# Language Model Rest Costs and Space-Efficient Storage

Kenneth Heafield Philipp Koehn Alon Lavie

Carnegie Mellon, University of Edinburgh

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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

**Make Search Expensive**

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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

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

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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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|---|---|
| Score with and without sentence boundaries. | [Sankaran et al, 2012] |
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| Coarse pass predicts scores for a finer pass. | [Vilar and Ney, 2011] |

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 |

Compress

**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 $q$

$$\begin{array}{rlcl}
 & \log q(\text{is}) & = & \text{-4.10} \\
 & \log q(\text{one} \mid \text{is}) & = & \text{-2.51} \\
 & \log q(\text{of} \mid \text{is one}) & = & \text{-0.94} \\
 & \log q(\text{the} \mid \text{is one of}) & = & \text{-1.61} \\
+ & \log q(\text{few} \mid \text{is one of the}) & = & 1.03 \\
\hline
= & \log q(\text{is one of the few}) & = & \text{-8.13}
\end{array}$$

Store $q$, forget probability and backoff.

# Using $q$

$$
\begin{array}{rlll}
 & \log q(\text{is}) & & = \text{-4.10} \\
 & \log q(\text{one} & \mid \text{is}) & = \text{-2.51} \\
 & \log q(\text{of} & \mid \text{is one}) & = \text{-0.94} \\
 & \log q(\text{the} & \mid \text{is one of}) & = \text{-1.61} \\
+ & \log q(\text{few} & \mid \text{is one of the}) & = \color{red}{1.03} \\
\hline
= & \log q(\text{is one of the few}) & & = \text{-8.13}
\end{array}
$$

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 $\implies$ more accurate search.

# Cube Pruning: Approximate Search

For each constituent, going bottom-up:

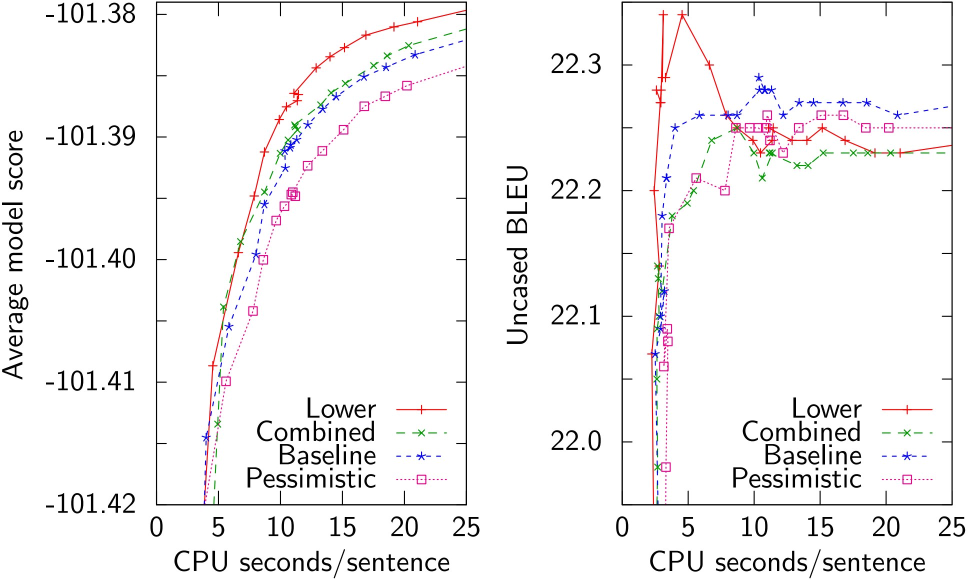
1. Make a priority queue over possible rule applications.
2. Pop a fixed number of hypotheses: the *pop limit*.

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

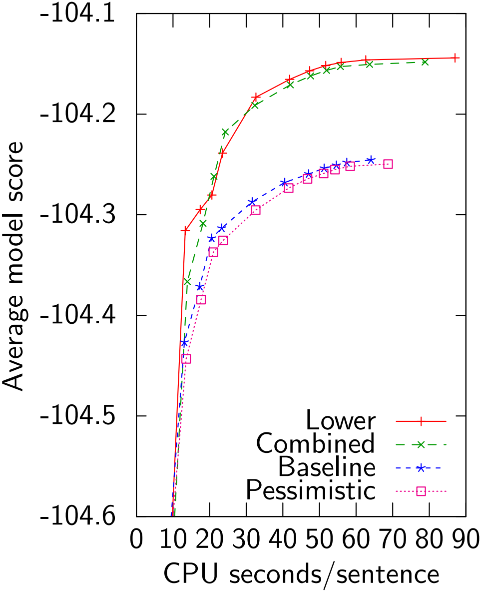
# Experiments

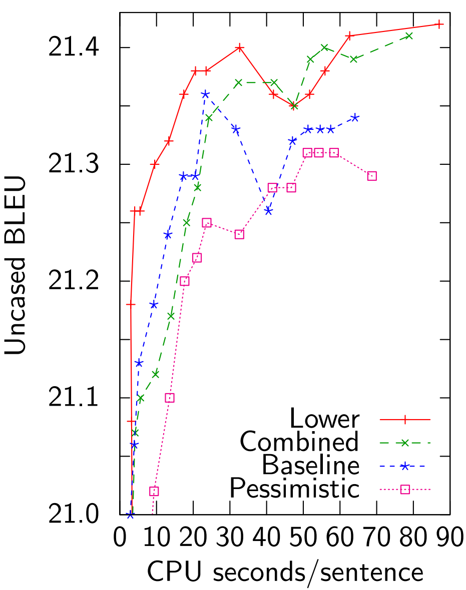
| | |
|---|---|
| Task | WMT 2011 German-English |
| Decoder | Moses |
| LM | 5-gram from Europarl, news commentary, and news |
| Grammar | Hierarchical and target-syntax systems |
| Parser | Collins |

# 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