We would like to learn latent representations that are low-dimensional and highly interpretable. A model that has these characteristics is the Gaussian Process Latent Variable Model (GP-LVM). The benefits and negative of the GP-LVM are complementary to the VAE, the former provides useful low-dimensional latent representations while the latter is able to handle large amounts of data and can use non-Gaussian likelihoods. Our inspiration for this paper is to marry these two approaches and reap the benefits of both.

**Motivation np-VAE**

- non-Gaussian likelihoods
- high interpretability
- explicit prior over structure via the choice of covariance function
- uncertainty estimation
- model complexity growing with the size of the data set

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**Abstract**

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**Model**

\[ p(y) = \int \left( \prod_{i=1}^{N} p(x_i | y_i) \right) p(z | x)p(x)p(z | x|x) \]

**Assumption**

- Low-dimensional manifold in latent high-dimensional \( Z \) space
- Tested by: Embedding high-dimensional \( Z \) space positions recovered from the VAE in a low-dimensional space \( X \) via a GP-LVM (see initial results).

**Variational Autoencoder**

\[ q(z | y_i) = \prod_{i=1}^{N} q(z_i | y_i), \]

\[ \hat{L} = \frac{1}{N} \sum_{i=1}^{N} \log p(y_i | z_i) - \text{KL}(q(z | y_i) || p(z)) \]

Standard VAE formulation [Kingma and Welling (2014)]:

- unit Gaussian prior \( p(z) = N(0, I) \)
- trade-off between the embedded data residing at the same location in the latent space and the ability to reconstruct the data in the observed space.

**Gaussian Process Latent Variable Model**

A Gaussian Process can:

- be used to model functions nonparametrically
- be fully defined by a covariance function

\[ p(y | x) = \int p(y | F)p(F | X)p(X) \sim N(0, k(X, X)) \]

\[ p(y_i | x_i, y_i) = \int p(y_i | x_i, F)p(F | y_i, X)p(X) \sim N(0, k(X, X)) \]

\[ \Sigma(x_i) = k(x_i, x_i) - k(x_i, X)k(X, X)^{-1}k(X, x_i) \]

Gaussian Process Latent Variable Model [Lawrence (2005)]:

\[ p(y) = \int p(y | F)p(F | X)p(x)p(x) \sim N(0, k(X, X)) \]

**References**


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