### Final Project Report

# Classification of Biomedical Abstracts: PubMed vs. BioRxiv

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# Introduction

For the final project, we compared abstracts of both peer-reviewed articles from *PubMed Central Open Access* Subset and pre-prints found on *Biorxiv.org* (inspired by *ArXiv.org*) with the goal of classifying the source of the article abstract. As articles submitted to pre-print repositories like *Biorxiv.org* are not required to have gone through peer review, it is possible these articles differ from peer-reviewed articles from *PubMed* in research quality, depth, and rigor. While this text analysis experiment does not hope to determine these features, if classification accuracy is found to be above chance level (using a balanced dataset in both source and field), further analysis into how this difference is determined would be worthwhile.

Our project uses 52962 instances (balanced at 39074) of moderately unstructured text pulled from the two sources in XML and HTML. Beyond having to derive linguistic features and patterns in these texts, machine learning can assist with the analysis and comparison in an efficient manner.

Some works prior to 2019 used manual processes for text analysis as follows:

Klein, M., Broadwell, P., Farb, S. E., & Grappone, T. (2018). Comparing published scientific journal articles to their pre-print versions. *International Journal on Digital Libraries*. <a href="https://doi.org/10.1007/s00799-018-0234-1">https://doi.org/10.1007/s00799-018-0234-1</a>

Amaral, O. B. (March 20, 2018). Comparing the quality of reporting between preprints and peer-reviewed articles – a crowdsourced initiative. Retrieved March 8, 2019, from ASAPbio website: <a href="https://asapbio.org/amaral-quality">https://asapbio.org/amaral-quality</a>

Carneiro, C. F. D., Queiroz, V. G. S., Moulin, T. C., Carvalho, C. A. M., Haas, C. B., Rayêe, D., ... Amaral, O. B. (March 22, 2019). Comparing the quality of reporting between preprints and peer-reviewed articles in the biomedical literature [Preprint]. <a href="https://doi.org/10.1101/581892">https://doi.org/10.1101/581892</a>

### Data

The *PubMed Central Open Access Subset* (PMC OA)<sup>1</sup> - offered by the National Institute of Health (NIH) - is a repository of medical and biomedical papers published across a number of journals. These texts are available for public access without subscription. Each article in the subset is available in HTML, XML, and (often) pdf data formats via the Entrez API. [1]

*Biorxiv.org* is a preprint service for biomedical articles, similar to the better known Cornell University's *ArXiv.org*. As preprints, the necessity of formal peer-review is not present and is indeed unlikely in many cases. The benefit of preprint services is twofold: Authors are able to make their findings immediately available to the scientific community and, due to the physical and monetary accessibility, feedback on draft manuscripts can be received before they are submitted to journals.

For this project, the corpora from either source were constrained so that each set comprised of the same set of topics. Additionally, number of articles *within* each topic was further constrained, providing the classes with equally representation. Due to the significantly more recent instantiation of the BiorXiv corpus (first papers were in 2013) relative to the PubMed corpus (at least pre 1970), BiorXiv is likely to be the constraining set.

### These topics are:

- Bioinformatics (BiorXiv: ~4800)
- Neuroscience (BiorXiv: ~7880)
- Microbiology (BiorXiv: ~3390)
- Pharmacology and Toxicology (BiorXiv: ~340)
- Epidemiology (BiorXiv: ~1200)
- Genomics (BiorXiv: ~3320)
- Immunology (BiorXiv: ~960)

In sum, there are around 21890 desirable articles on BiorXiv. Dependent on the accessibility of articles on BioArXiv, achieving equal representation from PubMed provides a maximum corpus size of ~43780 articles. [2] In our project, equal instances of each topic from either source were collected. Topics were mapped via PubMed's MeSH thesaurus. Duplicate articles were removed, and the remained articles were randomly sampled for equal instance count for each topic. The final corpus after deduplication consisted of 39074 instances.

# Method

### Retrieval Process

The initial step for this project was data aggregation. This required the acquisition of the source materials, necessitating two separate processes for either source. PubMed articles

<sup>&</sup>lt;sup>1</sup> https://www.ncbi.nlm.nih.gov/pmc/tools/openftlist/

were obtained through the Entrez API provided by the NIH's NCBI (National Institute of Health, National Center for Biotechnology Information). The Python package *BioPython* includes a premade wrapper for this API, which made a hand-made solution unnecessary. At the time of this paper, *BioArXiv* does not have an API. Due to this, a respectfully slow scrape of BioArXiv abstracts from each topic was conducted.

# Preprocessing and Data cleaning

The Entrez API offered several data formats, XML was chosen due to familiarity with their relatively consistent use of resource document framework (RDF) standards. As such, the necessary fields (abstracts in this case) could be transformed into a raw text without much trouble.

Initially, Biorxiv.org was thought to be the more challenging of the two. First, only a limited, non-historical RSS feed of incoming papers is officially offered by the service. Thankfully, they push titles and a link to the article to several Twitter accounts, each specific to an overarching topic. Another issue is that all full-text articles are exclusively available in PDF format; abstracts are available on the linked page, thus standardized and retrievable through HTML processing tools. Because of the standard formatting required to submit to BiorXiv, this HTML was cleaner than PubMed's XML.

For standardization and ingestion of the two sources, a custom preprocessing pipeline was developed. Each abstract was:

- 1) Converted to lowercase
- 2) The following characters were replaced with spaces:
  - a) tabs
  - b) new lines
  - c) carriage returns
  - d) numbers
  - e) email addresses
  - f) URLs
  - g) punctuation, and
  - h) other associated characters (e.g., ^, ;, &, {}, etc.) (See Appendix).
- 3) Text was tokenized
- 4) Stopwords were removed
- 5) Words under a prespecified length were removed (4 for the final).
- 6) Tokens were lemmatized with WordNet Lemmatizer using the NLTK package for Python.

### **Feature Selection**

Before being fed through the pipeline, the corpus was split 80/20 as 80% of the original corpus was used as the training set (28368 instances) and 20% was set aside for the final testing (7093 instances). The model pipeline was fit to the training data, then both the training and testing sets were transformed via this pipeline.

Background: Cardiometabolic affections greatly contribute to the global burden of disease. The susceptibility to these conditions associates with the ancestral genetic composition and gut microbiota. However, studies explicitly testing associations between genetic ancestry and gut microbes are rare. We examined whether the ancestral genetic composition was associated with gut microbiota, and split apart the effects of genetic and non-genetic factors on host health. ...

background cardiometabolic affection contribute global burden disease susceptibility condition ancestral genetic composition microbiota study explicitly test genetic ancestry microbe rare examine whether ancestral genetic composition microbiota split apart effect genetic genetic factor host health

Fig 1. An example of text transform

### Part 1: Latent Semantic Analysis

Initial vectorization of training instances was restricted to: terms with a document frequency less than 65%, with a total document occurrence of more than 25 and 10000 features returned (5847 unique terms returned).

Our initial pipeline was structured as a typical Latent Semantic Indexer/Analyzer (LSI/LSA). The count vector was then passed to a TF-IDF transformer and extracted singular values from the transformed matrix using Truncated SVD. Several component counts were tested as 5000 components returned a 97.95% total explained variance. The output was normalized and stored as a dataframe with appended article ID for reference back to the original document and label.

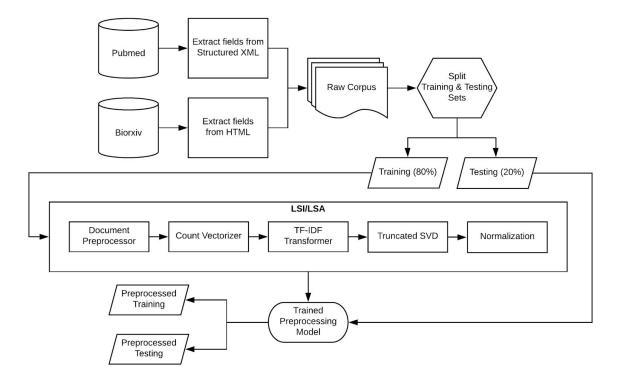


Fig 2. Original Feature Selection Pipeline

### Part 2: Vectorization Only

Using feedback from the presentation, we switched to using only count vectorization for the pipeline. Here, two different maximum document frequency parameters were used for vectorization, 65% and 40%. Minimum document frequency was kept, ignoring terms which appeared in less than 25 documents. All terms in less than 65% of the documents and more than 25 documents provided 6138 terms, where as 40% only reduced the number by 1, to 6137. Falling to a maximum frequency of 20% only removed 16 more terms to 6121, and going down to 10% left 6049 terms.

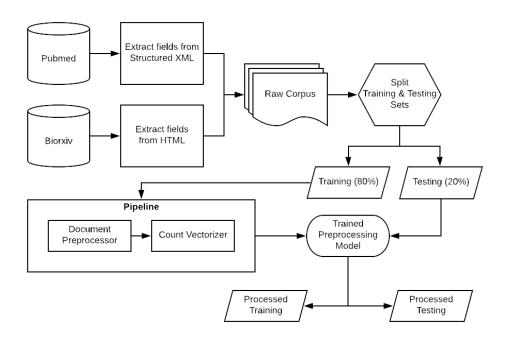


Fig 3. ModifiedFeature Selection Pipeline

Max. Document Frequency	Vocabulary Size (Term Count)
0.65	6138
0.4	6137
0.2	6121
0.1	6049

Table 1: Maximum document frequency and resulting vocabulary size

# **Algorithms**

### Part 1: Using Latent Semantic Analysis

Naive Bayes classifier has the advantage that it requires a small amount of training data to estimate parameters necessary for classification. Naïve Bayes has the simplicity which

makes the framework attractive in various tasks and reasonable performances are obtained in the tasks although this learning is based on an unrealistic independence assumption. As a member of probabilistic classifiers based on Bayes' theorem, Naïve Bayes is one of the most popular methods for text categorization.

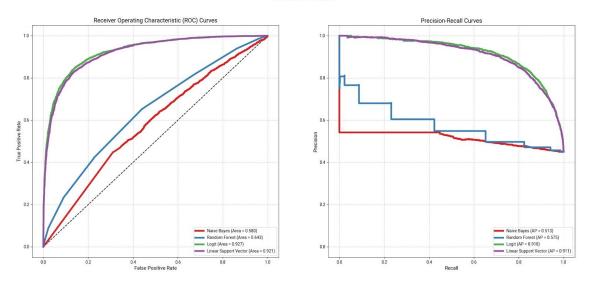
In addition, Random forests is an ensemble learning method for classification by constructing multiple decision trees at training time and outputting the class with a correction function to avoid overfitting caused by the decision tree.

Calibration of Classification

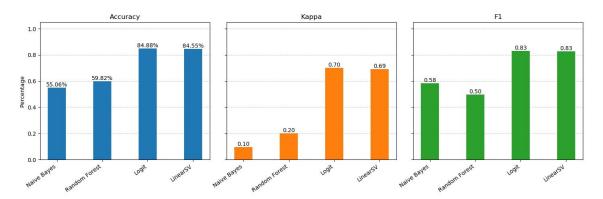
# Calibration plots (Reliability Curve) 1.0 0.8 Fraction of positives 0.6 0.4 0.2 ···· Perfectly Calibrated Naive Bayes Random Forest Logit 0.0 Linear Support Vector Naive Bayes Logit 4000 Linear Support Vector 3000 2000 Mean predicted value

Graph 1.1: Calibration of Classification

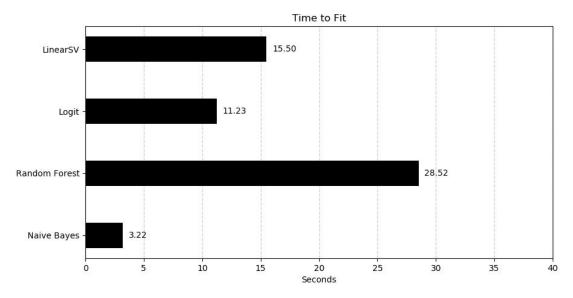
#### ROC and PR Curves



Graph 1.2: ROC and PR curves



Graph 1.3: Accuracy, Kappa and F1 measure of different algorithms.



Graph 1.4: Time taken to fit model.

The model outputs showed some interesting results. From the reliability curve, we can see that Logit classifier has performed really well. For SVM we can see that it is under-estimating in lower probabilities and over-estimating in higher probabilities. This can be seen as some sign of overfitting but cannot be conclusively be said so. We can see that Naive Bayes has performed the worst. For Random Forest we can see that it started overestimating at lower frequencies and underestimating at higher frequencies.

From the mean prediction plot, we can see that Logit has a very evenly paced curve compared to Naive Bayes which literally has only two values 0 and 1. We have the ROC curve and PR curves giving us a more clearer picture. Since our dataset doesn't have any class imbalance ROC curve will more accurately show the results rather than PR curves which generally gets more importance in case of imbalanced datasets. Even though we can see that both the plots clearly indicate that Logit and SVM classifiers have performed the best outperforming other classifiers. We can see the same trend in accuracy, kappa, and F1 scores. From the time-to-fit graph, we can see that Random Forest took maximum time to fit and as expected Naive Bayes took the least time followed by logit.

### Part 2: Using Vectorization Only

Additional algorithms were included in this phase<sup>2</sup>: Gaussian Naive Bayes, Multinomial Naive Bayes, Random Forest, Logit, and Linear Support Vector Machine were used. While hyperparameter tuning was minimal, the three different estimator counts for Random Forest (5, 10, and 50), and three C values were used for the Linear Support Vector (0.01, 0.1, and 1.0).

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<sup>&</sup>lt;sup>2</sup> Due to increased time and feedback

Analysis of the vectorized-only data<sup>3</sup> provided different results compared to the LSI pipeline, with a majority of models performing better across the board (except with respect to time). All tunings of the maximum document frequencies (65%, 40%, 20%, 10%) performed with nearly equal results, with only the calibration curves becoming more erratic as the percentage was lowered.

Calibration of Classification

#### Calibration plots (Reliability Curve) 1.0 0.8 reaction of positives Perfectly Calibrated 0.4 Gaussian Naive Bayes Multinomial Naive Bayes Random Forest (Est. = 5) Random Forest (Est. = 10) 0.2 Random Forest (Est. = 50) Logit Linear Support Vector (C = 0.01) Linear Support Vector (C = 0.1) Linear Support Vector (C = 1.0) 0.2 0.6 0.8 Gaussian Naive Bayes Multinomial Naive Bayes Linear Support Vector (C = 0.01) Random Forest (Est. = 5) Linear Support Vector (C = 0.1) 3000 Random Forest (Est. = 10) Linear Support Vector (C = 1.0) Random Forest (Est. = 50) 2000 1000

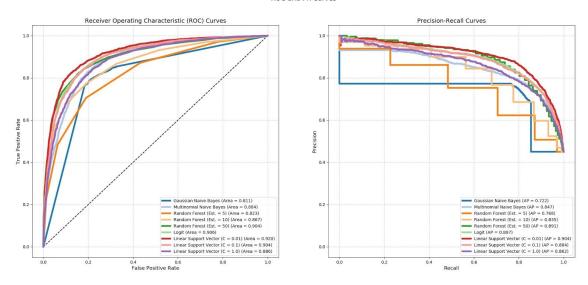
Graph 2.1: Calibration of Classification

0.4 0.6 Mean predicted value

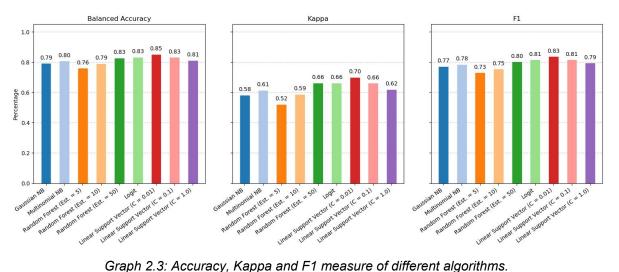
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<sup>&</sup>lt;sup>3</sup> Unfortunately completed after the final presentation

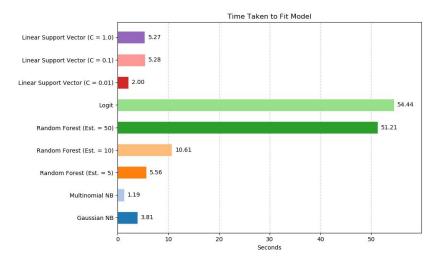
#### ROC and PR Curves



Graph 2.2: ROC and PR curves



Graph 2.3: Accuracy, Kappa and F1 measure of different algorithms.



Graph 1.4: Time taken to fit model.

# Discussion

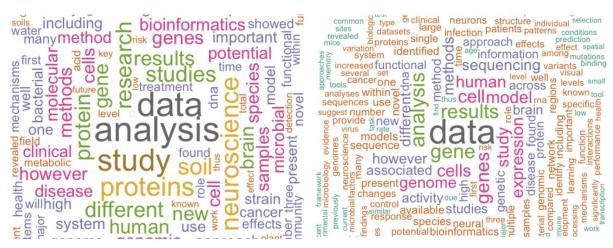


Fig 2. Word Cloud of PubMed (left) and Biorxiv (right) before pre-processing.

Above are word cloud graph of PubMed and Biorxiv before pre-processing which shows basic patterns of these two databases. According to them, we can found that they shared similar word patterns. Since a given color and size shows a particular range of word frequency, we can find that for words in PubMed, the word frequency is descending gradually; however, for the words in Biorxiv, only several green words around black word data, which lack of brown words and yellow ones so that the word frequency in Biorxiv is descending suddenly, or say the words in Biorxiv show more diversity. It makes sense that it is a pre-published corpus which may contain broader topics, but for the PubMed which only contains published paper which may focus on some popular topic.

Contrary to our hypothesis, we found there exists a marked difference between the two repositories. Due to the goal of the project and time constraints, no reason can be provided at this time. The possibility that there is information leakage cannot be ruled out. It was hoped, post-presentation, that limiting the maximum document frequency might show an imbalance, but changing the value significantly had minimal effect on the results. As mentioned in the presentation feedback, the S curves on the reliability plots may indicate overfitting. Increasing or randomizing the test set may alleviate this. Another option would be to introduce unrelated documents from both sources, such as articles from different topics.

We had originally considered adding more algorithms on our data (e.g., Bagging, non-linear SVC, k-Neighbors, NN, etc.) and comparing their performance with the other methods. However, given the results, a better path would be to determine methods which might provide more insight into the qualitative nature of the differences. Possible avenues include using word vectors instead of bag-of-words approach or analyzing part-of-speech tags as features attached terms (further distinguishing between word usage or even part of speech preference).

Our work was conducted largely online. We discussed and shared progress via Slack or email instead of a face-to-face meeting. This permitted a more fluid workflow, without having

to negotiate and strategize meeting times. We work separately and focuses on different parts of the work but discussed the problems we encountered together. Since different group member has different skills and background, we tried our best to let all group members involved in this project, but the most difficult parts were solved by particular people based on their specialties.

# **Appendix**

# **Preprocessing Regex**

numbers	[0-9]+?
url	(https::?\\?\\?)?(www\.)?[a-zA-Z0-9_\-\%]+?\.[a-z]{2,3}(\.[a-z]{2,3})\s
email	$([a-zA-Z0-9]+?\(?\s?\{?(at \0)\}?\)?\s?.+?\s)$
hyphens & underscore s	[\_\-]
punctuation	[\[\]\'\.,\/\#\!\?\\$\%\^\&\*;\:{}=\_`~\(\)\n\r�\<\>\@\\\�]+?
multiple spaces	\s{2,}

# Code

```
main.py

#/usr/bin/env python

"""

IS590ML - Final Project
   Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

import csv
import time
import pickle
import pandas as pd
```

```
from src.helpers import PATHS, get_raw_data, clean_tmp_data,
get_interim_corpus_path, get_processed_corpus_path
from src.data.extraction import CorpusExtractor
from src.data.preprocess import Preprocessor
from src.features.lsa import LSA
from src.models.classification import Classifier
from src.visualization.classification import ScorePlotter, TimePlotter
def preprocess():
  csv.field_size_limit(10000000)
  preprocessor = Preprocessor()
  outpath = (PATHS.PROCESSED / 'corpus.tsv')
  outpath.touch()
  with get_interim_corpus_path().open('r') as infd, outpath.open('w',
              = csv.DictReader(infd, delimiter='\t', quoting=csv.QUOTE_NONE)
       outfile = csv.DictWriter(outfd, infile.fieldnames, delimiter='\t')
       outfile.writeheader()
       current_id = None
       start_time = time.time()
               new_row = row.copy()
               current_id = new_row['id']
               new_row['abstract'] = preprocessor.preprocess(row.get('abstract'))
               outfile.writerow(new_row)
          print(count, current_id, e)
  lsa = LSA(PATHS.PROCESSED / 'corpus.tsv', max_tfidf_features=max_features,
max_df=max_df)
       'X': lsa.training_corpus['abstract'],
       'y': lsa.training_corpus['source']
       'X': lsa.testing_corpus['abstract'],
      'y': lsa.testing_corpus['source'],
  X = lsa.vectorizer.fit_transform(training.get('X'), training.get('y'))
  X_test = lsa.vectorizer.transform(testing.get('X'))
```

```
pd.DataFrame(X.toarray(), columns=lsa.vectorizer.get_feature_names(),
index=lsa.training_corpus.index)
  print(X df.head())
  X_df.insert(0, '_label_', training.get('y'))
  X_test_df = pd.DataFrame(X_test.toarray(),
columns=lsa.vectorizer.get_feature_names(), index=lsa.testing_corpus.index)
  X_test_df.insert(0, '_label_', testing.get('y'))
  training_filepath = 'vec_training_set'
  testing_filepath = 'vec_testing_set'
  if file_suffix:
      training_filepath += '_{}'.format(file_suffix)
       testing_filepath += '_{}'.format(file_suffix)
  training_filepath += '.pkl'
  testing_filepath += '.pkl'
  X_df.to_pickle(PATHS.PROCESSED / training_filepath)
  X_test_df.to_pickle(PATHS.PROCESSED / testing_filepath)
  print("Number of features:", len(lsa.vectorizer.get_feature_names()))
  classifier = Classifier(file_suffix)
  training_filepath = 'vec_training_set'
  testing_filepath = 'vec_testing_set'
  if file_suffix:
      training_filepath += '_{}'.format(file_suffix)
       testing_filepath += '_{}'.format(file_suffix)
  training_filepath += '.pkl'
  testing_filepath += '.pkl'
  training = pd.read_pickle(PATHS.PROCESSED / training_filepath)
  testing = pd.read_pickle(PATHS.PROCESSED / testing_filepath)
  y = training['_label_']
  X = training.drop('_label_', axis=1)
  y_test = testing['_label_']
  X_test = testing.drop('_label_', axis=1)
  stats = classifier.run(X, y, X_test, y_test)
  if file suffix:
       filename += '_{}'.format(file_suffix)
```

```
with (PATHS.REPORTS / filename).open('wb') as fd:
    pickle.dump(stats, fd)
run_vectorizer(10000, max_df=max_df, file_suffix=file_suffix)
run classifier(file suffix)
if file_suffix:
filename += '.pkl'
stats = None
with (PATHS.REPORTS / filename).open('rb') as fd:
    stats = pickle.load(fd)
score_plotter = ScorePlotter(file_suffix=file_suffix)
score_plotter.run(stats)
score_plotter.save()
time_plotter = TimePlotter(file_suffix=file_suffix)
time_plotter.run(stats)
time_plotter.save()
corpus_extractor = CorpusExtractor(get_raw_data())
corpus_extractor.run()
preprocess()
run_models(max_df=0.65, file_suffix='max_df_65')
run_models(max_df=0.4, file_suffix='max_df_40')
run_models(max_df=0.1, file_suffix='max_df_10')
```

```
#/usr/bin/env python

"""

IS590ML - Final Project
   Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

import re
import csv
from xml.etree import ElementTree as ET
```

```
from src.helpers import PATHS, get_raw_data, clean_tmp data
class CorpusExtractor():
      self.raw_data = raw_data
      self.headers = [
      self.spacings_regex = re.compile(r'(\t|\n+?|\r+?|\s{2,})')
      with (PATHS.INTERIM / 'corpus.tsv').open('w', errors='xmlcharrefreplace',
          csv_file = csv.DictWriter(fd, self.headers, delimiter='\t',
          for instance in self.raw_data:
              row = self.get_article_data(instance)
                  csv_file.writerow(row)
                  print(instance)
          return ' '.join([self.spacings_regex.sub(' ', s.strip()) for s in
text.itertext()]).strip()
```

```
id_texts = {}
    id_list = parent_tag.findall('article-id')
    for article_id in id_list:
        id_type = article_id.get('pub-id-type')
        id_text = self.clean_text(article_id)
        if len(id_text) > 64:
            print(id_type, id_text)
            id_text = 'https://doi.org/' + str(id_text)
        id_texts[id_type] = id_text
   print(e)
   raise(e)
instance.update(id_texts)
return instance
title = None
    title = parent_tag.find('article-title')
        title = parent_tag.find('title-group').find('article-title')
   title = self.clean_text(title)
    print(instance.get('pmc'), 'title', e)
instance[title] = title
return instance
abstract = None
    abstract = self.clean_text(parent_tag.find('abstract'))
```

```
print(instance.get('pmc'), 'abstracat', e)
instance['abstract'] = abstract
return instance
journal = None
    journal = self.clean_text(parent_tag.find('journal-title'))
    print(instance.get('pmc'), 'journal', e)
return instance
publisher = None
    publisher = parent_tag.find('publisher-name')
    if not publisher:
        publisher = parent_tag.find('publisher').find('publisher-name')
    publisher = self.clean_text(publisher)
    print(instance.get('pmc'), 'publisher', e)
    publisher = ''
instance['publisher'] = publisher
return instance
year = None
    pub_dates = parent_tag.findall('pub-date')
    for pub_date in pub_dates:
        year = pub_date.find('year')
        if year:
    year = self.clean_text(year)
    print(instance.get('pmc'), 'date', e)
```

```
instance['year'] = year
return instance
tree = ET.parse(xml_file)
root = tree.getroot()
instance_tmpl = {header: None for header in self.headers}
instance = instance_tmpl.copy()
   article_meta = front_tag.find('article-meta')
   journal_meta = front_tag.find('journal-meta')
   instance = self.get_ids(article_meta, instance)
   instance = self.get_title(article_meta, instance)
   instance = self.get_year(article_meta, instance)
   instance = self.get_abstract(article_meta, instance)
   instance = self.get_journal(journal_meta, instance)
   instance = self.get_publisher(journal_meta, instance)
   instance['body'] = self.clean_text(root.find('body'))
   print(xml_file, e)
return instance
```

```
#/usr/bin/env python

"""

IS590ML - Final Project
   Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

from pathlib import Path
import re
```

```
from src.helpers import PATHS, get_stopwords
import nltk
from nltk import PorterStemmer, word_tokenize, pos_tag
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer
from sklearn.preprocessing import Normalizer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer,
TfidfVectorizer
from sklearn.decomposition import TruncatedSVD
import numpy as np
import pandas as pd
class Preprocessor():
      new_stopwords=[]
      self.min_word_len = min_word_len
      self.append_pos_tags = append_pos_tags
      self.stemmer = PorterStemmer()
      self.lemmatizer = WordNetLemmatizer()
      self.stopwords = get_stopwords(new_stopwords)
      self.regex = [
```

```
('number', re.compile(r'[0-9]+'), ' '),
re.compile(r'(https?:?\\?\\?)?(www\.)?[a-zA-Z0-9_\-\%]+?\.[a-z]{2,3}(\.[a-z]{2,3}
re.compile(r'([a-zA-Z0-9]+?\(?\s?\{?(at|\a)\}?\)?\s?.+?\s)'), ''),
           ('hyscore', re.compile(r'[\_\]'), ' '), # add spacing
re.compile(r'[\[\]\'\.,\/\#\!\?\$\%\^\&\*;\:{}=\_`~\(\)\n\r�\<\>\@\\\�]+?'), '
          ('spaces', re.compile(r'\s{2,}'), ''),
  def update_stopwords(self, new_stopwords=[]):
      self.stopwords += new_stopwords
      if treebank_tag.startswith('J'):
      elif treebank_tag.startswith('V'):
           return wordnet.VERB
      elif treebank_tag.startswith('N'):
          return wordnet.NOUN
      elif treebank_tag.startswith('R'):
          return wordnet.ADV
      new_words = []
      doc = str(doc)
       doc = doc.lower()
       for name, edit, rep in self.regex:
          doc = edit.sub(rep, doc)
       doc = pos_tag(word_tokenize(doc))
       for word, tag in doc:
          tag = self.get_wordnet_pos(tag)
          if word in self.stopwords or len(word) < self.min_word_len:</pre>
```

### src/features/lsa.py

```
#/usr/bin/env python
"""
    IS590ML - Final Project
    Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""
from pathlib import Path
import re
import pickle

from src.helpers import PATHS

import nltk
# download necessary libraries
nltk.download('punkt', quiet=True)
nltk.download('wordnet', quiet=True)
```

```
from nltk import PorterStemmer, word_tokenize, pos_tag
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer
from sklearn.preprocessing import Normalizer
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer,
TfidfVectorizer
from sklearn.decomposition import TruncatedSVD
import numpy as np
import pandas as pd
class LSA():
      self.corpus = self.load_corpus(corpus_path, label_col=label_col,
corpus_frac=corpus_frac)
       self.training_corpus, self.testing_corpus = self.split_corpus()
      self.vectorizer_params = {
          'tokenizer': self.tokenizer,
          'max_df': max_df,
          'min_df': min_df,
          'max_features': max_tfidf_features,
      self.transformer_params = {
```

```
self.decomposer_params = {
           'n_components': n_components,
      self.pipeline = None
      self.vectorizer = self.update_vectorizer()
      self.transformer = self.update_transformer()
      self.decomposer = self.update_decomposer()
      self.pipeline_steps = [
          ('decomposer', self.decomposer),
          ('normalizer', Normalizer(copy=False))
      self.pipeline = Pipeline(steps=self.pipeline_steps)
      if kwargs:
          self.vectorizer_params.update(**kwargs)
          if 'max_df' in kwargs:
              self.max_df = kwargs.get('max_df')
          if 'max_features' in kwargs:
              self.max_features = kwargs.get('max_features')
      self.vectorizer = CountVectorizer(**self.vectorizer_params)
      if self.pipeline:
          self.pipeline.set_params(**{'vectorizer__{{}}'.format(k): v for k,v in
self.vectorizer_params.items()})
      return self.vectorizer
      if kwargs:
```

```
self.transformer_params.update(**kwargs)
      self.transformer = TfidfTransformer(**self.transformer_params)
      if self.pipeline:
          self.pipeline.set_params(**{'transformer__{{}}'.format(k): v for k,v in
self.vectorizer params.items()})
      return self.transformer
      if kwargs:
          self.decomposer_params.update(**kwargs)
      self.decomposer = TruncatedSVD(**self.decomposer_params)
      if self.pipeline:
          self.pipeline.set_params(**{'decomposer__{{}}'.format(k): v for k,v in
self.decomposer_params.items()})
      return self.decomposer
      self.pipeline = Pipeline(steps=self.pipeline_steps)
      return self.pipeline
      self.corpus = pd.read_csv(
          filepath,
      self.corpus.drop_duplicates(id_col, keep='first', inplace=True)
      self.corpus.dropna(inplace=True)
      self.corpus.set_index(id_col, drop=True, inplace=True)
      if label_col:
```

```
self.corpus.rename(columns={label_col: 'label'}, inplace=True)

if corpus_frac:
    original_size = self.corpus.shape[0]
    self.corpus = self.corpus.sample(frac=corpus_frac, random_state=17)
    print('Reducing corpus to {:02%} of original size: {} to

{}'.format(corpus_frac, original_size, self.corpus.shape[0]))

    return self.corpus

def split_corpus(self, test_size=0.2):
    self.training_corpus, self.testing_corpus = train_test_split(self.corpus, test_size=test_size, random_state=17)
    return self.training_corpus, self.testing_corpus

def store(self):
    with (PATHS.MODELS / 'lsa.pkl').open('wb') as fd:
        pickle.dump(self, fd)
```

### src/models/classification.py

```
#/usr/bin/env python
"""

IS590ML - Final Project
Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

from pathlib import Path
import time

from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.svm import LinearSVC

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import RepeatedStratifiedKFold, RepeatedKFold,
StratifiedKFold, GridSearchCV, train_test_split
from sklearn.metrics import classification_report, cohen_kappa_score as kappa,
confusion_matrix, auc, roc_auc_score, roc_curve, precision_recall_curve,
average_precision_score, f1_score, balanced_accuracy_score, recall_score
from sklearn.calibration import calibration_curve
```

```
from src.helpers import PATHS
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.svm import LinearSVC
from src.visualization.calibration import CalibrationPlotter
from src.visualization.classification import ScorePlotter
from src.visualization.rocauc import RocAucPlotter
class Classifier():
      self.file_suffix = file_suffix
      self.calib_plotter = CalibrationPlotter(file_suffix=file_suffix)
      self.roc_auc_plotter = RocAucPlotter(file_suffix=file_suffix)
      self.score_plotter = ScorePlotter(file_suffix=file_suffix)
      self.classifiers = {
           'Gaussian Naive Bayes': GaussianNB(),
           'Multinomial Naive Bayes': MultinomialNB(),
           'Random Forest (Est. = 5)': RandomForestClassifier(n_estimators=5),
           'Random Forest (Est. = 10)': RandomForestClassifier(n_estimators=10),
           'Random Forest (Est. = 50)': RandomForestClassifier(n_estimators=50),
           'Logit': LogisticRegression(solver='lbfgs', max_iter=1000),
          'Linear Support Vector (C = 0.01)': LinearSVC(C=0.01),
           'Linear Support Vector (C = 0.1)': LinearSVC(C=0.1),
          'Linear Support Vector (C = 1.0)': LinearSVC(C=1.0),
       filename = 'classification_report'
       if self.file_suffix or file_suffix:
           filename += '_{}'.format(self.file_suffix or file_suffix)
       filename += '.txt'
       print(filename)
      with (PATHS.REPORTS / filename).open('w') as report_file:
           for name, clf in self.classifiers.items():
```

```
stats = self.classify(clf, X, y, X_test, y_test, name=name,
report_file=report_file)
                   total stats[name] = stats
                  print(e)
      self.score_plotter.run(total_stats)
      self.calib_plotter.save()
       self.roc auc plotter.save()
      self.score_plotter.save()
      return total_stats
      skf = StratifiedKFold(folds)
       fit_times = {}
       stats = {}
       if report_file:
           report_file.write('\n--- Classifying with {} ---\n'.format(name))
          for i, (train_index, test_index) in enumerate(skf.split(X, y)):
              X_train, X_test = X.iloc[train_index], X.iloc[test_index]
              start_time = time.time()
               clf.fit(X_train, y_train)
               fit_time = time.time() - start_time
              y_pred = clf.predict(X_test)
               score = clf.score(X_test, y_test)
              if hasattr(clf, 'predict_proba'):
                  y_score = clf.predict_proba(X_test)[:, 1]
                  y_score = clf.decision_function(X_test)
                  y_score = (y_score - y_score.min()) / (y_score.max()
y_score.min()) # normalize
               bas = balanced_accuracy_score(y_test, y_pred)
               average_precision = average_precision_score(y_test, y_score,
```

```
f1 = f1_score(y_test, y_pred, pos_label='pubmed')
               k = kappa(y_test, y_pred)
               stats['Fold {}'.format(i)] = {
                  'time': fit time,
                   'mean accuracy': score,
                   'balanced accuracy': bas,
                   'avg precision': average_precision,
               if report_file:
                   report_file.write('\n--- Fold #{} ---\n\n'.format(i))
                   report_file.write('Fit Time: {} seconds\n'.format(fit_time))
                   report_file.write('Kappa: {}\n'.format(score))
                   report_file.write('Mean Accuracy: {}\n'.format(score))
                   report_file.write('Average Precision (Pubmed):
{}\n'.format(average_precision))
                  report_file.write('Classification report:\n'.format(i))
                   report file.write(classification_report(y_test, y_pred))
                   report_file.write('\n---\n\n')
       start_time = time.time()
       clf.fit(X, y)
       fit_time = time.time() - start_time
       fit_times['Final'] = fit_time
      y_pred_final = clf.predict(X_test_final)
       score = clf.score(X_test_final, y_test_final)
          y_score = clf.predict_proba(X_test_final)[:, 1]
          y_score = clf.decision_function(X_test_final)
          y_score = (y_score - y_score.min()) / (y_score.max() - y_score.min())
```

```
bas = balanced_accuracy_score(y_test_final, y_pred_final)
       average_precision = average_precision_score(y_test_final, y_score,
       f1 = f1_score(y_test_final, y_pred_final, pos_label='pubmed')
      k = kappa(y_test_final, y_pred_final)
       stats['Final'] = {
           'mean accuracy': score,
          'avg precision': average_precision,
          'f1': f1,
      positives_frac, mean_pred_val = calibration_curve(y_test_final, y_score,
      self.calib_plotter.plot(mean_pred_val, positives_frac, name)
      self.calib_plotter.hist(y_score, name)
       fp_rate, tp_rate, threshold = roc_curve(y_test_final, y_score,
       roc_auc = auc(fp_rate, tp_rate)
      self.roc_auc_plotter.roc_auc_curve(fp_rate, tp_rate, name, roc_auc)
      precision, recall, threshold = precision_recall_curve(y_test_final,
y_score, pos_label='pubmed')
       self.roc_auc_plotter.pr_curve(recall, precision,name, average_precision)
       if report_file:
           report_file.write('\n--- Test (Final) ---\n\n'.format(i))
           report_file.write('Fit Time: {} seconds\n'.format(fit_time))
           report_file.write('Kappa: {}\n'.format(score))
           report_file.write('Mean Accuracy: {}\n'.format(score))
           report_file.write('Average Precision (Pubmed):
{}\n'.format(average_precision))
           report_file.write('Classification Report:\n')
           report_file.write(classification_report(y_test_final, y_pred_final))
           report_file.write('\n--- End {} Classification ---\n'.format(name))
       return stats
```

### src/visualization/calibration.py

```
#/usr/bin/env python
import matplotlib as mpl
from matplotlib import cm
import matplotlib.pyplot as plt
from src.helpers import PATHS
colors = plt.get_cmap('tab20').colors
plt.rcParams['axes.prop_cycle'] = plt.cycler(color=colors)
      self.file_suffix = file_suffix
      self.figure = plt.figure(figsize=(10, 10))
      self.figure.subplots_adjust(left=0.05, right=1-0.05)
      self.figure.suptitle('Calibration of Classification', fontsize=16)
           plt.subplot2grid((3, 1), (0, 0), rowspan=2, fig=self.figure),
          plt.subplot2grid((3, 1), (2, 0), fig=self.figure)
      self.axs[0].plot([0, 1], [0, 1], "k:", label="Perfectly Calibrated")
      self.axs[0].grid(color='lightgray', linestyle='dashed', linewidth=1)
      self.axs[0].set_axisbelow(True)
      self.axs[0].set_ylabel("Fraction of positives", fontsize=12)
      self.axs[0].set_ylim([-0.05, 1.05])
       for tick in (self.axs[0].get_xticklabels() +
self.axs[0].get_yticklabels()):
          tick.set_fontsize(10)
      self.axs[1].grid(color='lightgray', linestyle='dashed', linewidth=1)
      self.axs[1].set axisbelow(True)
      self.axs[1].set_xlabel("Mean predicted value", fontsize=12)
      self.axs[1].set_ylabel("Count", fontsize=12)
```

```
for tick in (self.axs[1].get_xticklabels() +
self.axs[1].get_yticklabels()):
    tick.set_fontsize(10)

def plot(self, mean_pred_val, positives_frac, clf_name):
    self.axs[0].plot(mean_pred_val, positives_frac, "s-",
label="{}".format(clf_name), linewidth=4)

def hist(self, y_score, clf_name):
    self.axs[1].hist(y_score, range=(0, 1), bins=10, label=clf_name,
histtype="step", lw=4)

def save(self, file_suffix=None):
    self.axs[0].legend(loc="upper left")
    self.axs[1].legend(loc="upper center", ncol=2)

filename = 'calibration_plot'
    if self.file_suffix or file_suffix:
        filename += '_{}'.format(self.file_suffix or file_suffix)
    filename += '.jpg'

self.figure.savefig((PATHS.FIGURES / filename))
```

```
#/usr/bin/env python
"""

IS590ML - Final Project
   Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

from src.helpers import PATHS

import pandas as pd
import numpy as np

import matplotlib as mpl
from matplotlib import cm
import matplotlib.pyplot as plt

colors = plt.get_cmap('tab20').colors
plt.rcParams['axes.prop_cycle'] = plt.cycler(color=colors)
```

```
self.filename_root = filename_root
self.horizontal = horizontal
self.file_suffix = file_suffix
for name, ax in self.axs.items():
    ax.set_axisbelow(True)
    ax.set_title(name)
self.stats = {}
for model, v in clf_stats.items():
    if model in TERM_TRANSLATIONS:
        model = TERM_TRANSLATIONS[model]
    self.stats[model] = {
        k: v for k, v in v['Final'].items()
self.stats = pd.DataFrame(self.stats)
self.index = np.arange(len(self.clf_names))
```

```
barplot_fn = ax.barh if self.horizontal else ax.bar
       barplot = barplot_fn(self.index, scores, self.bar_thickness, label=label)
      self.format_barplot(ax, barplot, adjust_ticks=adjust_ticks,
adjust scale=adjust scale)
      if self.horizontal:
          ax.set yticks(self.index)
          ax.set_yticklabels(self.clf_names)
          if hide_dep_axis:
               ax.set_xticklabels([])
          ax.set_xticklabels(self.clf_names)
          if hide_dep_axis:
              ax.set_yticklabels([])
      for i, rect in enumerate(barplot):
          rect.set_color(colors[i])
           bar_length = rect.get_width() if self.horizontal else
rect.get_height()
              max_length = bar_length
          amount = '{:.02f}'.format(float(bar_length))
          if self.horizontal:
               ax.text(bar_length + 0.75, rect.get_y() + self.bar_thickness/2.,
              if adjust_scale:
                   ax.set_xlim([0.0, max_length * 1.1])
              if adjust_ticks:
                   for tick in ax.get_yticklabels():
                       tick.set_rotation(36)
                       tick.set va('center')
               ax.text(rect.get_x() + self.bar_thickness/2., bar_length + 0.02,
               if adjust scale:
```

```
ax.set_ylim([0.0, max_length * 1.1])
              if adjust_ticks:
                   for tick in ax.get xticklabels():
                       tick.set rotation(36)
       filename = self.filename_root
      if self.file_suffix or file_suffix:
           filename += '_{}'.format(self.file_suffix or file_suffix)
       if self.figure:
          self.figure.tight_layout()
          self.figure.savefig((PATHS.FIGURES / filename))
file_suffix=file_suffix)
      self.figure = plt.figure(figsize=(15, 6))
      self.figure.subplots_adjust(left=0.05, right=1-0.05, bottom=0.2,
           'Balanced Accuracy': plt.subplot2grid((1,3), (0,0), fig=self.figure),
           'Kappa': plt.subplot2grid((1,3), (0,1), fig=self.figure),
          'F1': plt.subplot2grid((1,3), (0,2), fig=self.figure)
      self.setup()
      self.axs['Balanced Accuracy'].set_ylabel('Percentage')
      for ax in self.axs.values():
          ax.set_ylim([-0.0, 1.05])
      super(ScorePlotter, self).run(clf_stats)
      hide_dep_axis = False
```

```
for score_name, ax in self.axs.items():
          stat = self.stats.loc[score_name.lower()]
          self.make_barplot(ax, stat, score_name, hide_dep_axis=hide_dep_axis,
          if not hide_dep_axis:
              hide dep axis = True
      super(TimePlotter, self).__init__('classification_times', horizontal=True,
file_suffix=file_suffix)
      self.figure = plt.figure(figsize=(10, 6))
          'Time Taken to Fit Model': self.figure.add_subplot(111)
      self.setup()
      self.axs['Time Taken to Fit Model'].set_xlabel('Seconds')
      self.make_barplot(self.axs['Time Taken to Fit Model'],
self.stats.loc['time'], adjust_ticks=False, adjust_scale=True)
```

```
#/usr/bin/env python

"""

IS590ML - Final Project
Preprocessing for comparison of 'Pubmed' against 'BiorXiv' article abstracts
"""

import matplotlib as mpl
from matplotlib import cm
import matplotlib.pyplot as plt

from src.helpers import PATHS

colors = plt.get_cmap('tab20').colors
plt.rcParams['axes.prop_cycle'] = plt.cycler(color=colors)
```

```
class RocAucPlotter():
      self.file_suffix = file_suffix
       self.figure = plt.figure(figsize=(20,10))
      self.figure.subplots_adjust(left=0.05, right=1-0.05)
      self.figure.suptitle('ROC and PR Curves', fontsize=16)
          plt.subplot2grid((1,2), (0,0), fig=self.figure),
          plt.subplot2grid((1,2), (0,1), fig=self.figure)
      self.axs[0].plot([0, 1], [0, 1], "k--")
      self.axs[0].grid(color='lightgray', linestyle='dashed', linewidth=1)
      self.axs[0].set_axisbelow(True)
      self.axs[0].set_ylabel('True Positive Rate', fontsize=12)
      self.axs[0].set_ylim([-0.05, 1.05])
       for tick in (self.axs[0].get_xticklabels() +
self.axs[0].get_yticklabels()):
      self.axs[1].grid(color='lightgray', linestyle='dashed', linewidth=1)
      self.axs[1].set_ylabel('Precision', fontsize=12)
      self.axs[1].set_xlabel('Recall', fontsize=12)
      self.axs[1].set_ylim([-0.05, 1.05])
      for tick in (self.axs[1].get_xticklabels()
self.axs[1].get_yticklabels()):
           tick.set_fontsize(10)
       label = '{} (Area = {:.03f})'.format(clf_name, roc_auc_score)
      self.axs[0].plot(fp_rate, tp_rate, label=label, linewidth=4)
      label = '{} (AP = {:.03f})'.format(clf_name, avg_precision_score)
      self.axs[1].step(recall, precision, where='post', label=label,
```

```
linewidth=4)

def save(self, file_suffix=None):
    self.axs[0].legend(loc='lower right')

self.axs[1].legend(loc='lower right')

filename = 'roc_auc_curve'
    if self.file_suffix or file_suffix:
        filename += '_{{}}'.format(self.file_suffix or file_suffix)
    filename += '.jpg'

self.figure.savefig((PATHS.FIGURES / filename))
```

### src/helpers.py

```
from pathlib import Path
import tarfile
import lzma
  ROOT = Path(os.path.realpath(__file__)).parent.parent
  RAWCORPUS = RAW / 'xml'
```

```
def get_raw_data():
  if not PATHS.RAWCORPUS.exists():
      with tarfile.open(PATHS.RAW / 'corpus.tar.xz', 'r:xz') as tar:
           tar.extractall(PATHS.RAWCORPUS)
  return PATHS.RAWCORPUS.glob('*.xml')
def clean_tmp_data():
  for fd in PATHS.RAWCORPUS.glob('*.xml'):
      fd.unlink()
  PATHS.RAWCORPUS.rmdir()
  corpus_path = (PATHS.INTERIM / 'corpus.tsv')
  if not corpus_path.exists():
  return corpus_path
def get_processed_corpus_path():
  corpus_path = (PATHS.PROCESSED / 'corpus.tsv')
  if not corpus_path.exists():
      corpus_path.touch()
  return corpus_path
def get_stopwords(new_stopwords = []):
  with (PATHS.REFERENCES / 'stopwords.txt').open('r') as fd:
       return [line.strip() for line in fd] + new_stopwords
```

Please contact Tre Tomaszewski at jtomasz2(at)illinois.edu for entire code base