Language Model Rest Costs and Space-Efficient Storage

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Complaint About Language Models

Make Search Expensive

$$\frac{p_5(\text{is one of the})}{p_5(\text{is one})p_5(\text{of the})} \neq 1$$

1. Better fragment scores

Complaints About Language Models

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1. Better fragment scores

Use Too Much Memory

$$\log p_5(\text{the} \mid \text{is one of}) = -0.5$$
$$\log b_5(\text{is one of the}) = -1.2$$

2. Collapse probability and backoff

Language Model Probability of Sentence Fragments

$$\log p_5(\text{is one of the few}) = -6.62$$

Why does it matter?

Decoders prune hypotheses based on score.

Baseline: How to Score a Fragment

$$
\begin{array}{rll}
 & \log p_5(\text{is}) & = -2.63 \\
 & \log p_5(\text{one} \mid \text{is}) & = -2.03 \\
 & \log p_5(\text{of} \mid \text{is one}) & = -0.24 \\
 & \log p_5(\text{the} \mid \text{is one of}) & = -0.47 \\
+ & \log p_5(\text{few} \mid \text{is one of the}) & = -1.26 \\
\hline
= & \log p_5(\text{is one of the few}) & = -6.62
\end{array}
$$

The Problem: Lower Order Entries

5-Gram Model: $\log p_5(\text{is}) = -2.63$

Unigram Model: $\log p_1(\text{is}) = -2.30$

Same training data.

Backoff Smoothing

$p_5(\text{is})$ should be used when a bigram was not found.

In the language model

$$\log p_5(\text{is} \mid \text{australia}) = -2.21$$

Not in the language model

$$\log p_5(\text{is} \mid \text{periwinkle}) = \log b_5(\text{periwinkle}) + \log p_5(\text{is}) = -2.95$$

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In Kneser-Ney smoothing, lower order probabilities assume backoff.

Use Lower Order Models for the First Few Words

		Baseline	**Lower**
	$\log p_5(\text{is})$	$= -2.63$	$-2.30 = \log p_1$
	$\log p_5(\text{one} \mid \text{is})$	$= -2.03$	$-1.92 = \log p_2$
	$\log p_5(\text{of} \mid \text{is one})$	$= -0.24$	$-0.08 = \log p_3$
	$\log p_5(\text{the} \mid \text{is one of})$	$= -0.47$	$-0.21 = \log p_4$
$+$	$\log p_5(\text{few} \mid \text{is one of the})$	$= -1.26$	$-1.26 = \log p_5$
$=$	$\log p_5(\text{is one of the few})$	$= -6.62$	$-5.77 = \log p_{\text{Low}}$

Which is Better?

$$\begin{aligned} \textbf{Baseline:} \quad & \log p_5(\text{is one of the few}) && = -6.62 \\ \textbf{Lower Order:} \quad & \log p_{\text{Low}}(\text{is one of the few}) && = -5.77 \end{aligned}$$

Which is Better: Prediction Task

			Error
Baseline:	$\log p_5(\text{is one of the few})$	$= -6.62$	-2.52
Lower Order:	$\log p_{\text{Low}}(\text{is one of the few})$	$= -5.77$	-1.67
Actual:	$\log p_5(\text{is one of the few} \mid \text{<s> australia})$	$= -4.10$	

The Lower Order Estimate is Better

Run the decoder and log error every time context is revealed.

Length	**1**	**2**	**3**	**4**
Baseline	.87	.24	.10	.09
Lower Order	.84	.18	.07	.04

Table : Mean squared error in predicting log probability.

Storing Lower Order Models

One extra float per entry, except for longest order.

Unigrams

Words	**log** p_5	**log** b_5	**log** p_1
australia	-3.9	-0.6	-3.6
is	-2.6	-1.5	-2.3
one	-3.4	-1.0	-2.9
of	-2.5	-1.1	-1.7

No need for backoff b_1

If backoff occurs, the Kneser-Ney assumption holds and p_5 is used.

Lower Order Summary

Fragment scores are more accurate, but require more memory.

Related Work

Score with and without sentence boundaries. [Sankaran et al, 2012]
Peek at future phrases. [Zens and Ney, 2008] [Wuebker et al, Wed.]
Coarse pass predicts scores for a finer pass. [Vilar and Ney, 2011]

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All of these use fragment scores as a subroutine.

Related Work II: Carter et al, Yesterday

This Work

$$p(\text{is one of the}) \approx p(\text{is one})p(\text{of the})$$

Their Work

$$p(\text{is one of the}) \leq p(\text{is one})p(\text{of the})$$

Implementing Upper Bounds Within This Work

- Store upper bound probabilities instead of averages
- Account for positive backoff with the context

Three values per n-gram instead of their four.

Lower Order Summary

Previously

Fragment scores are more accurate, but require more memory.

Next

Save memory but make fragment scores less accurate.

Saving Memory

Unigrams

Words	**log** p_5	**log** b_5
australia	-3.9	-0.6
is	-2.6	-1.5
one	-3.4	-1.0
of	-2.5	-1.1

Unigrams

Words	**log** q_5
australia	-4.5
is	-4.1
one	-4.4
of	-3.6

One less float per entry, except for longest order.

Related Work

Store counts instead of probability and backoff [Brants et al, 2007]
RandLM, ShefLM, BerkeleyLM

This Work

- Memory comparable to storing counts.
- Higher quality Kneser-Ney smoothing.

How Backoff Works

$$p(\text{periwinkle} \mid \text{is one of}) = p(\text{periwinkle} \mid \text{of}) b(\text{is one of}) b(\text{one of})$$

because "of periwinkle" appears but "one of periwinkle" does not.

Pessimism

Assume backoff all the way to unigrams.

$$q(\text{is one of}) = p(\text{is one of})b(\text{is one of})b(\text{one of})b(\text{of})$$

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Sentence Scores Are Unchanged

$$q(<\text{s}> \cdots </\text{s}>) = p(<\text{s}> \cdots </\text{s}>)$$

$$\text{because } b(\cdots </\text{s}>) = 1$$

Incremental Pessimism

$$q(\text{is}) = p(\text{is})b(\text{is})$$

$$q(\text{one} \mid \text{is}) = p(\text{one} \mid \text{is})\frac{b(\text{is one})b(\text{one})}{b(\text{is})}$$

These are terms in a telescoping series:

$$q(\text{is one}) = q(\text{is})q(\text{one} \mid \text{is})$$

Using q

$$
\begin{array}{rll}
 & \log q(\text{is}) & = \text{-4.10} \\
 & \log q(\text{one} \mid \text{is}) & = \text{-2.51} \\
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 & \log q(\text{the} \mid \text{is one of}) & = \text{-1.61} \\
+ & \log q(\text{few} \mid \text{is one of the}) & = \text{ 1.03} \\
\hline
= & \log q(\text{is one of the few}) & = \text{-8.13}
\end{array}
$$

Store q, forget probability and backoff.

Using q

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$$

Store q, forget probability and backoff.

q is not a proper probability distribution.

Pessimistic Backoff Summary

Collapse probability and backoff from two values to one value.

Stacking

Lower Order and Pessimistic Combined

- Same memory (one extra float, one less float).
- Better on the left, worse on the right.

Cube Pruning: Approximate Search

For each constituent, going bottom-up:

1. Make a priority queue over possible rule applications.
2. Pop a fixed number of hypotheses: the *pop limit*.

Larger pop limit $\Longrightarrow$ more accurate search.

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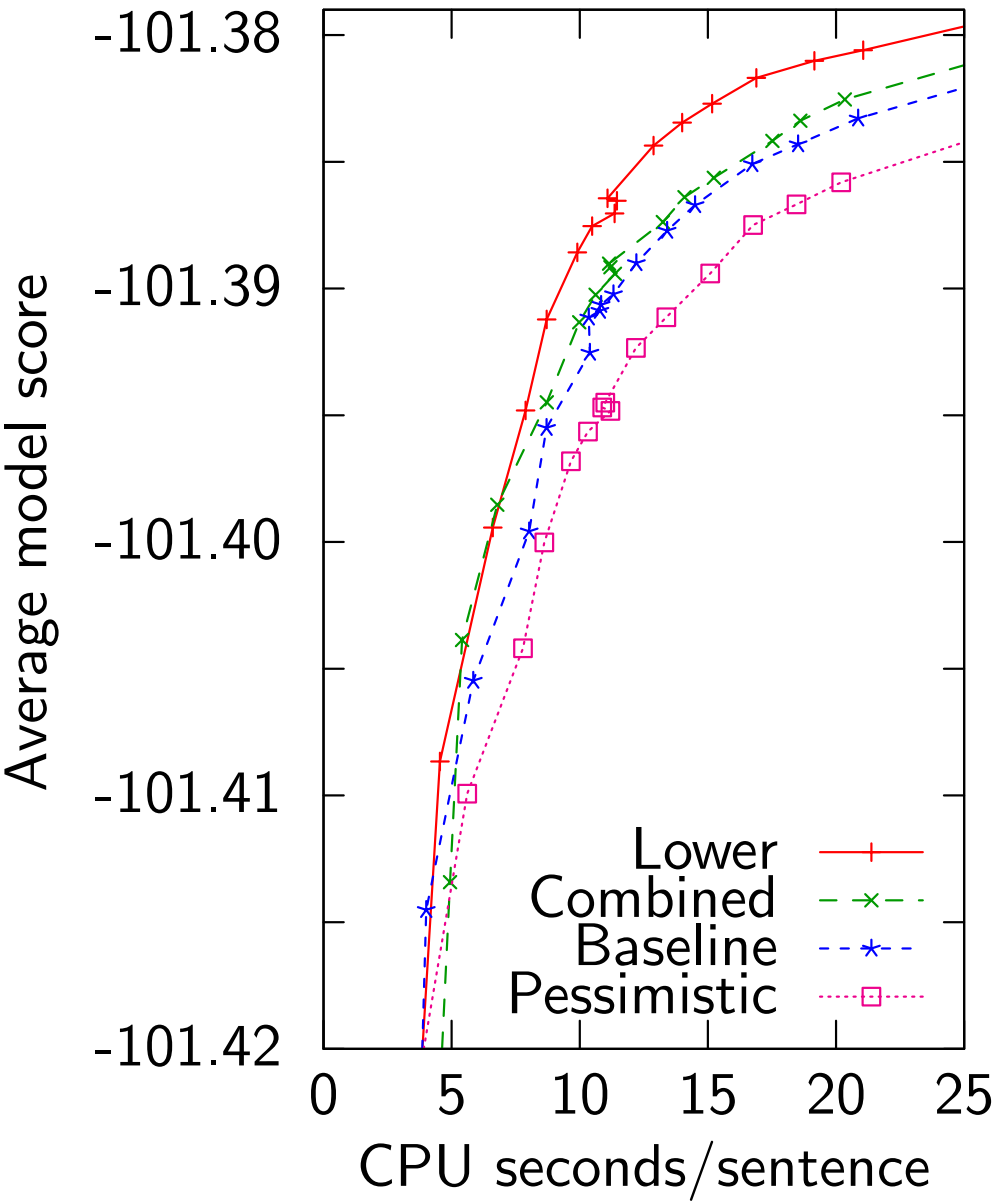
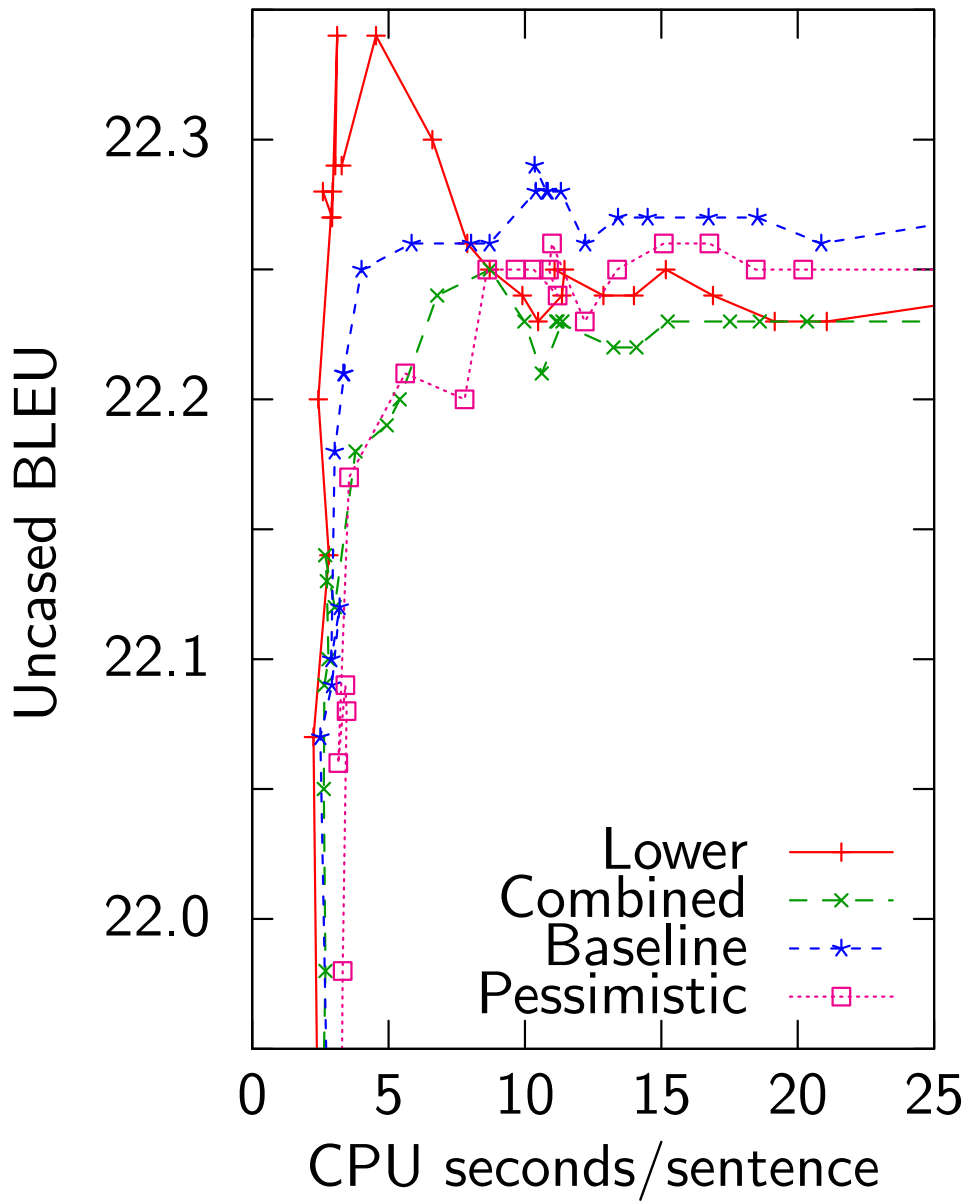
Larger pop limit
Accurate fragment scores $\Longrightarrow$ more accurate search.

Experiments

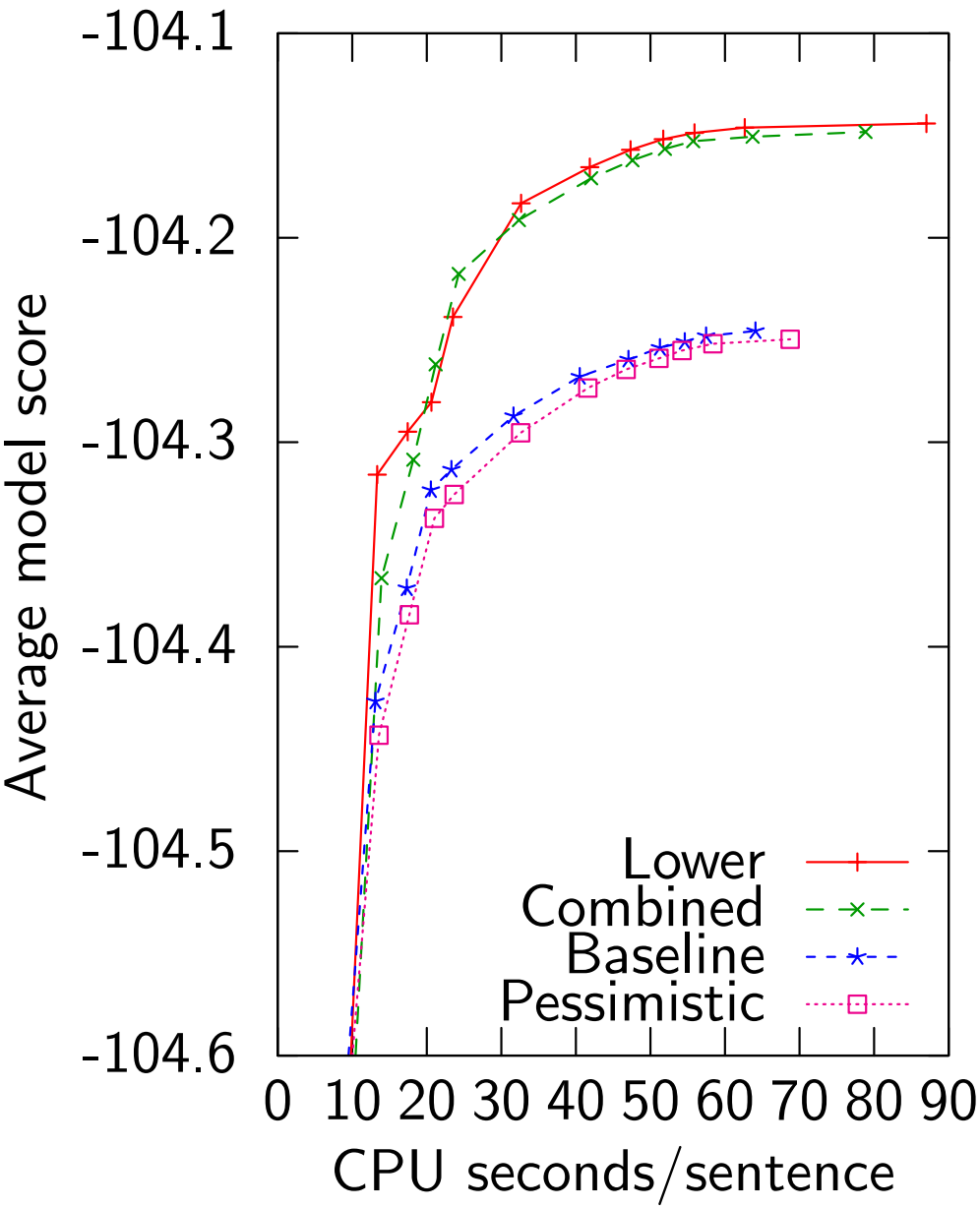
Task	WMT 2011 German-English
Decoder	Moses
LM	5-gram from Europarl, news commentary, and news
Grammar	Hierarchical and target-syntax systems
Parser	Collins

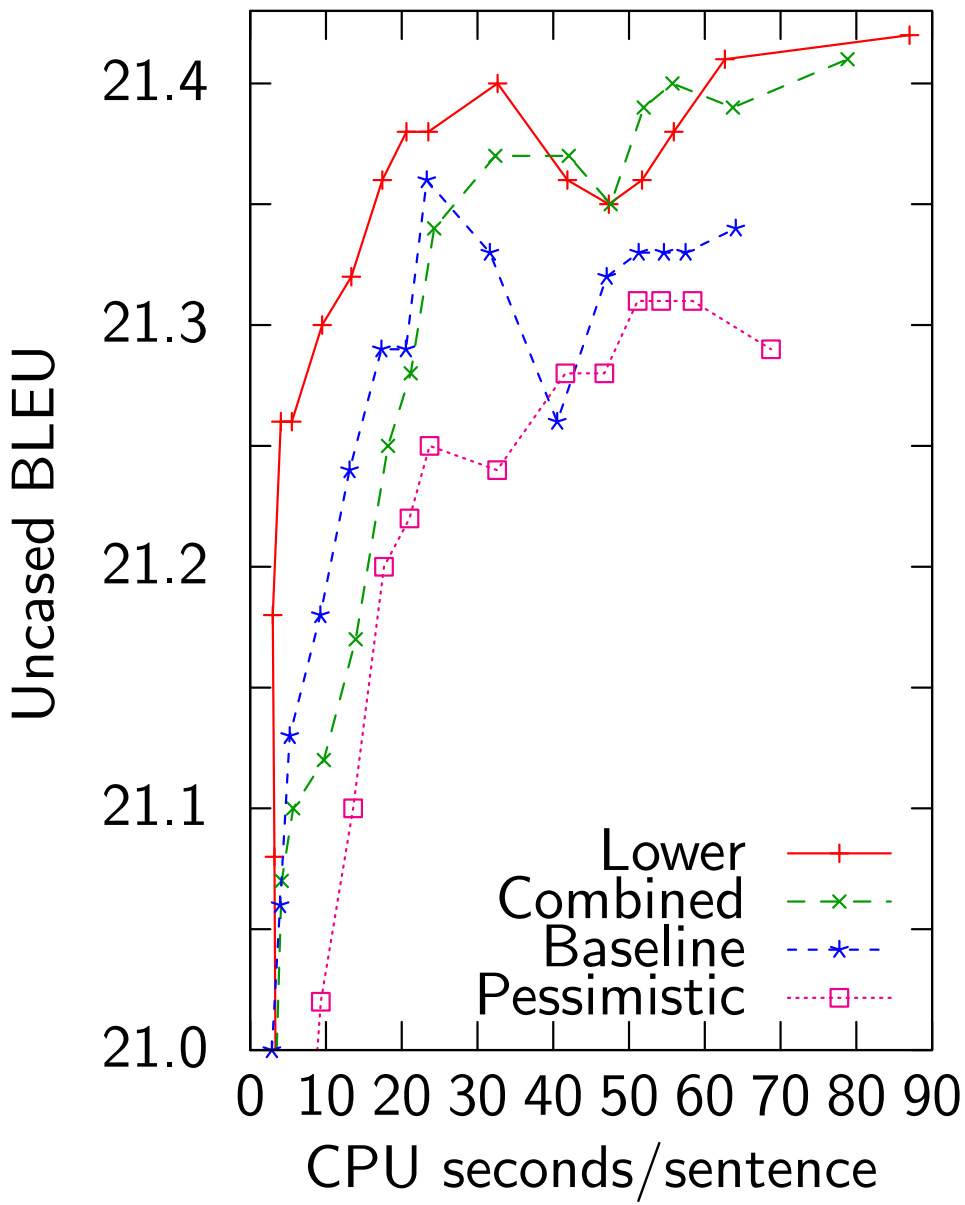
Hierarchical Model Score and BLEU





Target-Syntax Model Score and BLEU





Memory

Cost to add or savings from removing a float per entry.

Structure	**Baseline (MB)**	**Change (MB)**	**%**
Probing	4,072	517	13%
Trie	2,647	506	19%
8-bit quantized trie	1,236	140	11%
8-bit minimal perfect hash	540	140	26%

Summary

Lower Order Models

- 21-63% less CPU
- 13-26% more memory

Pessimistic Backoff

- 27% more CPU
- 13-26% less memory

Lower Order+Pessimistic

- 3% less CPU
- Same memory as baseline

Code

kheafield.com/code/kenlm
Also distributed with Moses and cdec.

Lower Order

build_binary -r "1.arpa 2.arpa 3.arpa 4.arpa" 5.arpa 5.binary

Pessimistic Backoff

Release planned