Introduction to text generation

DEEP LEARNING FOR TEXT WITH PYTORCH

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Text generation and NLP

- Key applications: chatbots, language translation, technical writing
- RNN, LSTM, GRU: remembering past information for better sequential data processing
- Input: The cat is on the m
- Output: The cat is on the m**at**

[1] Image by vectorjuice on Freepik

Building an RNN for text generation

```
import torch
import torch.nn as nn
data = "Hello how are you?"
chars = list(set(data))
char_to_ix = {char: i for i, char in enumerate(chars)}
ix_to_char = {i: char for i, char in enumerate(chars)}
class RNNModel(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(RNNModel, self).__init__()
        self.hidden_size = hidden_size
        self.rnn = nn.RNN(input_size, hidden_size, batch_first=True)
        self.fc = nn.Linear(hidden_size, output_size)
```

Forward propagation and model creation

```
    def forward(self, x):
        h0 = torch.zeros(1, x.size(0), self.hidden_size)
        out, _ = self.rnn(x, h0)
        out = self.fc(out[:, -1, :])
        return out

model = RNNmodel(1, 16, 1)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.01)
```

Preparing input and target data

```
inputs = [char_to_ix[ch] for ch in data[:-1]]
targets = [char_to_ix[ch] for ch in data[1:]]


inputs = torch.tensor(inputs, dtype=torch.long)
              .view(-1, 1)


inputs = nn.functional.one_hot(
       inputs, num_classes=len(chars)).float()


targets = torch.tensor(targets, dtype=torch.long)
```

- Creating indexes
- Tensor conversion
- One-Hot encoding
- Targets preparation

Training the RNN model

```
for epoch in range(100):
    model.train()
    outputs = model(inputs)
    loss = criterion(outputs, targets)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    if (epoch+1) % 10 == 0:
        print(f'Epoch {epoch+1}/100, Loss: {loss.item()}')
```

Testing the model

```
model.eval()
test_input = char_to_ix['h']
test_input = nn.functional.one_hot(torch.tensor(test_input)
                                   .view(-1, 1), num_classes=len(chars)).float()
predicted_output = model(test_input)
predicted_char_ix = torch.argmax(predicted_output, 1).item()
print(f'Test Input: 10, Predicted Output: {model(test_input).item()}')
```

```
Epoch 10/100, Loss: 3090.861572265625
Epoch 20/100, Loss: 2935.4580078125
...
Epoch 100/100, Loss: 1922.44140625
```

```
Test Input: h, Predicted Output: e
```

Let's practice!

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Generative adversarial networks for text generation

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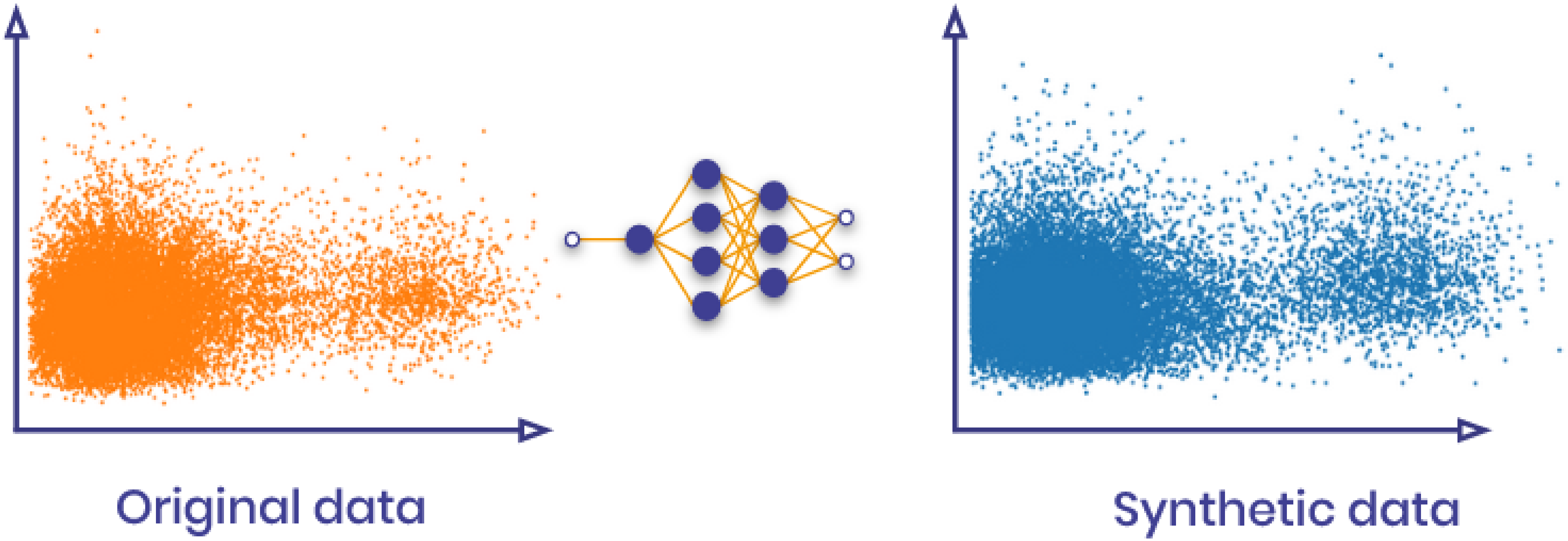
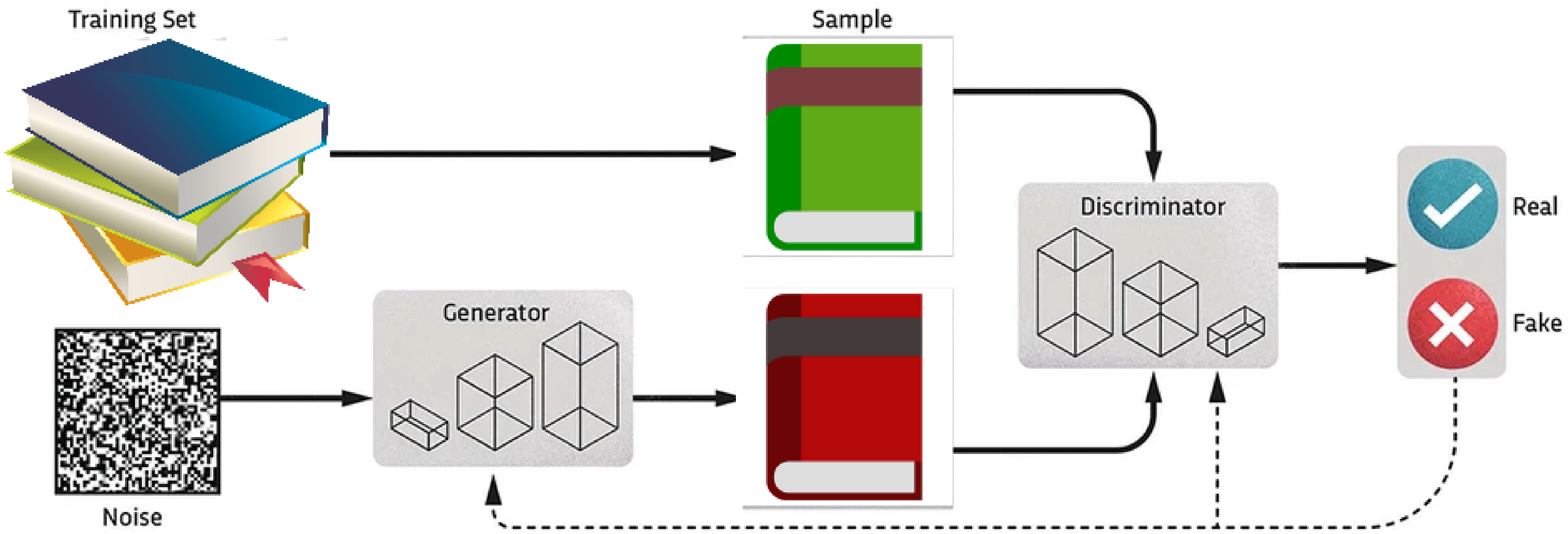
GANs and their role in text generation

- GANs can generate new content that seems original
  - Preserves statistical similarities
- Can replicate complex patterns unachievable by RNNs
- Can emulate real-world patterns



Structure of a GAN

- A GAN has two components:
  - Generator: creates fake samples by adding noise
  - Discriminator: differentiates between real and generated text data



[1] https://www.sciencefocus.com/future-technology/how-do-machine-learning-gans-work/

Building a GAN model in PyTorch: Generator

```
# Embedding reviews
# Convert reviews to tensors
class Generator(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(seq_length, seq_length),
            nn.Sigmoid()
        )
    def forward(self, x):
        return self.model(x)
```

Building the discriminator network

```
class Discriminator(nn.Module):
    def __init__(self):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(seq_length, 1),
            nn.Sigmoid()
        )
    def forward(self, x):
        return self.model(x)
```

Initializing networks and loss function

```
generator = Generator()
discriminator = Discriminator()

criterion = nn.BCELoss()

optimizer_gen = torch.optim.Adam(generator.parameters(), lr=0.001)
optimizer_disc = torch.optim.Adam(discriminator.parameters(), lr=0.001)
```

Training the discriminator

```
num_epochs = 50
for epoch in range(num_epochs):
    for real_data in data:
        real_data = real_data.unsqueeze(0)
        noise = torch.rand((1, seq_length))
        disc_real = discriminator(real_data)
        fake_data = generator(noise)
        disc_fake = discriminator(fake_data.detach())
        loss_disc = criterion(disc_real, torch.ones_like(disc_real)) +
                    criterion(disc_fake, torch.zeros_like(disc_fake))
        optimizer_disc.zero_grad()
        loss_disc.backward()
        optimizer_disc.step()
```

Training the generator

```
    # ... (continued from last slide)
     disc_fake = discriminator(fake_data)
     loss_gen = criterion(disc_fake, torch.ones_like(disc_fake))
     optimizer_gen.zero_grad()
     loss_gen.backward()
     optimizer_gen.step()

 if (epoch+1) % 10 == 0:
     print(f"Epoch {epoch+1}/{num_epochs}:\t
             Generator loss: {loss_gen.item()}\t
             Discriminator loss: {loss_disc.item()}")
```

Printing real and generated data

```
print("\nReal data: ")
print(data[:5])

print("\nGenerated data: ")
for _ in range(5):
    noise = torch.rand((1, seq_length))
    generated_data = generator(noise)
    print(torch.round(generated_data).detach())
```

GANs: generated synthetic data

```
Epoch 10/50: Generator loss: 0.8992824673652 Discriminator loss: 1.37682652473
Epoch 20/50: Generator loss: 0.7347183227539 Discriminator loss: 1.39010250568З
...
Epoch 50/50: Generator loss: 0.7019854784011 Discriminator loss: 1.3501529693603
```

Generated data

```
Real data:
tensor([[1., 0., 0., 1., 1.],
        [0., 0., 1., 0., 0.],
        [1., 0., 1., 1., 1.],
        [1., 0., 1., 0., 0.],
        [1., 1., 1., 1., 1.]])
```

```
Generated data:
tensor([[0., 1., 1., 0., 0.]]),
tensor([[0., 1., 1., 1., 1.]])
tensor([[1, 1., 1., 0., 0.]]),
tensor([[1., 1., 1., 0., 0.]])
tensor([[0., 1., 1., 1., 1.]])
```

- Evaluation metric: correlation matrix

Let's practice!

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Pre-trained models for text generation

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Why pre-trained models?

Benefits

1. Trained on extensive datasets
2. High performance across various text generation tasks
   - Sentiments analysis
   - Text completion
   - Language translation

Limitations

1. High computational cost for training
2. Large storage requirements
3. Limited customization options

Pre-trained models in PyTorch

- Hugging Face Transformers: library of pre-trained models
- Pre-trained models:
  - GPT-2
  - T5

Understanding GPT-2 Tokenizer and Model

GPT2LMHeadModel:

- HuggingFace's take on GPT-2
- Tailored for text generation

GPT2Tokenizer:

- Converts text into tokens
- Handles subword tokenization: 'larger' might become ['large', 'r']

GPT-2: text generation implementation

```python
import torch
from transformers import GPT2Tokenizer, GPT2LMHeadModel
tokenizer = GPT2Tokenizer.from_pretrained('gpt2')
model = GPT2LMHeadModel.from_pretrained('gpt2')
seed_text = "Once upon a time"
input_ids = tokenizer.encode(seed_text, return_tensors='pt')
```

GPT-2: text generation implementation II

```
output = model.generate(

                                                          )
```

GPT-2: text generation implementation II

```
output = model.generate(input_ids, max_length=40,


                                                        )
```

GPT-2: text generation implementation II

```
output = model.generate(input_ids, max_length=40, temperature=0.7,

                                                    )
```

GPT-2: text generation implementation II

```
output = model.generate(input_ids, max_length=40, temperature=0.7,
                        no_repeat_ngram_size=2,
                                                      )
```

GPT-2: text generation implementation II

```
output = model.generate(input_ids, max_length=40, temperature=0.7,
                        no_repeat_ngram_size=2,
                        pad_token_id=tokenizer.eos_token_id)
```

GPT-2: text generation output

```
generated_text = tokenizer.decode(output[0], skip_special_tokens=True)
print(generated_text)
```

```
Generated Text: Once upon a time, the world was a place of great beauty
and great danger. The world of the gods was the place where the great gods were
born, and where they were to live.
```

T5: Language translation implementation

- `t5-small` : Text-to-Text Transfer Transformer
- Pretrained model for language translation tasks

```
import torch
from transformers import T5Tokenizer, T5ForConditionalGeneration
tokenizer = T5Tokenizer.from_pretrained("t5-small")
model = T5ForConditionalGeneration.from_pretrained("t5-small")
input_prompt = "translate English to French: 'Hello, how are you?'"
input_ids = tokenizer.encode(input_prompt, return_tensors="pt")
output = model.generate(input_ids, max_length=100)
```

T5: Language translation output

```
generated_text = tokenizer.decode(output[0], skip_special_tokens=True)
print("Generated text:",generated_text)
```

```
Generated text:
"Bonjour, comment êtes-vous?"
```

Choosing the right pre-trained model

- Many exist!

- **GPT-2**: Text generation
- **DistilGPT-2** (Smaller version of GPT-2): Text generation
- **BERT**: Text classification, question-answering
- **T5** (t5-small is the smaller version of T5): Language translation, summarization

- Find them in HuggingFace and other repositories

Let's practice!

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Evaluation metrics for text generation

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Evaluating text generation

- Text Generation tasks create human-like text
- Standard accuracy metrics such as accuracy, F1 fall short for these tasks
- We need metrics that evaluate the quality of generated text
- BLEU and ROUGE

BLEU (Bilingual Evaluation Understudy)

- Compares the generated text and the reference text
- Checks for the occurrence of n-grams
- In the sentence "**The cat is on the mat**"
  - 1-grams (uni-gram): [the ,cat, is, on, the, mat]
  - 2-grams (bi-gram): ["the cat", "cat is", "is on", "on the", and "the mat"]
  - and so on for n-grams
- A perfect match: Score of 1.0
  - 0 means no match

Calculating BLEU score with PyTorch

```
from torchmetrics.text import BLEUScore

generated_text = ['the cat is on the mat']
real_text = [['there is a cat on the mat', 'a cat is on the mat']]

bleu = BLEUScore()
bleu_metric = bleu(generated_text, real_text)
print("BLEU Score: ", bleu_metric.item())
```

```
BLEU Score: tensor(0.7598)
```

ROUGE (Recall-Oriented Understudy for Gisting Evaluation)

- Compares a generated text to a reference text in two ways
- ROUGE-N: Considers overlapping n-grams (N=1 for unigrams, 2 for bigrams, etc.) in both texts
- ROUGE-L: Looks at the longest common subsequence (LCS) between the texts
- ROUGE Metrics:
  - F-measure: Harmonic mean of precision and recall
  - Precision: Matches of n-grams in generated text within the reference text
  - Recall: Matches of n-grams in reference text within the generated text
- 'rouge1', 'rouge2', and 'rougeL' prefixes refer to 1-gram, 2-gram, or LCS, respectively

Calculating ROUGE score with PyTorch

```
from torchmetrics.text import  ROUGEScore

generated_text='Hello, how are you doing?'
real_text= "Hello, how are you?"

rouge = ROUGEScore()

rouge_score = rouge([generated_text], [[real_text]])
print("ROUGE Score:", rouge_score)
```

ROUGE score: output

```
ROUGE Score: {'rouge1_fmeasure': tensor(0.8889),
              'rouge1_precision': tensor(0.8000),
              'rouge1_recall': tensor(1.),
              'rouge2_fmeasure': tensor(0.8571),
              'rouge2_precision': tensor(0.7500),
              'rouge2_recall': tensor(1.),
              'rougeL_fmeasure': tensor(0.8889),
              'rougeL_precision': tensor(0.8000),
              'rougeL_recall': tensor(1.),
              'rougeLsum_fmeasure': tensor(0.8889),
              'rougeLsum_precision': tensor(0.8000),
              'rougeLsum_recall': tensor(1.)}
```

Considerations and limitations

- Evaluate word presence, not semantic understanding
- Sensitive to the length of the generated text
- Quality of reference text affects the scores

Let's practice!

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