We will compare the following models:

- Auxiliary Deep Generative Model (ADGM) [2]
- Householder Flow [3]
- Importance Weighted Auto-Encoder (IWAE) [4]
- Non Linear Independent Components Estimation (NICE) [5]
- Normalizing (Planar) Flow [6]
- Markov Chain Monte Carlo (MCMC) and Variational Inference (VI) [7]

### Introduction

Variational auto-encoders (VAEs) [1] are an efficient probabilistic deep learning method that has gained a lot of popularity recently. They are widely applied due to their ease of use and promising results.

The quality of inference and the generative process are dependent on the accuracy of the inference network.

The basic VAE model is shown in Figure 4. The object of this work is to improve the inference network of the variational auto-encoders that are already widely applied due to their ease of use and promising results.

We will compare these different approaches on a range of applications to provide practical advice on the different trade-offs involved with each model with regards to accuracy and runtime.

### OBJECTIVES

There have been several proposals on how to improve the inference network of the variational auto-encoder which would improve the model’s capabilities. We will explore these different approaches on a range of applications to provide practical advice on the different trade-offs involved with each model with regards to accuracy and runtime.

### Tradeoffs in Neural Variational Inference

**VAE**

The **VAE** maximizes a different lower bound that is shown to be a tighter approximation than the standard VAE lower bound. This tighter bound is given by:

$$
\mathcal{L}_{\text{VAE}}(x) = \mathbb{E}_{q(z|x)} \left[ \log \frac{1}{k} \sum_{t=1}^{k} p(x, z_t | z_{t-1}) q(z_t | x) \right] 
$$

**IWAE**

The IWAE maximizes a different lower bound that is a lot of popularity recently. They are widely applied due to their ease of use and promising results.

**Householder Flow**

The transformation is defined as follow:

$$
z^{(t)} = \left( I - 2vT \frac{v}{||v||^2} \right) z^{(t-1)} 
$$

The Householder vector is known as the Householder vector. Importantly, $H_t$ is an orthogonal matrix which simplifies the objective calculations.

**Flow Transformations**

Normalizing flows can be divided into general normalizing flows and volume preserving flows. The tradeoff between these two is that the former is computationally more expensive but allows for more flexible posteriors. We will consider the Planar Flow for the general normalizing flow case and the Householder Flow for the case of a volume preserving flow.

**Householder Flow Transformation**

The transformation is defined as follow:

$$
H_t z^{(t-1)} = v z^{(t-1)} + b 
$$

**Planar Flow**

We will consider transformations of the following form:

$$
J_t(z) = z + uh(wT z + b) 
$$

The pipeline can be described with the following:

$$
\phi \rightarrow z \rightarrow \theta \rightarrow x
$$

**Sampled Data**

- Training data
- VAE
- IWAE
- Householder

**References**


