

# Creating Robust Supervised Classifiers via Web-Scale N-gram Data

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## Abstract

In this paper, we systematically assess the value of using web-scale N-gram data in state-of-the-art supervised NLP classifiers. We compare classifiers that include or exclude features for the counts of various N-grams, where the counts are obtained from a web-scale auxiliary corpus. We show that including N-gram count features can advance the state-of-the-art accuracy on standard data sets for adjective ordering, spelling correction, noun compound bracketing, and verb part-of-speech disambiguation. More importantly, when operating on new domains, or when labeled training data is not plentiful, we show that using web-scale N-gram features is essential for achieving robust performance.

## 1 Introduction

Many NLP systems use web-scale N-gram counts (Keller and Lapata, 2003; Nakov and Hearst, 2005; Brants et al., 2007). Lapata and Keller (2005) demonstrate good performance on eight tasks using unsupervised web-based models. They show web counts are superior to counts from a large corpus. Bergsma et al. (2009) propose unsupervised and supervised systems that use counts from Google’s N-gram corpus (Brants and Franz, 2006). Web-based models perform particularly well on *generation* tasks, where systems choose between competing sequences of output text (such as different spellings), as opposed to *analysis* tasks, where systems choose between abstract labels (such as part-of-speech tags or parse trees).

In this work, we address two natural and related questions which these previous studies leave open:

1. Is there a benefit in combining web-scale counts with the features used in state-of-the-art supervised approaches?

2. How well do web-based models perform on new domains or when labeled data is scarce?

We address these questions on two generation and two analysis tasks, using both existing N-gram data and a novel web-scale N-gram corpus that includes part-of-speech information (Section 2). While previous work has combined web-scale features with other features in specific classification problems (Modjeska et al., 2003; Yang et al., 2005; Vadas and Curran, 2007b), we provide a multi-task, multi-domain comparison.

Some may question why supervised approaches are needed at all for generation problems. Why not solely rely on direct evidence from a giant corpus? For example, for the task of prenominal adjective ordering (Section 3), a system that needs to describe a ball that is both big and red can simply check that *big red* is more common on the web than *red big*, and order the adjectives accordingly.

It is, however, suboptimal to only use N-gram data. For example, ordering adjectives by direct web evidence performs 7% worse than our best supervised system (Section 3.2). No matter how large the web becomes, there will always be plausible constructions that never occur. For example, there are currently no pages indexed by Google with the preferred adjective ordering for *bedraggled 56-year-old [professor]*. Also, in a particular domain, words may have a non-standard usage. Systems trained on labeled data can learn the domain usage and leverage other regularities, such as suffixes and transitivity for adjective ordering.

With these benefits, systems trained on labeled data have become the dominant technology in academic NLP. There is a growing recognition, however, that these systems are highly domain dependent. For example, parsers trained on annotated newspaper text perform poorly on other genres (Gildea, 2001). While many approaches have adapted NLP systems to specific domains (Tsu-ruoka et al., 2005; McClosky et al., 2006; Blitzer

et al., 2007; Daumé III, 2007; Rimell and Clark, 2008), these techniques assume the system knows on which domain it is being used, and that it has access to representative data in that domain. These assumptions are unrealistic in many real-world situations; for example, when automatically processing a heterogeneous collection of web pages. How well do supervised and unsupervised NLP systems perform when used uncustomized, *out-of-the-box* on new domains, and how can we best design our systems for robust *open-domain* performance?

Our results show that using web-scale N-gram data in supervised systems advances the state-of-the-art performance on standard analysis and generation tasks. More importantly, when operating out-of-domain, or when labeled data is not plentiful, using web-scale N-gram data not only helps achieve good performance – it is essential.

## 2 Experiments and Data

### 2.1 Experimental Design

We evaluate the benefit of N-gram data on multi-class classification problems. For each task, we have some labeled data indicating the correct output for each example. We evaluate with **accuracy**: the percentage of examples correctly classified in test data. We use one *in-domain* and two *out-of-domain* test sets for each task. Statistical significance is assessed with McNemar’s test,  $p < 0.01$ .

We provide results for unsupervised approaches and the majority-class baseline for each task.

For our supervised approaches, we represent the examples as feature vectors, and learn a classifier on the training vectors. There are two feature classes: features that use N-grams (N-GM) and those that do not (LEX). N-GM features are real-valued features giving the log-count of a particular N-gram in the auxiliary web corpus. LEX features are binary features that indicate the presence or absence of a particular string at a given position in the input. The name LEX emphasizes that they identify specific lexical items. The instantiations of both types of features depend on the task and are described in the corresponding sections.

Each classifier is a linear Support Vector Machine (SVM), trained using LIBLINEAR (Fan et al., 2008) on the standard domain. We use the one-vs-all strategy when there are more than two classes (in Section 4). We plot learning curves to measure the accuracy of the classifier when the number of labeled training examples varies. The size

of the N-gram data and its counts remain constant. We always optimize the SVM’s (L2) regularization parameter on the in-domain development set. We present results with L2-SVM, but achieve similar results with L1-SVM and logistic regression.

### 2.2 Tasks and Labeled Data

We study two generation tasks: prenominal adjective ordering (Section 3) and context-sensitive spelling correction (Section 4), followed by two analysis tasks: noun compound bracketing (Section 5) and verb part-of-speech disambiguation (Section 6). In each section, we provide references to the origin of the labeled data. For the out-of-domain Gutenberg and Medline data used in Sections 3 and 4, we generate examples ourselves.<sup>1</sup> We chose Gutenberg and Medline in order to provide challenging, distinct domains from our training corpora. Our Gutenberg corpus consists of out-of-copyright books, automatically downloaded from the Project Gutenberg website.<sup>2</sup> The Medline data consists of a large collection of online biomedical abstracts. We describe how labeled adjective and spelling examples are created from these corpora in the corresponding sections.

### 2.3 Web-Scale Auxiliary Data

The most widely-used N-gram corpus is the Google 5-gram Corpus (Brants and Franz, 2006).

For our tasks, we also use **Google V2**: a new N-gram corpus (also with N-grams of length one-to-five) that we created from the same one-trillion-word snapshot of the web as the Google 5-gram Corpus, but with several enhancements. These include: 1) Reducing noise by removing duplicate sentences and sentences with a high proportion of non-alphanumeric characters (together filtering about 80% of the source data), 2) pre-converting all digits to the 0 character to reduce sparsity for numeric expressions, and 3) including the part-of-speech (POS) tag distribution for each N-gram. The source data was automatically tagged with TnT (Brants, 2000), using the Penn Treebank tag set. Lin et al. (2010) provide more details on the

<sup>1</sup><http://webdocs.cs.ualberta.ca/~bergmsa/Robust/> provides our Gutenberg corpus, a link to Medline, and also the generated examples for both Gutenberg and Medline.

<sup>2</sup>[www.gutenberg.org](http://www.gutenberg.org). All books just released in 2009 and thus unlikely to occur in the source data for our N-gram corpus (from 2006). Of course, with removal of sentence duplicates and also N-gram thresholding, the possible presence of a test sentence in the massive source data is unlikely to affect results. Carlson et al. (2008) reach a similar conclusion.

N-gram data and N-gram search tools.

The third enhancement is especially relevant here, as we can use the POS distribution to collect counts for N-grams of mixed words and tags. For example, we have developed an N-gram search engine that can count how often the adjective *unprecedented* precedes another adjective in our web corpus (113K times) and how often it follows one (11K times). Thus, even if we haven't seen a particular adjective pair directly, we can use the positional preferences of each adjective to order them.

Early web-based models used search engines to collect N-gram counts, and thus could not use capitalization, punctuation, and annotations such as part-of-speech (Kilgarriff and Grefenstette, 2003). Using a POS-tagged web corpus goes a long way to addressing earlier criticisms of web-based NLP.

### 3 Prenominal Adjective Ordering

Prenominal adjective ordering strongly affects text readability. For example, while *the unprecedented statistical revolution* is fluent, *the statistical unprecedented revolution* is not. Many NLP systems need to handle adjective ordering robustly. In machine translation, if a noun has two adjective modifiers, they must be ordered correctly in the target language. Adjective ordering is also needed in Natural Language Generation systems that produce information from databases; for example, to convey information (in sentences) about medical patients (Shaw and Hatzivassiloglou, 1999).

We focus on the task of ordering a pair of adjectives independently of the noun they modify and achieve good performance in this setting. Following the set-up of Malouf (2000), we experiment on the 263K adjective pairs Malouf extracted from the British National Corpus (BNC). We use 90% of pairs for training, 5% for testing, and 5% for development. This forms our in-domain data.<sup>3</sup>

We create out-of-domain examples by tokenizing Medline and Gutenberg (Section 2.2), then POS-tagging them with CRFTagger (Phan, 2006). We create examples from all sequences of two adjectives followed by a noun. Like Malouf (2000), we assume that edited text has adjectives ordered fluently. We extract 13K and 9.1K out-of-domain pairs from Gutenberg and Medline, respectively.<sup>4</sup>

<sup>3</sup>BNC is not a domain *per se* (rather a balanced corpus), but has a style and vocabulary distinct from our OOD data.

<sup>4</sup>Like Malouf (2000), we convert our pairs to lower-case. Since the N-gram data includes case, we merge counts from the upper and lower case combinations.

The input to the system is a pair of adjectives,  $(a_1, a_2)$ , ordered alphabetically. The task is to classify this order as correct (the positive class) or incorrect (the negative class). Since both classes are equally likely, the majority-class **baseline** is around 50% on each of the three test sets.

#### 3.1 Supervised Adjective Ordering

##### 3.1.1 LEX features

Our adjective ordering model with LEX features is a novel contribution of this paper.

We begin with two features for each pair: an indicator feature for  $a_1$ , which gets a feature value of +1, and an indicator feature for  $a_2$ , which gets a feature value of -1. The parameters of the model are therefore weights on specific adjectives. The higher the weight on an adjective, the more it is preferred in the first position of a pair. If the alphabetic ordering is correct, the weight on  $a_1$  should be higher than the weight on  $a_2$ , so that the classifier returns a positive score. If the reverse ordering is preferred,  $a_2$  should receive a higher weight. Training the model in this setting is a matter of assigning weights to all the observed adjectives such that the training pairs are maximally ordered correctly. The feature weights thus implicitly produce a linear ordering of all observed adjectives. The examples can also be regarded as rank constraints in a discriminative ranker (Joachims, 2002). Transitivity is achieved naturally in that if we correctly order pairs  $a \prec b$  and  $b \prec c$  in the training set, then  $a \prec c$  by virtue of the weights on  $a$  and  $c$ .

While exploiting transitivity has been shown to improve adjective ordering, there are many conflicting pairs that make a strict linear ordering of adjectives impossible (Malouf, 2000). We therefore provide an indicator feature for the pair  $a_1 a_2$ , so the classifier can memorize exceptions to the linear ordering, breaking strict order transitivity. Our classifier thus operates along the lines of rankers in the *preference-based setting* as described in Ailon and Mohri (2008).

Finally, we also have features for all suffixes of length 1-to-4 letters, as these encode useful information about adjective class (Malouf, 2000). Like the adjective features, the suffix features receive a value of +1 for adjectives in the first position and -1 for those in the second.

##### 3.1.2 N-GM features

Lapata and Keller (2005) propose a web-based approach to adjective ordering: take the most-

System	IN	O1	O2
Malouf (2000)	91.5	65.6	71.6
web $c(a_1, a_2)$ vs. $c(a_2, a_1)$	87.1	83.7	86.0
SVM with N-GM features	90.0	<b>85.8</b>	<b>88.5</b>
SVM with LEX features	93.0	70.0	73.9
SVM with N-GM + LEX	<b>93.7</b>	83.6	85.4

Table 1: Adjective ordering accuracy (%). SVM and Malouf (2000) trained on BNC, tested on BNC (IN), Gutenberg (O1), and Medline (O2).

frequent order of the words on the web,  $c(a_1, a_2)$  vs.  $c(a_2, a_1)$ . We adopt this as our unsupervised approach. We merge the counts for the adjectives occurring contiguously and separated by a comma.

These are indubitably the most important N-GM features; we include them but also other, tag-based counts from Google V2. Raw counts include cases where one of the adjectives is not used as a modifier: “the *special present* was” vs. “the *present special* issue.” We include log-counts for the following, more-targeted patterns:<sup>5</sup>  $c(a_1 a_2 N.*)$ ,  $c(a_2 a_1 N.*)$ ,  $c(DT a_1 a_2 N.*)$ ,  $c(DT a_2 a_1 N.*)$ . We also include features for the log-counts of each adjective preceded or followed by a word matching an adjective-tag:  $c(a_1 J.*)$ ,  $c(J.* a_1)$ ,  $c(a_2 J.*)$ ,  $c(J.* a_2)$ . These assess the positional preferences of each adjective. Finally, we include the log-frequency of each adjective. The more frequent adjective occurs first 57% of the time.

As in all tasks, the counts are features in a classifier, so the importance of the different patterns is weighted discriminatively during training.

### 3.2 Adjective Ordering Results

In-domain, with both feature classes, we set a strong new standard on this data: 93.7% accuracy for the N-GM+LEX system (Table 1). We trained and tested Malouf (2000)’s program on our data; our LEX classifier, which also uses no auxiliary corpus, makes 18% fewer errors than Malouf’s system. Our web-based N-GM model is also superior to the direct evidence web-based approach of Lapata and Keller (2005), scoring 90.0% vs. 87.1% accuracy. These results show the benefit of our new lexicalized and web-based features.

Figure 1 gives the in-domain learning curve. With fewer training examples, the systems with N-GM features strongly outperform the LEX-only system. Note that with tens of thousands of test

<sup>5</sup>In this notation, capital letters (and regular expressions) are matched against tags while  $a_1$  and  $a_2$  match words.

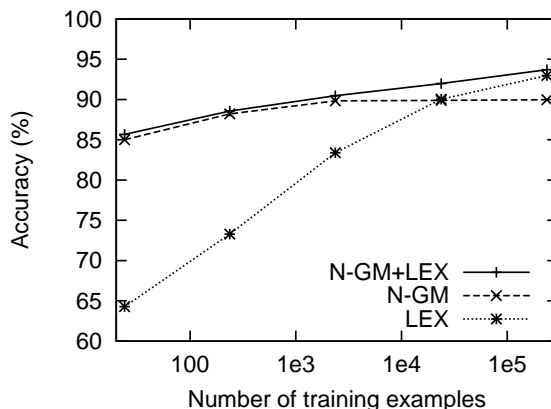


Figure 1: In-domain learning curve of adjective ordering classifiers on BNC.

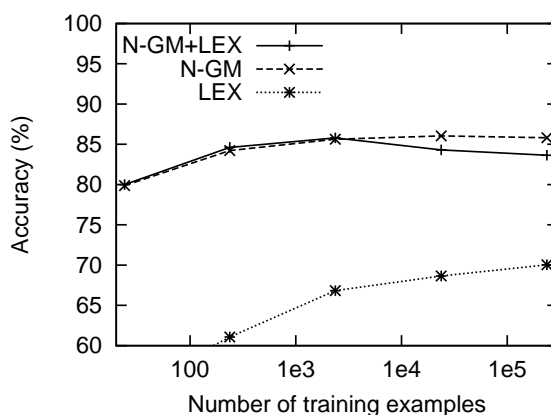


Figure 2: Out-of-domain learning curve of adjective ordering classifiers on Gutenberg.

examples, all differences are highly significant.

Out-of-domain, LEX’s accuracy drops a shocking 23% on Gutenberg and 19% on Medline (Table 1). Malouf (2000)’s system fares even worse. The overlap between training and test pairs helps explain. While 59% of the BNC test pairs were seen in the training corpus, only 25% of Gutenberg and 18% of Medline pairs were seen in training.

While other ordering models have also achieved “very poor results” out-of-domain (Mitchell, 2009), we expected our expanded set of LEX features to provide good generalization on new data. Instead, LEX is very unreliable on new domains.

N-GM features do not rely on specific pairs in training data, and thus remain fairly robust cross-domain. Across the three test sets, 84-89% of examples had the correct ordering appear at least once on the web. On new domains, the learned N-GM system maintains an advantage over the unsupervised  $c(a_1, a_2)$  vs.  $c(a_2, a_1)$ , but the difference is reduced. Note that training with 10-fold

cross validation, the N-GM system can achieve up to 87.5% on Gutenberg (90.0% for N-GM + LEX).

The learning curve showing performance on Gutenberg (but still training on BNC) is particularly instructive (Figure 2, performance on Medline is very similar). The LEX system performs much worse than the web-based models across all training sizes. For our top in-domain system, N-GM + LEX, as you add more labeled examples, performance begins *decreasing* out-of-domain. The system disregards the robust N-gram counts as it is more and more confident in the LEX features, and it suffers the consequences.

#### 4 Context-Sensitive Spelling Correction

We now turn to the generation problem of context-sensitive spelling correction. For every occurrence of a word in a pre-defined set of confusable words (like *peace* and *piece*), the system must select the most likely word from the set, flagging possible usage errors when the predicted word disagrees with the original. Contextual spell checkers are one of the most widely used NLP technologies, reaching millions of users via compressed N-gram models in Microsoft Office (Church et al., 2007).

Our in-domain examples are from the New York Times (NYT) portion of Gigaword, from Bergsma et al. (2009). They include the 5 confusion sets where accuracy was below 90% in Golding and Roth (1999). There are 100K training, 10K development, and 10K test examples for each confusion set. Our results are averages across confusion sets.

Out-of-domain examples are again drawn from Gutenberg and Medline. We extract all instances of words that are in one of our confusion sets, along with surrounding context. By assuming the extracted instances represent correct usage, we label 7.8K and 56K out-of-domain test examples for Gutenberg and Medline, respectively.

We test three unsupervised systems: 1) Lapata and Keller (2005) use one token of context on the left and one on the right, and output the candidate from the confusion set that occurs most frequently in this pattern. 2) Bergsma et al. (2009) measure the frequency of the candidates in all the 3-to-5-gram patterns that span the confusable word. For each candidate, they sum the log-counts of all patterns filled with the candidate, and output the candidate with the highest total. 3) The **baseline** predicts the most frequent member of each confusion set, based on frequencies in the NYT training data.

System	IN	O1	O2
Baseline	66.9	44.6	60.6
Lapata and Keller (2005)	88.4	78.0	87.4
Bergsma et al. (2009)	94.8	87.7	94.2
SVM with N-GM features	95.7	<b>92.1</b>	93.9
SVM with LEX features	95.2	85.8	91.0
SVM with N-GM + LEX	<b>96.5</b>	91.9	<b>94.8</b>

Table 2: Spelling correction accuracy (%). SVM trained on NYT, tested on NYT (IN) and out-of-domain Gutenberg (O1) and Medline (O2).

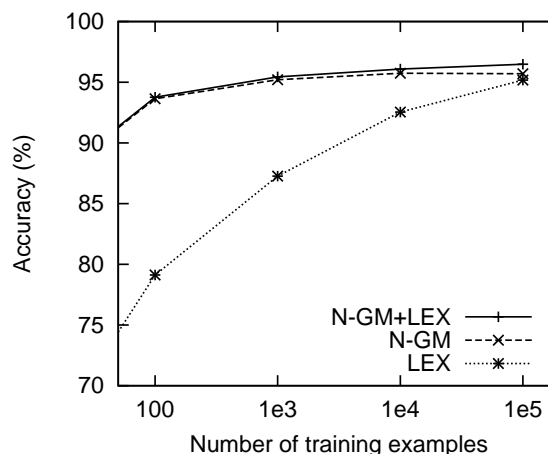


Figure 3: In-domain learning curve of spelling correction classifiers on NYT.

#### 4.1 Supervised Spelling Correction

Our LEX features are typical disambiguation features that flag specific aspects of the context. We have features for the words at all positions in a 9-word window (called collocation features by Golding and Roth (1999)), plus indicators for a particular word preceding or following the confusable word. We also include indicators for all N-grams, and their position, in a 9-word window.

For N-GM count features, we follow Bergsma et al. (2009). We include the log-counts of all N-grams that span the confusable word, with each word in the confusion set filling the N-gram pattern. These features do not use part-of-speech. Following Bergsma et al. (2009), we get N-gram counts using the original Google N-gram Corpus.

While neither our LEX nor N-GM features are novel on their own, they have, perhaps surprisingly, not yet been evaluated in a single model.

#### 4.2 Spelling Correction Results

The N-GM features outperform the LEX features, 95.7% vs. 95.2% (Table 2). Together, they achieve a very strong 96.5% in-domain accuracy.

This is 2% higher than the best unsupervised approach (Bergsma et al., 2009). Web-based models again perform well across a range of training data sizes (Figure 3).

The error rate of LEX nearly triples on Gutenberg and almost doubles on Medline (Table 2). Removing N-GM features from the N-GM + LEX system, errors increase around 75% on both Gutenberg and Medline. The LEX features provide no help to the combined system on Gutenberg, while they do help significantly on Medline. Note the learning curves for N-GM+LEX on Gutenberg and Medline (not shown) do not display the decrease that we observed in adjective ordering (Figure 2).

Both the baseline and LEX perform poorly on Gutenberg. The baseline predicts the majority class from NYT, but it’s not always the majority class in Gutenberg. For example, while in NYT *site* occurs 87% of the time for the (*cite, sight, site*) confusion set, *sight* occurs 90% of the time in Gutenberg. The LEX classifier exploits this bias as it is regularized toward a more economical model, but the bias does not transfer to the new domain.

## 5 Noun Compound Bracketing

About 70% of web queries are noun phrases (Barr et al., 2008) and methods that can reliably parse these phrases are of great interest in NLP. For example, a web query for *zebra hair straightener* should be bracketed as (*zebra (hair straightener)*), a stylish hair straightener with zebra print, rather than ((*zebra hair*) *straightener*), a useless product since the fur of zebras is already quite straight.

The noun compound (NC) bracketing task is usually cast as a decision whether a 3-word NC has a left or right bracketing. Most approaches are unsupervised, using a large corpus to compare the statistical association between word pairs in the NC. The adjacency model (Marcus, 1980) proposes a left bracketing if the association between words one and two is higher than between two and three. The dependency model (Lauer, 1995a) compares one-two vs. *one-three*. We include dependency model results using PMI as the association measure; results were lower with the adjacency model.

As in-domain data, we use Vadas and Curran (2007a)’s Wall-Street Journal (WSJ) data, an extension of the Treebank (which originally left NPs flat). We extract all sequences of three consecutive common nouns, generating 1983 examples

System	IN	O1	O2
Baseline	70.5	66.8	84.1
Dependency model	74.7	<b>82.8</b>	84.4
SVM with N-GM features	89.5	81.6	86.2
SVM with LEX features	81.1	70.9	79.0
SVM with N-GM + LEX	<b>91.6</b>	81.6	<b>87.4</b>

Table 3: NC-bracketing accuracy (%). SVM trained on WSJ, tested on WSJ (IN) and out-of-domain Grolier (O1) and Medline (O2).

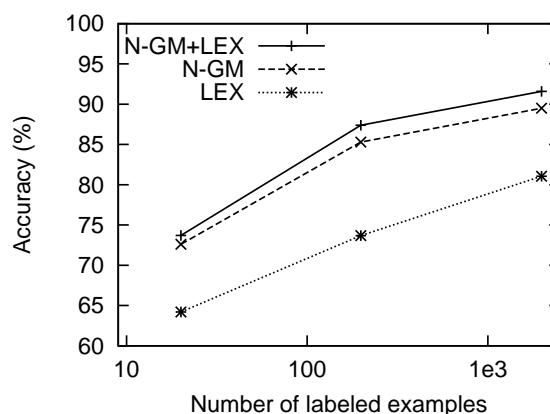


Figure 4: In-domain NC-bracketer learning curve

from sections 0-22 of the Treebank as training, 72 from section 24 for development and 95 from section 23 as a test set. As out-of-domain data, we use 244 NCs from Grolier Encyclopedia (Lauer, 1995a) and 429 NCs from Medline (Nakov, 2007).

The majority class **baseline** is left-bracketing.

### 5.1 Supervised Noun Bracketing

Our LEX features indicate the specific noun at each position in the compound, plus the three pairs of nouns and the full noun triple. We also add features for the capitalization pattern of the sequence.

N-GM features give the log-count of all subsets of the compound. Counts are from Google V2. Following Nakov and Hearst (2005), we also include counts of noun pairs collapsed into a single token; if a pair occurs often on the web as a single unit, it strongly indicates the pair is a constituent.

Vadas and Curran (2007a) use simpler features, e.g. they do not use collapsed pair counts. They achieve 89.9% in-domain on WSJ and 80.7% on Grolier. Vadas and Curran (2007b) use comparable features to ours, but do not test out-of-domain.

### 5.2 Noun Compound Bracketing Results

N-GM systems perform much better on this task (Table 3). N-GM+LEX is statistically significantly

better than LEX on all sets. In-domain, errors more than double without N-GM features. LEX performs poorly here because there are far fewer training examples. The learning curve (Figure 4) looks much like earlier in-domain curves (Figures 1 and 3), but truncated before LEX becomes competitive. The absence of a sufficient amount of labeled data explains why NC-bracketing is generally regarded as a task where corpus counts are crucial.

All web-based models (including the dependency model) exceed 81.5% on Grolier, which is the level of human agreement (Lauer, 1995b). N-GM + LEX is highest on Medline, and close to the 88% human agreement (Nakov and Hearst, 2005). Out-of-domain, the LEX approach performs very poorly, close to or below the baseline accuracy. With little training data and cross-domain usage, N-gram features are essential.

## 6 Verb Part-of-Speech Disambiguation

Our final task is POS-tagging. We focus on one frequent and difficult tagging decision: the distinction between a past-tense verb (VBD) and a past participle (VBN). For example, in *the troops stationed in Iraq*, the verb *stationed* is a VBN; *troops* is the head of the phrase. On the other hand, for *the troops vacationed in Iraq*, the verb *vacationed* is a VBD and also the head. Some verbs make the distinction explicit (*eat* has VBD *ate*, VBN *eaten*), but most require context for resolution.

Conflating VBN/VBD is damaging because it affects downstream parsers and semantic role labelers. The task is difficult because nearby POS tags can be identical in both cases. When the verb follows a noun, tag assignment can hinge on world-knowledge, i.e., the global lexical relation between the noun and verb (E.g., *troops* tends to be the object of *stationed* but the subject of *vacationed*).<sup>6</sup> Web-scale N-gram data might help improve the VBN/VBD distinction by providing relational evidence, even if the verb, noun, or verb-noun pair were not observed in training data.

We extract nouns followed by a VBN/VBD in the WSJ portion of the Treebank (Marcus et al., 1993), getting 23K training, 1091 development and 1130 test examples from sections 2-22, 24, and 23, respectively. For out-of-domain data, we get 21K

<sup>6</sup>HMM-style taggers, like the fast TnT tagger used on our web corpus, do not use bilinear features, and so perform especially poorly on these cases. One motivation for our work was to develop a fast post-processor to fix VBN/VBD errors.

examples from the Brown portion of the Treebank and 6296 examples from tagged Medline abstracts in the PennBioIE corpus (Kulick et al., 2004).

The majority class **baseline** is to choose VBD.

### 6.1 Supervised Verb Disambiguation

There are two orthogonal sources of information for predicting VBN/VBD: 1) the noun-verb pair, and 2) the context around the pair. Both N-GM and LEX features encode both these sources.

#### 6.1.1 LEX features

For 1), we use indicators for the noun and verb, the noun-verb pair, whether the verb is on an in-house list of *said*-verb (like *warned*, *announced*, etc.), whether the noun is capitalized and whether it's upper-case. Note that in training data, 97.3% of capitalized nouns are followed by a VBD and 98.5% of *said*-verbs are VBDs. For 2), we provide indicator features for the words before the noun and after the verb.

#### 6.1.2 N-GM features

For 1), we characterize a noun-verb relation via features for the pair's distribution in Google V2. Characterizing a word by its distribution has a long history in NLP; we apply similar techniques to *relations*, like Turney (2006), but with a larger corpus and richer annotations. We extract the 20 most-frequent N-grams that contain both the noun and the verb in the pair. For each of these, we convert the tokens to POS-tags, except for tokens that are among the most frequent 100 unigrams in our corpus, which we include in word form. We mask the noun of interest as *N* and the verb of interest as *V*. This converted N-gram is the feature label. The value is the pattern's log-count. A high count for patterns like (*N that V*), (*N have V*) suggests the relation is a VBD, while patterns (*N that were V*), (*N V by*), (*V some N*) indicate a VBN. As always, the classifier learns the association between patterns and classes.

For 2), we use counts for the verb's context co-occurring with a VBD or VBN tag. E.g., we see whether VBD cases like *troops ate* or VBN cases like *troops eaten* are more frequent. Although our corpus contains many VBN/VBD errors, we hope the errors are random enough for aggregate counts to be useful. The context is an N-gram spanning the VBN/VBD. We have log-count features for all five such N-grams in the (previous-word, noun, verb, next-word) quadruple. The log-count is in-

System	IN	O1	O2
Baseline	89.2	85.2	79.6
ContextSum	92.5	91.1	90.4
SVM with N-GM features	96.1	93.4	93.8
SVM with LEX features	95.8	93.4	93.0
SVM with N-GM + LEX	<b>96.4</b>	<b>93.5</b>	<b>94.0</b>

Table 4: Verb-POS-disambiguation accuracy (%) trained on WSJ, tested on WSJ (IN) and out-of-domain Brown (O1) and Medline (O2).

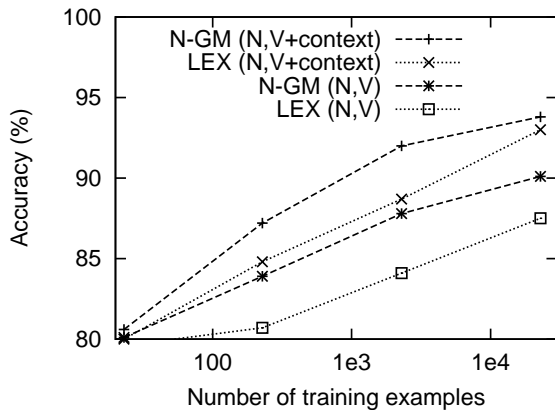


Figure 5: Out-of-domain learning curve of verb disambiguation classifiers on Medline.

dexed by the position and length of the N-gram. We include separate count features for contexts matching the specific noun and for when the noun token can match any word tagged as a noun.

**ContextSum:** We use these context counts in an unsupervised system, ContextSum. Analogously to Bergsma et al. (2009), we separately sum the log-counts for all contexts filled with VBD and then VBN, outputting the tag with the higher total.

## 6.2 Verb POS Disambiguation Results

As in all tasks, N-GM+LEX has the best in-domain accuracy (96.4%, Table 4). Out-of-domain, when N-grams are excluded, errors only increase around 14% on Medline and 2% on Brown (the differences are not statistically significant). Why? Figure 5, the learning curve for performance on Medline, suggests some reasons. We omit N-GM+LEX from Figure 5 as it closely follows N-GM.

Recall that we grouped the features into two views: 1) noun-verb (N,V) and 2) context. If we use just (N,V) features, we do see a large drop out-of-domain: LEX (N,V) lags N-GM (N,V) even using all the training examples. The same is true using only context features (not shown). Using both views, the results are closer: 93.8% for N-GM and

93.0% for LEX. With two views of an example, LEX is more likely to have domain-neutral features to draw on. Data sparsity is reduced.

Also, the Treebank provides an atypical number of labeled examples for analysis tasks. In a more typical situation with less labeled examples, N-GM strongly dominates LEX, even when two views are used. E.g., with 2285 training examples, N-GM+LEX is statistically significantly better than LEX on both out-of-domain sets.

All systems, however, perform log-linearly with training size. In other tasks we only had a handful of N-GM features; here there are 21K features for the distributional patterns of N,V pairs. Reducing this feature space by pruning or performing transformations may improve accuracy in and out-of-domain.

## 7 Discussion and Future Work

Of all classifiers, LEX performs worst on all cross-domain tasks. Clearly, many of the regularities that a typical classifier exploits in one domain do not transfer to new genres. N-GM features, however, do not depend directly on training examples, and thus work better cross-domain. Of course, using web-scale N-grams is not the only way to create robust classifiers. Counts from any large auxiliary corpus may also help, but web counts should help more (Lapata and Keller, 2005). Section 6.2 suggests that another way to mitigate domain-dependence is having multiple feature views.

Banko and Brill (2001) argue “a logical next step for the research community would be to direct efforts towards increasing the size of annotated training collections.” Assuming we really do want systems that operate beyond the specific domains on which they are trained, the community also needs to identify which systems behave as in Figure 2, where the accuracy of the best in-domain system actually decreases with more training examples. Our results suggest better features, such as web pattern counts, may help more than expanding training data. Also, systems using web-scale unlabeled data will improve automatically as the web expands, without annotation effort.

In some sense, using web counts as features is a form of domain adaptation: adapting a web model to the training domain. How do we ensure these features are adapted well and not used in domain-specific ways (especially with many features to adapt, as in Section 6)? One option may



be to regularize the classifier specifically for out-of-domain accuracy. We found that adjusting the SVM misclassification penalty (for more regularization) can help or hurt out-of-domain. Other regularizations are possible. In each task, there are domain-neutral unsupervised approaches. We could encode these systems as linear classifiers with corresponding weights. Rather than a typical SVM that minimizes the weight-norm  $\|w\|$  (plus the slacks), we could regularize toward domain-neutral weights. This regularization could be optimized on creative splits of the training data.

## 8 Conclusion

We presented results on tasks spanning a range of NLP research: generation, disambiguation, parsing and tagging. Using web-scale N-gram data improves accuracy on each task. When less training data is used, or when the system is used on a different domain, N-gram features greatly improve performance. Since most supervised NLP systems do not use web-scale counts, further cross-domain evaluation may reveal some very brittle systems. Continued effort in new domains should be a priority for the community going forward.

## Acknowledgments

We gratefully acknowledge the Center for Language and Speech Processing at Johns Hopkins University for hosting the workshop at which part of this research was conducted.

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