



Probabilistic Generative Models & Probabilistic Discriminative Models



What are Probabilistic Models?

- Probabilistic models are an essential component of machine learning, which aims to **learn patterns from data and make predictions on new, unseen data.**
- They are **statistical models** that capture the inherent uncertainty in data and incorporate it into their predictions.
- Probabilistic models are used in various applications such as image and speech recognition, [natural language processing](#), and recommendation systems.
- In recent years, significant progress has been made in developing probabilistic models that can **handle large datasets efficiently.**



Categories Of Probabilistic Models

These models can be classified into the following categories:

- Generative models
- Discriminative models.
- Graphical models



Generative models

- Generative models aim to model **the joint distribution of the input and output variables.**
- These models **generate new data** based on the probability distribution of the original dataset.
- Generative models are powerful because **they can generate new data that resembles the training data.**
- They can be used for tasks such as image and speech synthesis, language translation, and text generation.



Discriminative model

- The discriminative model aims to model the **conditional distribution of the output variable given the input variable**.
- They learn a decision boundary that separates the different classes of the output variable.
- Discriminative models are useful when the focus is on **making accurate predictions** rather than generating new data.
- They can be used for tasks such as [image recognition](#), speech recognition, and [sentiment analysis](#).



Laplace Approximation

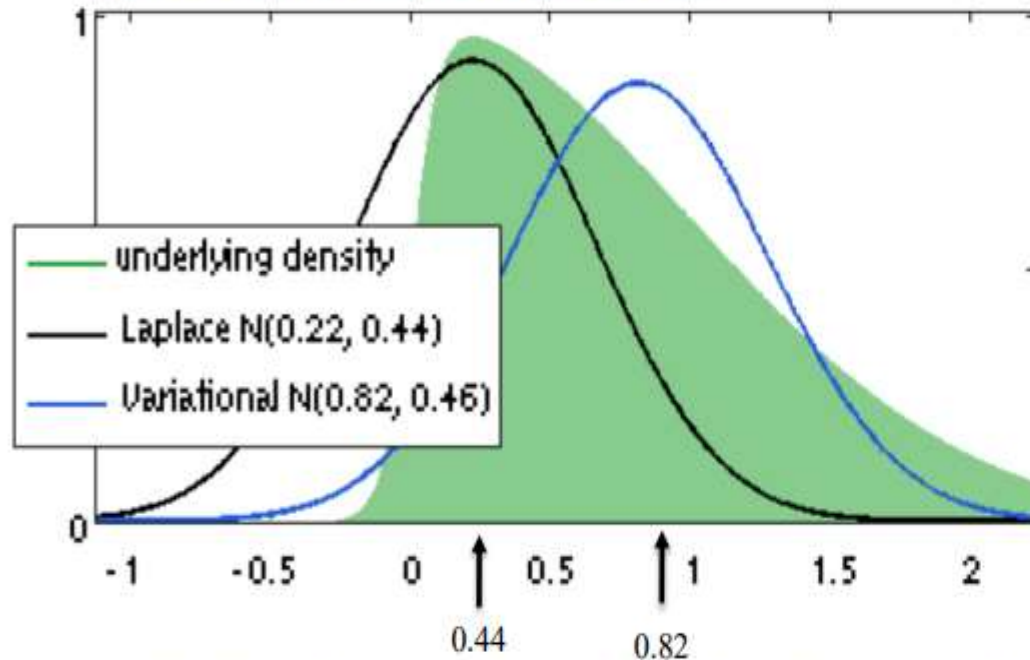
Topics in Laplace Approximation

- Motivation
- Finding a Gaussian approximation: 1-D case
- Approximation in M-dimensional space
- Weakness of Laplace approximation
- Model Comparison using BIC

What is Laplace Approximation?

- The Laplace approximation framework aims to find a Gaussian approximation to a continuous distribution

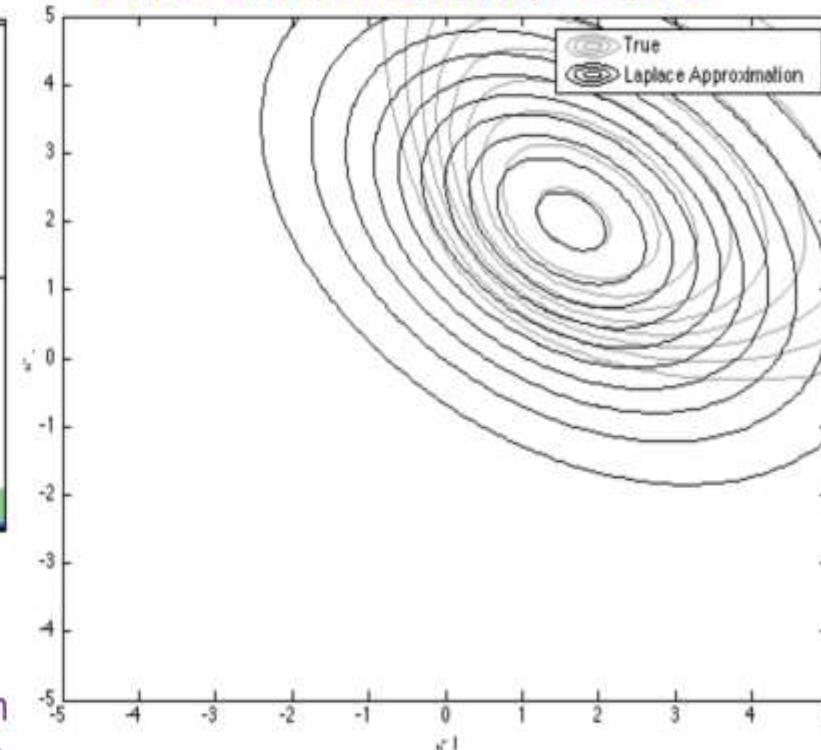
One-dimensional case



Laplace Approximation

Variational approximation
Based on KL-Divergence

Two-dimensional case





Laplace approximation framework

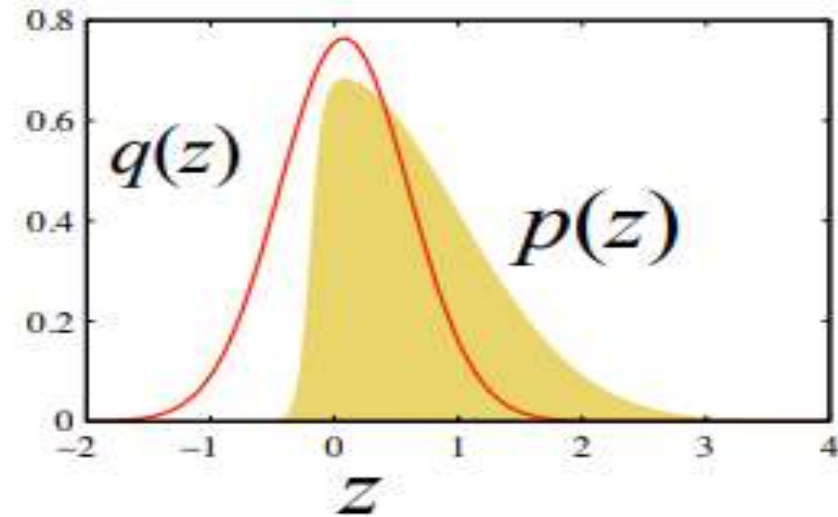
- Simple but widely used framework
- Aims to find a Gaussian approximation to a probability density defined over a set of continuous variables
- Method aims specifically at problems in which the distribution is unimodal
- Consider first the case of single continuous variable

Laplace Approximation: 1D case

- Single continuous variable z with distribution $p(z)$ defined by

$$p(z) = \frac{1}{Z} f(z)$$

where $Z = \int f(z) dz$ is a normalization coefficient





- Value of Z is unknown $f(z)$ is a scaled version of $p(z)$
- Goal is to find Gaussian approximation $q(z)$ which is centered on the mode of $p(z)$
- First step is to find mode of $p(z)$
 - i.e., a point z_0 such that $p'(z_0)=0$