ECE 469/ECE 568 Machine Learning

Textbook:
Machine Learning: a Probabilistic Perspective by Kevin Patrick Murphy

Southern Illinois University

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Finding optimal Lambda in Ridge Regularization using Cross Validation

This presentation provides a sample code on finding optimal lambda in Ridge Regularization/Regression using cross-validation.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score, KFold
```

Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Parameters
variance = 5  # variance value
NoS = 100000  # 100000 data points
x = 10*np.random.rand(NoS, 1) - 4

n = np.random.normal(0, np.sqrt(variance), x.shape)  # Gaussian
noise with mean 0 and variance sigma^2
y = 4 - 3*x + 7*x ** 2 -6*x **3 + n
x1 = np.squeeze(x,1)
y1 = np.squeeze(y,1)

# Create a DataFrame
data = pd.DataFrame({
'x': x1,
'y': y1
})
```

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```
# Save the DataFrame to a CSV file
filename = f'dataset4_variance_{variance}.csv'
data.to_csv(filename, index=False)

print(f'Dataset saved to {filename}')

plt.figure(figsize=(8,6))
plt.scatter(x, y, s=1, c='blue', alpha=0.5, label="Data points")
plt.title('Plot of x vs y')
plt.xlabel('x')
plt.ylabel('y')
plt.grid(True)
plt.legend()
plt.show()
```

Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Load dataset
data = pd.read_csv(f'dataset2_variance_{variance}.csv')
X = data['x'].values.reshape(-1, 1)
y = data['y'].values

# Polynomial degree
degree = 5

# Range of lambda values for Ridge regression
lambdas = np.logspace(-4, 2, 100)

# Number of folds for K-fold cross-validation
kf = KFold(n_splits=10, shuffle=True, random_state=1)
```

Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Transform the input features to include polynomial features
poly = PolynomialFeatures(degree)
X_poly = poly.fit_transform(X)

# To store the cross-validation results
mse_values = []
```

Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Perform cross-validation for each lambda value
for alpha in lambdas:
ridge = Ridge(alpha=alpha)

# Calculate MSE using cross_val_score
mse = -cross_val_score(ridge, X_poly, y, cv=kf,
 scoring='neg_mean_squared_error').mean()

mse_values.append(mse)
```

Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Find the lambda with the minimum MSE
best_lambda = lambdas[np.argmin(mse_values)]
print(f"Best lambda (with minimum MSE): {best_lambda}")

# Fit the model with the best lambda
ridge_best = Ridge(alpha=best_lambda)
ridge_best.fit(X_poly, y)

# Generate testing X values
x_fit = np.linspace(X.min(), X.max(), 1000).reshape(-1, 1)
x_poly_fit = poly.transform(x_fit)
y_fit = ridge_best.predict(x_poly_fit)
```

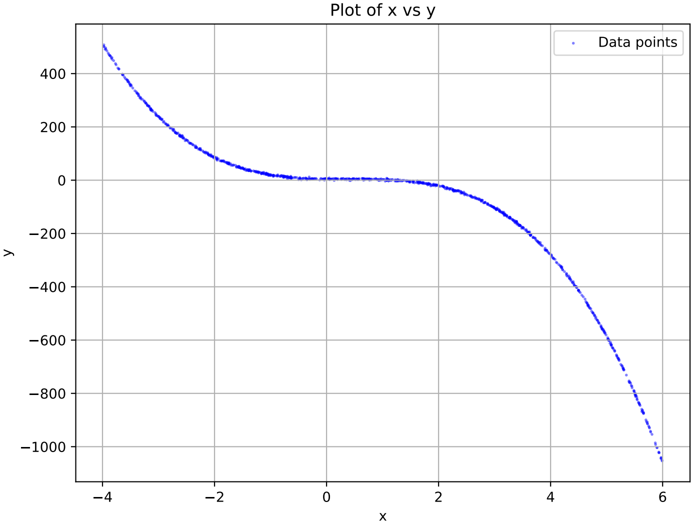
Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Plot MSE vs log(lambda)
plt.figure(figsize=(8, 6))
plt.plot(np.log10(lambdas), mse_values, label='MSE')
plt.xlabel('log10(lambda)')
plt.ylabel('Cross-Validated MSE')
plt.title('Cross-Validated MSE vs log(lambda)')
plt.grid(True)
plt.legend()
plt.show()
```

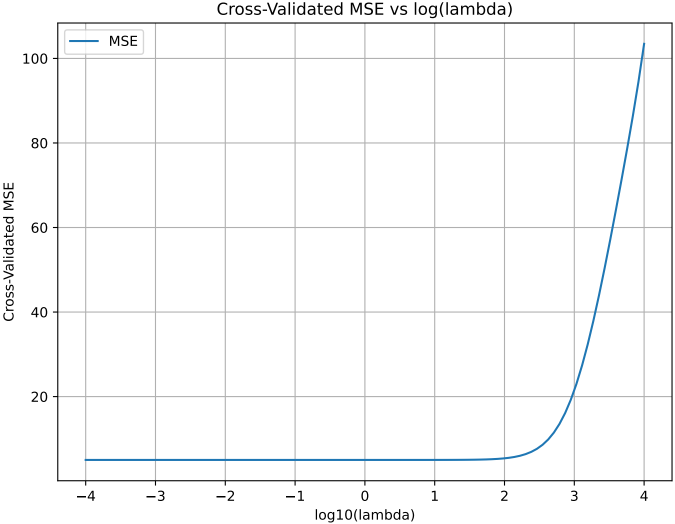
Finding optimal Lambda in Ridge Regression using Cross Validation

```
# Plot the data points and the fitted curve
plt.figure(figsize=(8,6))
plt.scatter(X, y, s=10, color='blue', alpha=0.5,
label='Data points')
plt.plot(x_fit, y_fit, color='red',
label=f'Polynomial Fit (lambda={best_lambda:.4f})')
plt.xlabel('x')
plt.ylabel('y')
plt.title('Polynomial Curve Fit with Best Lambda')
plt.legend()
plt.grid(True)
plt.show()
```

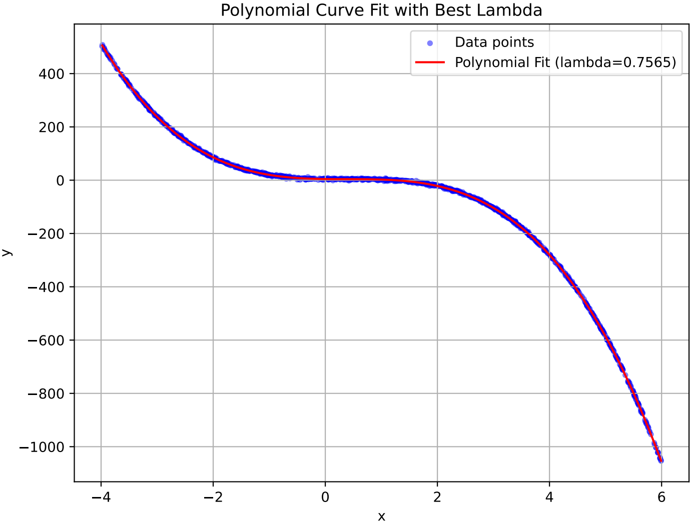
Finding optimal Lambda in Ridge Regression using Cross Validation



Finding optimal Lambda in Ridge Regression using Cross Validation



Finding optimal Lambda in Ridge Regression using Cross Validation



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