Language Modeling in the Era of Abundant Data

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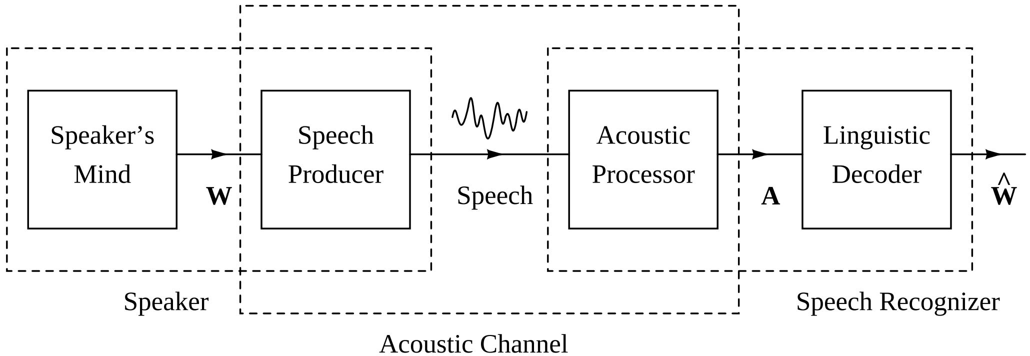
Statistical Modeling in Automatic Speech Recognition



$$\hat{W} = \text{argmax}_{\text{W}} P(W|A) = \text{argmax}_{\text{W}} P(A|W) \cdot P(W)$$

- $P(A|W)$ *acoustic model* (AM, Hidden Markov Model); varies depending on problem (machine translation, spelling correction, soft keyboard input)
- $P(W)$ *language model* (LM, usually Markov chain)
- *search* for the most likely word string $\hat{W}$

Language Modeling Usual Assumptions

- we have a word level tokenization of the text (not true in all languages, e.g. Chinese)
- some vocabulary is given to us (usually also estimated from data);
- out-of-vocabulary (OoV) words are mapped to `<UNK>` ("open" vocabulary LM)
- sentences are assumed to be independent and of finite length; LM needs to predict end-of-sentence symbol `</S>`
-

```
On my second day , I managed the uphill walk
to a waterfall called <UNK> Skok . </S>
```

Language Model Evaluation (1)

Word Error Rate (WER)

```
TRN: UP UPSTATE NEW YORK SOMEWHERE UH     OVER
HYP:    UPSTATE NEW YORK SOMEWHERE UH ALL ALL
     D  0       0   0    0         0  I   S
   :3 errors/7 words in transcript; WER = 43%
```

Perplexity (PPL) (Jelinek, 1997)

$$PPL(M) = \exp\left(-\frac{1}{N}\sum_{i=1}^{N}\ln\left[P_M(w_i|w_1\ldots w_{i-1})\right]\right)$$

- good models are "smoothed" ML estimates: $P_M(w_i|w_1\ldots w_{i-1}) > \epsilon$; also guarantees a proper probability model over sentences
- other metrics: out-of-vocabulary rate/n-gram hit ratios

Language Model Smoothing

Markov assumption leads to N-gram model:

$$P_\theta(w_i|w_1 \ldots w_{i-1}) = P_\theta(w_i|w_{i-N+1} \ldots w_{i-1}), \theta \in \Theta, w_i \in \mathcal{V}$$

Smoothing using Deleted Interpolation:

$$\begin{aligned} P_n(w|h) &= \lambda(h) \cdot P_{n-1}(w|h') + (1 - \lambda(h)) \cdot f_n(w|h) \\ P_{-1}(w) &= uniform(\mathcal{V}) \end{aligned}$$

where:

- $h = (w_{i-n+1} \ldots w_{i-1})$ is the n-gram context, and $h' = (w_{i-n+2} \ldots w_{i-1})$ is the back-off context
- weights $\lambda(h)$ must be estimated on held-out (cross-validation) data.

Language Model Smoothing: Katz

Katz Smoothing (Katz, 1987) uses Good-Turing discounting:

$$P_n(w|h) = \begin{cases} f_n(w|h), C(h,w) > K \\ (r+1)\frac{t_{r+1}}{t_r} \cdot f_n(w|h), 0 < C(h,w) \leq K \\ \beta(h) P_{n-1}(w|h') \end{cases}$$

where:

- t_r represents the number of n-grams (types) that occur r times: $t_r = |(w_{i-n+1} \dots w_i), C(w_{i-n+1} \dots w_i) = r|$
- $\beta(h)$ is the back-off weight ensuring proper normalization

Language Model Smoothing: Kneser-Ney

Kneser-Ney Smoothing (Kneser & Ney, 1995):

$$P_n(w|h) \;=\; \begin{cases} \frac{C(h,w)-D_1}{C(h)} + \lambda(h)P_{n-1}(w|h'), n = N \\ \frac{LeftDivC(h,w)-D_2}{\sum_w LeftDivC(h,w)} + \lambda(h)P_{n-1}(w|h'), 0 \leq n < N \end{cases}$$

where:

- $LeftDivC(h,w) = |v, C(v,h,w) > 0|$ is the “left diversity” count for an n-gram (h,w)

See (Goodman, 2001) for a detailed presentation on LM smoothing.

Language Model Representation: ARPA Back-off

```
p(wd3|wd1,wd2)=
 if(trigram exists)     p_3(wd1,wd2,wd3)
 else if(w1,w2 exists) bo_2(w1,w2)*p(wd3|wd2)
 else                   p(wd3|w2)
p(wd2|wd1)=
 if(w1,w2 exists)       p_2(wd1,wd2)
 else                   bo_1(wd1)*p_1(wd2)

\1-grams:
p_1     wd      bo_1
\2-grams:
p_2     wd1 wd2 bo_2
\3-grams:
p_3     wd1 wd2 wd3
```

Language Model Size Control: Entropy Pruning

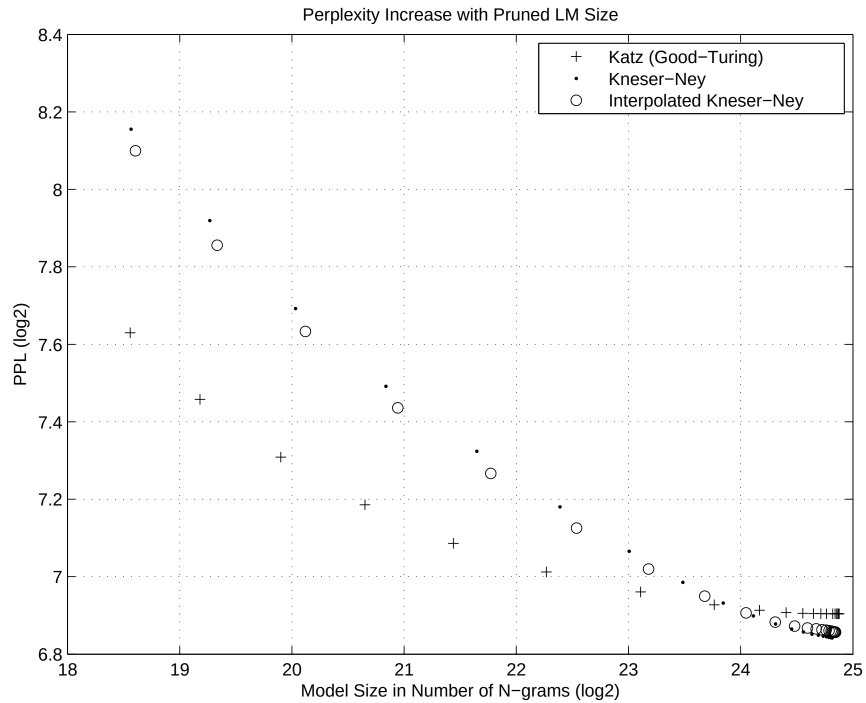
Entropy pruning (Stolcke, 1998) is required for use in 1st pass:

- should one remove n-gram (h, w)?

$$
\begin{aligned}
D[q(h)p(\cdot|h) \parallel q(h) \cdot p'(\cdot|h)] &= q(h) \sum_w p(w|h) \log \frac{p(w|h)}{p'(w|h)} \\
|\ D[q(h)p(\cdot|h) \parallel q(h) \cdot p'(\cdot|h)]\ | &< \mathit{pruning\ threshold}
\end{aligned}
$$

- lower order estimates: $q(h) = p(h_1) \ldots p(h_n|h_1 \ldots h_{n-1})$ or relative frequency: $q(h) = f(h)$
- greedily reduces LM size at min cost in PPL

On Smoothing and Pruning



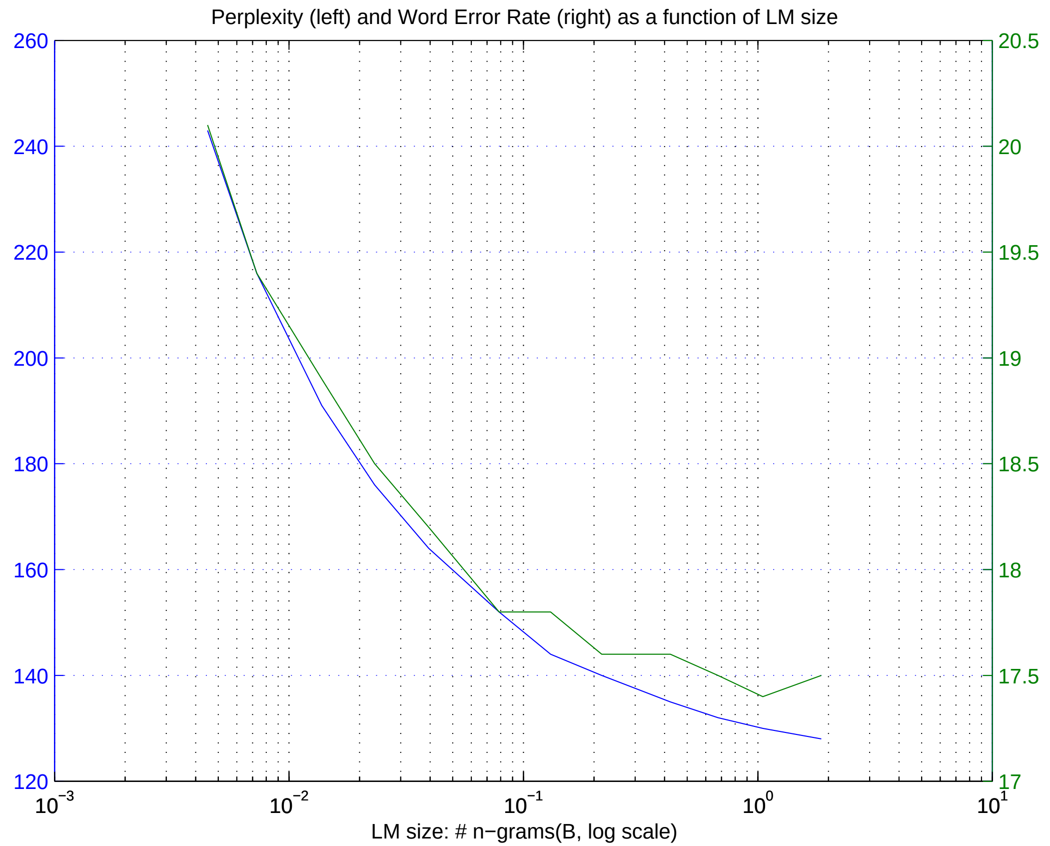
- KN degrades very fast with aggressive pruning (< 10% of original size) (Ciprian Chelba, 2010)
- switch from KN to Katz smoothing: 10% WER gain for voice-search

Voice Search LM Training Setup (Chelba & Schalkwyk, 2013)

- spelling corrected google.com queries, normalized for ASR, e.g. `5th -> fifth`
- vocabulary size: 1M words, OoV rate 0.57% (!), excellent n-gram hit ratios
- training data: 230B words

Order	no. n-grams	pruning	PPL	n-gram hit-ratios
3	15M	entropy	190	47/93/100
3	7.7B	none	132	97/99/100
5	12.7B	1-1-2-2-2	108	77/88/97/99/100

Is Bigger Better? YES!



- PPL is really well correlated with WER when controlling for vocabulary and training set.

Better Language Models: More Smarts

1-billion word benchmark (Chelba et al., 2013) results

Model	Num. Params	PPL
Katz 5-gram	1.74 B	79.9
Kneser-Ney 5-gram	1.76 B	67.6
SNM skip-gram	33 B	52.9
RNN	20 B	51.3
ALL, linear interpolation		41.0

- there are LMs that handily beat the N-gram by leveraging longer context (when available)
- how about increasing the amount of data, when we have it?

Better Language Models: More Smarts, More Data? Ideally Both

10/100 billion word query data benchmark results[a]

Model	Data Amount	Num. Params	PPL
Katz 6-gram	10B	3.2 B	123.9
Kneser-Ney 6-gram	10B	4.1 B	114.5
SNM skip-gram	10B	25 B	111.0
RNN	10B	4.1 B	111.1
Katz 6-gram	100B	19.6 B	92.7
Kneser-Ney 6-gram	100B	24.5 B	87.9
RNN	100B	4.1 B	101.0

- more data and model is an easy way to get solid gains
- complex models better scale up gracefully
- KN smoothing loses its edge over Katz

[a] Thanks Babak Damavandi for the RNN experimental results

More Data Is Not Always a Winner: Query Stream Non-stationarity (1)

- USA training data:
  - XX months
  - X months
- test data: 10k, Sept-Dec 2008
- very little impact in OoV rate for 1M wds vocabulary: 0.77% (X months vocabulary) vs. 0.73% (XX months vocabulary)

More Data Is Not Always a Winner: Query Stream Non-stationarity (2)

3-gram LM	Training Set	Test Set PPL
unpruned	X months	121
unpruned	XX months	132
entropy pruned	X months	205
entropy pruned	XX months	209

- bigger is not always better[a]
- 10% rel reduction in PPL when using the most recent X months instead of XX months
- no significant difference after pruning, in either PPL or WER

[a] The vocabularies are mismatched, so the PPL comparison is troublesome. The difference would be higher if we used a fixed vocabulary.

More Locales

- training data across 3 locales: USA, GBR, AUS, spanning same amount of time ending in Aug 2008
- test data: 10k/locale, Sept-Dec 2008

Out of Vocabulary Rate:

Training	**Test Locale**		
Locale	USA	GBR	AUS
USA	0.7	1.3	1.6
GBR	1.3	0.7	1.3
AUS	1.3	1.1	0.7

- locale specific vocabulary halves the OoV rate

Locale Matters (2)

Perplexity of unpruned LM:

Training Locale	Test Locale USA	GBR	AUS
USA	132	234	251
GBR	260	110	224
AUS	276	210	124

- locale specific LM halves the PPL of the unpruned LM

Open Problems

- Entropy of text from a given source:
  how much are we leaving on the table?
- How much data/model is enough for a given source:
  does such a bound exist for N-gram models?
- More data, relevance, transfer learning:
  not all data is created equal.
- Conditional ML estimation:
  LM estimation should take into account the channel model.

Entropy of English

High variance, depending on estimate, source of data; 0.1-0.2 bits/char is a significant difference in PPL at word level!

- (Cover & King, 1978): 1.3 bits/char
- (Brown, Pietra, Mercer, Pietra, & Lai, 1992): 1.75 bits/char
- 1-billion corpus: $\approx^a$ 1.17 bits/char for KN, $\approx$ 1.03 bits/char for the best reported LM mixing skip-gram SNM with RNN
- 10, 100 -billion query corpus: $\approx$ 1.43, 1.35 bits/char for KN, respectively.

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[a] Modulo OoV word modeling

Abundant Data: How Much is Enough for Modeling a Given Source?

A couple of observations:

- one can prune an LM to about 10% of unpruned size without significant impact on PPL
- increasing the amount of data and model size becomes unproductive after a while

For a given source, and N-gram order, is there a data size beyond which there is no benefit to the model quality?

Abundant Data: Not All Data is Created Equal

- It is not always possible to find very large amounts of data that is well matched to a given application/test set
- E.g. when building an LM for SMS text we may have very little such data, quite a bit more from posts on social networks, and a lot of text from a web crawl.
- LM adaptation: leveraging data in different amounts, and of various degrees of relevance[a] to a given test set.

[a] Relevance of data to a given test set is hard to describe, but you know it when you see it.

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