AMERICAN INTERNATIONAL UNIVERSITY-BANGLADESH

Faculty of Science and Technology

Assignment Cover Page

Assignment Title:	*FINAL ASSIGNMENT*			
Date of Submission:	14 May 2024			
Course Title:	Machine Learning			
Course Code:	01669		Section:	B
Semester:	Spring	2023-24	Course Teacher:	**TAIMAN ARHAM SIDDIQUE**

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FACULTY COMMENTS	**Marks Obtained**	
	Total Marks	

1. *Explain how locally weighted regression differs from linear regression, including their formulas.*
What is an advantage of locally weighted regression over linear regression? [2 points]

➔ **Linear Regression vs. Locally Weighted Regression**

- Linear Regression: Fits a single straight line to the entire dataset.
- Formula: y = mx + b where m (slope) and b (y-intercept) are coefficients learned from the data.

- Locally Weighted Regression: Fits a separate line to each data point, considering nearby points more heavily.
- Formula: No single formula but involves calculating weights for each data point based on its distance to the query point and then performing linear regression using those weights.

Advantage of Locally Weighted Regression: Handles non-linear relationships better than linear regression.

2. *Given you want to apply a model to predict whether a patient has malignant or benign tumor, where model output y = 1 means malignant and y = 0 means benign. Explain how the binary logistic regression model is used to train on patient data and then predict tumor of a new patient. Include formulas and learning algorithm used in your answer. [2 points]*

➔ **Binary Logistic Regression for Tumor Prediction**

- Logistic regression models the probability of an event (y = 1 for malignant) using a sigmoid function.

- Training:
  - Features (patient data) are represented by a vector x.
  - Model learns weights (w) for each feature and a bias term (b).
  - Sigmoid function (f(z)) transforms the linear combination (z = w^T * x + b) to a probability between 0 and 1.

- Prediction:
  - New patient data (x_new) is used to calculate z_new.
  - Predicted probability (y_hat) of malignancy is f(z_new).
  - A threshold (e.g., 0.5) is used to classify (y_hat > 0.5 = malignant, y_hat <= 0.5 = benign).

- Formula:
  $f(z) = 1 / (1 + exp(-z))$

- Learning Algorithm: Gradient descent or other optimization techniques are used to minimize the cost function and learn the weights (w) and bias (b).

3. *QUESTIONS:*

i. *Given the output, y(n), of 3 training items of softmax regression are represented by the following one-hot vectors where y ϵ {1,2,3}: y1 = [1 0 0], y2 = [0 1 0] and y3 = [0 0 1]. Write the expanded form of the softmax cost function J(w) for these 3 items, and the softmax output function f(x;w). [2 points]*

ANSWER: **Softmax Cost Function (J(w)) and Output Function (f(x;w)) for 3 Items:**

- Assuming y represents the true class labels, the expanded softmax cost function (J(w)) for 3 items (y1, y2, y3) becomes:
- J(w) = -sum(y_i * log(f_i(x;w)))
- where i iterates over the 3 items, y_i is the true class label (1, 0, or 0), and f_i(x;w) is the softmax output for class i.
- Softmax output function (f(i;w)) for each class (here k=3 classes):
- f_i(x;w) = exp(w_i^T * x) / sum(exp(w_j^T * x)) for j = 1 to k (all classes)

ii. *What is the relationship between softmax and binary logistic regression? [1 point]*

ANSWER: Relationship between Softmax and Logistic Regression:

- Softmax is a generalization of logistic regression for multi-class classification problems (more than two classes).
- Logistic regression is a special case of softmax with just two classes (binary classification).

4. *What is the penalty term of ridge/L2 regularization and how does it reduce overfitting? [1 point]*

➔ **Ridge/L2 Regularization Penalty Term**

- The L2 penalty term (lambda * ||w||^2) is added to the cost function during training.
- ||w||^2 represents the squared magnitude (sum of squares) of the weights vector (w).
- This penalizes models with large weight values, encouraging simpler models and reducing overfitting.

5. *QUESTIONS:*

i. *Write the pseudocode/steps of applying Policy iteration to solve an MDP, including the equations. [1 point]*

ANSWER: Policy Iteration Steps (MDP):

- Initialize policy (action selection strategy) arbitrarily.
- Policy Evaluation: Evaluate the current policy using value iteration to get the state-value function (V_pi(s)).
- Policy Improvement: Based on V_pi(s), improve the policy to a greedy policy (always choosing the action with the highest Q-value).
- Repeat steps 2 and 3 until the policy converges (no further improvement).

ii. *What is the advantage of using an exploration-based policy like ϵ-greedy, to solve an MDP? [1 point]*

ANSWER: Advantage of Exploration-Based Policies (e.g., epsilon-greedy):

- Purely greedy policies might get stuck in local optima.
- Exploration-based policies (e.g., epsilon-greedy) randomly choose actions with a small probability (epsilon) to explore the state space and potentially find better long-term rewards.

6. *QUESTIONS:*

i. *What makes Q-learning an off-policy algorithm? [1 point]*

ANSWER: Why Q-Learning is Off-Policy:

- Q-learning learns a separate Q-value function (Q(s, a)) that estimates the optimal future reward for taking action a in state s, following any policy.
- During training, the agent may use an exploration policy (e.g., epsilon-greedy) to select actions, but the Q-value update rule considers the reward received under this policy while learning the optimal Q-value function.
- This allows Q-learning to learn from data generated by different policies, making it more flexible.

ii. *What is the difference between on-policy and off-policy algorithms? [1 point]*

ANSWER: Difference Between On-Policy and Off-Policy Algorithms:

- **On-policy algorithms**: Learn and update the policy that is also used for selecting actions during training (behavior policy = target policy).
  Example: SARSA (State-Action-Reward-State-Action)
- **Off-policy algorithms**: Learn a separate policy (target policy) from the data generated by a potentially different behavior policy used for exploration during training.
  Example: Q-learning