## Lab Assignment 3

## **Machine Learning (UML501)**

Q 1	K-Fold Cross Validation for Multiple Linear Regression (Least Square Error Fit)  Download the dataset regarding USA House Price Prediction from the following link:
	https://drive.google.com/file/d/10_NwpJT-8xGfU3llUl2sgPu0xllOrX/view?usp=sharing
	Load the dataset and Implement 5- fold cross validation for multiple linear regression
	(using least square error fit).
	Steps:
	a) Divide the dataset into input features (all columns except price) and output variable (price)
	b) Scale the values of input features.
	c) Divide input and output features into five folds.
	d) Run five iterations, in each iteration consider one-fold as test set and remaining
	four sets as training set. Find the beta $(\beta)$ matrix, predicted values, and R2_score
	for each iteration using least square error fit.
	e) Use the best value of $(\beta)$ matrix (for which R2_score is maximum), to train the
	regressor for 70% of data and test the performance for remaining 30% data.
Q 2	Concept of Validation set for Multiple Linear Regression (Gradient Descent
\ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \	Optimization)
	Consider the same dataset of Q1, rather than dividing the dataset into five folds, divide the
	dataset into training set (56%), validation set (14%), and test set (30%).
	Consider four different values of learning rate i.e. {0.001,0.01,0.1,1}. Compute the values of
	regression coefficients for each value of learning rate after 1000 iterations.
	For each set of regression coefficients, compute R2_score for validation and test set and find
	the best value of regression coefficients.
Q 3	Pre-processing and Multiple Linear Regression
	Download the dataset regarding Car Price Prediction from the following link:
	https://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.data
	1. Load the dataset with following column names ["symboling", "normalized_losses",
	"make", "fuel_type", "aspiration", "num_doors", "body_style", "drive_wheels",
	"engine_location", "wheel_base", "length", "width", "height", "curb_weight",
	"engine_type", "num_cylinders", "engine_size", "fuel_system", "bore", "stroke",
	"compression_ratio", "horsepower", "peak_rpm", "city_mpg", "highway_mpg", "price"]
	and replace all ? values with NaN
	2. Replace all NaN values with central tendency imputation. Drop the rows with NaN
	values in price column
	3. There are 10 columns in the dataset with non-numeric values. Convert these values to
	numeric values using following scheme:
	(i) For "num_doors" and "num_cylinders": convert words (number names) to figures
	for e.g., two to 2
	(ii) For "body_style", "drive_wheels": use dummy encoding scheme
	(iii) For "make", "aspiration", "engine_location", fuel_type: use label encoding
	scheme
	(iv) For fuel_system: replace values containing string pfi to 1 else all values to 0.
	(v) For engine_type: replace values containing string ohc to 1 else all values to 0.
	4. Divide the dataset into input features (all columns except price) and output variable
	(price). Scale all input features.
	5. Train a linear regressor on 70% of data (using inbuilt linear regression function of
	Python) and test its performance on remaining 30% of data.
	6. Reduce the dimensionality of the feature set using inbuilt PCA decomposition and then
	again train a linear regressor on 70% of reduced data (using inbuilt linear regression
	function of Python). Does it lead to any performance improvement on test set?