National University of Singapore

SVM for Classification of Spam Email Messages

EE5904 / ME5404 Project I

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Report due on 21 April 2023, 23:59 Singapore time

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Project Description

Project Description

Project Goal

- Implement a SVM to classify spam or not a spam for the **Spam Email Data Set**
- Spam Email Data Set:
  - 4061 samples of email metadata taken from UC Irvine Machine Learning Repository
  - 57 features per sample
  - Label : +1 (spam), -1 (non-spam) | 1 and 0 in orginal dataset
  - http://archive.ics.uci.edu/ml/datasets/spambase

```
0.00000 0.01043 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000
0.00000 0.00000 0.01043 0.01043 0.02105 0.00000 0.00000 0.00000
0.00000 0.03166 0.06332 0.00000 0.02105 0.00000 0.00000 0.00000
0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000
0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000
0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000 0.00000
0.00000 0.00000 0.00000 0.00196 0.00000 0.00000 0.02601 0.12811
0.98827
```

```
Class Distribution:
   Spam      1813   (39.4%)
   Non-Spam  2788   (60.6%)
```

Project Description

Project Goal

- The dataset is divided into 3 subset according to **Project Requirement**
  - Training set: 2000
  - Test set: 1536
  - Eval set: 600 (will not provide)

Name	Value
train_data	57x2000 double
train_label	2000x1 double

Name	Value
eval_data	57x600 double
eval_label	600x1 double

Name	Value
test_data	57x1536 double
test_label	1536x1 double

Project Description

Train ➡ Construction: For a given training set $S = \{(\mathbf{x}_1, d_1), \ldots, (\mathbf{x}_N, d_N)\}$, find optimal hyperplane $(\mathbf{w}_\circ, b_\circ)$ such that, for all $i \in \{1, 2, \ldots, N\}$,

$$\xrightarrow{\mathbf{x}_i} \boxed{\mathbf{w}_\circ^T \mathbf{x}_i + b_\circ} \xrightarrow{g(\mathbf{x}_i)} \boxed{\mathrm{sgn}[g(\mathbf{x}_i)]} \xrightarrow{y_i = d_i}$$

Test ➡ Testing: For a given test set $\bar{S} = \{(\bar{\mathbf{x}}_1, \bar{d}_1), \ldots, (\bar{\mathbf{x}}_{\bar{N}}, \bar{d}_{\bar{N}})\}$, compute output $\bar{y}_i$ of SVM (with $\mathbf{w}_\circ$ and $b_\circ$) for all $i \in \{1, 2, \ldots, \bar{N}\}$, and compare it against the known $\bar{d}_i$ to evaluate performance of SVM

$$\xrightarrow{\bar{\mathbf{x}}_i} \boxed{\mathbf{w}_\circ^T \bar{\mathbf{x}}_i + b_\circ} \xrightarrow{g(\bar{\mathbf{x}}_i)} \boxed{\mathrm{sgn}[g(\bar{\mathbf{x}}_i)]} \xrightarrow{\bar{y}_i}$$

Evaluate ➡ Application: Given a SVM with hyperplane $(\mathbf{w}_\circ, b_\circ)$, classify a data point $\mathbf{x}_{\text{new}}$ that is not in $\Sigma = S \cup \bar{S}$:

$$\xrightarrow{\mathbf{x}_{\text{new}}} \boxed{\mathbf{w}_\circ^T \mathbf{x}_{\text{new}} + b_\circ} \xrightarrow{g(\mathbf{x}_{\text{new}})} \boxed{\mathrm{sgn}[g(\mathbf{x}_{\text{new}})]} \xrightarrow{y_{\text{new}}}$$

Task1: Training

Task1 – Data

Training set – 2000 samples

- Given – ‘train.mat’
  - Features – (57 x 2000)
  - Label (2000 x 1)

- Features of a sample

0.00000	0.01043	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.01043	0.01043	0.02105	0.00000	0.00000	0.00000
0.00000	0.03166	0.06332	0.00000	0.02105	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00196	0.00000	0.00000	0.02601	0.12811
0.98827							

Name	Value
train_data	57x2000 double
train_label	2000x1 double

- Label : +1 (spam), -1 (non-spam)

Task1 – Training Set

Import the training set (i.e. train.mat)

- train_data (57 x 2000)
- train_label (2000 x 1)

Preprocess the 'data' (Various methods can be used including Sample scaling and Standardization [CHOOSE ONE METHOD])[a, b]

- Scale the data – Rescale the individual sample x such that $||x|| = 1$

- Standardize the data – Transform each feature by removing the mean value of each feature and then dividing by each feature's standard deviation

Please ensure the 'label' is mapped into the set of {-1, +1}

[a] https://scikit-learn.org/stable/modules/preprocessing.html
[b] https://en.wikipedia.org/wiki/Feature_scaling

Task1 – Kernels

Hard-margin SVM with the linear kernel

$K(x_1, x_2) = x_1^T x_2$

Hard-margin SVM with a polynomial kernel

$K(x_1, x_2) = (x_1^T x_2 + 1)^p$

Soft-margin SVM with a polynomial kernel

$K(x_1, x_2) = (x_1^T x_2 + 1)^p$

Task1 – Hard and Soft Margins

Hard margin $0 \leq \alpha_i$

- C = $+\infty$ (In theory)

  $0 \leq \alpha_i \leq C$

- C = Large value (In practice e.g. 10^6)

Soft margin $0 \leq \alpha_i \leq C$

- C = 0.1, 0.6, 1.1, 2.1

Task1 – Calculate α

How to calculate α_i

$$\text{Maximize}: \quad Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(\mathbf{x}_i, \mathbf{x}_j)$$

$$\text{Subject to}: \quad \sum_{i=1}^{N} \alpha_i d_i = 0\,, \ \ 0 \leq \alpha_i \leq C$$

Use quadprog function (Quadratic programming)

Description

Solver for quadratic objective functions with linear constraints.

quadprog finds a minimum for a problem specified by

$$\min_x \frac{1}{2} x^T H x + f^T x \text{ such that } \begin{cases} A \cdot x \leq b, \\ Aeq \cdot x = beq, \\ lb \leq x \leq ub. \end{cases}$$

H, A, and Aeq are matrices, and f, b, beq, lb, ub, and x are vectors.

You can pass f, lb, and ub as vectors or matrices; see Matrix Arguments.

`x = quadprog(H,f,A,b,Aeq,beq,lb,ub,x0,options)` solves the preceding problem using the optimization options specified in `options`. Use `optimoptions` to create `options`. If you do not want to give an initial point, set `x0 = []`.

Task1 – Calculate α

Maximize $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(\mathbf{x}_i, \mathbf{x}_j)$

Subject to : $\sum_{i=1}^{N} \alpha_i d_i = 0\,,\ 0 \leq \alpha_i \leq C$

Description

Solver for quadratic objective functions with linear constraints.

quadprog finds a minimum for a problem specified by

$$\min_x \frac{1}{2} x^T H x + f^T x \text{ such that } \begin{cases} A \cdot x \leq b, \\ Aeq \cdot x = beq, \\ lb \leq x \leq ub. \end{cases}$$

Convert the problem from 'Max' to 'Min'

- Max Q(α) → Min - Q(α)

If f is to be maximized instead, such a maximization problem can be expressed as a minimization problem by the transformation

Slide 62

$$\max_{\mathbf{w}} f(\mathbf{w}) = -\min_{\mathbf{w}} [-f(\mathbf{w})]$$

Task1 – Calculate α

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Maximize : $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(\mathbf{x}_i, \mathbf{x}_j)$

Subject to : $\sum_{i=1}^{N} \alpha_i d_i = 0\,,\ 0 \leq \alpha_i \leq C$

Description

Solver for quadratic objective functions with linear constraints.

quadprog finds a minimum for a problem specified by

Not used

$$\min_x \frac{1}{2} x^T H x + f^T x \text{ such that } \begin{cases} A \cdot x \leq b, \\ Aeq \cdot x = beq, \\ lb \leq x \leq ub. \end{cases}$$

$$\min_x \frac{1}{2} x^T H x + f^T x \quad \begin{cases} H_{ij} = d_i d_j K(x_i, x_j) \\ f = (-1, -1, \cdots\cdots, -1)^T \end{cases}$$

$$A \cdot x \leq b, \quad \begin{cases} A = [\,] \\ b = [\,] \end{cases}$$

$$Aeq \cdot x = beq, \quad \begin{cases} Aeq = (d_1, d_2, \cdots\cdots, d_N) \\ beq = 0 \end{cases}$$

$$lb \leq x \leq ub. \quad \begin{cases} lb = (0, 0, \cdots\cdots, 0)^T \\ ub = (C, C, \cdots\cdots, C)^T \end{cases}$$

```
x = quadprog(H,f,A,b,Aeq,beq,lb,ub,x0,options)
```

Task1 – Calculate α

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Hard-margin SVM with the linear kernel

$$K(x_1, x_2) = x_1^T x_2$$

For illustration only

$$\min_x \frac{1}{2} x^T H x + f^T x \quad \begin{cases} H(i,j) = d_i d_j x_i^T x_j \\ f = -\text{ones}(2000,1) \end{cases}$$

$$A \cdot x \le b, \quad \begin{cases} A = [\,] \\ b = [\,] \end{cases}$$

$$Aeq \cdot x = beq, \quad \begin{cases} Aeq = train\_label' \\ beq = 0 \end{cases}$$

$$lb \le x \le ub. \quad \begin{cases} lb = zeros(2000,1) \\ ub = \text{ones}(2000,1) * C \end{cases}$$

Hard margin $0 \le \alpha_i$

C = $+\infty$ (In theory)

C = Large value (In practice e.g. 10^6)

$$x0 = [\,] \qquad options = optimset('LargeScale','off','MaxIter',1000)$$

Task1 – Calculate α

Hard-margin SVM with a polynomial kernel

$$K(x_1, x_2) = (x_1^T x_2 + 1)^p$$

For illustration only

$$\min_x \frac{1}{2} x^T H x + f^T x \quad \begin{cases} H(i,j) = d_i d_j (x_1^T x_2 + 1)^p \\ f = -\text{ones}(2000,1) \end{cases}$$

$$A \cdot x \le b, \quad \begin{cases} A = [\,] \\ b = [\,] \end{cases}$$

$$Aeq \cdot x = beq, \quad \begin{cases} Aeq = train\_label' \\ beq = 0 \end{cases}$$

$$lb \le x \le ub. \quad \begin{cases} lb = zeros(2000,1) \\ ub = \text{ones}(2000,1) * C \end{cases}$$

Hard margin $0 \le \alpha_i$

C = $+\infty$ (In theory)

C = Large value (In practice e.g. 10^6)

$$x0 = [\,] \qquad options = optimset('LargeScale','off','MaxIter',1000)$$

Task1 – Calculate α

Soft-margin SVM with a polynomial kernel

$$K(x_1, x_2) = (x_1^T x_2 + 1)^p$$

For illustration only

$$\min_x \frac{1}{2} x^T H x + f^T x \quad \begin{cases} H(i,j) = d_i d_j (x_1^T x_2 + 1)^p \\ f = -\text{ones}(2000,1) \end{cases}$$

$$A \cdot x \le b, \quad \begin{cases} A = [\,] \\ b = [\,] \end{cases}$$

$$Aeq \cdot x = beq, \quad \begin{cases} Aeq = train\_label' \\ beq = 0 \end{cases}$$

$$lb \le x \le ub. \quad \begin{cases} lb = zeros(2000,1) \\ ub = \text{ones}(2000,1) * \text{C} \end{cases}$$

Soft margin $0 \le \alpha_i \le C$

C = 0.1, 0.6, 1.1, 2.1

$x0 = [\,]$ $\quad options = optimset('LargeScale','off','MaxIter',1000)$

Task1 – Select support vectors

Based on KKT conditions

- For a support vector, $\alpha_i \neq 0$ (In theory, $\alpha_i > 0$)

- However, in practice, $\alpha_i > threshold$

- How to decide?
  - Choose an appropriate threshold (e.g. 1e-4) to determine the corresponding α_i to the support vectors
  - Then make the other smaller α_i values which are less than the threshold zero

Task1 – Discriminant function

Hard Margin SVM with Linear Kernel

Maximizing : $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j \mathbf{x}_i^T \mathbf{x}_j$

Subject to : (1) $\sum_{i=1}^{N} \alpha_i d_i = 0$

(2) $\alpha_i \geq 0$

Discriminant function

$$g(\mathbf{x}) = \mathbf{w}_\circ^T \mathbf{x} + b_\circ$$

After $\alpha_{\circ,i}$ is obtained, we can calculate $\mathbf{w}_\circ$ and $b_\circ$ as follows:

$$\mathbf{w}_\circ = \sum_{i=1}^{N} \alpha_{\circ,i} d_i \mathbf{x}_i , \quad b_\circ = \frac{1}{d^{(s)}} - \mathbf{w}_\circ^T \mathbf{x}^{(s)}$$

where $\mathbf{x}^{(s)}$ is a support vector with label $d^{(s)}$

Task1 – Discriminant function

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Soft Margin SVM with Linear Kernel

Maximize : $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j \mathbf{x}_i^T \mathbf{x}_j$

Subject to : $\sum_{i=1}^{N} \alpha_i d_i = 0$ and $0 \leq \alpha_i \leq C$

Discriminant function

$$g(\mathbf{x}) = \mathbf{w}_\circ^T \mathbf{x} + b_\circ$$

After $\alpha_{\circ,i}$ is obtained, we can calculate $\mathbf{w}_\circ$ as follows:

$$\mathbf{w}_\circ = \sum_{i=1}^{N} \alpha_{\circ,i}\, d_i\, \mathbf{x}_i$$

After $\mathbf{w}_\circ$ is obtained, we can calculate $b_\circ$ as follows:

1. For each example $\mathbf{x}_i$ with $0 < \alpha_i \leq C$,

$$b_{\circ,i} = \frac{1}{d_i} - \mathbf{w}_\circ^T \mathbf{x}_i$$

2. Take $b_\circ$ as the average of all such $b_{\circ,i}$

$$b_\circ = \frac{\sum_{i=1}^{m} b_{\circ,i}}{m}$$

where m is the total number of $\mathbf{x}_i$ with $0 < \alpha_i \leq C$.

Task1 – Discriminant function

Soft Margin SVM with Nonlinear Kernel

Maximize : $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j \boldsymbol{\varphi}^T(\mathbf{x}_i) \boldsymbol{\varphi}(\mathbf{x}_j)$

Subject to : $\sum_{i=1}^{N} \alpha_i d_i = 0\,,\; 0 \le \alpha_i \le C$

Discriminant function

$$g(\mathbf{x}) \;=\; \sum_{i=1}^{N} \alpha_{\circ,i} d_i K(\mathbf{x}, \mathbf{x}_i) + b_\circ$$

Determine $b_\circ$ in Slide 123

$$g(\mathbf{x}) = \sum_{i=1}^{N} \alpha_{\circ,i} d_i K(\mathbf{x}, \mathbf{x}_i) + b_\circ$$

using the fact that for a support vector $\mathbf{x}^{(s)}$

$$g(\mathbf{x}^{(s)}) = \pm 1 = d^{(s)}$$

Take $b_\circ$ as the average of all such $b_{\circ,i}$

$$b_\circ = \frac{\sum_{i=1}^{m} b_{\circ,i}}{m}$$

where m is the total number of $\mathbf{x}_i$ with $0 < \alpha_i \le C$.

Task1 – Summary

Given a training set $S = \{(\mathbf{x}_i, d_i)\}$, $i = 1, \ldots, N$

Slide 123

1 Find a suitable kernel

Choose expression then check Mercer's condition

Soft Margin

2 Choose a value for C

3 Solve for $\alpha_{\circ,i}$

Quadratic programming

Maximize : $Q(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j K(\mathbf{x}_i, \mathbf{x}_j)$

Subject to : $\sum_{i=1}^{N} \alpha_i d_i = 0\,,\ 0 \le \alpha_i \le C$

4 Determine $b_\circ$ in

Kernel

$$g(\mathbf{x}) = \sum_{i=1}^{N} \alpha_{\circ,i} d_i K(\mathbf{x}, \mathbf{x}_i) + b_\circ$$

using the fact that for a support vector $\mathbf{x}^{(s)}$

$$g(\mathbf{x}^{(s)}) = \pm 1 = d^{(s)}$$

Support vector machine: $\xrightarrow{\mathbf{x}} \boxed{\operatorname{sgn}[g(\mathbf{x})]} \xrightarrow{y}$

Task2: Testing

Task2 – Data

Test set – 1536 samples

- Given – ‘test.mat’
  - Features – (57 x 1536)
  - Label (1536 x 1)

- Features of a sample

0.00000	0.01043	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.01043	0.01043	0.02105	0.00000	0.00000	0.00000
0.00000	0.03166	0.06332	0.00000	0.02105	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.00000	0.00000	0.00196	0.00000	0.00000	0.02601	0.12811
0.98827							

- Label : +1 (spam), -1 (non-spam)

Task2 – Test set

Import the test set (i.e. test.mat)

- test_data (57 x 1536)
- test_label (1536 x 1)

Preprocess the 'data' (Various methods can be used including Sample scaling and Standardization [CHOOSE ONE USE for TRAINING])[a, b]

- Scale the data – Rescale the individual sample x such that $\|x\| = 1$

- Standardize the data – Transform each feature in the same manner with the training data. Use the mean and variance of each feature from your training set.

Please ensure the 'label' is mapped into the set of {-1, +1}

[a] https://scikit-learn.org/stable/modules/preprocessing.html
[b] https://en.wikipedia.org/wiki/Feature_scaling

Task2 – Test set

Discriminant function

$$g(\mathbf{x}) = \mathbf{w}_\circ^T \boldsymbol{\varphi}(\mathbf{x}) + b_\circ = \sum_{i=1}^{N} \alpha_{\circ,i} d_i \underbrace{\boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})}_{K(\mathbf{x}_i,\mathbf{x})} + b_\circ$$

To classify a new data point $\mathbf{x}_{\text{new}}$

$$d_{\text{new}} = \text{sgn}\left[g(\mathbf{x}_{\text{new}})\right]$$

For illustrations only

$$g(x_{test}) = \sum_{i=1}^{N} \alpha_{o,i} d_i K(x_i, x_{test}) + b_0$$

If g(x_test) > 0
    x_test_label = +1
Else
    x_test_label = -1

Task2 – Test set

Discriminant function

$$g(\mathbf{x}) = \mathbf{w}_\circ^T \boldsymbol{\varphi}(\mathbf{x}) + b_\circ = \sum_{i=1}^{N} \alpha_{\circ,i} d_i \underbrace{\boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})}_{K(\mathbf{x}_i,\mathbf{x})} + b_\circ$$

To classify a new data point $\mathbf{x}_{\text{new}}$

$$d_{\text{new}} = \text{sgn}\left[g(\mathbf{x}_{\text{new}})\right]$$

Type of SVM	Training accuracy				Test accuracy			
Hard margin with Linear kernel	?				?			
Hard margin with polynomial kernel	$p=2$	$p=3$	$p=4$	$p=5$	$p=2$	$p=3$	$p=4$	$p=5$
	?	?	?	?	?	?	?	?
Soft margin with polynomial kernel	$C=0.1$	$C=0.6$	$C=1.1$	$C=2.1$	$C=0.1$	$C=0.6$	$C=1.1$	$C=2.1$
$p=1$	?	?	?	?	?	?	?	?
$p=2$	?	?	?	?	?	?	?	?
$p=3$	?	?	?	?	?	?	?	?
$p=4$	?	?	?	?	?	?	?	?
$p=5$	?	?	?	?	?	?	?	?

If g(x_test) > 0

x_test_label = +1

Else

x_test_label = -1

Task3: Evaluation

Task3 – Data

Evaluation set – 600 samples

- Not Given – 'eval.mat'
  - eval_data (57 x 600)
  - eval_label (600 x 1)

Task3 – Evaluation

Design your own SVM

- Hard margin or Soft margin?
- Linear or Polynomial kernel?
- What are the values for p and C?

To produce the best performance

To classify the 600 samples in the evaluation set

Not Given – 'eval.mat'

eval_data (57 x 600)

eval_label (600 x 1)

Output : A column vector (600 x 1) named 'eval_predicted'

Important Notes

Important Notes

Preprocess your data – Choose one method

- Sample scaling/ Mean normalization/ standardization/ Rescaling ...

Use the training set statistics to preprocess the other data sets

- For training set, test set and eval set

Check Mercer Condition for Kernel suitability

Don’t use inbuilt MATLAB functions like ‘fitsvm’, ‘predict’

Important Notes

Mercer's condition

For training set $S = \{(\mathbf{x}_i, d_i)\}$, $i = 1, 2, \ldots, N$, the Gram matrix

$$\mathbf{K} = \begin{bmatrix} K(\mathbf{x}_1, \mathbf{x}_1) & \ldots & K(\mathbf{x}_1, \mathbf{x}_N) \\ \vdots & \ddots & \vdots \\ K(\mathbf{x}_N, \mathbf{x}_1) & \ldots & K(\mathbf{x}_N, \mathbf{x}_N) \end{bmatrix} \in R^{N \times N}$$

is positive semi-definite (i.e., its eigenvalues are nonnegative)

- In practice, the eigenvalues of the matrix K always contain some very small negative values. We need to set a very small negative value (-1e-4 or -1e-6) as the threshold. As long as there is no eigenvalue smaller than it, then we believe that Mercer's condition is established.

Important Notes

Procedure to build SVM

- Preprocess data
- Choose a suitable kernel
  - Linear/ Nonlinear ?
- Choose C
  - Hard margin/ Soft margin
    - Hard margin $0 \leq \alpha_i$
      - $C = +\infty$ (In theory)
      - C = Large value (In practice e.g. 10^6)
- Solve for α_i
  - Quadratic programming
- Support vector selection
  - Choose an appropriate threshold (e.g. 1e-4) to determine the corresponding α_i to the support vectors and make smaller α_i values zero.
- Determine the discriminant function g(x)

Important Notes

Submit all your codes that you have implemented for the entire project

Submit all required files – even if it is ‘train.mat’

Make sure your codes run without error

All codes should be executable with the given datasets in the workspace without any additional inputs

Important Notes

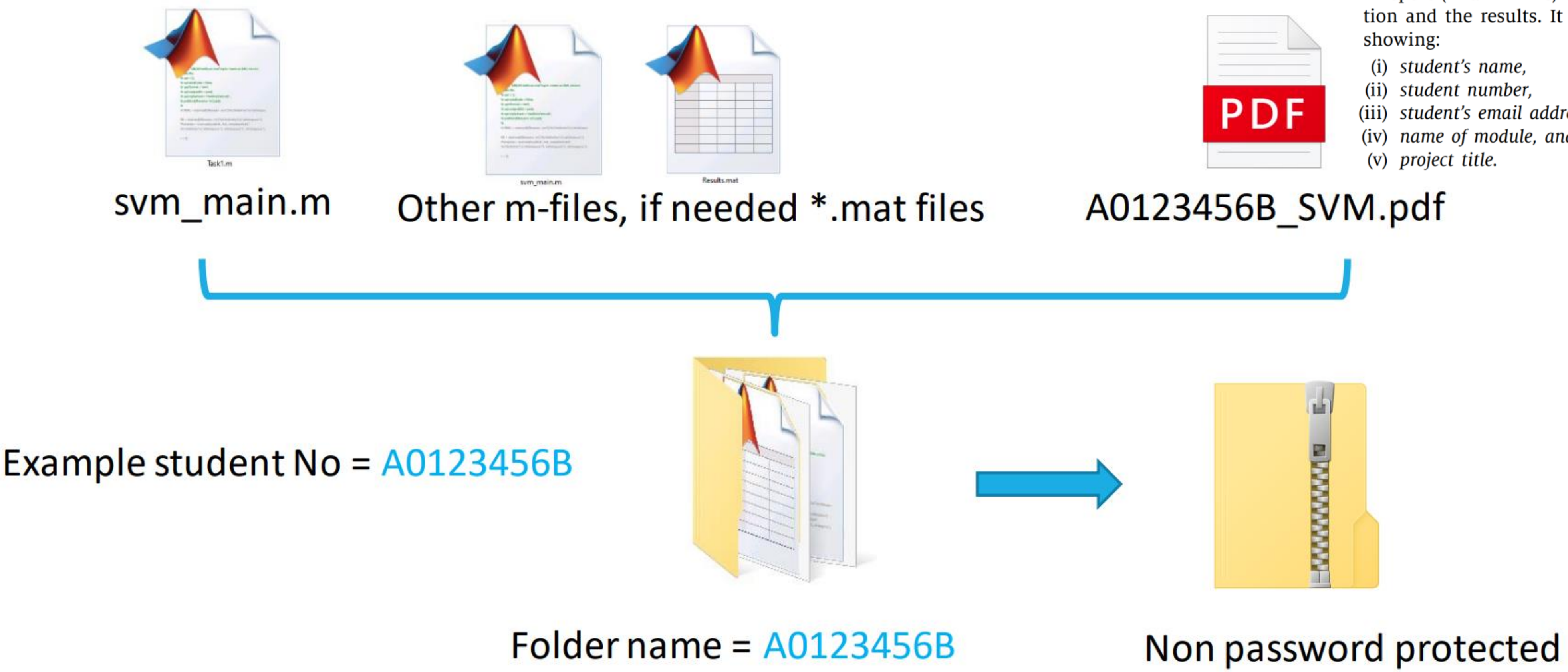
Report

- Details on Implementation
- Completed Table 1
- Discussion under following subheadings
  - Data pre-processing
  - Admissibility of the kernels
  - Existence of optimal hyperplanes
  - Table 1 - Comments on results (with supporting arguments)
  - Task 3 – Discussion on design decisions

Type of SVM	Training accuracy				Test accuracy			
Hard margin with Linear kernel	?				?			
Hard margin with polynomial kernel	$p=2$	$p=3$	$p=4$	$p=5$	$p=2$	$p=3$	$p=4$	$p=5$
	?	?	?	?	?	?	?	?
Soft margin with polynomial kernel	$C=0.1$	$C=0.6$	$C=1.1$	$C=2.1$	$C=0.1$	$C=0.6$	$C=1.1$	$C=2.1$
$p=1$	?	?	?	?	?	?	?	?
$p=2$	?	?	?	?	?	?	?	?
$p=3$	?	?	?	?	?	?	?	?
$p=4$	?	?	?	?	?	?	?	?
$p=5$	?	?	?	?	?	?	?	?

TABLE I: Results of SVM classification.

Important Notes



A report (in a PDF file) describing the implementation and the results. It must contain a cover page showing:

(i) *student's name,*
(ii) *student number,*
(iii) *student's email address,*
(iv) *name of module, and*
(v) *project title.*

Report due on 21 April 2023, 23:59 Singapore time

Thank you