CMPT-882: Statistical Learning of Natural Language

Lecture #5

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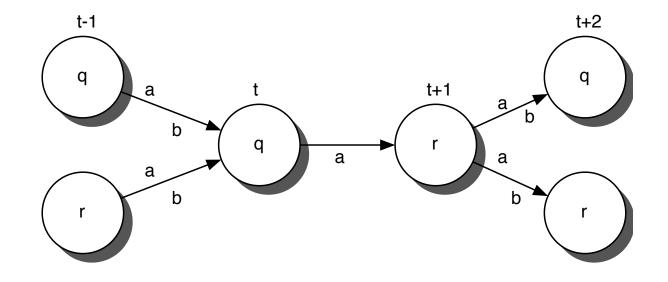
Previous and current homework

• HMM review

• Elworthy (1994) and Merialdo (1994)

$$\alpha_{j}(t) = \sum_{k=1}^{|Q|} \Box_{k}(t-1) P(s^{k} \longrightarrow s^{j}) \beta_{j}(t+1)$$

$$C(s^{i} \longrightarrow s^{j}) = \frac{1}{P(w_{1,n})} \sum_{t=1}^{n} \alpha_{j}(t) P(s^{i} \longrightarrow s^{j}) \beta_{j}(t+1)$$



$$\alpha_{q}(t) = \alpha_{q}(t-1)P(a, q | q) + \alpha_{q}(t-1)P(b, q | q) + \alpha_{r}(t-1)P(a, q | r) + \alpha_{r}(t-1)P(b, q | r)$$

$$\beta_{r}(t+1) = P(a, q | r)\beta_{q}(t+2) + P(b, q | r)\beta_{q}(t+2) + P(a, r | r)\beta_{r}(t+2) + P(b, r | r)\beta_{r}(t+2)$$

$$C(q \xrightarrow{a} r) = \frac{1}{P(w_{1,n})} \sum_{t=1}^{n} \alpha_{q}(t)P(a, r | q)\beta_{r}(t+1)$$

Forward-Backward Algorithm

- Set initial transition probabilities to appropriate values (usually random)
- Compute $C(s^i \xrightarrow{w} s^j)$ for each state i and then $P_e(s^i \xrightarrow{w} s^j) = \frac{C(s^i \xrightarrow{w} s^j)}{\sum_{k,w'} C(s^i \xrightarrow{w'} s^k)}$
- Compute likelihood $P(w_{1,n}) = \beta_{s^1}(1)$; iterate until likelihood is maximized (or entropy is minimized)
- Here we considered the case for one training sentence $w_{1,n}$. For a whole corpus, $\prod_k P(w_{1,n}^k)$ is the likelihood of the entire corpus with k sentences

Elworthy (1994)

- Using the Forward-Backward Algorithm to decrease human supervision
- Does Baum-Welch Re-estimation help taggers? (1994). David Elworthy. Proceedings of 4th ACL Conf on ANLP, Stuttgart. pp. 53-58.

Elworthy (1994)

Lexicon	Transitions
D0 : Fully Supervised $\frac{f(t^i,w)}{f(t^i)}$	T0 : Fully Supervised $rac{f(t^i,t^j)}{f(t^i)}$
D1: $w \mid t$ and $order(w \mid t)$	$ig \; T1 : rac{1}{N_a}$
D2: $p(w t) = p(t)$	Ч
D3: $p(w \mid t) = \frac{1}{N_t}$	

Elworthy (1994)

- Combinations (e.g. D0+T0) and their performance Table 1
- Patterns of Re-estimation Fig 1 and Table 2–3

Merialdo (1994)

 Viterbi tagging vs. ML tagging: best tag per word in a sequence as opposed to best tag sequence)

$$\Phi(W)_i = \underset{t}{\operatorname{arg max}} p(t_i = t \mid w) = \underset{t}{\operatorname{arg max}} \sum_{T: t_i = t} p(W, T)$$

- Table 2 HMM training from various initial starting conditions
- Constrained HMM training tw constraint and t constraint