Eric Hardisty, Jordan Boyd-Graber, and Philip Resnik. Modeling Perspective using Adaptor Grammars

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Contact Jordan Boyd-Graber (jbg@boydgraber.org) for questions about this paper.
Abstract

Strong indications of perspective can often come from collocations of arbitrary length; for example, someone writing get the government out of my X is typically expressing a conservative rather than progressive viewpoint. However, going beyond unigram or bigram features in perspective classification gives rise to problems of data sparsity. We address this problem using nonparametric Bayesian modeling, specifically adaptor grammars (Johnson et al., 2006). We demonstrate that an adaptive naive Bayes model captures multiword lexical usages associated with perspective, and establishes a new state-of-the-art for perspective classification results using the Bitter Lemons corpus, a collection of essays about mid-east issues from Israeli and Palestinian points of view.

1 Introduction

Most work on the computational analysis of sentiment and perspective relies on lexical features. This makes sense, since an author’s choice of words is often used to express overt opinions (e.g. describing healthcare reform as idiotic or wonderful) or to frame a discussion in order to convey a perspective more implicitly (e.g. using the term death tax instead of estate tax). Moreover, it is easy and efficient to represent texts as collections of the words they contain, in order to apply a well known arsenal of supervised techniques (Laver et al., 2003; Mullen and Malouf, 2006; Yu et al., 2008).

At the same time, standard lexical features have their limitations for this kind of analysis. Such features are usually created by selecting some small n-gram size in advance. Indeed, it is not uncommon to see the feature space for sentiment analysis limited to unigrams. However, important indicators of perspective can also be longer (get the government out of my). Trying to capture these using standard machine learning approaches creates a problem, since allowing n-grams as features for larger n gives rise to problems of data sparsity.

In this paper, we employ nonparametric Bayesian models (Orbanz and Teh, 2010) in order to address this limitation. In contrast to parametric models, for which a fixed number of parameters are specified in advance, nonparametric models can “grow” to the size best suited to the observed data. In text analysis, models of this type have been employed primarily for unsupervised discovery of latent structure — for example, in topic modeling, when the true number of topics is not known (Teh et al., 2006); in grammatical inference, when the appropriate number of nonterminal symbols is not known (Liang et al., 2007); and in coreference resolution, when the number of entities in a given document is not specified in advance (Haghighi and Klein, 2007). Here we use them for supervised text classification.

Specifically, we use adaptor grammars (Johnson et al., 2006), a formalism for nonparametric Bayesian modeling that has recently proven useful in unsupervised modeling of phonemes (Johnson, 2008), grammar induction (Cohen et al., 2010), and named entity structure learning (Johnson, 2010), to make supervised naive Bayes classification nonparametric in order to improve perspective modeling. Intuitively, naive Bayes associates each class or label with a probability distribution over a fixed vocabulary. We introduce adaptive naive Bayes (ANB), for which in principle the vocabulary can grow as needed to include collocations of arbitrary length, as determined
by the properties of the dataset. We show that using adaptive naïve Bayes improves on state of the art classification using the Bitter Lemons corpus (Lin et al., 2006), a document collection that has been used by a variety of authors to evaluate perspective classification.

In Section 2, we review adaptor grammars, show how naïve Bayes can be expressed within the formalism, and describe how — and how easily — an adaptive naïve Bayes model can be created. Section 3 validates the approach via experimentation on the Bitter Lemons corpus. In Section 4, we summarize the contributions of the paper and discuss directions for future work.

2 Adapting Naïve Bayes to be Less Naïve

In this work we apply the adaptor grammar formalism introduced by Johnson, Griffiths, and Goldwater (Johnson et al., 2006). Adaptor grammars are a generalization of probabilistic context free grammars (PCFGs) that make it particularly easy to express non-parametric Bayesian models of language simply and readily using context free rules. Moreover, Johnson et al. provide an inference procedure based on Markov Chain Monte Carlo techniques that makes parameter estimation straightforward for all models that can be expressed using adaptor grammars.1 Variational inference for adaptor grammars has also been recently introduced (Cohen et al., 2010).

Briefly, adaptor grammars allow nonterminals to be rewritten to entire subtrees. In contrast, a nonterminal in a PCFG rewrites only to a collection of grammar symbols; their subsequent productions are independent of each other. For instance, a traditional PCFG might learn probabilities for the rewrite rule $PP \rightarrow P NP$. In contrast, an adaptor grammar can learn (or “cache”) the production $PP \rightarrow (P up)(NP(\text{DET} a)(N tree))$. It does this by positing that the distribution over children for an adapted non-terminal comes from a Pitman-Yor distribution.

A Pitman-Yor distribution (Pitman and Yor, 1997) is a distribution over distributions. It has three parameters: the discount, $\alpha$, such that $0 \leq \alpha < 1$, the strength, $b$, a real number such that $-a < b$, and a probability distribution $G_0$ known as the base distribution. Adaptor grammars allow distributions over subtrees to come from a Pitman-Yor distribution with the PCFG’s original distribution over trees as the base distribution. The generative process for obtaining draws from a distribution drawn from a Pitman-Yor distribution can be described by the “Chinese restaurant process” (CRP). We will use the CRP to describe how to obtain a distribution over observations composed of sequences of $n$-grams, the key to our model’s ability to capture perspective-bearing $n$-grams.

Suppose that we have a base distribution $\Omega$ that is some distribution over all sequences of words (the exact structure of such a distribution is unimportant; such a distribution will be defined later in Table 1). Suppose further we have a distribution $\phi$ drawn from $PY(a, b, \Omega)$, and we wish to draw a series of observations $w$ from $\phi$. The CRP gives us a generative process for doing those draws from $\phi$, marginalizing out $\phi$. Following the restaurant metaphor, we imagine the $i^{th}$ customer in the series entering the restaurant to take a seat at a table. The customer sits by making a choice that determines the value of the $n$-gram $w_i$ for that customer: she can either sit at an existing table or start a new table of her own.2

If she sits at a new table $j$, that table is assigned a draw $y_j$ from the base distribution, $\Omega$; note that, since $\Omega$ is a distribution over $n$-grams, $y_j$ is an $n$-gram. The value of $w_i$ is therefore assigned to be $y_j$, and $y_j$ becomes the sequence of words assigned to that new table. On the other hand, if she sits at an existing table, then $w_i$ simply takes the sequence of words already associated with that table (assigned as above when it was first occupied).

The probability of joining an existing table $j$, with $c_j$ patrons already seated at table $j$, is $\frac{c_j-a}{c+b}$, where $c$ is the number of patrons seated at all tables: $c_i = \sum_j c_j$. The probability of starting a new table is $\frac{b+c_i}{c+b}$, where $t$ is the number of tables presently occupied.

Notice that $\phi$ is a distribution over the same space as $\Omega$, but it can drastically shift the mass of the distribution, compared with $\Omega$, as more and more pa-

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1And, better still, they provide code that implements the inference algorithm; see http://www.cog.brown.edu/ mj/Software.htm.

2Note that we are abusing notation by allowing $w_i$ to correspond to a word sequence of length $\geq 1$ rather than a single word.
tron are seated at tables. However, there is always
a chance of drawing from the base distribution, and
therefore every word sequence can also always be
drawn from $\phi$.
In the next section we will write a naïve Bayes-like
generative process using PCFGs. We will then use
the PCFG distribution as the base distribution for a
Pitman-Yor distribution, adapting the naïve Bayes
process to give us a distribution over $n$-grams, thus
learning new language substructures that are useful
for modeling the differences in perspective.

2.1 Classification Models as PCFGs
Naïve Bayes is a venerable and popular mechanism
for text classification (Lewis, 1998). It posits that
there are $K$ distinct categories of text — each with a
distinct distribution over words — and that every
document, represented as an exchangeable bag of words,
is drawn from one (and only one) of these distributions.
Learning the per-category word distributions and global prevalence of the classes is a problem of
posterior inference which can be approached using a
variety of inference techniques (Lowd and Domingos,
2005).

More formally, naïve Bayes models can be ex-
pressed via the following generative process:

1. Draw a global distribution over classes $\theta \sim Dir (\alpha)$
2. For each class $i \in \{1, \ldots, K\}$, draw a word
distribution $\phi_i \sim Dir (\lambda)$
3. For each document $d \in \{1, \ldots, M\}$:
   (a) Draw a class assignment $z_d \sim Mult (\theta)$
   (b) For each word position $n \in \{1, \ldots, N_d\}$,
draw $w_{d,n} \sim Mult (\phi_{z_d})$

A variant of the naïve Bayes generative process can
be expressed using the adaptor grammar formalism
(Table 1). The left hand side of each rule represents
a nonterminal which can be expanded, and the right
hand side represents the rewrite rule. The rightmost
indices show replication; for instance, there are $|V|
rules that allow $\text{WORD}_i$ to rewrite to each word in the

<table>
<thead>
<tr>
<th>SENT $\rightarrow$ DOC$_d$</th>
<th>DOC$_{d,0.001}$ $\rightarrow$ ID$<em>d$ WORD$</em>{s,i}$</th>
<th>WORD$_{s,i}$</th>
<th>WORD$<em>{i}$ $\rightarrow$ WORD$</em>{i}$, WORD$\cdots$ $\rightarrow$ WORD$_{i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d = 1, \ldots, m$</td>
<td>$d = 1, \ldots, m$; $i \in {1, K}$</td>
<td>$i \in {1, K}$</td>
<td>$v \in V; i \in {1, K}$</td>
</tr>
</tbody>
</table>

Table 1: A naïve Bayes-inspired model expressed as a
PCFG.

vocabulary. One can assume a symmetric Dirichlet
prior of $\text{Dir} (1)$ over the production choices unless
otherwise specified — as with the $\text{DOC}_d$ production
rule above, where a sparse prior is used.

Notice that the distribution over expansions for $\text{WORD}_i$ corresponds directly to $\phi_i$ in Figure 1(a).
There are, however, some differences between the
model that we have described above and the standard
naïve Bayes model depicted in Figure 1(a). In particular,
there is no longer a single choice of class per
document; each sentence is assigned a class. If the
distribution over per-sentence labels is sparse (as it
is above for $\text{DOC}_d$), this will closely approximate
naïve Bayes, since it will be very unlikely for the
sentences in a document to have different labels. A
non-sparse prior leads to behavior more like models
that allow parts of a document to express sentiment
or perspective differently.

2.2 Moving Beyond the Bag of Words
The naïve Bayes generative distribution posits that
when writing a document, the author selects a distribu-
tion of categories $z_d$ for the document from $\theta$. The
author then generates words one at a time: each word
is selected independently from a flat multinomial
distribution $\phi_{z_d}$ over the vocabulary.

However, this is a very limited picture of how text
is related to underlying perspectives. Clearly words
are often connected with each other as collocations,
and, just as clearly, extending a flat vocabulary to
include bigram collocations does not suffice, since
sometimes relevant perspective-bearing phrases are
longer than two words. Consider phrases like health
care for all or government takeover of health care,
connected with progressive and conservative positions,
respectively, during the national debate on
healthcare reform. Simply applying naïve Bayes,
or any other model, to a bag of $n$-grams for high $n$ is
going to lead to unworkable levels of data sparsity; a model should be flexible enough to support both unigrams and longer phrases as needed.

Following Johnson (2010), however, we can use adaptor grammars to extend naïve Bayes flexibly to include richer structure like collocations when they improve the model, and not including them when they do not. This can be accomplished by introducing adapted nonterminal rules: in a revised generative process, the author can draw from Pitman-Yor distribution whose base distribution is over word sequences of arbitrary length. Thus in a setting where, say, $K = 2$, and our two classes are PROGRESSIVE and CONSERVATIVE, the sequence health care for all might be generated as a single unit for the progressive perspective, but in the conservative perspective the same sequence might be generated as three separate draws: health care, for, all. Such a model is presented in Figure 1(b). Note the following differences between Figures 1(a) and 1(b):

- $z_d$ selects which Pitman-Yor distribution to draw from for document $d$.
- $\phi_i$ is the distribution over $n$-grams that comes from the Pitman-Yor distribution.
- $W_{d,n}$ represents an $n$-gram draw from $\phi_i$.
- $a, b$ are the Pitman-Yor strength and discount parameters.
- $\Omega$ is the Pitman-Yor base distribution with $\tau$ as its uniform hyperparameter.

4 As defined above, the base distribution is that of the PCFG production rule $\text{WORDS}_i$. Although it has non-zero probability of producing any sequence of words, it is biased toward shorter word sequences.

Returning to the CRP metaphor discussed when we introduced the Pitman-Yor distribution, there are two restaurants, one for the PROGRESSIVE distribution and one for the CONSERVATIVE distribution. Health care for all has its own table in the PROGRESSIVE restaurant, and enough people are sitting at it to make it popular. There is no such table in the CONSERVATIVE restaurant, so in order to generate those words, the phrase health care for all would need to come from a new table; however, it is more easily explained by three customers sitting at three existing, popular tables: health care, for, and all.

We follow the convention of Johnson (2010) by writing adapted nonterminals as underlined. The grammar for adaptive naïve Bayes is shown in Table 2. The adapted $\text{COLLOC}_i$ rule means that every time we need to generate that nonterminal, we are actually drawing from a distribution drawn from a Pitman-Yor distribution. The distribution over the possible yields of the $\text{WORDS}_i$ rule serves as the base distribution.

Given this generative process for documents, we can now use statistical inference to uncover the posterior distribution over the latent variables, thus discovering the tables and seating assignments of our metaphorical restaurants that each cater to a specific perspective filled with tables populated by words and $n$-grams.

The model presented in Table 2 is the most straightforward way of extending naïve Bayes to collocations. For completeness, we also consider the alternative of using a shared base distribution rather than distinguishing the base distributions of the two classes.
Table 2: An adaptive naïve Bayes grammar. The COLLOC nonterminal’s distribution over yields is drawn from a Pitman–Yor distribution rather than a Dirichlet over production rules.

<table>
<thead>
<tr>
<th>SENT</th>
<th>DOCd</th>
<th>d = 1, ..., m</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOCd,0.001</td>
<td>IDd, SPANi</td>
<td>d = 1, ..., m; i ∈ {1, K}</td>
</tr>
<tr>
<td>SPANi</td>
<td>SPAN, COLLOCi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>SPANi</td>
<td>COLLOCi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>COLLOCi</td>
<td>WORDSi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDSi</td>
<td>WORDS, WORDi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDS</td>
<td>WORDi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDi</td>
<td>v</td>
<td>v ∈ V: i ∈ {1, K}</td>
</tr>
</tbody>
</table>

Table 3: An adaptive naïve Bayes grammar with a common base distribution for collocations. Note that, in contrast to Table 2, there are no subscripts on WORDS or WORD.

<table>
<thead>
<tr>
<th>SENT</th>
<th>DOCd</th>
<th>d = 1, ..., m</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOCd,0.001</td>
<td>IDd, SPANi</td>
<td>d = 1, ..., m; i ∈ {1, K}</td>
</tr>
<tr>
<td>SPANi</td>
<td>SPAN, COLLOCi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>SPANi</td>
<td>COLLOCi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>COLLOCi</td>
<td>WORDSi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDSi</td>
<td>WORDS, WORDi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDS</td>
<td>WORDi</td>
<td>i ∈ {1, K}</td>
</tr>
<tr>
<td>WORDi</td>
<td>v</td>
<td>v ∈ V</td>
</tr>
</tbody>
</table>

Briefly, using a shared base distribution posits that the two classes use similar word distributions, but generate collocations unique to each class, whereas using separate base distributions assumes that the distribution of words is unique to each class.

3 Experiments

3.1 Corpus Description

We conducted our classification experiments on the Bitter Lemons (BL) corpus, which is a collection of 297 essays averaging 700-800 words in length, on various Middle East issues, written from both the Israeli and Palestinian perspectives. The BL corpus was compiled by Lin et al. (2006) and is derived from a website that invites weekly discussions on a topic and publishes essays from two sets of authors each week.\(^5\) Two of the authors are guests, one from each perspective, and two essays are from the site’s regular contributors, also one from each perspective, for a total of four essays on each topic per week. We chose this corpus to allow us to directly compare our results with Greene and Resnik’s (2009) Observable Proxies for Underlying Semantics (OPUS) features and Lin et al.’s Latent Sentence Perspective Model (LSPM). The classification goal for this corpus is to label each document with the perspective of its author, either Israeli or Palestinian.

Consistent with prior work, we prepared the corpus by dividing it into two groups, one group containing all of the essays written by the regular site contributors, which we call the Editor set, and one group comprised of all the essays written by the guest contributors, which we call the Guest set. Similar to the above mentioned prior work, we perform classification using one group as training data and the other as test data and perform two folds of classification. The overall experimental setup and corpus preparation process is presented in Figure 3.

\(^5\)http://www.bitterlemons.org
3.2 Experimental Setup

The vocabulary generator determines the vocabulary used by a given experiment by converting the training set to lower case, stemming with the Porter stemmer, and filtering punctuation. We remove from the vocabulary any words that appeared in only one document regardless of frequency within that document, words with frequencies lower than a threshold, and stop words.\footnote{In these experiments, a frequency threshold of 4 was selected prior to testing.} The vocabulary is then passed to a grammar generator and a corpus filter.

The grammar generator uses the vocabulary to generate the terminating rules of the grammar from the ANB grammar presented in Tables 2 and 3. The corpus filter takes in a set of documents and replaces all words not in the vocabulary with “out of vocabulary” markers. This process ensures that in all experiments the vocabulary is composed entirely of words from the training set. After the groups have been filtered, the group used as the test set has its labels removed. The test and training set are then sent, along with the grammar, into the adaptor grammar inference engine.

Each experiment ran for 3000 iterations. For the runs where adaptation was used we set the initial Pitman-Yor $a$ and $b$ parameters to 0.01 and 10 respectively, then slice sample (Johnson and Goldwater, 2009).

We use the resulting sentence parses for classification. By design of the grammar, each sentence’s words will belong to one and only one distribution. We identify that distribution from each of the test set sentence parses and use it as the sentence level classification for that particular sentence. We then use majority rule on the individual sentence classifications in a document to obtain the document classification. (In most cases the sentence-level assignments are overwhelmingly dominated by one class.)

3.3 Results and Analysis

Table 4 gives the results and compares to prior work. The support vector machine (SVM), NB-B and LSPM results are taken directly from Lin et al. (2006). NB-B indicates naïve Bayes with full Bayesian inference. LSPM is the Latent Sentence Perspective Model, also from Lin et al. (2006). OPUS results are taken from Greene and Resnik (2009). Briefly, OPUS features are generated from observable grammatical relations that come from dependency parses of the corpus. Use of these features provided the best classification accuracy for this task prior to this work. ANB* refers to the grammar from Table 2, but with adaptation disabled. The reported accuracy values for ANB*, ANB with a common base distribution (see Table 3), and ANB with separate base distributions (see Table 2) are the mean values from five separate sampling chains. Bold face indicates statistical significance ($p < 0.05$) by unpaired t-test between the reported value and ANB*.

Consistent with all prior work on this corpus we found that the classification accuracy for training on editors and testing on guests was lower than the other direction since the larger number of editors in the guest set allows for greater generalization. The difference between ANB* and ANB with a common base distribution is not statistically significant. Also of note is that the classification accuracy improves for testing on Guests when the ANB grammar is allowed to adapt and a separate base distribution is used for the two classes (88.28% versus 84.98% without adaptation).

Table 5 presents some data on adapted rules

<table>
<thead>
<tr>
<th>Training Set</th>
<th>Test Set</th>
<th>Classifier</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>SVM</td>
<td>88.22</td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>NB-B</td>
<td>93.46</td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>LSPM</td>
<td>94.93</td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>OPUS</td>
<td>97.64</td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>ANB*</td>
<td>99.32</td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>ANB Com</td>
<td><strong>99.93</strong></td>
</tr>
<tr>
<td>Guests</td>
<td>Editors</td>
<td>ANB Sep</td>
<td><strong>99.87</strong></td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>SVM</td>
<td>81.48</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>NB-B</td>
<td>85.85</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>LSPM</td>
<td>86.99</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>OPUS</td>
<td>85.86</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>ANB*</td>
<td>84.98</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>ANB Com</td>
<td>82.76</td>
</tr>
<tr>
<td>Editors</td>
<td>Guests</td>
<td>ANB Sep</td>
<td><strong>88.28</strong></td>
</tr>
</tbody>
</table>

Table 4: Classification results. ANB* indicates the same grammar as Adapted Naïve Bayes, but with adaptation disabled. Com and Sep refer to whether the base distribution was common to both classes or separate.
Table 5: Counts of cached unigrams and $n$-grams for the two classes compared to the vocabulary sizes.

<table>
<thead>
<tr>
<th>Class</th>
<th>Group</th>
<th>Unique Unigrams Cached</th>
<th>Unique $n$-grams Cached</th>
<th>Percent of Group Vocabulary Cached</th>
</tr>
</thead>
<tbody>
<tr>
<td>Israeli</td>
<td>Editors</td>
<td>2,292</td>
<td>19,614</td>
<td>77.62</td>
</tr>
<tr>
<td>Palestinian</td>
<td>Editors</td>
<td>2,180</td>
<td>17,314</td>
<td>86.54</td>
</tr>
<tr>
<td>Israeli</td>
<td>Guests</td>
<td>2,262</td>
<td>19,398</td>
<td>79.91</td>
</tr>
<tr>
<td>Palestinian</td>
<td>Guests</td>
<td>2,005</td>
<td>16,946</td>
<td>74.94</td>
</tr>
</tbody>
</table>

Table 6: Charged bigrams captured by the framework.

<table>
<thead>
<tr>
<th>Israeli</th>
<th>Palestinian</th>
</tr>
</thead>
<tbody>
<tr>
<td>zionist dream</td>
<td>american jew</td>
</tr>
<tr>
<td>zionist state</td>
<td>achieve freedom</td>
</tr>
<tr>
<td>zionist movement</td>
<td>palestinian freedom</td>
</tr>
<tr>
<td>american leadership</td>
<td>support palestinian</td>
</tr>
<tr>
<td>american victory</td>
<td>palestinian suffering</td>
</tr>
<tr>
<td>abandon violence</td>
<td>palestinian territory</td>
</tr>
<tr>
<td>freedom (of the) press</td>
<td>palestinian statehood</td>
</tr>
<tr>
<td>palestinian violence</td>
<td>palestinian refugee</td>
</tr>
</tbody>
</table>

In this paper, we have applied adaptor grammars in a supervised setting to model lexical properties of text and improve document classification according to perspective, by allowing nonparametric discovery of collocations that aid in perspective classification. The adaptive naïve Bayes model improves on state of the art supervised classification performance in head-to-head comparisons with previous approaches.

Although there have been many investigations on the efficacy of using multiword collocations in text classification (Bekkerman and Allan, 2004), usually such approaches depend on a preprocessing step such as computing $tf-idf$ or other measures of frequency based on either word bigrams (Tan et al., 2002) or character $n$-grams (Raskutti et al., 2001). In contrast, our approach combines phrase discovery with the probabilistic model of the text. This allows for the collocation selection and classification to be expressed in a single model, which can then be extended later; it also is truly generative, as compared with feature induction and selection algorithms that either under- or over-generate data.

There are a number of interesting directions in which to take this research. As Johnson et al. (2006) argue, and as we have confirmed here, the adaptor
grammars formalism makes it quite easy to work with latent variable models, in order to automatically discover structures in the data that have predictive value. For example, it is easy to imagine a model where in addition to a word distribution for each class, there is also an additional shared “neutral” distribution: for each sentence, the words in that sentence can either come from the class-specific content distribution or the shared neutral distribution. This turns out to be the Latent Sentence Perspective Model of Lin et al. (2006), which is straightforward to encode using the adaptor grammar formalism simply by introducing two new nonterminals to represent the neutral distribution:

\[
\text{SENT} \rightarrow \text{DOC}_d \quad d = 1, \ldots, m \\
\text{DOC}_d \rightarrow \text{ID}_d \text{ WORDS}_i \quad d = 1, \ldots, m; \quad i \in \{1, K\} \\
\text{WORD}_i \rightarrow \text{NEUTs} \quad v \in V; i \in \{1, K\}
\]

Running this grammar did not produce improvements consistent with those reported by Lin et al. We plan to investigate this further, and a natural follow-on would be to experiment with adaptation for this variety of latent structure, to produce an adapted LSPM-like model analogous to adaptive naïve Bayes.

Viewed in a larger context, computational classification of perspective is closely connected to social scientists’ study of framing, which Entman (1993) characterizes as follows: “To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described.” Here and in other work (e.g. (Laver et al., 2003; Mullen and Malouf, 2006; Yu et al., 2008; Monroe et al., 2008)), it is clear that lexical evidence is one key to understanding how language is used to frame discussion from one perspective or another; Resnik and Greene (2009) have shown that syntactic choices can provide important evidence, as well. Another promising direction for this work is the application of adaptor grammar models as a way to capture both lexical and grammatical aspects of framing in a unified model.

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