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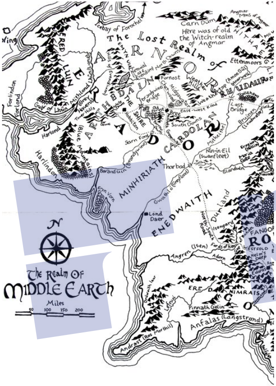
The Lost Realm of
ARNOR
Here was of old the Witch-realm of Angmar
Carn Dûm
Ettenmoors
Fornost
Weather Hills
Last Bridge
Bree
South Downs
Sarn Ford
Tharbad
CARDOLAN
MINHIRIATH
ENEDWAITH
Lond Daer
Dunland
Isengard
Fords of Isen
Helm's Deep
Edoras
Angren (Isen)
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Harlindon
Harlond
Gulf of Lhûn
Forlindon
Forlond
Blue Mountains
N
The Realm of Middle Earth
Miles
50 100 150 200

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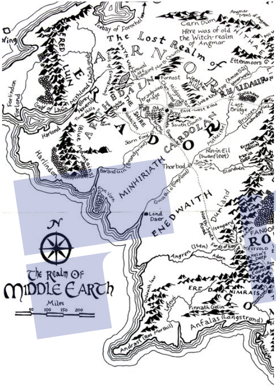

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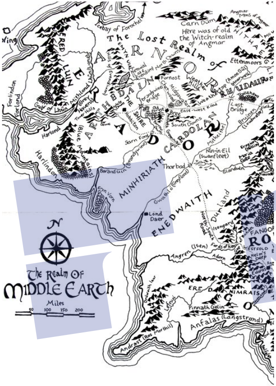

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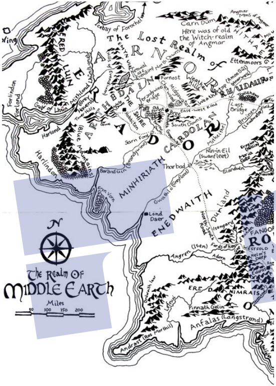

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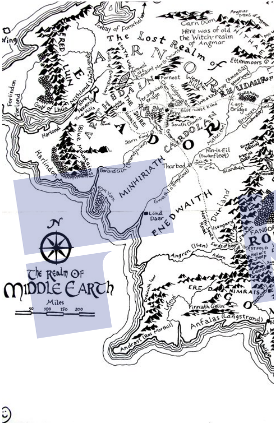

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These techniques involve some important decisions about the bias-variance tradeoff, and the use of (cross) validation in checking model performance and selecting the best model.

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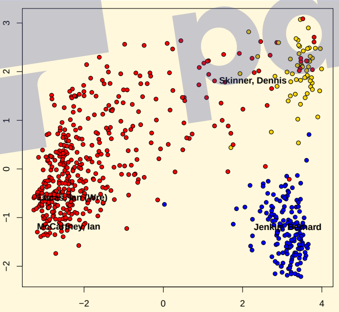

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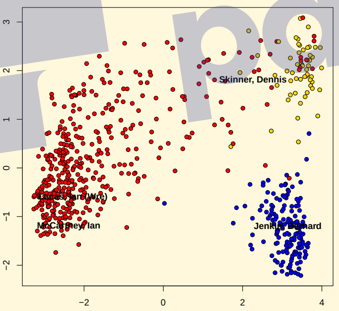

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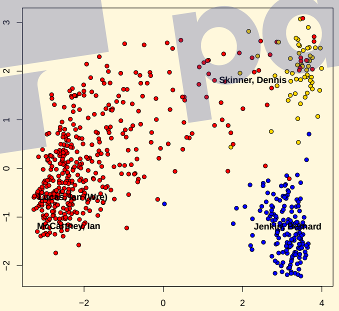

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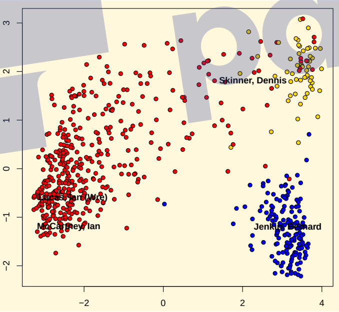

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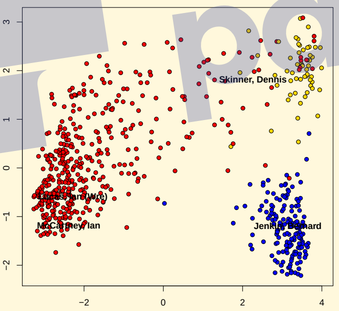

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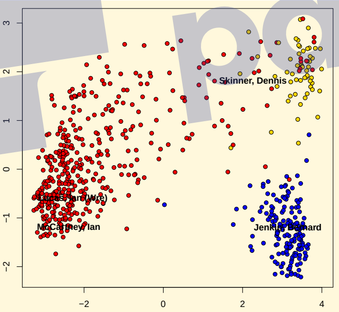

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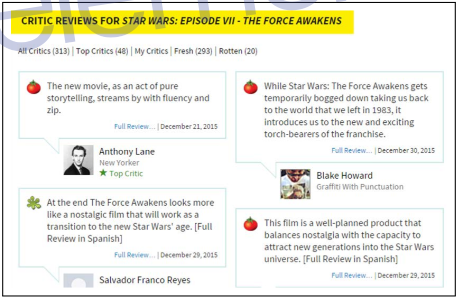

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4 Report accuracy in test set, possibly combine with other learners in ensemble.

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So techniques may require careful tuning of *regularization parameters* to obtain good performance.

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So managing the *bias-variance tradeoff* is a key element of supervised learning, and we may need to tune our algorithms with that in mind.

Bias-Variance Tradeoff (Hastie et al, p38)

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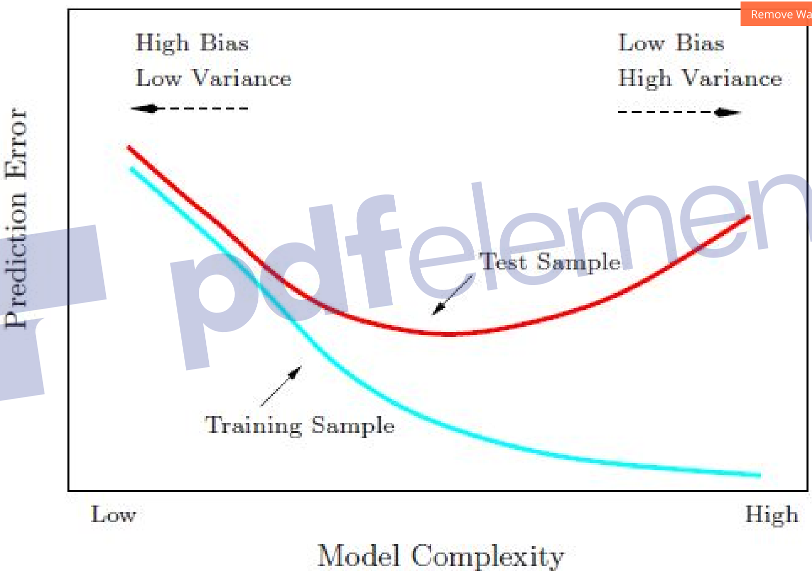

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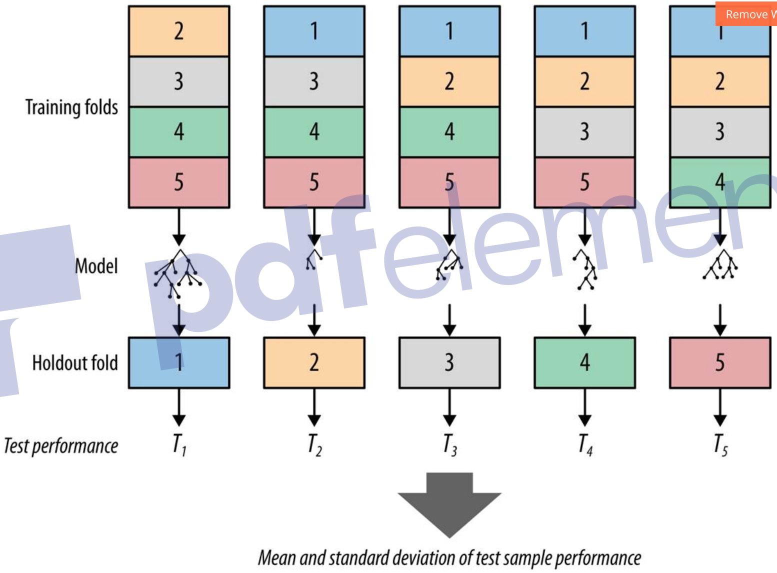

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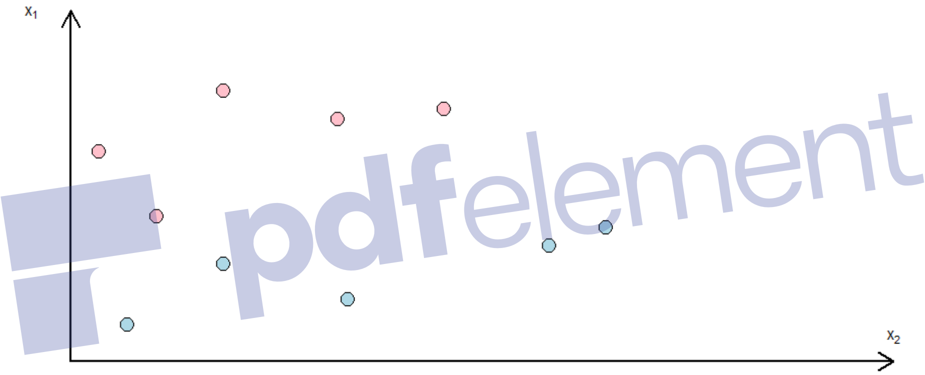

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As the parties linearly separably? Where could you draw the line?

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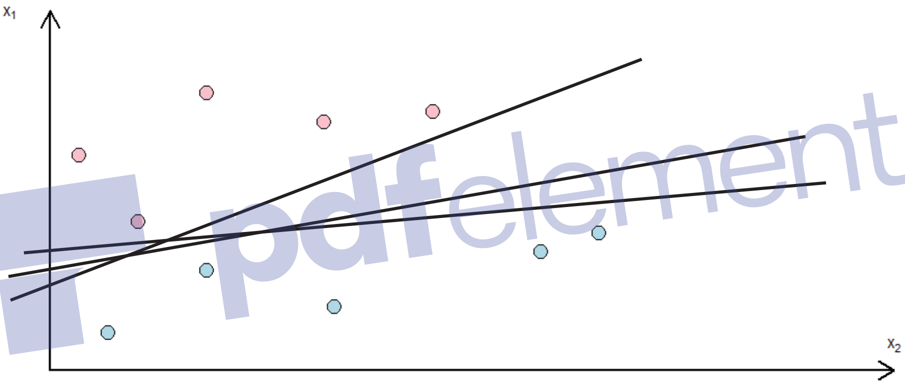

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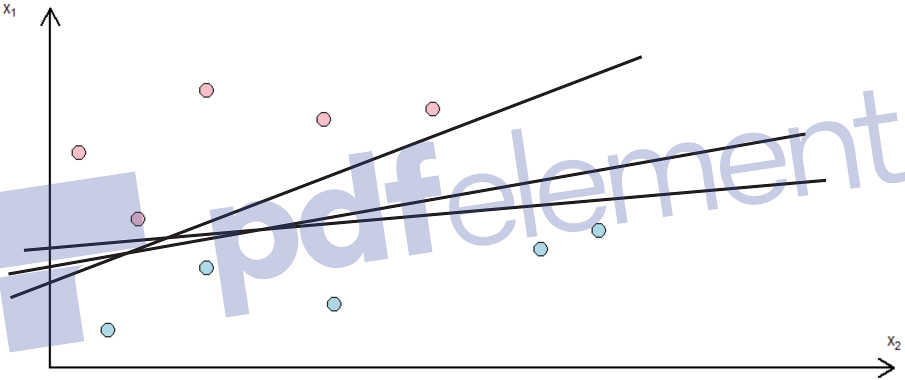

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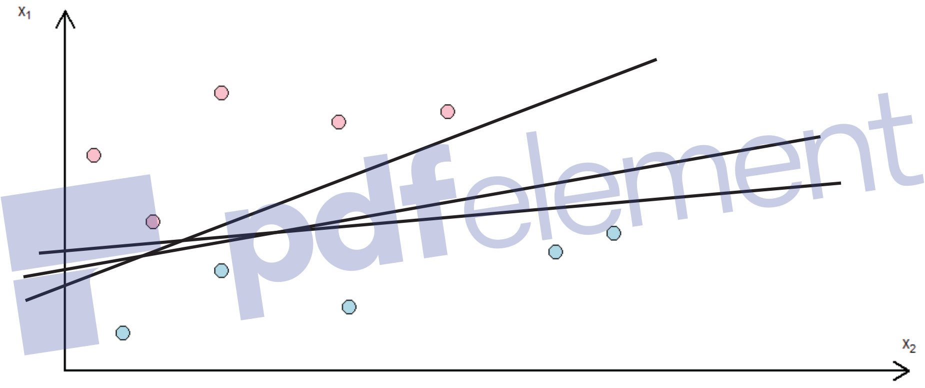

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$\rightarrow$ That optimal line—the separating hyperplane—is the maximum margin hyperplane. It will maximize the margin of the training data.

Partner Exercise

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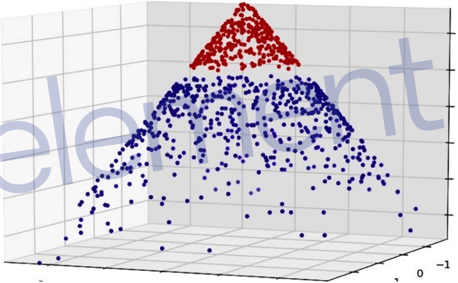
Consider the figure.

It's a situation where each Senator's features are of three dimensions (rather than two).

How could we (optimally) separate the data in a linear way?

Can we still use a line?



from http://www.edvancer.in/

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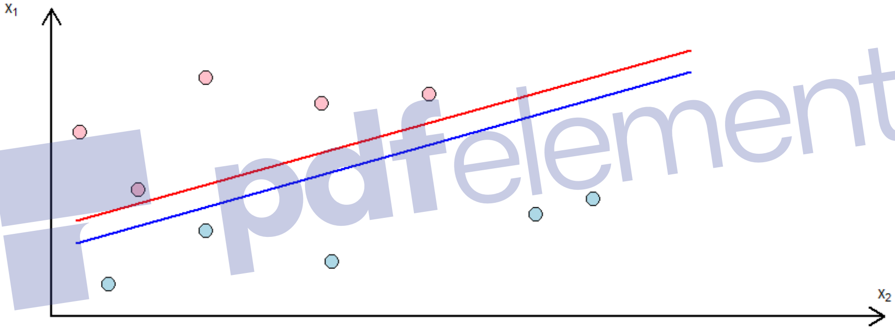

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NB The hyperplane cannot be anywhere other than equidistant because then it will break the rule about ensuring the largest minimum distance.

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Turns out that the minimization of $||\mathbf{w}||$ is amenable to quadratic programming methods.

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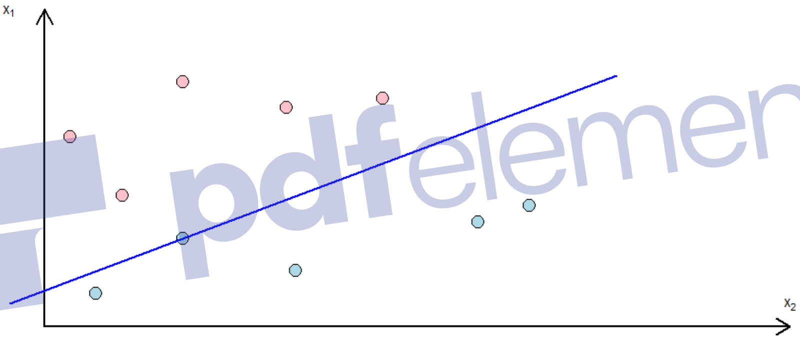

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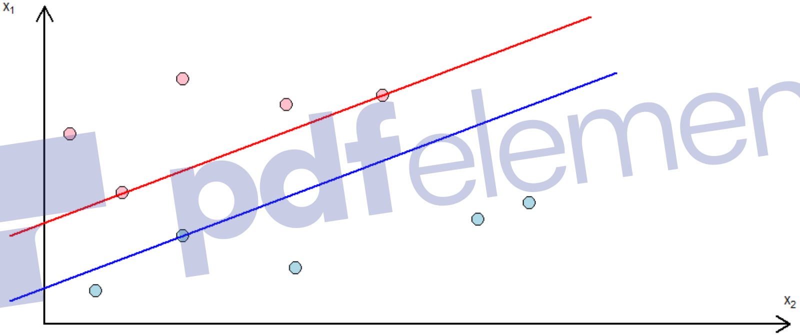

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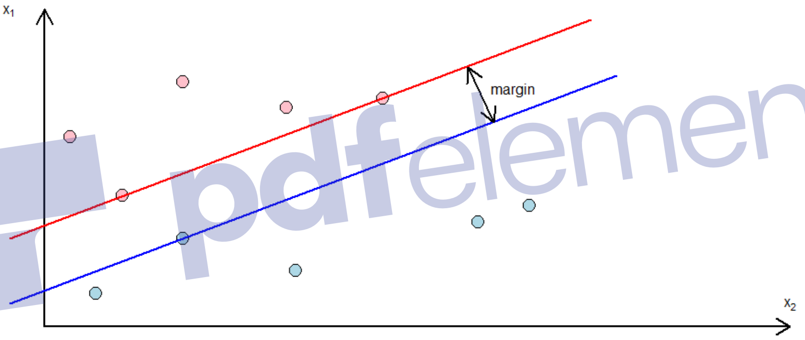

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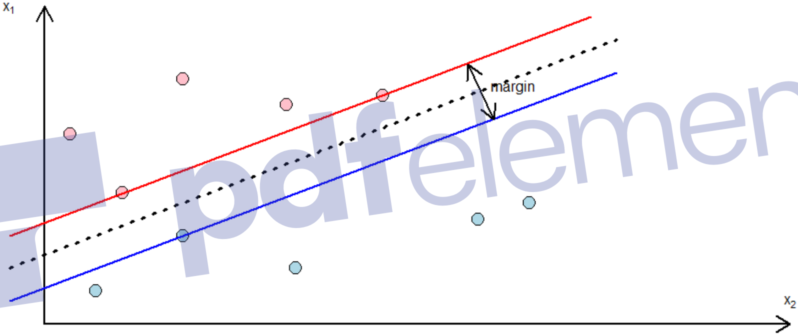

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We use the term support vectors to describe the training examples closest to the hyperplane. Those support vectors completely determine where our maximum-margin hyperplane will be.

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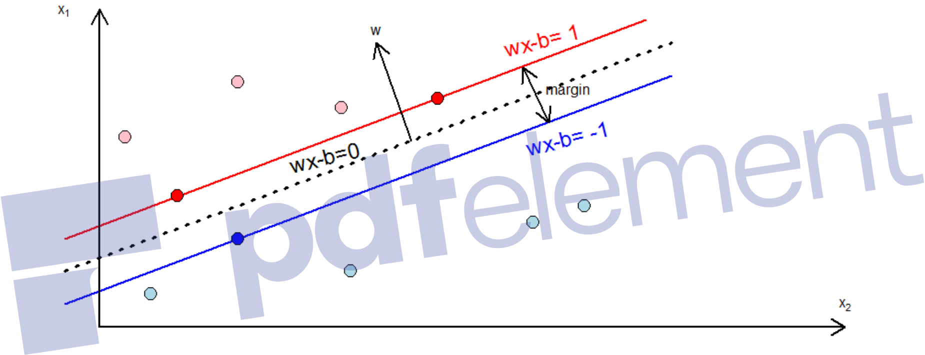

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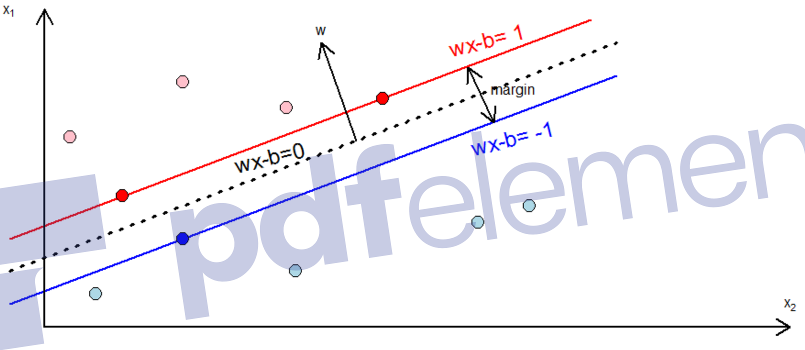

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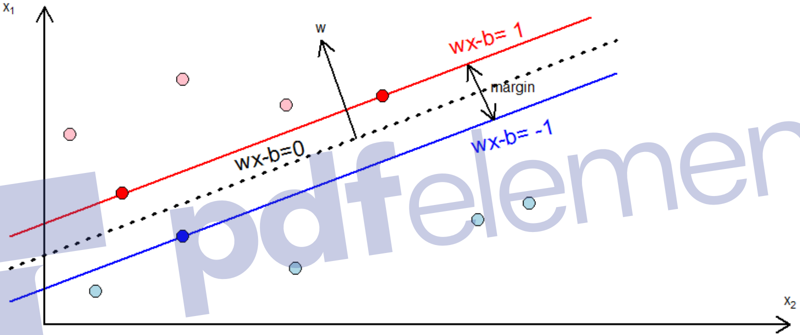

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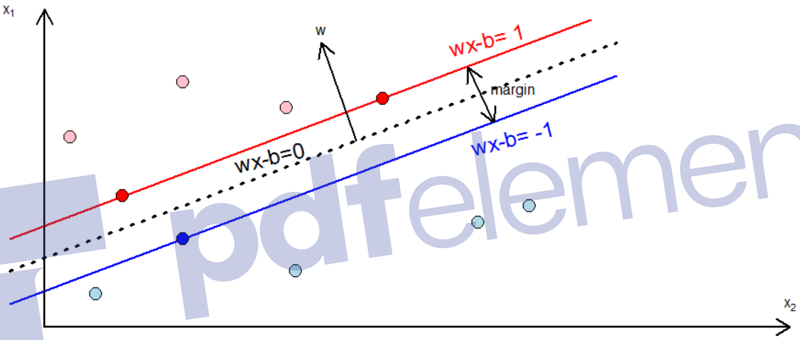

The support vectors lie on...

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NB SVMs typically have few features with non-zero weights, and those that are non-zero come from the support vectors (the 'important' observations)

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Words			
Liberal		Conservative	
FAS: −199.49	SBA: −113.10	habeas: 193.55	homosexual: 103.07
Ethanol: −198.92	Nursing: −109.38	CFTC: 187.16	everglades: 102.87
Wealthiest: −159.74	Providence: −108.73	surtax: 151.81	tower: 101.67
Collider: −142.28	Arctic: −108.30	marriage: 145.79	tripartisan: 101.23
WIC: −140.14	Orange: −107.98	cloning: 141.71	PRC: 102.90
ILO: −139.89	Glaxo: −107.81	tritium: 133.49	scouts: 97.55
Handgun: −129.01	Libraries: −107.70	ranchers: 132.95	nashua: 99.32
Lobbyists: −128.95	Disabilities: −106.44	BTU: 121.92	ballistic: 97.22
Enron: −127.71	Prescription: −106.31	grazing: 121.59	salting: 94.28
Fishery: −127.30	NIH: −105.52	unfunded: 120.82	abortion: 91.94
Hydrogen: −122.59	Lobbying: −105.35	catfish: 120.82	NTSB: 93.81
Souter: −121.40	NRA: −105.20	IRS: 114.91	Haiti: 97.28
PTSD: −119.87	Trident: −104.15	unborn: 111.88	PAC: 92.85
Gun: −119.52	RNC: −103.46	Taiwan: 111.13	taxing: 90.39

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1 Does that imply that making conservative Senators use the word '`handgun`' more often will make them more liberal? What does your answer suggest about prediction vs explanation with supervised techniques?

2 what is the (most likely) problem in the causal claim that $X \rightarrow Y$ in the Diermeier et al study?

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BTW RLR can cope well with noise, and (hard margin) SVM will struggle if there is no linear seperability...

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Graphically. . .

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Hyperplane(s) will be drawn in way that is more sensitive to 'bigger' mistakes in classification.

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   $1 - f(x)y$ is $1 - (-2)(+1)$ in first case and $1 - (-100)(+1)$ in second case. Hinge loss larger in second case!

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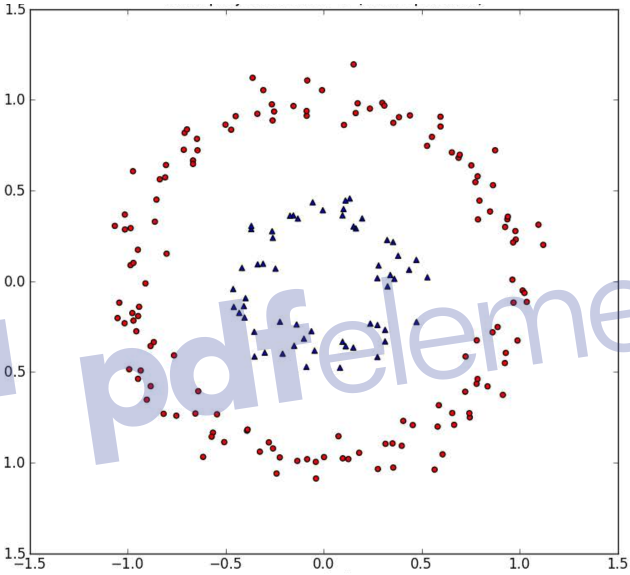

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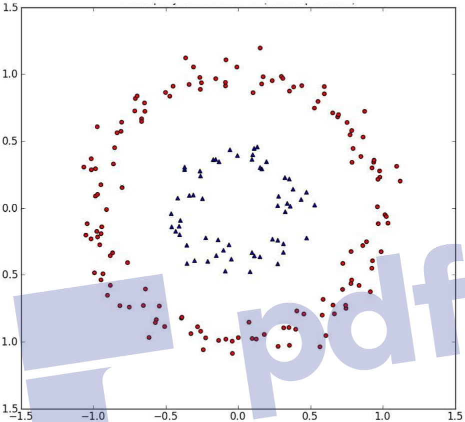
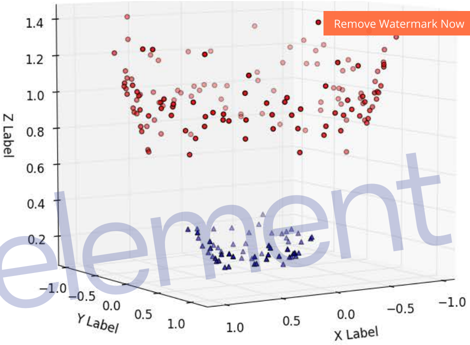
$\rightarrow$ Results in a non-linear hyperplane once back in 2 dimensions.





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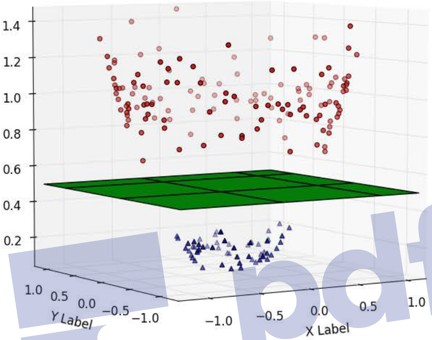
1.4
1.2
1.0
0.8
0.6
0.4
0.2
1.0
0.5
0.0
−0.5
−1.0
Y Label
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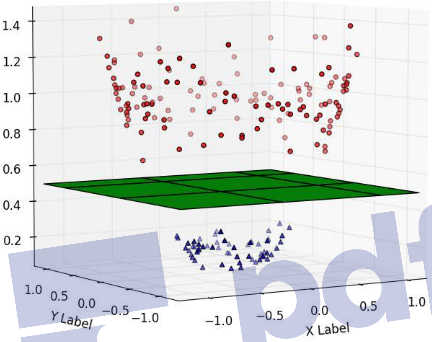

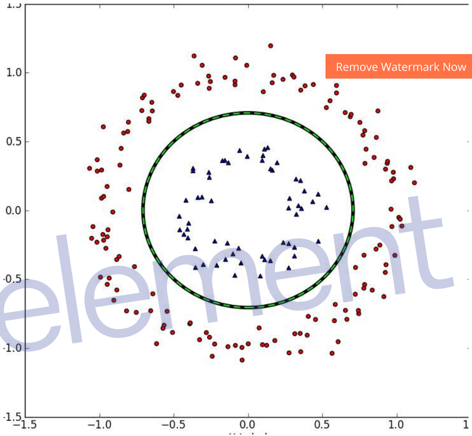

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For text analysis, string kernels use a function $K(a, b)$ to implicity calculate the distance between strings of characters via the number of subsequences they have in common.

Partner Exercise

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Using the ideas we discussed at the start of lecture, how should one go about picking a kernel (from the large variety on offer) for the problem at hand?