Scalable Modified Kneser-Ney Language Model Estimation

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Estimating LMs is Costly

MIT RAM SRI RAM, time IRST RAM, time, approximation Berkeley RAM, time, approximation

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Microsoft Delay some computation to query time Google 100–1500 machines, optional stupid backoff

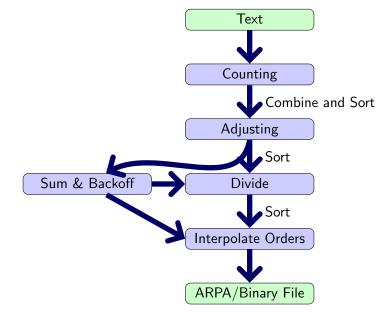
This Work

- Disk-based streaming and sorting
- User-specified RAM
- Fast
- Interpolated modified Kneser-Ney

7.7% of SRI's RAM, 14% of SRI's wall time

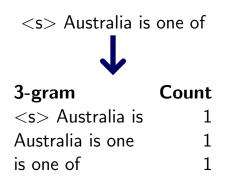
Outline

- Estimation Pipeline
- Streaming and Sorting
- Section 2 Experiments



Estimating	
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Counting



Combine in a hash table, spill to merge sort.

Adjusting

Adjusted counts are:

Trigrams Same as counts.

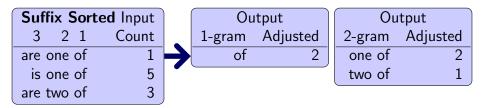
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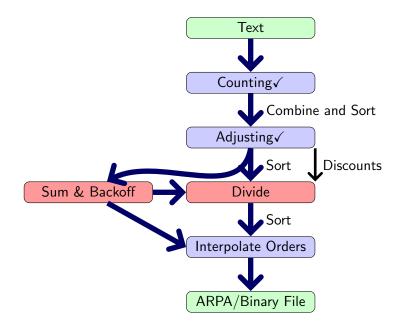


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Count singletons, doubletons, tripletons, and quadrupletons for each order.



Chen and Goodman



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Discounting and Normalization

Save mass for unseen events

$$\mathsf{pseudo}(w_n|w_1^{n-1}) = \frac{\mathsf{adjusted}(w_1^n) - \mathsf{discount}_n(\mathsf{adjusted}(w_1^n))}{\sum_x \mathsf{adjusted}(w_1^{n-1}x)}$$

Normalize

Discounting and Normalization

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Normalize

Contex	t Sorted Input		Output		
2 1	3 Adjusted		3-gram	Pseudo	
are one	of 1	\rightarrow	are one of	0.26	
are one	that 2		are one that	0.47	
is one	of 5		is one of	0.62	

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Experiments

Denominator Looks Ahead

Save mass for unseen events

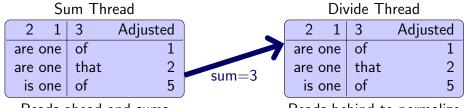
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Estimating	
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Two Threads



Reads ahead and sums

Reads behind to normalize

Computing Backoffs

Backoffs are penalties for unseen events.

Bin the entries "are one x" by their adjusted counts

continue(are one) = (number with adjusted count 1,

- ... adjusted count 2,
- \ldots adjusted count > 3)

Computing Backoffs Backoffs are penalties for unseen events.

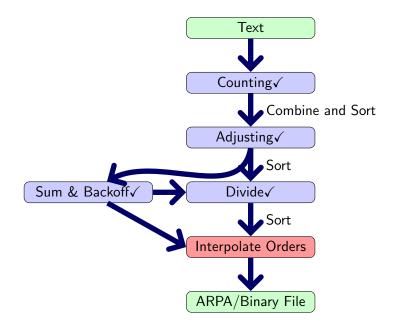
Bin the entries "are one x" by their adjusted counts

continue(are one) = (number with adjusted count 1, ... adjusted count 2,

... adjusted count \geq 3)

Compute backoff in the sum thread

$$\mathsf{backoff}(\mathsf{are one}) = \frac{\mathsf{continue}(\mathsf{are one}) \cdot \mathsf{discount}_3}{\sum_x \mathsf{adjusted}(\mathsf{are one } x)}$$



	Streaming and Sorting
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Estimating

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Interpolate Orders

Interpolate unigrams with the uniform distribution. $p(of) = pseudo(of) + backoff(\epsilon) \frac{1}{|vocabulary|}$

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Suffix Lexicographic Sorted Input				Outpu	ıt	
<i>n</i> -gram	pseudo	interpola	ation weight		<i>n</i> -gram	р
of	0.1	backoff(ϵ) = 0.1	\rightarrow	of	0.110
one of	0.2	backoff(one) $= 0.3$		one of	0.233
are one of	0.4	backoff(ar	e one) = 0.2		are one of	0.447

Estimating	
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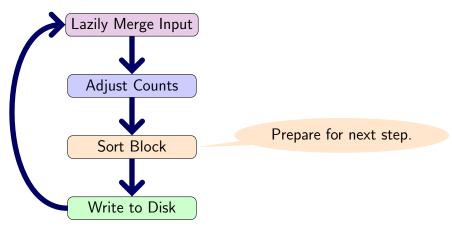
Summary

Compute interpolated modified Kneser-Ney without pruning in Four streaming passes and three sorts.

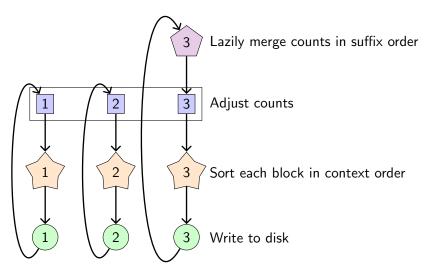
How do we make this efficient?

Streaming Framework

Memory is divided into blocks. Blocks are recycled.



Adjusted Counts Detail

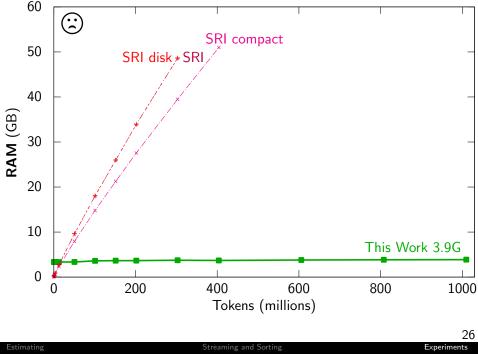


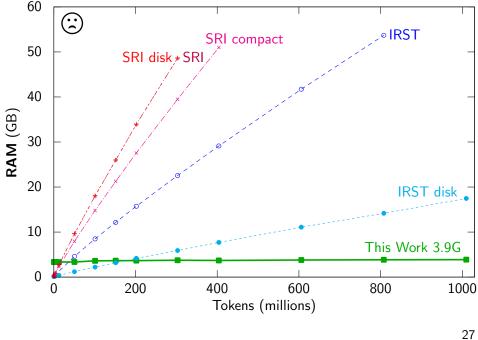
Each vertex is a thread \implies Simultaneous disk and CPU.

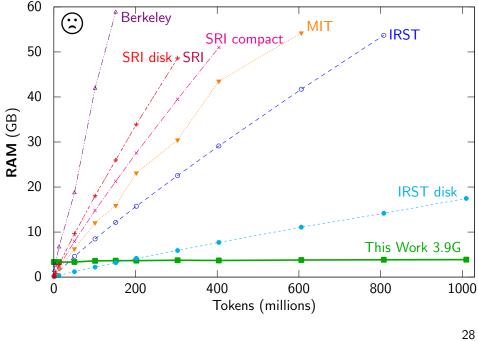
Experiment: Toolkit Comparison

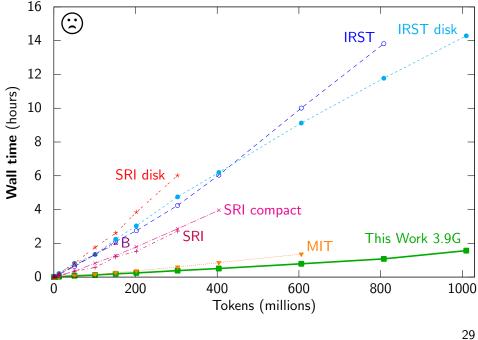
TaskBuild an unpruned 5-gram language modelDataSubset of English ClueWeb09 (webpages)Machine64 GB RAMOutput FormatBinary (or ARPA when faster)

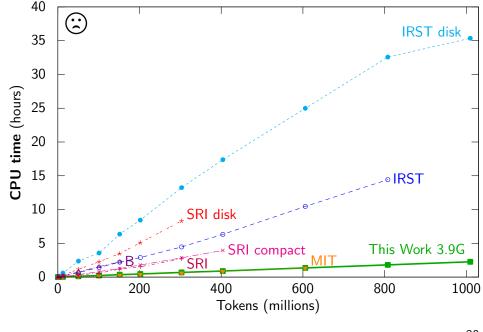
IRST disk: 3-way split. Peak RAM of any one process (as if run serially). Berkeley: Binary search for minimum JVM memory.













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Experiments

Scaling



Counts					
	1	2	3	4	5
This Work 126B	393m	3,775m	17,629m	39,919m	59,794m
Pruned Google 1T	14m	315m	977m	1,313m	1,176m

(This work used a machine with 140 GB RAM and a RAID5 array.)

Scaling

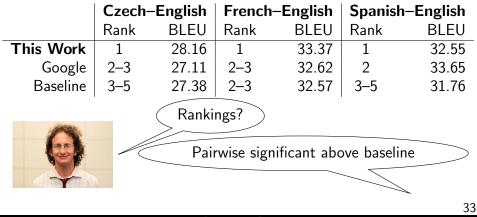
	Tokens	Smoothing	Machines	Days	Year
This Work	126 billion	Kneser-Ney	1	2.8	2013
Google	31 billion	Kneser-Ney	400	2	2007
Google	230 billion	Kneser-Ney	?	?	2013
Google	1800 billion	Stupid	1500	1	2007

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WMT 2013 Results

- Compress the big LM to 676 GB
- 2 Decode with 1 TB RAM
- Make three WMT submissions

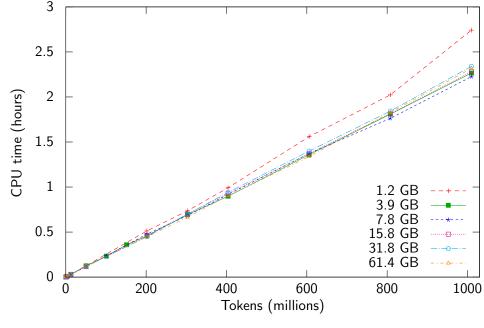


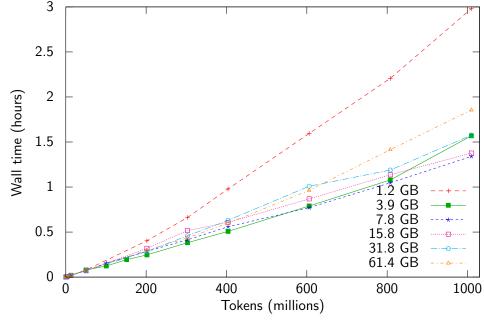
Build language models with user-specified RAM kheafield.com/code/kenlm/

bin/Implz -o 5 -S 10G <text >arpa

Future Work

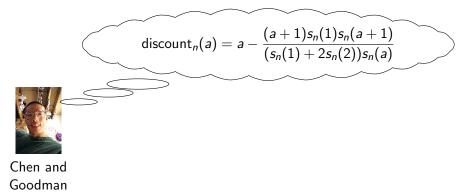
- Interpolating models trained on separate data
- Pruning
- CommonCrawl corpus





Summary statistics are collected while adjusting counts: $s_n(a) =$ number of *n*-grams with adjusted count *a*.

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