

# RNNs and LSTM Quiz

## Multiple Choice Questions

**Q1.** What is `not` primary benefit of stacking multiple RNN layers (i.e., stacked RNNs)?

- A. Faster training
- B. Lower memory usage
- C. Better learning of hierarchical features
- D. Simpler architecture

**Q2.** Which of the following is the main reason RNNs struggle with long-term dependencies?

- A. Overfitting
- B. Vanishing gradients
- C. Lack of non-linearity
- D. Insufficient data

**Q3.** What differentiates an  $t^{100}$  cell from a standard RNN cell?

- A. It uses ReLU instead of tanh
- B. It introduces gates to control the flow of information
- C. It has fewer parameters
- D. It is a convolutional architecture

**Q4.** In a standard  $RNN^{100}$ , which gate is responsible for deciding how much of the past memory to keep?

- A. Output gate
- B. Forget gate
- C. Input gate
- D. Update gate

## Descriptive Questions

**Q5.** Why is the forget gate bias in  $RNNs^{100}$  often initialized to a high value (e.g., 2 or 3)? Explain its effect on long-term dependency learning.

**Q6.** Bidirectional  $CNNs$  are often used for POS tagging but not machine translation. Explain why, considering input-output alignment and context flow.

**Q7.** Designing an RNN model for variable-length legal documents with long dependencies:

- (a) Choose between vanilla RNN or LSTM.
- (b) Stack layers or keep it shallow?
- (c) Make it `unidirectional`?

Justify each choice based on model behavior and task needs.

**Q8.** Consider a vanilla  $CNN$  with recurrent weight matrix  $W_h$  and sequence length  $t^{100}$ . Analyze gradient behavior:

- (1) If  $\|W_h\| = 0.9$ : Will gradients vanish or explode? Justify.
- (2) If  $\|W_h\| = 1.2$ : Will gradients vanish or explode? Justify. Suggest an easy fix and explain how it helps.

*Hint: Consider eigenvalue effects on gradient propagation over time.*