

1. Define

[3]

- **Zero-shot learning:** The model is given zero example to refer/learn from before making predictions on unseen samples. No training happens.
- **One-shot learning:** The model is given one example to refer/learn from before making predictions on unseen samples.
- **Few-shot learning:** The model is given more than one example to refer/learn from before making predictions on unseen samples.

2. Why do we use an Add layer in Transformer?

[1]

The add layer in Transformer acts as a residual/skip connection, which allows gradients to propagate back to the lower layer through a bypass path.

3. Write steps (incl equations, if possible) of Bahadanu's and Vaswani's Attention mechanism. Do NOT draw the encoder-decoder architecture. [6]

Bahadanu's (Standard attention)

1. Compute hidden representations h_j
2. Compute attention model

$$e_{ij} = a(s_{i-1}, h_j)$$

3. Compute softmax (attention weights)

$$a_{ij} = \frac{\exp(e_{ij})}{\sum \exp(e_{ik})}$$

4. Compute context vector

$$c_i = \sum a_{ij} h_j$$

Vaswani's (Self-attention)

1. Compute query (Q), key (K) and value (V) through projection.

$$Q = W_Q \cdot X$$

$$K = W_K \cdot X$$

$$V = W_V \cdot X$$

2. Compute dot product between a query vector and all other key vectors.

$$\forall_j s_{ij} = q_i \cdot k_j$$

3. Scale by $\text{sqrt}(d_k)$

$$s'_{ij} = s_{ij} / \text{sqrt}(d_k)$$

4. Compute softmax (attention weights)

$$a_{ij} = \text{Softmax}(s'_{ij})$$

5. Compute attended value vectors

$$v'_{ij} = a_{ij} \cdot v_j$$

6. Sum all value vectors

$$\sum_j v'_{ij}$$