Factored Language Models Tutorial

Katrin Kirchhoff, Jeff Bilmes, Kevin Duh
{katrin,bilmes,duh}@ee.washington.edu

Dept of EE, University of Washington
Seattle WA, 98195-2500

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Department of Electrical Engineering
University of Washington
Box 352500
Seattle, Washington 98195-2500
PHN: (206) 543-2150
FAX: (206) 543-3842
URL: http://www.ee.washington.edu

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Abstract

The Factored Language Model (FLM) is a flexible framework for incorporating various information sources, such as morphology and part-of-speech, into language modeling. FLMs have so far been successfully applied to tasks such as speech recognition and machine translation; it has the potential to be used in a wide variety of problems in estimating probability tables from sparse data.

This tutorial serves as a comprehensive description of FLMs and related algorithms. We document the FLM functionalities as implemented in the SRI Language Modeling toolkit and provide an introductory walk-through using FLMs on an actual dataset. Our goal is to provide an easy-to-understand tutorial and reference for researchers interested in applying FLMs to their problems.

Overview of the Tutorial

We first describe the factored language model (Section 1) and generalized backoff (Section 2), two complementary techniques that attempt to improve statistical estimation (i.e., reduce parameter variance) in language models, and that also attempt to better describe the way in which language (and sequences of words) might be produced.

Researchers familar with the algorithms behind FLMs may skip to Section 3, which describes the FLM programs and file formats in the publicly-available SRI Language Modeling (SRILM) toolkit.[1] Section 4 is a step-by-step walk-through with several FLM examples on a real language modeling dataset. This may be useful for beginning users of the FLMs.

Finally, Section 5 discusses the problem of automatically tuning FLM parameters on real datasets and refers to existing software. This may be of interest to advanced users of FLMs.

1 Introduction to Factored Language Models

1.1 Background

In most standard language models, it is the case that a sentence is viewed as a sequence of T words $w_1, w_2, \ldots, w_T$. The goal is to produce a probability model over a sentence in some way or another, which can be denoted by $p(w_1, w_2, \ldots, w_T)$ or more concisely as $p(w_{1:T})$ using a matlab-like notation for ranges of words.

It is most often the case that the chain rule of probability is used to factor this joint distribution thus:

$$p(w_{1:T}) = \prod_t p(w_t | w_{1:t-1}) = \prod_t p(w_t | h_t)$$

[1]This tutorial currently documents the FLM functionalities in SRILM version 1.4.1. Note that while the core FLM functionalities are already implemented in the SRI language modeling toolkit, additional extensions are still being added. We will update this tutorial to reflect new extensions. The SRILM toolkit may be downloaded at: `http://www.speech.sri.com/projects/srilm/`.

where $h_t = w_{1:t-1}$. The key goal, therefore, is to produce the set of models $p(w_t|h_t)$ where w_t is the current word and h_t is the multi-word immediately preceding history leading up to word w_t. In a standard n-gram based model, it is assumed that the immediate past (i.e., the preceding $n-1$ words) is sufficient to capture the entire history up to the current word. In particular, conditional independence assumptions about word strings are made in an n-gram model, where it is assumed that $W_t \perp\!\!\!\perp W_{1:t-n} | W_{t-n+1:t-1}$. In a trigram ($n = 3$) model, for example, the goal is to produce conditional probability representations of the form $p(w_t|w_{t-1}, w_{t-2})$.

Even when n is small (e.g., 2 or 3) the estimation of the conditional probability table (CPT) $p(w_t|w_{t-1}, w_{t-2})$ can be quite difficult. In a standard large-vocabulary continuous speech recognition system there is, for example, a vocabulary size of at least 60,000 words (and 150,000 words would not be unheard of). The number of entries required in the CPT would be $60,000^3 \approx 2 \times 10^{14}$ (about 200,000 gigabytes using the quite conservative estimate of one byte per entry). Such a table would be far to large to obtain low-variance estimates without significantly more training data than is typically available. Even if enough training data was available, the storage of such a large table would be prohibitive.

Fortunately, a number of solutions have been proposed and utilized in the past. In class-based language models, for example, words are bundled into classes in order to improve parameter estimation robustness. Words are then assumed to be conditionally independent of other words given the current word class. Assuming that c_t is the class of word w_t at time t, the class-based model can be represented as follows:

$$\begin{aligned} p(w_t|w_{t-1}) &= \sum_{c_t, c_{t-1}} p(w_t|c_t)p(c_t|c_{t-1}, w_{t-1})p(c_{t-1}|w_{t-1}) \\ &= \sum_{c_t, c_{t-1}} p(w_t|c_t)p(c_t|c_{t-1})p(c_{t-1}|w_{t-1}) \end{aligned}$$

where to get the second equality it is assumed that $C_t \perp\!\!\!\perp W_{t-1} | C_{t-1}$. In order to simplify this further, a number of additional assumptions are made, namely:

1. There is exactly one possible class for each word, or that there is a deterministic mapping (lets say a function $\bar{c}(\cdot)$) from words to classes. This makes it such that $p(c_t|w_t) = \delta_{c_t = \bar{c}(w_t)}$, where $\delta(\cdot)$ is the Dirac delta function. It also makes it such that $p(w_t|c_t) = p(w_t|\bar{c}(w_t))\delta_{c_t=\bar{c}(w_t)}$.

2. A class will contain more than one word. This assumption is in fact what makes class-based language models easier to estimate.

With the assumptions above, the class-based language model becomes.

$$p(w_t|w_{t-1}) = p(w_t|\bar{c}(w_t))p(\bar{c}(w_t)|\bar{c}(w_{t-1}))$$

Other modeling attempts to improve upon the situation given above include particle-based language models [13], maximum-entropy language models [1], mixture of different-ordered models [9], and the backoff procedure [9, 6], the last of which is briefly reviewed in Section 2. Many others are surveyed in [9, 6].

1.2 Factored Language Models

In this section, we describe a novel form of model entitled a *factored language model* or FLM. The FLM was first introduced in [10, 4] for incorporating various morphological information in Arabic language modeling, but its applicability is more general. In a factored language model, a word is seen as a collection or bundle of K (parallel) factors, so that $w_t \equiv \{f_t^1, f_t^2, \ldots, f_t^K\}$. Factors of a given word can be anything, including morphological classes, stems, roots, and any other linguistic features that might correspond to or decompose a word. A factor can even be a word itself, so that the probabilistic language model is over both words and its decompositional factors. While it should be clear that such a decomposition will be useful for languages that are highly inflected (such as Arabic), the factored form can be applied to any language. This is because data-driven word-classes or simple word stems or semantic features that occur in any language can be used as factors. Therefore, the factored representation is quite general and widely applicable.

Once a set of factors for words has been selected, the goal of an FLM is to produce a statistical model over the individual factors, namely:

$$p(f_{1:T}^{1:K})$$

or, using an n-gram-like formalism, the goal is to produce accurate models of the form:

$$p(f_t^{1:K}|f_{t-n+1:t-1}^{1:K})$$

In this form, it can be seen that an FLM opens up the possibility for many modeling options in addition to those permitted by a standard n-gram model over words. For example, the chain rule of probability can be used to represent the above term as follows:

$$\prod_k p(f_t^k|f_t^{1:k-1}, f_{t-n+1:t-1}^{1:K})$$

This represents only one possible chain-rule ordering of the factors. Given the number of possible chain-rule orderings (i.e., the number of factor permutations which is $K!$) and (approximately) the number of possible options for subsets of variables to the right of the conditioning bar (i.e., $\approx 2^{nK}$) we can see that an FLM represents a huge family of statistical language models (approximately $K!2^{nK}$). In the simplest of cases, an FLM includes standard n-grams or standard class-based language models (e.g., choose as one of the factors the word class, ensure that the word variable depends only on that class, and the class depends only on the previous class). A FLM, however, can do much more than this.

There are two main issues in forming an FLM. A FLM user must make the following two design decisions:

1. First, choose an appropriate set of factor definitions. This can be done using data-driven techniques or linguistic knowledge.

2. Second, find the best statistical model over these factors, one that mitigates the statistical estimation difficulties found in standard language models, and also one that describes the statistical properties of the language in such a way that word predictions are accurate (i.e., true word strings should be highly probable and any other highly-probable word strings should have minimal word error).

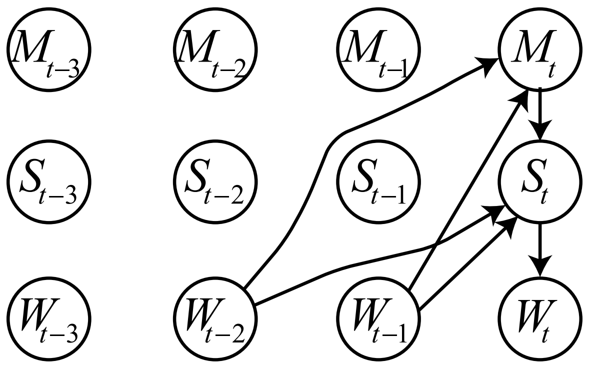


Figure 1: An example of a factored language model seen as a directed graphical model over words W_t, morphological factors W_t, and stems S_t. The figure shows the dependencies for the variables only at time t for simplicity.

The problem of identifying the best statistical model over a given set of factors can be described as an instance of the structure learning problem in graphical models [11, 8, 3]. In a directed graphical model the graph depicts a given probability model. The conditional probability $p(A|B, C)$ is depicted by a directed graph where there is a node in the graph for each random variable, and arrows point from B and C (the parents) to A (the child).

We here give several examples of FLMs and the their corresponding graphs. In both examples, only three factors are used, the word variable at each time W_t, the words morphological class M_t (the "morph" as we call it), and the words stem S_t.

The first example corresponds to the following model:

$$p(w_t|s_t, m_t)p(s_t|m_t, w_{t-1}, w_{t-2})p(m_t, w_{t-1}, w_{t-2})$$

and is shown in Figure 1. This is an example of a factored class-based language model in that the word class variable is represented in factored form as a stem S_t and morphological class M_t. In the ideal case, the word is (almost) entirely determined by the stem and the morph, so that the model $p(w_t|s_t, m_t)$ itself would have very low perplexity (of not much more than unity). It is in the models $p(s_t|m_t, w_{t-1}, w_{t-2})$ and $p(m_t, w_{t-1}, w_{t-2})$ that prediction (and uncertainty) becomes apparent. In forming such a model, the goal would be for the product of the perplexities of the three respective models to be less than the perplexity of the word-only trigram. This might be achievable if it were the case that the estimation of $p(s_t|m_t, w_{t-1}, w_{t-2})$ and $p(m_t, w_{t-1}, w_{t-2})$ is inherently easier than that of $p(w_t|w_{t-1}, w_{t-2})$. It might be because the total number of stems and morphs will each be much less than the total number of words. In any event, one can see that there are many possiblities for this model. For example, it might be useful to add M_{t-1} and S_{t-1} as additional parents of M_t which then might reduce the perplexity of the M_t model. In theory, the addition of parents can only reduce entropy which in term should only reduce perplexity. On the other hand, it might not do this because the difficulty of the estimation problem (i.e., the dimensionality of the corresponding CPT) increases with the addition of parents. The goal of finding an appropriate FLM is that of finding the best compromise between predictability (which reduces model entropy and perplexity) and estimation error. This is a standard problem in statistical inference where bias and variance can be traded for each other.

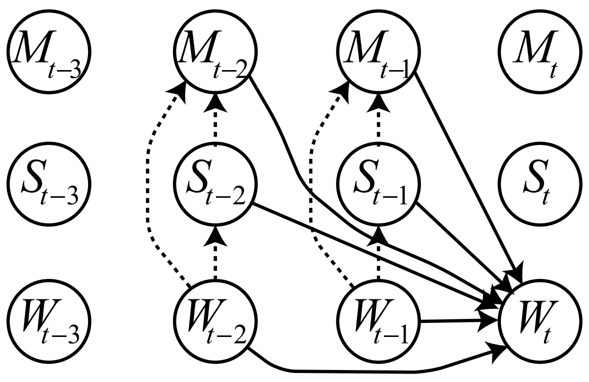


Figure 2: Another example of a factored language model seen as a directed graphical model over words W_t, morphological factors W_t, and stems S_t. The figure shows the child variable W_t and all of its parents. It also shows that the stem and morph might be (almost) deterministic functions of their parents (in this case the corresponding word) as dashed lines.

The next example of an FLM is the following:

$$p(w_t|w_{t-1}, w_{t-2}, s_{t-1}, s_{t-2}, m_{t-1}, m_{t-2}).$$

This model is similar to the standard word-based trigram but where the two previous stems and morphs have been added as parents. It is typical that both stems and morphs can be predicted deterministically from the word. I.e., given a word w_t the stem s_t and the morphological class m_t can be determined with certainty[2] This model is shown in Figure 2. The word variable W_t is shown as the child with parents W_{t-1}, W_{t-2}, S_{t-1}, S_{t-2}, M_{t-1}, M_{t-2}. Also the deterministic variables are shown with their parents as dashed lines.

There are two interesting issues that become apparent when examining this model. First, the previous morph class and stem variables are (often) deterministic functions of their parents (previous words). In such a case, therefore, it should not be useful to use them as additional parents. This is because no additional information can be gleaned from a new parent if it is only a deterministic function of the set of parents that already exist. For example, given the model $P(A|B, C)$ and where D is a deterministic function of C, then the models $P(A|B, C)$ and $P(A|B, C, D)$ would have exactly the same entropy.

Even in this case, however, the model above (Figure 2) might have a benefit over a standard word trigram. The reason is that there might be word trigrams that do not occur in training-data, but the word preceded by the corresponding stems and/or morphs **do** occur in the same training data set. By using the model in the appropriate way, it might be detected when a preceding word history does not occur, but the corresponding stem and/or morph history does occur. This, therefore, would have a benefit in a backoff algorithm over just simply backing-off down to the bigram or unigram (see Section 2.1 for a brief overview of the standard backoff algorithm).

The second interesting issue that arises is the following. When considering just the set of parents in a word trigram W_{t-1} and W_{t-2}, and when considering a backoff algorithm, it can reasonably be argued that the best parent to drop

[2]In some cases, they might not be predictable with certainty, but even then there would be only a small number of different possibilities.

first when backing off is the most distant parent W_{t-2} from the current word W_t. This rests on the assumption that the more distant parent has less predictive power (i.e., ability to reduce perplexity) than does the less distant parent.

On the other hand, when considering a set of parents of a word such as W_{t-1}, W_{t-2}, S_{t-1}, S_{t-2}, M_{t-1}, M_{t-2}, as shown in Figure 2, it is not immediately obvious nor is there any reasonable a-priori assumption, which can be used to determine which parent should be dropped when backing off in all cases at all times. In some circumstances, it might be best to first drop W_{t-2}, but in other cases it might be best to drop W_{t-1}, or perhaps some other parent. In other words, what backoff order should be chosen in a general model?

The next section addresses both of these issues by introducing the notion we call generalized backoff.

2 Generalized Backoff for FLMs

In this section, we describe the generalized backoff procedure that was initially developed with factored language models in mind, but turns out to be generally applicable even when using typical word-only based language models or even when forming arbitrary smoothed conditional probability tables over arbitrary random variables. We will first briefly review standard backoff in language models, and then present the generalized backoff algorithms.

2.1 Background on Backoff and Smoothing

A common methodology in statistical language model is the idea of *backoff*. Backoff is used whenever there is insufficient data to fully estimate a high-order conditional probability table — instead of attempting to estimate the entire table, only a portion of the table is estimated, and the remainder is constructed from a lower-order model (by dropping one of the variables on the right of the conditioning bar, e.g., going from a trigram $p(w_t|w_{t-1}, w_{t-2})$ down to a bigram $p(w_t|w_{t-1})$). If the higher-order model was estimated in a maximum-likelihood setting, then the probabilities would simply be equal to the ratio counts of each word string, and there would be no left-over probability for the lower order model. Therefore, probability mass is essentially "stolen" away from the higher order model and is distributed to the lower-order model in such a way that the conditional probability table is still valid (i.e., sums to unity). The procedure is then applied recursively on down to a uniform distribution over the words.

The most general way of presenting the backoff strategy is as follows (we present backoff from a trigram to a bigram for illustrative purposes, but the same general idea applies between any n-gram and $(n-1)$-gram). We are given a goal distribution $p(w_t|w_{t-1}, w_{t-2})$. The maximum-likelihood estimates of this distribution is:

$$p_{ML}(w_t|w_{t-1}, w_{t-2}) = \frac{N(w_t, w_{t-1}, w_{t-2})}{N(w_{t-1}, w_{t-2})}$$

where $N(w_t, w_{t-1}, w_{t-2})$ is equal to the number of times (or the count) that the the word string w_{t-2}, w_{t-1}, w_t occurred in training data. We can see from this definition that for all values of w_{t-1}, w_{t-2}, we have that

$$\sum_w p_{ML}(w|w_{t-1}, w_{t-2}) = 1$$

leading to a valid probability mass function.

In a backoff language model, the higher order distribution is used only when the count of a particular string of words exceeds some specified threshold. In particular, the trigram is used only when $N(w_t, w_{t-1}, w_{t-2}) > \tau_3$ where τ_3 is some given threshold, often set to 0 but it can be higher depending on the amount of training data that is available. The procedure to produce a backoff model $p_{BO}(w_t|w_{t-1}, w_{t-2})$ can most simply be described as follows:

$$p_{BO}(w_t|w_{t-1}, w_{t-2}) = \begin{cases} d_{N(w_t,w_{t-1},w_{t-2})} p_{ML}(w_t|w_{t-1}, w_{t-2}) & \text{if } N(w_t, w_{t-1}, w_{t-2}) > \tau_3 \\ \alpha(w_{t-1}, w_{t-2}) p_{BO}(w_t|w_{t-1}) & \text{otherwise} \end{cases}$$

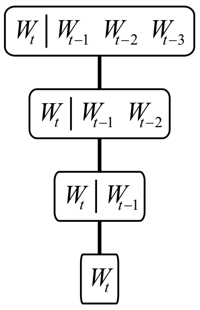
As can be seen, the maximum-likelihood trigram distribution is used only if the trigram count is high enough, and if it is used it is only used after the application of a discount $d_{N(w_t,w_{t-1},w_{t-2})}$, a number that is generally between 0 and 1 in value.

The discount is a factor that steals probability away from the trigram so that it can be given to the bigram distribution. The discount is also what determines the *smoothing* methodology that is used, since it determines how much of the higher-order maximum-likelihood model's probability mass is smoothed with lower-order models. Note that in this form of backoff, the discount $d_{N(w_t,w_{t-1},w_{t-2})}$ can be used to represent many possible smoothing methods, including Good-Turing, absolute discounting, constant discounting, natural discounting, modified Kneser-Ney smoothing, and many others [9, 5] (in particular, see Table 2 in [6] which gives the from d for each smoothing method).

The quantity $\alpha(w_{t-1}, w_{t-2})$ is used to make sure that the entire distribution still sums to unity. Starting with the constraint $\sum_{w_t} p_{BO}(w_t|w_{t-1}, w_{t-2}) = 1$, it is simple to obtain the following derivation:

$$\begin{aligned}\alpha(w_{t-1}, w_{t-2}) &= \frac{1 - \sum_{w:N(w,w_{t-1},w_{t-2})>\tau_3} d_{N(w,w_{t-1},w_{t-2})} p_{ML}(w|w_{t-1}, w_{t-2})}{\sum_{w:N(w,w_{t-1},w_{t-2})<=\tau_3} p_{BO}(w|w_{t-1})} \\ &= \frac{1 - \sum_{w:N(w,w_{t-1},w_{t-2})>\tau_3} d_{N(w,w_{t-1},w_{t-2})} p_{ML}(w|w_{t-1}, w_{t-2})}{1 - \sum_{w:N(w,w_{t-1},w_{t-2})>\tau_3} p_{BO}(w|w_{t-1})}\end{aligned}$$

While mathematically equivalent, the second form is preferred for actual computations because there are many fewer trigrams that have a count that exceed the threshold than there are trigrams that have a count that do not exceed the threshold (as implied by the first form).



$W_t \mid W_{t-1}\ W_{t-2}\ W_{t-3}$
$W_t \mid W_{t-1}\ W_{t-2}$
$W_t \mid W_{t-1}$
W_t

Figure 3: An example of the *backoff path* taken by a 4-gram language model over words. The graph shows that first the 4-gram language model is attempted ($p(w_t|w_{t-1}, w_{t-2}, w_{t-3})$), and is used as long as the string $w_{t-3}, w_{t-2}, w_{t-1}, w_t$ occurred enough times in the language-model training data. If this is not the case, the model "backs off" to a trigram model $p(w_t|w_{t-1}, w_{t-2})$ which is use only if the string w_{t-2}, w_{t-1}, w_t occurs sufficiently often in training data. This process is recursively applied until the unigram language model $p(w_t)$ is used. If there is a word found in test data not found in training data, then even $p(w_t)$ can't be used, and the model can be further backed off to the uniform distribution.

While there are many additional details regarding backoff which we do not describe in this report (see [6]), the crucial issue for us here is the following: In a typical backoff procedure, we backoff from the distribution $p_{BO}(w_t|w_{t-1}, w_{t-2})$ to the distribution $p_{BO}(w_t|w_{t-1})$ and in so doing, we drop the most distant random variable W_{t-2} from the set on the right of the conditioning bar. Using graphical models terminology, we say that we drop the most distant parent W_{t-2} of the child variable W_t. The procedure, therefore, can be described as a graph, something we entitle a *backoff graph*, as shown in Figure 3. The graph shows the path, in the case of a 4-gram, from the case where all three parents are used down to the unigram where no parents are used. At each step along the procedure, only the parent most distant in time from the child w_t is removed from the statistical model.

2.2 Backoff Graphs and Backoff Paths

As described above, with a factored language model the distributions that are needed are of the form $p(f_t^i|f_{t_1}^{j_1}, f_{t_2}^{j_2}, \ldots, f_{t_N}^{j_N})$ where the j_k and t_k values for $k = 1 \ldots N$ can be in the most general case be arbitrary. For notational simplicity and to make the point clearer, let us re-write this model in the following form:

$$p(f|f_1, f_2, \ldots, f_N)$$

which is the general form of a conditional probability table (CPT) over a set of $N + 1$ random variables, with child variable F and N parent variables F_1 through F_N. Note that f is a possible value of the variable F, and $f_{1:N}$ is a possible vector value of the set of parents $F_{1:N}$.

As mentioned above, in a backoff procedure where the random variables in question are words, it seems reasonable to assume that we should drop the most temporally distant word variable first, since the most distant variable is likely to have the least amount of mutual information about the child given the remaining parents. Using the least distant words has the best chance of being able to predict with high precision the next word.

When applying backoff to a general CPT with random variables that are not words (as one might want to do when using an FLM), it is not immediately obvious which variables should be dropped first when going from a higher-order model to a lower-order model. One possibility might be to choose some arbitrary order, and backoff according to that order, but that seems sub-optimal.

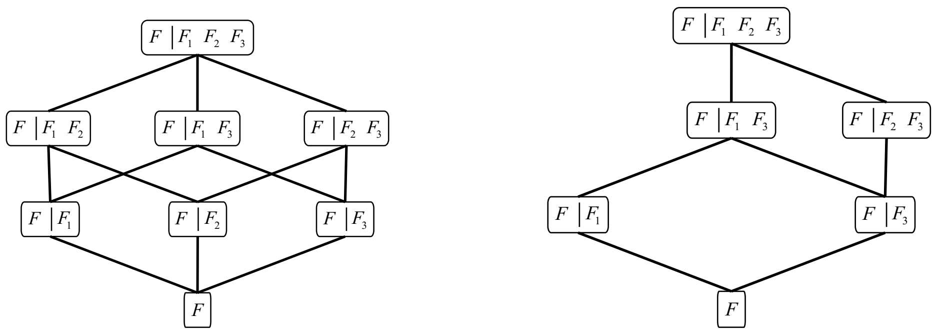


Figure 4: **Left:** An example of a general *backoff graph* for a CPT $p(F|F_1, F_2, F_3)$ showing all possible backoff paths in moving from the model $p(F|F_1, F_2, F_3)$ down to $p(F)$. **Right:** An example of a backoff graph where only a subset of the paths from the top to bottom are allowed. In this graph, the model $p(F|F_1, F_2, F_3)$ is allowed only to backoff to $p(F|F_1, F_3)$ or $p(F|F_2, F_3)$. This means that only the parents F_1 or F_2 may be dropped, but not parent F_3 since all backoff models must have parent F_3. Similarly, the model $p(F|F_2, F_3)$ may backoff only to $p(F|F_3)$, so only the parent F_2 may be dropped in this case. This notion of specifying a subset of the parents that may be dropped to determine a constrained set of backoff paths is used in the SRILM language-model toolkit [12] extensions, described in Section 3.

Under the assumption that we always drop one parent at a time[3], we can see that there are quite a large number of possible orders. We will refer to this as a *backoff path*, since it can be viewed as a path in a graph where each node corresponds to a particular statistical model. When all paths are depicted, we get what we define as a *backoff graph* as shown on the left in Figure 4 and Figure 5, the latter of which shows more explicitly the fact that each node in the backoff graph corresponds to a particular statistical model. When training data for that statistical model is not sufficient (below a threshold) in training data, then there is an option as to which next node in the backoff graph can be used. In the example, the node $p(F|F_1, F_2, F_3)$ has three options, those corresponding to dropping any one of the three parents. The nodes $p(F|F_1, F_2)$, $p(F|F_1, F_3)$, and $p(F|F_2, F_3)$ each have two options, and the nodes $p(F|F_1)$, $p(F|F_2)$, and $p(F|F_3)$ each have only one option.

Given the above, we see that there are a number of possible options for choosing a backoff path, and these include:

1. Choose a fixed path from top to bottom based on what seems reasonable (as shown in Figure 6). An example might be to always drop the most temporally distant parent when moving down levels in the backoff graph (as is done with a typical word-based n-gram model). One might also choose the particular path based on other linguistic knowledge about the given domain. Stems, for example, might be dropped before morphological classes because it is believed that the morph classes possess more information about the word the stems. It is also possible to choose the backoff path in a data-driven manner. The parent to be dropped first might be the one which is found to possess the least information (in an information-theoretic sense) about the child variable. Alternatively, it might be possible to choose the parent to drop first based on the tradeoff between statistical predictability and statistical estimation. For example, we might choose to drop a parent which does not raise the entropy the least if the child model is particularly easy to estimate given the current training data (i.e., the child model will have low statistical variance).

[3]It is possible to drop more than one parent during a backoff step (see Section 3.3 for an example). It is also possible to add parents at a backoff step. This latter case is not further considered in this report.

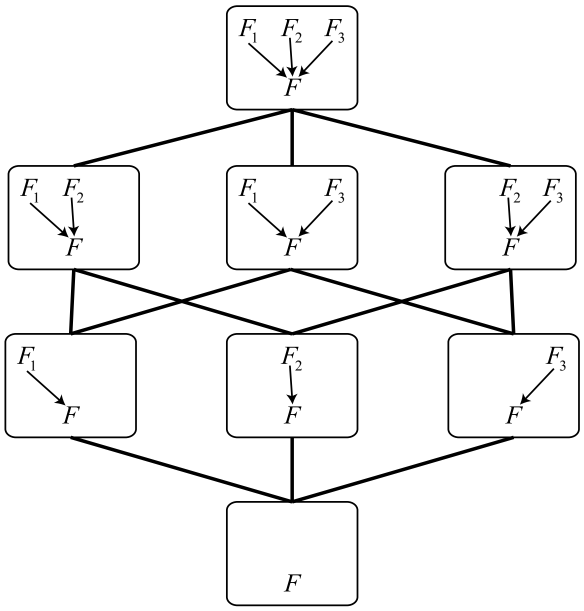


Figure 5: An example of a general *backoff graph* for a CPT $p(F|F_1, F_2, F_3)$ showing all possible backoff paths in moving from the model $p(F|F_1, F_2, F_3)$ down to $p(F)$. In this example, the individual nodes of the backoff graph show the directed graphical model for that node. If an instantiation of a child variable with its parents exists in a language model training corpus above a given number of times, then there is a language model "hit" for the corresponding node in the backoff graph, and that particular model provides a probability. If not, then the next node (or nodes) below are then attempted.

2. Generalized all-child backoff. In this case, multiple child nodes in the backoff graph are chosen at "run-time." This is described in the next section.
3. Generalized constrained-child backoff. In this case, any of a subset of the child nodes in the backoff graph are chosen at "run-time." This is also described in the next section.

2.3 Generalized Backoff

During the workshop, a novel form of backoff was developed and implemented in order to produce backoff models for FLMs and any other CPT. We call this methodology *generalized backoff*.

Rather than choosing a given fixed path when moving from higher-to-lower level in a backoff graph as shown in Figure 6, it is possible to choose multiple different paths dynamically at run time. In general, there are two options here:

1. In the first case, only one path is chosen at a time at run-time, but depending on the particular sequence of words or factors that are in need of a probability, the backoff path will change. In other words, for a given set of factor instances $f^a|f_1^a, f_2^a, f_3^a$ one particular backoff path might be used, but for $f^b|f_1^b, f_2^b, f_3^b$ a different path will be used.
2. It is also possible for *multiple* backoff paths to be used simultaneously at runtime. This means that for a given $f^a|f_1^a, f_2^a, f_3^a$, multiple paths through the backoff graph will be used to produce a probability. Again, the set of multiple paths that are used might change depending on the particular factor sequence.

This approach can only improve over choosing only a fixed backoff path, since the path(s) that are used can be chosen to best suit the given factor instances $f|f_1, f_2, f_3$.

The procedure we developed is a generalization of standard backoff and probabilities are formed in our technique using the following equation:

$$p_{GBO}(f|f_1, f_2, f_3) = \begin{cases} d_{N(f,f_1,f_2,f_3)} p_{ML}(f|f_1, f_2, f_3) & \text{if } N(f, f_1, f_2, f_3) > \tau_4 \\ \alpha(f_1, f_2, f_3) g(f, f_1, f_2, f_3) & \text{otherwise} \end{cases}$$

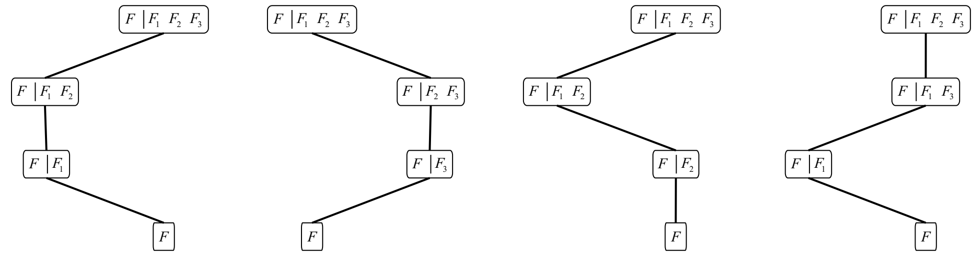


Figure 6: Examples of fixed-backoff-path backoff graphs. Each backoff graph shows a fixed path from the top-level (where all parents are present) to bottom level (where no parents are present). Also, each example shows a separate language model (or more generally a CPT) where the path is fixed at all times. If $F = W_t$, $F_1 = W_{t-1}$, $F_2 = W_{t-2}$, $F_3 = W_{t-3}$, then the left example corresponds to standard backoff in a 4-gram language model — using these definitions, however, shows that when the factors are words there are many other possible backoff schemes, most of which correspond to not dropping first the most temporally distant word.

where

$$p_{ML}(f|f_1, f_2, f_3) = \frac{N(f, f_1, f_2, f_3)}{N(f_1, f_2, f_3)}$$

is the maximum likelihood distribution (equal to the ratio of counts as seen in training data), and where τ_4 is a user-specified threshold used to determine when a "hit" occurs at the current level, or whether to backoff to the next level. The function $g(f, f_1, f_2, f_3)$ is the backoff distribution and can be any *non-negative* function of f, f_1, f_2, f_3 (we discuss g further below).

The function $\alpha(f_1, f_2, f_3)$ is produced to ensure that the entire distribution is valid (e.g., non-negative and integrates to unity), and is can be simply derived in way similar to the standard equation:

$$\alpha(f_1, f_2, f_3) = \frac{1 - \sum_{f:N(f,f_1,f_2,f_3)>\tau_4} d_{N(f,f_1,f_2,f_3)} p_{ML}(f|f_1, f_2, f_3)}{\sum_{f:N(f,f_1,f_2,f_3)<=\tau_4} g(f, f_1, f_2, f_3)}$$

It should be noted, however, that the denominator in this equation can not be simplified to use the sum form $\sum_{f:N(f,f_1,f_2,f_3)>\tau_4}$. This is because there is no guarantee that $g(f, f_1, f_2, f_3)$ will sum to unity (it is no-longer a probability distribution, and is only guaranteed to be positive). This inability could lead to significant computational increases when using such language models. As will be seen in the sections below, however, these computational costs are not prohibitive on today's fast computers — many of the experiments were run just on a portable laptop computer (Pentium-3 at 1GHz with 500Mb RAM) during the workshop. Moreover, the SRILM toolkit extensions (to be described in Section 3) attempted to use the $\sum_{f:N(f,f_1,f_2,f_3)>\tau_4}$ form for certain g functions when possible.

The choice of functions $g(f, f_1, f_2, f_3)$ is where the different backoff strategies are determined. For example, in a typical backoff procedure, we would chose $g(f, f_1, f_2, f_3) = p_{BO}(f|f_1, f_2)$. If the factors corresponded to words (using the mapping from factors to words given in the caption in Figure 6, then this corresponds to dropping the most temporally distant word as is typical.

In general, however, $g(f, f_1, f_2, f_3)$ can be any non-negative function, and essentially the same backoff weight algorithm for computing $\alpha(f_1, f_2, f_3)$ can be used. If $g(f, f_1, f_2, f_3)$ were allowed to be negative, then the standard algorithm for producing $\alpha(f_1, f_2, f_3)$ no longer works since the determination of when $g(f, f_1, f_2, f_3)$ is negative for a given f_1, f_2, f_3 might depend on f, something $\alpha(f_1, f_2, f_3)$ may not use. In any event, as we will see the generalization of standard backoff is quite broad even under the assumption of non-negative $g(f, f_1, f_2, f_3)$ functions.

There are a number of possible $g(f, f_1, f_2, f_3)$ that were considered (and as will be seen in Section 3 implemented) during the workshop. These include:

- **Fixed backoff path, standard backoff:** In this case the backoff path is fixed for all times as described in Section 2.2. Notationally, this may be described as follows:

$$g(f, f_1, f_2, f_3) = \begin{cases} p_{BO}(f|f1, f2) & \text{or} \\ p_{BO}(f|f1, f3) & \text{or} \\ p_{BO}(f|f2, f3) & \end{cases}$$

where the "or" means "exclusive or" (so one and only one choice is taken) and where the choice is decided by the user and is fixed for all time. This case therefore includes standard backoff (as in a word n-gram) but also allows for arbitrary fixed (but single) backoff-paths to be specified (see Figure 6).

- **Max Counts:** In this case, the backoff probability model is chosen based on the number of counts of the current "gram" (i.e., random variable assignments). Specifically,

  $$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

  where

  $$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} N(f, f_{m_1}, f_{m_2})$$

  Because this is slightly notationally cumbersome, we here describe this approach in the case when there are only two parents, thus giving the definition for $g(f, f_1, f_2)$. In this case, the above equations can be written as:

  $$g(f, f_1, f_2) = p_{GBO}(f|f_\ell)$$

  where

  $$\ell = \underset{j\in\{1,2\}}{\text{argmax}}\, N(f, f_j)$$

  In other words, for each set of factor values, the backoff model chosen to be the one that corresponds to the factor values that have maximum counts. This means that a different backoff path will be used for each instance, and one will always backoff down the path of maximum counts. This approach tends to prefer backoff models that have better (non-relative) statistical estimation properties, but it ignores the statistical predictability of the resulting backoff models.

- **Max Normalized Counts:** In this case, rather than the absolute counts, the normalized counts are used to determine the backoff model. Thus,

  $$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

  where

  $$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \frac{N(f, f_{m_1}, f_{m_2})}{N(f_{m_1}, f_{m_2})} = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} p_{ML}(f|f_{m_1}, f_{m_2})$$

  This approach therefore chooses the backoff model according to the one that has the highest probability score using the maximum-likelihood distribution. This approach therefore favors models that yield high-predictability possibly at the expense of statistical estimation quality.

- **Max Num-Words Normalized Counts:** In this case, the counts are normalized by the number of possible factor values for a given set of parent values, as computed using the training set.

  The set of possible factor values for a given parent context f_1, f_2, f_3 can be expressed as the following set:

  $$\{f : N(f, f_1, f_2, f_3) > 0\}$$

  and the number of possible following words is equal to the cardinality of this set. Using the standard notation to express set cardinality, we obtain the following equations:

  $$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

  where

  $$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \frac{N(f, f_{m_1}, f_{m_2})}{|\{f : N(f, f_{m_1}, f_{m_2}) > 0\}|}$$

  Note that if the factors correspond to words, then the normalization is equal to the number of possible following words for a given history.

- **Max Backoff-Graph Node Probability:** In this approach, we choose the backoff model to be the one that gives the factor and parent context in question the maximum probability. This can be written as:

$$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

where

$$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \quad p_{GBO}(f|f_{m_1}, f_{m_2})$$

This approach therefore chooses the next backoff graph node to be the one that supplies the highest probability, but where the probability is itself obtained via using a backoff procedure.

- **Max Product-of-Cardinality Normalized Counts:** In this approach, the counts are normalized by the product of the cardinalities of the underlying random variables. In this case, we use the term "cardinality of a random variable" to mean the number of possible values that random variable may take on in the training set. Again using set notation, we will notate the cardinality of a random variable as $|F|$, where the cardinality of a random variable F is taken to be:

$$|F| \triangleq |\{f : N(f) > 0\}|$$

This leads to:

$$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

where

$$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \frac{N(f, f_{m_1}, f_{m_2})}{|F||F_{m_1}||F_{m_2}|}$$

- **Max Sum-of-Cardinality Normalized Counts:** In this case the sum of the of the random variable cardinalities are used for the normalization, giving:

$$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

where

$$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \frac{N(f, f_{m_1}, f_{m_2})}{|F| + |F_{m_1}| + |F_{m_2}|}$$

- **Max Sum-of-Log-Cardinality Normalized Counts:** In this case the sum of the of the random variable natural log cardinalities are used for the normalization, giving:

$$g(f, f_1, f_2, f_3) = p_{GBO}(f|f_{\ell_1}, f_{\ell_2})$$

where

$$(\ell_1, \ell_2) = \underset{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}}{\text{argmax}} \frac{N(f, f_{m_1}, f_{m_2})}{\ln|F| + \ln|F_{m_1}| + \ln|F_{m_2}|}$$

Several other $g(f, f_1, f_2, f_3)$ functions were also implemented, including minimum versions of the above (these are identical to the above except that the the *argmin* rather than the *argmax* function is used. Specifically,

- **Min Counts**
- **Min Normalized Counts**
- **Min Num-Words Normalized Counts**
- **Min Backoff-Graph Node Probability**
- **Min Product-of-Cardinality Normalized Counts**
- **Min Sum-of-Cardinality Normalized Counts**
- **Min Sum-of-Log-Cardinality Normalized Counts**

Still, several more $g(f, f_1, f_2, f_3)$ functions were implemented that take neither the min nor max of their arguments. These include:

- **Sum:**
$$g(f, f_1, f_2, f_3) = \sum_{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}} p_{GBO}(f|f_{m_1}, f_{m_2})$$

- **Average (arithmetic mean):**
$$g(f, f_1, f_2, f_3) = \frac{1}{3} \sum_{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}} p_{GBO}(f|f_{m_1}, f_{m_2})$$

- **Product:**
$$g(f, f_1, f_2, f_3) = \prod_{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}} p_{GBO}(f|f_{m_1}, f_{m_2})$$

- **Geometric Mean:**
$$g(f, f_1, f_2, f_3) = \left(\prod_{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}} p_{GBO}(f|f_{m_1}, f_{m_2}) \right)^{1/3}$$

- **Weighted Mean:**
$$g(f, f_1, f_2, f_3) = \prod_{(m_1,m_2)\in\{(1,2),(1,3),(2,3)\}} p_{GBO}^{\gamma_{m_1,m_2}}(f|f_{m_1}, f_{m_2})$$

  where the weights γ_{m_1,m_2} are specified by the user.

Note that these last examples correspond to approaches where multiple backoff paths are used to form a final probability score rather than a single backoff path for a given factor value and context (as described earlier in this section). Also note that rather taking the sum (respectively average, product, etc.) over all children in the backoff graph, it can be beneficial to take the sum (respectively average, product, etc.) over an *a priori* specified subset of the children. As will be seen, this subset functionality (and all of the above) was implemented as extensions to the SRI toolkit as described in the next section. Readers interested in the perplexity experiments rather than the details of the implementation may wish to skip to Section 4.

3 FLM Programs in the SRI Language Model Toolkit

Significant code extensions were made to the SRI language modeling toolkit SRILM [12] by Jeff Bilmes and Andreas Stolcke in order to support both factored language models and generalized backoff.

Essentially, the SRI toolkit was extended with a graphical-models-like syntax (similar to [2]) to specify a given statistical model. A graph syntax was used to specify the given child variable and its parents, and then a specific syntax was used to specify each possible node in the backoff graph (Figure 5), a set of node options (e.g., type of smoothing), and the set of each nodes possible backoff-graph children. This therefore allowed the possibility to create backoff graphs of the sort shown in the right of Figure 4. The following sections serve to provide complete documentation for the extensions made to the SRILM toolkit.

3.1 New Programs: `fngram` and `fngram-count`

Two new programs have been added to the SRILM program suite. They are `fngram` and `fngram-count`. These programs are analogous to the normal SRILM programs `ngram` and `ngram-count` but they behave in somewhat different ways.

The program `ngram-count` will take a factored language data file (the format is described in Section 3.2) and will produce both a count file and optionally a language model file. The options for this program are described below.

One thing to note about these options is that, unlike `ngram-count`, `fngram-count` does not include command-line options for language model smoothing and discounting at each language model level. This is because potentially a different set of options needs to be specified for each node in the backoff graph (Figure 3). Therefore, the smoothing and discounting options are all specified in the language model description file, described in Section 3.3.
The following are the options for the `fngram-count` program, the program that takes a text (a stream of feature bundles) and estimates factored count files and factored language models.

- `-factor-file` $< str >$ Gives the name of the FLM description file that describes the FLM to use (See Section 3.3).
- `-debug` $< int >$ Gives debugging level for the program.
- `-sort` Sort the ngrams when written to the output file.
- `-text` $< str >$ Text file to read in containing language model training information.
- `-read-counts` Try to read counts information from counts file first. Note that the counts file are specified in the FLM file (Section 3.3).
- `-write-counts` Write counts to file(s). Note that the counts file are specified in the FLM file (Section 3.3).
- `-write-counts-after-lm-train` Write counts to file(s) after (rather than before) LM training. Note that this can have an effect if Kneser-Ney or Modified Kneser-Ney smoothing is in effect, as the smoothing method will change the internal counts. This means that without this option, the non Kneser-Ney counts will be written.
- `-lm` Estimate and write lm to file(s). If not given, just the counts will be computed.
- `-kn-counts-modified` Input counts already modified for KN smoothing, so don't do it internally again.
- `-no-virtual-begin-sentence` Do **not** use a virtual start sentence context at the sentence begin. A FLM description file describes a model for a child variable C given its set of parent variables $P_1, P_2, \ldots, P_N$. The parent variables can reside any distance into the past relative to the parent variable. Let us say that the maximum number of feature bundles (i.e., time slots) into the past is equal to τ. When the child variable corresponds to time slot greater than τ it is always possible to obtain a true parent variable value for LM training. Near the beginning of sentences (i.e., at time slots less than τ) there are no values for one or more parent variable. The normal behavior in this case is to assume a virtual start of sentence value for all of these parent values (so we can think of a sentence as containing an infinite number of start of sentence tokens extending into the past relative to the beginning of the sentence). For example, if an FLM specified a simple trigram model over words, the following contexts would be used at the beginning of a sentence: $< s >$ $< s >$ `w1`, $< s >$ `w1 w2`, `w1 w2 w3`, and so on.

  This is not the typical behavior of SRILM in the case of a trigram, and in order to recover the typical behavior, this option can be used, meaning do not add virtual start of sentence tokens before the beginning of each sentence.

  Note that for an FLM simulating a word-based n gram, if you want to get *exactly* the same smoothed language model probabilities as the standard SRILM programs, you need to include the options `-no-virtual-begin-sentence` and `-nonull`, and make sure `gtmin` options in the FLM are the same as specified on the command line for the usual SRILM programs.
- `-keepunk` Keep the symbol $< unk >$ in LM. When $< unk >$ is in the language model, each factor automatically will contain a special $< unk >$ symbol that becomes part of the valid set of values for a tag. If $< unk >$ is in the vocabulary, then probabilities will (typically) be given for an instance of this symbol even if it does not occur in the training data (because of backoff procedure smoothing, assuming the FLM options use such backoff).

  If $< unk >$ is not in the language model (and it did not occur in training data), then zero probabilities will be returned in this case. If this happens, and the child is equal to the $< unk >$ value, then that will be considered an out-of-vocabulary instance, and a special counter will be incremented (and corresponding statistics reported). This is similar to the standard behavior of SRILM.

- `-nonull` Remove $< NULL >$ from LM. Normally the special word $< NULL >$ is included as a special value for all factors in a FLM. This means that the language model smoothing will also smooth over (and therefore give probability to) the $< NULL >$ token. This option says to remove $< NULL >$ as a special token in the FLM (unless it is encountered in the training data for a particular factor).

  Note that for an FLM simulating a word-based n gram, if you want to get *exactly* the same smoothed language model probabilities as the standard SRILM programs, you need to include the options `-no-virtual-begin-sentence` and `-nonull`, and make sure `gtmin` options in the FLM are the same as specified on the command line for the usual SRILM programs.
- `-meta-tag` Meta tag used to input count-of-count information. Similar to the other SRILM programs.
- `-tolower` Map vocabulary to lowercase. Similar to the other SRILM programs.
- `-vocab` vocab file. Read in the vocabulary specified by the vocab file. This also means that the vocabulary is closed, and anything not in the vocabulary is seen as an OOV.
- `-non-event` non-event word. The ability to specify another "word" that is set to be a special *non-event* word. A non-event word is one that is not smoothed over (so if it is in the vocabulary, it still won't effect LM probabilities). Note that since we are working with FLMs, you need to specify the corresponding tag along with the word in order to get the correct behavior. For example, you would need to specify the non-event word as "`P-noun`" for a part of speech factor, where "`P`" is the tag. Non-events don't count as part of the vocabulary (e.g., the size of the vocabulary), contexts (i.e., parent random variable values) which contain non-events are not estimated or included in a resulting language model, and so on.
- `-nonevents` non-event vocabulary file. Specifies a file that contains a list of non-event words — good if you need to specify more than one additional word as a non-event word.
- `-write-vocab` write vocab to file. Says that the current vocabulary should be written to a file.

The following are the options for the `fngram` program. This program uses the counts and factored language models previously computed, and can either compute perplexity on another file, or can re-score n-best lists. The n-best list rescoring is similar to the

- `-factor-file` build a factored LM, use factors given in file. Same as in `fngram-count`.
- `-debug` debugging level for lm. Same as in `fngram-count`.
- `-skipoovs` skip n-gram contexts containing OOVs.
- `-unk` vocabulary contains $< unk >$ Same as in `fngram-count`.
- `-nonull` remove $< NULL >$ in LM. Same as in `fngram-count`.
- `-tolower` map vocabulary to lowercase. Same as in `fngram-count`.
- `-ppl` text file to compute perplexity from. This specifies a text file (a sequence of feature bundles) on which perplexity should be computed. Note that multiple FLMs from the FLM file might be used to compute perplexity from this file simultaneously. See Section 3.3.
- `-escape` escape prefix to pass data through. Lines that begin with this are printed to the output.
- `-seed` seed for randomization.
- `-vocab` vocab file. Same as in `fngram-count`.
- `-non-event` non-event word. Same as in `fngram-count`.
- `-nonevents` non-event vocabulary file. Same as in `fngram-count`.
- `-write-lm` re-write LM to file. Write the LM to the LM files specified in the FLM specification file.

- `-write-vocab` write LM vocab to file. Same as in `fngram-count`.
- `-rescore` hyp stream input file to rescore. This is similar to the `-rescore` option in the program `ngram` (i.e., `ngram` supports a number of different ways of doing n-best rescoring, while `fngram` supports only one, namely the one corresponding to the `-rescore` option).
- `-separate-lm-scores` print separate lm scores in n-best file. Since an FLM file might contain multiple FLMs, this option says that separate scores for each FLM and for each item in the n-best file should be printed, rather than combining them into one score. This would be useful to, at a later stage, combine the scores for doing language-model weighting.
- `-rescore-lmw` rescoring LM weight. The weight to apply to the language model scores when doing rescoring.
- `-rescore-wtw` rescoring word transition weight. The weight to apply to a word transition when doing rescoring.
- `-noise` noise tag to skip, similar to the normal SRILM programs.
- `-noise-vocab` noise vocabulary to skip, but a list contained in a file. Similar to the normal SRILM programs.

3.2 Factored Language Model Training Data File Format

Typically, language data consists of a set of words which are used to train a given language model. For an FLM, each word might be accompanied by a number of factors. Therefore, rather than a stream of words, a stream of vectors must be specified, since a factored language model can be seen to be a model over multiple streams of data, each stream corresponding to a given factor as it evolves over time.

To support such a representation, language model files are assumed to be a stream of *feature bundles*, where each feature in the bundle is separated from the next by the "`:`" (colon) character, and where each feature consists of a $< tag >$`-`$< value >$ pair.[4] The $< tag >$ can be any string (of any length), and the toolkit will automatically identify the tag strings in a training data file with the corresponding string in the language-model specification file (to be described below). The $< value >$ can be any string that will, by having it exist in the training file, correspond to a valid value of that particular tag. The tag and value are separated by a dash "`-`" character.

A language model training file may contain many more tag-value pairs than are used in a language model specification file — the extra tag-value pairs are simply ignored. Each feature bundle, however, may only have one instance of a particular tag. Also, if for a given feature a tag is missing, then it is assumed to be the special tag "`W`" which typically will indicate that the value is a word. Again, this can happen only one time in a given bundle.

A given tag-value pair may also be missing from a feature bundle. In such a case, it is assumed that the tag exists, but has the special value "`NULL`" which indicates a missing tag (note that the behavior for the start and end of sentence word is different, see below). This value may also be specified explicitly in a feature bundle, such as `S-NULL`. If there are many such NULLs in a given training file, it could reduce file size by not explicitly stating them and using this implicit mechanism.

The following are a number of examples of training files:

```
the brown dog ate a bone
```

In this first example, the language model file consists of a string of what are (presumably) words that have not been tagged. It is therefore assumed that they are words. The sentence is equivalent to the following where the word tags are explicitly given:

```
W-the W-brown W-dog W-ate W-a W-bone
```

If we then wanted to also include part-of-speech information as a separate tag and using the string "`P`" to identify part of speech, then could would be specified as follows:

[4]Note, that the `tag` can be any tag such as a purely data-driven word class, and need not necessarily be a lexical tag or other linguistic part-of-speech tag. The name "tag" here therefore is used to represent any feature.

```
W-the:P-article W-brown:P-adjective W-dog:P-noun
W-ate:P-verb W-a:P-article W-bone:P-noun
```

The order of the individual features within a bundle do not matter, so the above example is identical to the following:

```
P-article:W-the P-adjective:W-brown P-noun:W-dog
P-verb:W-ate P-article:W-a P-noun:W-bone
```

More generally, here is a string from a tagged version of the Call-Home Arabic corpus. Note that the example shows one feature bundle per line only for formatting purposes in this document. In the actual file, an entire sentence of feature bundles is given on each line (i.e., a newline character separates one sentence from the next).

```
<s>
W-Tayyib:M-adj+masc-sg:S-Tayyib:R-Tyb:P-CVyyiC
W-xalAS:M-noun+masc-sg:S-xalAS:R-xlS:P-CaCAC
W-lAzim:M-adj+masc-sg:S-lAzim:R-Azm:P-CVCiC
W-nitkallim:M-verb+subj-1st-plural:S-itkallim:R-klm:P-iCCaCCiC
W-carabi:M-adj+masc-sg:S-carabi:R-crb:P-CaCaCi
W-cala$An:M-prep:S-cala$An:R-cl$:P-CaCaCAn
W-humma:M-pro+nom-3rd-plural:S-humma:R-hm:P-CuCma
W-cayzIn:M-pple-act+plural:S-cAyiz:R-cwz:P-CVyiC
W-%ah:M-%ah:S-%ah:R-%ah:P-%ah
W-il+mukalmaB:M-noun+fem-sg+article:S-mukalmaB:R-klm:P-CuCaCCaB
W-tibqa:M-verb+subj-2nd-masc-sg:S-baqa:R-bqq:P-CaCa
W-bi+il+*FOR:M-bi+il+*FOR:S-bi+il+*FOR:R-bi+il+*FOR:P-bi+il+*FOR
W-*FOR:M-*FOR:S-*FOR:R-*FOR:P-*FOR
W-cala$An:M-prep:S-cala$An:R-cl$:P-CaCaCAn
W-humma:M-pro+nom-3rd-plural:S-humma:R-hm:P-CuCma
W-biysaggilu:M-verb+pres-3rd-plural:S-saggil:R-NULL:P-NULL
</s>
```

The example shows one sentence of Arabic that provides the words (tag name "W"), has been tagged with the morphological class (tag name "M"), the stem (tag name "S"), the root of the word (tag name "R"), and the word pattern (tag name "P"). Just like in a normal word file in SRILM, the sentence begins with the special (word) token $< s >$ to indicate the start of sentence, and $< /s >$ to indicate the end of sentence.

For the purposes of an FLM file, giving a start of sentence without any tags means that all other tags will also have a start of sentence value. Note that this is distinct from the standard missing tag behavior (see above) where a missing tag is filled in with the values `NULL`.

Note that SRILM expects all words (feature bundles) to have the same format (e.g. W-__:M-__:P-__). If a word has fewer features/factors (e.g. a word doesn't have a morph factor), a dummy factor must be inserted.

3.3 Factored Language Model File

An FLM file consists of one or more specifications of a given FLM. When multiple FLMs are specified in a file, each one is simultaneously trained, used for perplexity computation, or used for sentence n-best scoring (depending on the program that is called and the given command-line options, see Section 3.1). This section describes the format and options of these files.

An FLM file may contain comments, which consist of lines that begin with the "##" character pair — anything after that is ignored.

An FLM file begins with an integer N that specifies the number of FLM specifications that are to follow. After the N FLMs, the remainder of the file is ignored, an can be considered to be a comment. The integer N specifies the number of FLMs that are to be simultaneously used by the FLM programs.

Each FLM specification consists of a specification of a child, the number of parents, a set of that many parent names, a count file name, a language model file name, and a sequence of nodes in the corresponding backoff-gram and a set of node options. We next provide a number of simple examples:

Simple Unigram: Here is an FLM for a simple word unigram:

```
## word unigram
W : 0  word_1gram.count.gz word_1gram.lm.gz 1
   0b0 0b0 kndiscount gtmin 1
```

This is a unigram over words (the tag is `W`). It is a unigram because there are zero (0) parents. It uses a count file named `word_1gram.count.gz` and a language model named `word_1gram.lm.gz`, and it specifies one (1) additional backoff-gram node specification which follows on the next line.

The backoff-gram node specification corresponds to the node with no parents (the number `0b0` is a binary string saying that there are no parents). The next number indicates the set of parents that may be dropped, but in this case it is ignored since there are no parents, and then it says that Kneser-Ney discounting should be used, with a minimum `gtmin` count of unity (1) before backing off to (in this case) the unigram.

Simple Trigram: The next example shows an FLM for a standard word-based trigram with a number of options.

```
## normal trigram LM
W : 2 W(-1) W(-2) word_3gram.count.gz word_3gram.lm.gz 3
 W1,W2   W2  kndiscount gtmin 2 interpolate
    W1   W1  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1
```

In this case, the child is again the word variable (tag is `W`), which has two parents, the word at the previous time slot (`W(-1)`), and the word two time-slots into the past (`W(-2)`).[5] It uses a count file named `word_3gram.count.gz`, a language model file named `word_3gram.lm.gz`, and specifies options for three (3) backoff-gram nodes.

The first backoff-graph node corresponds to the complete model, meaning that there are two parents which are the two preceding words. The syntax is `W1` and `W2` which means the preceding word and two words ago. Rather than respecify the time-slot index as being negative, positive indices are used here to shorten the line lengths and since it is never the case that there is a need to specify a model that has parents coming both from the future and the past. In any event, the first backoff-graph node corresponds to the normal trigram since both parents are present, as given by the string `W1,W2`.

The next string in the line is the set of parents that may be dropped in going from this backoff-gram node to nodes in the next level below. In this case, only the parent `W2` may be dropped, so this therefore corresponds to a normal trigram language model where parents are dropped in the priority order of most-distant temporal parent first.

Following this are the set of node options for this node. It says to use Kneser-Ney discounting, to have a minimum count of two (2) in this case, and to produce an interpolated language model between this backoff-graph node and the nodes below.

The next line specifies the node identifier, which is `W1` in this case meaning it is the model containing only the previous word. The next string is also `W1` meaning that that parent may be dropped to go down to the next level, and again a set of node options are given.

The last line gives the unigram model where there are no parents (specified by the number 0), no additional parents may be dropped (again with 0) and a set of node options.

Trigram With Time-Reversed Backoff Path: The next example shows an FLM for a word-based trigram, but where the parent variables are dropped in least-distant-in-time order, the reverse order of what is done in a typical trigram.

```
## trigram with time-reversed backoff path
W : 2 W(-1) W(-2) word_3gram.count.gz word_3gram.lm.gz 3
 W1,W2   W1  kndiscount gtmin 2 interpolate
    W2   W2  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1
```

[5] On the other hand, specifying `W(+1)`, `W(+2)` will specify words in the future.

As can be seen, the backoff graph node for the case where two parents are present (node `W1,W2`) says that only one parent can be dropped, but in this case that parent is `W1`. This means that the next node to be used in the backoff graph corresponds to the model $p(W_t|W_{t-2})$. It should be understood exactly what counts are used to produce this model. $p(W_t|W_{t-2})$ corresponds to the use of counts over a distance of two words, essentially integrating all possible words in between those two words. In other words, this model will use the counts $N(w_{t-2}, w_t) = \sum_{w_{t-1}} N(w_{t-2}, w_{t-1}, w_t)$ to produce, in the maximum likelihood case (i.e., no smoothing), the model $p_{ML}(W_t|W_{t-2}) = N(w_{t-2}, w_t)/N(w_{t-2})$ where $N(w_{t-2}) = \sum_{w_t} N(w_{t-2}, w_t)$.

Note that this model is quite distinct from the case where the model $p(W_t|W_{t-1})$ is used, but where the word from two time slots ago is substituted into the position of the previous word (this is what a SRILM skip-n-gram would do). We use the following notation to make the distinction. The FLM above corresponds to the case where $P(W_t = w_t|W_{t-2} = w_{t-2})$ is used for the backoff-graph node probability. A skip-n-gram, on the other hand, would utilize (for the sake of interpolation) $P(W_t = w_t|W_{t-1} = w_{t-2})$ where the random variable W_{t-1} is taken to have the value of the word w_{t-2} from two time-slots into the past. In this latter case, the same actual counts are used $N(w_t, w_{t-1})$ to produce the probability, only the word value is changed. In the former case, an entirely different count quantity $N(w_t, w_{t-2})$ is used.

Note that a skip-n-gram would not work in the case where the parents correspond to different types of random variables (e.g., if parents were words, stems, morphs, and so on). For example, if one parent is a word and another is a stem, one could not substitute the stem in place of the word unless a super-class is created that is the union of both words and stems. Such a super-class could have an effect on smoothing (in particular for the Kneser-Ney case) and table storage size. A FLM allows different random variable types to be treated differently in each parent variable, and allows counts to be computed separately for each subset of parents.

Stem Given Morph and 2-Word Context: Our next example is where the child and parent variables are not of the same type (i.e., they are not all words). This example corresponds to a probability model for $p(S_t|M_t, W_{t-1}, W_{t-2})$ where S_t is the stem at time t, M_t is a morphological class at time t, and W_t is the word at time t. This model can be specified as follows:

```
## stem given morph word word
S : 3 M(0) W(-1) W(-2) s_g_m0w1w2.count.gz s_g_m0w1w2.lm.gz 4
  M0,W1,W2  W2 kndiscount gtmin 1 interpolate
  M0,W1     W1 kndiscount gtmin 1 interpolate
  M0        M0 kndiscount gtmin 1
  0         0  kndiscount gtmin 1
```

In this case, the stem `S` at time t is given as the child variable, and there are three parents: 1) the morph at the current time `M(0)`, 2) the word at the previous time `W(-1)`, and 3) the word two time-slots ago `W(-2)`. It produces and uses a count file named `s_g_m0w1w2.count.gz` and a language model file named `s_g_m0w1w2.lm.gz`, and specifies options for four backoff-graph nodes.

The first node, as always, corresponds to when all parent variables are present `M0,W1,W2`. This node will back-off only to the case when one parent is dropped, namely `W2`. Again it uses Kneser-Ney smoothing with a minimum count of unity and interpolation. The next node (on the next line) is for the case when the parents `M0,W1` are present (i.e., the backoff-graph node above when the parent `W2`) has been dropped. This node may only drop parent `W1`, and has similar additional node options. The next two lines specify last two backoff-graph node options, namely for nodes `M0` and for the case when there are no parents. The options should be clear at this point from the above discussion.

Note that all of the examples we have encountered so far correspond to a fixed and single backoff path from root to leaf node (as shown in the examples in Figure 6). The next several examples indicate multiple backoff-paths.

trigram with generalized backoff: The following example shows a trigram that allows a backoff path, meaning that both backoff-paths in the backoff graph are traversed in order to obtain a final probability. This case therefore must specify and use one of the combining functions mentioned in Section 2.3.

Here is the example:

```
## general backoff, max trigram LM
W : 2 W(-1) W(-2) word_gen3gram.max.count.gz word_gen3gram.max.lm.gz 4
   W1,W2 W1,W2 kndiscount gtmin 2 combine max strategy bog_node_prob interpolate
```

```
  W2    W2    kndiscount gtmin 1 interpolate
  W1    W1    kndiscount gtmin 1 interpolate
  0     0     kndiscount gtmin 1 kn-count-parent 0b11
```

In this case, four backoff graph nodes are specified. The first (as always) is the case when all parents are present, in this case `W1,W2`. The next field says that both parents `W1,W2` are allowed to drop to descend down to the next level. In other words, the next field is a set of parents which may be dropped one-by-one, and implicitly defines the set of lower nodes in the backoff graph. This is then followed by a set of node options: Kneser-Ney discounting, a minimum count of two, and a combination strategy that takes the maximum `max` of the lower nodes' backoff graph probabilities `bog_node_prob` (backoff-graph node probability). This option therefore corresponds to the *Max Backoff-Graph Node Probability* case given in Section 2.3.

The remaining nodes in the backoff graph are specified in the same way as given in the examples above.

Dropping more than one parent at a time - Skipping a level in an FLM backoff-graph: Using the mechanism of minimum counts (`gtmin`), it is possible also to produce FLMs that skip an entire level on the backoff-graph altogether. In other words, this is the case when it is desirable to drop more than one parent at a time, going from, say, the model $P(C|P_1, P_2, P_3)$ backing off directly to either $P(C|P_1)$ or $P(C|P_2)$.

The following provides an example of how this can be done.

```
## word given word morph stem
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine mean
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

In this case, the first backoff-graph node `W1,M1,S1` containing all parents (and corresponding to $p(W_t|W_{t-1}, M_{t-1}, S_{t-1})$ says that only the word variable may be dropped, moving down to node `M1,S1` (model $p(W_t|M_{t-1}, S_{t-1})$). . This node, however, has a very large minimum count threshold (a `gtmin` of $100,000,000$). This means that this node in the language model will not "hit", and all scores from this backoff graph node will be a combination of the lower-level backoff graph nodes. The node says that both parents `S1` and `M1` may be dropped, meaning that there are two models at the next lower level in the backoff graph, corresponding to models $p(W_t|M_{t-1})$ and $p(W_t|S_{t-1})$. The mean of the probabilities of these models will be used to produce a score for the `M1,S1` node (and this is specified by the string `combine mean`).

As can be seen, using a combination of a restricted set of parents that may be dropped at a given backoff-graph node, and a very large `gtmin` count, a wide variety of backoff graphs (some of which can even skip levels) can be specified.

General Description of FLM syntax: The above examples gave a taste of some of the language models that can be specified using the syntax. This section describes the syntax and functionality in the most general case. Many of these models will be used and further described in Section 4.

A FLM consists of a *model specifier* line of text, followed by one or more *node specifier* lines of text.

The *model specifier* line is a graphical-model inspired syntax for specifying a statistical model over the tags that exist in a set of training data. This line takes the form:

```
child : num_parents par_1 par_2 ... par_N  cnt_file lm_file num_bg_nodes
```

The name `child` is the child random variable, and corresponds to any one of the tags that exist in language model training data. For example, using the tags that are specified in the CallHome training file given in Section 3.2, the child could be any of the strings `W`, `M`, `S`, `R`, or `P`.

The next field is the number of parent random variables in the model, and is an integer $N \geq 0$.

The next set of fields are the N parents, each one taking the form `parent_name(time_offset)`. The string `parent_name` can again be any of the tags that exist in the training data. The `time_offset` value is an integer that gives how many time-slots into the past or future the parent should reside (e.g. -1 indicates previous factor, +1 indicates next factor.)

What follows is a name to be used for the count file (keeping language model counts) and then the name of the language model file. Note that both count files and language model file are specified since counts are, for certain cases as described in Section 2.3, needed to determine the backoff probability.

The last field on the line is `num_bg_nodes`, which is the number of backoff-graph node specifications that are following. Only the next such-number of lines are assumed to be part of the FLM file (anything after that is either ignored, or is assumed to be part of the next FLM specified in the file). One should be careful to ensure that the number of actual backoff-graph node specifiers given is equal to this number, as it is easy to add more node specifiers while forgetting to update this field.

Once the *model specifier* is given, it is followed by `num_bg_nodes` *model specifier*s. Each *model specifier* consists of the following form:

```
parent_list drop_list [node options]
```

The `parent_list` is a comma-separated list (without spaces) of parent variables that correspond to this node. In other words, each node in a backoff graph can be identified with a set of parent variables, and this string identifies the node by giving that set. The parents are specified in a shortened syntax — each parent is given using its name (again one of the tags in the file), and the absolute value of the time offset with no space. Examples of parent lists include `W1,W2,W3` to give the three preceding words, `W1,M1,S1` to give the preceding word, morph, and stem, and so on.

The next field `drop_list` gives the list of parents that may be dropped one at a time from this backoff-graph node. This is the field that specifies the set of lower-level backoff-graph nodes that are used in case there is not a language-model "hit" at this level. For example, if `parent_list` is `W1,M1,S1` and `drop_list` is `W1`, then the only next lower-level node used is the one with `parent_list` `M1,S1`. If, on the other hand, a `drop_list` of `W1,M1,S1` is used for parent list `W1,M1,S1`, then three nodes are used for the next lower-level — namely, the nodes with parent lists `M1,S1`, `W1,S1`, and `W1,M1`.

The node options are one or more option for this backoff-graph node. Each backoff-graph node can have its own discounting, smoothing, combination options, and so on. Many of the node options are similar to the command-line options that can be given to the SRLIM program `ngram-count`. These options are included in the FLM file because a different set might be given for each node. The following gives a list of all the node options that are currently supported.

- `gtmin [num]` the lower GT discounting cutoff. When not using Good-Turing discounting, this gives the threshold that the count needs to meet or exceed in order for there to be a language model "hit" at this backoff graph node. Therefore, `gtmin` corresponds to the τ variables in the equations given in Section 2.
- `gtmax [num]` upper GT discounting cutoff. Note that if only this and `gtmin` are specified, then Good-Turing smoothing is used.
- `gt [fileName string]` Good-Turing discount parameter file for this node.
- `cdiscount [double]` Says that constant discounting should be used, and this gives the discounting constant.
- `ndiscount` Says that natural discounting should be used.
- `wbdiscount` Says that Witten-Bell discounting should be used.
- `kndiscount` Says that modified Kneser-Ney discounting should be used.
- `ukndiscount` Says that *unmodified* (i.e., the original or normal) Kneser-Ney discounting should be used.
- `kn-counts-modified` says that the input counts already modified for KN smoothing (this is similar to `ngram-count`.
- `kn-counts-modify-at-end` says that the counts should be turned into KN-counts after discount estimation rather than before. In other words, if this option is specified, the quantities such as n_1, n_2, n_3, n_4, and so on (typically used for modified KN discounting) should be computed from the usual counts rather than from the meta-meta-counts needed for Kneser-Ney smoothing.

- `kn [fileName string]` The Kneser-Ney discount parameter file for this backoff-graph node.
- `kn-count-parent [parent spec]` The backoff-graph parent that is used to compute the meta-meta-counts needed for Kneser-Ney smoothing. Normally, the parent is the node immediately above the current node in the backoff graph, but it is sometimes useful to specify a different parent, especially when the set of parents do not correspond to the same random variables at different times (i.e., when the parents are truly different random variables).
- `interpolate` use interpolated estimates for computing the probabilities for this node. In other words, the probabilities should be interpolated with hits in the current nodes and whatever the $g()$ function returns for the lower node probabilities. This is therefore a generalization of the `interpolated` option in `ngram-count`.
- `write [fileName string]` Write the counts, just of this node alone, to the given file.
- `combine [option]` This option is active only when there multiple backoff paths (backoff-graph children) possible (i.e., when the `drop_list` specifies more than one parent variable. See Section 2.3. In this case, `[option]` is one of:
  - `max` the maximum of the next backoff-graph level nodes. This is the **default** if no `combine` option is given.
  - `min` the maximum of the next backoff-graph level nodes
  - `sum` the maximum of the next backoff-graph level nodes
  - `avg||mean` the arithmetic average (mean) of the next backoff-graph level nodes
  - `prod` the product of the next backoff-graph level nodes
  - `gmean` the geometric mean of the next backoff-graph level nodes
  - `wmean [` $< node\_specweight > < node\_specweight >$ `... ]` the weighted mean of the next backoff-graph level nodes. The weights are given by providing a node specification (a list of comma separated parents) to identify the node, and then a weight for that node. For example, one might used:

    ```
    wmean W1,M2 7 W1,S2 3
    ```

    which means that backoff-grpah node `W1,M2` has a weight of 7, and node `W1,S2` has a weight of 3.
- `strategy [option]` This option also is active only when there are multiple backoff paths (backoff-graph children) possible, and when the `combine` option above is either `min` or `max`. See Section 2.3 for more information. In this case, `[option]` is one of:
  - `counts_sum_counts_norm` The *Max/Min Normalized Counts* cases in Section 2.3. This is the default case if no `strategy` option is given.
  - `counts_no_norm` The *Max/Min Counts* cases in Section 2.3.
  - `counts_sum_num_words_norm` The *Max/Min Num-Words Normalized Counts* cases in Section 2.3.
  - `counts_prod_card_norm` The *Max/Min Product-of-Cardinality Normalized Counts* cases in Section 2.3.
  - `counts_sum_card_norm` The *Max/Min Sum-of-Cardinality Normalized Counts* cases in Section 2.3.
  - `counts_sum_log_card_norm` The *Max/Min Sum-of-Log-Cardinality Normalized Counts* cases in Section 2.3.
  - `bog_node_prob` The *Max/Min Backoff-Graph Node Probability* cases in Section 2.3.

Other ways to specify backoff-graph nodes and drop sets. A backoff graph node is typically identified using a comma separated list of parents. Similarly, a set of parents that may be dropped is also specified using such a list. In some cases, specifying these lists can be tedious, and it might be more concise (albeit more error prone) to specify nodes and sets using a numeric representation.

Each parent list may also be specified using an integer, where the integer is a bit representation of the parents in the set. When the line in the FLM file is given of the form:

```
child : num_parents par_1 par_2 ... par_N  cnt_file lm_file num_bg_nodes
```

then `par_1` corresponds to bit 0, `par_2` corresponds to bit 1, and so on until `par_N` corresponds to bit $N-1$, in an N-element bit vector. This means that the left-most parent corresponds to the least significant bit, and the right most parent the most significant bit. The reason for this is, given the string `W(-1) W(-2) W(-3)` as a parent list, the right-most parent is the *highest-order* parent.

These bit vectors may be specified numerically rather than as a string form of a list of parents. The numeric form may be either a decimal integer, a hexadecimal integer (one preceded by `0x`), or a binary integer (one preceded by `0b`).

For example, a normal trigram can be specified as follows:

```
W : 2 W(-1) W(-2) word_3gram_rev.count.gz word_3gram_rev.lm 3
  0b11 0b10 kndiscount gtmin 1
  0b01 0b01 kndiscount gtmin 1
  0b00 0b00 kndiscount gtmin 1
```

a construct equivalent to the following:

```
W : 2 W(-1) W(-2) word_3gram_rev.count.gz word_3gram_rev.lm 3
  0x3 0x2 kndiscount gtmin 1
  0x1 0x1 kndiscount gtmin 1
  0x0 0x0 kndiscount gtmin 1
```

Any combination of decimal, hexadecimal, binary, and string form can be used in an FLM file, so the following is valid.

```
W : 2 W(-1) W(-2) word_3gram_rev.count.gz word_3gram_rev.lm 3
  W1,W2 0b10 kndiscount gtmin 1
  0b01 W1 kndiscount gtmin 1
  0    0 kndiscount gtmin 1
```

One way that this can be useful is when specifying very large backoff-graphs with little sparsity. For example, the example in Figure 7 shows an FLM for generalize backoff when there six parents, and all backoff-paths are taken. As can be seen, the use of a numeric representation to specify parents greatly facilitates the declaration of this model.

4 A Step-by-Step Walk-through of using FLMs for language modeling

In this section, we present a number of perplexity experiments when using FLMs and generalized backoff on the CallHome Arabic corpus. This is intended as a step-by-step walk-through that demonstrates various types of FLMs on real data.

The CallHome Arabic corpus is prepared as a factored text file with words (tag name "`W`"), morphological classes (tag name "`M`"), stems (tag name "`S`"), word roots (tag name "`R`"), and words patterns (tag name "`P`"). For details regarding how the data was prepared, see [10]. In this case, therefore, the first of the two design issues for an FLM as given in Section 1.2 are solved — the factors are defined. It is therefore necessary to find a good statistical model over these factors, one that minimizes perplexity or, say, word-error rate in a speech recognition system.

In order to report all information regarding an FLM, it is necessary not only to report the factors that are used and the model structure over those factors, but also the generalized backoff method and the other smoothing options at each node in the backoff graph. Since all of this information is given in the FLM definition (see Section 3.3), we will here use the FLM definitions themselves to provide this information.

We begin by providing the perplexity for a simple optimized unigram, bigram, and trigram language model.

```
## normal unigram LM
## 0 zeroprobs, logprob= -93324.9 ppl= 279.382 ppl1= 799.793
W : 0 word_1gram.count.gz word_1gram.lm.gz 1
     0    0  kndiscount gtmin 1
```

```
## word given word word morph morph stem stem model, all backoff paths.
## gtmin set to the number of bits set in the node. This model will
## take about 2 days to train on a typical machine.
W : 6 W(-1) W(-2) S(-1) S(-2) M(-1) M(-2) w_g_w1w2s1s2m1m2.count.gz w_g_w1w2s1s2m1m2.lm.gz 64
 0x3F 0xFF gtmin 6 kndiscount strategy bog_node_prob combine max
 0x3E 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x3D 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x3C 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x3B 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x3A 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x39 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x38 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x37 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x36 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x35 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x34 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x33 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x32 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x31 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x30 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x2F 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x2E 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x2D 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x2C 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x2B 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x2A 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x29 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x28 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x27 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x26 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x25 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x24 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x23 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x22 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x21 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x20 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x1F 0xFF gtmin 5 kndiscount strategy bog_node_prob combine max
 0x1E 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x1D 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x1C 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x1B 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x1A 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x19 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x18 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x17 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x16 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x15 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x14 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x13 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x12 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x11 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x10 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x0F 0xFF gtmin 4 kndiscount strategy bog_node_prob combine max
 0x0E 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x0D 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x0C 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x0B 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x0A 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x09 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x08 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x07 0xFF gtmin 3 kndiscount strategy bog_node_prob combine max
 0x06 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x05 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x04 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x03 0xFF gtmin 2 kndiscount strategy bog_node_prob combine max
 0x02 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x01 0xFF gtmin 1 kndiscount strategy bog_node_prob combine max
 0x00 0xFF gtmin 0 kndiscount strategy bog_node_prob combine max
```

Figure 7: A large FLM model for W with six parents, and all $2^6 = 64$ backoff nodes are utilized.

```
## normal bigram LM
## 0 zeroprobs, logprob= -85610.4 ppl= 175.384 ppl1= 460.267
W : 1 W(-1) word_2gram.count.gz word_2gram.lm.gz 2
    W1   W1  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1
```

```
## BASLINE TRIGRAM: normal trigram LM
## logprob= -85370 ppl= 172.857 ppl1= 452.409
W : 2 W(-1) W(-2) word_3gram.count.gz word_3gram.lm.gz 3
 W1,W2   W2  kndiscount gtmin 2 interpolate
    W1   W1  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1
```

As can be seen, the unigram achieves a perplexity of 279, while the introduction of the previous word as a parent results in 175, and the previous two words achieves 173 (our baseline for this section). It appears that the addition of the additional parent does not yield a significant additional amount of information.

Next we produce results for the distance-2 bigram and context-reversed trigram in order to verify this assumption.

```
## distance 2 bigram LM
## 0 zeroprobs, logprob= -94994.7 ppl= 309.005 ppl1= 901.399
W : 1 W(-2) word_2gram.count.gz word_2gram.lm.gz 2
    W2   W2  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1

## distance 2 bigram LM
## 0 zeroprobs, logprob= -93324.9 ppl= 279.382 ppl1= 799.793
W : 1 W(-2) word_2gram.count.gz word_2gram.lm.gz 2
    W2   W2  kndiscount gtmin 1 interpolate
     0    0  gtmin 1

## context-reversed trigram LM
## 0 zeroprobs, logprob= -93040.3 ppl= 274.623 ppl1= 783.652
W : 2 W(-1) W(-2) word_3gram.count.gz word_3gram.lm.gz 3
 W1,W2   W1  kndiscount gtmin 2 interpolate
    W2   W2  kndiscount gtmin 1 interpolate
     0    0  kndiscount gtmin 1
```

Note that these models utilize the distance-2 counts The FLM above corresponds to case where the probability model $P(W_t = w_t | W_{t-2} = w_{t-2})$, so the previous word is entirely not present. This means that the counts for this table correspond to the quantity $N(w_t, w_{t-2})$. The verbatim section shows two models, one where the uni-gram node uses Kneser-Ney discounting (the first one) and one where that is not the case. As can be seen, neither of these perplexities (309 and 279) beat even the case of the unigram language model above (perplexity of 279). This does not mean, however, that the parent $W(-2)$ is not informative — it means only that the additional information that it provides is not sufficient to offset the loss in estimation quality. The third example shows the context-reversed trigram, where the model $p(W_t|W_{t-1}, W_{t-2})$ backs off first to $p(W_t|W_{t-2})$ and then to $p(W_t)$. This example corresponds to a different backoff-path in the backoff graph. Again, we see that while this is a bit better than the distance-2 bigram, by choosing the wrong backoff parent order (in this case, reverse time), perplexity can increase.

This last example shows how crucial it is to obtain a language model and use a set of parent random variables that balance predictability while at the same time do not decrease estimation accuracy. Predictability can be improved for example by choosing parents that have a high degree of mutual information with a child. If a given parent has a large number of values, however, estimation quality can decrease because the amount of training data for each value of the parent variable is reduced. The balance must of course be seen in the context of language-model backoff, since backoff is an attempt to utilize high predictability in a context where estimation quality is high, but to backoff to a lower-order model (where, essentially, different sets of parent values are pooled together) in order to improve estimation quality.

Next, we present results where the word depends on a number of different factors at the same time in order to determine which factors, by themselves yield the most information about a word.

```
## word given M
## 0 zeroprobs, logprob= -39289.7 ppl= 10.7114 ppl1= 16.6782
W : 1 M(0) wgm.count.gz wgm.lm.gz 2
    M0   M0  kndiscount gtmin 1 interpolate
    0    0  gtmin 1

## word given S
## 0 zeroprobs, logprob= -21739.2 ppl= 3.71382 ppl1= 4.74486
W : 1 S(0) wgs.count.gz wgs.lm.gz 2
    S0   S0  kndiscount gtmin 1 interpolate
    0    0  gtmin 1
```

```
## word given R
## 0 zeroprobs, logprob= -31967.6 ppl= 6.88531 ppl1= 9.87163
W : 1 R(0) wgr.count.gz wgr.lm.gz 2
    R0   R0  kndiscount gtmin 1 interpolate
    0    0  gtmin 1

## word given P
## 0 zeroprobs, logprob= -38468.2 ppl= 10.1933 ppl1= 15.7253
W : 1 P(0) wgp.count.gz wgp.lm.gz 2
    P0   P0  kndiscount gtmin 1 interpolate
    0    0  gtmin 1
```

As can be seen, all of the perplexities are quite low, meaning that the factors for a word if known at the same time as the word are quite informative. We can see that the stem $P(W_t|S_t)$ is the most predictive of the word, with a perplexity of 3.7. This is followed by the root $P(W_t|R_t)$ (perplexity 6.9), pattern $P(W_t|P_t)$ (perplexity 10.2), and the morphological class $P(W_t|M_t)$ (perplexity 10.7).

Note that even though these perplexities are low, to use this during decoding in a language model, it is necessary also to obtain probability models for the corresponding parent. For example, if the $P(W_t|S_t)$ model is used in decoding, it is necessary to utilize a model $P(S_t|\text{parents})$.

In any case, it is also possible to combine these as parents as the following shows (note that in this case Witten-Bell smoothing was used as it was found to be better).

```
## word given stem morph,
## 0 zeroprobs, logprob= -10497.6 ppl= 1.88434 ppl1= 2.12099
W : 2 S(0) M(0) wgsm1.count.gz wgsm1.lm.gz 3
  S0,M0 M0 wbdiscount gtmin 1 interpolate
  S0    S0 wbdiscount gtmin 1
  0     0  wbdiscount gtmin 1

## word given stem morph,
## 0 zeroprobs, logprob= -11571.3 ppl= 2.01049 ppl1= 2.29054
W : 2 S(0) M(0) wgsm2.count.gz wgsm2.lm.gz 3
  S0,M0 S0 wbdiscount gtmin 1 interpolate
  M0    M0 wbdiscount gtmin 1
  0     0  wbdiscount gtmin 1

## word given stem root,
## 0 zeroprobs, logprob= -17954.1 ppl= 2.95534 ppl1= 3.61812
W : 2 S(0) R(0) wgsr1.count.gz wgsr1.lm.gz 3
  S0,R0 R0 wbdiscount gtmin 1 interpolate
  S0    S0 wbdiscount gtmin 1
  0     0  wbdiscount gtmin 1

## word given stem root,
## 0 zeroprobs, logprob= -18861.2 ppl= 3.12163 ppl1= 3.86099
W : 2 S(0) R(0) wgsr2.count.gz wgsr2.lm.gz 3
  S0,R0 S0 wbdiscount gtmin 1 interpolate
  R0    R0 wbdiscount gtmin 1
  0     0  wbdiscount gtmin 1
```

As can be seen, the best example uses as parents both the stem and the morph, parents that do *not* correspond to the best two individual parents in the previous example (stem and root). This example therefore indicates that the two best parents can be redundant with respect to each other. This example also shows the effect of different backoff paths. The first stem-morph model first chooses to drop the morph and then the stem (perplexity of 1.88), and the second stem-morph example drops first the stem and then the morph (perplexity of 2.01). Again, different backoff orders can lead to differences in perplexity, which can at times be quite dramatic.

Next, we investigate a number of different models for the current morph and stem (i.e., $P(M_t|\text{parents})$ and $P(S_t|\text{parents})$ where parents come from the past) to see if they might lead to low perplexity when combined with the models above for $P(W_t|S_t, M_t)$. The first set utilize the previous two words along with possibly the other corresponding factors.

```
## morph given word word
## 0 zeroprobs, logprob= -73287 ppl= 83.3629 ppl1= 190.404
M : 2 W(-1) W(-2) m_g_w1w2.count.gz m_g_w1w2.lm.gz 3
  W1,W2  W2 kndiscount gtmin 1 interpolate
  W1     W1 kndiscount gtmin 1 interpolate
  0      0  kndiscount gtmin 1

## morph given stem word word
## 0 zeroprobs, logprob= -25741.1 ppl= 4.72842 ppl1= 6.31983
M : 3 S(0) W(-1) W(-2) m_g_s1w1w2.count.gz m_g_s1w1w2.lm.gz 4
  S0,W1,W2  W2 kndiscount gtmin 1 interpolate
  S0,W1     W1 kndiscount gtmin 1 interpolate
  S0        S0 kndiscount gtmin 1
  0         0  kndiscount gtmin 1

## stem given word word
## 0 zeroprobs, logprob= -87686.6 ppl= 198.796 ppl1= 534.061
S : 2 W(-1) W(-2) s_g_w1w2.count.gz s_g_w1w2.lm.gz 3
  W1,W2  W2 kndiscount gtmin 1 interpolate
  W1     W1 kndiscount gtmin 1 interpolate
  0      0  kndiscount gtmin 1

## stem given morph word word
## 0 zeroprobs, logprob= -39275.6 ppl= 10.7023 ppl1= 16.6614
S : 3 M(0) W(-1) W(-2) s_g_m0w1w2.count.gz s_g_m0w1w2.lm.gz 4
  M0,W1,W2  W2 kndiscount gtmin 1 interpolate
  M0,W1     W1 kndiscount gtmin 1 interpolate
  M0        M0 kndiscount gtmin 1
  0         0  kndiscount gtmin 1
```

The first model is for $P(M_t|W_{t-1}, W_{t-2})$ and shows a perplexity of 83. The second model adds an additional parent $P(M_t|S_t, W_{t-1}, W_{t-2})$ reducing the perplexity to 4.7. While this might sound encouraging, this latter model could be used with the model for $P(S_t|W_{t-1}, W_{t-2})$ with a perplexity of 198.8. Therefore, these last two models could be used with $P(W_t|S_t, M_t)$ to yield a total perplexity of $4.7 \times 198.8 \times 1.88 = 1756.6$, a value *much* higher than the baseline trigram perplexity of 172.9. Alternatively, the $P(M_t|W_{t-1}, W_{t-2})$ model could be used with the $P(S_t|M_t, W_{t-1}, W_{t-2})$ model leading to $4.7 \times 83 \times 10.7 = 4174.1$ (a graph for this model is shown in Figure 1). Apparently there is a perplexity cost to split the word into factors as such and model each factor separately (possibly due to the fact that multiple smoothings are occurring). Note that this is exactly a form of a class-based language model, or perhaps more precisely a factored-class-based language model since the word class (M_t, S_t) is represented in factored form as is class model.

Next, we provide perplexities for word-based language models where the factors additional to words can be used as parents. We present a number of models in this category, leading up to a bigram model that ultimately will improve on our baseline.

```
## word given word-1 word-2 morph-1 morph-2
## 0 zeroprobs, logprob= -85748.4 ppl= 176.85 ppl1= 464.838
W : 4  W(-1) W(-2) M(-1) M(-2) w_g4_w1w2m1m2.count.gz s_g4_w1w2m1m2.lm.gz 5
 0b1111 0b0010 kndiscount gtmin 4 interpolate
 0b1101 0b1000 kndiscount gtmin 3 interpolate
 0b0101 0b0001 kndiscount gtmin 2 interpolate
 0b0100 0b0100 kndiscount gtmin 1 interpolate
 0b0000 0b0000 kndiscount gtmin 1

## word given word-1 word-2 stem-1 stem-2
## 0 zeroprobs, logprob= -85522.1 ppl= 174.452 ppl1= 457.366
W : 4  W(-1) W(-2) S(-1) S(-2) w_g4_w1w2s1s2.count.gz s_g4_w1w2s1s2.lm.gz 5
 0b1111 0b0010 kndiscount gtmin 4 interpolate
 0b1101 0b1000 kndiscount gtmin 3 interpolate
 0b0101 0b0001 kndiscount gtmin 2 interpolate
 0b0100 0b0100 kndiscount gtmin 1 interpolate
 0b0000 0b0000 kndiscount gtmin 1

## word given word-1 word-2 morph-1 stem_2
## 0 zeroprobs, logprob= -85732.8 ppl= 176.684 ppl1= 464.319
W : 4  W(-1) W(-2) M(-1) S(-2) w_g4_w1w2m1s2.count.gz s_g4_w1w2m1s2.lm.gz 5
 0b1111 0b0010 kndiscount gtmin 4 interpolate
 0b1101 0b1000 kndiscount gtmin 3 interpolate
 0b0101 0b0001 kndiscount gtmin 2 interpolate
 0b0100 0b0100 kndiscount gtmin 1 interpolate
 0b0000 0b0000 kndiscount gtmin 1


## word given word-1 word-2 stem-1 morph-2
## 0 zeroprobs, logprob= -85543 ppl= 174.672 ppl1= 458.051
W : 4  W(-1) W(-2) S(-1) M(-2) w_g4_w1w2s1m2.count.gz s_g4_w1w2s1m2.lm.gz 5
 0b1111 0b0010 kndiscount gtmin 4 interpolate
 0b1101 0b1000 kndiscount gtmin 3 interpolate
 0b0101 0b0001 kndiscount gtmin 2 interpolate
 0b0100 0b0100 kndiscount gtmin 1 interpolate
 0b0000 0b0000 kndiscount gtmin 1
```

Note that in this set, the parent node identifiers and backoff selectors are specified using binary strings rather than a comma-separated list of parents (see Section 3.3). In all cases, however, the additional parents actually *increase* the perplexity relative to the baseline.

In general, the following question might be asked at this point. Why should one include additional parents to a model when the parents are a deterministic function of pre-existing parents? For example, the stem is a deterministic function of the word, which means that $P(W_t|W_{t-1}, S_{t-1}) = P(W_t|W_{t-1})$, or that the current word is conditionally independent of the previous stem given the previous word. The answer, however, is that we are not using the true probability distributions. Instead, we are used models that have been estimated using the backoff method. There might be a word context that did not exist in the training data, but the corresponding stems for those words that did not occur as a context in training might exist in training data via other words that had the same stems. In other words, suppose the context w_{t-1}, w_{t-2} in $P(w_t|w_{t-1}, w_{t-2})$ did not occur in training data but w'_{t-1}, w'_{t-2} as a context for w_t did occur in training data. Also suppose that both w_{t-1}, w_{t-2} and w'_{t-1}, w'_{t-2} have the same corresponding stems s_{t-1}, s_{t-2}. Then it would be the case that while $P(w_t|w_{t-1}, w_{t-2})$ would need to backoff to the unigram, $P(w_t|w_{t-1}, w_{t-2}, s_{t-1}, s_{t-2})$ would backoff only to $P(w_t|s_{t-1}, s_{t-2})$ presumably providing a better prediction for w_t than only the unigram model. The argument can be seen as a standard bias-variance tradeoff in statistics – we add bias to the model in the form of backoff in order to reduce the variance of the estimate. We will try to exploit this fact below.

Consider the following model.

```
##  logprob= -85087.9 ppl= 169.939 ppl1= 443.359
W : 6 W(-1) M(-1) S(-1) W(-2) M(-2) S(-2) dev.count.gz dev.lm.gz 7
  W1,M1,S1,W2,M2,S2  W2 kndiscount gtmin 2 interpolate
  W1,M1,S1,M2,S2     S2 kndiscount gtmin 40000000 interpolate
  W1,M1,S1,M2        S1 kndiscount gtmin 40000000 interpolate
  W1,M1,M2           M2 kndiscount gtmin 40000000 interpolate
  W1,M1              W1 kndiscount gtmin 1 interpolate kn-count-parent 0b111111
  M1                 M1 kndiscount gtmin 3
  0                  0  kndiscount gtmin 1 kn-count-parent W1,M1
```

This model can be seen to improve on our baseline perplexity by a small amount. The model first attempts to utilize the entire context — since both stems and morphs are deterministic functions of words, the context `W1,M1,S1,W2,M2,S2` is identical to that of `W1,W2`. If that context does not exist in the training data (with a count of 2 or more), we drop the parents `W2`, `W2`, and `S1` (via very large min-counts as described in Section 3.3) and "land" on node `W1,M1`. This node is attempted and used if a hit occurs, and otherwise the previous word is dropped, moving down until the unigram.

The next example improves on this as follows.

```
## logprob= -84924.5 ppl= 168.271 ppl1= 438.201
W : 6 W(-1) W(-2) M(-1) S(-1) M(-2) S(-2) dev.count.gz dev.lm.gz 9
  W1,W2,M1,S1,M2,S2  W2 kndiscount gtmin 3 interpolate
  W1,M1,S1,M2,S2     S2,M2 kndiscount gtmin 10000000 combine mean
  W1,M1,S1,M2        M2 kndiscount gtmin 4 kn-count-parent 0b111111
  W1,M1,S1,S2        S2 kndiscount gtmin 2 kn-count-parent 0b111111
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine mean
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

This example first uses the complete context, and if a hit does not occur drops the parent `W2`. The next node `W1,M1,S1,M2,S2` uses generalized backoff to take a mean between the lower nodes where the parents `S2` or `M2` have been dropped. Each of these nodes are tried, and they respectively drop either `M2` or `S2`, meaning they both backoff to the same model `W1,M1,S1`. This node is attempted, and if a hit does not occur parent `W1` is dropped. Then at node `M1,S1` generalized backoff is used again backing off to the mean of model `M1` or `S1`, and then finally ending up at the unigram. The perplexity achieved is 168.

The next trigram improves upon this even further.

```
## logprob= -84771.4 ppl= 166.724 ppl1= 433.423
W : 6 W(-1) W(-2) M(-1) S(-1) M(-2) S(-2) dev.count.gz dev.lm.gz 9
  W1,W2,M1,S1,M2,S2  W2 kndiscount gtmin 3 interpolate
  W1,M1,S1,M2,S2     S2,M2 kndiscount gtmin 10000000 combine mean
  W1,M1,S1,M2        M2 kndiscount gtmin 4 kn-count-parent 0b111111
  W1,M1,S1,S2        S2 kndiscount gtmin 2 kn-count-parent 0b111111
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine max strategy bog_node_prob
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

This example is identical to the one above, except that rather than using mean combination at node `M1,S1`, max combination is used. As can be seen the resulting perplexity achieved is 166.7.

This last example improves on this a bit more, but with a simpler model.

```
## Best perplexity found
## logprob= -84709 ppl= 166.097 ppl1= 431.488
W : 4 W(-1) W(-2) M(-1) S(-1)  w_g_w1w2m1s1.count.gz w_g_w1w2m1s1.lm.gz 6
  W1,W2,M1,S1  W2 kndiscount gtmin 3 interpolate
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine max strategy bog_node_prob
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

In this case, we use a trigram but only add additional parents `M1` and `S1`. The entire context is first attempted, removing `W2` and then `W1` if hits do not occur. Then generalized backoff inspired from the above is used to finish off down to the unigram. The perplexity achieved is 166, the best perplexity we achieved on this data with any model.

While we expected that it would be possible to produce significant additional perplexity reductions with these trigram like models (trigram because they depend on nothing farther in the past than the two previous words or deterministic functions of these two previous words), the model search space is very large. Due to the time limitations of the 6-week workshop, we decided to investigate bigrams for the remainder of the time. As you recall, the baseline bigram had a perplexity of 175, much higher than the 166.7 achieved above and certainly higher than the baseline trigram (173).

The next example is our first bigram that beats the baseline trigram perplexity, achieving 171. It does this by conditioning on both the previous morph class and stem in addition to the word (so the model is for $P(W_t|W_{t-1}, M_{t-1}, S_{t-1})$, but also uses one of the generalized backoff methods, `bog_node_prob` combining using the maximum. It first attempts to use a context consisting of the previous word (`W1,M1,S1` which is equivalent to `W1` since `M1,S1` are deterministic functions of `W1`). If there is no language-model hit at that level, it jumps directly down to either using a context consisting of either only `M1` or `S1`. It does this "jump", however, via a node that takes the maximum probability of these two contexts, via the large `gtmin` parameter (so the node itself does not ever contribute a real probability, it just acts to combine lower-level backoff-graph nodes). Lastly, notice that `kn-count-parent` was used to specify that the original node should be used to form the Kneser-Ney meta-counts (the default would have been to use node `M1,S1`. It was found in general that specifying a `kn-count-parent` node that included the word variable had a beneficial effect on perplexity, when the model was a word model (i.e., when W_t was on the left of the conditioning bar in $P(W_t|\text{parents})$).

```
##  logprob= -85204.8 ppl= 171.142 ppl1= 447.086
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine max
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

The next example shows an even simpler bigram that also improves upon the baseline bigram and almost matches the baseline trigram. In this case, generalized backoff is not used. Rather, the word context is augmented with the morph variable.

```
## bigram that gets as good as a trigram.
##  logprob= -85379.6 ppl= 172.958 ppl1= 452.721
W : 2 W(-1) M(-1)  w_g_w1m1.count.gz w_g_w1m1.lm.gz 3
  W1,M1  W1 kndiscount gtmin 1 interpolate
  M1     M1 kndiscount gtmin 3
  0      0  kndiscount gtmin 1 kn-count-parent W1,M1
```

The next several examples show that perplexity can depend on adjusting the `gtmin` parameter. In this case, changing `gtmin` for nodes `M1`, `S1`, and for no-parents might lead either to perplexity increases or decreases as the example shows.

```
## logprob= -85140 ppl= 170.474 ppl1= 445.015
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine max
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 2 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1

##  logprob= -85296 ppl= 172.087 ppl1= 450.016
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine max
  M1        M1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1

##  logprob= -85267.8 ppl= 171.794 ppl1= 449.109
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine max
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1 interpolate
  S1        S1 kndiscount gtmin 2 kn-count-parent W1,M1,S1 interpolate
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1

##  logprob= -85132.5 ppl= 170.396 ppl1= 444.776
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine max
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

The next example next shows that by using a different combination method (the mean in this case) it is possible to retain the perplexity improvement. This is particularly relevant because the mean combination rule does not lead to a costly language model to evaluate as does some of the other combination procedures.

```
## logprob= -85129.9 ppl= 170.37 ppl1= 444.693
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob combine mean
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

The following example shows that using a weighted mean, it is possible to achieve still better perplexity. In this case, most of the weight is given to the `M1` node rather than to the `S1` node.

```
## logprob= -85066.8 ppl= 169.723 ppl1= 442.691
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy bog_node_prob \
                          combine wmean M1 7 S1 3
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

Changing the strategy to `counts_prod_card_norm` does not seem to show any appreciable change.

```
##   logprob= -85187 ppl= 170.959 ppl1= 446.518
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 \
                         strategy counts_prod_card_norm combine max
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

Changing the strategy to `counts_sum_counts_norm` and combining method to `gmean` leads to a slight increase in perplexity.

```
## logprob= -85252.5 ppl= 171.635 ppl1= 448.616
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 \
                      strategy counts_sum_counts_norm combine gmean
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1

## logprob= -85156.7 ppl= 170.646 ppl1= 445.548
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy counts_sum_counts_norm \
                                              combine mean
  M1        M1 kndiscount gtmin 2 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1

##  logprob= -85150.3 ppl= 170.58 ppl1= 445.346
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 1 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy counts_sum_counts_norm \
                                              combine mean
  M1        M1 kndiscount gtmin 4 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

Using a weighted mean with `counts_sum_counts_norm` improves things a bit further.

```
## logprob= -84948.9 ppl= 168.519 ppl1= 438.966
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 strategy counts_sum_counts_norm \
                                                 combine wmean M1 7 S1 3
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

Using the mean, however, produces a slight modification.

```
## logprob= -84967 ppl= 168.703 ppl1= 439.536
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine mean
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

The last example shows our best bigram, achieving a perplexity of 167.4, which is not only better than the baseline trigram, but is close to the much more expensive generalized-backoff trigram perplexity seen above.

```
##  logprob= -84845.2 ppl= 167.468 ppl1= 435.719
W : 3 W(-1) M(-1) S(-1)  dev.count.gz dev.lm.gz 5
  W1,M1,S1  W1 kndiscount gtmin 2 interpolate
  M1,S1     S1,M1 kndiscount gtmin 100000000 combine max strategy bog_node_prob
  M1        M1 kndiscount gtmin 3 kn-count-parent W1,M1,S1
  S1        S1 kndiscount gtmin 1 kn-count-parent W1,M1,S1
  0         0  kndiscount gtmin 1 kn-count-parent W1,M1,S1
```

This model increases `gtmin` to 2 for the `W1,M1,S1` node yielding the further improvements.

As can be seen, the space of possible models is quite large, and searching through such a model space by hand can be quite time consuming. We expect that automatic data-driven structure learning procedures to produce these models might yield improvements over the models above (all of which were derived and specified by-hand).

5 Data-driven Search of FLM Parameters

In order to use an FLM, three types of parameters need to specified: the initial conditioning factors, the backoff graph, and the smoothing options. The initial conditioning factors specifies which factors shall be used in estimating n-gram probabilities (design issue 1 in Section 1.2). The backoff graph and smoothing options indicate the procedures for robust estimation in the case of insufficient data (design issue 2). The goal of data-driven search is to find the parameter combinations that create FLMs that achieve a low perplexity on unseen test data.

The resulting model space is extremely large: given a factored word representation with a total of k factors, there are $\sum_{n=1}^{k} \binom{k}{n}$ possible subsets of initial conditioning factors. For a set of m conditioning factors, there are up to $m!$ backoff paths, each with its own smoothing options. Unless m is very small, exhaustive search is infeasible.

Moreover, nonlinear interactions between parameters make it difficult to guide the search into a particular direction. For instance, a particular backoff path may work well with Kneser-Ney smoothing, while a slightly different path may find poor performance using the same method. Good structures are ultimately dependent on the data, so parameter sets that work well for one corpus cannot necessarily be expected to perform well on another.

We have developed an efficient search algorithm called GA-FLM for tuning FLMs. It is based on genetic algorithms and takes as inputs a factored training text and a factored development text and attempts to find FLM parameters that minimize perplexity on the development text. The code is publicly-available at

`http://ssli.ee.washington.edu/people/duh/research/gaflm.html`.

We recommend FLM users to use this GA procedure or other data-driven search methods if hand-tuning of FLMs becomes too time-consuming. In the following, we provide a brief description of the GA-FLM code. More information is availabe in [7].

5.1 GA-FLM Code Overview

The general flow of the program is illustrated in Figure 8. First, we initialize a population of genes. Each gene represents an FLM with specific conditioning factors, backoff graph, and smoothing options. For each gene, we print out its factor-file and from this factor-file we train and test the language model using the conventional `fngram-count` and `fngram` tools in SRILM. The perplexity on the user-supplied development set is used to determine the fitness value of the gene. After fitness evaluation, selection/crossover/mutation occurs and the next population of genes is ready to be evaluated. The program runs until convergence or maximum generation specified by the user. Finally, “elitist” selection is implemented, so the best gene of each generation is gauranteed a spot in the next generation. Refer to [7] for details on how an FLM is encoded as a gene.

5.2 GA-FLM: General Requirements and Installation

Make sure you have the SRI Language Modeling Toolkit Version 1.4.1 or above. The two executables that are needed in that package are ”fngram-count” and ”fngram”, which builds and tests factored language models, respectively. The GA-FLM tool can be downloaded at:

`http://ssli.ee.washington.edu/people/duh/research/gaflm.html`

To install, simply download and unzip the tarball. Then type ”make” in the root directory. This will create an executable `ga-flm`, as well as other supporting scripts.

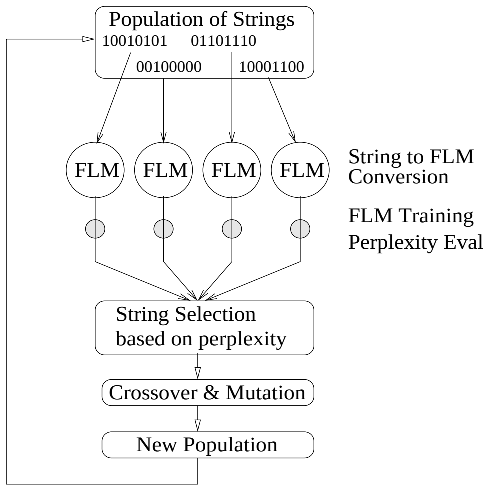


Figure 8: Overall program flow of GA search for FLM structure.

5.3 GA-FLM: Running the program

There are two executables that can be used when running a genetic algorithm search. In general, the Perl wrapper version is more convenient because it allows for repeated genetic algorithm runs and prints out summary files after each run.

5.3.1 Running the C++ executable directly: ga-flm

```
ga-flm [-g gaparam] [-f flmparam] [-p pmakeparam] [-s seed]
```

- `[-g gaparam]` specifies filename that stores GA parameters, such as population, max generation, crossover/selection type, mutation/crossover rate, etc. It also specifies the path where all factor-file data are stored. The default file is GA-PARAMS.
- `[-f flmparam]` tells GA-FLM about factored language model specification, e.g. what factors are available, where is the train or dev set, etc. The default is file FLM-PARAMS.
- `[-p pmakeparam]` include specialized options for PMAKE, a program that helps distribute parallel jobs to a compute cluster. This is specific to the PMAKE program. If PMAKE is not availabe, then set the USE_PMAKE option to “no”. Alternatively, implement another parallel execution function in the ga-flm code. The default file is PMAKE-PARAMS.
- `[-s seed]` is a file specifying a number of seed genes. Usually genetic algorithms begin with a randomly initialized population. Seed genes are user-specified genes that directly inserted in the initial population. In this file, each line represents a gene (see example/SEED_example). There can be any number of seed genes; the SEED file can also be empty (in which case, all genes will be randomly generated). The default file is SEED. (Be careful that the length of the gene in SEED is the same as the total length of the gene expected by the program. If there are M factors available total, then there are M initial factor bits, $B = \sum_{i=2}^{M}(i)$ backoff bits. The final length is thus $M + B + S$, where S is whatever length specified for smoothing options.
- Almost all of the information about the genetic algorithm and factored language model are contained in the parameter files. In general, the user should find it sufficient in his/her use of GA-FLM to just modify parameter files (i.e. FLM-PARAMS, GA-PARAMS, and PMAKE-PARAMS.)

5.3.2 Running the Perl wrapper: repeat-gaflm.pl

```
perl repeat-gaflm.pl [num] [-g gaparam] [-f flmparam] [-p pmakeparam] [-s seed]
```

- `repeat-gaflm.pl` is a Perl wrapper to `ga-flm`. There are two additions that make this Perl wrapper more flexible:
- 1. The user can specify [num], which will call `ga-flm` repeatedly for [num] times. This is useful for when the user wants to run several genetic algorithm experiments.
- 2. The Perl wrapper produces a "timelog" and a "summary" file, which summarizes the perplexity results across the entire genetic algorithm run. This easy-to-read summary file is a convenient way to acquire the best factor-files after a genetic algorithm run.
- The `[g|f|p|s]` parameters are simply passed on to `ga-flm`, and are therefore the same.
- The default for [num], when omitted, is 1.

5.4 Example runs of GA-FLM

The following two examples illustrates the use of GA-FLM to find factored language model structures. The data used is the CoNLL 2002 shared task corpus. It is included in example/data/

5.4.1 Serial execution example

Try the following command:

```
perl repeat-gaflm.pl 2
```

This will run GA-FLM twice. No `[g|f|p|s]` options are given, so the defaults (e.g. GA-PARAMS, FLM-PARAMS, PMAKE-PARAMS, SEED) are read. Note that PMAKE-PARAMS specifies USE_PMAKE to "no", which in the current implementation implies serial execution for evaluating language model fitness. This may be a bit slow, but we have set the population and generation in GA-PARAMS to be small, so the GA-FLM should not take too long.

From GA-PARAMS, we know that the results are stored in example/serial. Go to that directory. You'll find a bunch of files:

- `.flm` files and `.EvalLog` files are the factor-file and perplexity file of a specific gene, respectively. The `.flm` files are generated from transforming the gene sequence to a factored language model. The `.EvalLog` are obtained after training the factored language model on the train-set and testing on the dev-set.
- The `logfile` files contain information about population fitness across generations.
- The `summary` file contains all the factor-files of the genes over the entire genetic algorithm run, together with their corresponding perplexities. The end of the file contains a list of genes in descending order of perplexity.
- The `.complexity` files represents the number of parameters used by the factor file and is used by the Bayesian Info Criteria (BIC) fitness function. If the InversePPL fitness function is specified instead, these files are not needed.

5.4.2 Parallel Pmake execution example

Genetic algorithms are very suited to parallel processing. The building and testing of each factored language model can be done independently at parallel machines, and no communication between machines are needed. Try the following command if you have the PMAKE parallel jobs distribution program available:

```
perl repeat-gaflm.pl -g example/GA-PARAMS-parallel -p example/PMAKE-PARAMS-parallel
```

Note that we have only changed the GA-PARAMS and PMAKE-PARAMS files. Specifically, the PMAKE-PARAMS file now tells GA-FLM to use parallel processing. The GA-PARAMS file specifies the results to be stored in example/parallel.

If you do not have PMAKE, you should implement an interface to whatever parallel processing program exist on your computer system. (Serial processing is inherently slow and not recommended; it is included in this package only for demonstration and debugging purposes). See Section 5.5.3 for instructions on how to do this.

5.5 GA-FLM Parameters Files

There are three parameter files read in by `ga-flm`. They allow the user to specific the particular GA options or FLM options to use in the search. In the following we shall explain each parameter file in detail.

5.5.1 GA-PARAMS File

Here is an example GA-PARAMS file:

```
Population Size = 4
Maximum no of generations = 2
P(Crossover) = 0.9
P(Mutation) = 0.01
Crossover type = 2-point
Selection type = SUS
(tournament_selection) n = 3
Fitness scaling constant = 1000000
Fitness function = BIC
BIC_constant_k = 1.0
PATH_for_GA_FLM_files = example/serial/
```

All the above parameters are quite useful to the general user. They can be divided into three groups.

Genetic algorithm operators

The first 5 parameters are standard parameters to genetic algorithm. Usually, to find good factored language models, one needs to experiment with several different crossover/selection/mutation and population sizes. In more detail:

- Crossover type may be {2-point,1-point,uniform}
- Selection type may be {SUS, roulette, tournament}
- (tournament_selection) n is the number of genes picked in tournament selection

Fitness function

The following 3 parameters define the fitness function:

- Fitness scaling constant is a linear scaling constant that makes sure fitness values are in reasonable ranges. Make this very high if you want a high convergence threshold (genetic algorithm stops quicker), or lower if you want to fine-tune the last generations.
- Fitness function is currently {BIC,inversePPL}, two different methods to evaluate fitness of a language model.
- BIC_k can be any float number. It is used as the Bayesian Info Criteria weight for complexity penalty. It is ignored when inversePPL is selected as fitness function.

The inversePPL fitness function is implemented as:

$$fitness_{inversePPL} = c * (\frac{1}{perplexity}) \tag{1}$$

where c is the fitness scaling constant.
The BIC fitness function is implemented as:

$$fitness_{BIC} = c * (-logprobability + \frac{k}{2} * log(N)) \tag{2}$$

where c is the fitness scaling constant, k is the weighting for logprobability vs. complexity penality, and N is the number of parameters used by the factored language model under evaluation. (N is the total number of n-gram types for the factored language model, which is taken from the `.complexity` file).

You may wish to implement your own fitness function. To do so, hack the following part of the code:

`ga-flm.cc::collectPPL()`.

Add your own fitness function after the BIC and inversePPL fitness functions. The quantities "logprob", "complexity", and "ppl" (perplexity) are available for fitness computation. Your fitness function may also need some input specified through parameter files. In that case, add some code to the "READ GA-PARAMS FILE" portion of `ga-flm.cc::initialize(void)`. Refer to the "BIC k value" implementation there for an example.

Path for GA-FLM files

- PATH_for_GA_FLM_files is where all the EvalLog, ga.pmake, and factor-files are stored

5.5.2 FLM-PARAMS File

Here is an example FLM-PARAMS File:

Data Path = example/data/
TrainSet = wsj_20_train.factored.txt
DevSet = wsj_20_dev.factored.txt
fngram-count Path = fngram-count
fngram Path = fngram
fngram-count Options = ""
fngram Options = ""
Factor to Predict = W
Total Available Factors = W,P,C
Context of Factors = 1,2
Smoothing Options Length = 16
Discount Options = kndiscount, cdiscount 1,wbdiscount, ndiscount
Default Discount = wbdiscount
Max cutoff (max gtmin) = 5

The above parameters relate to the factored language model training/testing and can be divided into 3 general sections: parameters regarding data, parameters regarding the SRI Language Modeling program, and parameters regarding the factored language model specification:

Data location

- Data_Path is the directory path for both training and dev sets.
- TrainSet and DevSet are the filenames of the training and dev set. These files are the factored textfiles assumed by the SRILM fngram programs. (e.g. The sentences are composed of factored bundles like W-word:P:pos:C:chunk). See example/data for examples.

SRI Language Modeling program options

- FngramCount_Path and Fngram_Path are the paths of the `fngram-count` and `fngram` files, respectively.
- FngramCount_options and Fngram_options may contain any command-line options for training/testing the language model. These options are passed directly to `fngram-count` and `fngram`. For example,
  FngramCount_options = "-unk"
  If no options are needed, use FngramCount_options = "" (with the quotes)

Factored Language Model Specifications

- Factor_to_Predict is the factor we wish to predict through the language model. Usually, this is W (word), but may be any factor.
- Total_Available_Factors and Context_of_Factors together specify the tags of factors that will be used in the GA optimization. There are two ways to specify these two parameters:
  1. Specify both factors and context desired, e.g.
     Total_Available_Factors = W,S,P
     Context = 1,2
     = You'll get factors W(-1),S(-1),P(-1),W(-2),S(-2),P(-2).
  2. Specify factor-tags directly without specifying context,e.g.
     Total_Available_Factors = W1,S1,P1,W2,S2,P2
     Context = 0
     = Note that in this case, you must set context=0.

  The advantage of method 1 is that there's less typing to do. The advantage of method 2 is that you can specify arbitrary factor combinations. For example, you can specify W1,S1,S2 which is not possible with method 1.

  Be sure that the tags and numbers for context are separated by commas (,) as that is the delimiter that signals the program how to tell the tags apart.
- Smoothing_Options_Length is the number of smoothing option parameters. This defines the length of the smoothing options gene. Since smoothing is defined as tuples of (discount,gtmin), this should be any even number {0,2,4,...}. If you believe smoothing options are important in the optimization, make this gene long.
- Discount_options can be any of the usual fngram discounting options (e.g. kndiscount,ukndiscount,wbdiscount,cdiscount 1,kndiscount). Like the Total_Available_Factors, be sure to use commas to delimit discounting options. Any number of discounting options may be used.
- Default Discount is the one used for unigram and other cases when there are more backoff edges to smooth than number of smoothing options specified in Smoothing_Options_Length.
- Max_Cutoff indicates the max possible value for gtmin. gtmin is the min cutoff count for a ngram to be included in the language model estimation.

5.5.3 PMAKE-PARAMS File

Here is an example of the PMAKE-PARAMS file:

```
Use Pmake? = yes
Num_Pmake_Jobs = 20
Scratch_Space_to_Use = example/parallel/
Export_Attributes = Linux !1000RAM !2000RAM
```

- Use_Pmake = {yes,no}. Current implementation can evaluate FLMs serially or parallelly using Pmake. Enter yes here if Pmake is available. Otherwise, enter no to use serial or adapt the code to your own parallel processing platform.
- Num_Pmake_Jobs is the max number of pmake jobs (e.g. -J option in pmake)
- Scratch_space is the place for storing big language model files, count files, and train/dev set data. In the Pmake implementation, all these files are stored locally in the scratch space of each computer. They are deleted after each fitness evaluation.
- Export attributes are the Pmake export attributes. (e.g. Linux !1000RAM !2000RAM).

You may wish to implement your own parallel execution code. To do so, hack the following part of the code: `ga-flm.cc::executeFngramCommands(fngramCommands)`.

The `fngramCommands` is a queue object containing a list of commands for all genes that need to be evaluated in this generation. These commands are independent, and can therefore be executed in parallel without any mutual communication. As long as you ensure that all commands in `fngramCommands` are executed before `ga-flm.cc::executeFngramCommands(fngramCommands)` exits, then GA-FLM will work fine. Refer to the serial execution and the `executeFngramCommandsByPmake(fngramCommands)` for example implementations.

After implementing this code, be sure to modify the `USE_PMAKE` variable and the PMAKE-PARAMS file so you can tell GA-FLM which execution mode you desire.

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