PORTABILITY OF SYNTACTIC STRUCTURE FOR LANGUAGE MODELING

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ABSTRACT
The paper presents a study on the portability of statistical syntactic knowledge in the framework of the structured language model (SLM). We investigate the impact of porting SLM statistics from the Wall Street Journal (WSJ) to the Air Travel Information System (ATIS) domain. We compare this approach to applying the Microsoft rule-based parser (NLPwin) for the ATIS data and to using a small amount of data manually parsed at UPenn for gathering the initial SLM statistics. Surprisingly, despite the fact that it performs modestly in perplexity (PPL), the model initialized on WSJ parses outperforms the other initialization methods based on in-domain annotated data, achieving a significant 0.4% absolute and 7% relative reduction in word error rate (WER) over a baseline system whose word error rate is 5.8%; the improvement measured relative to the minimum WER achievable on the N-best lists we worked with is 12%.

1. INTRODUCTION

The structured language model uses hidden parse trees to assign conditional word-level language model probabilities. The model is trained in two stages: first the model parameters are intialized from a treebank and then an N-best EM variant is employed for reestimating the model parameters.

Assuming that we wish to port the SLM to a new domain we have four alternatives for initializing the SLM:
• manual annotation of sentences with parse structure. This is expensive, time consuming and requires linguistic expertise. Consequently, only a small amount of data could be annotated this way.
• parse the training sentences in the new domain using an automatic parser ([1], [2], [3]) trained on a domain where a treebank is available already
• use a rule-based domain-independent parser ([4])
• port the SLM statistics as intialized on the treebanked-domain. Due to the way the SLM parameter reestimation works, this is equivalent to using the SLM as an automatic parser trained on the treebanked-domain and then applied to the new-domain training data.

We investigate the impact of different initialization methods and whether one can port statistical syntactic knowledge from a domain to another. The second training stage of the SLM is invariant during the experiments presented here.

We show that one can successfully port syntactic knowledge from the Wall Street Journal (WSJ) domain — for which a manual treebank ([5]) was developed (approximately 1M words of text) — to the Air Travel Information System (ATIS) ([6]) domain. The choice for the ATIS domain was motivated by the fact that it is different enough in style and structure from the WSJ domain and there is a small amount of manually parsed ATIS data (approximately 5k words) which allows us to train the SLM on in-domain hand-parsed data as well and thus make a more interesting comparison.

The remaining part of the paper is organized as follows: Section 2 briefly describes the SLM followed by Section 3 describing the experimental setup and results. Section 4 discusses the results and indicates future research directions.

2. STRUCTURED LANGUAGE MODEL OVERVIEW

An extensive presentation of the SLM can be found in ([7]). The model assigns a probability $P(W, T)$ to every sentence $W$ and its every possible binary parse $T$. The terminals of $T$ are the words of $W$ with POS tags, and the nodes of $T$ are annotated with phrase headwords and non-terminal labels. Let $W$ be a sentence of length $n$ words to which we have prepended the sentence begining marker $<$s> and appended the sentence end marker $</s>$ so that $w_0 = <s>$ and $w_{n+1} = </s>$. Let $W_k = w_0 \ldots w_k$ be the word $k$-prefix of the sentence — the words from the begining of

![Fig. 1. A word-parse k-prefix](image-url)
the sentence up to the current position $k$ — and $W_k T_k$ the word-parse $k$-prefix. Figure 2 shows a word-parse $k$-prefix; $h_0 \ldots h_{-m}$ are the exposed heads, each head being a pair (headword, non-terminal label), or (word, POS tag) in the case of a root-only tree. The exposed heads at a given position $k$ in the input sentence are a function of the word-parse $k$-prefix.

2.1. Probabilistic Model

The joint probability $P(W, T)$ of a word sequence $W$ and a complete parse $T$ can be broken into:

$$P(W, T) = \prod_{k=1}^{T_k} \left[ P(w_k/W_{k-1}T_{k-1}) \cdot P(t_k/W_{k-1}T_{k-1}, w_k) \cdot \prod_{i=1}^{N_k} P(p_i^k/W_{k-1}T_{k-1}, w_k, t_k, p_{i-1}^k) \right]$$

(1)

where:

- $W_{k-1}T_{k-1}$ is the word-parse $(k-1)$-prefix
- $w_k$ is the word predicted by WORD-PREDICTOR
- $t_k$ is the tag assigned to $w_k$ by the TAGGER
- $N_k - 1$ is the number of operations the PARSER executes at sentence position $k$ before passing control to the WORD-PREDICTOR (the $N_k$-th operation at position $k$ is the null transition); $N_k$ is a function of $T$
- $p_i^k$ denotes the $i$-th PARSER operation carried out at position $k$ in the word string; the operations performed by the PARSER are illustrated in Figures 2-3 and they ensure that all possible binary branching parses with all possible headword and non-terminal label assignments for the $w_1 \ldots w_k$ word sequence can be generated. The $p_1^k \ldots p_{N_k}^k$ sequence of PARSER operations at position $k$ grows the word-parse $(k-1)$-prefix into a word-parse $k$-prefix.

Our model is based on three probabilities, each estimated using deleted interpolation and parameterized (approximated) as follows:

$$P(w_k/W_{k-1}T_{k-1}) = P(w_k/h_0, h_{-1})$$

(2)

$$P(t_k/w_k, W_{k-1}T_{k-1}) = P(t_k/w_k, h_0, h_{-1})$$

(3)

$$P(p_i^k/W_kT_k) = P(p_i^k/h_0, h_{-1})$$

(4)

It is worth noting that if the binary branching structure developed by the parser were always right-branched and we mapped the POS tag and non-terminal label vocabularies to a single type then our model would be equivalent to a tri-gram language model. Since the number of parses for a given word prefix $W_k$ grows exponentially with $k$, $|\{T_k\}| \sim O(2^k)$, the state space of our model is huge even for relatively short sentences, so we had to use a search strategy that prunes it. Our choice was a synchronous multi-stack search algorithm which is very similar to a beam search.

The **language model** probability assignment for the word at position $k + 1$ in the input sentence is made using:

$$P_{SLM}(w_{k+1}/W_k) = \sum_{T_k \in S_k} P(w_{k+1}/W_kT_k) \cdot \rho(W_k, T_k),$$

$$\rho(W_k, T_k) = P(W_kT_k)/\sum_{T_k \in S_k} P(W_kT_k)$$

(5)

which ensures a proper probability over strings $W^*$, where $S_k$ is the set of all parses present in our stacks at the current stage $k$.

2.2. Model Parameter Estimation

Each model component — WORD-PREDICTOR, TAGGER, PARSER — is initialized from a set of parsed sentences after undergoing headword percolation and binarization. Separately for each model component we:

- gather counts from “main” data — about 90% of the training data
- estimate the interpolation coefficients on counts gathered from “check” data — the remaining 10% of the training data.

An N-best EM variant is then employed to jointly reestimate the model parameters such that the PPL on training data is decreased — the likelihood of the training data under our model is increased. The reduction in PPL is shown experimentally to carry over to the test data.

3. EXPERIMENTS

We have experimented with three different ways of gathering the initial counts for the SLM — see Section 2.2:

- parse the training data (approximately 76k words) using Microsoft’s NLPwin and then initialize the SLM from these parse trees. NLPwin is a rule-based domain-independent parser developed by the natural language processing group at Microsoft.
- use the limited amount of manually parsed ATIS-3 data (approximately 5k words)
- use the manually parsed data in the WSJ section of the Upenn Treebank. We have used the 00-22 sections (about 1M words) for initializing the WSJ SLM. The word vocabulary used for initializing the SLM on the WSJ data was
the ATIS open vocabulary — thus a lot of word types were mapped to the unknown word type.

After gathering the initial counts for all the SLM model components as described above, the SLM training proceeds in exactly the same way in all three scenarios. We reestimate the model parameters by training the SLM on the same training data (word level information only, all parse annotation information used for initialization is ignored during this stage), namely the ATIS-3 training data (approximately 76k words), and using the same word vocabulary. Finally, we interpolate the SLM with a 3-gram model estimated using deleted interpolation:

\[ P(\cdot) = \lambda \cdot P_{3\text{-gram}}(\cdot) + (1 - \lambda) \cdot P_{SLM}(\cdot) \]

For the word error rate (WER) experiments we used the 3-gram scores assigned by the baseline back-off 3-gram model used in the decoder whereas for the perplexity experiments we have used a deleted interpolation 3-gram built on the ATIS-3 training data tokenized such that it matches the UPenn Treebank style.

### 3.1. Experimental Setup

The vocabulary used by the recognizer was re-tokenized such that it matches the UPenn vocabulary — e.g. don’t is changed to do n’t, see [4] for an accurate description. The re-tokenized vocabulary size was 1k. The size of the test set was 9.6k words. The OOV rate in the test set relative to the recognizer’s vocabulary was 0.5%.

The settings for the SLM parameters were kept constant across all experiments to typical values — see [7]. The re-tokenization setup. As can be seen from the results presented in Table 1. Judging on the initial perplexity of the stand-alone SLM (\(\lambda = 0.0\)), the best way to initialize the SLM seems to be by using the NLPwin parsed data; the meager 5k words of manually parsed data available for ATIS leads to sparse statistics in the SLM and the WSJ statistics are completely mismatched. However, the SLM iterative training procedure is able to overcome both these handicaps and after 13 iterations we end up with almost the same perplexity — within 5% relative of the NLPwin trained SLM but still above the 3-gram performance. Interpolation with the 3-gram model brings the perplexity of the trained models at roughly the same value, showing an overall modest 6% reduction in perplexity over the 3-gram model.

### 3.2. Perplexity results

The perplexity results obtained in our experiments are summarized in Table 1. Judging on the initial perplexity of the stand-alone SLM (\(\lambda = 0.0\)), the best way to initialize the SLM seems to be by using the NLPwin parsed data; the meager 5k words of manually parsed data available for ATIS leads to sparse statistics in the SLM and the WSJ statistics are completely mismatched. However, the SLM iterative training procedure is able to overcome both these handicaps and after 13 iterations we end up with almost the same perplexity — within 5% relative of the NLPwin trained SLM but still above the 3-gram performance. Interpolation with the 3-gram model brings the perplexity of the trained models at roughly the same value, showing an overall modest 6% reduction in perplexity over the 3-gram model.

| Initial Stats | Iter | \(\lambda = 0.0\) | \(\lambda = 0.6\) | \(\lambda = 1.0\) |
|---------------|------|-----------------|-----------------|-----------------|
| NLPwin parses | 0    | 21.3            | 16.7            | 16.9            |
| NLPwin parses | 13   | 17.2            | 15.9            | 16.9            |
| SLM-atis parses | 0   | 64.4            | 18.2            | 16.9            |
| SLM-atis parses | 13  | 17.8            | 15.9            | 16.9            |
| SLM-wsj parses | 0   | 8311            | 22.5            | 16.9            |
| SLM-wsj parses | 13  | 17.7            | 15.8            | 16.9            |

Table 1. Deleted Interpolation 3-gram + SLM; PPL Results

One important observation that needs to be made at this point is that although the initial SLM statistics come from different amounts of training data, all the models end up being trained on the same number of words — the ATIS-3 training data. Table 2 shows the number of distinct types (number of parameters) in the PREDICTOR and PARSER (see Eq. 2 and 4) components of the SLM in each training scenario. It can be noticed that the models end up having roughly the same number of parameters (iteration 13) despite the vast differences at initialization (iteration 0).

| Initial Stats | Iter | PREDICTOR | PARSER |
|---------------|------|-----------|--------|
| NLPwin parses | 0    | 23,621    | 37,702 |
| NLPwin parses | 13   | 58,405    | 83,321 |
| SLM-atis parses | 0   | 2,048     | 2,990  |
| SLM-atis parses | 13  | 52,588    | 60,983 |
| SLM-wsj parses | 0   | 171,471   | 150,731|
| SLM-wsj parses | 13  | 58,073    | 76,975 |

Table 2. Number of parameters for SLM components

### 3.3. N-best rescoring results

We have evaluated the models initialized in different conditions in a two pass — N-best rescoring — speech recognition setup. As can be seen from the results presented
in Table 3 the SLM interpolated with the 3-gram performs best. The SLM reestimation does not help except for the model initialized on the highly mismatched WSJ parses, in which case it proves extremely effective in smoothing out the SLM component statistics coming from out-of-domain. Not only is the improvement from the mismatched initial model large, but the trained SLM also outperforms the baseline and the SLM initialized on in-domain annotated data. We attribute this improvement to the fact that the initial model statistics on WSJ were estimated on a lot more data (more reliable) than the statistics coming from the little amount of ATIS data.

The SLM trained on WSJ parses achieved 0.4% absolute and 7% relative reduction in WER over the 3-gram baseline of 5.8%. The improvement relative to the minimum — ORACLE — WER achievable on the N-best list we worked with is in fact 12%. We have evaluated the statistical significance of the best result relative to the baseline using the standard test suite in the SCLITE package provided by NIST. The results are presented in Table 4. We believe that for WER statistics the most relevant significance test is the Matched Pair Sentence Segment one under which the SLM interpolated with the 3-gram is significant at the 0.003 level.

| Initial Stats          | Iter | $\lambda = 0.0$ | $\lambda = 0.6$ | $\lambda = 1.0$ |
|-----------------------|------|-----------------|-----------------|-----------------|
| NLPwin parses         | 0    | 6.4             | 5.6             | 5.8             |
| NLPwin parses         | 13   | 6.4             | 5.7             | 5.8             |
| SLM-atis parses       | 0    | 6.5             | 5.6             | 5.8             |
| SLM-atis parses       | 13   | 6.6             | 5.7             | 5.8             |
| SLM-wsj parses        | 0    | 12.5            | 6.3             | 5.8             |
| SLM-wsj parses        | 13   | 6.1             | 5.4             | 5.8             |

Table 3. Back-off 3-gram + SLM; WER Results

The syntactic knowledge embodied in the SLM statistics is portable but only in conjunction with the SLM parameter reestimation technique. The significance of this result lies in the fact that it is possible to use the SLM on a new domain where a treebank (be it generated manually or automatically) is not available.

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