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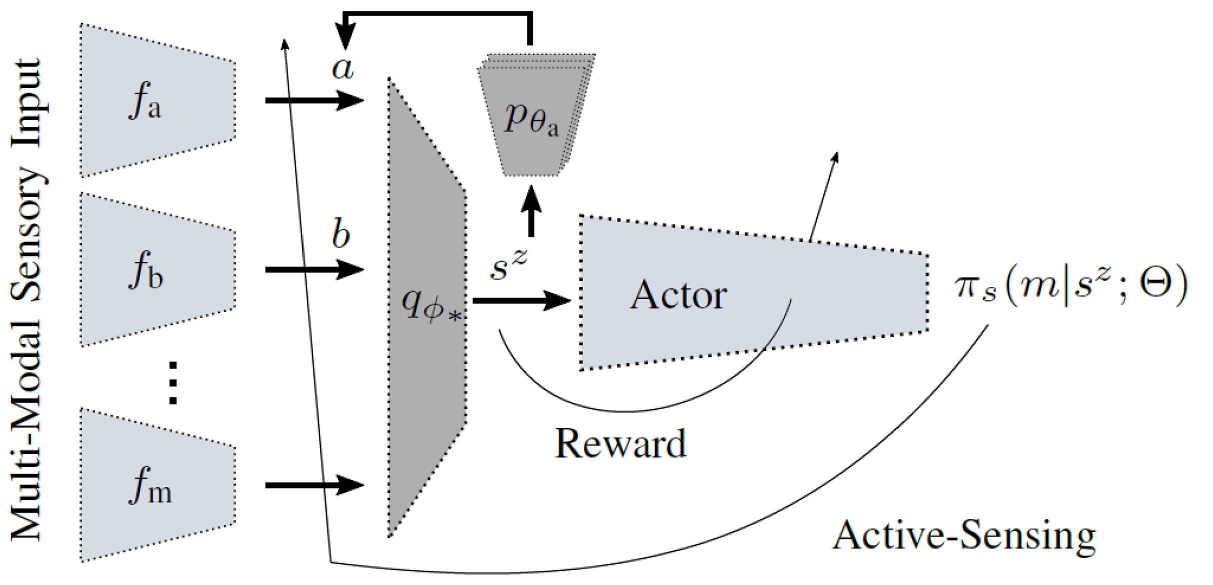
Multi-Modal Generative Models for Learning Epistemic Active Sensing

Timo Korthals [1], Daniel Rudolph, Jürgen Leitner [2], Marc Hesse [1], and Ulrich Rückert [1]

[1] Bielefeld University, Cognitronics & Sensor Systems, Bielefeld, Germany
[2] Queensland University of Technology, Australian Centre for Robotic Vision, Brisbane, Australia

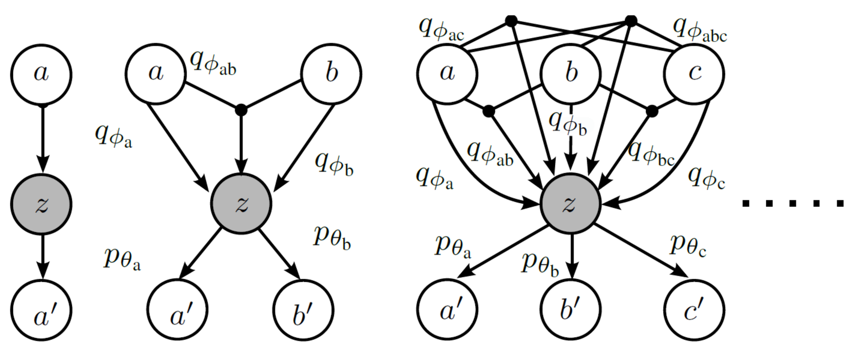
Approach

We present a novel approach of multi-modal deep generative models and apply this to coordinated heterogeneous multi-agent active sensing [2]. A major approach to achieve this objective is to train a **multi-modal variational Auto Encoder (M²VAE)** [1] that integrates all the information different sensor modalities into a **joint latent representation**. Furthermore, we derive an objective from the M²VAE that enables the maximization of the evidence lower bound **via selection of sensor modalities**. Using this approach as a direct reward signal to a multi-modal and multi-agent deep reinforcement learning setup **leads intuitively to an epistemic active sensing behavior** [3] that coordinately resolves the ambiguity of observations.



Multi-Modal Generative Models (M²VAE)

- Objective is derived from the full marginal joint log likelihood [1]
- M²VAE respects all permutations
- All mod. are trained jointly



- VAE objective

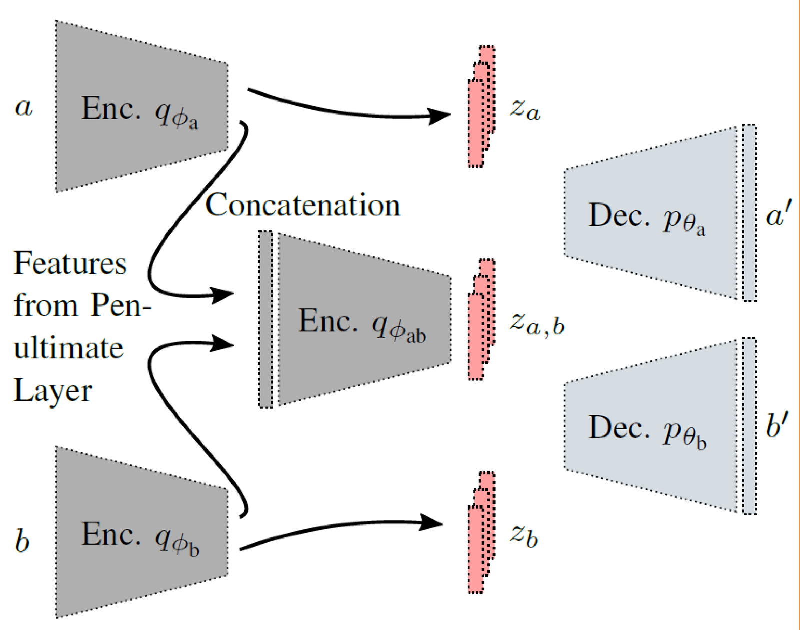
$$L_a \geq \mathcal{L} = \underbrace{-D_{KL}(q_\phi(z|a)\|p(z))}_{\text{Regularization}} + \underbrace{\mathbb{E}_{q_\phi(z|a)} \log(p_\theta(a|z))}_{\text{Reconstruction}}$$

- Joint VAE objective

$$L_J \geq \mathcal{L}_J = \underbrace{-D_{KL}(q_{\phi_{ab}}(z|a,b)\|p(z))}_{\text{Regularization}} + \underbrace{\mathbb{E}_{q_{\phi_{ab}}(z|a,b)} \log(p_{\theta_a}(a|z))}_{\text{Reconstruction wrt. } a} + \underbrace{\mathbb{E}_{q_{\phi_{ab}}(z|a,b)} \log(p_{\theta_b}(b|z))}_{\text{Reconstruction wrt. } b}$$

- MVAE objective

$$L_M \geq \mathcal{L}_M \geq \mathcal{L}_J - \underbrace{D_{KL}(q_{\phi_{ab}}(z|a,b)\|q_{\phi_b}(z|b))}_{\text{Unimodal PDF fitting of encoder b}} - \underbrace{D_{KL}(q_{\phi_{ab}}(z|a,b)\|q_{\phi_a}(z|a))}_{\text{Unimodal PDF fitting of encoder a}}$$



- Proposed M²VAE objective

2 modalities: $2L_{M^2} \geq 2\mathcal{L}_{M^2} = \mathcal{L}_a + \mathcal{L}_b + \mathcal{L}_M$

$|\mathcal{M}|$ modalities:

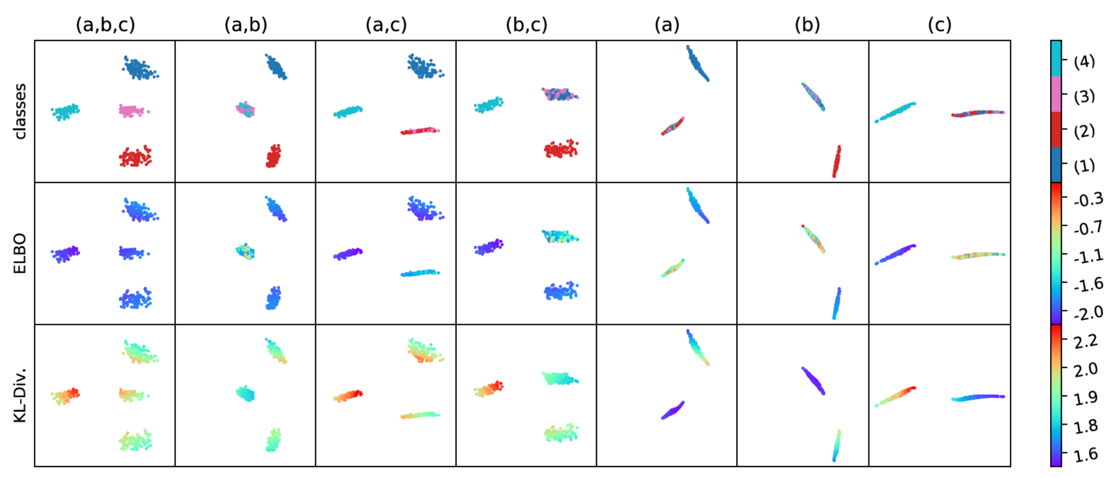
$$L_{M^2_\mathcal{M}} = \frac{1}{(|\mathcal{M}|^2 - |\mathcal{M}|)} \sum_{\widetilde{m} \in \widetilde{\mathcal{M}}} L_{M^2_{\widetilde{m}}} + \frac{1}{|\mathcal{M}|} L_{M_\mathcal{M}}$$

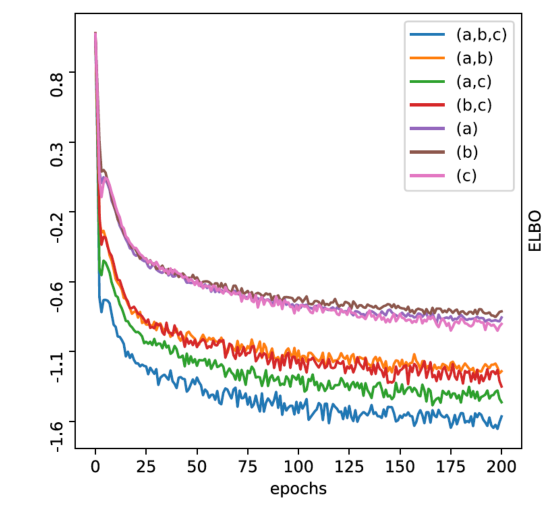
$$\geq \frac{1}{(|\mathcal{M}|^2 - |\mathcal{M}|)} \sum_{\widetilde{m} \in \widetilde{\mathcal{M}}} \mathcal{L}_{M^2_{\widetilde{m}}} + \frac{1}{|\mathcal{M}|} \mathcal{L}_{M_\mathcal{M}} =: \mathcal{L}_{M^2_\mathcal{M}}.$$

Learning Epistemic Active Sensing

Training of M²VAE

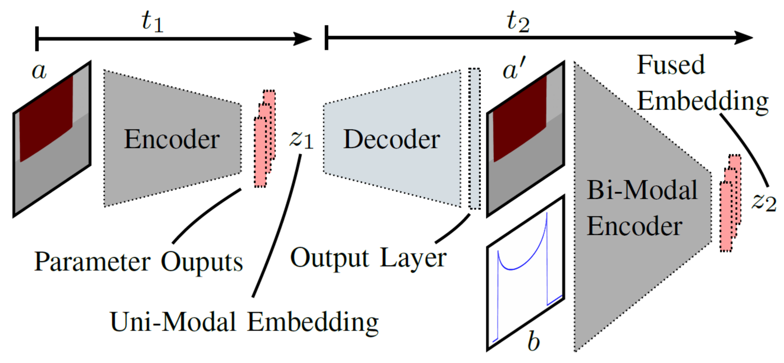
- All permutations of modalities (a,b,c) are trained on the environment observations
- ELBO becomes higher for greater information content in the observation
- KL behaves proportional to the ELBO, as the M²VAE prevents confusion in the latent space



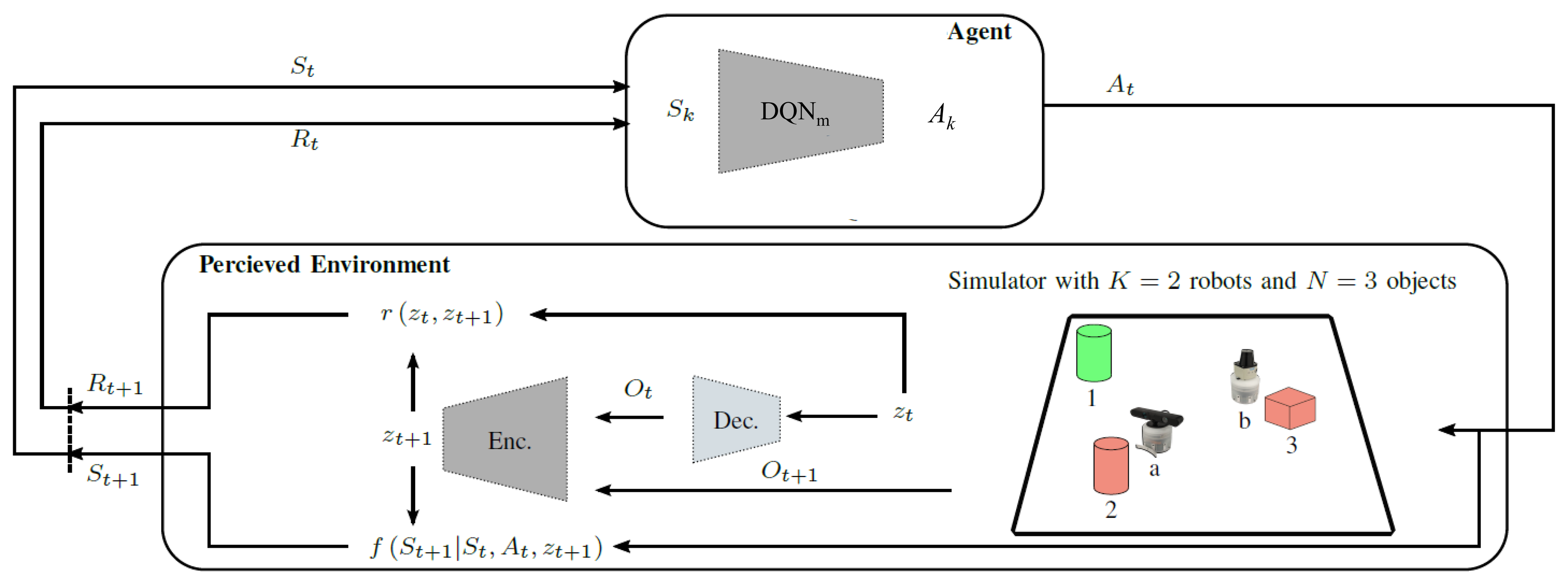


Training Epistemic Sensing

- All perceptions in the environment are embedded by the M²VAE for every object, to build a perceived env.
- New observations are fused with prior observations via de-/encoding
- As the M²VAE derives the state and reward information, the env. Becomes a perceived environment



$q_{\phi_{m,\mathcal{M}'}}(z_n|m,\mathcal{M}')$ with $\mathcal{M}' = \bigcup_{m' in \mathcal{M}'} p_{\theta_{m'}}(m'|z'_n)$



State & Reward Construction

Distance & Latent Space

$$Z = \begin{pmatrix} \mu_{1,o_1} & D_{kl_{1,o_1}} & \mu_{2,o_1} & D_{kl_{2,o_1}} & \dots & \mu_{j,o_1} & D_{kl_{j,o_1}} \\ \mu_{1,o_2} & D_{kl_{1,o_2}} & \mu_{2,o_2} & D_{kl_{2,o_2}} & \dots & \mu_{j,o_2} & D_{kl_{j,o_2}} \\ \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots \\ \mu_{1,o_m} & D_{kl_{1,o_m}} & \mu_{2,o_m} & D_{kl_{2,o_m}} & \dots & \mu_{j,o_m} & D_{kl_{j,o_m}} \end{pmatrix}$$

$$D = \begin{pmatrix} d(c_1,o_1) & d(c_1,o_2) & \dots & d(c_1,o_m) \\ d(c_2,o_1) & d(c_2,o_2) & \dots & d(c_2,o_m) \\ \vdots & \vdots & & \vdots \\ d(c_k,o_1) & d(c_k,o_2) & \dots & d(c_k,o_m) \end{pmatrix}$$

- Observation S is constructed as {Z,D_i} for every robot i
- Reward results from M²VAE's KL

$$r_i = \begin{cases} 0 & \text{If NOP} \\ -0{,}5 & \text{if already seen} \\ -(D^t_{kl_{j,o_i}} - D^{t+1}_{kl_{j,o_i}}) - \varepsilon & \text{modality results in no KL increase} \\ (D^t_{kl_{j,o_i}} - D^{t+1}_{kl_{j,o_i}}) + (1 - d(a_i, o_i)) & \text{modality results in KL increase} \end{cases}$$

Conclusion

- M²VAE enables inference, sensor fusion, and epistemic behavior through ambiguity-resolving actions in a deep reinforcement application
- M²VAE is trained unsupervised based on sensory outputs to build a coherent and expressive posterior distribution between all subsets of modalities
- Max. of the M²VAE's ELBO via actions leads inherently to the principle of active sensing and min. of free energy [3]

[1] Korthals, Timo, M²VAE - Derivation of a Multi-Modal Variational Autoencoder Objective from the Marginal Joint Log-Likelihood, http://arxiv.org/abs/1903.07303, 2019
[2] R. Bajcsy, Y. Aloimonos, and J. K. Tsotsos, "Revisiting active perception," Autonomous Robots, vol. 42, no. 2, pp. 177–196, 2018
[3] Friston, Karl, "The free-energy principle: A unified brain theory?" Nature Reviews Neuroscience, vol. 11, 2010

Contact
Bielefeld University
Center of Excellence Cognitive Interaction Technology
Cognitronics & Sensor Systems
Inspiration 1, 33619 Bielefeld - Germany

Contact Persons
Timo Korthals
Room: 3.413
Tel: +49 521 106 67367
tkorthals@cit-ec.uni-bielefeld.de

Submission Video