

Supplementary Information A Derivation of the ELBO Loss for VAE

$p_{\phi_d}(\mathbf{x} \mid \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf})$ and $p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf} \mid \mathbf{x})$ are the true likelihood and true posterior respectively. The posterior is hard to evaluate, so we have to approximate the true posterior to the product of the factorized known distributions $q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})$, $q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})$, $q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})$ and $q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x})$ by minimising the KL divergence as follows,

$$\begin{aligned}
& KL(q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \parallel p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf} \mid \mathbf{x})) \\
&= \int \int \int \int q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \\
&\quad \left[\log \frac{q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})}{p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf} \mid \mathbf{x})} \right] d\mathbf{z}_x d\mathbf{z}_t d\mathbf{z}_{yf} d\mathbf{z}_{ycf} \\
&= \int \int \int \int q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \\
&\quad \left[\log q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x}) + \log q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x}) + \log q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x}) + \log q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \right. \\
&\quad \left. - \log p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf} \mid \mathbf{x}) \right] d\mathbf{z}_x d\mathbf{z}_t d\mathbf{z}_{yf} d\mathbf{z}_{ycf} \\
&= \int \int \int \int q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \\
&\quad \left[\log q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x}) + \log q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x}) + \log q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x}) + \log q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \right. \\
&\quad \left. - \log p_{\phi_d}(\mathbf{x} \mid \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf}) - \log p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf}) \right. \\
&\quad \left. + \log p_{\phi_d}(\mathbf{x}) \right] d\mathbf{z}_x d\mathbf{z}_t d\mathbf{z}_{yf} d\mathbf{z}_{ycf} \\
&= \int q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x}) \log \frac{q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})}{p_{\phi_d}(\mathbf{z}_x)} d\mathbf{z}_x + \int q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x}) \log \frac{q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})}{p_{\phi_d}(\mathbf{z}_t)} d\mathbf{z}_t \\
&\quad + \int q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x}) \log \frac{q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})}{p_{\phi_d}(\mathbf{z}_{yf})} d\mathbf{z}_{yf} + \int q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \log \frac{q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x})}{p_{\phi_d}(\mathbf{z}_x)} d\mathbf{z}_{ycf} \\
&\quad - \int \int \int \int [q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x}) \\
&\quad q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \log p_{\phi_d}(\mathbf{x} \mid \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf})] d\mathbf{z}_x d\mathbf{z}_t d\mathbf{z}_{yf} d\mathbf{z}_{ycf} + \log p_{\phi_d}(\mathbf{x}) \\
&= KL(q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x}) \parallel p_{\phi_d}(\mathbf{z}_x)) + KL(q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x}) \parallel p_{\phi_d}(\mathbf{z}_t)) \\
&\quad + KL(q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x}) \parallel p_{\phi_d}(\mathbf{z}_{yf})) + KL(q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x}) \parallel p_{\phi_d}(\mathbf{z}_{ycf})) \\
&\quad - \mathbb{E}_{q_{\phi_x}, q_{\phi_t}, q_{\phi_{yf}}, q_{\phi_{ycf}}} [\log p(\mathbf{x} \mid \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf})] \\
&\quad + \log p_{\phi_d}(\mathbf{x})
\end{aligned}$$

where, the distributions $q_{\phi_x}(\mathbf{z}_x \mid \mathbf{x})$, $q_{\phi_t}(\mathbf{z}_t \mid \mathbf{x})$, $q_{\phi_{yf}}(\mathbf{z}_{yf} \mid \mathbf{x})$, $q_{\phi_{ycf}}(\mathbf{z}_{ycf} \mid \mathbf{x})$ and $p_{\phi_d}(\mathbf{x} \mid \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf})$ are parameterized by the parameters $\phi_x, \phi_t, \phi_{yf}, \phi_{ycf}, \phi_d$.

The KL divergence of two distributions is always greater than or equal to zero. So,

$$\begin{aligned}
& KL(q_{\phi_x}(\mathbf{z}_x | x) q_{\phi_t}(\mathbf{z}_t | x) q_{\phi_{yf}}(\mathbf{z}_{yf} | \mathbf{x}) q_{\phi_{ycf}}(\mathbf{z}_{ycf} | x) || p_{\phi_d}(\mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf} | x)) \geq 0, \\
& \log p_{\phi_d}(\mathbf{z}) \geq \mathcal{L}_{ELBO} \quad \text{where,} \\
& \mathcal{L}_{ELBO}(\phi_x, \phi_t, \phi_{yf}, \phi_{ycf}; \mathbf{x}, \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf}) \\
& = \mathbb{E}_{q_{\phi_x}, q_{\phi_t}, q_{\phi_{yf}}, q_{\phi_{ycf}}} [\log p(\mathbf{x} | \mathbf{z}_x, \mathbf{z}_t, \mathbf{z}_{yf}, \mathbf{z}_{ycf})] \\
& \quad - KL(q_{\phi_x}(\mathbf{z}_x | \mathbf{x}) || p_{\phi_d}(\mathbf{z}_x)) - KL(q_{\phi_t}(\mathbf{z}_t | \mathbf{x}) || p_{\phi_d}(\mathbf{z}_t)) \\
& \quad - KL(q_{\phi_{yf}}(\mathbf{z}_{yf} | \mathbf{x}) || p_{\phi_d}(\mathbf{z}_{yf})) - KL(q_{\phi_{ycf}}(\mathbf{z}_{ycf} | \mathbf{x}) || p_{\phi_d}(\mathbf{z}_{ycf}))
\end{aligned}$$

Supplementary Information B Derivation of the ELBO Loss for VAE

In DR-VIDAL we aimed to maximize the mutual information of the latent factors $\mathbf{z}_c$ and the output of the generator $G(\mathbf{z}_G, \mathbf{z}_c)$ as follows:

$$\begin{aligned}
I(\mathbf{z}_c; G(\mathbf{z}_G, \mathbf{z}_c)) &= H(\mathbf{z}_c) - H(\mathbf{z}_c | G(\mathbf{z}_G, \mathbf{z}_c)) \\
&= H(\mathbf{z}_c) + \int \int p(\mathbf{Z}_c = \mathbf{z}'_c, \mathbf{X} = G(\mathbf{z}_G, \mathbf{z}_c)) \\
&\quad \log p(\mathbf{Z}_c = \mathbf{z}'_c | \mathbf{X} = G(\mathbf{z}_G, \mathbf{z}_c)) d\mathbf{z}_c d\mathbf{x} \\
&= H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log(p(\mathbf{z}'_c | \mathbf{x})) \\
&= H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[\frac{p(\mathbf{z}'_c | \mathbf{x})}{Q(\mathbf{z}'_c | \mathbf{x})} Q(\mathbf{z}'_c | \mathbf{x}) \right] \\
&= H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[\frac{p(\mathbf{z}'_c | \mathbf{x})}{Q(\mathbf{z}'_c | \mathbf{x})} \right] \\
&\quad + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[Q(\mathbf{z}'_c | \mathbf{x}) \right] \\
&= H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \int p(\mathbf{z}'_c | \mathbf{x}) \log \frac{p(\mathbf{z}'_c | \mathbf{x})}{Q(\mathbf{z}'_c | \mathbf{x})} d\mathbf{c}' \\
&\quad + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{c}' \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[Q(\mathbf{z}'_c | \mathbf{x}) \right] \\
&= H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} [KL(p(\mathbf{z}'_c | \mathbf{x}) || Q(\mathbf{z}'_c | \mathbf{x}))] \\
&\quad + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[Q(\mathbf{z}'_c | \mathbf{x}) \right] \\
&\geq H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}_G, \mathbf{z}_c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[Q(\mathbf{z}'_c | \mathbf{x}) \right]
\end{aligned}$$

$$\begin{aligned}
&\geq H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{z}_c \sim p(\mathbf{z}_c)} \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}, c)} \mathbb{E}_{\mathbf{z}'_c \sim p(\mathbf{z}_c | \mathbf{x})} \log \left[Q(\mathbf{z}'_c | \mathbf{x}) \right] \\
&\geq H(\mathbf{z}_c) + \mathbb{E}_{\mathbf{z}_c \sim p(\mathbf{z}_c)} \mathbb{E}_{\mathbf{x} \sim G(\mathbf{z}, c)} \log \left[Q(\mathbf{z}_c | \mathbf{x}) \right] \\
&\text{(by Lemma 5.1 of [1])} \\
&= L_I(G, Q)
\end{aligned}$$

Supplementary Information C Supplementary Figures and Tables

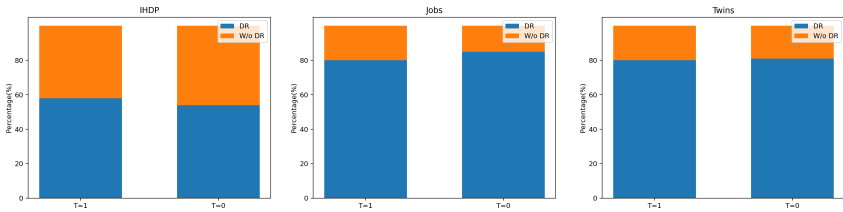


Fig. C1 Performance comparison of doubly robust vs. non-doubly robust version of DR-VIDAL. Panels, from left to right, show results on IHDP, Jobs and Twins datasets (100, 10, 100 iterations), respectively.

Table C1 Performance of the all the different DR-VIDAL configurations on the IHDP, Jobs and Twins datasets (1000, 10, and 100 realizations, respectively). Results show the out-of-sample (mean $\pm$ st.dev) error (PEHE) and policy risk (R_{Pol}).

	IHDP $\sqrt{\epsilon_{PEHE}^{out-of-s}}$	Jobs $R_{Pol}^{out-of-s}$	Twins $\sqrt{\epsilon_{PEHE}^{out-of-s}}$
DR-VIDAL	0.62 $\pm$ 0.06	0.102 $\pm$ 0.01	0.318 $\pm$ 0.008
DR-VIDAL (w/o DR loss)	0.85 $\pm$ 0.06	0.110 $\pm$ 0.01	0.324 $\pm$ 0.007
DR-VIDAL (w/o Info loss)	0.67 $\pm$ 0.04	0.109 $\pm$ 0.01	0.318 $\pm$ 0.012
DR-VIDAL (w/o DR + Info loss)	0.81 $\pm$ 0.05	0.113 $\pm$ 0.01	0.326 $\pm$ 0.008

References

- [1] Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., Abbeel, P.: Infogan: Interpretable representation learning by information maximizing generative adversarial nets. Advances in neural information processing systems **29**, 2172–2180 (2016)

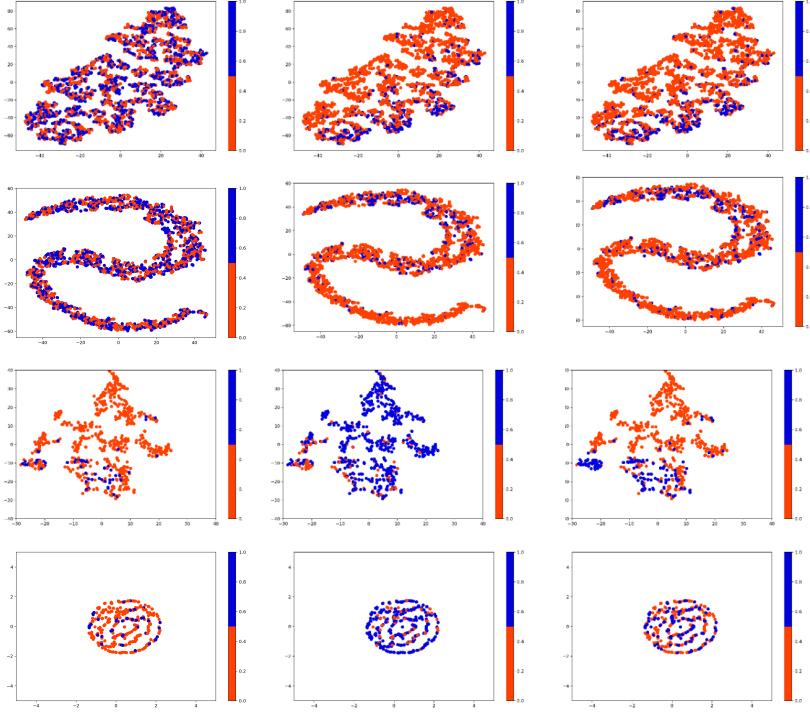


Fig. C2 Visualization of the latent representation learned by the VAE module of DR-VIDAL for the Twins and Jobs dataset using t-SNE. The 1st and 2nd panels show the t-SNE before and after training the network for Twins dataset. The 3rd and 4th panels show the same for Jobs dataset. From left to right, the plots show the t-SNE of treatment, factual and counterfactual outcomes.