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Ex 4

Task 1) A python jupyter notebook is uploaded for this and also is attached at the end of this pdf.

Task 2)

$$a) L(\theta) = \frac{1}{N} \sum_{n=1}^N (f_{\theta}(x_n) - y_n)^2 + \lambda \|\theta\|_2^2$$

$$\frac{dL(\theta)}{d\theta} = \frac{1}{N} (-x)^T 2(y - x\theta) + 2\lambda\theta \quad : \text{from slides}$$

we put  $\theta^*$

$$\frac{dL(\theta^*)}{d\theta} = -\frac{2}{N} x^T (y - x(x^T x + N\lambda I)^{-1} x^T y) + 2\lambda (x^T x + N\lambda I)^{-1} x^T y$$
$$= -\frac{2}{N} x^T y + \frac{2}{N} (x^T x + \lambda I N) (x^T x + \lambda N I)^{-1} (x^T y) = -\frac{2}{N} (x^T y - x^T y)$$
$$= 0$$

$$b) \nabla^2 L = \frac{2}{N} x^T x + \underbrace{2\lambda}_{\text{we had } \lambda > 0 \Rightarrow 2\lambda > 0}$$

$x^T x$  is positive indefinite if there is  $\theta \in \mathbb{R}^m$  that

$$\theta^T x^T x \theta > 0$$

$$\text{so, } \theta^T x^T x \theta = (\theta x)^T (\theta x) = \|\theta x\|_2^2 > 0 \Rightarrow x^T x \text{ is positive indefinite}$$

$\textcircled{I}, \textcircled{II} \rightarrow$  Hessian is positive indefinite.

Task 3) A python notebook and a pdf is attached.

```
In [ ]: import numpy as np
from sklearn.datasets import fetch_california_housing
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

## Task 1

### Part a)

The formulas are taken from the slides

- The maximum likelihood parameters can be computed as follows (no proof):

number of examples with  $y=t$   $n_t = \sum_{n=1}^N I(y_n = t)$  where  $I(\text{condition}) = \begin{cases} 1: \text{condition is true} \\ 0: \text{condition is false} \end{cases}$

$\pi_t = \frac{n_t}{N}$  intuitively: probability for class  $t$  is fraction of examples with  $y=t$

$\mu_t = \frac{1}{n_t} \sum_{n=1}^N I(y_n = t) \mathbf{x}_n$  intuitively: mean vector for class is average over instances in that class (the  $I(\dots)$  expression picks out the instances of class  $t$ )

Lecture „Machine Learning“

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$$\Sigma_t = \frac{1}{n_t} \sum_{n=1}^N I(y_n = t) (\mathbf{x}_n - \mu_t)(\mathbf{x}_n - \mu_t)^T$$

$\in \mathbb{R}^{M \times M}$

covariance matrix for class  $t$  is computed from instances of that class

```
In [ ]: x = np.array(
    [
        [1, 3],
        [2, 4],
        [1, 4],
        [2, 2],
        [3, 3],
        [3, 2]
    ]
)
y = np.array(
    [
        [2], [2], [2], [1], [1], [1]
    ]
)
# parameters
n_1 = len([value[0] for value in y if value[0] == 1])
n_2 = len([value[0] for value in y if value[0] == 2])
N = y.shape[0]
pi_1 = n_1/N
pi_2 = n_2/N
Mu_1 = np.mean(
    [value for index, value in enumerate(x) if y[index,0] == 1], axis=0
```

```

)
Mu_2 = np.mean(
    [value for index, value in enumerate(x) if y[index,0] == 2], axis=0
)
covar_matrix_1 = np.mean(
    [((value - Mu_1).reshape((len(value), 1)))@((value - Mu_1).reshape((len(value),
    , axis=0)
covar_matrix_2 = np.mean(
    [((value - Mu_2).reshape((len(value), 1)))@((value - Mu_2).reshape((len(value),
    , axis=0)
print(f'n_1: {n_1}')
print(f'n_2: {n_2}')
print(f'pi_1: {pi_1}')
print(f'pi_2: {pi_2}')
print(f'Mu_1: {Mu_1}')
print(f'Mu_2: {Mu_2}')
print(f'covariance matrix 1: {covar_matrix_1}')
print(f'covariance matrix 2: {covar_matrix_2}')

```

```

n_1: 3
n_2: 3
pi_1: 0.5
pi_2: 0.5
Mu_1: [2.66666667 2.33333333]
Mu_2: [1.33333333 3.66666667]
covariance matrix 1: [[0.22222222 0.11111111]
 [0.11111111 0.22222222]]
covariance matrix 2: [[0.22222222 0.11111111]
 [0.11111111 0.22222222]]

```

## Part b)

```

In [ ]: X = np.array([[1.5, 3]])

decision_function_class1 = -0.5 * np.log(np.linalg.det(covar_matrix_1)) - \
    0.5 * np.sum(np.dot((X - Mu_1), np.linalg.inv(covar_matrix_1))) + \
    np.log(pi_1)

decision_function_class2 = -0.5 * np.log(np.linalg.det(covar_matrix_2)) - \
    0.5 * np.sum(np.dot((X - Mu_2), np.linalg.inv(covar_matrix_2))) + \
    np.log(pi_2)

predictions = (decision_function_class1 > decision_function_class2).astype(int) + 1

print(f'The predicted class is: {predictions[0]}')

```

The predicted class is: 1

## Task 3

### Part a)

```

In [ ]: np.random.seed(123)
dataset = fetch_california_housing()
Xdata = dataset["data"]
Ydata = dataset["target"]

```

```

N, M = Xdata.shape
# Split into training and validation sets
ridx = np.random.permutation(N)
split = int(0.8*N)
Xtrain = Xdata[ridx[:split]]
Ytrain = Ydata[ridx[:split]]
Xvalid = Xdata[ridx[split:]]
Yvalid = Ydata[ridx[split:]]
reg = LinearRegression().fit(Xtrain, Ytrain) # fit model
intcp = reg.intercept_ # get intercept
coefs = reg.coef_ # get coefficients
# Get Predictions for training and validation sets
pred_train = reg.predict(Xtrain)
pred_val = reg.predict(Xvalid)
# Calculate Loss on training and validation sets
train_loss = mean_squared_error(pred_train, Ytrain)
val_loss = mean_squared_error(pred_val, Yvalid)
print(f'Train loss with sklearn: {train_loss}')
print(f'Test loss with sklearn: {val_loss}')

```

Train loss with sklearn: 0.5257192588422376

Test loss with sklearn: 0.5308531303306663

```

In [ ]: class regression:
    def __init__(self, x, y, x_valid, y_valid):
        self.x = np.column_stack((x, np.ones(len(x))))
        self.y = y
        self.x_valid = np.column_stack((x_valid, np.ones(len(x_valid))))
        self.y_valid = y_valid
        self.theta = None

    def fit(self):
        A = self.x.T @ self.x
        B = self.x.T @ self.y
        self.theta = np.linalg.lstsq(A, B, rcond=None)[0]

    def predict(self, data):
        return data@self.theta

    def validate(self):
        self.train_error = mean_squared_error(
            self.predict(self.x), self.y
        )
        self.valid_error = mean_squared_error(
            self.predict(self.x_valid), self.y_valid
        )

    def print_results(self):
        print(f'Train loss with regression: {self.train_error}')
        print(f'Test loss with regression: {self.valid_error}')

reg = regression(Xtrain, Ytrain, Xvalid, Yvalid)
reg.fit()
reg.validate()
reg.print_results()

```

Train loss with regression: 0.5257192588422377

Test loss with regression: 0.530853130330998

They match the results from sklearn

### Part b)

```
In [ ]: def forward_search():
    selected_variables = []
    remaining_variables = list(range(Xtrain.shape[1]))
    while remaining_variables:
        best_variable = None
        best_loss = float('inf')
        best_train_loss = None # just for printing as the question wanted
        for variable in remaining_variables:
            selected_vars = selected_variables + [variable]
            model = regression(Xtrain[:, selected_vars], Ytrain, Xvalid[:, selected_vars])
            model.fit()
            model.validate()
            loss_val = model.valid_error
            if loss_val < best_loss:
                best_loss = loss_val
                best_variable = variable
                best_train_loss = model.train_error
        selected_variables.append(best_variable)
        remaining_variables.remove(best_variable)

    print(f"Selected variables: {selected_variables}")
    print(f"Training loss: {best_train_loss}")
    print(f"Validation loss: {best_loss}")
    print("\n")
```

```
In [ ]: forward_search()
```

Selected variables: [0]  
Training loss: 0.7057142611240419  
Validation loss: 0.6828174174305537

Selected variables: [0, 1]  
Training loss: 0.6565408330102636  
Validation loss: 0.6421602037629112

Selected variables: [0, 1, 6]  
Training loss: 0.6454676255374441  
Validation loss: 0.6327294459135423

Selected variables: [0, 1, 6, 7]  
Training loss: 0.5412654842398897  
Validation loss: 0.5379723120836373

Selected variables: [0, 1, 6, 7, 3]  
Training loss: 0.5356213901380866  
Validation loss: 0.5284987345411443

Selected variables: [0, 1, 6, 7, 3, 2]  
Training loss: 0.5277066774799533  
Validation loss: 0.5191577098527762

Selected variables: [0, 1, 6, 7, 3, 2, 4]  
Training loss: 0.5275119429508665  
Validation loss: 0.5198925555672947

Selected variables: [0, 1, 6, 7, 3, 2, 4, 5]  
Training loss: 0.5257192588422377  
Validation loss: 0.5308531303309508

```
In [ ]: def backward_search():
        selected_variables = list(range(Xtrain.shape[1]))

        while len(selected_variables) > 1:
            best_variable = None
            best_loss = float('inf')
            best_train_loss = None # just for printing as the question wanted
            for variable in selected_variables:
                remaining_vars = selected_variables.copy()
                remaining_vars.remove(variable)
                model = regression(Xtrain[:, remaining_vars], Ytrain, Xvalid[:, remaining_vars])
                model.fit()
                model.validate()
                loss_val = model.valid_error
```

```

        if loss_val < best_loss:
            best_loss = loss_val
            best_variable = variable
            best_train_loss = model.train_error

    selected_variables.remove(best_variable)

    print(f"Selected variables: {selected_variables}")
    print(f"Training loss: {best_train_loss}")
    print(f"Validation loss: {best_loss}")
    print("\n")

```

In [ ]: backward\_search()

Selected variables: [0, 1, 2, 3, 4, 6, 7]  
 Training loss: 0.5275119429508663  
 Validation loss: 0.5198925555672468

Selected variables: [0, 1, 2, 3, 6, 7]  
 Training loss: 0.5277066774799533  
 Validation loss: 0.5191577098527814

Selected variables: [0, 1, 3, 6, 7]  
 Training loss: 0.5356213901380866  
 Validation loss: 0.5284987345411519

Selected variables: [0, 1, 6, 7]  
 Training loss: 0.5412654842398897  
 Validation loss: 0.5379723120836373

Selected variables: [0, 6, 7]  
 Training loss: 0.5552242366588557  
 Validation loss: 0.5470577783938771

Selected variables: [0, 6]  
 Training loss: 0.6948452870930405  
 Validation loss: 0.6729338841159962

Selected variables: [0]  
 Training loss: 0.7057142611240419  
 Validation loss: 0.6828174174305537

In [ ]: