

Question 1 EM for Probabilistic PCA

(a) *E-step. Calculate the statistics of the posterior distribution $q(z) = p(z|\mathbf{x})$ which you'll need for the M-step.*

From the Appendix, we know how to get the distribution of z given \mathbf{x} , where z is drawn from Gaussian distribution and \mathbf{x} is drawn from a spherical Gaussian distribution.

In our setting,

$$p(z) = \mathcal{N}(z|0, 1)$$

$$p(\mathbf{x}|z) = \mathcal{N}(\mathbf{x}|z\mathbf{u}, \sigma^2\mathbf{I})$$

To apply the parameters in the formulae of the Appendix, we have

$$\mu = 0, \Sigma = 1,$$

$$\mathbf{A} = \mathbf{u}, \mathbf{B} = 0, \mathbf{S} = \sigma^2\mathbf{I}$$

$$\mathbf{C} = (1 + \mathbf{u}^T(\sigma^2)^{-1}\mathbf{u})^{-1} = \frac{\sigma^2}{\sigma^2 + \mathbf{u}^T\mathbf{u}}$$

Thus, we can obtain the following formulae:

$$p(\mathbf{x}) = \mathcal{N}(\mathbf{x}|0, \mathbf{u}^T\mathbf{u} + \sigma^2)$$

$$p(z|\mathbf{x}) = \mathcal{N}(z|\mathbf{C}(\mathbf{u}^T(\sigma^2)^{-1}\mathbf{x}), \mathbf{C})$$

$$= \mathcal{N}(z|\frac{\mathbf{u}^T\mathbf{x}}{\sigma^2 + \mathbf{u}^T\mathbf{u}}, \frac{\sigma^2}{\sigma^2 + \mathbf{u}^T\mathbf{u}})$$

As a result,

$$m = E[z|\mathbf{x}] = \frac{\mathbf{u}^T\mathbf{x}}{\sigma^2 + \mathbf{u}^T\mathbf{u}}$$

$$\text{Var}[z|\mathbf{x}] = \frac{\sigma^2}{\sigma^2 + \mathbf{u}^T\mathbf{u}}$$

$$s = E[z^2|\mathbf{x}] = \text{Var}[z|\mathbf{x}] + E[z|\mathbf{x}]^2$$

$$= \frac{\sigma^4 + \sigma^2\mathbf{u}^T\mathbf{u} + (\mathbf{u}^T\mathbf{x})^2}{(\sigma^2 + \mathbf{u}^T\mathbf{u})^2}$$

(b) *M-step. Re-estimate the parameters, which consist of the vector \mathbf{u} . derive a formula for \mathbf{u}_{new} that maximizes the expected log-likelihood, i.e.,*

$$\mathbf{u}_{new} = \arg \max_{\mathbf{u}} \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{q(z^{(i)})} [\log p(z^{(i)}, \mathbf{x}^{(i)})]$$

Denote the function to be maximized as

$$\mathbb{F} = \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{q(z^{(i)})} [\log p(z^{(i)}, \mathbf{x}^{(i)})]$$

$$= \frac{1}{N} \sum_{i=1}^N \mathbb{E}_{q(z^{(i)})} [\log q(z^{(i)}) p(\mathbf{x}^{(i)})]$$

Then,

$$\begin{aligned}
 \log p(\mathbf{x}^{(i)})q(z^{(i)}) &= \log \frac{1}{\sqrt{2\pi(\mathbf{u}^T \mathbf{u} + \sigma^2)}} e^{-\frac{\mathbf{x}^{(i)2}}{2(\mathbf{u}^T \mathbf{u} + \sigma^2)}} \frac{1}{\sqrt{2\pi \frac{\sigma^2}{\mathbf{u}^T \mathbf{u} + \sigma^2}}} e^{-\frac{(z^{(i)} - \frac{\mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2 + \mathbf{u}^T \mathbf{u}})^2}{2 \frac{\sigma^2}{\mathbf{u}^T \mathbf{u} + \sigma^2}}} \\
 &\propto -\frac{\mathbf{x}^{(i)2}}{2(\mathbf{u}^T \mathbf{u} + \sigma^2)} - \frac{(z^{(i)} - \frac{\mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2 + \mathbf{u}^T \mathbf{u}})^2}{2 \frac{\sigma^2}{\mathbf{u}^T \mathbf{u} + \sigma^2}} \\
 &\propto -\frac{\mathbf{x}^{(i)2} \sigma^2 + [\mathbf{u}^T \mathbf{x}^{(i)} - (\sigma^2 + \mathbf{u}^T \mathbf{u}) z^{(i)}]^2}{2\sigma^2(\mathbf{u}^T \mathbf{u} + \sigma^2)} \\
 &\propto -\frac{z^{(i)2}(\sigma^2 + \mathbf{u}^T \mathbf{u})}{2\sigma^2} + \frac{z^{(i)} \mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2} \\
 &\propto -\frac{z^{(i)2} \mathbf{u}^T \mathbf{u}}{2\sigma^2} + \frac{z^{(i)} \mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2}
 \end{aligned}$$

Apply the linearity of expectation,

$$\begin{aligned}
 \mathbb{F} &= \frac{1}{N} \sum_{i=1}^N \mathbb{E}[\log p(\mathbf{x}^{(i)})q(z^{(i)})] \\
 &= \frac{1}{N} \sum_{i=1}^N \left[-\frac{\mathbb{E}[z^{(i)2} | \mathbf{x}^{(i)}] \mathbf{u}^T \mathbf{u}}{2\sigma^2} + \frac{\mathbb{E}[z^{(i)} | \mathbf{x}^{(i)}] \mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2} \right] \\
 &= \frac{1}{N} \sum_{i=1}^N \left[-\frac{s^{(i)} \mathbf{u}^T \mathbf{u}}{2\sigma^2} + \frac{m^{(i)} \mathbf{u}^T \mathbf{x}^{(i)}}{\sigma^2} \right]
 \end{aligned}$$

To get the gradient with respect to \mathbf{u} ,

$$\begin{aligned}
 \frac{\partial \mathbb{F}}{\partial \mathbf{u}} &= -\frac{1}{N} \sum_{i=1}^N \left[\frac{s^{(i)} \mathbf{u}}{\sigma^2} + \frac{m^{(i)} \mathbf{x}^{(i)}}{\sigma^2} \right] = 0 \\
 \mathbf{u} &\leftarrow \frac{\frac{1}{N} \sum_{i=1}^N m^{(i)} \mathbf{x}^{(i)}}{\frac{1}{N} \sum_{i=1}^N s^{(i)}} \\
 \mathbf{u} &\leftarrow \frac{\sum_{i=1}^N m^{(i)} \mathbf{x}^{(i)}}{\sum_{i=1}^N s^{(i)}}
 \end{aligned}$$

Question 2 Contraction Maps

(a) Show that the Bellman backup operator T^π is a contraction map in the $\|\cdot\|_\infty$ norm.

Our claim is that the Bellman backup operator T^π is a contraction map, which means

$$\|T^\pi Q_1 - T^\pi Q_2\|_\infty \leq \gamma \|Q_1 - Q_2\|_\infty$$

By applying Bellman equation:

$$Q_{k+1}(s, a) \leftarrow r(s, a) + \gamma \sum_{s'} P(s' | a, s) \sum_{a'} \pi(a' | s') Q_k(s', a')$$

we have

$$\begin{aligned}
& |T^\pi Q_1(s, a) - T^\pi Q_2(s, a)|_\infty \\
&= |[r(s, a) + \gamma \sum_{s'} P(s'|a, s) \sum_{a'} \pi(a'|s') Q_1(s', a')] - [r(s, a) + \gamma \sum_{s'} P(s'|a, s) \sum_{a'} \pi(a'|s') Q_2(s', a')]|_\infty \\
&= \gamma |\sum_{s'} P(s'|a, s) \sum_{a'} \pi(a'|s') [Q_1(s', a') - Q_2(s', a')]|_\infty \\
&\leq \gamma \sum_{s'} P(s'|a, s) \sum_{a'} \pi(a'|s') |Q_1(s', a') - Q_2(s', a')|_\infty \\
&\leq \gamma |Q_1(s', a') - Q_2(s', a')|_\infty \sum_{s'} P(s'|a, s) \sum_{a'} \pi(a'|s') \\
&= \gamma |Q_1(s', a') - Q_2(s', a')|_\infty
\end{aligned}$$

This is true for any (s, a) , so

$$||T^\pi Q_1 - T^\pi Q_2||_\infty \leq \gamma ||Q_1 - Q_2||_\infty$$

which is what we wanted to show.

Question 3 Q-Learning

(a) Determine the optimal policy and the Q-function for the optimal policy.

The optimal policy will be

$$\pi(Stay|s_1) = 0; \pi(Switch|s_1) = 1; \pi(Stay|s_2) = 1; \pi(Switch|s_2) = 2;$$

Then, by applying Bellman equation

$$Q^*(s, a) = r(s, a) + \gamma \sum_{s'} P(s'|a, s) \max_{a'} Q^*(s', a')$$

, we get

$$\begin{aligned}
Q^*(s_1, Stay) &= 1 + 0.9 \max_{a'} Q^*(s_1, a') \\
Q^*(s_1, Switch) &= 1 + 0.9 \max_{a'} Q^*(s_2, a') \\
Q^*(s_2, Stay) &= 2 + 0.9 \max_{a'} Q^*(s_2, a') \\
Q^*(s_2, Switch) &= 2 + 0.9 \max_{a'} Q^*(s_1, a')
\end{aligned}$$

To solve it, we get

$$Q^*(s_1, Stay) = 18.1; Q^*(s_1, Switch) = 19; Q^*(s_2, Stay) = 20; Q^*(s_2, Switch) = 19.1$$

or

	Stay	Switch
s_1	18.1	19
s_2	20	19.1

(b) Now suppose we apply Q-learning, except that instead of the ϵ -greedy policy, the agent follows the greedy policy which always chooses $\pi(s) = \arg \max_a Q(s, a)$. Assume the agent starts in state $S_0 = s_1$. Give an example of a Q-function that is in equilibrium (i.e. it will never change after the Q-learning update rule is applied), but which results in a suboptimal policy.

According to Q-Learning, we should initialize $Q(s, a)$ for all the $(s, a) \in \mathcal{S} \times \mathcal{A}$. We could assign them as 0's, where the Q-function is shown as

	Stay	Switch
s_1	0	0
s_2	0	0

For the time step $t = 0$,

Choose A_t according to the greedy policy, i.e., $A_0 \leftarrow \arg \max_{a \in \mathcal{A}} Q(S_0, a) = \arg \max_{a \in \mathcal{A}} Q(s_1, a)$

Because all the $Q(s_1, a)$'s are 0, we could just choose $A_0 = \text{Stay}$.

Then, the new state becomes $S_1 = s_1$, as we choose to *Stay*.

Also, $R_0 = r(s_1, \text{Stay}) = 1$.

Finally, we update the action-value function at state-action (s_1, Stay) as

$$\begin{aligned}
 Q(s_1, \text{Stay}) &\leftarrow Q(s_1, \text{Stay}) + \alpha [R_0 + \gamma \max_{a' \in \mathcal{A}} Q(S_1, a') - Q(S_0, A_t)] \\
 &= 0 + \alpha [1 + 0.9 \times 1 - 0] \\
 &= 1.9\alpha
 \end{aligned}$$

The table of Q-function becomes

	Stay	Switch
s_1	1.9α	0
s_2	0	0

Continue the algorithm, we will find it choose *Stay* all the time.

It is an equilibrium situation, but never converging to the optimal policy.