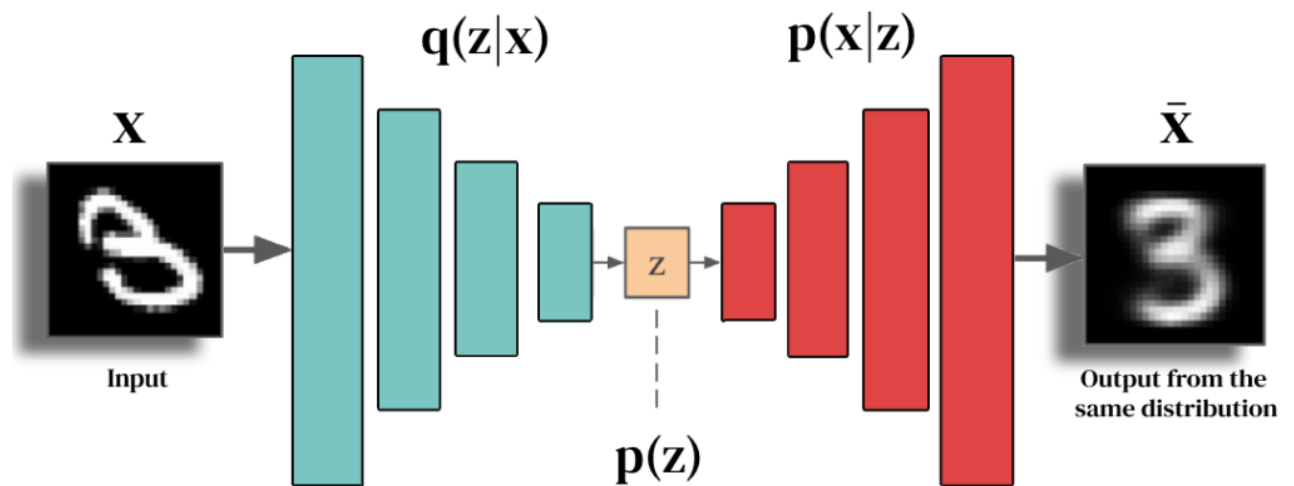


## ✓ Algorithm 1 VAE

This is the first algorithm of the paper for Variational AutoEncoder



We model each pixel value  $\in \{0,1\}$  as a sample drawn from a Bernoulli distribution. Through a decoder, the latent random variable  $z_n$  associated with an image  $n$  is mapped to the success parameters of the Bernoulli distributions associated with the pixels of that image. Our generative model is described as follows:

$$z_n \sim N(0, I)$$

$$\theta_n = g(z_n)$$

$$x_n \sim \text{Bern}(\theta_n)$$

where  $g$  is the decoder. We choose the prior on  $z_n$  to be the standard multivariate normal distribution, for computational convenience.

**Inference model:** We infer the posterior distribution of  $z_n$  via variational inference. The variational distribution  $q(z_n|x_n)$  is chosen to be multivariate Gaussian with a diagonal covariance matrix. The mean and covariance of this distribution are obtained by applying an encoder to  $x_n$ .

$$q(z_n|x_n) \sim q(\mu_n, \sigma_n^2)$$

where  $\mu_n, \sigma_n^2 = f(x_n)$  and  $f$  is the encoder.

```
import torch
import torch.nn as nn
import torch.distributions as dist

import numpy as np

from tqdm import tqdm

# Do not change the seeds
torch.manual_seed(0)
np.random.seed(0)

if torch.cuda.is_available():
    device = torch.device("cuda:0")
elif torch.backends.mps.is_available():
    device = torch.device("mps")
else:
    device = torch.device("cpu")
print(f"Using device: {device}")

dataset_path = '~/datasets'

batch_size = 128

# Dimensions of the input, the hidden layer, and the latent space.
x_dim = 784
hidden_dim = 200
latent_dim = 20

# Learning rate
lr = 1e-4

# Number of epoch
epochs = 20
```

```
Using device: mps
```

```

from torchvision.datasets import MNIST
import torchvision.transforms as transforms
from torch.utils.data import DataLoader

mnist_transform = transforms.Compose([
    transforms.ToTensor(),
])

train_dataset = MNIST(dataset_path, transform=mnist_transform, train=True)
test_dataset = MNIST(dataset_path, transform=mnist_transform, train=False)
test_labels = test_dataset.targets

train_loader = DataLoader(dataset=train_dataset, batch_size=batch_size)
test_loader = DataLoader(dataset=test_dataset, batch_size=batch_size)

```

```

class Encoder(nn.Module):
    # encoder outputs the parameters of variational distribution "q"
    def __init__(self, input_dim, hidden_dim, latent_dim):
        super(Encoder, self).__init__()

        self.FC_enc1 = nn.Linear(input_dim, hidden_dim) # FC = fully connected
        self.FC_enc2 = nn.Linear(hidden_dim, hidden_dim)
        self.FC_mean = nn.Linear(hidden_dim, latent_dim)
        self.FC_std = nn.Linear(hidden_dim, latent_dim)

        self.LeakyReLU = nn.LeakyReLU(0.2)

        self.training = True

    def forward(self, x):
        h_1 = self.LeakyReLU(self.FC_enc1(x))
        h_2 = self.LeakyReLU(self.FC_enc2(h_1))
        mu = self.FC_mean(h_2) # mean / location
        log_var = self.FC_std(h_2) # log variance

        return mu, log_var

```

```

class Decoder(nn.Module):
    # decoder generates the success parameter of each pixel
    def __init__(self, latent_dim, hidden_dim, output_dim):
        super(Decoder, self).__init__()
        self.FC_dec1 = nn.Linear(latent_dim, hidden_dim)
        self.FC_dec2 = nn.Linear(hidden_dim, hidden_dim)
        self.FC_output = nn.Linear(hidden_dim, output_dim)

        self.LeakyReLU = nn.LeakyReLU(0.2)

    def forward(self, z):
        h_out_1 = self.LeakyReLU(self.FC_dec1(z))
        h_out_2 = self.LeakyReLU(self.FC_dec2(h_out_1))

        theta = torch.sigmoid(self.FC_output(h_out_2))
        return theta

```

```

class Model(nn.Module):
    # it wrap the encoder and the decoder
    def __init__(self, Encoder, Decoder):
        super(Model, self).__init__()
        self.Encoder = Encoder
        self.Decoder = Decoder

    def reparameterization(self, mean, std):
        # 1. Sample standard normal noise epsilon:  $\epsilon \sim N(0, I)$ 
        # Use torch.randn_like(mean) to ensure 'eps' has the same shape
        # as 'mean' (or 'std').
        eps = torch.randn_like(mean)
        z = mean + eps * std
        return z

    def forward(self, x):
        # insert your code here
        mean, log_var = self.Encoder.forward(x)

        std = torch.sqrt(torch.exp(log_var))

        z = self.reparameterization(mean, std)

        theta = self.Decoder.forward(z)
        return theta, mean, log_var, z

```

```

encoder = Encoder(input_dim=x_dim, hidden_dim=hidden_dim, latent_dim=latent_dim)
decoder = Decoder(latent_dim=latent_dim, hidden_dim=hidden_dim, output_dim=output_dim)

model = Model(Encoder=encoder, Decoder=decoder)

model.to(device)

```

```

Model(
  (Encoder): Encoder(
    (FC_enc1): Linear(in_features=784, out_features=200, bias=True)
    (FC_enc2): Linear(in_features=200, out_features=200, bias=True)
    (FC_mean): Linear(in_features=200, out_features=20, bias=True)
    (FC_std): Linear(in_features=200, out_features=20, bias=True)
    (LeakyReLU): LeakyReLU(negative_slope=0.2)
  )
  (Decoder): Decoder(
    (FC_dec1): Linear(in_features=20, out_features=200, bias=True)
    (FC_dec2): Linear(in_features=200, out_features=200, bias=True)
    (FC_output): Linear(in_features=200, out_features=784, bias=True)
    (LeakyReLU): LeakyReLU(negative_slope=0.2)
  )
)

```

```

def loss_function(x, theta, mean, log_var): # should return the loss
    eps = 1e-9

    log_px_z = x * torch.log(theta + eps) + (1 - x) * torch.log(1 - theta + eps)
    log_px_z = log_px_z.sum(dim=1)
    recon_term = log_px_z.mean(dim=0)

    var = torch.exp(log_var)
    m_kl_per_sample = 0.5 * torch.sum(1 + log_var - var - mean.pow(2))
    m_kl_term = m_kl_per_sample.mean(dim=0)

    elbo = recon_term + m_kl_term
    loss = -elbo
    return loss

```

```

from torch.optim import Adam

print("Start training VAE...")
model.train()

# optimizer
optimizer = Adam(model.parameters(), lr=lr)
pbar = tqdm(range(epochs))
elbo_1 = []
for epoch in pbar:
    total_loss = 0
    total_samples = 0
    for batch_idx, (x, _) in enumerate(train_loader):
        x = x.to(device)
        x = x.view(-1, x_dim)
        x = torch.round(x)

        optimizer.zero_grad()

        # insert your code here
        theta, mean, log_var, _ = model.forward(x)

        loss = loss_function(x, theta, mean, log_var)
        loss.backward()
        optimizer.step()

        # loss.item() is the mean. Multiply by batch size to get the
        total_loss += loss.item() * x.size(0)
        total_samples += x.size(0)

    # Correct global average
    avg_loss = total_loss / total_samples

    pbar.set_description(f"Epoch {epoch+1}/{epochs}, "
                        f" Loss: {avg_loss:.4f}, "
                        f" ELBO: {-avg_loss:.4f}")
    elbo_1.append(-avg_loss)

print("Finish!!!")

```

```

Start training VAE...
Epoch 20/20, Loss: 106.7578, ELBO: -106.7578: 100%|██████████| 20/20

```

## ✓ Algorithm 2 VAE - Sticking the Landing

```
class Model(nn.Module):
    # it wrap the encoder and the decoder
    def __init__(self, Encoder, Decoder):
        super(Model, self).__init__()
        self.Encoder = Encoder
        self.Decoder = Decoder

    def reparameterization(self, mean, std):
        # 1. Sample standard normal noise epsilon: epsilon ~ N(0, I)
        # Use torch.randn_like(mean) to ensure 'eps' has the same s
        # as 'mean' (or 'std').
        eps = torch.randn_like(mean)
        z_pathwise = mean + eps * std

        z_stop_grad = z_pathwise.detach()

        return z_pathwise, z_stop_grad

    def forward(self, x):
        # insert your code here
        mean, log_var = self.Encoder.forward(x)

        std = torch.sqrt(torch.exp(log_var))

        z_pathwise, z_stop_grad = self.reparameterization(mean, std)

        theta = self.Decoder.forward(z_stop_grad)
        return theta, mean, log_var, z_pathwise, z_stop_grad
```



```

encoder = Encoder(input_dim=x_dim, hidden_dim=hidden_dim, latent_dim=latent_dim)
decoder = Decoder(latent_dim=latent_dim, hidden_dim=hidden_dim, output_dim=output_dim)

model = Model(Encoder=encoder, Decoder=decoder)

model.to(device)

```

```

Model(
  (Encoder): Encoder(
    (FC_enc1): Linear(in_features=784, out_features=200, bias=True)
    (FC_enc2): Linear(in_features=200, out_features=200, bias=True)
    (FC_mean): Linear(in_features=200, out_features=20, bias=True)
    (FC_std): Linear(in_features=200, out_features=20, bias=True)
    (LeakyReLU): LeakyReLU(negative_slope=0.2)
  )
  (Decoder): Decoder(
    (FC_dec1): Linear(in_features=20, out_features=200, bias=True)
    (FC_dec2): Linear(in_features=200, out_features=200, bias=True)
    (FC_output): Linear(in_features=200, out_features=784, bias=True)
    (LeakyReLU): LeakyReLU(negative_slope=0.2)
  )
)

```

```

def loss_function(x, theta, mean, log_var): # should return the loss
    eps = 1e-9

    log_px_z = x * torch.log(theta + eps) + (1 - x) * torch.log(1 - theta + eps)
    log_px_z = log_px_z.sum(dim=1)
    recon_term = log_px_z.mean(dim=0)

    var = torch.exp(log_var)
    m_kl_per_sample = 0.5 * torch.sum(1 + log_var - var - mean.pow(2))
    m_kl_term = m_kl_per_sample.mean(dim=0)

    elbo = recon_term + m_kl_term
    loss = -elbo
    return loss

```

```

from torch.optim import Adam

print("Start training VAE...")
model.train()

# optimizer
optimizer = Adam(model.parameters(), lr=lr)
pbar = tqdm(range(epochs))
elbo_2= []
for epoch in pbar:
    total_loss = 0
    total_samples = 0
    for batch_idx, (x, _) in enumerate(train_loader):
        x = x.to(device)
        x = x.view(-1, x_dim)
        x = torch.round(x)

        optimizer.zero_grad()

        # insert your code here
        theta_ng, mean, log_var,_,_= model.forward(x)

        loss = loss_function(x,theta_ng,mean,log_var) # it is compu
        loss.backward()
        optimizer.step()

        # loss.item() is the mean. Multiply by batch size to get th
        total_loss += loss.item() * x.size(0)
        total_samples += x.size(0)

    # Correct global average
    avg_loss = total_loss / total_samples

    pbar.set_description(f"Epoch {epoch+1}/{epochs},"
                        f" Loss: {avg_loss:.4f},"
                        f" ELBO: {-avg_loss:.4f}")
    elbo_2.append(-avg_loss)

print("Finish!!!")

```

```

Start training VAE...
Epoch 20/20, Loss: 206.3120, ELBO: -206.3120: 100%|██████████| 20/20

```

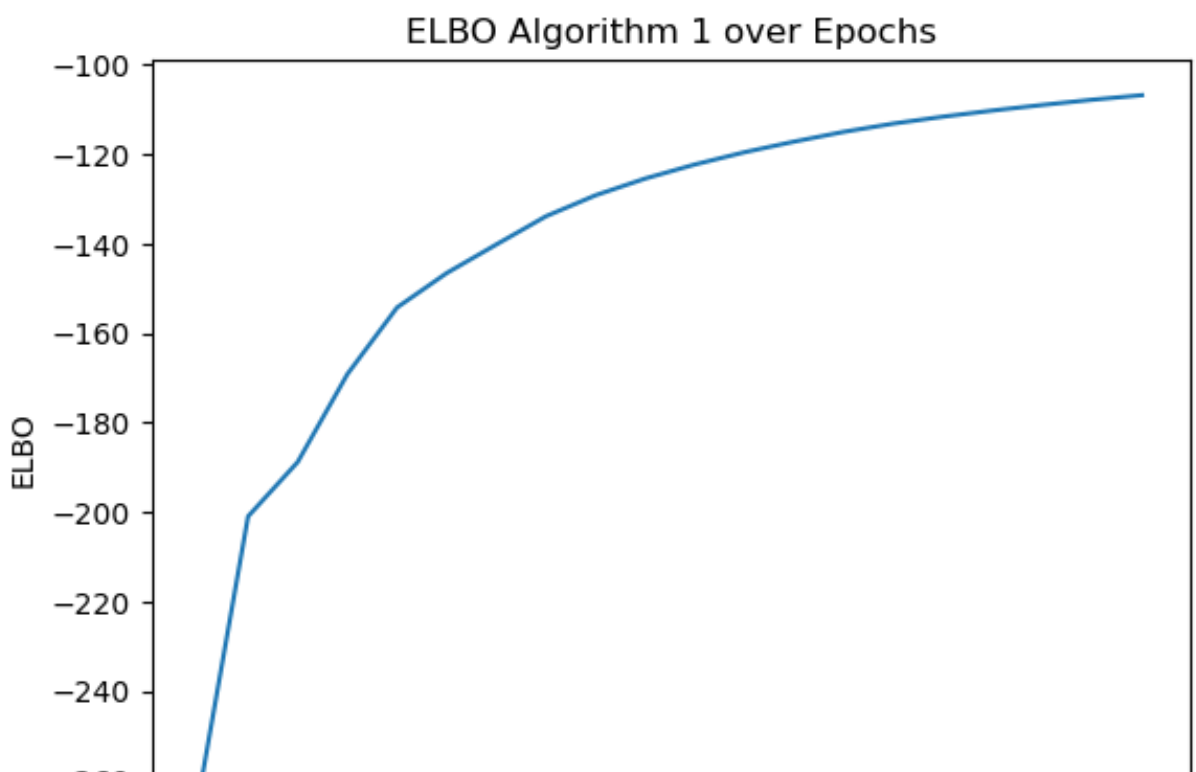
## ✓ Comparison

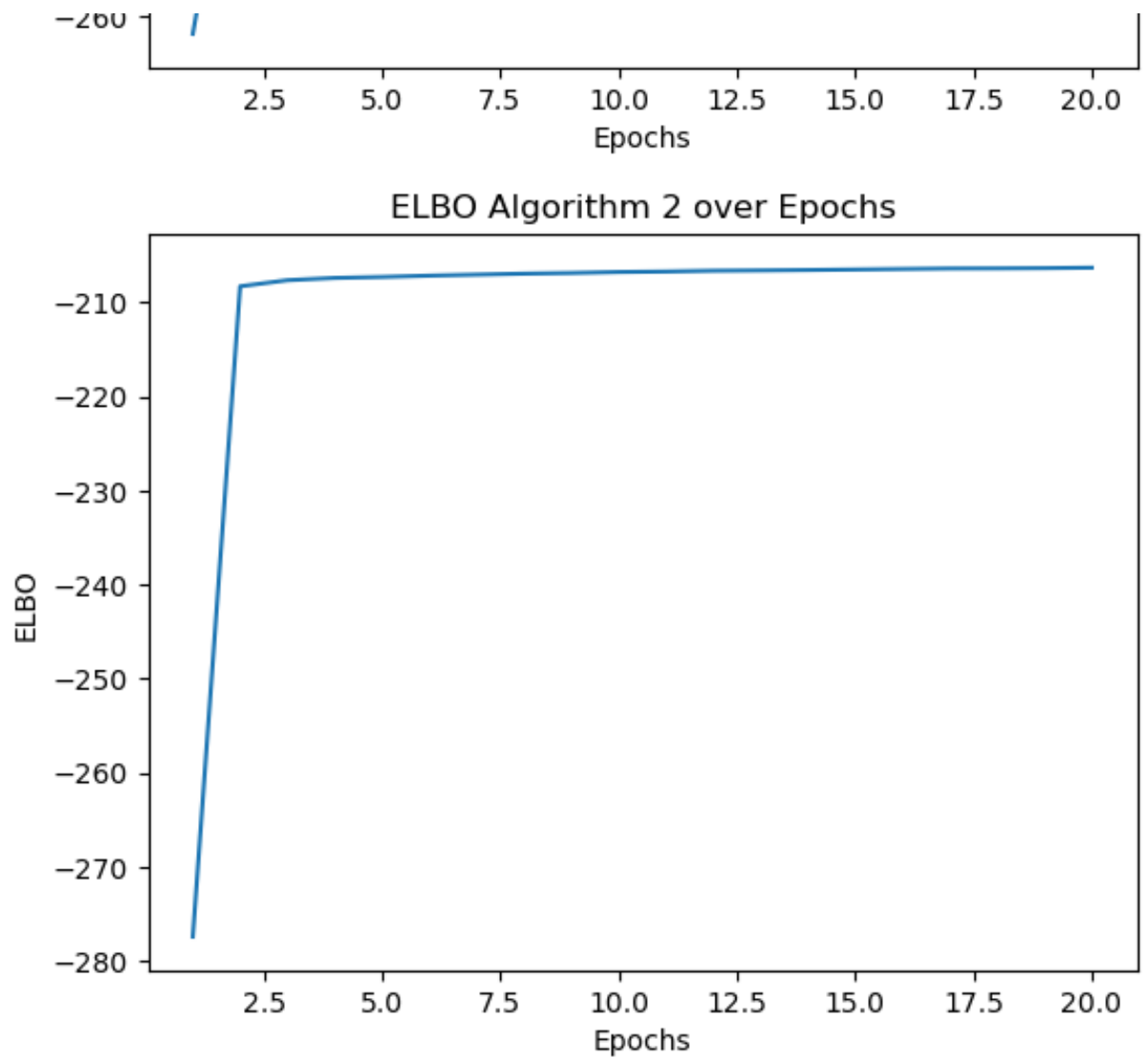
Comparing the ELBO over iterations for the standard VAE and the modified VAE of algorithm 2.

```
# Plot ELBO curve
import matplotlib.pyplot as plt
plt.plot(range(1, epochs + 1), elbo_1)
plt.xlabel('Epochs')
plt.ylabel('ELBO')
plt.title('ELBO Algorithm 1 over Epochs')
plt.show()

# Plot ELBO curve
import matplotlib.pyplot as plt
plt.plot(range(1, epochs + 1), elbo_2)
plt.xlabel('Epochs')
plt.ylabel('ELBO')
plt.title('ELBO Algorithm 2 over Epochs')
plt.show()

# Final ELBO
print(f"Final ELBO for Algorithm 1: {elbo_1[-1]}")
print(f"Final ELBO for Algorithm 2: {elbo_2[-1]}")
```





Final ELBO for Algorithm 1: -106.75783197428386

Final ELBO for Algorithm 2: -206.31198584798176

Fai doppio clic (o premi Invio) per modificare

Inizia a programmare o genera codice con l'IA.

