CSCI567 Machine Learning (Fall 2025) Viterbi Algorithm Exercises

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What is the most likely sequence $z_{1:T_0}^*$ given $x_{1:T_0}$ for some $T_0 < T$?

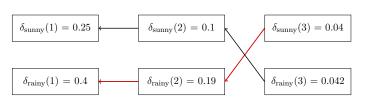
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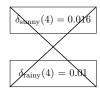
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• Is it the first T_0 outputs of the Viterbi algorithm (with all data)?

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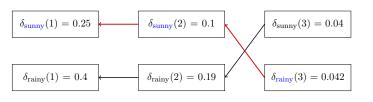
The answer for $T_0 = 3$ is: rainy, rainy, sunny?

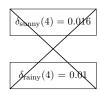
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• Is it the first T_0 outputs of the Viterbi algorithm (with all data)?

No. It should be

- $z_{T_0}^* = \operatorname{argmax}_s \delta_s(T_0)$
- for each $t = T_0, \dots, 2$: $z_{t-1}^* = \Delta_{z_t^*}(t)$





The answer for $T_0 = 3$ is: "sunny, sunny, rainy"

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• Is it the same as Exercise 1?

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- Is it the same as Exercise 1?
- Is it the first T_0 outputs of the Viterbi algorithm (with all data)?

Neither. It should be

- $z_{T_0}^* = \operatorname{argmax}_s \delta_s(T_0) \beta_s(T_0)$
- for each $t = T_0, \dots, 2$: $z_{t-1}^* = \Delta_{z_t^*}(t)$

$$z_{T_0}^* = \operatorname*{argmax}_{s} \max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T} = x_{1:T})$$

$$z_{T_0}^* = \underset{s}{\operatorname{argmax}} \max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T} = x_{1:T})$$

$$= \underset{s}{\operatorname{argmax}} \max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T_0} = x_{1:T_0}) \times$$

$$P(X_{T_0+1,T} = x_{T_0+1:T} \mid Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T_0} = x_{1:T_0})$$

$$\begin{split} z_{T_0}^* &= \underset{s}{\operatorname{argmax}} \max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T} = x_{1:T}) \\ &= \underset{s}{\operatorname{argmax}} \max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T_0} = x_{1:T_0}) \times \\ &P(X_{T_0+1,T} = x_{T_0+1:T} \mid Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T_0} = x_{1:T_0}) \\ &= \underset{s}{\operatorname{argmax}} \left(\max_{z_{1:T_0-1}} P(Z_{T_0} = s, Z_{1:T_0-1} = z_{1:T_0-1}, X_{1:T_0} = x_{1:T_0}) \right) \times \\ &P(X_{T_0+1,T} = x_{T_0+1:T} \mid Z_{T_0} = s) \end{split}$$

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Again, neither is true.

Viterbi Algorithm with partial data $x_{1:T_0}$

For each $s \in [S]$, compute $\delta_s(1) = \pi_s b_{s,x_1}$.

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For each $t = 2, \ldots, T$,

• for each $s \in [S]$, compute

$$\delta_s(t) = \begin{cases} b_{s,x_t} \max_{s'} a_{s',s} \delta_{s'}(t-1) & \text{if } t \le T_0 \end{cases}$$

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Backtracking: let $z_T^* = \operatorname{argmax}_s \delta_s(T)$.

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Backtracking: let $z_T^* = \operatorname{argmax}_s \delta_s(T)$. For each $t = T, \dots, 2$: set $z_{t-1}^* = \Delta_{z_t^*}(t)$.

Output the most likely path z_1^*, \ldots, z_T^* .

Difference compared to "most likely path $z_{1:T}^*$ given $x_{1:T}$ ":

 $\bullet \ \ \text{most likely path} \ z_{1:T_0}^* \ \ \text{given} \ x_{1:T_0} \\$

- $\bullet \ \, \text{most likely path} \,\, z_{\mathbf{1}:T_{\mathbf{0}}}^* \,\, \text{given} \,\, x_{\mathbf{1}:T_{\mathbf{0}}}$
 - ullet exact same δ , Δ
 - find the last state using $\delta_s(T_0)$

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 - find the last state using $\delta_s(T_0)$
- ullet most likely path $z_{1:T_0}^*$ given $x_{1:T}$

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- ullet most likely path $z_{1:T_0}^*$ given $x_{1:T}$
 - ullet exact same δ , Δ
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- most likely path $z_{1:T_0}^*$ given $x_{1:T}$
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- ullet most likely path $z_{1:T}^*$ given $x_{1:T_0}$
 - different δ , Δ
 - find the last state using $\delta_s(T)$

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 - exact same δ , Δ
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- most likely path $z_{1:T_0}^*$ given $x_{1:T}$
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The rest of the backtracking is always the same: **follow the arrows!**