Answer 1

Logistic regression's primary goal is to predict the probability of an event occurring, rather than a specific numerical value. It differs from linear regression in that it uses a \*\*sigmoid function\*\* to constrain its output between 0 and 1, representing probabilities. Linear regression, on the other hand, produces a continuous output that can range from negative infinity to positive infinity. Logistic regression is therefore used for classification problems, while linear regression is used for regression problems.

Answer 2

In logistic regression, the sigmoid function acts as an activation function. It takes the linear combination of input features (weighted sum) and transforms it into a probability value. Mathematically, it's defined as 1 / (1 + e^-x), where x is the linear combination. The key properties are:

Range It outputs values strictly between 0 and 1, which is essential for representing probabilities.

Smoothness:he S-shape allows for a smooth transition from 0 to 1, which is important for gradient-based optimization.

\*Monotonicity: It's a monotonically increasing function, meaning that as the input increases, the output also increases.

Answer 3

Response: "Maximizing the log-likelihood in logistic regression means adjusting the model's parameters to make the predicted probabilities as close as possible to the actual outcomes in the training data. It's like trying to make the model agree with the training data as much as possible."

Explanation This answer shows a better grasp of the goal. It connects maximizing log-likelihood to the idea of aligning predicted probabilities with actual outcomes. It also uses an analogy to make it more understandable. However, it still doesn't explain why log-likelihood is used over other measures.