

Gated Recurrent Unit (GRU) is a type of Recurrent Neural Network (RNN) that was introduced to solve the **vanishing gradient** problem and improve long-term dependency learning, similar to LSTMs, but with a simpler architecture.

4 1. What is GRU?

GRU introduces two gates:

- Update Gate ztz_t
- Reset Gate rtr_t

These gates control the flow of information, allowing the network to retain relevant information and forget irrelevant data.

2. Mathematical Formulation

Let:

- xtx_t: input at time step tt
- hth_t: hidden state at time step tt
- ht-1h_{t-1}: hidden state at previous time step
- σ\sigma: sigmoid function
- tanh tanh: hyperbolic tangent function

2.1 Update Gate (z_t)

Determines how much of the previous memory to keep.

 $zt=\sigma(Wzxt+Uzht-1+bz)z_t = sigma(W_z x_t + U_z h_{t-1} + b_z)$

2.2 Reset Gate (r_t)

Controls how much of the past information to forget.

 $rt = \sigma(Wrxt + Urht - 1 + br)r_t = sigma(W_r x_t + U_r h_{t-1}) + b_r$

2.3 Candidate Activation (h~t\tilde{h}_t)

Generates new candidate memory.

 $h^t=\tanh(Whxt+Uh(rtOht-1)+bh) = \tanh(W_h x_t + U_h (r_t \cdot h_1) + b_h)$

Here, ⊙\odot represents element-wise multiplication.

2.4 Final Memory at Time t

 $ht=(1-zt)\odot ht-1+zt\odot h^{t}=(1-z_t) \cdot h_{t-1}+z_t \cdot h_{t-1}$

This mixes the old memory and the new candidate based on the update gate.

3. Intuition

- If zt≈1z_t \approx 1: keep new candidate h~t\tilde{h}_t
- If zt≈0z_t \approx 0: retain old state ht-1h_{t-1}
- If rt≈0r_t \approx 0: ignore previous hidden state when generating h~t\tilde{h}_t

4. Simple Example

Suppose we're trying to predict the next number in a sequence like:

Input: [0, 1, 0, 1, 0]

Target: [1, 0, 1, 0, 1]

This is a pattern learning task.

5. Code Example (PyTorch)

import torch

import torch.nn as nn

Sample data

```
X = torch.tensor([[0], [1], [0], [1], [0]], dtype=torch.float32).view(1, 5, 1)
Y = torch.tensor([[1], [0], [1], [0], [1]], dtype=torch.float32).view(1, 5, 1)
# Define GRU model
class GRUNet(nn.Module):
  def __init__(self, input_size, hidden_size, output_size):
    super(GRUNet, self).__init__()
    self.hidden_size = hidden_size
    self.gru = nn.GRU(input_size, hidden_size, batch_first=True)
    self.fc = nn.Linear(hidden_size, output_size)
  def forward(self, x):
    h0 = torch.zeros(1, x.size(0), self.hidden_size)
    out, \_ = self.gru(x, h0)
    out = self.fc(out)
    return out
# Instantiate model
model = GRUNet(input_size=1, hidden_size=8, output_size=1)
# Loss and optimizer
criterion = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), Ir=0.01)
# Training loop
for epoch in range(300):
  output = model(X)
  loss = criterion(output, Y)
```

```
optimizer.zero_grad()
loss.backward()
optimizer.step()

if epoch % 50 == 0:
    print(f"Epoch {epoch}, Loss: {loss.item():.4f}")

# Predict
with torch.no_grad():
    prediction = model(X)
    print("Prediction:", prediction.view(-1).numpy())
```

6. Why GRU over LSTM?

Feature GRU LSTM

Gates 2 (Update, Reset) 3 (Input, Forget, Output)

Simpler? ✓ Yes X No (more parameters)

Performance Similar Similar

Training Speed Faster Slower

7. Use Cases

- Text Generation
- Time Series Prediction
- Machine Translation
- Speech Recognition