Great! Let's go through **Sequence-to-Sequence (Seq2Seq) Models** step-by-step, covering:

1. **Concept and Applications**
2. **Mathematics Behind Seq2Seq**
3. **Hands-on Python Implementation**

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1. 🔁 Concept and Applications

Seq2Seq models are a type of model used when both inputs and outputs are sequences, possibly of different lengths.

🔧 Applications

- **Machine Translation**: Translating a sentence from English to French.
- **Text Summarization**: Condensing a long paragraph into a concise summary.
- **Speech Recognition**: Converting audio signals to text.
- **Chatbots**: Generating responses to a conversation.

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2. 📐 Mathematics Behind Seq2Seq

A Seq2Seq model typically consists of:

- **Encoder RNN**: Processes input sequence and encodes it to a fixed-size context vector.
- **Decoder RNN**: Takes the context vector and generates the output sequence.

Let’s say:

- Input sequence: X=(x1,x2,...,xT)X = (x_1, x_2, ..., x_T)
- Output sequence: Y=(y1,y2,...,yT′)Y = (y_1, y_2, ..., y_{T'})

Encoder:

At each time step tt:

ht=f(ht−1,xt)h_t = f(h_{t-1}, x_t)

Where:

- hth_t: hidden state
- ff: RNN cell function (e.g., LSTM or GRU)

Final hidden state hTh_T is the **context vector**.

Decoder:

st=f(st−1,yt−1,c)s_t = f(s_{t-1}, y_{t-1}, c) y^t=softmax(Wst+b)\hat{y}_t = \text{softmax}(Ws_t + b)

Where:

- sts_t: decoder hidden state
- yt−1y_{t-1}: previous target word
- cc: context vector from encoder

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3. 🧑‍💻 Implementation in Python (with TensorFlow/Keras)

Let's build a basic machine translation model (English → French-like) using **Keras**.

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, LSTM, Dense

# Sample data
input_texts = ["hello", "how are you"]
target_texts = ["<start> bonjour", "<start> comment ça va"]

input_characters = sorted(list(set("".join(input_texts))))
target_characters = sorted(list(set("".join(" ".join(target_texts)))))

num_encoder_tokens = len(input_characters)
num_decoder_tokens = len(target_characters)
max_encoder_seq_length = max([len(txt) for txt in input_texts])
max_decoder_seq_length = max([len(txt) for txt in target_texts])

# Token index
input_token_index = dict([(char, i) for i, char in enumerate(input_characters)])
target_token_index = dict([(char, i) for i, char in enumerate(target_characters)])
```

```
# One-hot encoding
encoder_input_data = np.zeros((len(input_texts), max_encoder_seq_length, num_encoder_tokens))
decoder_input_data = np.zeros((len(input_texts), max_decoder_seq_length, num_decoder_tokens))
decoder_target_data = np.zeros((len(input_texts), max_decoder_seq_length, num_decoder_tokens))

for i, (input_text, target_text) in enumerate(zip(input_texts, target_texts)):
    for t, char in enumerate(input_text):
        encoder_input_data[i, t, input_token_index[char]] = 1.
    for t, char in enumerate(target_text):
        decoder_input_data[i, t, target_token_index[char]] = 1.
        if t > 0:
            decoder_target_data[i, t - 1, target_token_index[char]] = 1.

# Model Architecture
latent_dim = 256

# Encoder
encoder_inputs = Input(shape=(None, num_encoder_tokens))
encoder = LSTM(latent_dim, return_state=True)
encoder_outputs, state_h, state_c = encoder(encoder_inputs)
encoder_states = [state_h, state_c]

# Decoder
decoder_inputs = Input(shape=(None, num_decoder_tokens))
decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)
decoder_outputs, _, _ = decoder_lstm(decoder_inputs, initial_state=encoder_states)
decoder_dense = Dense(num_decoder_tokens, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)
```

```
# Full model
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

# Compile and train
model.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit([encoder_input_data, decoder_input_data], decoder_target_data,
          batch_size=64, epochs=100, validation_split=0.2)
```

🔍 Summary

Component	Description
Encoder	Converts input sequence to context vector
Decoder	Generates output sequence using context
Application	E.g., English to French translation
Model Type	LSTM/GRU-based encoder-decoder
Training Goal	Minimize sequence loss via teacher forcing
