



Improving Back-off Models with Bag of Words and Hollow-grams

Benjamin Lecouteux, Raphaël Rubino, Georges Linarès
Laboratoire Informatique d'Avignon (LIA), University of Avignon, France
{benjamin.lecouteux, raphael.rubino, georges.linares}@univ-avignon.fr



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Introduction

- We propose a simple and efficient model based on **word co-occurrences** and a **new hollow-gram model**.
- Our approaches are applied to traditional modified Kneser-Ney back-off language models. []
- We decide to take into account the short context around n -grams to tackle the issue of **sparse training data**.
- A slight improvement on word error rate (WER) is reached, with and without acoustic adaptation.

Proposed Approaches

Hollow-gram model

- We propose an alternative to the independence assumption between two distant words in modified Kneser-ney back-off models.
- A 2-gram model based on the pairs (start, end) of each 3-gram, allowing relationship between short distant words.
- Can be assimilated to a regular expression ($w1, *, w3$), where $*$ is an unobserved word.
- In the case of an unseen event, the hollow-gram backs off using the equation:
$$\tilde{p}(w_3|w_1, w_2) = \alpha(w_1, w_2)^{1-\beta} p_\phi(w_3|w_1)^\beta p(w_3|w_2)$$
where $\tilde{p}(w_3|w_1, w_2)$: resulting updated probability of the 3-gram, $\alpha(w_1, w_2)$: initial back-off value of the word pair (w_1, w_2) , $p_\phi(w_3|w_1)$: hollow-gram probability, β : empirical fudge factor.

Word co-occurrence model

- We combine a word association score [?] to the back-off based on classical n -gram language model.
- It eliminates word frequency effects and emphasizes relations between significant word co-occurrences.
- Our model can be interpolated with an initial modified Kneser-ney back-off model, on 2-gram and 1-gram.
- In the case of a full back-off behavior,
$$\tilde{p}(w_3|w_1, w_2) = \alpha(w_1, w_2)^{1-\beta} p_\psi(w_1, w_3)^\beta \alpha(w_2)^{1-\beta} p_\psi(w_2, w_3)^\beta p(w_3)$$
where $\alpha(w_1, w_2)$: initial back-off value of the words, β : empirical fudge factor, p_ψ : back-off smoothing function based on word co-occurrences.

Experimental Framework

- Experiments are carried out by using the **LIA broadcast news system** [?], which relies on the HMM-decoder **LIA SPEERAL**. []
- A **classical 3-gram model** built on *Le Monde* French Newspaper and Gigaword corpus (1.3G words).
- Training and development parts of the data set are based on the **ESTER-2** [?] evaluation campaign corpus (100h).

Shows	baseline WER	baseline SER	baseline CWR
Inter (4h)	33.1	75.0	69.7
TVME (1h)	31.3	67.6	71.2
RFI (1h)	18.7	66.6	84

Table: Baseline with the experimental framework

Experiments

- Four series of experiments: for each approach separately, for the combination and for a compact model.
- For each experiment, the initial back-off value is re-estimated according to: $\tilde{\alpha}(w_{i-n}, \dots, w_i) = \alpha(w_{i-n}, \dots, w_{i-1})^{1-\beta} p_\phi(w_{i-n}, w_i)^\beta$ with $\tilde{\alpha}$: updated back-off value, α : initial back-off value, $p_\phi(w_{i-n}, w_i)$: smoothing function
- The **back-off based hollow grams** has two advantages: it is a regular expression based model, it can capture hollow-grams events into the training corpora.
- For the **back-off based on word co-occurrences**, a word co-occurrence symmetric matrix is built on the whole training corpora, counting word pairs with a window size of five words.
- The **compact model** depicts the binary possibility of a back-off. This binary possibility is computed from the co-occurrence matrix: if the value is not null, we consider as true the possibility of the combination.

Results

Hollow-gram model

Shows	WER	SER	CWR
Inter (4h)	32.8 (-0.3)	74.5 (-0.5)	70.5 (+0.8)
TVME (1h)	31.3 (0.0)	67.0 (-0.3)	71.7 (+0.5)
RFI (1h)	18.5 (-0.2)	65.7 (-0.9)	84.4 (+0.4)
GLOBAL	-0.2	-0.5	+0.7

Table: WER, SER, CWR using the hollow-gram based backoff model

Word co-occurrence model

Shows	WER	SER	CWR
Inter (4h)	32.7 (-0.4)	74.5 (-0.5)	70.5 (+0.8)
TVME (1h)	31.0 (-0.3)	66.8 (-0.8)	71.8 (+0.6)
RFI (1h)	18.4 (-0.3)	65.6 (-1)	84.5 (+0.5)
GLOBAL	-0.4	-0.6	+0.7

Table: WER, SER, CWR using the cooccurrences based backoff model

Combination

Shows	WER	SER	CWR
Inter (4h)	32.4 (-0.7)	74.6 (-.4)	70.8 (+1.1)
TVME (1h)	30.9 (-0.4)	67.2 (-.4)	72.0 (+0.8)
RFI (1h)	18.4 (-0.3)	65.6 (-1.0)	84.5 (+0.5)
GLOBAL	-0.6	-0.5	+0.9

Table: WER, SER, CWR using combination between cooccurrences based backoff and hollow-gram models

Compact model

Shows	WER	SER	CWR
Inter (4h)	32.7(-0.3)	74.8(-0.2)	70.3(+0.6)
TVME (1h)	31.1(-0.2)	67.5(-0.1)	71.6(+0.3)
RFI (1h)	18.6(-0.1)	65.7(-0.9)	84.2(+0.2)
GLOBAL	-0.25	-0.3	+0.5

Table: WER, SER, CWR using combination between cooccurrences based backoff and hollow-gram models

Conclusion

- A simple back-off values reordering can improve a Kneser-Ney based model for a **0.6% absolute gain of WER and 0.9% of CWR**.
- Our compact version leads to a slight improvement of the classical back-off model, with a very **low memory consumption**.
- The **hollow-gram model** can be extended to n -grams.
- We plan to extend the **co-occurrence model** to more sophisticated heuristics and algorithms, smoothing values with word distances.

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