



Language Modeling

Interpolation, Backoff, and Web-Scale LMs



Backoff and Interpolation

- Sometimes it helps to use **less** context
 - Condition on less context for contexts you haven't learned much about
- **Backoff:**
 - use trigram if you have good evidence,
 - otherwise bigram, otherwise unigram
- **Interpolation:**
 - mix unigram, bigram, trigram
- Interpolation works better



Linear Interpolation

- Simple interpolation

$$\begin{aligned}\hat{P}(w_n|w_{n-1}w_{n-2}) &= \lambda_1 P(w_n|w_{n-1}w_{n-2}) \\ &\quad + \lambda_2 P(w_n|w_{n-1}) \\ &\quad + \lambda_3 P(w_n)\end{aligned}$$

$$\sum_i \lambda_i = 1$$

- Lambdas conditional on context:

$$\begin{aligned}\hat{P}(w_n|w_{n-2}w_{n-1}) &= \lambda_1(w_{n-2}^{n-1})P(w_n|w_{n-2}w_{n-1}) \\ &\quad + \lambda_2(w_{n-2}^{n-1})P(w_n|w_{n-1}) \\ &\quad + \lambda_3(w_{n-2}^{n-1})P(w_n)\end{aligned}$$



How to set the lambdas?

- Use a **held-out** corpus

Training Data

Held-Out
Data

Test
Data

- Choose λ s to maximize the probability of held-out data:
 - Fix the N-gram probabilities (on the training data)
 - Then search for λ s that give largest probability to held-out set:

$$\log P(w_1 \dots w_n \mid M(\lambda_1 \dots \lambda_k)) = \sum_i \log P_{M(\lambda_1 \dots \lambda_k)}(w_i \mid w_{i-1})$$



Unknown words: Open versus closed vocabulary tasks

- If we know all the words in advanced
 - Vocabulary V is fixed
 - Closed vocabulary task
- Often we don't know this
 - **Out Of Vocabulary** = OOV words
 - Open vocabulary task
- Instead: create an unknown word token $\langle \text{UNK} \rangle$
 - Training of $\langle \text{UNK} \rangle$ probabilities
 - Create a fixed lexicon L of size V
 - At text normalization phase, any training word not in L changed to $\langle \text{UNK} \rangle$
 - Now we train its probabilities like a normal word
 - At decoding time
 - If text input: Use UNK probabilities for any word not in training



Huge web-scale n-grams

- How to deal with, e.g., Google N-gram corpus
- Pruning
 - Only store N-grams with count $>$ threshold.
 - Remove singletons of higher-order n-grams
 - Entropy-based pruning
- Efficiency
 - Efficient data structures like tries
 - Bloom filters: approximate language models
 - Store words as indexes, not strings
 - Use Huffman coding to fit large numbers of words into two bytes
 - Quantize probabilities (4-8 bits instead of 8-byte float)



Smoothing for Web-scale N-grams

- “Stupid backoff” (Brants *et al.* 2007)
- No discounting, just use relative frequencies

$$S(w_i | w_{i-k+1}^{i-1}) = \begin{cases} \frac{\text{count}(w_{i-k+1}^i)}{\text{count}(w_{i-k+1}^{i-1})} & \text{if } \text{count}(w_{i-k+1}^i) > 0 \\ 0.4S(w_i | w_{i-k+2}^{i-1}) & \text{otherwise} \end{cases}$$

$$S(w_i) = \frac{\text{count}(w_i)}{N}$$



N-gram Smoothing Summary

- Add-1 smoothing:
 - OK for text categorization, not for language modeling
- The most commonly used method:
 - Extended Interpolated Kneser-Ney
- For very large N-grams like the Web:
 - Stupid backoff



Advanced Language Modeling

- Discriminative models:
 - choose n-gram weights to improve a task, not to fit the training set
- Parsing-based models
- Caching Models
 - Recently used words are more likely to appear

$$P_{CACHE}(w | history) = \lambda P(w_i | w_{i-2} w_{i-1}) + (1 - \lambda) \frac{c(w \in history)}{|history|}$$

- These perform very poorly for speech recognition (why?)



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