```
□ Обозначения:
- H: Hidden size
- I: Input size = Output size + Context size (в декодере)
- C: Context size (2 * encoder hidden size, если BiLSTM)
- A: Attention vector size
- D: Output size (vocab embedding dim)
□ Decoder: Output Layer
• Y_t = p__ @ W output.T + B output
                                                       \# [1 \times D] = [1 \times (H+C)] \times [(H+C) \times D] + [1 \times D]
• d\overline{Y} t = \overline{Y}^{\hat{}} \underline{t} - Y_{true}t
                                                         # [1×D]
dW output += dY t.T @ p
                                                        \# [D\times1] \times [1\times(H+C)] = [D\times(H+C)]
• dB output += dY t
                                                         # [1×D]
П LayerNorm (на р)
• p = (p - mean) / sqrt(var + eps)
                                                         # Нормализованное р
• p = p_* * \gamma + \beta
                                                         # Выход после LayerNorm

    dGamma += dY t @ W_output * p_

                                                        # [1×(H+C)]
• dBeta += dY_t @ W_output
                                                        # [1×(H+C)]
```

☐ Seq2Seq with Attention: Gradient Checklist

• $dX = (d * \gamma - mean d - x^* mean d x^*) / std # [1×(H+C)]$

```
□ Decoder LSTM
• dS t = dX[:H] + or attention
                                                          # [1×H]

    dContext t = dX[H:] + oτ attention

                                                           # [1×C]
• d0 t = dS t * tanh(C t) * 0 t * (1 - 0 t)
• dC_t = _dC_t + dS_t * 0_t * (1 - tanh(C_t)^2)
• dC_t = dC_t * I_t * (1 - C_t^2)
• dI \overline{t} = dC \overline{t} * C\overline{t} * I t * (\overline{1} - I t)
• dF^{T} = dC^{T} * C \{t-1\} * F t * (1 - F t)
• dGates = concat(dF, dI, dC~, d0)
                                                           # [1×4H]
• dW += x t.T @ dGates
                                                          # [I×4H]
• dU += h_{t-1}.T @ dGates
                                                          # [H×4H]
• dB += dGates
                                                          # [1×4H]
```

```
□ Attention (Dot-product)
• \alpha_t = softmax(score(s_{t-1}, h_j))
                                                       # [N×1]
• context = \Sigma \alpha j * h j
                                                       # [1×C]
• dContext t.dot(h k) → dAlpha k
                                                        # scalar
• dE tj = \overline{\Sigma} k dAlpha k * \alpha k * \overline{(\delta)} jk - \alpha j)
                                                        # softmax grad
• dU_tj = dE_tj * attention_vector
                                                        # [1×A]

    dPreact = dU_tj * (1 - tanh²)

                                                        # [1×A]
                                                       # [A×C]
• dW e += dPreact.T @ h j
• dW_d += dPreact.T @ s_{t-1}
                                                       # [A×H]
• dV += u tj.T * dE tj
                                                       # [A×1]
```

```
Тот же процесс, как и в декодере
dO_j = dH_j * tanh(C_j) * O_j * (1 - O_j)
dC_j = dH_j * O_j * (1 - tanh²(C_j)) + _dC
Остальные — аналогично декодеру
dGates_j = concat(dF, dI, dC², dO) # [1×4H]
dW_enc += x_j.T @ dGates_j # [I×4H]
dU_enc += h_{j-1}.T @ dGates_j # [H×4H]
dB_enc += dGates_j # [1×4H]
```

□ Encoder LSTM (forward и backward)