

# Towards Self-Supervised Semantic Representation with a Viewpoint-Dependent Observation Model

## Supplementary Material

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This document provides supplementary material to [1]. Therefore, it should not be considered a self-contained document, but instead regarded as an appendix of [1]. Throughout this report, all notations and definitions are with compliance to the ones presented in [1].

### A Derivation of the ELBO for the Viewpoint-Dependent Model

In the following we detail the derivation of Eq. (12) from Feldman and Indelman [1].

$$\begin{aligned}
 & KL(q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) \parallel \mathbb{P}(e \mid \mathcal{Z}_k, \beta_k, \mathcal{X}_k^{(rel)})) = & (1) \\
 & \mathbb{E}_{e \sim q_\phi} \{ \log q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) - \log \mathbb{P}(e, \mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)}) \} + \log \mathbb{P}(\mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)}) \\
 & = KL(q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) \parallel \mathbb{P}(e, \mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)})) + \log \mathbb{P}(\mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)}).
 \end{aligned}$$

Hence, we can write the evidence lower bound as

$$\begin{aligned}
 \log \mathbb{P}(\mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)}) & \geq -KL(q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) \parallel \mathbb{P}(e, \mathcal{Z}_k, \beta_k \mid \mathcal{X}_k^{(rel)})) & (2) \\
 & = -KL(q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) \parallel \mathbb{P}(e \mid \mathcal{X}_k^{(rel)}) \cdot \mathbb{P}(\mathcal{Z}_k, \beta_k \mid e, \mathcal{X}_k^{(rel)})) \\
 & = -KL(q_\phi(e \mid \mathcal{Z}_k, \mathcal{X}_k^{(rel)}) \parallel \mathbb{P}(e)) + \mathbb{E}_{e \sim q_\phi} \{ \log \mathbb{P}(\mathcal{Z}_k, \beta_k \mid e, \mathcal{X}_k^{(rel)}) \},
 \end{aligned}$$

where  $\mathbb{P}(e \mid \mathcal{X}_k^{(rel)}) = \mathbb{P}(e)$  since the semantic variable  $e$  and robot movement  $\mathcal{X}_k^{(rel)}$  are independent in absence of measurements.

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## B Derivation of the ELBO for the Viewpoint-Predictive Model

In this section we detail the derivation of Eq. (20) from Feldman and Indelman [1].

$$\begin{aligned}
 & KL(q_\phi(e | \mathcal{Z}_k) \parallel \mathbb{P}(e | \mathcal{Z}_{k+1}, \mathcal{Z}_k, \Delta\mathcal{X}_k)) = \\
 & \mathbb{E}_{e \sim q_\phi} \{ \log q_\phi(e | \mathcal{Z}_k) - \log \mathbb{P}(e, \mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k) + \log \mathbb{P}(\mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k) \} \\
 & = KL(q_\phi(e | \mathcal{Z}_k) \parallel \mathbb{P}(e, \mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k)) + \log \mathbb{P}(\mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k).
 \end{aligned} \tag{3}$$

Hence, we can write the evidence lower bound as

$$\begin{aligned}
 & \log \mathbb{P}(\mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k) \geq -KL(q_\phi(e | \mathcal{Z}_k) \parallel \mathbb{P}(e, \mathcal{Z}_{k+1} | \mathcal{Z}_k, \Delta\mathcal{X}_k)) \\
 & = - \mathbb{E}_{e \sim q_\phi} \{ \log q_\phi(e | \mathcal{Z}_k) - \log \frac{\mathbb{P}(\mathcal{Z}_{k+1}, \mathcal{Z}_k | e, \Delta\mathcal{X}_k) \cdot \mathbb{P}(e | \Delta\mathcal{X}_k)}{\mathbb{P}(\mathcal{Z}_k | \Delta\mathcal{X}_k)} \} \\
 & = - \mathbb{E}_{e \sim q_\phi} \{ \log q_\phi(e | \mathcal{Z}_k) - \log \mathbb{P}(e) - \log \mathbb{P}(\mathcal{Z}_{k+1}, \mathcal{Z}_k | e, \Delta\mathcal{X}_k) \} - \log \mathbb{P}(\mathcal{Z}_k | \Delta\mathcal{X}_k),
 \end{aligned} \tag{4}$$

the last equation true since as before  $\mathbb{P}(e | \Delta\mathcal{X}_k) = \mathbb{P}(e)$ , as  $e$  and  $\Delta\mathcal{X}_k$  are independent in absence of measurements, and since the last term is constant w.r.t. the expectation. We can further develop the expression to reach the final evidence lower bound:

$$\begin{aligned}
 & = -KL(q_\phi(e | \mathcal{Z}_k) \parallel \mathbb{P}(e)) + \\
 & \mathbb{E}_{e \sim q_\phi} \{ \log \mathbb{P}(\mathcal{Z}_{k+1} | \mathcal{Z}_k, e, \Delta\mathcal{X}_k) + \mathbb{P}(\mathcal{Z}_k | e) \} - \log \mathbb{P}(\mathcal{Z}_k | \Delta\mathcal{X}_k),
 \end{aligned} \tag{5}$$

where  $\mathbb{P}(\mathcal{Z}_k | e, \Delta\mathcal{X}_k) = \mathbb{P}(\mathcal{Z}_k | e)$  i.e. we can drop the conditioning on  $\Delta\mathcal{X}_k$  since it only contains relative pose information and thus is by definition

## References

- [1] Y. Feldman and V. Indelman. Towards self-supervised semantic representation with a viewpoint-dependent observation model. In *Workshop on Self-Supervised Robot Learning, in conjunction with Robotics: Science and Systems*, July 2020.