The Web as a Baseline: Evaluating the Performance of Unsupervised Web-based Models for a Range of NLP Tasks

Mirella Lapata
Department of Computer Science
University of Sheffield
211 Portobello St., Sheffield S1 4DP
mlap@dcs.shef.ac.uk

Frank Keller
School of Informatics
University of Edinburgh
2 Buccleuch Pl., Edinburgh EH8 9LW
keller@inf.ed.ac.uk

Abstract
Previous work demonstrated that web counts can be used to approximate bigram frequencies, and thus should be useful for a wide variety of NLP tasks. So far, only two generation tasks (candidate selection for machine translation and confusion-set disambiguation) have been tested using web-scale data sets. The present paper investigates if these results generalize to tasks covering both syntax and semantics, both generation and analysis, and a larger range of \( n \)-grams. For the majority of tasks, we find that simple, unsupervised models perform better when \( n \)-gram frequencies are obtained from the web rather than from a large corpus. However, in most cases, web-based models fail to outperform more sophisticated state-of-the-art models trained on small corpora. We argue that web-based models should therefore be used as a baseline for, rather than an alternative to, standard models.

1 Introduction
Keller and Lapata (2003) investigated the validity of web counts for a range of predicate-argument bigrams (verb-object, adjective-noun, and noun-noun bigrams). They presented a simple method for retrieving bigram counts from the web by querying a search engine and demonstrated that web counts (a) correlate with frequencies obtained from a carefully edited, balanced corpus such as the 100M words British National Corpus (BNC), (b) correlate with frequencies recreated using smoothing methods in the case of unseen bigrams, (c) reliably predict human plausibility judgments, and (d) yield state-of-the-art performance on pseudo-disambiguation tasks.

Keller and Lapata’s (2003) results suggest that web-based frequencies can be a viable alternative to bigram frequencies obtained from smaller corpora or recreated using smoothing. However, they do not demonstrate that realistic NLP tasks can benefit from web counts. In order to show this, web counts would have to be applied to a diverse range of NLP tasks, both syntactic and semantic, involving analysis (e.g., disambiguation) and generation (e.g., selection among competing outputs). Also, it remains to be shown that the web-based approach scales up to larger \( n \)-grams (e.g., trigrams), and to combinations of different parts of speech (Keller and Lapata 2003 only tested bigrams involving nouns, verbs, and adjectives). Another important question is whether web-based methods, which are by definition unsupervised, can be competitive alternatives to supervised approaches used for most tasks in the literature.

This paper aims to address these questions. We start by using web counts for two generation tasks for which the use of large data sets has shown promising results: (a) target language candidate selection for machine translation (Grefenstette, 1998) and (b) context sensitive spelling correction (Banko and Brill, 2001a,b). Then we investigate the generality of the web-based approach by applying it to a range of analysis and generations tasks, involving both syntactic and semantic knowledge: (c) ordering of prenominal adjectives, (d) compound noun bracketing, (e) compound noun interpretation, and (f) noun countability detection. Table 1 gives an overview of these tasks and their properties.

In all cases, we propose a simple, unsupervised \( n \)-gram based model whose parameters are estimated using web counts. We compare this model both against a baseline (same model, but parameters estimated on the BNC) and against state-of-the-art models from the literature, which are either supervised (i.e., use annotated training data) or unsupervised but rely on taxonomies to recreate missing counts.

| Task                        | \( n \) | POS | Ling | Type       |
|-----------------------------|--------|-----|------|------------|
| MT candidate select.        | 1,2    | V, N| Sem  | Generation |
| Spelling correction        | 1,2,3  | Any | Syn/Sem | Generation |
| Adjective ordering         | 1,2    | Adj | Sem  | Generation |
| Compound bracketing        | 1,2    | N   | Syn  | Analysis   |
| Compound interpret.        | 1,2,3  | N, P| Sem  | Analysis   |
| Countability detection     | 1,2    | N, Det| Sem  | Analysis  |

Table 1: Overview of the tasks investigated in this paper (\( n \): size of \( n \)-gram; POS: parts of speech; Ling: linguistic knowledge; Type: type of task)
2 Method

Following Keller and Lapata (2003), web counts for n-grams were obtained using a simple heuristic based on queries to the search engine Altavista.1 In this approach, the web count for a given n-gram is simply the number of hits (pages) returned by the search engine for the queries generated for this n-gram. Three different types of queries were used for the NLP tasks in the present paper:

**Literal queries** use the quoted n-gram directly as a search term for Altavista (e.g., the bigram *history changes* expands to the query "history changes").

**Near queries** use Altavista’s NEAR operator to expand the n-gram; a NEAR b means that a has to occur in the same ten word window as b; the window is treated as a bag of words (e.g., *history changes* expands to "history" NEAR "changes").

**Inflected queries** are performed by expanding an n-gram into all its morphological forms. These forms are then submitted as literal queries, and the resulting hits are summed up (e.g., *history changes* expands to "history change", "histories change", "history changed", etc.). John Carroll’s suite of morphological tools (morpha, morphp, and ana) was used to generate inflected forms of verbs and nouns.2 In certain cases (detailed below), determiners were inserted before nouns in order to make it possible to recognize simple NPs. This insertion was limited to a/an, the, and the empty determiner (for bare plurals). All queries (other than the ones using the NEAR operator) were performed as exact matches (using quotation marks in Altavista). All search terms were submitted to the search engine in lower case. If a query consists of a single, highly frequent word (such as the), Altavista will return an error message. In these cases, we set the web count to a large constant (10^8). This problem is limited to unigrams, which were used in some of the models detailed below. Sometimes the search engine fails to return a hit for a given n-gram (for any of its morphological variants). We smooth zero counts by setting them to .5.

For all tasks, the web-based models are compared against identical models whose parameters were estimated from the BNC (Burnard, 1995). The BNC is a static 100M word corpus of British English, which is about 1000 times smaller than the web (Keller and Lapata, 2003). Comparing the performance of the same model on the web and on the BNC allows us to assess how much improvement can be expected simply by using a larger data set. The BNC counts were retrieved using the Gsearch corpus query tool (Corley et al., 2001); the morphological query expansion was the same as for web queries; the NEAR operator was simulated by assuming a window of five words to the left and five to the right.

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1We did not use Google counts, as Google limits the number of queries to 1000 per day, which makes the process of retrieving a large number of web counts very time consuming.

2The tools can be downloaded from [http://www.cogs.susx.ac.uk/lab/nlp/carroll/morph.html](http://www.cogs.susx.ac.uk/lab/nlp/carroll/morph.html).

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| # | best model on development set |
|---|-------------------------------|
| * | (not) sign. different from best BNC model on test set |
| † | (not) sign. different from baseline |
| ‡ | (not) sign. different from best model in the literature |

Table 2: Meaning of diacritics indicating statistical significance (χ² tests)

Gsearch was used to search solely for adjacent words; no POS information was incorporated in the queries, and no parsing was performed.

For all of our tasks, we have to select either the best of several possible models or the best parameter setting for a single model. We therefore require a separate development set. This was achieved by using the gold standard data set from the literature for a given task and randomly dividing it into a development set and a test set (of equal size). We report the test set performance for all models for a given task, and indicate which model shows optimal performance on the development set (marked by a ‘#’ in all subsequent tables). We then compare the test set performance of this optimal model to the performance of the models reported in the literature. It is important to note that the figures taken from the literature were typically obtained on the whole gold standard data set, and hence may differ from the performance on our test set. We work on the assumption that such differences are negligible.

We use χ² tests to determine whether the performance of the best web model on the test set is significantly different from that of the best BNC model. We also determine whether both models differ significantly from the baseline and from the best model in the literature. A set of diacritics is used to indicate significance throughout this paper, see Table 2.

3 Candidate Selection for Machine Translation

Target word selection is a generation task that occurs in machine translation (MT). A word in a source language can often be translated into different words in the target language and the choice of the appropriate translation depends on a variety of semantic and pragmatic factors. The task is illustrated in (1) where there are five translation alternatives for the German noun *Geschichte* listed in curly brackets, the first being the correct one.

(1) a. Die *Geschichte* ändert sich, nicht jedoch die Geographie.
   b. {History, story, tale, saga, strip} changes but geography does not.

Statistical approaches to target word selection rely on bilingual lexica to provide all possible translations of words in the source language. Once the set of translation candidates is generated, statistical information gathered from target language corpora is used to select the most appropriate alternative (Dagan and Itai, 1994). The task is somewhat simplified by Grefenstette (1998) and Prescher
et al. (2000) who do not produce a translation of the entire sentence. Instead, they focus on specific syntactic relations. Grefenstette translates compounds from German and Spanish into English, and uses BNC frequencies as a filter for candidate translations. He observes that this approach suffers from an acute data sparseness problem and goes on to obtain counts for candidate compounds through web searches, thus achieving a translation accuracy of 86–87%.

Prescher et al. (2000) concentrate on verbs and their objects. Assuming that the target language translation of the verb is known, they select from the candidate translations the noun that is semantically most compatible with the verb. The semantic fit between a verb and its argument is modeled using a class-based lexicon that is derived from unlabeled data using the expectation maximization algorithm (verb-argument model). Prescher et al. also propose a refined version of this approach that only models the fit between a verb and its object (verb-object model), disregarding other arguments of the verb. The two models are trained on the BNC and evaluated against two corpora of 1,340 and 814 bilingual sentence pairs, with an average of 8.63 and 2.83 translations for the object noun, respectively. Table 4 lists Prescher et al.’s results for the two corpora and for both models together with a random baseline (select a target noun at random) and a frequency baseline (select the most frequent target noun).

Grefenstette’s (1998) evaluation was restricted to compounds that are listed in a dictionary. These compounds are presumably well-established and fairly frequent, which makes it easy to obtain reliable web frequencies. We wanted to test if the web-based approach extends from lexicalized compounds to productive syntactic units for which dictionary entries do not exist. We therefore performed our evaluation using Prescher et al.’s (2000) test set of verb-object pairs. Web counts were retrieved for all possible verb-object translations; the most likely one was selected using either co-occurrence frequency \( f(v,n) \) or conditional probability \( f(v,n)/f(n) \). The web counts were gathered using inflected queries involving the verb, a determiner, and the object (see Section 2). Table 3 compares the web-based models against the BNC models. For both the high ambiguity and the low ambiguity data set, we find that the performance of the best Altavista model is not significantly different from that of the best BNC model. Table 4 compares our simple, unsupervised methods with the two sophisticated class-based models discussed above. The results show that there is no significant difference in performance between the best model reported in the literature and the best Altavista or the best BNC model. However, both models significantly outperform the baseline. This holds for both the high and low ambiguity data sets.

### Table 3: Performance of Altavista counts and BNC counts for candidate selection for MT (data from Prescher et al. 2000)

| Model                          | Altavista high | Altavista low | BNC high | BNC low |
|-------------------------------|----------------|---------------|----------|---------|
|                               | high/ambig     | low/ambig     | high/ambig | low/ambig |
| \( f(v,n) \)                  | 45.74          | 68.73‡         | 45.89#    | 70.06†  |
| \( f(v,n)/f(n) \)             | 45.16‡         | 64.96         | 46.18     | 66.07   |

### Table 4: Performance comparison with the literature for candidate selection for MT

| Model                          | high/ambig     | low/ambig     |
|-------------------------------|----------------|---------------|
| Random baseline               | 14.20          | 45.90         |
| Frequency baseline            | 31.90          | 45.50         |
| Prescher et al. (2000): verb-argument model | 43.30          | 61.50         |
| Best Altavista                | 45.16‡         | 68.73‡         |
| Best BNC                      | 45.89#         | 70.06†         |
| Prescher et al. (2000): verb-object model | 49.40          | 68.20         |

### 4 Context-sensitive Spelling Correction

Context-sensitive spelling correction is the task of correcting spelling errors that result in valid words. Such a spelling error is illustrated in (4) where *principal* was typed when *principal* was intended.

\( \text{(2)} \) Introduction of the dialogue *principal* proved strikingly effective.

The task can be viewed as a generation task, as it consists of choosing between alternative surface realizations of a word. This choice is typically modeled by confusion sets such as \{principal, principle\} or \{then, than\} under the assumption that each word in the set could be mistakenly typed when another word in the set was intended. The task is to infer which word in a confusion set is the correct one in a given context. This choice can be either syntactic (as for \{then, than\}) or semantic (as for \{principal, principle\}).

A number of machine learning methods have been proposed for context-sensitive spelling correction. These include a variety of Bayesian classifiers (Golding, 1995; Golding and Schabes, 1996), decision lists (Golding, 1995) transformation-based learning (Mangu and Brill, 1997), Latent Semantic Analysis (LSA) (Jones and Martin, 1997), multiplicative weight update algorithms (Golding and Roth, 1999), and augmented mixture models (Cucerzan and Yarowsky, 2002). Despite their differences, most approaches use two types of features: context words and collocations. Context word features record the presence of a word within a fixed window around the target word (bag of words); collocational features capture the syntactic environment of the target word and are usually represented by a small number of words and/or part-of-speech tags to the left or right of the target word.

The results obtained by a variety of classification methods are given in Table 6. All methods use either the full set or a subset of 18 confusion sets originally gathered by Golding (1995). Most methods are trained and tested on
i.e., words that are adjacent to the target word. For each

The method takes into account collocational features,
immediately to its left or right. Disambiguation is then
performed by selecting the word in the confusion set with
the highest co-occurrence frequency or probability. The
to the word with the highest one. Table 5 shows the types
Brown corpus) and confusion sets as Golding and Sch-
performing spelling correction using web counts.

Unfortunately the direct evidence method performs
poorly when a given order is unseen in the training
data. To compensate for this, Shaw and Hatzivassiloglou
(1999) propose to compute the transitive closure of the
ordering relation: if \( a \prec c \) and \( c \prec b \), then \( a \prec b \). Mal-
ouf (2000) further proposes a back-off bigram model of
adjective pairs for choosing among alternative orders
\( P(\langle a,b \rangle | \{a,b\}) \) vs. \( P(\langle b,a \rangle | \{a,b\}) \). He also proposes
positional probabilities as a means of estimating how
likely it is for a given adjective \( a \) to appear first in a se-
quence by looking at each pair in the training data that
contains the adjective \( a \) and recording its position. Fi-
nally, he uses memory-based learning as a means to en-
code morphological and semantic similarities among dif-
ferent adjective orders. Each adjective pair \( ab \) is encoded
as a vector of 16 features (the last eight characters of \( a \)
and the last eight characters of \( b \)) and a class \( \langle a,b \rangle or

| Model    | Alta  | BNC  | Model    | Alta  | BNC  |
|----------|-------|------|----------|-------|------|
| \( f(t) \) | 72.98 | 70.00 | \( f(w_1, t, w_2) \) | 87.77 | 76.53 |
| \( f(w_1, t) \) | 84.40 | 83.02 | \( f(w_1, t, w_2) \) | 75.96 | 74.47 |
| \( f(t, w_1) \) | 84.89 | 82.74 | \( f(w_1, t, w_2) \) | 84.94 | 74.23 |
| \( f(w_1, t, w_2) \) | 89.24 | 77.13 | \( f(w_1, t, w_2) \) | 80.70 | 73.69 |
| \( f(w_1, w_2, t) \) | 87.13 | 74.89 | \( f(w_1, t, w_2) \) | 82.24 | 75.10 |
| \( f(t, w_1, w_2) \) | 84.68 | 75.08 | \( f(w_1, t, w_2) \) | 72.11 | 69.28 |
| \( f(w_1, t) / f(t) \) | 82.81 | 77.84 | \( f(w_1, w_2, t) / f(t, w_1) \) | 75.65 | 72.57 |
| \( f(w_1, t) / f(t) \) | 77.49 | 80.71 |

Table 5: Performance of Altavista counts and BNC
counts for context sensitive spelling correction (data from
Cucerzan and Yarowsky 2002)

| Model            | Accuracy |
|------------------|----------|
| Baseline BNC     | 70.00    |
| Baseline Altavista | 72.98   |
| Best BNC         | 80.71\(\dagger\) |
| Golding (1995)   | 81.40    |
| Jones and Martin (1997) | 84.26 |
| Best Altavista   | 89.24\(\ddagger\) |
| Golding and Schabes (1996) | 89.82 |
| Mangu and Brill (1997) | 92.79 |
| Cucerzan and Yarowsky (2002) | 92.20 |
| Golding and Roth (1999) | 94.23 |

Table 6: Performance comparison with the literature for
corpus sensitive spelling correction

the Brown corpus, using 80% for training and 20% for
testing.\(^3\)

We devised a simple, unsupervised method for
performing spelling correction using web counts.
The method takes into account collocational features,
i.e., words that are adjacent to the target word. For each
word in the confusion set, we used the web to estimate how
frequently it co-occurs with a word or a pair of words
immediately to its left or right. Disambiguation is then
performed by selecting the word in the confusion set with
the highest co-occurrence frequency or probability. The
web counts were retrieved using literal queries (see Section
2). Ties are resolved by comparing the unigram fre-
frequencies of the words in the confusion set and defaulting
to the word with the highest one. Table 5 shows the types
of collocations we considered and their corresponding ac-
curacy. The baseline \( f(t) \) in Table 5 was obtained by
always choosing the most frequent unigram in the confu-
sion set. We used the same test set (2056 tokens from the
Brown corpus) and confusion sets as Golding and Sch-
abes (1996), Mangu and Brill (1997), and Cucerzan and
Yarowsky (2002).

Table 5 shows that the best result (89.24%) for the web-
based approach is obtained with a context of one word
to the left and one word to the right of the target word
\( f(w_1, t, w_2) \). The BNC-based models perform consis-
tently worse than the web-based models with the except-
ion of \( f(t, w_1) / t \); the best Altavista model performs sig-
ificantly better than the best BNC model. Table 6 shows

\(^3\)An exception is Golding (1995), who uses the entire Brown
corpus for training (1M words) and 3/4 of the Wall Street Jour-
nal corpus (Marcus et al., 1993) for testing.

that both the best Altavista model and the best BNC
model outperform their respective baselines. A compari-
son with the literature shows that the best Altavista model
outperforms Golding (1995), Jones and Martin (1997)
and performs similar to Golding and Schabes (1996). The
highest accuracy on the task is achieved by the class of
multiplicative weight-update algorithms such as Winnow
(Golding and Roth, 1999). Both the best BNC model and
the best Altavista model perform significantly worse than
this model. Note that Golding and Roth (1999) use al-
gorithms that can handle large numbers of features and are
robust to noise. Our method uses a very small feature set,
relying only on co-occurrence frequencies and does not
have access to POS information (the latter has been shown
to have an improvement on confusion sets whose words
belong to different parts of speech). An advantage of
our method is that it can be used for a large number of
corpus without relying on the availability of
training data.

5 Ordering of Prenominal Adjectives

The ordering of prenominal modifiers is important for
natural language generation systems where the text must
be both fluent and grammatical. For example, the se-
quence big fat Greek wedding is perfectly acceptable,
whereas fat Greek big wedding sounds odd. The ordering
of prenominal adjectives has sparked a great deal of the-
etorical debate (see Shaw and Hatzivassiloglou 1999 for
an overview) and efforts have concentrated on defin-
ing rules based on semantic criteria that account for different
orders (e.g., age < color, value < dimension).

Data intensive approaches to the ordering problem rely
on corpora for gathering evidence for the likelihood of
different orders. They rest on the hypothesis that the rela-
tive order of premodifi ers is fixed, and independent of
context and the noun being modify ed. The simplest stra-
gy is what Shaw and Hatzivassiloglou (1999) call di-
rect evidence. Given an adjective pair \( \langle a,b \rangle \), they count
how many times \( \langle a,b \rangle \) and \( \langle b,a \rangle \) appear in the corpus and
choose the pair with the highest frequency.

Unfortunately the direct evidence method performs
poorly when a given order is unseen in the training
data. To compensate for this, Shaw and Hatzivassiloglou
(1999) propose to compute the transitive closure of the
ordering relation: if \( a \prec c \) and \( c \prec b \), then \( a \prec b \). Mal-
ouf (2000) further proposes a back-off bigram model of
adjective pairs for choosing among alternative orders
\( P(\langle a,b \rangle | \{a,b\}) \) vs. \( P(\langle b,a \rangle | \{a,b\}) \). He also proposes
positional probabilities as a means of estimating how
likely it is for a given adjective \( a \) to appear first in a se-
quence by looking at each pair in the training data that
contains the adjective \( a \) and recording its position. Fi-
nally, he uses memory-based learning as a means to en-
code morphological and semantic similarities among dif-
ferent adjective orders. Each adjective pair \( ab \) is encoded
as a vector of 16 features (the last eight characters of \( a \)
and the last eight characters of \( b \)) and a class \( \langle a,b \rangle or
Malouf (2000) extracted 263,838 individual pairs of adjectives from the BNC which he randomly partitioned into test (10%) and training data (90%) and evaluated all the above methods for ordering prenominal adjectives. His results showed that a memory-based classifier that uses morphological information as well as positional probabilities as features outperforms all other methods (see Table 7). For the ordering task we restricted ourselves to the direct evidence strategy which simply chooses the adjective order with the highest frequency (data from Malouf 2000).

Table 7: Performance of Altavista counts and BNC counts for adjective ordering (data from Malouf 2000)

| Model | Altavista | BNC |
|-------|-----------|-----|
| \( f(a_1,a_2) : f(a_2,a_1) \) | 89.69\#‡ | 80.44‡ |
| \( f(a_1,a_2)/f(a_2,a_1) \) | 83.2 | 77.0 |
| \( f(a_1,a_2)/f(a_2,a_1)/f(a_1) \) | 80.2 | 80.6 |

Table 8: Performance of Altavista counts and BNC counts for compound bracketing (data from Lauer 1995)

| Model | Accuracy |
|-------|----------|
| Baseline | 63.93 |
| Best BNC | 68.03‡‡ |
| Lauer (1995): adjacency | 68.90 |
| Lauer (1995): dependency | 77.50 |
| Best Altavista | 78.68‡‡ |
| Lauer (1995): tuned | 80.70 |
| Upper bound | 81.50 |

Table 9: Performance comparison with the literature for compound bracketing

| Model | Baseline | Altavista | BNC |
|-------|----------|-----------|-----|
| \( f(n_1,n_2) : f(n_2,n_1) \) | 77.86 | 66.39 |
| \( f(n_1,n_2) : f(n_1,n_3) \) | 70.49 | 63.11 |
| \( f(n_1,n_2)/f(n_1) : f(n_2,n_1)/f(n_2) \) | 68.85 | 65.57 |
| \( f(n_1,n_2)/f(n_1,n_3)/f(n_3) \) | 70.49 | 63.11 |
| \( f(n_1,n_2)/f(n_1)/f(n_2,n_1)/f(n_2)/f(n_3) \) | 80.32 | 66.39 |
| \( f(n_1,n_2)/f(n_1,n_3) \) (NEAR) | 68.03 | 63.11 |
| \( f(n_1,n_2)/f(n_1,n_3) \) (NEAR) | 71.31 | 67.21 |
| \( f(n_1,n_2)/f(n_1)/f(n_2,n_1)/f(n_2)/f(n_3) \) (NEAR) | 68.85 | 65.57 |
| \( f(n_1,n_2)/f(n_1)/f(n_2,n_1)/f(n_2)/f(n_3) \) (NEAR) | 65.57 | 57.37 |
| \( f(n_1,n_2)/f(n_1)/f(n_2,n_1)/f(n_2)/f(n_3) \) (NEAR) | 75.40 | 68.03‡ |

6 Bracketing of Compound Nouns

The first analysis task we consider is the syntactic disambiguation of compound nouns, which has received a fair amount of attention in the NLP literature (Pustejovsky et al., 1993; Resnik, 1993; Lauer, 1995). The task can be summarized as follows: given a three word compound \( n_1 n_2 n_3 \), determine the correct binary bracketing of the word sequence (see 3) for an example.

\[ (b, a) \]

Previous approaches typically compare different bracketings and choose the most likely one. The adjacency model compares \([n_1 n_2] \) against \([n_2 n_3] \) and adopts a right branching analysis if \([n_2 n_3] \) is more likely than \([n_1 n_2] \). The dependency model compares \([n_1 n_2] \) against \([n_1 n_3] \) and adopts a right branching analysis if \([n_1 n_3] \) is more likely than \([n_1 n_2] \).

The simplest model of compound noun disambiguation compares the frequencies of the two competing analyses and opts for the most frequent one (Pustejovsky et al., 1993). Lauer (1995) proposes an unsupervised method for estimating the frequencies of the competing bracketings based on a taxonomy or a thesaurus. He uses a probability ratio to compare the probability of the left-branching analysis to that of the right-branching (see 4) for the dependency model and (5) for the adjacency model.

\[
R_{dep} = \frac{\sum_{t_i \in cat(w_i)} P(t_1 \rightarrow t_2) P(t_2 \rightarrow t_3)}{\sum_{t_i \in cat(w_i)} P(t_1 \rightarrow t_3) P(t_2 \rightarrow t_3)},
\]

(4)

\[
R_{adj} = \frac{\sum_{t_i \in cat(w_i)} P(t_1 \rightarrow t_2)}{\sum_{t_i \in cat(w_i)} P(t_2 \rightarrow t_3)}
\]

(5)

Here \( t_1, t_2 \) and \( t_3 \) are conceptual categories in the taxonomy or thesaurus, and the nouns \( w_1 \ldots w_i \) are members of these categories. The estimation of probabilities over concepts (rather than words) reduces the number of model parameters and effectively decreases the amount of training data required. The probability \( P(t_1 \rightarrow t_2) \) denotes the modification of a category \( t_1 \) by a category \( t_2 \).

Lauer (1995) tested both the adjacency and dependency models on 244 compounds extracted from Grolier’s encyclopedia, a corpus of 8 million words. Frequencies for the two models were obtained from the same corpus and from Roget’s thesaurus (version 1911) by counting pairs of nouns that are either strictly adjacent or co-occur within a window of a fixed size (e.g., two, three, or four words). The majority of the bracketings in our test set were left-branching, yielding a baseline of 63.93% (see Table 9). Lauer’s best results (77.50%) were obtained with the dependency model and a training
scheme which takes strictly adjacent nouns into account. Performance increased further by 3.2% when POS tags were taken into account. The results for this tuned model are also given in Table 9. Finally, Lauer conducted an experiment with human judges to assess the upper bound for the bracketing task. An average accuracy of 81.50% was obtained.

We replicated Lauer’s (1995) results for compound noun bracketing using the same test set. We compared the performance of the adjacency and dependency models (see (4) and (5)), but instead of relying on a corpus and a thesaurus, we estimated the relevant probabilities using web counts. The latter were obtained using inflected queries (see Section 2) and Altavista’s NEAR operator. Ties were resolved by defaulting to the most frequent scheme which takes strictly adjacent nouns into account. Performance increased further by 3.2% when POS tags were taken into account. The results for this tuned model are also given in Table 9. Finally, Lauer conducted an experiment with human judges to assess the upper bound for the bracketing task. An average accuracy of 81.50% was obtained.

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Here, \( t_1 \) and \( t_2 \) represent concepts in Roget’s thesaurus. Lauer (1995) also experimented with a lexicalized version of (7) where probabilities are calculated on the basis of word (rather than concept) frequencies which Lauer obtained from Grolier’s encyclopedia heuristically via pattern matching.

Lauer (1995) tested the model in (7) on 282 compounds that he selected randomly from Grolier’s encyclopedia and annotated with their paraphrasing prepositions. The preposition of accounted for 33% of the paraphrases in this data set (see Baseline in Table 11). The concept-based model (see (7)) achieved an accuracy of 28% on this test set, whereas its lexicalized version reached an accuracy of 40% (see Table 11).

We attempted the interpretation task with the lexicalized version of the bigram model (see (7)), but also tried the more data intensive trigram model (see (6)), again in its lexicalized form. Furthermore, we experimented with several conditional and unconditional variants of (7) and (6). Co-occurrence frequencies were estimated from the web using inflected queries (see Section 2). Determiners were inserted before nouns resulting in queries of the type \textit{story/storys about and about the/a/0 war/wars for the compound war story}.

As shown in Table 10, the best performance was obtained using the web-based trigram model \( f(n_1, p, n_2) \); it signiﬁcantly outperformed the best BNC model. The comparison with the literature in Table 11 showed that the best Altavista model signiﬁcantly outperformed both the baseline and the best model in the literature (Lauer’s word-based model). The BNC model, on the other hand, performs significantly worse than the best model in the literature.

### Table 10: Performance of Altavista counts and BNC counts for compound interpretation (data from Lauer 1995)

| Model          | Accuracy |
|----------------|----------|
| Best BNC       | 27.85†‡  |
| Lauer (1995): concept-based | 28.00    |
| Baseline       | 33.00    |
| Lauer (1995): word-based | 40.00    |
| Best Altavista | 55.71†‡  |

### Table 11: Performance comparison with the literature for compound interpretation

| Model     | Accuracy |
|-----------|----------|
| Lauer (1995): word-based | 40.00    |
| BNC       | 27.85†‡  |
| Baseline  | 33.00    |
| Altavista | 55.71†‡  |

In (7) \( p^* = \underset{p}{\arg \max} \sum_{t_1 \in \text{cats}(n_1)} \sum_{t_2 \in \text{cats}(n_2)} P(t_1|p)P(t_2|p) \)

Here, \( t_1 \) and \( t_2 \) represent concepts in Roget’s thesaurus. Lauer (1995) also experimented with a lexicalized version of (7) where probabilities are calculated on the basis of word (rather than concept) frequencies which Lauer obtained from Grolier’s encyclopedia heuristically via pattern matching.

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### 7 Interpretation of Compound Nouns

The second analysis task we consider is the semantic interpretation of compound nouns. Most previous approaches to this problem have focused on the interpretation of two word compounds whose nouns are related via a basic set of semantic relations (e.g., \textit{at}, \textit{on}, \textit{from}, \textit{with}, \textit{about})

Lauer (1995) points out that the above model contains one parameter for every triple \((p, n_1, n_2)\), and as a result hundreds of millions of training instances would be necessary. As an alternative to (6), he proposes the model in (7) which combines the probability of the modifier given a certain preposition with the probability of the head given the same preposition, and assumes that these two probabilities are independent.

\[
(7) \quad p^* = \underset{p}{\arg \max} \sum_{t_1 \in \text{cats}(n_1)} \sum_{t_2 \in \text{cats}(n_2)} P(t_1|p)P(t_2|p)
\]

Here, \( t_1 \) and \( t_2 \) represent concepts in Roget’s thesaurus. Lauer (1995) also experimented with a lexicalized version of (7) where probabilities are calculated on the basis of word (rather than concept) frequencies which Lauer obtained from Grolier’s encyclopedia heuristically via pattern matching.

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achieved a performance that is not significantly different from the baseline, and significantly worse than Lauer’s best model.

8 Noun Countability Detection

The next analysis task that we consider is the problem of determining the countability of nouns. Countability is the semantic property that determines whether a noun can occur in singular and plural forms, and affects the range of permissible modifiers. In English, nouns are typically tested: (a) compare the frequency of the singular and plural forms of the noun; (b) compare the frequency of the semantic property that determines whether a noun can occur in singular and plural forms, and affects the range of permissible modifiers; (c) same as model (b), but the det-noun frequencies are normalized by the frequency of the noun; (d) backoff: try to make a decision using det-noun frequencies; if these are too sparse, back off to singular/plural frequencies.

Unigram and bigram frequencies were estimated from the web using literal queries; for models (a)–(c) a threshold parameter was optimized on the development set (this parameter determines the ratio of singular/plural frequencies or det-noun frequencies above which a noun was considered as countable). For model (b), an additional backoff parameter was used, specifying the minimum frequency that triggers backoff.

The models and their performance on the test set are listed in Table 12. The best Altavista model is the conditional det-noun model \( f(d,e,n)/f(n) \), which achieves 88.38% on countable and 91.22% on uncountable nouns. On the BNC, the simple unigram model performs best. Its performance is not statistically different from that of the best Altavista model. Note that for the BNC models, data sparseness means the det-noun models perform poorly, which is why the backoff model was not attempted here.

Table 13 shows that both the Altavista model and BNC model significantly outperform the baseline (relative frequency of the majority class on the gold-standard data). The comparison with the literature shows that both the Altavista and the BNC model perform significantly worse than the best model proposed by Baldwin and Bond (2003); this is a supervised model that uses many more features than just singular/plural frequency and det-noun frequency.

9 Conclusions

We showed that simple, unsupervised models using web counts can be devised for a variety of NLP tasks. The tasks were selected so that they cover both syntax and semantics, both generation and analysis, and a wider range of n-grams than have been previously used.

For all but two tasks (candidate selection for MT and noun countability detection) we found that simple, unsupervised models perform significantly better when n-gram frequencies are obtained from the web rather than from a standard large corpus. This result is consistent with Keller and Lapata’s (2003) findings that the web yields better counts than the BNC. The reason for this seems to be that the web is much larger than the BNC (about 1000 times); the size seems to compensate for the fact that simple heuristics were used to obtain web counts, and for the noise inherent in web data.

Our results were less encouraging when it comes to comparisons with state-of-the-art models. We found that in all but one case, web-based models fail to significantly outperform the state of the art. The exception was compound noun interpretation, for which the Altavista model was significantly better than the Lauer’s (1995) model. For three tasks (candidate selection for MT, adjective ordering, and compound noun bracketing), we found that the performance of the web-based models was not significantly different from the performance of the best models reported in the literature.

Note that for all the tasks we investigated, the best performance in the literature was obtained by supervised models that have access not only to simple bigram or tri-
gram frequencies, but also to linguistic information such as part-of-speech tags, semantic restrictions, or context (or a thesaurus, in the case of Lauer’s models). When unsupervised web-based models are compared against supervised methods that employ a wide variety of features, we observe that having access to linguistic information makes up for the lack of vast amounts of data.

Our results therefore indicate that large data sets such as those obtained from the web are not the panacea that they are claimed to be (at least implicitly) by authors such as Grefenstette (1998) and Keller and Lapata (2003). Rather, in our opinion, web-based models should be used as a new baseline for NLP tasks. The web baseline indicates how much can be achieved with a simple, unsupervised model based on n-grams with access to a huge data set. This baseline is more realistic than baselines obtained from standard corpora; it is generally harder to beat, as our comparisons with the BNC baseline throughout this paper have shown.

Note that for certain tasks, the performance of a web baseline model might actually be sufficient, so that the effort of constructing a sophisticated supervised model and annotating the necessary training data can be avoided. Another possibility that needs further investigation is the combination of web-based models with supervised methods. This can be done with ensemble learning methods or simply by using web-based frequencies (or probabilities) as features (in addition to linguistically motivated features) to train supervised classifiers.

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