a) We can map X and & to vectors that represent the presense of a word. Each vector is the length of all possible words that appear in any document and is index matched to a word. If that word appears in X, it will have a last that index and a O otherwise. Thus to find the number of unique words, we can take the dot product of vectors X and &. This is a kernal function as & is I if the word is present in this downent.

b)

K(x, z) = X · z

f(x) = \frac{1}{1|x|1}

f(z) = \frac{1}{1|x|1}

180 X & 15 a kernel foreture

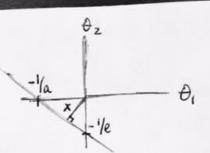
1 is a Kernel Rineton if  $\beta = 1$  so the dot product is 1. Thus  $1 + \frac{1}{11 \times 11} \cdot \frac{1}{11 \times 11}$  is kernel Punethon.

Because of the product rule,  $1+\frac{x}{11\times11}\cdot\frac{2}{11\times11}$  times by street 3 times is also a kernel Function. thus  $(1+\frac{x}{11\times11}\cdot\frac{2}{11\times11})^3$  is a kernel function.

 $\begin{array}{l} \text{Te} \left( \begin{array}{c} x = \langle \lambda_{1}, x_{2} \rangle \\ \\ \xi = \langle \xi_{1}, \xi_{2} \rangle \\ \\ \text{Kg} \left( x_{1} \, \xi \right) = \left( 1 + B \left( x_{1} \, \xi_{1} + x_{2} \, \xi_{2} \right) \right)^{3} \\ \\ = \beta^{3} \, x_{1}^{3} \xi_{1}^{3} \, + 3 \beta^{5} \, x_{1}^{2} \, \xi_{1}^{2} \, x_{2} \, \xi_{2} \, + 3 \beta^{2} \, x_{1}^{2} \, \xi_{1}^{2} \, + 3 \beta^{3} \, x_{1} \, \xi_{1}^{2} \, \xi_{2}^{2} \\ \\ + 6 \, \beta^{2} \, x_{1} \, \xi_{1} \, x_{2} \, \xi_{2} \, + 3 \beta \, x_{1} \, \xi_{1} \, + \beta^{3} \, x_{2}^{3} \, \xi_{2}^{3} \, + 3 \beta^{2} \, x_{2}^{2} \, \xi_{2}^{2} \, + 3 \beta \, x_{2} \, \xi_{2} \, + 1 \\ \phi_{B} = \left( \begin{array}{c} \beta^{3/2} \, x_{1}^{3} \, + \sqrt{3} \, \beta^{3/2} \, x_{1}^{2} \, x_{2} \, \sqrt{3} \, \beta \, x_{2}^{2} \, \sqrt{3} \, \beta \,$ 

B scales each term to some degree so it can scale or decrease the magnitude of the Warnel Function,

Problem 2  
a) MINIMITING 
$$\frac{1}{2}(\theta_1^2 + \theta_2^2)$$
  
Constraints:  $+(a\theta_1 + e\theta_2) \ge 1$   
 $a\theta_1 + e\theta_2 \le -1$ 



$$\frac{V}{||V||} = \frac{a\hat{\theta}_1}{\sqrt{a^2 e^2}} + \frac{e\hat{\theta}_2}{\sqrt{a^2 + e^2}}$$

$$X = \frac{\hat{\theta}_1}{-a_1} \cdot \left( \frac{a\hat{\theta}_1}{\sqrt{a^2 + e^2}} \cdot \frac{e\hat{\theta}_2}{\sqrt{a^2 + e^2}} \right)$$

$$= \sqrt{a^2 + e^2}$$

$$\theta_1 = \frac{-a}{a^2 e^2}$$
  $\theta_2 = \frac{-e}{a^2 + e^2}$ 

b) 
$$\theta_1 + \theta_2 \ge 1$$
  
 $-\theta_1 \ge 1 \Rightarrow \theta_1 \le -1$   
 $\theta_1 \ge 0$ 

$$\begin{array}{ccc}
-\theta_1 \geq 1 \Rightarrow \theta_1 \leq -1 \\
\vec{\nabla} = \hat{\theta}_1 + \hat{\theta}_2
\end{array}$$

$$\theta_{2}^{*} = 2 \frac{1}{\sqrt{12...22}}$$

$$\theta_z^* = 2 \frac{1}{\sqrt{1^2 + 2^2}} = \frac{1}{\sqrt{5}}$$

c) 
$$\theta_1 + \theta_2 + b \ge 1$$
 >  $\theta_1 + \theta_2 \ge 1 - b$   
-  $(\theta_1 + b) \ge 1$  >  $\theta_1 \le -1 - b$ 

to the origin

$$b^* = \frac{-1}{2^2} = \frac{1}{2}$$

Problem 3 accoracy | FI-score | AUROC | precision | sensitivity | specificity ii.d) 0.7089 0.0062 10-3 0.7089 0.8297 0.5 0.7102 0.5081 10-2 0.5031 0.7107 0.8306 0.9294 0.8356 10-1 0.6045 0.7187 0.80 60 0.8755 0.9016 100 0.8561 0.6166 0.7531 0.8146 0.8748 0.9016 0.8595 10' 0.7591 0.6166 0.8765 0.8182 102 0,9016 0.8595 0.7591 0.8182 0.8765 10.0 0.001 best C 10.0 10.0 10.0 10.0

For accuracy, FI-score, AUROC, and precision the performance increases with increased C. As for sensitivity, performance decreases with higher C. Specificity also increases performance with higher C.

8 defines how far the influence of a single training example reaches.
A large gamma leads to high bias and low variance while a small gamma leads to low bias and high variance.

which had possible values from 10-3 to 102 like part 3.2.

iii.c) metric Score accuracy 0.8165 0.01 100 0.01 0.8763 FI-Score 0.01 100 0.7545 AUROC 0.01 0.8583 100 precision 0.00 sensitivitu specificary 0.6047 100 0.01

A higher C and lower & gave better performance for all metrics except for sensitivity. 100 as C and 8=0.01 seemed to be the best parameters.

(v.e)	linear score	rbf score
accuracy		0.7571
fl-score	0.4375	0.4516
avroc		0.6360
precision	0.6363	0.7
sensitivity	0.333	0.3333
sensitivity specificity	0.9184	0,9388

The rbf classifier SVM performs better than the linear SVM.