

Data Accessibility Paper

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Sep 11, 2025

- Abstract

5 • Importance

- Incentivize authors to publish/make available their original data
- Publishing data helps get more use out of research
- Helps eliminate file drawer effect as it shows negative data

- Keywords

10 – Data accessibility
 – Data reproducibility

Introduction

Data availability (DA) is the practice of making raw experimental data and analyses publicly accessible, often via upload in maintained databases. DA is a newly emerging and yet deeply important component of the scientific process in the digital age. With the latest and greatest methodologies available across fields, increasing amounts of data are being generated each day, especially in the biological sciences. Availability of these large quantities of study data and metadata (data about data) is a necessary resource for appropriate use and re-use of data and protocols as well as the recreation of analyses. We believe that policies of data “available on request” are not sufficient to be considered available data. One example was published in *Microbiome*, that a reader

in search of data may email the corresponding author, with varying results ((1)). We believe that this is simply unacceptable, and set out to determine rates of published raw data in the biological sciences, specifically microbiology, by examining the American Society for Microbiology's (ASM) library of published primary research journals.

25 Scientific Data as a Public Good

The United States Government spent over two hundred million dollars (USD) in 2024 on research expenditures ((2)). The result of all of these investments are data, paid for in part by taxpayers. Therefore, data is a public good, and best used as a benefit to those who provided the funds for it. Once data has been generated, it can be used not only for initial analyses, but over and over again in future studies or meta analyses. Additionally, data can be used to eliminate possible solutions to a problem by the publishing of “negative data.” Thinking of data as a public good, if negative data is published, it can help researchers avoid sinking time and financial resources into the investigation of non-viable hypotheses. This lack of publication of non-fruitful investigation is more commonly known as the “file drawer effect.” Data as a public good also is subject to the tragedy of the commons. If no one contributes to the public “commons”, data that is available for public use, how can we advance our understanding of our study systems?

Current DA Policies

Current data availability guidelines have been informed by a number of policies created by funding agencies, peer-review journals, conference and special task groups, as well as community interest groups. In 2011, after the Future of Research Communication (FoRC) conference in Germany to establish FORCE11, a community interest group which seeks to encourage and promote data availability standards. Also in 2011, the Genomic Standards Consortium (GSC) published the MIMARKS/MIxS standards in *Nature Biotechnology* to promote the publication of the “minimum information about a marker gene sequence” (MIMARKS) or “minimum information about x sequence”

45 (MIXS) ((3)). These standards are checklists usable by data generators and uploaders towards inclusion of relevant data with sequence uploads in the International Nucleotide Sequence Database Collaboration (INSDC).

In 2014 the group published the Joint Declaration of Data Citation Principles (JDDCP), a document towards the standardization of data citation and its future availability((**Data?**) Citation Synthesis 50 Group 2014). The Findable, Accessible, Interoperable, and Reuseable (FAIR) data science guiding principles were put forth in 2016 by Wilkinson et al in *Nature Scientific Data* urges readers to “improve the infrastructure supporting the reuse of scholarly data” ((4)). Neither the JDDCP nor the FAIR principles are enforceable by any agency. Finally, the National Institutes of Health (NIH) began enforcing the “Policy for Data Management and Sharing” (NOT-OD-21-013) in January of 55 2023, requiring NIH funded studies to submit a data management and sharing plan (DMS) with their funding applications, and comply with their DMS plan after generation and publication of the funded work((**NIH2023?**)). Non-compliance with NOT-OD-21-013 is identified by funding agencies during annual Research Performance Progress Reports (RPPRs), and may impact future funding decisions ((**NIH2023?**)).

60 **ASM Journals**

With the advent of next generation sequencing, microbiology research has generated large amounts of sequencing data, and it is common to upload sequence data to a public repository as well as to include data in research publications. The American Society for Microbiology(ASM) is the major professional body recognized by microbiologists. They have eighteen journals, thirteen primary 65 research journals, three review journals, and two archive journals. In addition, several journals have been folded into others or renamed over time. The ASM family of journals requires that authors “make data fully available, without restriction, except in rare circumstances” ((**ASM?**) open data policy). They have adapted this policy from journals *Microbial Genomics* and *PLOS*. In the ASM open data policy they describe the use of a “Data Availability Statement” which includes “data 70 description, name(s) of the repositories, and digital object identifiers (DOIs) or accession numbers”

and encourages publishing data on relevant public repositories ((**ASM?**) website open data policy). Consequences of non-compliance to the ASM open data policy include contacting research article authors to inform of non-compliance, publication of an “Expression of Concern” for the author and their compliance issues, sanctions on publication in ASM journals, as well as contacting the
75 affiliated research institution and/or funding agencies of the authors ((**ASMcompliance?**)). We endeavor to evaluate how well the microbiology community is using reproducible data practices as we believe that this group of researchers will be early adopters of the technologies available as a result of both the ASM and NIH policies towards data availability.

Nucleic Acid Sequencing Efforts

80 Beginning in 1996 with the International Strategy Meeting on Human Genome Sequencing in Bermuda, researchers have prioritized the release of all human genome sequencing information so that it may “maximize its benefit to society” (@bermuda1996). The meeting participants agreed that “primary sequence data should be rapidly released”, with “sequence assemblies [to] be released as soon as possible, in some centres, assemblies of greater than 1 kb would be released automatically
85 on a daily basis”, and that “finished annotated sequence should be submitted immediately to public databases” (@bermuda1996). The “Bermuda Principles,” as they became known, have been embraced by the large scale Human Genome Project (HGP) since 1998. In 2003, another meeting, held in Ft. Lauderdale, FL, re-affirmed the 1996 Bermuda Principles, expanded upon them to apply more broadly towards sequencing data, and called for further support of these practices
90 (@ftlauderdale). These foundation agreements set the stage for both the HGP and the Human Microbiome Project (HMP) to generate and share massive amounts of data over the course of their studies (@HGP/HMP source needed).

Starting with projects such as the HGP and HMP, nucleic acid sequencing efforts have been commonly uploaded and released using public databases. There are three major databases
95 worldwide to support sequencing and sharing efforts. The National Library of Medicine’s (NLM) National Center for Biotechnology (NCBI) in the United States, the Research Organization of

Information Systems' (ROIS) National Institute of Genetics (NIG) in Japan, and the European Molecular Biology Lab's (EMBL) European Bioinformatics Institutue (EBI) in Europe. These three databases are part of the International Nucleotide Sequence Database Collaboration (INSDC).

100 These large databases make research by comparison possible. Genetic lineages of microbes are determined by creating phylogenetic trees which compare a new sequence to existing sequences. Phylogenetic trees show how closely related a new microbial genetic sequence is related to others studied before both in terms of evolution and mutation and in structure and function. An important tool for creating phylogenies is the NCBI Basic Local Alignment Search Tool (BLAST)

105 ((altschul1990?)). The BLAST algorithm allows users to compare a nucleic acid or protein sequence to the NCBI database of over 1TB of data to find similar and related sequences. Without the upload of sequences to the NCBI database, the use and success of BLAST would not be possible, despite the effort required on part of the researcher to upload of sequences to one of the INSDC databases.

110 Examples of Data Availability

A key tenet of the scientific method is the ability to replicate scientific findings to ensure that they are not due to error. One way that scientific findings can be replicated is by re-completing the same analyses by another researcher. This is only possible if the data used to complete the original analyses is available for use. The availability of datasets also allows new questions to

115 be answered with existing data or the combination of multiple datasets, such as the use of the Human Microbiome Project's (HMP) sequencing data by researchers to create over 650 scientific publications ((HMP?)), and the completion of metadata studies. Availability of data contributed to the rapid sequencing of the SARS-CoV-2 virus during the 2020 pandemic and subsequent expedition of vaccine development ((needCOVIDref?)).

120 With microbiologists commonly uploading nucleic acid sequences to public databases, the aim of this study was to determine the current state of data availability in twelve primary research journals from the ASM family of journals. Primary research articles were classified with using two machine

learning models to answer two questions; “Does this paper contain new sequence data?”, and “Is the data available?” Once these questions were answered, we moved to analyses to answer further
125 questions, “How does making my data available impact my citation metrics over time?”

Results

General Description of the Experiment

We set out to determine the current state of data availability in twelve primary research journals from the ASM family of journals. This objective was completed by first acquiring all papers published
130 in the journals of interest between 2000 and 2024 using the Crossref database and command line tools. We then trained random forest machine learning models to differentiate if each paper contained “New Sequencing Data” (NSD) and then if the paper had “Data Available” (DA). To avoid overfitting the model, we trained each model multiple times, performing validations on a subset of data after each iteration. This allowed us to have a greater number of papers in the training dataset,
135 as well as to have great accuracy and precision within our models. Using our trained models, we were able to classify over 150,000 papers from the whole dataset to determine if they were NSD or DA. After this, we could perform statistical modeling to describe the data, and generate summary statistics. We were especially interested in the ways in which NSD and DA impact citation metrics.

ASM Journals

140 We used twelve of the ASM primary research journals in this study. Of note, several journals had changes to their publication goals during the 2000-2024 time period. The *Journal of Bacteriology* was the primary place to publish new genome announcements until 2013 when ASM announced journal *Genome Announcements* as a more permanent place for this type of data. *Genome Announcements* was active from 2013 until 2018, when it was re-branded to *Microbiology Resource
145 Announcements*, which has been active from 2018 until present. These two journals appear separately in our analyses as a result of the Crossref database. New genome announcements

have a high percentage of NSD papers, and a high percentage of DA within those papers. As a result, the *Journal of Bacteriology* has had fewer NSD papers, and fewer papers with DA since 2013. Another journal of note is *Microbiology Spectrum* and its re-brand. From 2013 until the fall of 150 2021, *Microbiology Spectrum* was a review journal. After this point, *Microbiology Spectrum* became a primary research journal. Review journals are less likely to publish articles with NSD, and to have DA. Several journals, including *Microbiology Spectrum*, do not span the entire time period for the study. Journals *mBio* (b.2010), *Microbiology Spectrum* (b. 2013, re-brand 2021), *mSphere* (b. 2016), *mSystems* (b. 2016), and *Genome Announcements* (2013-2018). Not all journals are 155 equally likely to contain NSD and have sequencing DA as a result of their field of interest. Journals *Antimicrobial Agents and Chemotherapy*; *Infection and Immunity*; and the *Journal of Microbiology and Biology Education*; are all less likely to contain NSD and have DA than the other journals in the dataset.

Descriptive Statistics:

container.title	n_total	n_fract	n_nsd	fract_nsd	n_da	fract_da
Antimicrobial Agents and Chemotherapy	82	7.846890	23	28.04878	10	43.47826
Applied and Environmental Microbiology	92	8.803828	38	41.30435	28	73.68421
Genome Announcements	30	2.870813	29	96.66667	29	100.00000
Infection and Immunity	76	7.272727	16	21.05263	9	56.25000
Journal of Bacteriology	75	7.177034	25	33.33333	15	60.00000
Journal of Clinical Microbiology	77	7.368421	23	29.87013	14	60.86957
Journal of Microbiology & Biology	60	5.741627	0	0.00000	0	NaN
Education						
Journal of Virology	87	8.325359	21	24.13793	6	28.57143
<i>mBio</i>	63	6.028708	17	26.98413	11	64.70588
Microbiology Resource Announcements	155	14.832536	146	94.19355	145	99.31507

container.title	n_total	n_fract	n_nsd	fract_nsd	n_da	fract_da
Microbiology Spectrum	111	10.622010	49	44.14414	38	77.55102
mSphere	57	5.454546	25	43.85965	20	80.00000
mSystems	80	7.655502	45	56.25000	45	100.00000

container.title	n_total	n_fract	n_da	fract_da
Antimicrobial Agents and Chemotherapy	3237	6.7708333	805	24.86871
Applied and Environmental Microbiology	8638	18.0681058	2640	30.56263
Genome Announcements	6578	13.7592035	6254	95.07449
Infection and Immunity	1854	3.8780120	280	15.10248
Journal of Bacteriology	4867	10.1803046	1351	27.75837
Journal of Clinical Microbiology	4374	9.1490964	493	11.27115
Journal of Microbiology & Biology Education	7	0.0146419	0	0.00000
Journal of Virology	4583	9.5862617	936	20.42330
mBio	2498	5.2250669	1500	60.04804
Microbiology Resource Announcements	5738	12.0021754	5708	99.47717
Microbiology Spectrum	2957	6.1851573	2138	72.30301
mSphere	1041	2.1774598	747	71.75793
mSystems	1436	3.0036814	1253	87.25627

160 Whole Dataset

Using the Crossref database, with validation from WOS, NCBI, and Scopus databases, we downloaded 155779(XXX- find way to get this not hard coded in) unique records of papers published in ASM journals between 2000 and 2024. After web scraping there were YYYY papers downloaded with text available for the models to be applied on, as not all records had text available. See table 165 YYYY for number of papers downloaded from each journal. Overall, XXXX% of papers had NSD,

and YYYY% of papers with NSD, had DA. See table YYYY for percentages of NSD and DA for each journal. The journal with the highest rate of NSD was XXXXX at XXXX%, and the lowest was XXXX at XXXX%. The journal with the highest rate of DA was XXXXX at XXXX%, and the lowest was XXXX at XXXX%. This was expected as *Microbiology Resource Annoucements* publishes mainly new genomic sequence data and makes the data available. On average, papers in the dataset had XXXX citations/article. This number varies by journal, see table YYYY for data by journal. The journal with the highest rate of citations/article was XXXXX at XXXX%, and the lowest was XXXX at XXXX%. **SENTENCE ABOUT THIS BEING GOOD AND WHAT WE WANTED TO SEE IN THIS DATASET.** The journals in the dataset span years 2000-2024. See table YYYYYY for the distribution of papers per year in the dataset.

year.published	n
2000	30
2001	43
2002	23
2003	22
2004	21
2005	36
2006	29
2007	18
2008	12
2009	13
2010	21
2011	41
2012	24
2013	29
2014	31
2015	34

year.published	n
2016	38
2017	40
2018	40
2019	63
2020	65
2021	119
2022	70
2023	57
2024	116
NA	10

Training Dataset (pretty much the same as the above paragraph, but with stats for the training dataset)

We created a subset of the whole dataset to train our machine learning models. The training dataset initially had N = 500 papers, but was increased over time due to gaps in the dataset, and

180 after subsequent validation of the trained models (see below), with a total of N = 1045. See table YYYY for the distribution of papers per journal in the training dataset. The journals in the dataset also span years 2000-2024. See table YYYYYY for the distribution of papers per year in the training dataset. Overall, 43.7320574% of papers had NSD, and 80.9628009% of papers with NSD, had DA. See table YYYY for percentages of NSD and DA for each journal. The journal with the highest rate 185 of NSD was Genome Announcements at 96.6666667%, and the lowest was Journal of Microbiology & Biology Education at 0%. The journals with the highest rate of DA in NSD papers were Genome Announcements and mSystems at 100%, and the lowest was Journal of Virology at 28.5714286%. On average, papers in the dataset had median 10 citations/article. This number varies by journal, see table YYYY for data by journal. The journal with the highest rate of citations/article was Infection

190 and Immunity at 40%, and the lowest was Microbiology Resource Announcements at 0%.

Descriptive Statistics about the Trained Models

Two random forest models were trained to predict if published scientific papers “contained new sequence data” (NSD), and if the paper “had data available” (DA), one model for each variable.

Other models such as generalized linear regression and boosted trees were explored, but were

195 ultimately discarded in favor of the random forest model (data not shown). Random forest models

were chosen to aid in this classification problem as the creation of many decision trees helps to improve accuracy and precision. This type of model has one hyperparameter, ‘mtry’ or the number of predictors to be sampled at each decision. During iterative model training, a subset of papers

were validated after each completed training and deployment of each model. Papers from each

200 journal, and extras from certain journals were hand-validated against model predictions to generate

confusion matrices. Confusion matrices for the final version of each trained model are available in YYYY table(supplement?). The NSD model used an mtry value of 300 had an Area Under the Curve(AUC) of 0.9549XXX and an accuracy of 0.8925XXX. The sensitivity of the NSD model was

0.9130XXX, and the specificity of the model was 0.8683XXX. The DA model used an mtry value of

205 400 had an AUC of 0.9824XXX and an accuracy of 0.9353XXX. The sensitivity of the DA model was

0.9545XXX, and the specificity of the model was 0.9005XXX ([\(Data/final/best_model_stats.csv?\)](#)

for internal ref). This shows that the models fit the data well, and can provide classifications on new

data with an expected error rate of approximately 10%. We deemed this as acceptable, accounting

for variability in papers and data, and due to the large size of the dataset to deploy the models on.

210 Regression Model using Negative Binomial Models

In this study we sought to investigate the effect of NSD and DA on the number of citations received by a given paper. We focused on NSD papers to determine the effect of having DA. This led us to the use of a negative binomial regression model to best describe our data. All regression data was

NSD yes. We focused on the continuous outcome of “number of citations” with predictor variables
215 journal (categorical), age in months (continuous), and DA status (dichotomous). Due to the number
of citations being fairly bell shaped with a long right tail (very few papers at advanced age with many
citations), the model that best described our data was the negative binomial regression model. A
negative binomial model is appropriate for data that begins at zero and has a long ‘tail’ of data. This
model also includes a dispersion parameter to describe the spread of the data. We applied a log
220 transformation to our age variable (age.in.months) to better describe the relationship between time
and number of citations received. ???HOW DO I DESCRIBE THE PRODUCED MODEL??? In
general, we found that NSD papers that made DA received more citations over time than those that
did not. See figure YYYY for trends in each major journal. ??HOW else do i describe the figure??

Discussion

- 225 • Percent of ASM papers that have new sequence data available (nsd Yes, da Yes)
- trends by journal
 - trends by year
- Making data available
- provides more citations per paper than not doing so by XXX number
 - Allows for replication of studies
- 230 • Why bother doing this?
- What advantage does it give you as a data generator
 - Is it worth the work?
-

235 **Materials and Methods**

Creation of the Training set

To train our random forest machine learning model, we first created an appropriate training data set. Using the crossref database, we first downloaded all papers from the selected ASM family of journals from the time period beginning January 1st, 2000, and ending on December 31st, 2024.

240 The data was updated as of February 10th, 2025 with all citation counts frozen at that date. For our initial training set, we chose N = 500 papers from across each journal and time period, adding special emphasis to include papers that were part of our desired set of interest (i.e. contained published data) to ensure that our two models could adequately characterize each paper as a new sequencing paper and if it published raw sequencing data or not. After creating our initial 245 dataset, it was necessary to identify the status of both variables by hand and determine if each paper contained “new sequencing data” (NSD), and if each one had “data available” (DA). This was completed by opening each paper in an internet browser window, and searching for a “data availability” or similar statement. See table XXX for specific cases and how each of these cases were identified for the purpose of this study.

250 **Adding Additional Training Set Papers**

After initial trainings of our random forest models, a random sampling of papers was collected for each journal to audit the efficacy of the models. To audit the efficacy of the models, we hand identified the status of both variables of interest, NSD and DA. We looked for weaknesses in the models, and updated methodology to reflect important areas of interest. For example, in 2023 the

255 ASM journals changed their formatting to include the data availability statement of a paper in a sidebar of the webpage. We identified this by noticing that all papers from journal *Microbiology Resource Announcements* from 2023-2024 were incorrectly characterized by the model as DA = No. The sidebar of the webpage was not included in the text the model was considering, and code had to be updated to include all sidebar data for all papers. These improvements to the model

260 created a larger and more comprehensive training set of N = 9XX. These validations allowed us to
create confusion matrices for each model. Confusion matrices for the final version of each trained
model are available in YYYY table(supplement?).

Descriptive Statistics about the Training Set

There were XXX papers in the training data set from 12 ASM journals. These papers came
265 from journals *Applied and Environmental Microbiology*; *Antimicrobial Agents and Chemotherapy*;
Infection and Immunity; *Journal of Clinical Biology*; *Journal of Virology*; *Journal of Bacteriology*;
Journal of Microbiology and Biology Education; *Microbiology Resource Announcements* (formerly
known as *Genome Announcements*); * mSystems; mSphere; mBio; and Microbiology Spectrum.*
See table XXXX for the number of papers from each journal in the training dataset. The training
270 dataset includes journal articles published between January 1st, 2000 and December 31st, 2024.
See table XXXXX for the number of papers included from each year from 2000-2024. XXX% of
training set data was NSD = Yes, and XXX% of training set data was DA = Yes.

Creation of the Training Data from Training dataset

To perform the computational steps required for these experiments, we used the python tool
275 Snakemake ((**snakeref?**)), and the University of Michigan's high performance computing cluster
((**arc?**) ref). Using our selected papers from the training dataset, we downloaded the entirety of
each paper's source HTML using the command line tool wget. This allowed us to use the source
HTML multiple times for updated analyses without the need to re-query the ASM web servers
numerous times. Next, we performed cleaning of the HTML using R packages rvest ((**rvest?**)
280 ref) and xml2 ((**xml2?**) ref) to get the desired portions of the paper from the HTML including the
abstract, the body of paper, all tables and figures with captions, as well as the side panels for all
papers, but especially those containing the data availability statements in papers published after
the 2023 change in webpage format (see above). Then we removed unnecessary text using R

packages tm(text manipulation)((**tm?**) ref) and textstem ((**textstem?**) ref), as well as converting
285 all text to lowercase, and the removal of digits and non-alphabetic characters such as whitespace.

To have the fewest number of unique words, we lemmatized (sort words by grouping inflected or variant forms of the same word) words to trace them back to their root words and eliminate any possible issues with word tense. After this, we created and counted our ‘tokens’, phrases of up to 1-3 consecutive words from the text of the paper using R package tokeinziers ((**tokeinziers?**) ref).

290 Towards the goal of the fewest meaningful number of words, we used the ‘Snowball’ ((**snowball?**) ref) dictionary of ‘stop words’ to remove non-meaningful words such as articles ‘a’, ‘an’, and ‘the’. We removed the ‘space’ character with an underscore in multi-word tokens for ease of procesing, and created a count table for the tokens in each paper.

Once the tokens in each paper were counted, we transformed the data into a sparse matrix format
295 useable by the R package mikropml ((**mikropml?**) ref), using R packages caret and dplyr ((**caret?**) ref, (**dplyr?**) ref). Tokens were filtered to those which appear in greater than one paper. This allows comparison between papers by the model. We removed near zero variants (tokens with frequency very close to zero) as well as collapsing perfectly correlated tokens (tokens that always appear together) using R packages caret and mikropml to reduce model complexity. The data was then
300 simplified to keep only the following variables; tokens, frequency, journal information, and hand identified NSD and DA variables. This simiplified sparse matrix data had the mean and standard deviation calcultated and saved for the frequency of each token to later apply a z-scoring method to future data to be predicted by the model.

Training of the DA and NSD Models

305 We trained two random forest machine learning models using mikropml’s “run_ml” function, one to determine if a paper contained new sequence data (NSD), and another to determine if the paper had data available (DA). The mikropml “run_ml” function uses methodology described by Topcuoglu et al ((**topcuoglu2020?**)) to split data for model training. Random forest models have one hyperparameter to tune, the mtry value. We began with mtry values of 100, 200, 300, 400,

310 500, and 600, to find peak hyperparameter performance given N tokens. We trained the models multiple times in accordance with existing methodologies, first to find the optimal Area Under the Receiver-Operator Curve (AUROC) value for each model with $N=100$ seeds. Then to find the best mtry performance for each model, with $N=1$ seed. Finally, with $N=1$ seed to train each final model for use on experimental data.

315 **Preparation of the Experimental Dataset**

To fully answer our research questions, we created a larger database with $N = 155779$ papers curated from reference datasets Crossref, NCBI, Scopus, and the Web of Science (([crossref?](#)), ([ncbi?](#)), ([scopus?](#)), ([wos?](#))). These papers span all twelve ASM journals of interest from the start of 2000 to the end of 2024. Once database was curated, we applied the same steps to ready 320 papers for application of machine learning models as the model training datasets. See above for descriptions of webscraping html, cleaning html, removing unnecessary text, and creation of token count table for application in each of the machine learning models to determine the NSD and DA statuses for each paper. Once the frequency count tables were prepared for each paper, a z-score was applied using the saved data from each model appropriately, using the formula 325 $\text{XXX}((\text{observed_token_frequency} - \text{model_token_frequency_mean}) / (\text{model_token_frequency_sd}))$. This z-scoring formula was applied to standardize the frequency of each token. Only tokens included in the machine learning models were retained in experimental datasets. Finally, each model was deployed on each paper to determine its NSD and DA status.

- Statistical methodology
 - negative binomial modeling using r package MASS
 - * fixed modeling
 - * log transformation of age.in.months
 - * 95% CI
 - Supplemental Material file list (where applicable)

- 335 • Acknowledgments
• References
• Figures/Tables/stats to make/get
– Table showing # of papers from each journal in training dataset
– Table showing # of papers from each year in training dataset
340 – % of papers nsd yes total (training)
– % of papers da yes total (training)
– table of conditions to add to the methods of classification?

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