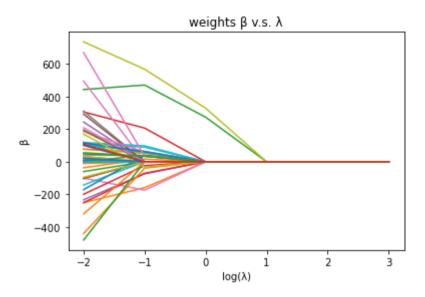
Problem 1 (LASSO and Ridge regression)

(a)

```
In [ ]: import scipy.io
         import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.linear model import Lasso, Ridge
In [ ]: data = scipy.io.loadmat('05HW1_diabetes.mat')
         train x = data['x train']
         train y = data['y train']
         test x = data['x test']
         test y = data['y test']
         Lambda = (0.01, 0.1, 1, 10, 100, 1000)
         Lambda log = np.log10(Lambda)
In [ ]: weight = []
         test loss = []
         for 1 in Lambda:
             model = Lasso(alpha=1)
             model.fit(train x, train y)
             weight.append(model.coef )
             test equ = test x.dot(model.coef ) + model.intercept
             test loss.append(sum(np.transpose(np.array([test equ]) - test y)**2))
         plt.figure()
         plt.plot(Lambda log, weight)
         plt.title('weights \beta v.s. \lambda')
         plt.xlabel('log(\lambda)')
         plt.ylabel('β')
         plt.show()
```



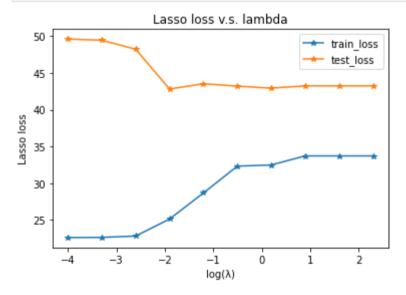
Problem 2 (LASSO regression)

(a)

```
import scipy.io
In [ ]:
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.linear model import Lasso, Ridge
In [ ]: Lambda = (0.0001, 0.0005, 0.0025, 0.0125, 0.0625, 0.3125, 1.5625, 7.815, 39.0625, 195.3125)
        Lambda_log = np.log10(Lambda)
        train = np.loadtxt('05HW2 wine training.txt')
        train_x = train[:,:-1]
        train y = train[:,-1]
        test = np.loadtxt('05HW2_wine_test.txt')
        test_x = test[:,:-1]
        test_y = test[:,-1]
        test_loss = []
        train_loss = []
        for 1 in (Lambda):
```

```
model = Lasso(alpha=1)
  model.fit(train_x, train_y)
  train_equ = train_x.dot(model.coef_) + model.intercept_
        train_loss.append(sum(np.transpose(np.array([train_equ]) - train_y)**2))
  test_equ = test_x.dot(model.coef_) + model.intercept_
        test_loss.append(sum(np.transpose(np.array([test_equ]) - test_y)**2))

plt.figure()
plt.plot(Lambda_log, train_loss, '*-', label="train_loss")
plt.plot(Lambda_log, test_loss, '*-', label="test_loss")
plt.legend()
plt.xlabel('log(\lambda)')
plt.ylabel('Lasso loss')
plt.title('Lasso loss v.s. lambda')
plt.show()
```



(b)

- $1.\lambda < 0.025$, test loss很高,然而train loss卻在很低的值,應有發生overfitting現象
- $2.\lambda = 0.025$, test loss最低,並且train loss也並無太高,應為最佳參數
- $3.\lambda > 0.025$, 兩者皆迅速攀升,應是被 λ 限制model表現,因此發生underfitting

我會選擇 $\lambda = 0.025$,原因與上小題2.相同,此時的test error表現最小