**Tyler Boda**

This module introduced linear regression, optimization, and regularization, are foundational machine learning in learning to create accurate predictions. Using the housing data, linear regression models the relationship between multiple features and a numeric target by predicting house prices. The module setup showed data analysis, model building, evaluation, and interpretation through graphs.

Optimization in machine learning is given features in hope that the input variables can be turned into rules that give exact target values. Realistically, predictions don’t always match the targets due to data complexity. The goal of optimization is to adjust the model parameters, also known as, weights (w), to reduce the error between predicted values and actual values as much as possible. This error is measured by an error function. MSE (Mean Squared Error) averages the squared differences of predictions and actual values, by giving a target for optimization algorithms to minimize.

Often used in optimization is the gradient descent method. It calculates the gradient (which is the of change of error with relation to the weights) and then updates each weight in the opposite direction of the gradient to move toward a minimum error. This is a small step process which continues until the model provides optimal weights that allow the predictions to be as accurate as possible based on the data given.

Regression models also use the optimization process to find a relationship between features and continuous target values. The linear regression equation  shows the target  as a function of features  multiplied by weights. For example, predicting house prices based on square footage uses a relationship (with the model learning the best multipliers during training). The loss function during this learning is MSE, which leads predicted prices to stay close to actual prices.

Logistic regression classifies problems by turning linear outputs into probabilities through the sigmoid function. It predicts the chances that an input belongs to a particular class (like a "yes" or "no") and uses log loss as an error metric, which measures the quality of these probability predictions.

A recurring problem in machine learning is avoiding underfitting, where the model is too simple to capture patterns, and overfitting, where the model is so complex that it memorizes the training data noise and performs poorly on new data. This is where regularization plays an important role. Regularization introduces a penalty term to the error function that stops large weight values. This penalty forces the model to prefer simple solutions with smaller weights. This improves generalization to unseen data by controlling its complexity.