NPFL116 Compendium of Neural Machine Translation

Model Ensembling and Beam Search

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Greedy Decoding

- In each step, the model computes a distribution over the vocabulary V (given source $\mathbf{x}$, the previous outputs h, and the model parameters θ).

$$\mathrm{p}(y|h) = g(\mathbf{x}, h, \theta)$$

- In greedy decoding:

$$y^* = \operatorname*{argmax}_{y \in V} \mathrm{p}(y|h)$$

- Repeat, until an end-of-sentence symbol (</s>) is decoded.

Greedy Decoding — cont.

- Pros:
  - Fast and memory-efficient
  - Gives reasonable results
- Cons:
  - We are interested in the most probable *sentence*:

$$(y^*)_{i=0}^{N} = \operatorname*{argmax}_{(y)_{i=0}^{N}} \mathrm{p}(y_0, \ldots, y_N | h)$$

  - Other methods: *much better* results for the cost of a slow-down.

Model Ensembling

- Combine word probabilities from M models:

$$\mathrm{p}(y|h) = \bigoplus_{m=0}^{M} p(y|h, \theta_m)$$

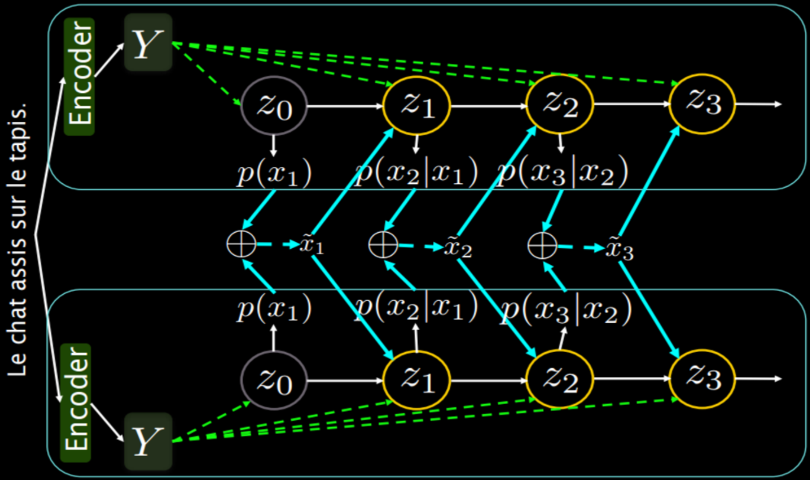
- The additive function $\bigoplus$:
  - Majority voting scheme (arithmetic mean):

$$\bigoplus_{m=0}^{M} \mathbf{f}(x) = \frac{1}{M} \sum_{m=0}^{M} f_m(x)$$

  - Consensus building scheme (geometric mean):

$$\bigoplus_{m=0}^{M} \mathbf{f}(x) = \sqrt[M]{\prod_{m=0}^{M} f_m(x)}$$

Model Ensembling — picture



Source: `https://nlp.stanford.edu/projects/nmt/Luong-Cho-Manning-NMT-ACL2016-v4.pdf`

Beam Search

- Instead of taking the $\arg\max$ in every, step, keep a list (or *beam*) of k-best scoring *hypotheses*.
- Hypothesis = partially decoded sentence $\rightarrow$ score
- Hypothesis score $\psi_t = (y_1, y_2 \ldots, y_t)$ is the probability of the decoded sentence prefix up to t-th word.

$$\mathrm{p}(y_1, \ldots, y_t | h) = \mathrm{p}(y_1 | h) \cdot \cdots \cdot \mathrm{p}(y_t | y_1, \ldots, y_{t-1} | h)$$

- Rule to compute the score of an *extended* hypothesis ψ_t:

$$\mathrm{p}(\psi_t, y_{t+1} | h) = \mathrm{p}(\psi_t | h) \cdot \mathrm{p}(y_{t+1} | h)$$

- Prefers shorter hypotheses $\rightarrow$ normalization necessary.

Beam Search — algorithm

1. Begin with a single empty hypothesis in the beam.
2. In each time step:
   2.1 Extend all hypotheses in the beam by k most probable words (we call these *candidate hypotheses*)
   2.2 Sort the candidate hypotheses by their score.
   2.3 Put the best k hypotheses in the new beam.
   2.4 If a hypothesis from the beam reaches the end-of-sentence symbol, we move it to the list of finished hypotheses.
3. Finish (1) at the final time step or (2) all k-best hypotheses end with `</s>`
4. Sort the hypotheses by their score and output the best one.

Beam Search — picture

Closing Remarks

- The probabilities are never actually computed — everything is done in the logarithmic space.
- For probabilities p_1, p_2 and their logarithms e_1 and e_2, we use these rules:
  - Product of the probabilities becomes their sum in logarithmic space:

$$\log(p_1 \cdot p_2) = \log p_1 + \log p_2 = e_1 + e_2$$

  - Sum of the probabilities becomes the *log-sum-exp* in log-space:

$$\log(p_1 + p_2) = \log(\exp(e_1) + \exp(e_2)) = LSE(e_1, e_2)$$

  - Log-sum-exp function can be computed without any arithmetic operation in the linear space.
    For sorted sequence $e_1 > e_2 > \ldots > e_n$:

$$LSE(e_1, e_2, \ldots, e_n) = e_1 + LSE(e_2 - e_1, \ldots, e_n - e_1)$$