ENGN 2520 Pattern Recognition and Machine Learning

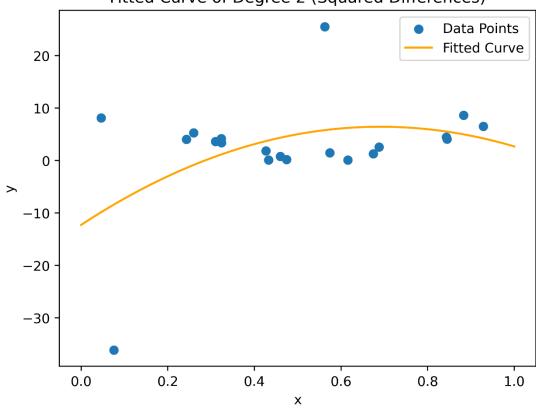
Homework 2

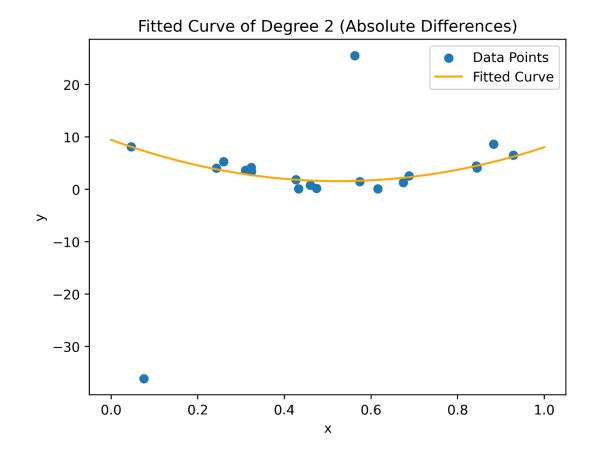
Zhuo Wang

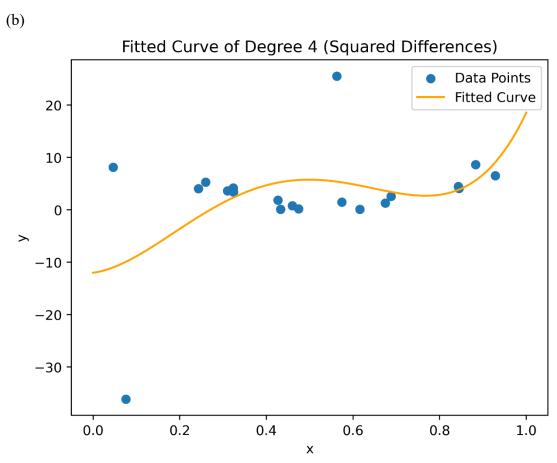
Problem 1

(a)

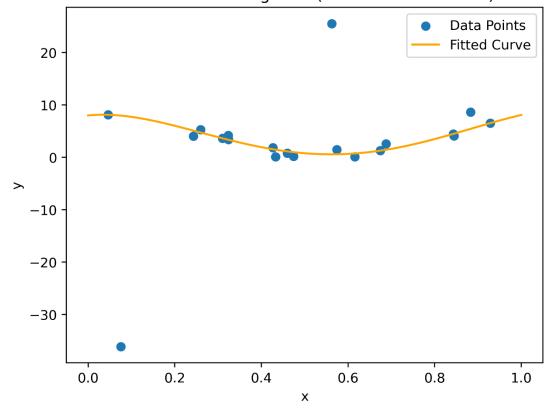
Fitted Curve of Degree 2 (Squared Differences)







Fitted Curve of Degree 4 (Absolute Differences)



(c)
It can be seen from the results that the effect of regression based on the sum of absolute differences is better than that based on the sum of squared differences.
Because sum of squared differences regression tends to fit most data points, it is more sensitive to outliers. The sum of absolute difference is more robust for outliers because it weights the error evenly and does not depend on the size of the error.

When using degree 2 polynomials, regression based on the sum of squared differences can suffer from outliers in the training set, causing the polynomial curve to attempt to fit these points at the expense of fitting the overall dataset.

When using degree 4 polynomials, the model becomes more complex due to the increase in the order of the polynomials and is more susceptible to outliers in the training data.

Problem 2

	min $\left(\frac{N}{27}\right)y_2 - W^T $	b(Ni)] + 711W	/ ,
	$V_{i} = max(0, y_{i} - W^{T}\phi(x_{i}))$		
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Source Code

```
import numpy as np
from scipy.io import loadmat
from scipy.optimize import linprog
import matplotlib.pyplot as plt
def polynomial_features(x, degree):
   for i in range(degree + 1):
          feature.append(xi ** i)
      a.append(feature)
   a = np.array(a).T
   a = np.squeeze(a)
def fit_polynomial_regression(x, y, degree):
   X = polynomial features(x, degree)
def calculate_loss(x, y, w):
def robust regression(phi, X, y):
   M = phi.shape[1]
```

```
A ub.append(a1)
      b ub.append(y[i])
      a2 = np.concatenate((-phi[i], np.zeros(N)))
      A ub.append(a2)
      b ub.append(-y[i])
   result = linprog(c, A ub=A ub, b ub=b ub, bounds=bounds,
x train = loadmat('Xtrain.mat')['Xtrain']
ws = fit_polynomial_regression(x_train, y_train, 2)
xp = np.linspace(0, 1, 100)
yp = np.dot(polynomial features(xp, len(ws) - 1), ws)
plt.scatter(x_train, y_train, label='Data Points')
plt.plot(xp, yp,color='orange', label='Fitted Curve')
plt.xlabel('x')
plt.ylabel('y')
plt.title('Fitted Curve of Degree 2 (Squared Differences)')
plt.legend()
plt.savefig('2sd.png', dpi=400, bbox inches='tight')
plt.show()
```

```
wa = robust regression(polynomial features(x train, 2), x train,
xp = np.linspace(0, 1, 100)
yp = np.dot(polynomial features(xp, len(wa) - 1), wa)
plt.scatter(x_train, y_train, label='Data Points')
plt.plot(xp, yp,color='orange', label='Fitted Curve')
plt.xlabel('x')
plt.ylabel('y')
plt.title('Fitted Curve of Degree 2 (Absolute Differences)')
plt.legend()
plt.savefig('2ad.png', dpi=400, bbox inches='tight')
plt.show()
ws4 = fit polynomial regression(x train, y train, 4)
xp = np.linspace(0, 1, 100)
yp = np.dot(polynomial features(xp, len(ws4) - 1), ws4)
plt.scatter(x_train, y_train, label='Data Points')
plt.plot(xp, yp,color='orange', label='Fitted Curve')
plt.xlabel('x')
plt.ylabel('y')
plt.title('Fitted Curve of Degree 4 (Squared Differences)')
plt.legend()
plt.savefig('4sd.png', dpi=400, bbox inches='tight')
plt.show()
wa4 = robust regression(polynomial features(x train, 4), x train,
y train)
xp = np.linspace(0, 1, 100)
yp = np.dot(polynomial features(xp, len(wa4) - 1), wa4)
plt.scatter(x_train, y_train, label='Data Points')
plt.plot(xp, yp,color='orange', label='Fitted Curve')
```

```
plt.xlabel('x')
plt.ylabel('y')
plt.title('Fitted Curve of Degree 4 (Absolute Differences)')
plt.legend()
plt.savefig('4ad.png', dpi=400, bbox_inches='tight')
plt.show()
```