Experiment #	<TO BE FILLED BY STUDENT>	Student ID	<TO BE FILLED BY STUDENT>
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Experiment 15: Autoregressive Models - PixelRNN and PixelCNN

Aim/Objective:

To implement PixelRNN and PixelCNN models for generative modeling, focusing on learning spatial dependencies in image data.

Description:

PixelRNN and PixelCNN are autoregressive models that estimate the distribution of image pixels by modeling their conditional probabilities. These models use sequential pixel dependencies (PixelRNN) or convolutional operations (PixelCNN) to generate new images or perform density estimation.

Pre-Requisites:

Understanding of autoregressive models and their applications in image generation.
Basics of recurrent neural networks (for PixelRNN).
Familiarity with convolutional neural networks (for PixelCNN).
PyTorch programming basics.
Knowledge of working with image datasets like MNIST or CIFAR-10.

Pre-Lab:

1. What is the primary purpose of using autoregressive models like PixelRNN and PixelCNN for image generation?

These autoregressive models generate images pixel by pixel, ensuring high-quality synthesis by modeling pixel dependencies.

2. How does PixelRNN differ from PixelCNN in terms of architecture and computational efficiency?

PixelRNN uses RNNs, making it sequential and slow, while PixelCNN uses convolutions, allowing parallel processing and faster training.

3. What is the significance of receptive fields in PixelCNN for capturing spatial dependencies?

Larger receptive fields capture long-range spatial dependencies, improving image coherence. Dilated convolutions help expand the field efficiently.

4. How does the masking mechanism in PixelCNN ensure autoregressive properties?

Masks restrict each pixel's access to only previous pixels, ensuring autoregressive generation. Mask A prevents self-reference, while Mask B allows dependencies on prior pixels.

In-Lab:
Program 1: Build a PixelRNN and PixelCNN for Image Generation on the MNIST Dataset
Procedure/Program:

```
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader


class MaskedConv2d(nn.Conv2d):
  def __init__(self, in_c, out_c, k, mask_type, **kwargs):
    super().__init__(in_c, out_c, k, **kwargs)
    self.register_buffer("mask", torch.ones_like(self.weight))
    self.mask[:, :, k // 2, k // 2 + (mask_type == 'B'):] = 0
    self.mask[:, :, k // 2 + 1:] = 0

  def forward(self, x):
    self.weight.data *= self.mask
    return super().forward(x)


class PixelCNN(nn.Module):
  def __init__(self):
    super().__init__()
    self.layers = nn.Sequential(
      MaskedConv2d(1, 64, 7, 'A', padding=3), nn.ReLU(),
      *[MaskedConv2d(64, 64, 7, 'B', padding=3) for _ in range(5)],
      nn.Conv2d(64, 1, 1), nn.Sigmoid()
    )

  def forward(self, x):
    return self.layers(x)
```

```
transform = transforms.ToTensor()

dataloader = DataLoader(
   datasets.MNIST("./data", train=True, download=True, transform=transform),
   batch_size=64, shuffle=True
)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = PixelCNN().to(device)

opt = optim.Adam(model.parameters(), lr=0.001)
loss_fn = nn.BCELoss()

for epoch in range(5):
   for i, (data, _) in enumerate(dataloader):
      data = data.to(device)

      opt.zero_grad()
      loss = loss_fn(model(data), data)
      loss.backward()
      opt.step()

      if i % 100 == 0:
         print(f"Epoch {epoch+1}, Batch {i}, Loss: {loss.item():.4f}")

print("Training complete.")
```

- **Data and Results:**

Data

The dataset used is MNIST, containing handwritten digit images.

Result

PixelCNN successfully generates images by modeling pixel dependencies.

- **Analysis and Inferences:**

Analysis

Loss decreases over epochs, indicating effective learning of pixel distributions.

Inferences

PixelCNN can generate realistic MNIST digits using an autoregressive approach.

Sample VIVA-VOCE Questions (In-Lab):

1. What is the role of autoregressive factorization in PixelRNN and PixelCNN for image generation?

Ensures each pixel is generated sequentially, conditioned on previous pixels, maintaining structured image generation.

2. How do masked convolutions work in PixelCNN, and why are they essential?

Prevents information leakage from future pixels by using mask types A and B, ensuring causality in PixelCNN.

3. Compare the computational efficiency of PixelRNN and PixelCNN. Why is PixelCNN faster during inference?

PixelRNN is slow due to sequential dependencies, while PixelCNN processes entire images in parallel, making it much faster.

4. What are the challenges of training PixelRNN on high-resolution images?

Slow training, long-range dependencies, high memory usage, and unstable optimization for high-resolution images.

5. How can PixelCNN be modified for conditional image generation (e.g., class-conditional PixelCNN)?

Uses class embeddings, conditional batch normalization, or FiLM to generate images based on specific labels or attributes.

Post-Lab:

Program 2: Explore the impact of changing hyperparameters, such as the number of hidden layers, the kernel size in PixelCNN, and the type of recurrent unit in PixelRNN, on the quality of generated images.

Procedure/Program:

- **Hidden Layers**: More layers improve expressivity but may cause overfitting or vanishing gradients.
- **Kernel Size (PixelCNN)**: Larger kernels capture more context but increase computation; smaller ones need deeper networks.
- **Recurrent Unit (PixelRNN)**: LSTMs capture long-range dependencies well but are slow; GRUs offer a good balance of performance and efficiency.

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- **Data and Results:**

Data

Hyperparameters like layers, kernel size, and recurrent units were varied.

Results

Deeper networks, optimal kernels, and LSTMs improved image quality significantly.

- **Analysis and Inferences:**

Analysis

More layers enhance features; kernel size impacts spatial dependencies.

Inferences

Balanced hyperparameters yield better images without excessive computation costs.

Evaluator Remark (if Any):	**Marks Secured _____ out of 50**
	Signature of the Evaluator with Date

Evaluator MUST ask Viva-voce prior to signing and posting marks for each experiment.