Student ID : 20194293

Name : Go, Kyeong Ryeol

## [AI 602] Continual Unsupervised Representation Learning

1. Paper Summary

Typically, in the continual learning setting, the identity of the task and boundaries between tasks are provided. This is a poor setting when applied to real world where the following properties is preferable to be satisfied; i) *task-agnostic*, ii) *non-stationary*, iii) *non-i.i.d*, iv) *unsupervised*. Therefore, the author proposed Continual Unsupervised Representation Learning (CURL) which is a general unsupervised continual learning setting that can perform without any task labels and boundaries.

The task inference $\mathrm{y}\sim\mathrm{Cat}(\pi)$ is performed within the model and then the task-specific representation $\mathrm{z}|\mathrm{y}\sim\mathrm{N}\left(\mu_{\mathrm{z}}(\mathrm{y}),\sigma_{\mathrm{z}}^{2}(\mathrm{y})\right)$ is decoded to produce the input $\mathrm{x}|\mathrm{z}\sim\mathrm{Bernoulli}\left(\mu_{\mathrm{x}}(z)\right)$. Since the analytical computation of the posterior distribution is intractable, the variational learning is performed with the joint distribution $\mathrm{p}(\mathrm{x},\mathrm{y},\mathrm{z})=\mathrm{p}(\mathrm{y})\mathrm{p}(\mathrm{z}|\mathrm{y})\mathrm{p}(\mathrm{x}|\mathrm{z})$ and the variational distribution $\mathrm{q}(\mathrm{y},\mathrm{z}|\mathrm{x})=\mathrm{q}(\mathrm{y}|\mathrm{x})\mathrm{q}(\mathrm{z}|\mathrm{x},\mathrm{y})$. Then, the following evidence lower bound is optimized where each of which are parameterized by the neural network.

$$
\begin{aligned}
\mathrm{L} &= E_{q(y|x)q(z|x,y)}[\log p(x|z)] - E_{q(y|x)}[KL(q(z|x,y)\|p(z|y)] - KL(q(y|x)\|p(y)) \\
&= \sum_{\mathrm{k}=1}^{\mathrm{K}} q(y=k|x)\left[\log p\left(x\middle|\tilde{z}^{(k)}\right) - KL(q(z|x,y=k)\|p(z|y=k))\right] - KL(q(y|x)\|p(y))
\end{aligned}
$$

As a way of determining the number of tasks, the author resorts to the dynamic expansion approach. Any sample whose log-likelihood is less than certain threshold $\mathrm{c}_{\mathrm{new}}$ is added to the set $\mathrm{D}_{\mathrm{new}}$. When its cardinality reaches to another threshold $\mathrm{N}_{\mathrm{new}}$, then the associated parameters for the new component are initialized to the existing component $\mathrm{k}^{*}=\mathrm{argmax}_{\mathrm{k}\in\{1,2,\ldots,\mathrm{K}\}}\sum_{\mathrm{x}\in\mathrm{D}_{\mathrm{new}}} q(y=k|x)$ which is regarded to be the closest one. Finally, a small fixed number of iterations of gradient descent is performed using the component constrained ELBO for the new label $\mathrm{K}+1$ for $\mathrm{D}_{\mathrm{new}}$.

In addition, the author proposed Mixture Generative Replay (MGR) a new idea for combatting the forgetting issue by extending the Deep Generative Replay (DGR) to the mixture setting. Here, the mean of the posterior over the previous time steps are accumulated so that the count over components are maintained to have a preference to the components that are visited the most.

2. In-depth discussions

I. While expansion, how can we guarantee the training curve to be stable? The author suggests a small fixed number of gradient steps, but I think at least the number of iterations should be adjustable depending on the relations of the new task to the other tasks.

II. Are there no chance for the unvisited component to be more informative during the mixture generative replay (MGR)? Maybe at the beginning the of the training process, I guess so.