3/18/24, 12:52 AM CS6140_HW4

```
In [ ]: import numpy as np
        import matplotlib.pyplot as plt
        np.random.seed(42)
       def f(x):
In [ ]:
            return 1 + 2 * x - 2 * x**2
        num train samples = 7
        x train = np.random.rand(num train samples)
        y train = f(x train) + 0.1 * np.random.normal(size=num train samples)
        num validation samples = 100
        x_validation = np.random.rand(num_validation_samples)
        y validation = f(x validation) + 0.1 * np.random.normal(size=num validati
In []: x_values = np.linspace(0, 1, 100)
        plt.figure(figsize=(10, 6))
        plt.plot(x_values, f(x_values), 'r-', label='True Function')
        plt.scatter(x train, y train, color='blue', label='Training Data')
        plt.scatter(x validation, y validation, color='green', label='Validation
        plt.xlabel('x')
        plt.ylabel('y')
        plt.title('Training and Validation Data')
        plt.legend()
        plt.grid(True)
        plt.show()
```



```
In [ ]: def polynomial_features(x, degree):
    return np.array([x**i for i in range(degree + 1)]).T

def ridge_regression(x, y, lambda_val):
    X = polynomial_features(x, degree=6)
    XtX = np.dot(X.T, X)
```

3/18/24, 12:52 AM CS6140_HW4

```
lambda_I = lambda_val * np.eye(X.shape[1])
weights = np.linalg.solve(XtX + lambda_I, np.dot(X.T, y))
return weights

def mean_squared_error(y_true, y_pred):
    return np.mean((y_true - y_pred)**2)
```

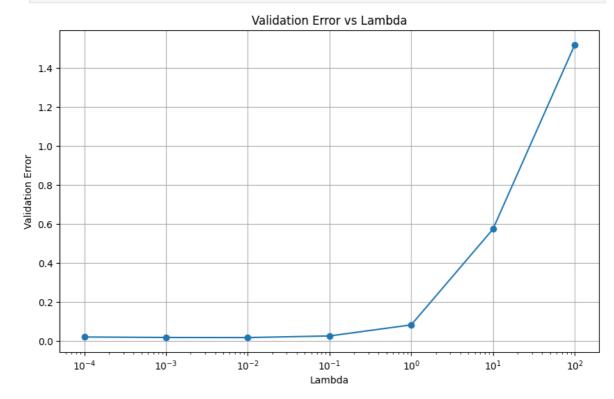
```
In []: lambda_values = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
  validation_errors = []

for lambda_val in lambda_values:
    weights = ridge_regression(x_train, y_train, lambda_val)

    X_validation = polynomial_features(x_validation, degree=6)
    y_pred_validation = np.dot(X_validation, weights)

    validation_error = mean_squared_error(y_validation, y_pred_validation, validation_errors.append(validation_error)
```

```
In []: plt.figure(figsize=(10, 6))
    plt.plot(lambda_values, validation_errors, marker='o', linestyle='-')
    plt.xscale('log')
    plt.xlabel('Lambda')
    plt.ylabel('Validation Error')
    plt.title('Validation Error vs Lambda')
    plt.grid(True)
    plt.show()
```



```
In []: underfit_lambda_index = np.argmax(validation_errors)
    optimal_lambda_index = np.argmin(validation_errors)
    overfit_lambda_index = np.argmin(validation_errors[:optimal_lambda_index]

    underfit_lambda = lambda_values[underfit_lambda_index]
    overfit_lambda = lambda_values[overfit_lambda_index]
    optimal_lambda = lambda_values[optimal_lambda_index]
```

3/18/24, 12:52 AM CS6140_HW4

```
In []: fig, axs = plt.subplots(1, 3, figsize=(18, 6))
         # Optimal Lambda
         axs[0].scatter(x train, y train, color='blue', label='Training Data')
         axs[0].plot(x values, f(x values), 'r-', label='True Function')
         weights optimal = ridge regression(x train, y train, optimal lambda)
         y pred optimal = np.dot(polynomial features(x values, degree=6), weights
         axs[0].plot(x values, y pred optimal, label=f'Optimal Lambda: {optimal la
         axs[0].set xlabel('x')
         axs[0].set ylabel('y')
         axs[0].set title('Fitted Polynomial for Optimal Lambda')
         axs[0].legend()
         axs[0].grid(True)
         # Overfitting Lambda
         axs[1].scatter(x_train, y_train, color='blue', label='Training Data')
         axs[1].plot(x values, f(x values), 'r-', label='True Function')
         weights overfit = ridge regression(x_train, y_train, overfit_lambda)
         y pred overfit = np.dot(polynomial features(x values, degree=6), weights
         axs[1].plot(x values, y pred overfit, label=f'Overfitting Lambda: {overfi
         axs[1].set xlabel('x')
         axs[1].set ylabel('y')
         axs[1].set title('Fitted Polynomial for Overfitting Lambda')
         axs[1].legend()
         axs[1].grid(True)
         # Underfitting Lambda
         axs[2].scatter(x train, y train, color='blue', label='Training Data')
         axs[2].plot(x values, f(x values), 'r-', label='True Function')
         weights_underfit = ridge_regression(x_train, y_train, underfit_lambda)
         y_pred_underfit = np.dot(polynomial_features(x_values, degree=6), weights
         axs[2].plot(x values, y pred underfit, label=f'Underfitting Lambda: {unde
         axs[2].set xlabel('x')
         axs[2].set ylabel('y')
         axs[2].set title('Fitted Polynomial for Underfitting Lambda')
         axs[2].legend()
         axs[2].grid(True)
         plt.tight layout()
         plt.show()
              Fitted Polynomial for Optimal Lambda
                                        Fitted Polynomial for Overfitting Lambda
                                                                   Fitted Polynomial for Underfitting Lambda
                                   1.3
                                                             > 0.8
                                  1.1
                                   1.0
        1.0
                                   0.9
```