

# Encoders and Decoders

- Encoders and decoders are two key components in many ML models, especially for sequence-to-sequence tasks like CLM
- Encoders take inputs (like a sentence, img or audio) and transform it into a compact, informative representation that captures its meaning or features
- The decoders then use that representation to generate or reconstruct the desired output, such as a translated sentence, summarized text or reconstructed img.

Ex (in transformers): in transformers used for translation the encoder reads and processes the input sentence (eg in english) to produce contextual embeddings that capture the meaning of each word in relation to the whole sentence. The decoder then takes these embeddings and generates the output sentence (ie in French) one word at a time using attention to focus on the most relevant parts of the encoded input

## Normalization and standardization

- Normalization is the process of scaling data so all features are within a specific range typically  $[0, 1]$  or  $[-1, 1]$  this ensures that no feature dominates others simply because it has large numeric values
  - for min-max normalization (most common)  $x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \rightarrow [0, 1]$
  - for feature scaling to  $[-1, 1]$  do:  $x_{\text{norm}} = 2x \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} - 1 \rightarrow$  do for each data point
- Standardization (also called Z-score norm) rescales data so that it has a mean ( $\mu$ ) of 0 and a standard deviation ( $\sigma$ ) of 1, this centers the data and ensures all features have comparable variance formula:  $z = \frac{x - \mu}{\sigma} \rightarrow$  for each point
- Both together help model convergence/stable training by ensuring features contribute equally

**Rotary Positional Embedding** • RoPE are a way to encode token positions (positional embeddings see pg 112 for what these are) in transformers by rotating the query and key vectors in multi-headed attention, allowing the model to capture relative positions efficiently without adding separate position (RoPE) vectors, it works because the dot product of rotated K, Q vectors naturally encodes relative position. 115, why: goes well to longer text sequences  
• is more efficient, cuts extra vectors