1. Explain the basic architecture of RNN cell.
2. Explain Backpropagation through time (BPTT)
3. Explain Vanishing and exploding gradients
4. Explain Long short-term memory (LSTM)
5. Explain Gated recurrent unit (GRU)
6. Explain Peephole LSTM
7. Bidirectional RNNs
8. Explain the gates of LSTM with equations.
9. Explain BiLSTM
10. Explain BiGRU

Answers:

1. Basic Architecture of RNN cell: A recurrent neural network (RNN) cell is a type of neural network architecture that is designed to process sequential data. The basic architecture of an RNN cell consists of a single neuron that takes as input the current input data point and the output from the previous time step, as well as a set of learnable weights and biases. The output of the RNN cell is then used as input for the next time step. This architecture enables the RNN to maintain a "memory" of the previous time steps, allowing it to process sequential data.
2. Backpropagation through time (BPTT): Backpropagation through time (BPTT) is a type of gradient descent algorithm used to train recurrent neural networks (RNNs). BPTT works by unfolding the RNN over time and treating it as a deep feedforward neural network. The gradients are then propagated backwards through time, allowing the RNN to learn the relationships between the inputs and outputs over multiple time steps.
3. Vanishing and exploding gradients: Vanishing and exploding gradients refer to the problem of the gradients in a neural network becoming either too small or too large, respectively, during the training process. This can cause the weights in the network to become stuck at their current values, preventing the network from learning. Vanishing and exploding gradients are particularly problematic in recurrent neural networks, where the gradients can be propagated backwards through time and accumulate over multiple time steps.
4. Long short-term memory (LSTM): Long short-term memory (LSTM) is a type of recurrent neural network architecture that is designed to address the problem of vanishing gradients in traditional RNNs. LSTMs use a series of "memory cells" that can store information over long periods of time, as well as "gates" that control the flow of information into and out of the memory cells. The gates are controlled by sigmoid functions and allow the LSTM to selectively remember or forget information.
5. Gated recurrent unit (GRU): Gated recurrent unit (GRU) is a type of recurrent neural network architecture that is similar to LSTMs but with fewer parameters. GRUs also use gates to control the flow of information, but they do not use separate memory cells like LSTMs. Instead, they use a single "hidden state" that stores information over time.
6. Peephole LSTM: Peephole LSTM is a type of LSTM architecture that extends the traditional LSTM architecture by allowing the gates to use information from the cell state as well as the hidden state. This allows the gates to better control the flow of

information into and out of the memory cells, improving the performance of the LSTM.

7. Bidirectional RNNs: Bidirectional RNNs are a type of recurrent neural network architecture that processes data in both forward and backward directions. This allows the network to capture information from both past and future time steps, improving its ability to model sequential data.
8. Gates of LSTM with equations: The LSTM architecture includes three types of gates that control the flow of information: the input gate, the forget gate, and the output gate. The equations for each gate are as follows:

Input gate: $i_t = \sigma(W_i[x_t, h_{(t-1)}] + b_i)$

Forget gate: $f_t = \sigma(W_f[x_t, h_{(t-1)}] + b_f)$

Output gate: $o_t = \sigma(W_o[x_t, h_{(t-1)}] + b_o)$

where σ is the sigmoid function, W_i, W_f, and W_o are weight matrices, x_t is the input at time step t, $h_{(t-1)}$ is the hidden state from the previous time step, and b_i, b_f, and