

Training Day-78 Report:

1. Long Short-Term Memory (LSTM) Architecture

LSTMs are an advanced type of Recurrent Neural Network (RNN) designed to overcome the vanishing gradient problem and handle long-term dependencies in sequences. They achieve this with a memory cell and gating mechanisms.

LSTM Components:

1. Cell State (C_t):

- The "memory" of the network.
- Modified by input, forget, and output gates.

2. Gates:

- **Forget Gate:** Decides what information to discard. $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$
 $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$
- **Input Gate:** Decides what new information to store. $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$
 $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$
 $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$
 $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$
Update the cell state: $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$
 $C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$
- **Output Gate:** Determines what part of the cell state contributes to the output. $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$
 $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$
 $h_t = o_t \cdot \tanh(C_t)$
 $h_t = o_t \cdot \tanh(C_t)$

3. Hidden State (h_t):

- The output at time t , influenced by the cell state and output gate.

2. Building a Story Writer using Character-Level RNN

A character-level RNN generates text one character at a time by predicting the next character given the current sequence.

Steps:

1. **Prepare the Data:** Convert text into a sequence of integers, each representing a character.
2. **Build the Model:** Use an LSTM layer to process the character sequences.
3. **Train the Model:** Train the RNN to predict the next character in a sequence.

4. **Generate Text:** Use the trained model to generate text by sampling predictions iteratively.

Implementation: Character-Level RNN with LSTM

```
import tensorflow as tf
import numpy as np

# Sample text data
text = "Once upon a time in a faraway land, there was a little girl named Red Riding Hood."
chars = sorted(set(text)) # Unique characters
char_to_idx = {char: idx for idx, char in enumerate(chars)}
idx_to_char = {idx: char for char, idx in char_to_idx.items()}

# Convert text to integer sequence
encoded_text = np.array([char_to_idx[char] for char in text])

# Prepare input-output pairs
seq_length = 40
input_sequences = []
output_sequences = []
for i in range(len(encoded_text) - seq_length):
    input_sequences.append(encoded_text[i:i + seq_length])
    output_sequences.append(encoded_text[i + seq_length])

input_sequences = np.array(input_sequences)
output_sequences = np.array(output_sequences)

# One-hot encode the input and output
vocab_size = len(chars)
X = tf.keras.utils.to_categorical(input_sequences, num_classes=vocab_size)
y = tf.keras.utils.to_categorical(output_sequences, num_classes=vocab_size)
```

```
# Build the LSTM model
```

```
model = tf.keras.Sequential([  
    tf.keras.layers.LSTM(256, input_shape=(seq_length, vocab_size),  
        return_sequences=True),  
    tf.keras.layers.Dropout(0.2),  
    tf.keras.layers.LSTM(256),  
    tf.keras.layers.Dense(vocab_size, activation='softmax')  
])
```

```
# Compile the model
```

```
model.compile(optimizer='adam', loss='categorical_crossentropy')  
model.summary()
```

```
# Train the model
```

```
model.fit(X, y, epochs=20, batch_size=64)
```

```
# Generate text
```

```
def generate_text(model, start_string, gen_length=100):  
    input_seq = [char_to_idx[char] for char in start_string]  
    input_seq = tf.keras.utils.to_categorical(input_seq, num_classes=vocab_size).reshape(1, -1, vocab_size)
```

```
    generated_text = start_string
```

```
    for _ in range(gen_length):
```

```
        pred = model.predict(input_seq, verbose=0)
```

```
        next_char = idx_to_char[np.argmax(pred)]
```

```
        generated_text += next_char
```

```
# Update input sequence
```

```
    next_input = tf.keras.utils.to_categorical([np.argmax(pred)], num_classes=vocab_size)
```

```
input_seq = np.concatenate((input_seq[:, 1:, :], next_input.reshape(1, 1, vocab_size)),
axis=1)
```

```
return generated_text
```

```
# Generate a story snippet
```

```
start = "Once upon a time"
```

```
print(generate_text(model, start))
```

Key Points:

1. LSTM:

- Manages long-term dependencies effectively using gates.

2. Character-Level RNN:

- Generates text by learning patterns in sequences of characters.

3. Applications:

- Chatbots, story generation, code autocompletion, and more.