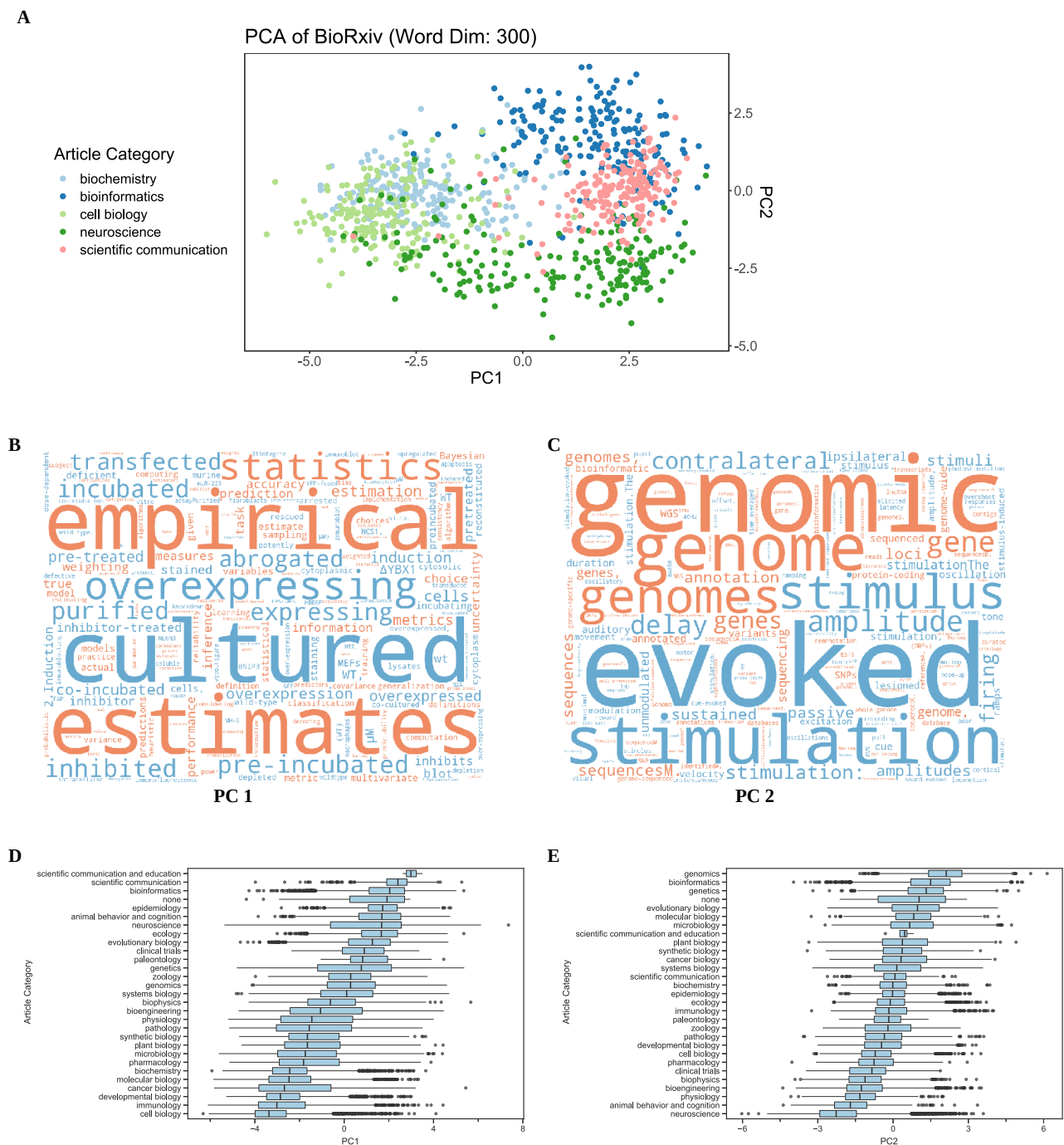
Figure 2: A. Principal components (PC) analysis of bioRxiv word2vec embeddings groups documents based on author-selected categories. We visualized documents from key categories on a scatterplot for the first two PCs. The first PC separated cell biology from informatics-related fields and the second PC separated bioinformatics from neuroscience fields. **B.** A word cloud visualization of PC1. Each word cloud depicts the cosine similarity score between tokens and the first PC. Tokens in orange were most similar to the PC's positive direction while tokens in blue were most similar to the PC's negative direction. The size of each token indicates the magnitude of the similarity. **C.** A word cloud visualization of PC2, which separated bioinformatics from neuroscience. Similar to the first PC, tokens in orange were most similar to the PC's positive direction while tokens in blue were most similar to the PC's negative direction. The size of each token indicates the magnitude of the similarity. **D.** Examining PC1 values for each article by category created a continuum from informatics-related fields on the top through cell biology on the bottom. Certain article categories (neuroscience, genetics) were spread throughout PC1 values. **E.** Examining PC2 values for each article by category revealed fields like genomics, bioinformatics, and genetics on the top and neuroscience and behavior on the bottom.

Document embeddings provide a means to categorize the language of documents in a way that takes into account the similarities between terms [34,62,63]. We found that the first two PCs separated articles from different author-selected categories (Figure 2A). Certain neuroscience papers appeared
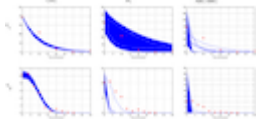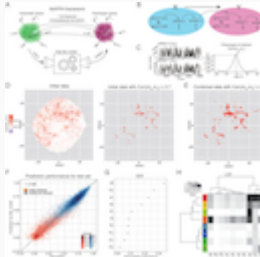
to be more associated with the cellular biology direction of PC1, while others appeared to be more associated with the informatics-related direction Figure 2A). This suggests that the concepts captured by PCs were not exclusively related to field.
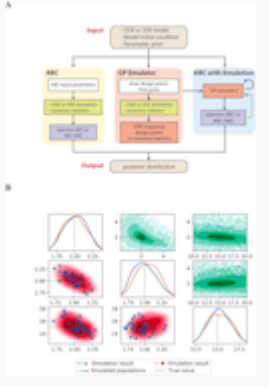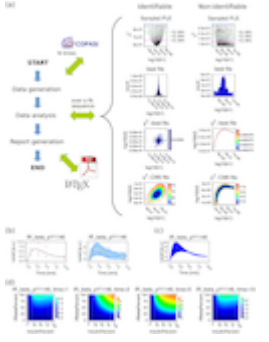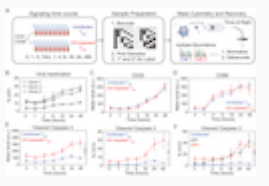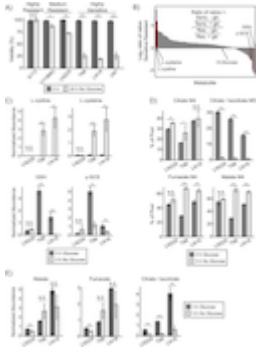
Visualizing token-PC similarity revealed tokens associated with certain research approaches (Figures 2B and 2C). Token association of PC1 shows the separation of cell biology and informatics related fields through tokens: "empirical", "estimates" and "statistics" depicted in orange and "cultured" and "overexpressing" depicted in blue (Figure 2B). Association for PC2 shows the separation of bioinformatics and neuroscience via tokens: "genomic", "genome" and "genomes" depicted in orange and "evoked", "stimulus" and "stimulation" depicted in blue (Figure 2C).
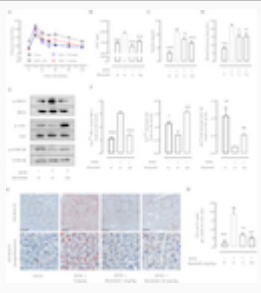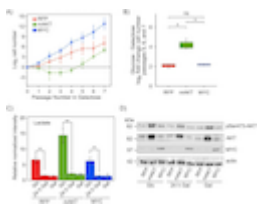
Examining the value for PC1 across all author-selected categories revealed an ordering of fields from cell biology to informatics-related disciplines (Figure 2D). These results suggest that a primary driver of the variability within the language used in bioRxiv could be the divide between informatics and cell biology approaches. A similar analysis for PC2 suggested that neuroscience and bioinformatics present a similar language continuum (Figure 2E). This result supports the notion that bioRxiv contains an influx of neuroscience and bioinformatics related research results. For both of the top two PCs, the submitter-selected category of systems biology preprints was near the middle of the distribution and had a relatively large interquartile range when compared with other categories (Figure 2D and 2E), suggesting that systems biology is a broader subfield containing both informatics and cellular biology approaches.

Examining the top five and bottom five preprints within the systems biology field reinforces PC1's dichotomous theme (Table 2). Preprints with the highest values [64,65,66,67,68] included software packages, machine learning analyses, and other computational biology manuscripts, while preprints with the lowest values [69,70,71,72,73] were focused on cellular signaling and protein activity. We provide the rest of our 50 generated PCs in our online repository (see Software and Data Availability).

Table 2: PC1 divided the author-selected category of systems biology preprints along an axis from computational to molecular approaches.

Title [citation]	PC1	License	Figure Thumbnail
Conditional Robust Calibration (CRC): a new computational Bayesian methodology for model parameters estimation and identifiability analysis [64]	4.700554908074704	None	
Machine learning of stochastic gene network phenotypes [65]	4.410660604449826	CC-BY-NC-ND	
Notions of similarity for computational biology models [66]	4.355295926618207	CC-BY-NC-ND	

Title [citation]	PC1	License	Figure Thumbnail
GpABC: a Julia package for approximate Bayesian computation with Gaussian process emulation [67]	4.351517618262304	CC-BY-NC-ND	
SBpipe: a collection of pipelines for automating repetitive simulation and analysis tasks [68]	4.321847854182741	CC-BY-NC-ND	
Spatiotemporal proteomics uncovers cathepsin-dependent host cell death during bacterial infection [69]	-4.263964235099807	CC-BY-ND	
Systems analysis by mass cytometry identifies susceptibility of latent HIV-infected T cells to targeting of p38 and mTOR pathways [70]	-4.279016673409032	CC-BY-NC-ND	
NADPH consumption by L-cystine reduction creates a metabolic vulnerability upon glucose deprivation [71]	-4.592209988884236	None	

Title [citation]	PC1	License	Figure Thumbnail
Inhibition of Bruton's tyrosine kinase reduces NF-kB and NLRP3 inflammasome activity preventing insulin resistance and microvascular disease [72]	-4.736613689905791	None	
AKT but not MYC promotes reactive oxygen species-mediated cell death in oxidative culture [73]	-4.826793742506695	None	

Document embedding similarities reveal unannotated preprint-publication pairs
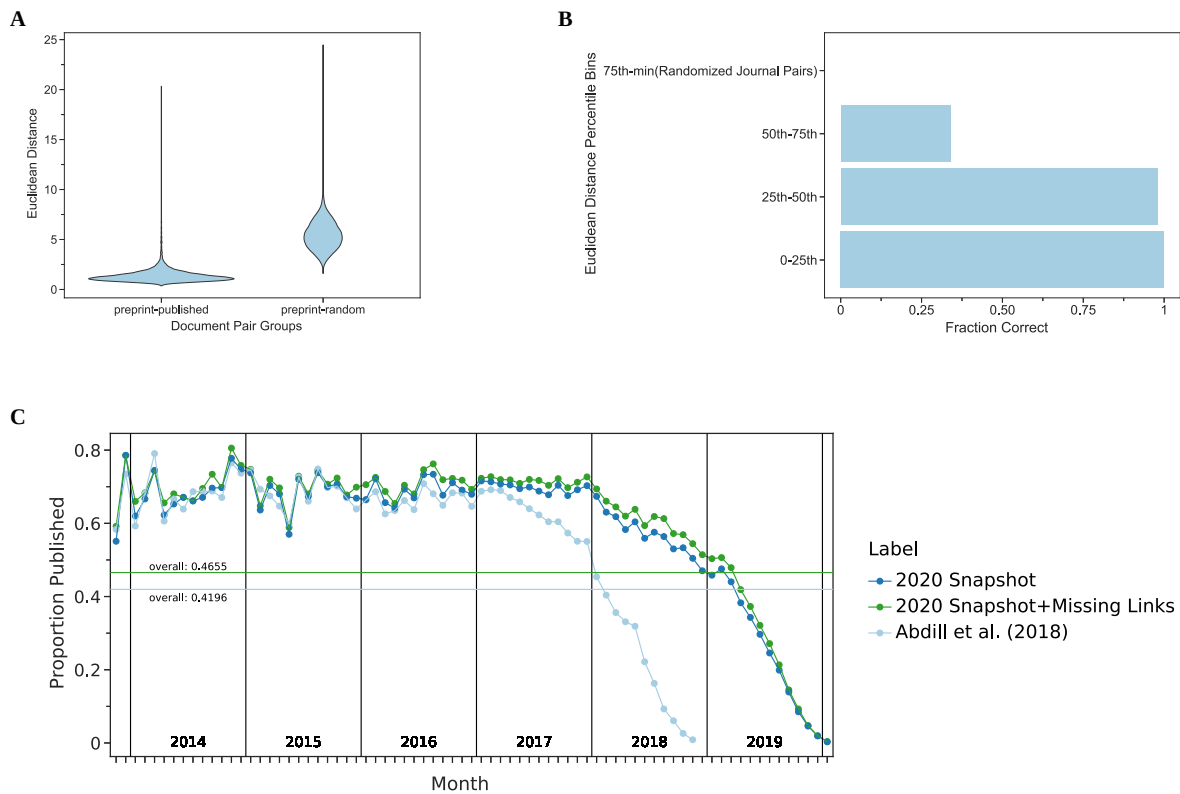
Figure 3: **A.** Preprints are closer in document embedding space to their corresponding peer reviewed publication than they are to random papers published in the same journal. **B.** Potential preprint-publication pairs that are unannotated but within the 50th percentile of all preprint-publication pairs in the document embedding space are likely represent true preprint-publication pairs. We depict the fraction of true positives over the total number of pairs in each bin. Accuracy is derived from curation of a randomized list of 200 potential pairs (50 per quantile) performed in duplicate with a third rater used in the case of disagreement. **C.** Most preprints are eventually published. We show the publication rate of preprints since bioRxiv first started. The x-axis represents months since bioRxiv started and the y-axis represents the proportion of preprints published given the month they were posted. The light blue line represents the publication rate previously estimated by Abdill et al. [60]. The dark blue line represents the updated publication rate using only CrossRef-derived annotations, while the dark green line includes annotations derived from our embedding space

approach. The horizontal lines represent the overall proportion of preprints that are were published as of the time of the annotation snapshot.

Distances between preprints and their corresponding published versions were nearly always lower than preprints paired with a random article published in the same journal (Figure 3A). This suggests that embedding distances can identify documents with similar textual content. Approximately 98% of our 200 pairs with an embedding distance in the 0-25th and 25th-50th percentile bins were scored as true matches (Figure 3B). These two bins contained 1,720 preprint-article pairs, suggesting that many preprints may have been published but not previously connected with their published versions. There is a particular enrichment for preprints published but unlinked within the 2017-2018 interval (Figure 3C). We expected a higher proportion of such preprints before the year 2019 (many of which may not have been published yet); however, observing relatively few missed annotations before 2017 was against our expectations. Overall, these results suggest that as the number of preprints posted on bioRxiv grows, it becomes harder to establish a link between preprints and their published counterparts.

Preprints with more versions or more text changes took longer to publish
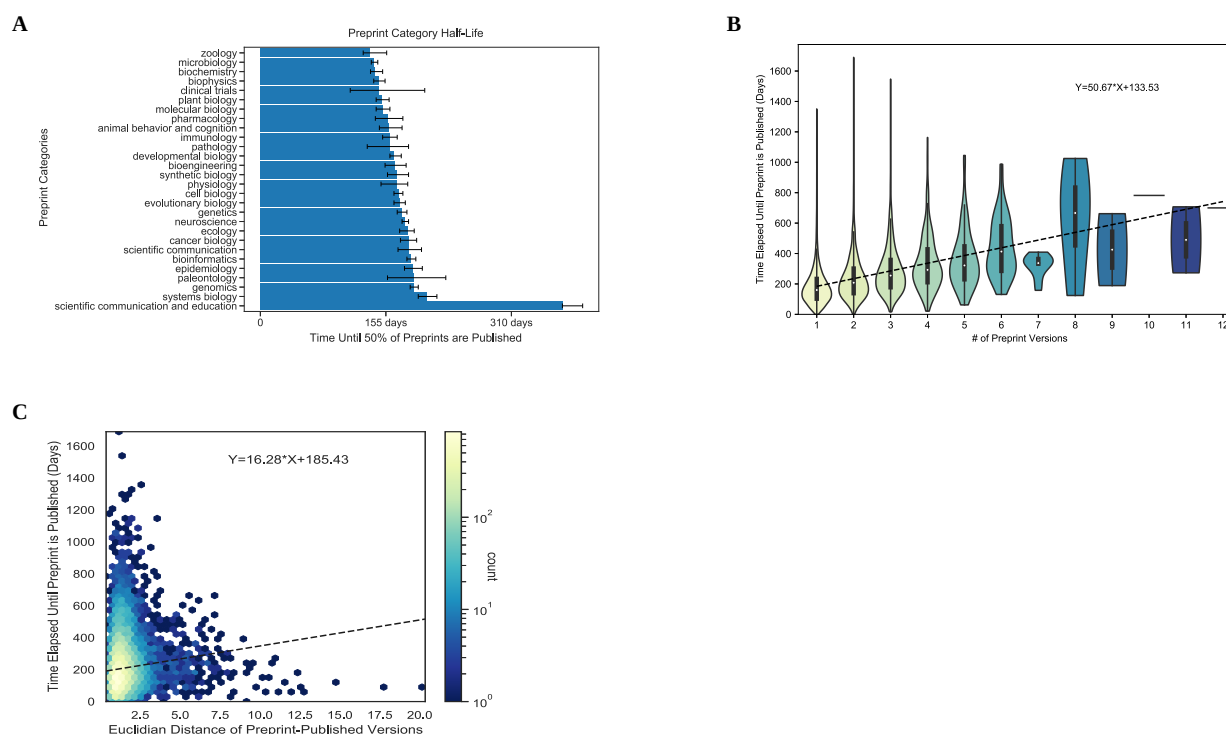
Figure 4: A. Author-selected categories were associated with modest differences in respect to publication halflife. Author selected preprint categories are shown on the y-axis, while the x-axis shows the median time-to-publish for each category. Error bars represent 95% confidence intervals for each median measurement. **B.** Preprints with more versions were associated with a longer time to publish. The x-axis shows the number of versions of a preprint that were posted on bioRxiv and the y-axis shows the number of days that elapsed between when the first version of a preprint was posted on bioRxiv and the date at which the peer reviewed publication appeared. The density of observations are depicted in the violin plot with an embedded boxplot. **C.** Preprints with more substantial text changes took longer to be published. The x-axis shows the Euclidean distance between document representations of the first version of a preprint and it's peer reviewed form. The y-axis shows the number of days elapsed between when the first version of a preprint posted on bioRxiv and the time a preprint is published. The color bar on the right represents the density of each hexbin in this plot where more dense regions are shown in a brighter color.

The process of peer review includes a number of steps which take variable amounts of time [74] and we sought to measure if there is a difference in publication time between author-selected categories of preprints (Figure 4A). Of the most abundant preprint categories microbiology was the fastest to

publish (140 days, (137, 145 days) [95% CI]) and genomics was the slowest (190 days, (185, 195 days) [95% CI]) (Figure 4A). We did observe category-specific differences; however, these differences were generally modest, suggesting that the peer review process did not differ dramatically between preprint categories. One exception was the Scientific Communication and Education category, which took substantially longer to be peer reviewed and published (373 days, (373, 398 days) [95% CI]). This hints that there is a key step or steps within the peer review process that greatly halts preprints in this category.

Examining peer review's affect on individual preprints, we found a positive correlation between preprints with multiple versions and the time elapsed until publication (Figure 4B). Each new version adds additional 51 days before a preprint is published. This time duration seems broadly compatible with the amount of time it would take to receive reviews and revise a manuscript, suggesting that many authors may be updating their preprints in response to peer reviews or other external feedback. Furthermore, we found that preprints with large embedding space distances from their corresponding peer reviewed publication took longer to publish (Figure 4C). Each unit of distances in the embedding space corresponds to approximately sixteen additional days to make textual changes (Figure 4C). We found that that average distance of two randomly selected papers from the bioinformatics category in bioRxiv is 5.068, while the average distance of two randomly selected papers from bioRxiv is 6.210. The percent change between these two means is 18%, suggesting that a single distance unit represents changing roughly 18%% of a preprint's total text. Overall, our findings support a notion that preprints reviewed multiple times or require larger revisions take longer to publish.

Preprints with similar document embeddings share publication venues

We developed an online application that returns a listing of published papers and journals that are closest to a query preprint in document embedding space. This application uses two k-nearest neighbor classifiers that achieved better performance than our baseline model (Supplemental Figure S2) to identify these entities. Users supply our app with digital object identifiers (DOIs) from bioRxiv or medRxiv and the corresponding preprint is downloaded from the repository. Next the preprint's PDF is converted to text and this text is used to construct a document embedding representation. This representation is supplied to our classifiers to generate a listing of the ten papers and journals with the most similar representations in the embedding space (Figures 5A, 5B and 5C). Furthermore, the user-requested preprint's location in this embedding space is then displayed on our interactive map and users can select regions to identify the terms most associated with those regions (Figures 5D and 5E). Users can also explore the terms associated with the top 50 PCs derived from the document embeddings and those PCs vary across the document landscape.
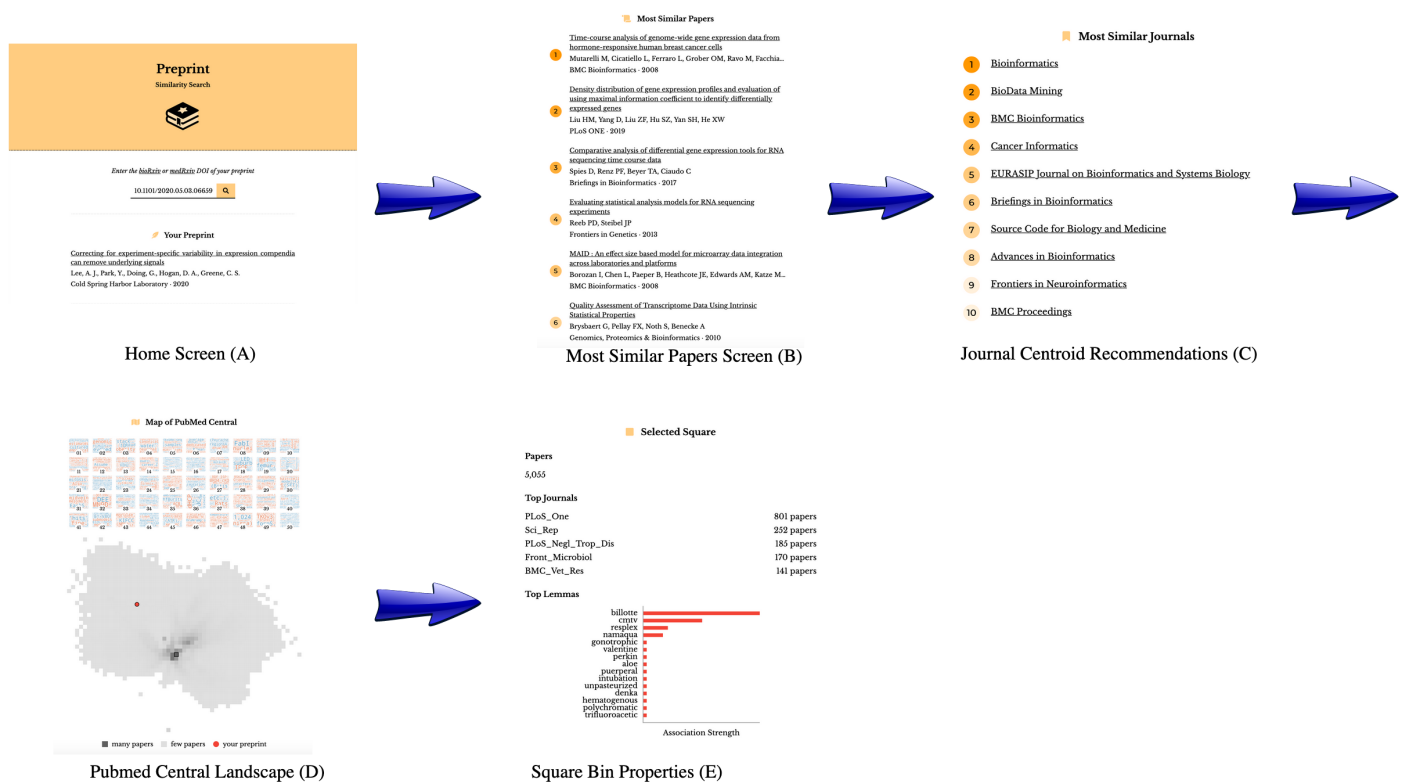
Figure 5: The preprint similarity search app workflow allows users to examine where an individual preprint falls in the overall document landscape. **A.** Starting with the home screen, users can paste in a bioRxiv or medRxiv DOI, which sends a request to bioRxiv or medRxiv. Next the app preprocesses the requested preprint and returns a listing of (**B**) the top ten most similar papers and (**C**) the ten closest journals. **D.** The app also displays the location of the query preprint in PMC. **E.** Users can select a square within the landscape to examine statistics associated with the square including the top journals by article count in that square and the odds ratio of tokens.

Conclusions

We analyzed the full text of bioRxiv, comparing it with the open access portion of PMC, and found that the overall manner of writing is consistent with the biomedical literature. A benefit of analyzing bioRxiv text is that we can compare preprint and published versions to examine the influence of the publication process. Token-level analyses suggest that differences between corpora are driven by fields, while comparisons of preprints with their corresponding publication reveals differences in typesetting and supplementary materials.

Previous analyses have focused on article metadata, including which papers are heavily downloaded and discussed [60] and by which communities discuss them [75]. We found that some preprints are highly similar to published articles within the PMC open access corpus, and a detailed examination revealed that many preprints were published but not previously annotated. Using the full text of documents to correct these missing annotations provides a comprehensive understanding of the extent to which preprints are published and this correction resulted in a publication rate that is higher than previously estimated. Importantly, this only accounts for papers that are published open access, so our analysis should be considered to raise the lower bound but the truly published fraction is likely to be higher.

Our work presents a first step towards understanding the process by which peer review alters life sciences papers through an analysis of the full text of preprints and their corresponding publication. Our broad-based examination suggests certain changes, but the scale of changes appears modest. We lay the groundwork for future work that aims to identify sentences and claims that are altered during review. Our finding that document embeddings reveal manuscripts with similar outcomes is likely to be important to new tools that accelerate publishing, including those that automatically perform integrity checks and other critically important contributions. We also found that document

embeddings captured many elements of how authors use language in preprints. Fields were separated first on an informatics / molecular axis, and author-selected categories could be distinguished based on embeddings. Document embeddings were also associated with the eventual journal at which the work was published. Based on this observation, we supply a web application that returns the papers and journals that are most similar to a bioRxiv or medRxiv preprint.

Software and Data Availability

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Competing Interests

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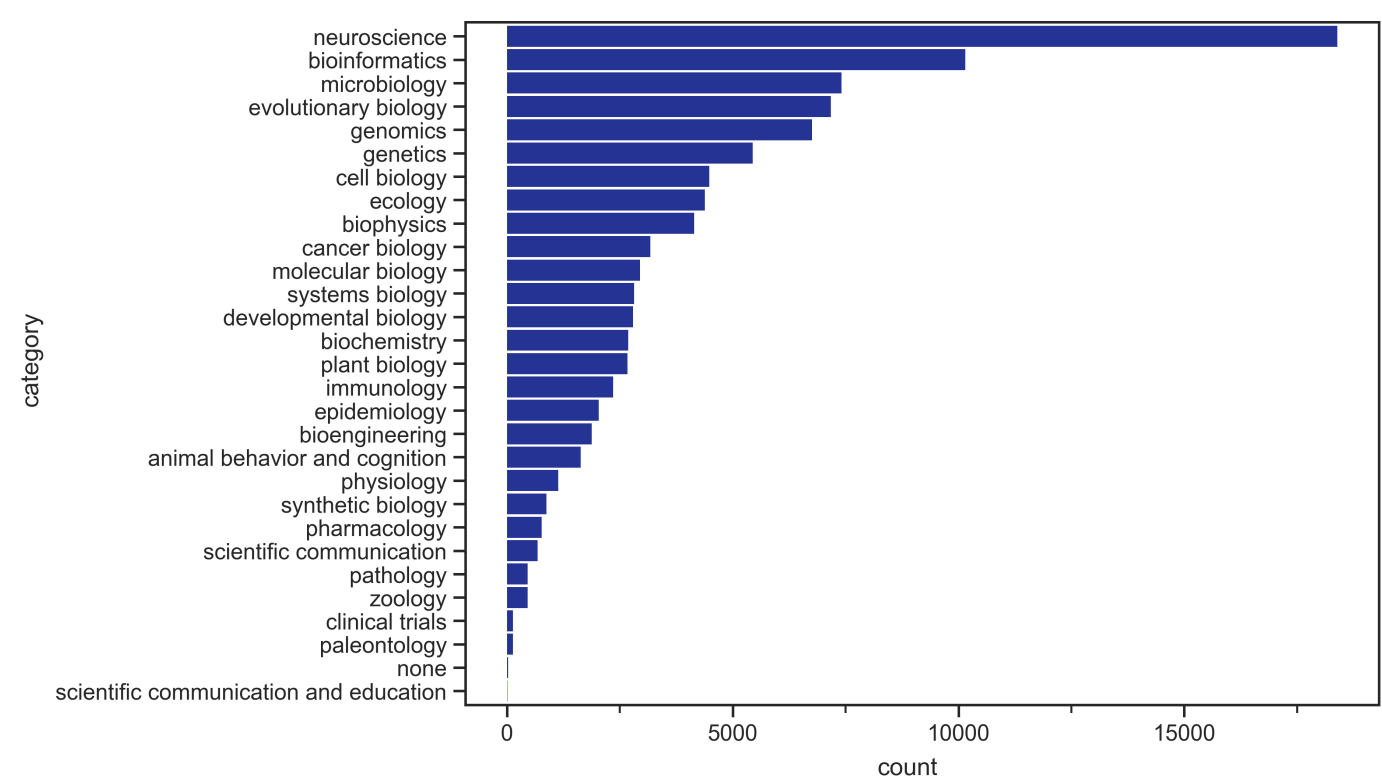
Supplemental Figures

Figure S1: Neuroscience and bioinformatics are the two most common author-selected topics for bioRxiv preprints.
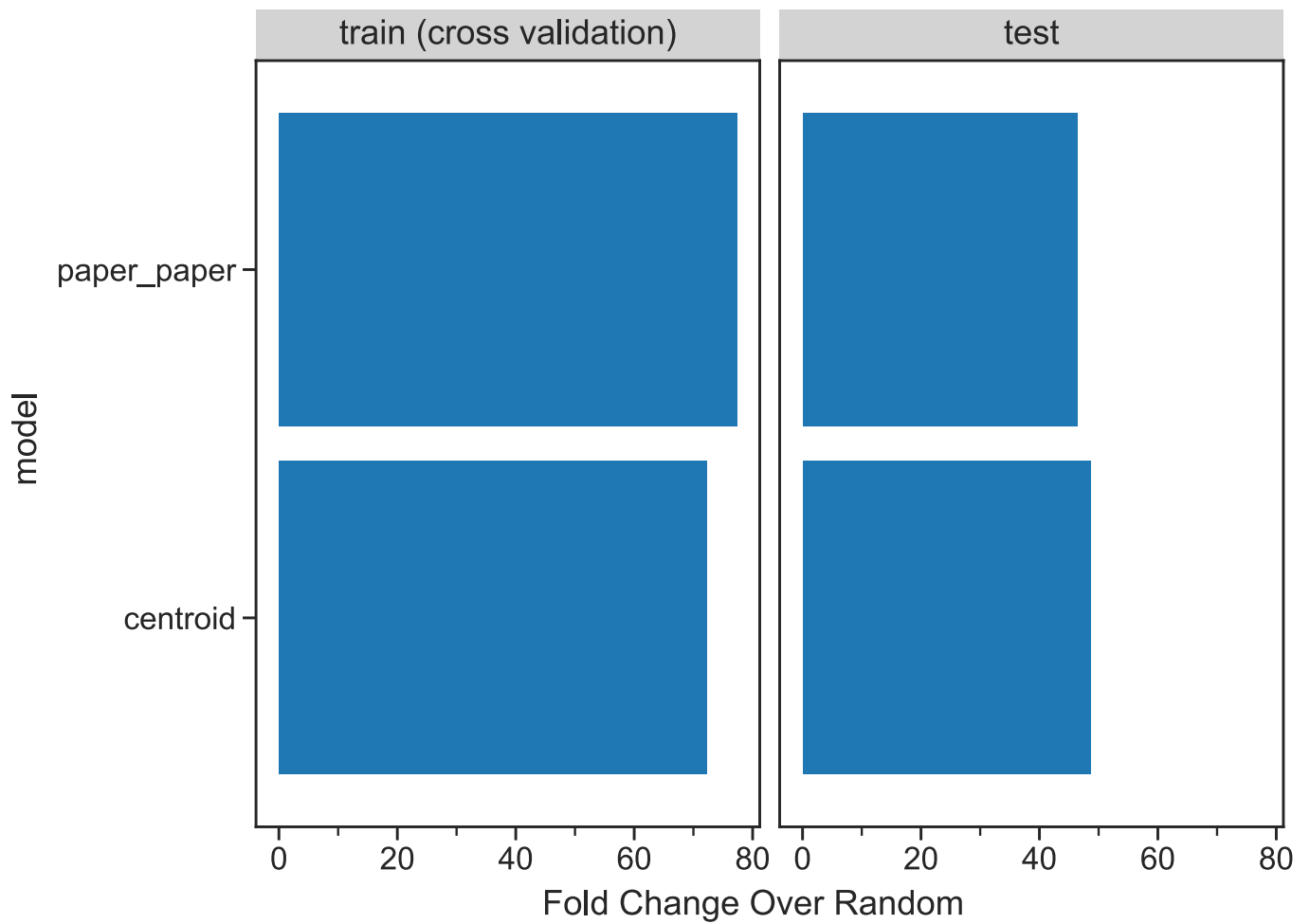
Figure S2: Both classifiers outperform the randomized baseline when predicting a paper's journal endpoint. This bargraph shows each model's accuracy in respect to predicting the training and test set.