Q 2.4.17. Standard Gradient Descent vs. Natural Gradient Descent

In this notebbook, we compare standard gradient descent (GD) and natural gradient descent (NGD) for estimating the parameters of a 1D Gamma distribution from observed data. We will generate synthetic data from a known Gamma distribution and then attempt to recover its shape and scale parameters using both optimization methods.

1. Configuration

We define the true parameters of the Gamma distribution, the number of data points to generate, the learning rate, the number of epochs for optimization, and the initial guesses for the parameters. We also set a random seed for reproducibility.

```
import torch
import numpy as np
import matplotlib.pyplot as plt
from torch.distributions import Gamma
# ------------------------

# True parameters of the Gamma distribution we want to discover
ALPHA_TRUE = 3.0   # shape
BETA_TRUE  = 2.0   # scale

# Number of observed data points
N_DATA = 1000

# Optimization parameters
LEARNING_RATE = 0.1
EPOCHS = 150

# Initial "wrong" guess for our parameters (still positive)
ALPHA_INIT = 0.5
BETA_INIT  = 8.0

# Fix random seed for reproducibility (optional)
torch.manual_seed(0)
```

```
<torch._C.Generator at 0x122105750>
```

2. Data Generation

We generate synthetic data from the true Gamma distribution using PyTorch's `Gamma` distribution class. We sample `N_DATA` points and print the sample mean and variance to verify the generated data.

```
# Our parameterisation is shape–scale, but PyTorch's Gamma uses sha
rate_true = 1.0 / BETA_TRUE
dist_true = Gamma(concentration=torch.tensor(ALPHA_TRUE),
                  rate=torch.tensor(rate_true))

data = dist_true.sample((N_DATA,))

print(f"Generated {N_DATA} data points from Gamma(alpha={ALPHA_TRUE
print(f"Sample mean:     {data.mean().item():.4f}")
print(f"Sample variance: {data.var().item():.4f}\n")
```

```
Generated 1000 data points from Gamma(alpha=3.0, beta=2.0)
Sample mean:     6.0692
Sample variance: 11.9481
```

3. Loss function & parameter init

We define the negative log-likelihood loss function for the Gamma distribution. We also initialize the parameters for both standard gradient descent and natural gradient descent, and set up history trackers to record the parameter values over epochs.

```
# ToDo: Loss function
def gamma_nll(alpha, beta, data_points):
    """
    ToDo:
        Implement the average negative log-likelihood for Gamma dis

        Hints:
        - Enforce positivity using clamp (e.g. min=1e-4).
        - PyTorch's Gamma takes (concentration=alpha, rate=1/beta).
        - Return the *mean* negative log-likelihood.

    """
    alpha = torch.clamp(alpha, min=1e-4)
    beta = torch.clamp(beta, min=1e-4)

    # Convert data_points to tensor if not already
    data_tensor = torch.tensor(data_points) if not torch.is_tensor(

    empirical_mean_x = data_tensor.mean()
    empirical_mean_log_x = torch.log(data_tensor).mean()
    nll = +alpha*torch.log(beta) + torch.lgamma(alpha) - (alpha-1)*
    return nll
```

```
# Parameters for Standard Gradient Descent (GD)
alpha_gd = torch.tensor(ALPHA_INIT, requires_grad=True)
beta_gd  = torch.tensor(BETA_INIT,  requires_grad=True)

# Parameters for Natural Gradient Descent (NGD)
alpha_ngd = torch.tensor(ALPHA_INIT, requires_grad=True)
beta_ngd  = torch.tensor(BETA_INIT,  requires_grad=True)

# History trackers
history_gd  = []
history_ngd = []
history_loss_gd =[]
history_loss_ngd = []
```

4. Fisher Information inverse

```
def fisher_inverse(alpha, beta):
    """
    TODO:
      Implement the inverse Fisher Information matrix F^{-1}(α, β)
      for the Gamma(shape=α, scale=β) distribution.

      Theory:
        F(α, β) =
            [ ψ1(α)        1/β      ]
            [  1/β     α/β^2        ]

        F^{-1}(α, β) =
            1 / (α ψ1(α) - 1) *
            [  α           -β             ]
            [  -β       β^2 ψ1(α)         ]

      Hints:
      - Use torch.polygamma(1, alpha) for ψ1(α) (trigamma).
      - Make sure to detach alpha, beta so F^{-1} is not part of th
    """
    alpha_detached = alpha.detach()
    beta_detached = beta.detach()

    external_factor = 1/(alpha_detached* torch.polygamma(1, alpha_d
    inv11 = alpha_detached * external_factor
    inv12 = -beta_detached * external_factor
    inv22 = beta_detached**2 *  torch.polygamma(1, alpha_detached)
    return inv11, inv12, inv22
```

4. Optimization Loop

We run the optimization loop for a specified number of epochs. In each epoch, we perform both standard gradient descent and natural gradient descent updates. We compute the gradients, build the Fisher Information Matrix for NGD, and update the parameters accordingly. We also log the parameter values and losses at regular intervals.

```
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```

```
print(f"Optimizing with LR={LEARNING_RATE} for {EPOCHS} epochs...")

for epoch in range(EPOCHS):
    # ===== A. Standard Gradient Descent (GD) =====

    if alpha_gd.grad is not None:
        alpha_gd.grad.zero_()
    if beta_gd.grad is not None:
        beta_gd.grad.zero_()

    loss_gd = gamma_nll(alpha_gd, beta_gd, data)

    loss_gd.backward()

    with torch.no_grad():
        alpha_gd -= LEARNING_RATE * alpha_gd.grad
        beta_gd  -= LEARNING_RATE * beta_gd.grad

        alpha_gd.clamp_(min=1e-4)
        beta_gd.clamp_(min=1e-4)

    history_loss_gd.append(loss_gd.item())
    history_gd.append((alpha_gd.item(), beta_gd.item()))

    # ===== B. Natural Gradient Descent (NGD) =====

    if alpha_ngd.grad is not None:
        alpha_ngd.grad.zero_()
    if beta_ngd.grad is not None:
        beta_ngd.grad.zero_()

    loss_ngd = gamma_nll(alpha_ngd, beta_ngd, data)
    loss_ngd.backward()

    g_alpha = alpha_ngd.grad
    g_beta  = beta_ngd.grad

    # ToDo : compute natural gradient using F^{-1}(α, β)
    #  1) Get F^{-1} entries using fisher_inverse(...)
    #  2) Compute:
    #       - ng_alpha
    #       - ng_beta

    inv11, inv12, inv22 = fisher_inverse(alpha_ngd, beta_ngd)

    ng_alpha =  inv11*g_alpha + inv12*g_beta
    ng_beta  =  inv12*g_alpha + inv22*g_beta

    with torch.no_grad():
        alpha_ngd -= LEARNING_RATE * ng_alpha
```

```
            beta_ngd  -= LEARNING_RATE * ng_beta

            alpha_ngd.clamp_(min=1e-4)
            beta_ngd.clamp_(min=1e-4)

        history_loss_ngd.append(loss_ngd.item())
        history_ngd.append((alpha_ngd.item(), beta_ngd.item()))

        if (epoch + 1) % 15 == 0 or epoch == 0:
            print(f"\n--- Epoch {epoch + 1} ---")
            print(f"  GD:  alpha={alpha_gd.item():.4f}, beta={beta_gd.i
                  f"Loss={loss_gd.item():.4f}")
            print(f"  NGD: alpha={alpha_ngd.item():.4f}, beta={beta_ngd
                  f"Loss={loss_ngd.item():.4f}")


    print("\nOptimization finished.")
```

```
Optimizing with LR=0.1 for 150 epochs...

--- Epoch 1 ---
  GD:  alpha=0.6516, beta=8.0032, Loss=3.1866
  NGD: alpha=0.5340, beta=7.8695, Loss=3.1866

--- Epoch 15 ---
  GD:  alpha=1.0504, beta=7.9743, Loss=2.8331
  NGD: alpha=1.2770, beta=4.3331, Loss=2.7370

--- Epoch 30 ---
  GD:  alpha=1.0853, beta=7.9160, Loss=2.8296
  NGD: alpha=2.3102, beta=2.5556, Loss=2.5688

--- Epoch 45 ---
  GD:  alpha=1.0933, beta=7.8551, Loss=2.8270
  NGD: alpha=2.8686, beta=2.1013, Loss=2.5450

--- Epoch 60 ---
  GD:  alpha=1.0989, beta=7.7937, Loss=2.8245
  NGD: alpha=3.0273, beta=2.0018, Loss=2.5435

--- Epoch 75 ---
  GD:  alpha=1.1045, beta=7.7319, Loss=2.8219
  NGD: alpha=3.0627, beta=1.9810, Loss=2.5434

--- Epoch 90 ---
  GD:  alpha=1.1101, beta=7.6698, Loss=2.8193
  NGD: alpha=3.0701, beta=1.9768, Loss=2.5434

--- Epoch 105 ---
```

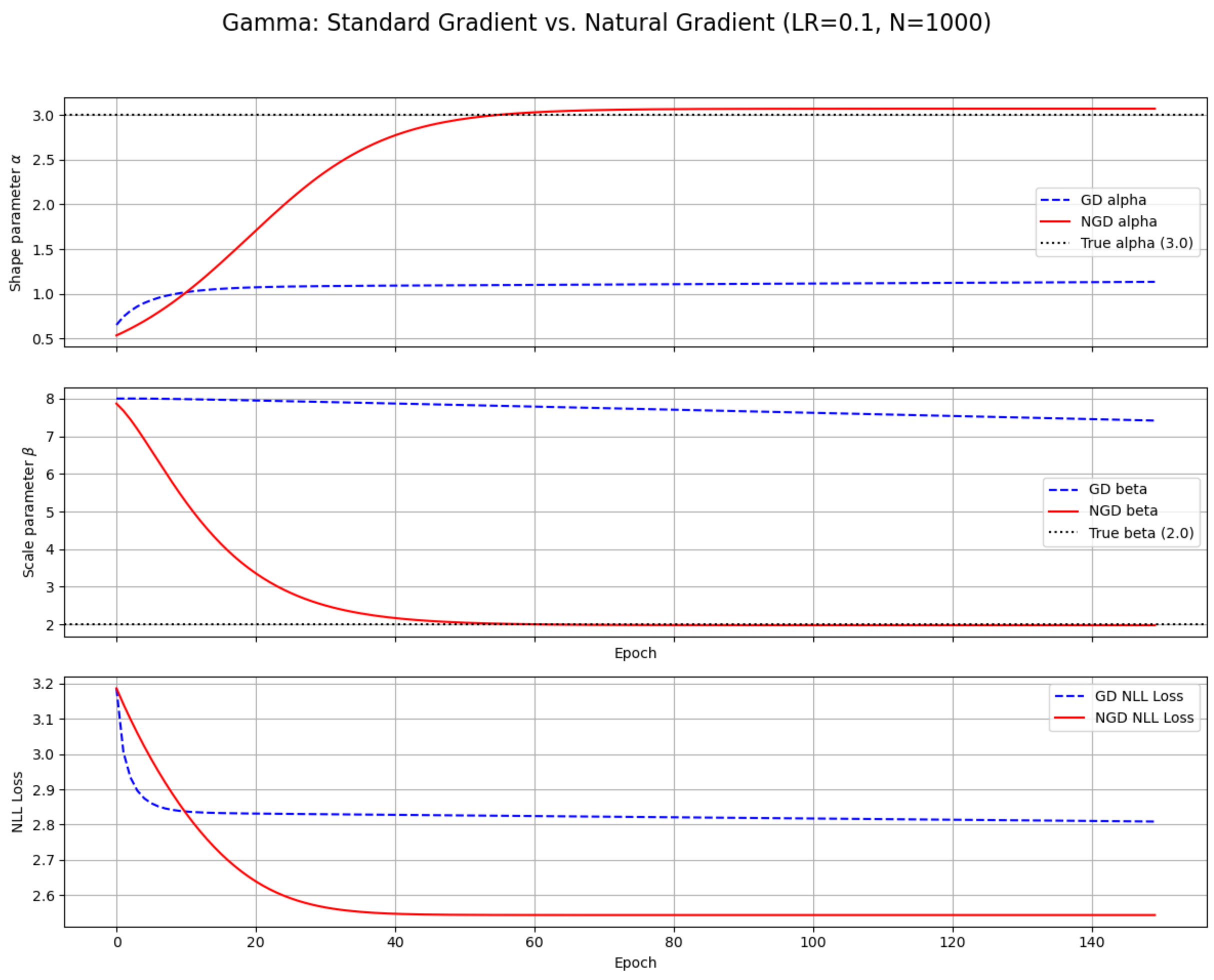
```
  GD:  alpha=1.1159, beta=7.6072, Loss=2.8167
  NGD: alpha=3.0716, beta=1.9759, Loss=2.5434

--- Epoch 120 ---
  GD:  alpha=1.1217, beta=7.5444, Loss=2.8141
  NGD: alpha=3.0719, beta=1.9757, Loss=2.5434

--- Epoch 135 ---
  GD:  alpha=1.1277, beta=7.4811, Loss=2.8114
  NGD: alpha=3.0720, beta=1.9757, Loss=2.5434

--- Epoch 150 ---
  GD:  alpha=1.1339, beta=7.4175, Loss=2.8086
  NGD: alpha=3.0720, beta=1.9756, Loss=2.5434

Optimization finished.
```

Q 2.4.18. Plotting Results

To illustrate the difference between standard gradients and natural gradients, we print out the gradients computed in the first epoch for both methods.

```
hist_gd_np  = np.array(history_gd)
hist_ngd_np = np.array(history_ngd)
hist_loss_gd = np.array(history_loss_gd)
hist_loss_ngd = np.array(history_loss_ngd)



fig, (ax1, ax2,ax3) = plt.subplots(3, 1, figsize=(12, 10), sharex=T
fig.suptitle(f"Gamma: Standard Gradient vs. Natural Gradient "
             f"(LR={LEARNING_RATE}, N={N_DATA})", fontsize=16)

# Plot 1: alpha (shape)
ax1.plot(hist_gd_np[:, 0],  label="GD alpha",  color='blue', linest
ax1.plot(hist_ngd_np[:, 0], label="NGD alpha", color='red')
ax1.axhline(ALPHA_TRUE, color='black', linestyle=':', label=f"True 
ax1.set_ylabel("Shape parameter $\\alpha$")
ax1.legend()
ax1.grid(True)

# Plot 2: beta (scale)
ax2.plot(hist_gd_np[:, 1],  label="GD beta",  color='blue', linesty
ax2.plot(hist_ngd_np[:, 1], label="NGD beta", color='red')
ax2.axhline(BETA_TRUE, color='black', linestyle=':', label=f"True b
ax2.set_xlabel("Epoch")
```

```
ax2.set_ylabel("Scale parameter $\\beta$")
ax2.legend()
ax2.grid(True)

# Plot 3: Negative Log-Likelihood (NLL) Loss
ax3.plot(hist_loss_gd,  label="GD NLL Loss",  color='blue', linesty
ax3.plot(hist_loss_ngd, label="NGD NLL Loss", color='red')
ax3.set_xlabel("Epoch")
ax3.set_ylabel("NLL Loss")
ax3.legend()
ax3.grid(True)



plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```


Gamma: Standard Gradient vs. Natural Gradient (LR=0.1, N=1000)
Shape parameter α
GD alpha
NGD alpha
True alpha (3.0)
Scale parameter β
GD beta
NGD beta
True beta (2.0)
Epoch
NLL Loss
GD NLL Loss
NGD NLL Loss
Epoch