Incremental Learning for Fully Unsupervised Word Segmentation Using Penalized Likelihood and Model Selection

Ruey-Cheng Chen

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Abstract

We present a novel incremental learning approach for unsupervised word segmentation that combines features from probabilistic modeling and model selection. This includes super-additive penalties for addressing the cognitive burden imposed by long word formation, and new model selection criteria based on higher-order generative assumptions. Our approach is fully unsupervised; it relies on a small number of parameters that permits flexible modeling and a mechanism that automatically learns parameters from the data. Through experimentation, we show that this intricate design has led to top-tier performance in both phonemic and orthographic word segmentation.

1 Introduction

Information criteria are meta-heuristics that measure the quality of statistical fits. Well-known examples such as Akaike information criterion [1] and minimum description length [24] were developed in the context of model selection. These powerful tools deal directly with statistical fits regardless of how these models are inferred, thereby allowing one to efficiently test a large amount of hypotheses of different distributional assumptions.

Despite being around for many decades, this level of optimization was scarce in computational linguistics. One reason is that most solutions developed in the past for linguistic problems rest on fairly simple distributional assumptions, and few needs to go beyond conventional techniques for the inference. But as many recent methods are beginning to embrace sophisticated structural assumptions such as context or syntax, the complexity of inference can be overwhelmingly large. One such troubling case is the nonparametric Bayesian approach for unsupervised word segmentation. Nonparametric Bayesian modeling [14,19] is commonly deemed as state of the art for unsupervised word segmentation, but the computation overhead has largely impeded its application on orthographic data, such as texts written in Chinese, Japanese, ancient languages, or even those with little linguistic resources.

This need for efficiently processing large text body has inspired some focused deployment of minimum description length (MDL) into the area [7,17,32]. Troubled by the lack of efficient search procedure for MDL, these methods use specialized algorithms to explore the hypothesis space. The search algorithm is usually light on execution and takes one or more input parameters that serve as knobs for biasing search direction. It is therefore easy to induce many “search models” at the same time by just changing the parameters, and then combine these outputs altogether using information criteria such as MDL. This approach has proven to be efficient and scales well to large benchmarks in orthographic word segmentation. But as these search algorithms lean more towards using simple heuristics and hardly take structural assumptions into account, MDL-based methods are sometimes criticized for having inferior performance in the modeling of language.

In this paper, we seek to bridge this gap between more sophisticated probabilistic models and more efficient MDL-based methods. We develop a fully unsupervised, simplistic approach called incremental
learning that combines the best of both worlds: We use a model selection framework for efficiently testing hypotheses, but for better language modeling we use a probabilistic search procedure that optimizes over the penalized likelihood. The incremental learning approach is so named because the search procedure is a greedy algorithm that checks only nearby configurations. Each search instance maintains an assumption about the language to be modeled; in each iteration, the instance would incrementally update its hypothesis based on the boundary placement decision it has made so far. Also it is known that using over-simplistic generative assumptions can easily lead to undersegmentation. To fix this problem, we propose using a new length-based penalty term as in Bayesian modeling [14]. This penalty term is developed to approximate the cognitive burden (the number of meanings, in a sense) imposed by long word formation. Thus it is introduced into our method as a super-additive function, which penalizes longer words harder than shorter ones. We compared this incremental learning algorithm with many reference methods on both phonemic and orthographic word segmentation tasks. The result shows that the performance of incremental learning surpassed existing MDL-based algorithms and compared well to the best records on both benchmarks.

The rest of the paper is organized as follows. Section 2 briefly reviews the development of unsupervised word segmentation and some of the recent advances. In Section 3, we describe the proposed method, model selection criteria, and some other design features. Section 4 covers our test result on two standard benchmarks for phonemic and orthographic word segmentation. The analysis is expanded later in Section 5 to look at the correlation between F-score and information criteria. We give out concluding remarks in Section 6.

2 Unsupervised Word Segmentation

Unsupervised word segmentation has been a focus in natural language processing for certain East-Asian languages such as Japanese or Chinese. Some early traces of unsupervised word segmentation dates back to 1950s in linguistic studies. Harris [16] studied morpheme segmentation and suggested that low transition probability between two phonemes may indicate a potential morpheme boundary. This idea has been a major influence on several approaches in orthographic Chinese word segmentation, such as accessor variety [12] and branching entropy [18,28]. Besides the focus on word boundaries, some effort has been put into measurement of the quality of word-like strings. Sproat and Shih [26] used pointwise mutual information to measure the association strength of a string in Chinese texts. Kit and Wilks [20] proposed using the amount of information gained by modeling subword units as a single word to measure word quality. See Zhao and Kit [31] for a detailed review.

Nonparametric Bayesian methods have been introduced to unsupervised word segmentation by Goldwater et al. [14] to address the problem of context modeling. They relied on a hierarchical Dirichlet process (HDP) to better capture between-word dependencies and avoid misidentifying common word collocations as whole words. This approach was later extended by Mochihashi et al. [23] that installs two Pitman-Yor processes at both word and character levels, aiming at a joint resolution of the dependency issues. Johnson and Goldwater [19] proposed an extension of HDP on probabilistic context-free grammar, called adaptor grammars, whose performance is currently state of the art for unsupervised phonemic word segmentation.

Minimum description length (MDL) is an inductive principle in information theory that equates salience to parsimony in statistical modeling [24,25]. It is perhaps best known for the connection between the famous two-part code and the Bayesian formalism. Early applications of MDL in computational linguistic target mainly on very general unsupervised learning problems, such as grammar induction [15] and language acquisition [4,5,9,10]. There has been some constant interest from problem subareas in applying MDL to their work, but in the early days MDL served mainly as a motive for Bayesian modeling. Not much work has been done to explore the true merit of MDL as an information criterion until recently in lexical acquisition subareas such as morphology [8,13] and unsupervised word segmentation [2,30].

This idea has later been extended in Zhikov et al. [32]. They varied the decision threshold on branching entropy to generate a number of candidate segmentations, each would later go through an adjustment procedure for locally reducing the description length. All these candidates are then judged using the MDL criterion to produce the final output. This method works well on both phonemic and orthographic corpora, and has gather some attention from the research community. A number of follow-up work has devoted to experimenting with different boundary placing strategies. Hewlett and Cohen [17] used Bootstrapped Voting
Let $T$ be the input character sequence and $\theta$ be a language model.

1. Compute $\Delta(s)$ for all $n$-gram $s$ in sequence $T$, for all $2 \leq n \leq n_{\text{max}}$:

$$\Delta(s) = [L(T(s), \theta(s)) - L(T, \theta)] + [\text{pen}(T(s)) - \text{pen}(T)].$$  \hspace{1cm} (1)

($T(s)$ and $\theta(s)$ are new sequence and model created by “compressing” $s$ into a single token.)

2. Let $s^*$ be the minimizer of $\Delta(\cdot)$. If $\Delta(s^*) < 0$, stop and output $T$.

3. Update $T$ by substituting all occurrences of $s^*$ in $T$ with a new token $s'$, thereby reducing the total number of words in the original word sequence. Add an definition $s' = s_1^* s_2^* \ldots s_n^*$ (token-wise representation of the $n$-gram) into the lexicon.

4. Go back to Step 1.

Figure 1: The incremental learning framework.

Experts, a sophisticated algorithm also based on branching entropy, to take the job of segmentation generation. Chen et al. [7] proposed using regularized compression, a compression-based algorithm that builds up word representation from characters in a bottom-up fashion; a later version of this algorithm in Chen [6] had been shown to work well on phonemic data. Recently, some negative result with MDL on orthographic Chinese segmentation was reported in Magistry and Sagot [22], suggesting that MDL has sometimes failed to improve their baseline measure.

3 Incremental Learning Using Maximum Penalized Likelihood

There has been some efforts aiming at formalizing the MDL-based approach for unsupervised word segmentation [7, 32]. In this section, we propose a general framework that incorporates many design elements from these previous attempts. We chose between two types of search strategies: in a space of boundary placements [32] or a space spanned by lexemes in [7]. As our goal is to have something simple to work on, eventually we settle on Chen et al.’s method for ease of implementation.

Framework Our algorithm is given in Figure 1. Let us first assume the input to algorithm is a sequence of $N$ characters, denoted as $X^N$. The basic idea of incremental learning is to iteratively process this sequence of “words” and make it more compact. Initially, this sequence contains only characters, $t_1 t_2 \ldots t_N = X^N$. Then, in each iteration our algorithm would pick a contiguous subsequence of words from the input, say $s = t_i t_{i+1} \ldots t_{i+n-1}$ (for some $i$ and $n \leq n_{\text{max}}$), and concatenate all its components into one single string. We do this for all occurrences of $s$, thereby reducing the total number of words in the original word sequence.

For simplicity let us write the input sequence as $T$ and the new sequence produced by compressing some candidate $s$ as $T(s)$. In each iteration, we look for some candidate $s^*$ that minimizes

$$L(T(s), \theta(s)) + \text{pen}(T(s)),$$ \hspace{1cm} (2)

where $L(T, \theta)$ is the sum of the log likelihood estimate and the complexity term for $\theta$, as in:

$$- \log p(T | \theta) - \frac{1}{2} (\# \text{ unigram}) \log N.$$ \hspace{1cm} (3)

Note that $p(T | \theta)$ is a categorical distribution over unigram words; we use maximum likelihood to estimate this probability.

Since our goal is to find the candidate that minimizes the change plus the penalty, it suffices in each iteration to calculate only the change in the penalized maximum likelihood estimate. We have implemented
efficient update steps similar to Chen [6] by deriving a bound for the likelihood component using the mean-value theorem. These steps are omitted here for space limitation.

**Penalized Likelihood** Our objective function (2) in the incremental learning algorithm can be seen as a joint log-likelihood estimate $p(X^N, T, \theta)$. The first component $p(T, \theta)$ has been accounted for in $L(T, \theta)$; what was left is $p(X^N|T, \theta)$, the probability of generating the input based on a sequence of words $T$ and a language model $\theta$. This is not about testing whether $T$ is a feasible segmentation for $X^N$, but more about assessing how likely one may think the segmentation is reasonable. Inspired by the string-length-based priors used in Bayesian modeling [14], we assign this component as a penalty prior for demoting long word formation. This penalty term is by design a summation of super-additive function values of individual token length (in characters). A super-additive function $f$ satisfies that $f(x + y) > f(x) + f(y)$ for all $x$ and $y$. This definition aims to approximate the cognitive overhead created by composition: putting more sub-word units together would create new meanings. This is best illustrated by considering the number of possible collocations and singletons in $n$ word units, which is a quadratic function $\binom{n}{2} + \binom{n}{1}$, or more naively the number of possible combinations $2^n$. Both examples here are in super-additive forms.

In this paper, we consider the following two types of penalties, $x \log x$ and $x^2$. We also find it useful to have an intercept term. The penalties are defined as follows:

$$pen_1(T) = -\alpha |t| + \beta \sum_{t \in T} |t| \log |t|,$$

$$pen_2(T) = -\alpha |t| + \beta \sum_{t \in T} |t|^2. \quad (4)$$

**Model Selection** In this paper, we use Akaike information criterion (AIC) and minimum description length (MDL) to measure the quality of a specific segmentation output. These criteria are applied to data-model pair $(T, \theta)$. For AIC, we use the finite correction proposed by Sugiura [27]:

$$\text{AIC}_c = -\log p_{\hat{\theta}}(X^N) + \frac{Nk}{N - k - 1},$$

where $p_{\hat{\theta}}(X^N)$ is the maximum likelihood estimate for observations $X^N$ and $k$ is the complexity term (number of parameters needed for fitting the model $\hat{\theta}$.) For the definition of MDL, we follow Rissanen [25] and add a complexity term for coding the word-level codebook, as in Zhikov et al. [32]. Our final formula is defined as:

$$\text{MDL} = -\log p_{\hat{\theta}}(X^N) + \frac{k}{2} \log N + cbl(\theta),$$

where $cbl(\theta)$ is the code length of the lexicon. Both criteria depends on a log-likelihood component, whose estimation is based on the designated language model $\theta$. In this study, we consider unigram, bigram, and trigram models.

### 4 Experiment

Our incremental learning algorithm relies on two free parameters $\alpha$ and $\beta$ to assign correct penalty weights to each segmentation candidate. The best combination may depend on language, representation, and even corpus statistics. It is therefore infeasible to assume one magic setting that works well universally. In this experiment, we show how the adaption to data can be achieved using model selection. Furthermore, we justify how super-additive penalty may improve incremental learning, and also verify the influence of higher-order dependencies to model selection. Standard performance measures such as precision (P), recall (R) and F-measures (F) are used for evaluating segmentation accuracy. We report these figures at three levels: token, boundary, and lexicon. The experimental setup and our methodology are detailed as follows.
Table 1: Test results on the Bernstein-Ratner corpus for different incremental learning settings: zero penalty (top), \(x \log x\) penalty (middle) and \(x^2\) penalty (bottom).

### 4.1 Phonemic Word Segmentation

We used the Brent’s version of Bernstein-Ratner corpus to evaluate our method. [3, 5]. This corpus is the phonemic transcription of English child-directed speech from the CHILDES database [21], and has been widely used as a standard testbed for unsupervised word segmentation. It has 9,790 utterances that comprise totally 95,809 words in phonemic representation.

Our result will be compared with the following methods: (1) incremental learning without adding the penalty, i.e., setting \(\alpha = 0.0\) and \(\beta = 0.0\), (2) MDL-based methods such as regularized compression [6] and EntropyMDL [32], and (3) adaptor grammars [19].

We used two classes of information criteria in this experiment, derived from AIC and MDL. Both classes depend on a likelihood term \(-\log P(X^n)\), for which in this study we obtained three estimates under the unigram, bigram, and trigram assumptions. We denote these criteria as AIC\(_n\) and MDL\(_n\) respectively for \(n = 1, 2, 3\). The complexity term \(K\) (degrees of freedom) for AIC\(_n\) is given by:

\[
\begin{align*}
\text{AIC}_1 &= \sum_w (1 + |w|) + \# \text{unigrams}, \\
\text{AIC}_2 &= \sum_w (1 + |w|) + 1 + 2 \times \# \text{bigrams}, \\
\text{AIC}_3 &= \sum_w (1 + |w|) + 1 + 2 \times \# \text{trigrams}.
\end{align*}
\]

(5)

For MDL\(_n\), we have the following formula:

\[
\text{MDL}_n = \# n\text{-grams}
\]

(6)

We ran a grid search for both \(\alpha\) and \(\beta\) from 0 to 5 with step size 0.1, which amounts to 2,601 combinations in total. For each combination, we first let the algorithm run to finish, collect the output, and then compute the AIC and MDL values. This procedure is repeated on both penalty settings. Each AIC or MDL criteria will have one combination that achieves the minimum. We collected these combinations and then chose the one that minimize over the entire family as the designated output for AIC\(_n\) or MDL\(_n\).

**Result** The test result is summarized in Table 1. From top to bottom we have the results using different penalties: zero penalty, \(x \log x\), and \(x^2\). Zero-penalty and its upper bound (the best possible result among intermediate output) are included here merely as lab controls for the super-additive penalties. Zero penalty
Table 2: Performance results for top-10 ensemble using $x \log x$ (top) and $x^2$ (bottom) penalties.

| $P$ | $R$ | $F$ | $BP$ | $BR$ | $BF$ | $LP$ | $LR$ | $LF$ |
|-----|-----|-----|------|------|------|------|------|------|
| AIC$_3$ | 82.9 | 79.4 | 81.1 | 92.7 | 87.2 | 89.9 | 62.7 | 63.1 | 62.9 |
| MDL$_2$ | 83.7 | 84.2 | 84.0 | 91.0 | 91.8 | 91.4 | 59.9 | 58.0 | 58.9 |
| AIC$_3$ | 82.5 | 81.0 | 81.7 | 91.2 | 88.9 | **90.0** | 59.9 | 59.3 | 57.8 |
| MDL$_2$ | 80.7 | 80.6 | 80.6 | 89.5 | 89.3 | 89.4 | 59.3 | 57.8 | 58.6 |

Table 3: Performance comparison with MDL-based methods (left) and adaptor grammars (right). Figures for the latter were reproduced from the reference implementation [19] using batch initialization and maximum marginal decoding. Note that colloc3-syllable adaptor grammars is not fully unsupervised due to a small amount of phoneme productions built into its core.

| $P$ | $R$ | $F$ | $BP$ | $BR$ | $BF$ | $LP$ | $LR$ | $LF$ |
|-----|-----|-----|------|------|------|------|------|------|
| MDL$_2$, $x \log x$ + ensemble | 83.7 | 84.2 | 84.0 | Adaptor grammars, colloc3-syllable | 87.0 |
| AIC$_3$, $x^2$ + ensemble | 82.5 | 81.0 | 81.7 | MDL$_2$, $x \log x$ + ensemble | 84.0 |
| Chen [6] | 79.1 | 81.7 | 80.4 | AIC$_3$, $x^2$ + ensemble | 81.7 |
| Hewlett and Cohen [17] | 79.3 | 73.4 | 76.2 | Adaptor grammars, colloc | 76.0 |
| Zhikov et al. [32] | 76.3 | 74.5 | 75.4 | Adaptor grammars, unigram | 56.0 |

itself did not do very well, achieving only 21.6 for token F-score (hereafter abbreviated as F-score or F-measure); its best intermediate output was found in 500 iterations, giving a mediocre 52.6 in F-measure.

With $x \log x$ penalty, AIC$_n$ has achieved 23.8, 34.0, and 80.5 in F-score, respectively for $n = 1, 2, 3$. MDL$_n$ does slightly better in general, giving 64.1, 83.7, and 76.2 in F-score. The best performance for AIC and MDL is on AIC$_3$ and MDL$_2$. These two runs are still clear winners on $x^2$ penalty. In F-measure, AIC$_3$ and MDL$_2$ does equally well, delivering 80.0 and 80.4 respectively in terms of F-measure. The performance for both criteria on $x^2$ is very close to AIC$_3$ on $x \log x$.

In general, the trigram estimate AIC$_3$ works the best for AIC, constantly achieving the least decision value among the three and the best performance. The same goes for the bigram estimate MDL$_2$ in the MDL camp, whose performance surpassed the other three consistently across two penalty settings. Furthermore, the unigram and bigram estimates do not seem to play well with AIC. On either penalty setting, both AIC$_1$ and AIC$_2$ have struggled to catch up with the zero-penalty upper-bound performance. The result on MDL runs seem more coherent in performance. MDL$_1$ and MDL$_3$ lagged behind MDL$_2$ only by a small margin about 3 to 4 points in F-score. From the test result, it seems fair to conclude that the proposed incremental learning framework is effective in unsupervised word segmentation.

We also experimented with a simple ensemble method that combines top-$k$ segmentation outputs. Suppose there are totally $n$ plausible positions for placing boundaries on the input corpus. For each position, we check how many in the $k$ outputs have actually placed a boundary there and seek to obtain a majority decision. These $n$ decisions are later put together as a combined output; ties are interpreted as "no-boundary-here". We tested top-10 ensemble for AIC$_3$ and MDL$_2$ on both penalty settings. The result is given in Table 2. The token-level performance for all four experimental runs was improved by 0.2 to 1.7 points in F-score. Top-10 ensemble also slightly improves lexicon F-measure on $x \log x$ penalties, although in general it has a mixed effect on the other measures. The overall best performance is now on MDL$_2$ using $x \log x$ penalty, achieving 84.0 in token F-score.

In Table 2 we make an overall comparison between our result and reference methods, including MDL-based methods and adaptor grammars. The summary on the left shows that our incremental learning framework has outperformed all the existing MDL-based approaches, winning out regularized compression by about 4 points in F-score. On the right, we find the performance of incremental learning has surpassed both unigram and colloc adaptor grammars by a large margin. We also compared our approach with colloc3-syllable adaptor grammars, which is commonly thought as weakly supervised. The result shows that incremental learning approach lagged behind colloc3-syllable by 3 points in F-score. Our interpretation is that this more advanced version of adaptor grammars has built in some linguistic/structural assumptions that have
Table 4: Timing results on the Bernstein-Ratner corpus, all methods tested on an Intel Xeon 2.5GHz 8-core machine with 8GB RAM. All the tests were done on a single core; no parallelization was intended in this timing benchmark.

| Method                                      | Time (s) |
|---------------------------------------------|----------|
| MDL\(_2\), \(x \log x + \) ensemble, 51 \(\times\) 51 | 9,350    |
| Adaptor grammars, colloc                     | 73,356   |
| Adaptor grammars, colloc3-syllable          | 376,732  |

Table 5: Test results in token F-measure on the SIGHAN Bakeoff-2005 training sets. The baseline results all come from the literature.

| Method                                      | AS  | MSR | CityU | PKU |
|---------------------------------------------|-----|-----|-------|-----|
| MDL\(_2\), \(x \log x\)                   | 80.9| 80.0| 80.5  | 80.6|
| Wang et al. [29], Setting 3                | 76.9| 79.7| 80.8  | 79.3|
| Zhikov et al. [32]                          | –   | 79.5| 79.8  | –   |
| Chen et al. [7]                             | –   | 77.4| 77.0  | –   |
| Zhao and Kit [31]                           | –   | 66.5| 68.4  | –   |

Despite the inability of modeling sophisticated generative nature in language, incremental learning has good processing speed that permits more CPU cycles to go into parameter estimation. On our test machine, it took merely 3 to 4 seconds for testing one combination of \(\alpha\) and \(\beta\). Running 7-fold colloc3-syllable adaptor grammars would take roughly 4 days; our approach would finish in 3 hours even on a 51 \(\times\) 51 grid search.

4.2 Orthographic Word Segmentation

We also tested our approach under the setting for orthographic word segmentation on a public corpus SIGHAN Bakeoff-2005 [11]. This corpus is a standard benchmark for Chinese word segmentation; it has 4 subsets, and each comes with an official training/test split. For simplicity, our experiment was conducted exclusively on these training sets. The details are given below.

| # passages | # words |
|------------|---------|
| AS         | 708,953 | 5.45M   |
| MSR        | 86,924  | 2.37M   |
| CityU      | 53,019  | 1.46M   |
| PKU        | 19,056  | 1.10M   |

It is easy to see that each of these sets is much more sizable than our previous experiment. As of this writing, it remains difficult if not impossible to apply hierarchical Bayesian methods to a corpus of this size. Hence, in this experiment, we chose to compare with less sophisticated approaches such as MDL-based methods, DLG [31], and ESA [29]. The latter is known to have the best segmentation accuracy on the Bakeoff-2005 corpus, although the best figures reported was achieved by explicitly hand-picking the parameter. To make this a fair comparison, we instead took the median from all the reported runs for 10-iteration ESA. Note that ESA still has the best performance after this fix. Our experiment setup is compatible with the setting 3 for ESA, meaning that hard boundaries are set up around punctuation marks. Besides that, little preprocessing was done to the corpus body.

Due to the scale of experiment, we chose to test only the best setting found in the previous round: MDL\(_2\) with \(x \log x\) penalty. Even so, the experiment remains very time-consuming; on the largest set AS, it took several hours for our incremental learning algorithm to complete. Therefore, for estimating the parameters we first ran a search on \(\alpha\) and then a second on \(\beta\) in a way analogous to the previous experiment. We ran this
Figure 2: Heat maps printed in greyscale for token F-score (left), AIC\(_3\) (middle), and MDL\(_2\) (right) in a truncated hypothesis space represented by \(\alpha\) and \(\beta\), based on \(x \log x\) (top) and \(x^2\) (bottom) penalties. Note that AIC\(_3\) and MDL\(_2\) are log-transformed for better contrast.

| Penalty | AIC\(_1\) | AIC\(_2\) | AIC\(_3\) | MDL\(_1\) | MDL\(_2\) | MDL\(_3\) |
|---------|-----------|-----------|-----------|-----------|-----------|-----------|
| Output  | \(x \log x\) | -0.80     | -0.79     | -0.76     | -0.93     | -0.78     | -0.46     |
|         | \(x^2\)   | -0.94     | -0.89     | -0.87     | -0.90     | -0.87     | -0.54     |
| Full trace | \(x \log x\) | 0.44      | -0.47     | -0.79     | -0.79     | -0.96     | -0.92     |
|         | \(x^2\)   | 0.03      | -0.53     | -0.78     | -0.73     | -0.93     | -0.86     |

Table 6: Rank correlations (Spearman’s \(\rho\)) between token F-measure and information criteria

grid search only once on the AS set; the found combination \((\alpha, \beta) = (2.0, 3.0)\) was used throughout the rest of the experiment on other subsets.

**Result** We had our method run to stop on each of the subsets. The improvement on F-score over iterations is steady and consistent; this trend is made obvious in Figure 3. The found parameters seemed to generalize well across subsets, in spite of the difference on orthographic representation and usage. The overall performance is given in Table 5. Our incremental learning method achieved in F-score above 80.0 on all four subsets, and it compares favorably with weaker baselines such as MDL-based methods and DLG. On two sets AS and PKU, incremental learning outperformed the strong baseline ESA, winning out by 4.0 and 1.3 in F-score respectively. On the other two sets MSR and CityU, incremental learning seems on a par with ESA: it improved over the baseline by 0.3 on MSR, but it also lagged behind by 0.3 on CityU.

To conclude, our result suggests that incremental learning is effective and efficient for unsupervised word segmentation. The main reason is that penalized likelihood has better coverage in the hypothesis space; through varying the parameters \(\alpha\) and \(\beta\), we are able to explore many more search paths than an ordinary greedy method can. Moreover, the information criteria such as AIC and MDL allow us to make a guess fairly efficiently on the solution quality. It is the combination of the two that makes incremental learning a plausible alternative for this specific application.

\(^1\)AS and CityU are in traditional Chinese; MSR and PKU in simplified Chinese.
Figure 3: The improvement on F-score across iterations on the Bakeoff-2005 corpus.

5 Post-Hoc Analysis

We have initial evidence to support that information criteria can suggest good ways to segment words. It nevertheless raises a question on the reliability of these meta-heuristics. By reliability, we mean how consistent the prediction made matches the truth. This has little to do with the exact decision values; in our application, we care only about whether an information criterion assigns sensible ranking to the given hypotheses. In this section, we discuss two ways to examine this relation.

Spectral Correlation The first one is to look for spectral patterns for the response values in the hypothesis space; a simple visualization as in Figure 2 would do the trick. We plot the F-score, AIC\(_3\), and MDL\(_2\) values as individual heat maps on the parameter search plane. It is interesting to note that, on both penalties, the best segmentation performance concentrates on a cone-like region with its peak facing the y-axis. For any \(\alpha\), performance declines as \(\beta\) moves away from this region either towards zero or infinity. As \(\alpha\) increases, the spread gets larger and results in more gentle decline, so it is not hard to imagine the true performance contour as a mountain that has a fat end at large \(\alpha\). We found that in general AIC\(_3\) and MDL\(_2\) assign similar rankings to hypothesis, although the AIC\(_3\) ranking seems more fine-grained. Both criteria have missed on the true optimal solutions, but MDL\(_2\) does a bit better in modeling by using two “valleys” to cap the true region.

Rank Correlation The second angle is to check on the rank correlation. We computed Spearman’s \(\rho\) between token F-measure and all the information criteria used in the experiment. For comparison, we also used the full trace, which is the intermediate outputs collected every 100 iteration for all the combinations. The result is given in Table 6. We notice that on the output set both AIC and MDL give strong, negative correlation, i.e., \(\rho < -0.7\), with the true performance, with one exception MDL\(_3\) that shows medium correlation. This however does not match our empirical result. Note that the output set alone is not sufficient to draw conclusion on the predictability over the entire hypothesis space; the criteria may still assign good ranking to a bad hypothesis not covered in the output set.

The rank correlation on the full trace has shown a better fit to the true result. Only 4 criteria, including AIC\(_3\), MDL\(_1\), MDL\(_2\), and MDL\(_3\), are strongly correlated with the F-score. It was suggested that MDL correlates well with data under generative assumptions that vary in complexity. The best correlation is found on MDL\(_2\), which sets record by achieving -0.96 on \(x \log x\) penalty. This has once again been evidence in favor of our empirical findings.

The analysis can be further enhanced with some visual cues as given in Figure 4, which plots F-score against ranking for all six decision criteria using the full trace data. It suggests that AIC\(_3\), MDL\(_2\), and
MDL, AIC, and AIC3 are all able to find good segmentation hypotheses reliably, although AIC3 has some serious problem in pushing solutions towards mid-ranked regions.

6 Conclusions

In this paper, we introduce an incremental learning algorithm for unsupervised word segmentation that combines probabilistic modeling and model selection in one framework. We show with extensive experiments that simple ideas, such as the super-additive penalties and higher-order generative assumptions in model selection, can achieve very competitive performance in both phonemic and orthographic word segmentation. Our algorithm is very efficient and scales well on large corpora, making it more useful than other algorithms in real-world applications. Besides all that, this framework is general enough so that it is easy to replace the objective function or model selection method with more sophisticated ones. For our future work, we will focus on enhancing accuracy by incorporating more complex structural assumptions such as syntax and context.

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