

**Introduction to AI (ID-AI101B)**  
**Even Semester**  
**Session 2025-26**

# Language Translation with Sequence Models

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# Language Translation with Sequence Models

- Converts text from one language to another while preserving meaning.
- Sequence models handle text as ordered data, capturing word relationships.
- Uses Encoder-Decoder architecture for understanding and generating text.
- Powered by models like RNNs, LSTMs, GRUs, and Transformers.



# Objectives

- To **automate translation** between different human languages.
- To **preserve meaning and context** while translating text.
- To **handle variable-length sequences** like full sentences or paragraphs.
- To **improve translation quality** using advanced models (e.g., attention, transformers).
- To **enable real-time translation** in applications like chatbots and translators.



# The Encoder-Decoder Architecture

- Encoder:** Processes the input sentence and compresses it into a fixed-size context vector (a summary of the sentence).
- Context Vector:** Acts as a bridge, carrying the essential meaning from the encoder to the decoder.
- Decoder:** Takes the context vector and generates the translated sentence one word at a time.
- Training:** The model learns to map input sequences to output sequences using large parallel corpora (source-target language pairs).



# Attention Mechanisms: A Breakthrough

- **Problem with Basic Encoder-Decoder:** Fixed-size context vector struggles with long or complex sentences.
- **Solution – Attention:** Allows the decoder to focus on different parts of the input sentence at each step.
- **How it Works:** Calculates a set of weights that highlight relevant words in the input for each output word.
- **Impact:** Greatly improves translation accuracy, especially for longer texts and complex sentence structures.

# Algorithms Used in Language Translation

- **Sequence-to-Sequence (Seq2Seq) Algorithm**

- Translates a sequence (like a sentence) from one language to another using encoder-decoder models.

- **Attention Mechanism**

- Allows the model to focus on specific words in the input while generating each word of the output.

- **Transformer Algorithm**

- Uses self-attention to process all words at once, improving translation speed and accuracy.

- **Beam Search**

- A smart search algorithm that chooses the best possible translation from multiple candidates.

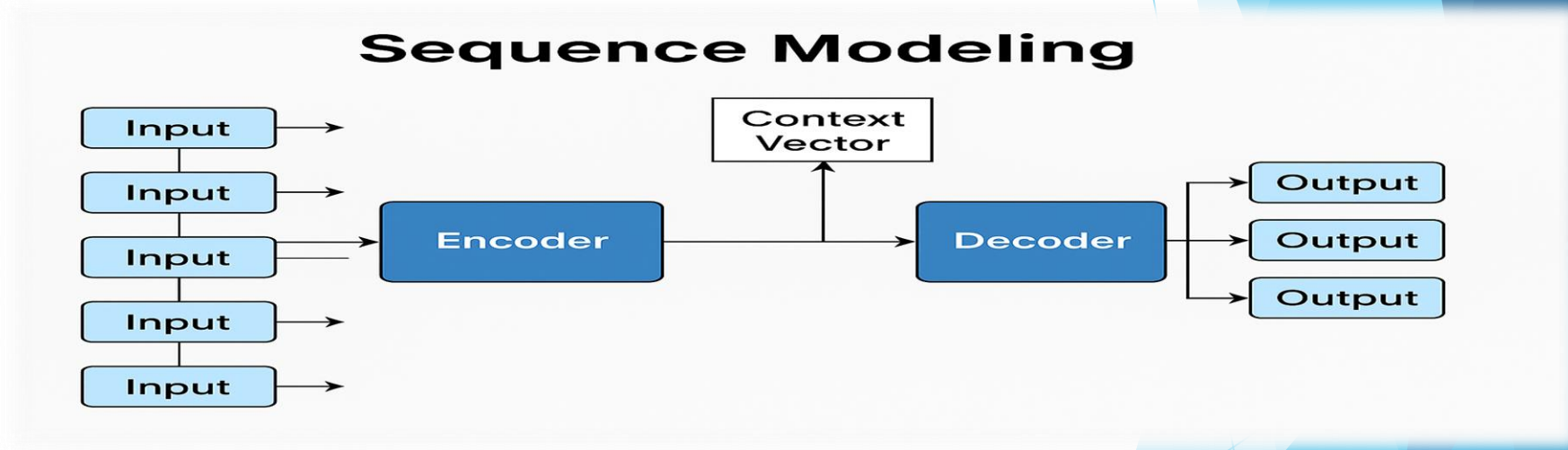
- **Tokenization**

- Splits text into smaller pieces (words or subwords) that the model can understand and translate.



# Sequence-to-Sequence Models

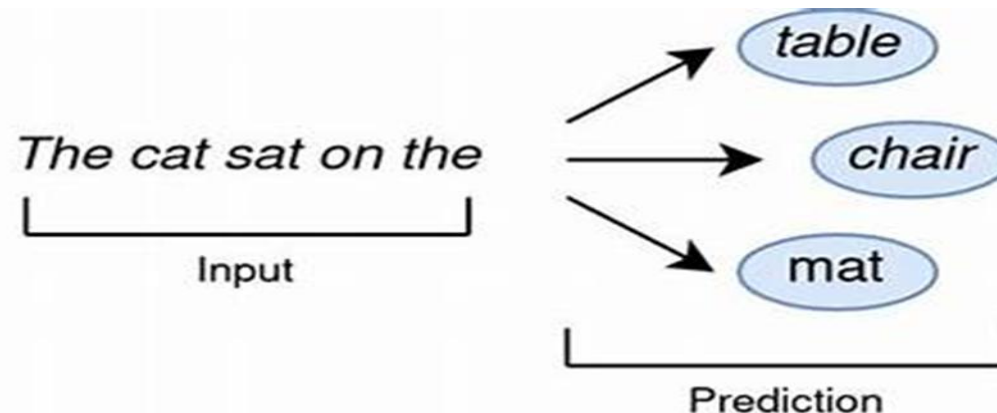
- **Definition:** Neural network models designed to convert one sequence into another — commonly used for tasks like language translation.
- **Architecture:** Composed of two main parts —
  - **Encoder** (processes input)
  - **Decoder** (generates output).



- **Training:** Learns to map input-output pairs (e.g., English ↔ Hindi) using supervised learning on parallel datasets.
- **Applications:** Language translation, text summarization, chatbot responses, and more

# TRAINING SEQUENCE MODELS

- Data:** Requires large parallel datasets (input and translated text pairs).
- Tokenization:** Converts sentences into tokens (words or subwords) that the model can process.
- Loss Function:** Uses **Cross-Entropy Loss** to measure how close the prediction is to the actual output.
- Backpropagation:** Updates model weights using **Backpropagation Through Time (BPTT)**.



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# Output

## English to Hindi Translator

Enter English text and get the Hindi translation.

Enter text to translate

i am doing my work

Clear

Submit

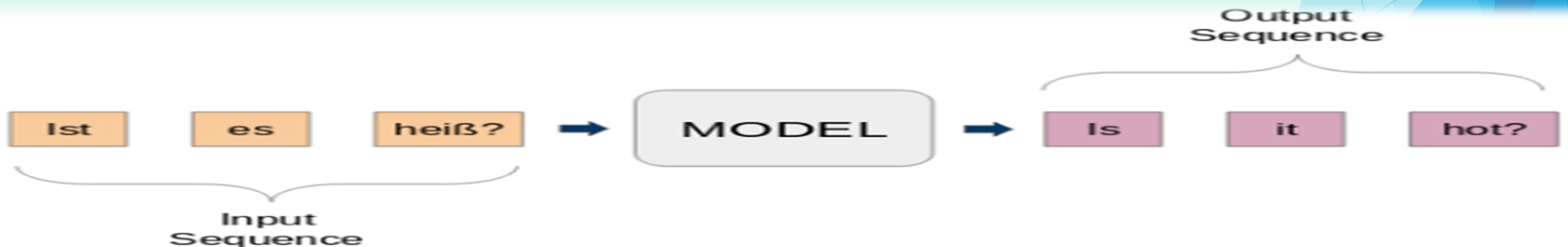
Translated text

मैं अपना काम कर रहा हूँ

Flag

# OBSERVATION AND FINDINGS

- Sequence models can translate languages accurately.
- Attention mechanism improves focus on important words.
- Transformer models perform better than older models (like RNN, LSTM).
- Models can be trained for multiple languages.
- Still face problems with rare words, slang, and cultural meaning.
- Can be used in real-time apps (like Gradio demo).



# Challenges and Limitations

- Long-Term Dependencies: Difficulty in capturing relationships between distant words in a sentence.
- Fixed Context Vector (in basic models): Limits performance on long or complex sentences.
- Data Dependency: Requires large, high-quality parallel datasets for effective training.
- Generalization Issues: Struggles with rare words, idioms, and out-of-domain language use



RNN

Encoder



## Future Directions

- **Transformer Models:** Continued advancements with architectures like BERT, GPT, and T5.
- **Multilingual Models:** Unified models that handle multiple languages with shared representations.
- **Low-Resource Translation:** Improved techniques for translating underrepresented languages.
- **Real-Time & Context-Aware Systems:** Smarter, faster translation with cultural and contextual understanding.

**THANK YOU**