Language Modeling in Automatic Speech Recognition

ZRE lecture

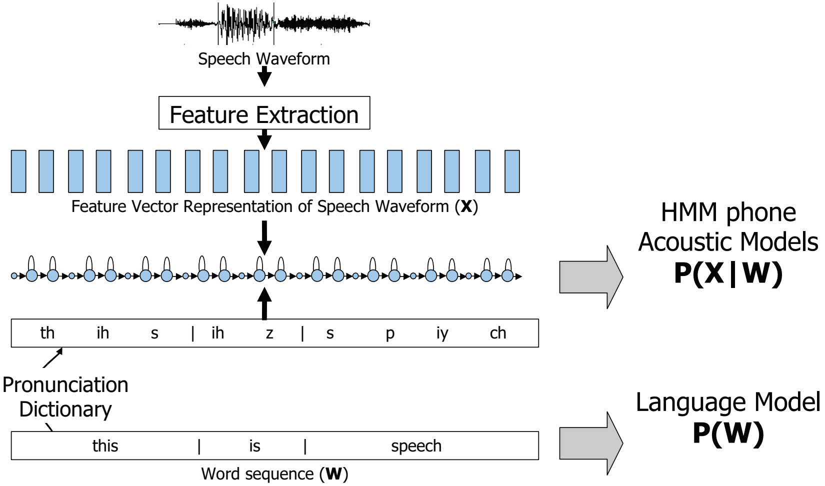
Karel Beneš

08.04.2024

Roadmap of the Lecture

1. ASR Intro
2. Count-based Language Modeling
3. Neural-network Language Modeling

Automatic speech recognition



Automatic speech recognition

- Determine the most probable word sequence $\tilde{W}$ given the observed acoustic signal Y

$$\tilde{W} = argmax\ P(W|Y) = \frac{argmax\ P(W)P(Y|W)}{P(Y)}$$

- Search for word sequence $\tilde{W}$ that maximizes P(W) and P(Y|W)
  - P(W) = language model (likelihood of word sequence)
  - P(Y|W) = acoustic model
    (likelihood of observed acoustic signal given word sequence)

Roadmap of the Lecture

1. ASR Intro
2. Count-based Language Modeling
3. Neural-network Language Modeling

Language model

Estimate probability of a word sequence W:

$$P(W) = P(w_1, w_2, \ldots, w_N) \tag{1}$$

$$P(W) = P(w_1) \cdot P(w_2|w_1) \cdot P(w_3|w_1, w_2) \cdot \cdots \cdot P(w_N|w_1, \ldots, w_{N-1}) \tag{2}$$

Markov assumption, n-grams counting

Approximate by only considering 1-word history, e.g.:

$$P(W) \approx P(w_1) \cdot P(w_2|w_1) \cdot P(w_3|w_2) \cdot \dots \cdot P(w_N|w_{N-1}) \tag{3}$$

Gives raise to *2-gram / bigram* language model. Probabilities $P(w_a|w_b)$ are estimated as:

$$P(w_a|w_b) = \frac{C(w_b, w_a)}{C(w_b)} \tag{4}$$

Markov assumption, n-grams counting

Approximate by only considering 2-word history, e.g.:

$$P(W) \approx P(w_1) \cdot P(w_2|w_1) \cdot P(w_3|w_1, w_2) \cdot \dots \cdot P(w_N|w_{N-2}, w_{N-1}) \quad (5)$$

Gives raise to *3-gram / trigram* language model. Probabilities $P(w_a|w_b, w_c)$ are estimated as:

$$P(w_a|w_b, w_c) = \frac{C(w_b, w_c, w_a)}{C(w_b, w_c)} \quad (6)$$

Problem of n-grams

1. limited context, e.g.

   "*. . . to Paris, we couldn't wait to see the ???* "

   Unfortunate, but acceptable.
2. unseen n-grams, e.g. 2M words from Wikipedia -> 2.6 % of unseen words in other wiki texts. Cca 1/3 of trigrams not seen since 1970s. So called *Curse of Dimensionality*, severe.

Katz's backoff

If we have enough data, $C(w_{i-n+1}, \dots, w_{i-1}, w_i) > k$:

$$P(w_i | w_{i-n+1}, \dots, w_{i-1}) = d_{C(w_{i-n+1},\dots,w_{i-1},w_i)} \frac{C(w_{i-n+1}, \dots, w_{i-1}, w_i)}{C(w_{i-n+1}, \dots, w_{i-1})} \tag{7}$$

The discount factor $d_{C(\cdot)}$

Determines how much do we take away from n-grams appearing $C(\cdot)$ times; estimated typically with Good-Turing algorithm.

If $C(w_{i-n+1}, \dots, w_{i-1}, w_i) \leq k$:

$$P(w_i | w_{i-n+1}, \dots, w_{i-1}) = \alpha_{w_{i-n+1},\dots,w_{i-1}} P(w_i | w_{i-n+2}, \dots, w_{i-1}) \tag{8}$$

The redistribution factor α

Determines how much of discounted probability is assigned to the (n-1)-gram $w_{i-n+1}, \dots, w_{i-1}$.

The threshold k for "enough" can in practice be set to 0.

Kneser-Ney smoothing

For bigrams:

$$P(w_i|w_{i-1}) = \frac{\max(C(w_{i-1}w_i) - \delta, 0)}{C(w_{i-1})} + \lambda \frac{N_{1+}(\bullet w_i)}{N_{1+}(\bullet\bullet)} \tag{9}$$

The mysterious $N_{1+}(\cdot)$ just counts how many unique bigrams have we seen:

$$N_{1+}(\bullet w_i) = |\{w_{i-1}|C(w_{i-1}, w_i)\}| \tag{10}$$

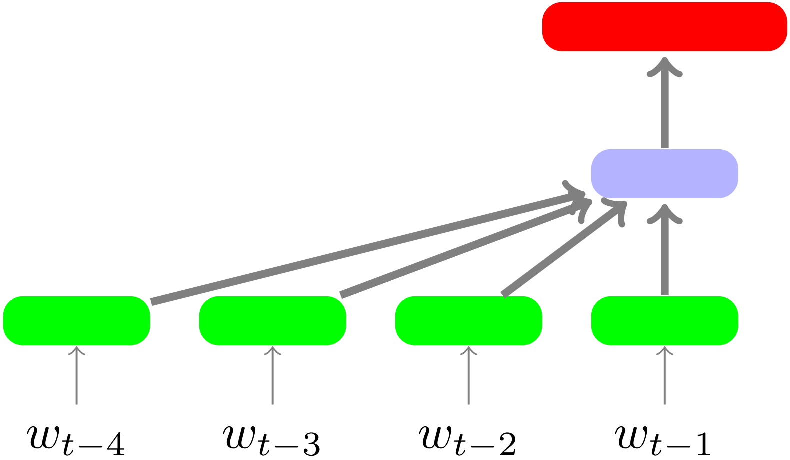
$$N_{1+}(\bullet\bullet) = |\{w_{i-1}, w_i|C(w_{i-1}, w_i)\}| \tag{11}$$

So effectively, we only believe the unigram w_i, if we have seen it in many different contexts.

Roadmap of the Lecture

1. ASR Intro
2. Count-based Language Modeling
3. Neural-network Language Modeling

Battling the Curse of Dimensionality using NNs



Battling the Curse of Dimensionality using NNs

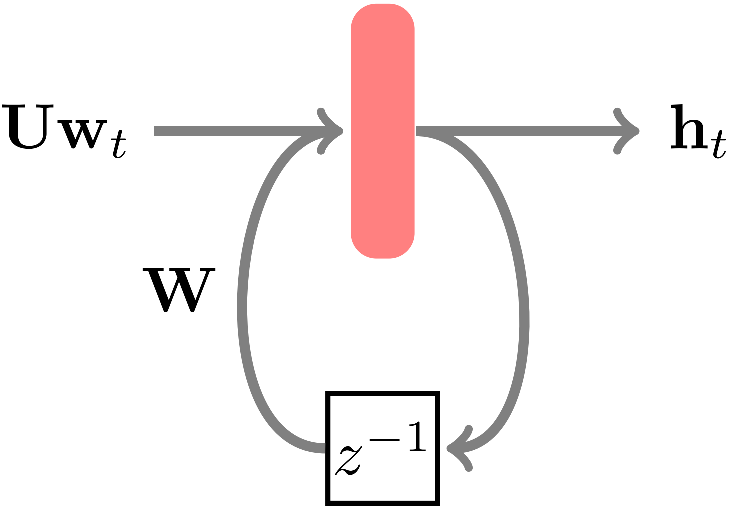
$$\mathbf{e}_t = \mathbf{E}[w_t] \tag{12}$$

$$\mathbf{h}_t = \tanh(\mathbf{W}(\mathbf{e}_{t-2}||\mathbf{e}_{t-1}) + \mathbf{b}_h) \tag{13}$$

$$\mathbf{y}_t = \text{softmax}(\mathbf{V}\mathbf{h}_t + \mathbf{b}_y) \tag{14}$$

First, words are replaced by embeddings (12). Then, several embeddings (two) are concatenated and serve as input to a hidden layer (13). Finally, the next word is predicted (14).

Battling the Curse of Dimensionality using RNNs



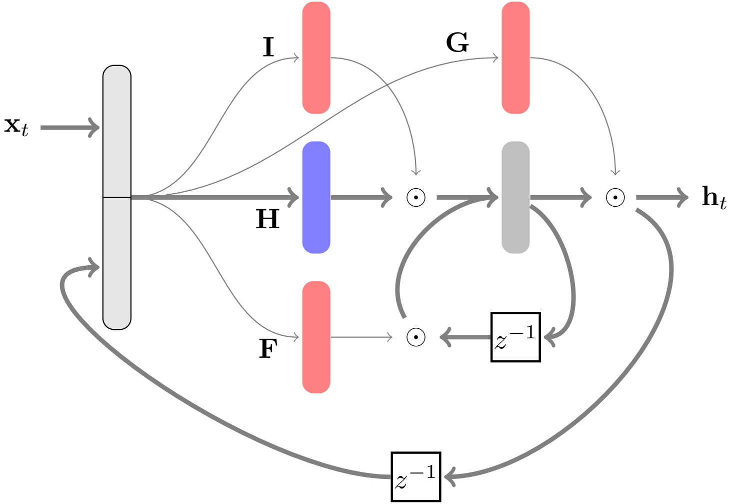
Battling the Curse of Dimensionality using RNNs

$$\mathbf{e}_t = \mathbf{E}[w_t] \tag{15}$$

$$\mathbf{h}_t = \tanh(\mathbf{e}_{t-1} + \mathbf{W}\mathbf{h}_{t-1} + \mathbf{b}_h) \tag{16}$$

$$\mathbf{y}_t = \text{softmax}(\mathbf{V}\mathbf{h}_t + \mathbf{b}_y) \tag{17}$$

Only the neural magic in the middle changes!



Rather effective in processing longer contexts (up to 200 words).

Take-away

- LMs help recognition
- Effective LM can be based on simple counts . . .
- . . . but smoothing is needed. When in doubt, pick Kneser-Ney.
- Neural networks pay with compute to reduce curse of dimensionality
- Commonly, LSTMs are used; in many variants (incl. GRUs)
- Transformers taking over, but more expensive
  - Linearly increasing size of hidden state
  - Linearly increasing cost of each step (=> quadratic overall)
  - Visit ZPJa (winter semester) for all the crazy applications of huge transformers LMs.