arXiv vs. snarXiv

Tyler Blanton   **Sam Kowash**

Abstract

1   Introduction

2   Language models

2.1 n-grams

Assume that each abstract X has a probability $\mathbb{P}(X|Y)$ of being from source $Y \in \{-1, 1\}$, where $Y = 1$ represents the label "snarXiv" and $Y = -1$ represents the label "arXiv." Suppose $X = (w_1, w_2, \ldots, w_N)$ is an abstract containing N words $\{w_i\}_{i=1}^N$, and let w_i^{i+k} denote the word sequence $(w_i, w_{i+1}, \ldots, w_{i+k})$. The n-grams language model approximates $\mathbb{P}(X|Y)$ as

$$\mathbb{P}(X|Y) = \mathbb{P}(w_1^N|Y) = \prod_{i=1}^N \mathbb{P}(w_i|w_1^{i-1}, Y) \tag{1}$$

$$\approx \prod_{i=1}^N \mathbb{P}(w_i|w_{i-n+1}^{i-1}, Y) \quad (n\text{-grams approx.}) \tag{2}$$

In other words, in the n-grams model we assume that the probability of a given word w occurring in some abstract only depends on what the previous $n - 1$ words in the abstract are, where n is some (typically small) positive integer; the $n - 1$ words on which w depends are called the "context" of w.

In the simplest case $n = 1$, each word occurrence is assumed to be completely independent of any context, which is why the 1-gram language model is often referred to as the "bag-of-words" (BoW) model. Given some training set of abstracts from source Y, we define our BoW training estimate $\widehat{\mathbb{P}}(X|Y)_{\text{BoW}}$ as

$$\widehat{\mathbb{P}}(X|Y)_{\text{BoW}} = \widehat{\mathbb{P}}(w_1^N|Y)_{\text{BoW}} \equiv \prod_{i=1}^N \widehat{\mathbb{P}}(w_i|Y), \tag{3}$$

$$\text{where} \quad \widehat{\mathbb{P}}(w_i|Y) \equiv \frac{C_Y(w_i) + 1}{\sum_w [C_Y(w) + 1]} = \frac{C_Y(w_i) + 1}{\sum_{w \in \mathcal{V}} C_Y(w) + V}, \tag{4}$$

$C_Y(w_i)$ is the number of times that w_i appears, $\mathcal{V}$ is a vocabulary of size $V = |\mathcal{V}|$ containing all of the words that we wish to learn about, and $\sum_{w \in \mathcal{V}} C_Y(w)$ is the total number of words in the training set. The extra $+1$ on each word count $C_Y(w)$ comes from Laplace smoothing, which is a precautionary measure taken to prevent zero probabilities from occurring in cases where we need to classify an abstract that contains a word that did not appear in the training set. Other technical details regarding bag-of-words and n-grams implementation (including parsing) can be found in Appendix A.

The generalization to $n > 1$ is straightforward: we define our estimate $\widehat{\mathbb{P}}(X|Y)_{n\text{-gram}}$ for a given training set from source Y to be

$$\widehat{\mathbb{P}}(X|Y)_{n\text{-gram}} = \widehat{\mathbb{P}}(w_1^N|Y)_{n\text{-gram}} \equiv \prod_{i=1}^{N} \widehat{\mathbb{P}}(w_i|w_{i-n+1}^{i-1}, Y), \tag{5}$$

$$\text{where} \quad \widehat{\mathbb{P}}(w_i|w_{i-n+1}^{i-1}, Y) \equiv \frac{C_Y(w_{i-n+1}^{i}) + 1}{C_Y(w_{i-n+1}^{i-1}) + V}, \tag{6}$$

$C_Y(w_{i-n+1}^{i})$ is the number of times that the n-gram w_{i-n+1}^{i} occurs, and $C_Y(w_{i-n+1}^{i-1})$ is the number of times that the $(n-1)$-gram w_{i-n+1}^{i-1} appears.

Note that since a typical arXiv/snarXiv abstract contains roughly 100 words, so the abstract probability $\mathbb{P}(X|Y) = \prod_{i=1}^{N} \mathbb{P}(w_i|w_1^{i-1}, Y)$ is a product of $N \approx 100$ different word probabilities, each of which is typically much less than one. As a result, the size of $\mathbb{P}(X|Y)$ is heavily dependent on the abstract length and is usually extremely small, causing our estimates to hit numerical underflow in some cases. To combat the issue of length dependence, we prefer to work with the perplexity

$$\text{PP}(X|Y) \equiv \sqrt[N]{\frac{1}{\mathbb{P}(X|Y)}} = \left[\prod_{i=1}^{N} \mathbb{P}(w_i|w_1^{i-1}, Y)\right]^{-1/N}, \tag{7}$$

which normalizes the abstract probability by taking the geometric mean of the individual word probabilities (and inverting). To prevent numerical underflow from rendering our algorithms useless, we always work with logs of probabilities in our code, which turns products into sums and keeps the numbers reasonable. Note that the log of the perplexity is a simple arithmetic mean:

$$\log \text{PP}(X|Y) = -\frac{1}{N} \log \mathbb{P}(X|Y) = -\frac{1}{N} \sum_{i=1}^{N} \log \mathbb{P}(w_i|w_1^{i-1}, Y). \tag{8}$$

In practice, we use the logs of the classification conditions given below in Section 3 to classify our test abstracts as arXiv or snarXiv; we only exponentiate back to perplexities for the purposes of figures.

2.2 tf–idf

3 Classifiers

3.1 Naive Bayes classifier

Our first attempt at creating a program that distinguishes between arXiv and snarXiv abstracts utilized a naive Bayes (NB) classifier. The theory behind this classifier is simple: if $\mathbb{P}(Y = 1|X) > \mathbb{P}(Y = -1|X)$, then we classify X as snarXiv; otherwise, we classify it as arXiv. We can use Bayes' theorem $\mathbb{P}(Y|X) = \frac{\mathbb{P}(Y)\mathbb{P}(X|Y)}{\mathbb{P}(X)}$ to rewrite this classification condition as

$$\widehat{Y}_{NB} \equiv \arg \max_{Y \in \{-1,1\}} \mathbb{P}(Y)\mathbb{P}(X|Y). \tag{9}$$

We estimate each probability in (9) by training on a large number of arXiv and snarXiv abstracts. We define our estimate[1] for $\mathbb{P}(Y)$ as the number of abstracts in training set Y over the total number of abstracts in both the arXiv and snarXiv training sets. The conditional probabilities $\mathbb{P}(X|Y)$ are more complicated, and are approximated using a language model from Section 2.

3.2 Likelihood-ratio test

A slightly more sophisticated classification rule is the likelihood-ratio (LR) test. For a given abstract X, define the likelihood ratio $\Lambda(X) \equiv \frac{\mathbb{P}(X|Y=1)}{\mathbb{P}(X|Y=-1)}$. While we certainly want our classifier to correctly

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[1]The probabilities $\mathbb{P}(Y = \pm 1)$ are somewhat trivial since we generate the snarXiv abstracts ourselves and can control over how many arXiv vs. snarXiv abstracts will be in the train and test sets. Since the snarXiv was originally created to make abstracts that compete one-on-one with arXiv abstracts, we chose to set $\mathbb{P}(Y = \pm 1) = \frac{1}{2}$ for all tests reported in this paper.

label all snarXiv abstracts as fakes, we also want to minimize the probability that an arXiv abstract gets incorrectly classified as fake. The Neyman-Pearson lemma states that the optimal classifier

$$\delta_{LR}^* \equiv \arg\max_{\delta} \mathbb{P}(\delta(X) = 1 | Y = 1), \quad \text{subject to} \quad \mathbb{P}(\delta(X) = 1 | Y = -1) \leq \alpha \tag{10}$$

for any fixed false-positive tolerance α takes the form

$$\mathbb{P}\left(\delta_{LR}^*(X) = 1\right) = \begin{cases} 1, & \Lambda(X) > \eta \\ \gamma, & \Lambda(X) = \eta \\ 0, & \Lambda(X) < \eta, \end{cases} \tag{11}$$

where η and γ can be treated as hyperparameters to be tuned in cross-validation. In practice, γ is almost completely irrelevant since for any η, the odds that a language model like n-grams would yield an estimate for $\Lambda(X)$ that is *exactly* equal to η are essentially zero.[2] We arbitrarily use $\gamma = 0.5$, meaning the only hyperparameter we tune is η. Because of the issues of small $\mathbb{P}(X|Y)$ probabilities discussed in Section 2.1, it is more practical to instead compare the perplexities $\text{PP}(X|Y) = \mathbb{P}(X|Y)^{-1/|X|}$. The relevant parameter in the LR-test is thus $\eta^{1/|X|}$. We would like our hyperparameter to not depend on the specifics of the input though, so we note that the average abstract length is about 120 words and define $\eta_{\text{PP}} \equiv \eta^{1/120}$ to be our new LR-hyperparameter.

4   Results

We report results for three different algorithms: bag-of-words model with naive Bayes classifer (BoW-NB), bag-of-words model with likelihood-ratio test (BoW-LR), and bigrams=(2-grams) model with likelihood-ratio test (bi-LR). In each case, we trained on an equal number $N_{\text{train}}^Y = 1000$ of arXiv and snarXiv abstracts, and we also tested on 1000 arXiv abstracts and 1000 snarXiv abstracts.

For BoW-NB, we found the classification accuracy to be 77%, with the only misclassifications being false positives (arXiv abstracts that the classifier mistakes as snarXiv); when a snarXiv abstract is tested, it is correctly identified as snarXiv 100% of the time. This is somewhat expected for a classifier which does nothing to constrain the false-positive rate.

For BoW-LR and bi-LR, we tuned the LR-hyperparameter η_{PP} through cross-validation to maximize the classification accuracy on abstracts from both arXiv and snarXiv. We found $\eta_{\text{PP}} = 0.7$ to perform best in both models; the true positive rate (TPR) vs. false discovery rate (FDR) is plotted in Figure **??**. We also made histograms of $\frac{\text{PP}(X|\text{snarXiv})}{\text{PP}(X|\text{arXiv})}$, which show exactly how the ...
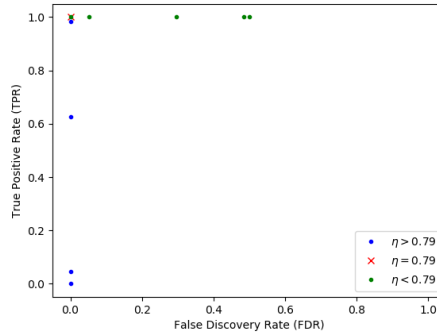
5   Conclusions

5.1   Possible extension

Our results thus far suggest that the language produced by snarXiv may just be too artificial and constrained to put up much of a fight in the classification task. The naive Bayes classifier never

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[2]The borderline case of the naive Bayes classifier where $\mathbb{P}(Y = \pm 1 | X) = \frac{1}{2}$ is irrelevant for the same reason.

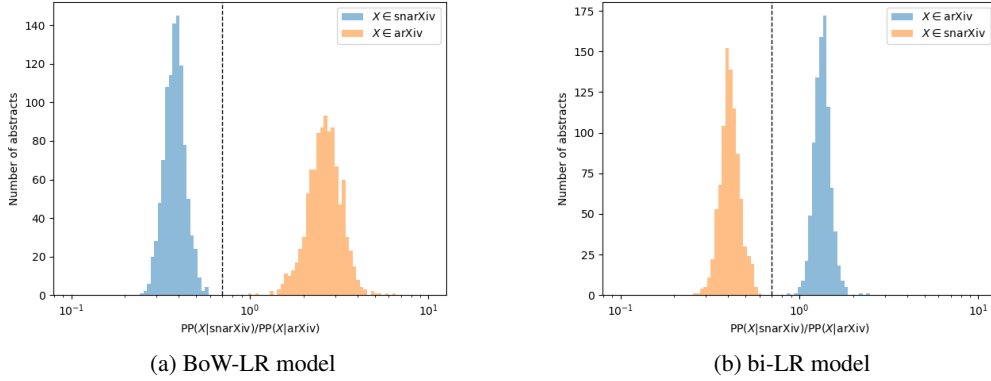|	
(a) BoW-LR model	(b) bi-LR model

Figure 1: Perplexity ratio histograms for both LR-models. The dotted black line corresponds to $\eta_{PP} = 0.7$.

mistakes a snarXiv paper for real, although it still accidentally flags a decent chunk of real papers as fake. We will continue this work with more sophisticated feature generation and classifiers to explore different methods and try to reduce the remaining error, but it is worth looking in other directions as well.

In particular, if snarXiv cannot produce abstracts that are convincing to our classifier, what can? The field of generative adversarial networks has become prominent recently, as reviewed in Creswell et al. [2018], and we are considering extending our project in this direction. The aim would be to produce, effectively, a next-generation snarXiv that achieves a meaningful error rate against its discriminating counterpart. Several sources note that GANs are not naturally suited to contexts with discrete data streams, so this may prove unworkable, but is one direction to pursue if our original plan leads to shallow results.

A   Technical details

A.1   Parsing abstract text

Our parser attempts to translate the raw abstract text (a string) to a list of formatted words that are easily identifiable between different abstracts. We first split the text on all spaces, newlines, and hyphens, and for uniformity we make all words lowercase. Next, we look for words that end in a period or question mark and insert the special word tokens `<e>` and `<s>` afterwards to mark the end of one sentence and the start of another. Lastly, we strip out all punctuation (except for the special tokens), prepend `<s>` to the list (marking the start of the first sentence), and delete the last word if the list ends `<e>` `<s>` (otherwise, we append `<e>`).

An example of parser input/output is

Input: ``I'm taking a `CSE` class on `machine-learning`. It's a lot of `work`, but `pretty interesting`.''

Output: `[<s>, im, taking, a, cse, class, on, machine, learning, <e>, <s>, its, a, lot, of, work, but, pretty, interesting, <e>],`

where each "word" in the output list is a string.

Our parsing scheme works well, but it leaves traces of some TeX commands from the raw abstract text; for example, it sends `\mathbb{Z}` → `mathbbz`. This would be fine if all arXiv and snarXiv abstracts have TeX commands written the same way, though it is possible in some cases for abstracts to write the same command in different ways. In practice, we find that these instances are rare enough for the concern to be negligible.

A.2 Vocabulary

We defined our vocabulary $\mathcal{V}$ as the collection of $V = 15,315$ unique words that appeared at least twice in a training corpus of 12,000 randomly chosen parsed arXiv abstracts and 12,000 (randomly generated) parsed snarXiv abstracts. We decided not to include the 13,960 words that only appeared once since they seem to be relatively uncommon (often they are the residuals of TeX commands), and including them would nearly double our vocabulary size. This pruning can be thought of as a feature-processing step.

A.3 n-grams

It is fairly common for a word to appear in the test set that is not in the vocabulary. When this happens, we change the word to a special token `<UNK>`. We then treat `<UNK>` as we would any other word when counting n-gram occurrences $C_Y(\cdot)$.

We prepend copies of the start sentence token `<s>` to each parsed abstract to ensure that the first n-gram consists of $n - 1$ copies of `<s>` and one "real" word. Similarly, we append copies of `<e>` to the end of each parsed abstract.

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