

Topic: POS Tagging

$S = \{ \text{今天} \quad \text{天气} \quad \text{真好} \}$
 $S = w_1, w_2, w_3, w_4, w_5$
 $\downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow$
 z_1, z_2, z_3, z_4, z_5

$S' = w'_1, w'_2, w'_3, \dots, w'_N$
 $\downarrow \quad \downarrow \quad \downarrow \quad \downarrow$
 $z = z_1, z_2, z_3, \dots, z_N = ?$

Noisy Channel Model

$$\Rightarrow \underbrace{P(z|S)}_{\text{argmax}} \stackrel{\text{argmax}}{=} \underbrace{P(S|z)}_{\text{Translation Model}} \cdot \underbrace{P(z)}_{\text{Language Model}} \quad (1)$$

$$= P(w_1, w_2, \dots, w_N | z_1, z_2, \dots, z_N) \cdot P(z_1, z_2, \dots, z_N)$$

$$= \underbrace{\prod_{i=1}^N P(w_i | z_i)}_{\text{Emission Prob}} \cdot \underbrace{P(z_1) P(z_2 | z_1) P(z_3 | z_1, z_2) \dots P(z_N | z_1, \dots, z_{N-1})}_{\text{LM}}$$

$$\hat{z} = \text{argmax}_z P(z|S)$$

$$= \text{argmax}_z \prod_{i=1}^n P(w_i | z_i) \cdot P(z_1) \cdot \prod_{t=2}^n P(z_t | z_{t-1})$$

$$= \text{argmax}_z \log \left(\prod_{i=1}^n P(w_i | z_i) \cdot P(z_1) \cdot \prod_{t=2}^n P(z_t | z_{t-1}) \right)$$

$$= \text{argmax}_z \sum_{i=1}^n \log P(w_i | z_i) + \log P(z_1) + \sum_{t=2}^n \log P(z_t | z_{t-1})$$

$$\Rightarrow \hat{z} = \text{argmax}_z \underbrace{\sum_{i=1}^n \log P(w_i | z_i)}_A + \underbrace{\log P(z_1)}_\pi + \underbrace{\sum_{t=2}^n \log P(z_t | z_{t-1})}_B \quad (2)$$

$$\Theta = \{A, B, \pi\}$$

Step 1: Compute A, B, π

Step 2: Viterbi Alg

$$P(w_1, w_2, w_3 | z_1, z_2, z_3) \neq P(w_1 | z_1) P(w_2 | z_2) P(w_3 | z_3)$$

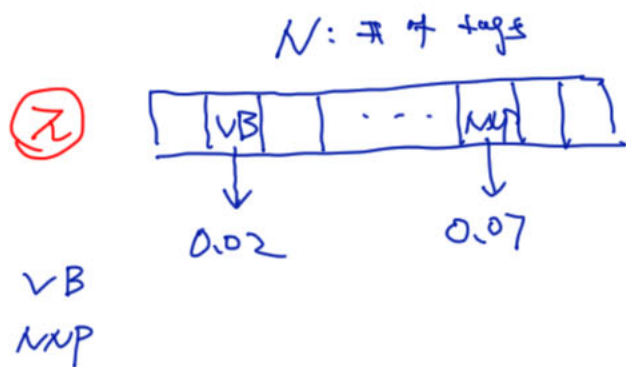
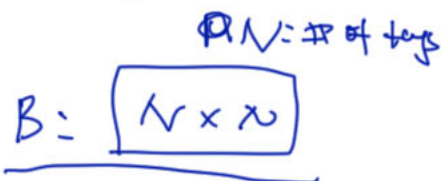
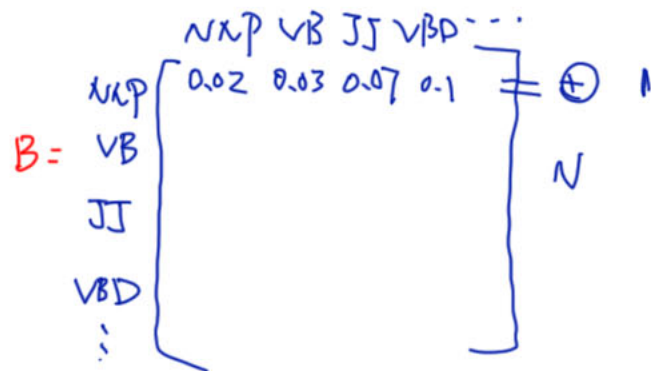
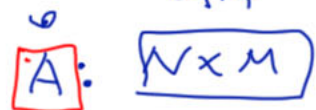
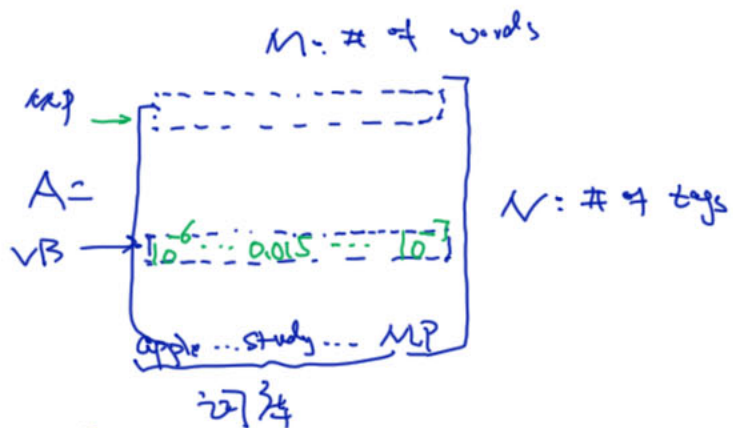
$$\xrightarrow{\text{Viterbi}} P(w_1 | z_1) \cdot P(w_2 | z_2) \cdot P(w_3 | z_3)$$

Tag: $w_i(\text{天气}) \rightleftharpoons z_i(\text{Tag})$

$$\hat{z} = \underset{z}{\operatorname{argmax}} \sum_{i=1}^n \log P(w_i | z_i) + \log P(z_1) + \sum_{t=2}^N \underbrace{P(z_t | z_{t-1})}_B$$

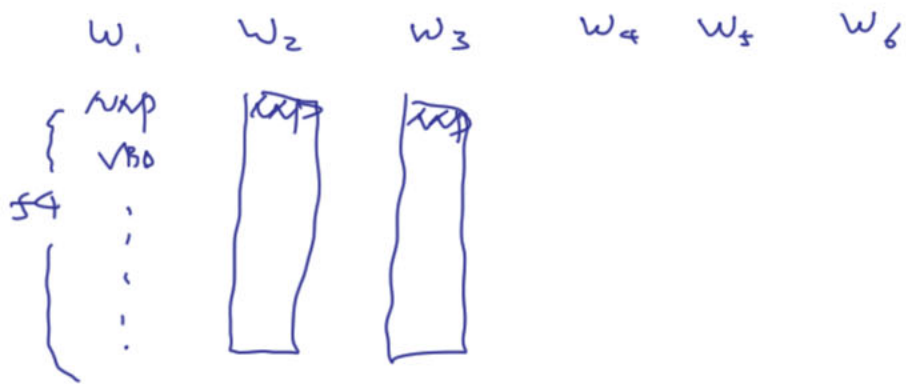
A
 π
B

(状态转移)



$$\hat{z} = \operatorname{argmax}_{z_1} \left[\sum_{i=1}^T \log P(w_i | z_i) + \log(z_1) + \sum_{t=2}^T P(z_t | z_{t-1}) \right]$$

Newsweek said it will introduce the
 (NKP VBD PRP MD VB DT)



$$O(54^6) \leq \Delta \hat{z} = O(P^n)$$

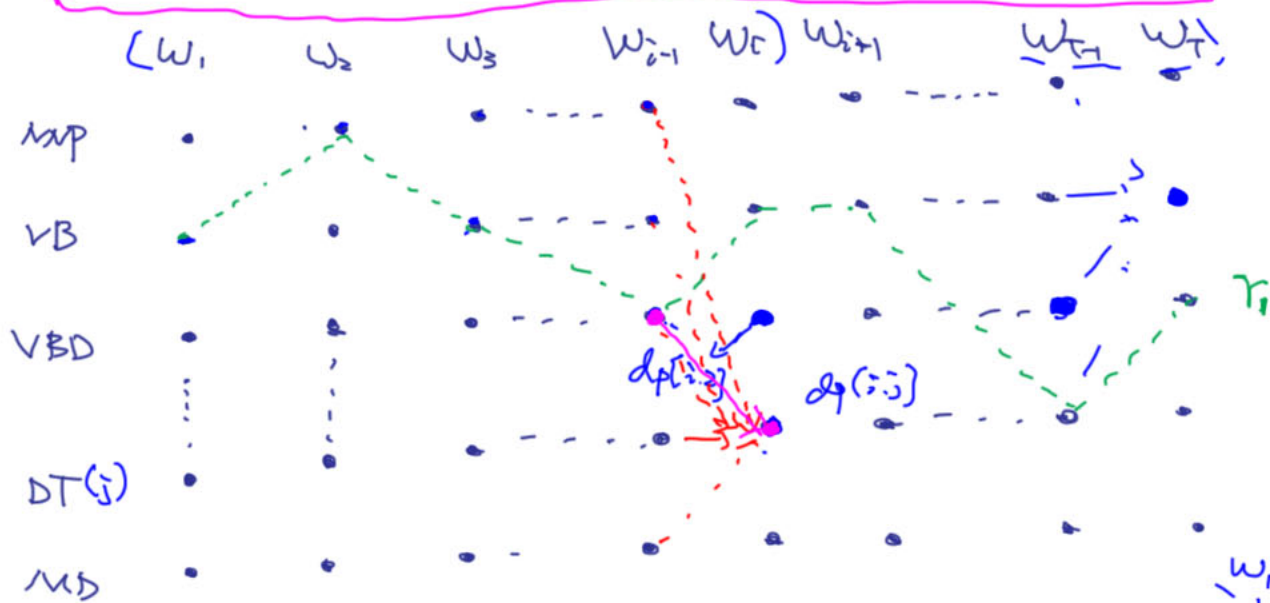
$$\Rightarrow (NKP, VB, VBD, DT, NKP, NKP)$$

$$\begin{aligned} & \log P(\text{Newsweek} | NKP) \cdot P(\text{said} | VB) \cdots P(\text{the} | NKP) \\ & + \log P(NKP) + \log P(VB | NKP) + \log(VBD | VB) \\ & + \cdots + \log(NKP | NKP) = \checkmark \end{aligned}$$

给定 w_1, w_2, \dots, w_T , 找出 z_1, z_2, \dots, z_T

单词序列 词性

$$\hat{z} = \arg \max_z \sum_{t=1}^T \log P(w_t | z_t) + \log P(z_t) + \sum_{t=2}^T \log P(z_t | z_{t-1})$$



54⁶ $Score(r_i) = \log P(VB) + \log P(w_1 | VB) + \dots + w_1$
 $+ \log P(NP | VB) + \log P(w_2 | NP) \dots w_2$
 $+ \log P(VB | NP) + \log P(w_3 | VB) \dots w_3$
 $+ \dots$

~~f(i,j)~~ dp

$dp[i:j]$: the best path such that ending at j at time i

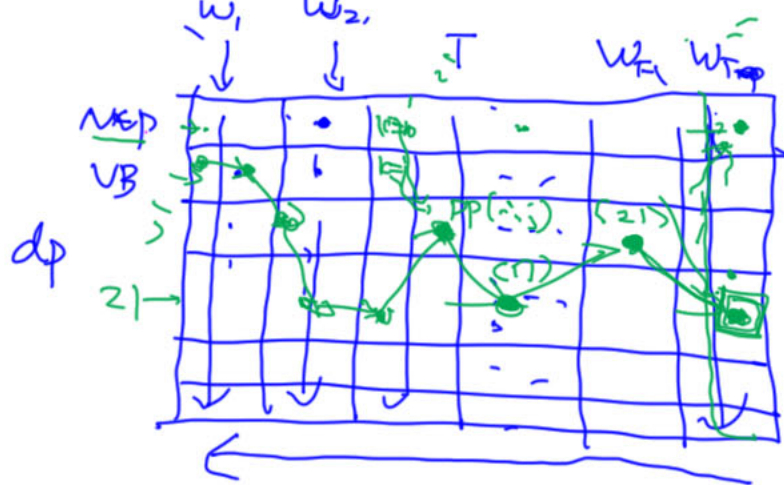
(w_1, \dots, w_i) , $w_i \leftarrow$ 第 j 个 tag

$$dp[i:j] = \begin{cases} dp[i-1,0] + \log P[DT | NP] + \log P(w_i | DT) \\ dp[i-1,1] + \log P[PT | VB] + \log P(w_i | PT) \\ dp[i-1,2] + \log P[PT | VBD] + \log P(w_i | PT) \\ \dots \end{cases}$$

Max

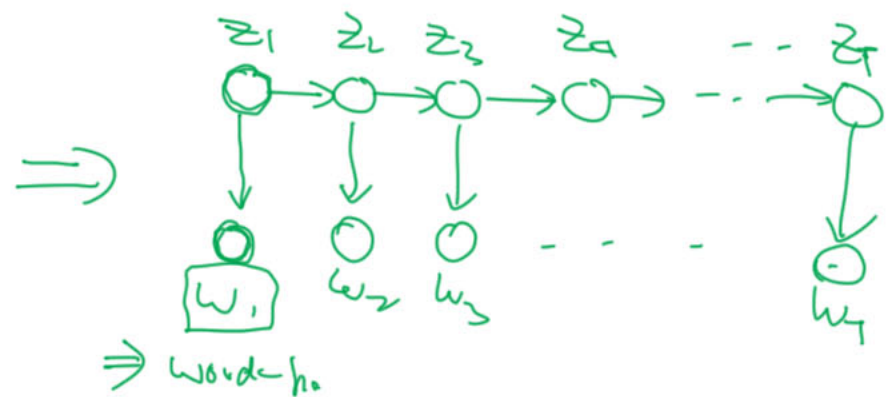
$i = 1 \dots T$, $j = 0 \dots 54$

$(w_1 \dots w_T) \Rightarrow dp[T,0], dp[T,1], dp[T,2], \dots, dp[T,54]$



$O(T \cdot N \cdot N)$

$\sim O(N^2 T)$
 \downarrow
 $\# \text{ of tags}$ len(sentence)



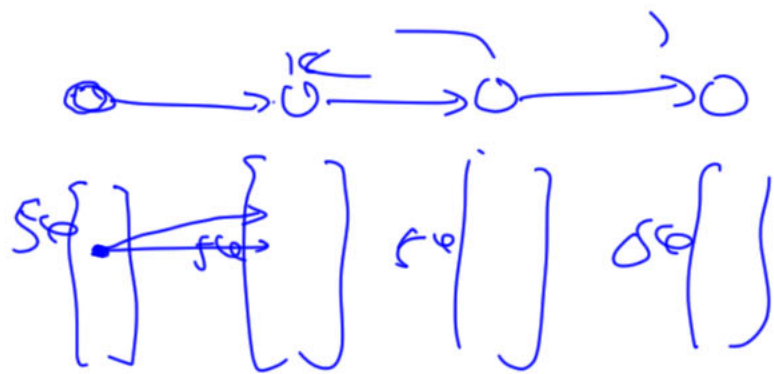
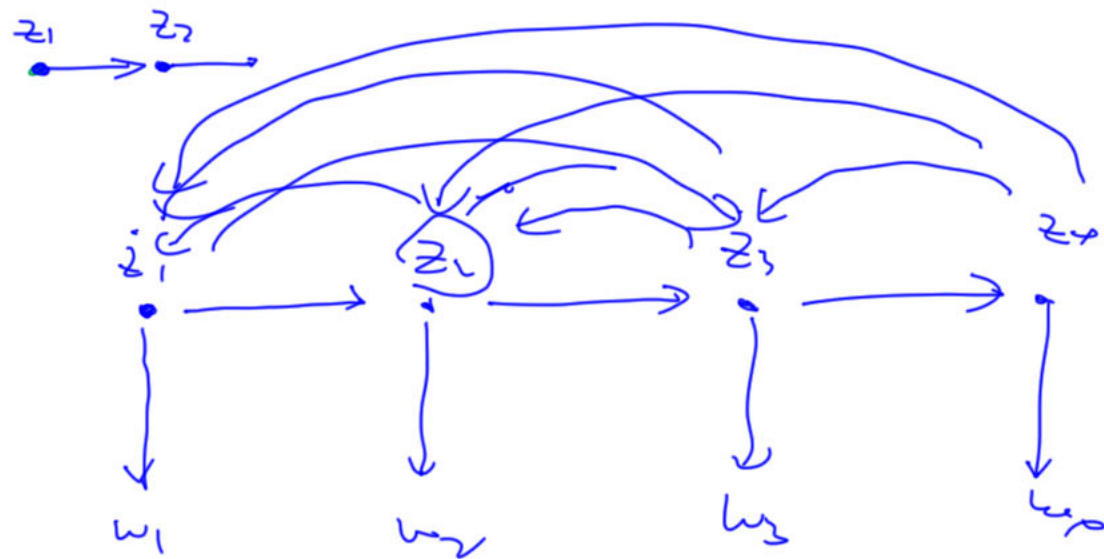
Def: Viterbi

Extensions:

① 今天: $D = \{(s_1, z_1), (s_2, z_2), \dots, (s_n, z_n)\}$ 已知 $D = \{s_1, s_2, s_3, \dots, s_n\}$
 这里使用 z_n 来记录

② $P(w_i | z_i) \Rightarrow$ 当前词与前面词的关系 \Rightarrow 当前词与 (单词, 前面单词, 前面前单词, 前面前单词的可变性, 前面前词的可变性, 前面前词的可变性/可变性)
 \Downarrow
 + CRF 模型

③ LSTM + CRF



Let $h_i = \text{全局最优解}$