6. Supervised Techniques III

DS-GA 3001, Text as Data
Arthur Spirling

March 6, 2018

Housekeeping

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1. Speaker series Thursday: Justine Zhang on “Unsupervised Models of Conversational Dynamics”.

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2. Homework 2 out soon—due $\sim$ March 25.

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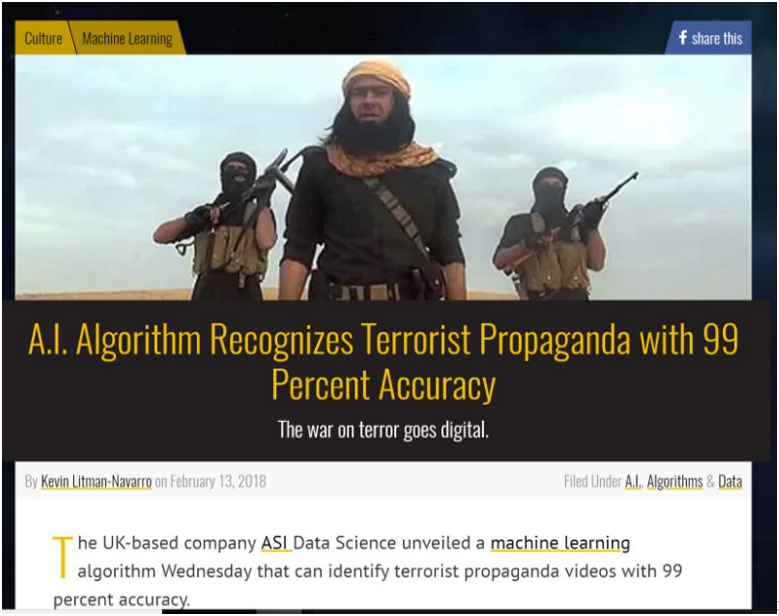

Culture \ Machine Learning

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A.I. Algorithm Recognizes Terrorist Propaganda with 99 Percent Accuracy

The war on terror goes digital.

By Kevin Litman-Navarro on February 13, 2018

Filed Under A.I., Algorithms & Data

The UK-based company ASI Data Science unveiled a machine learning algorithm Wednesday that can identify terrorist propaganda videos with 99 percent accuracy.

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Where Are We?

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Icebay of Forochel
Carn Dûm
Here was of old the Witch-realm of Angmar
The Lost Realm of
ARNOR
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
RHUDAUR
Last Bridge
East-West Road
Bree
South Downs
CARDOLAN
THE SHIRE
Hobbiton
Sarn Ford
Grey Havens
Gulf of Lhûn
Forlindon
Forlond
Harlond
Harlindon
Blue Mountains
ERIADOR
MINHIRIATH
Tharbad
Nîn-in-Eilph (Swanfleet)
ENEDWAITH
Dunland
Lond Daer
Isengard
FANGORN
WESTFOLD
Helm's Deep
Angren (Isen)
Adorn
ERED NIMRAIS
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
The Realm of Middle Earth
Miles
50 100 150 200

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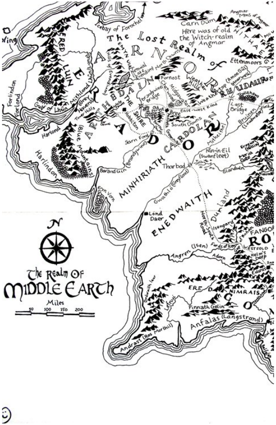

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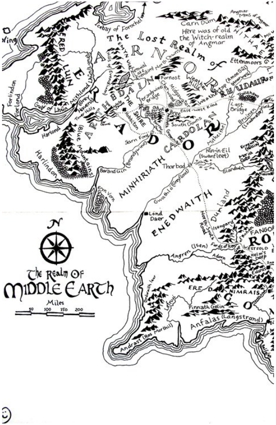

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These techniques involve some important decisions about the bias-variance tradeoff, and the use of (cross) validation in checking model performance and selecting the best model.

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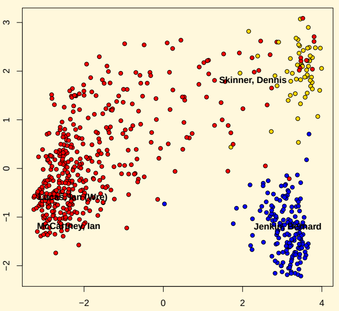

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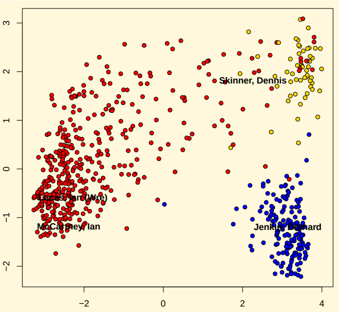

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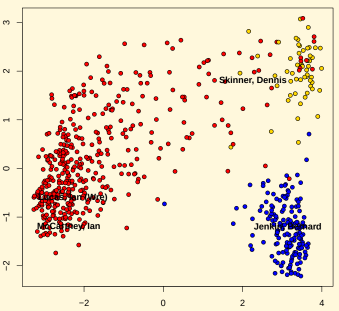

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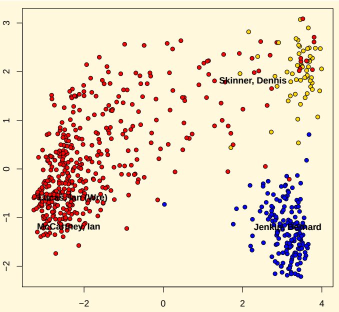

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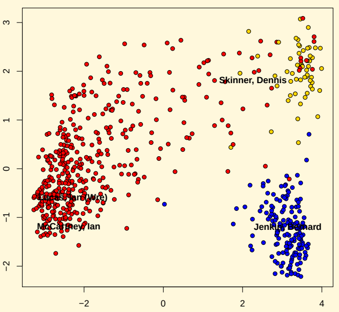

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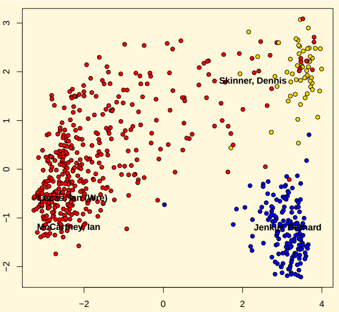

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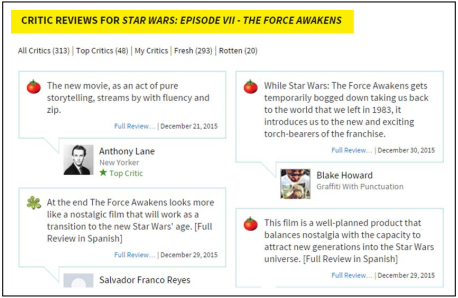

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So techniques may require careful tuning of *regularization parameters* to obtain good performance.

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Bias-Variance Tradeoff (Hastie et al, p38)

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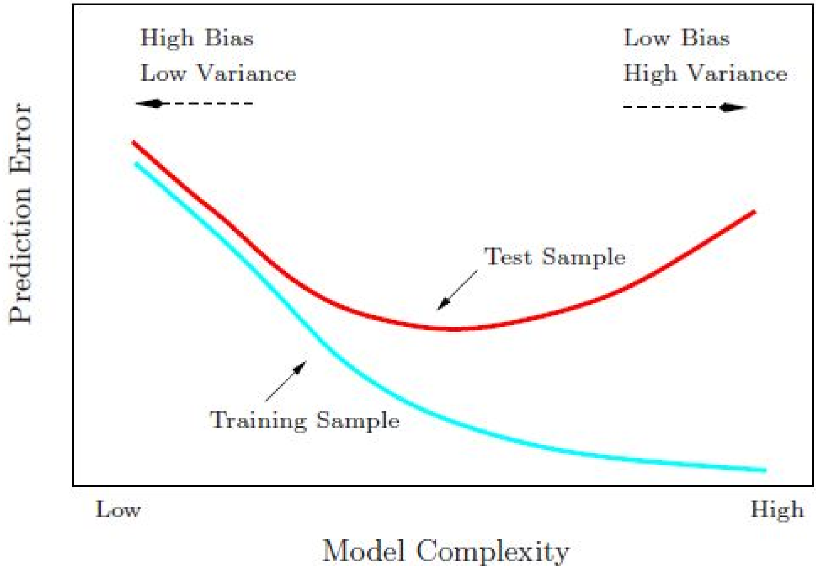

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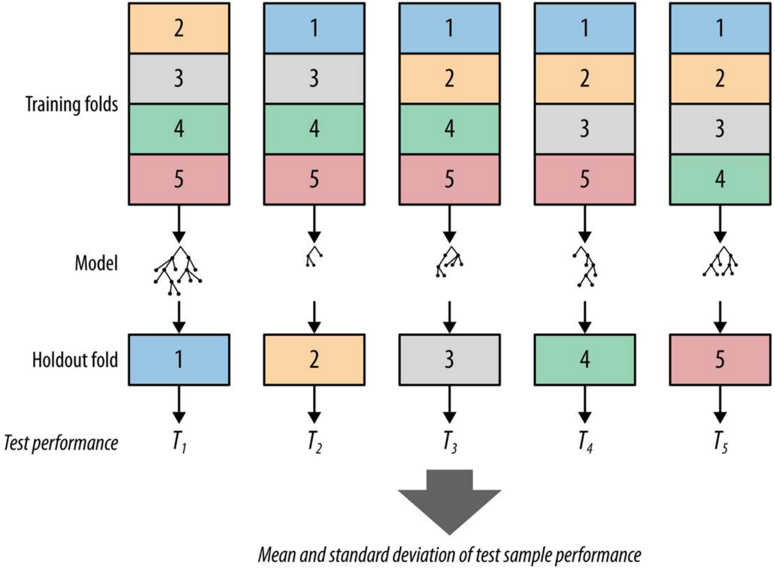

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Motivating Example Diermeier et al, 2011

Diermeier et al want to know what terms are most indicative of conservative or liberal positions in legislative debates.

Study the speeches of the 25 most liberal and the 25 most conservative senators (1989–2004), selected based on their NOMINATE scores (from roll call behavior, only)

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Have the (stemmed, stopped, weighted etc) speech term matrix for each Senator as X.

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What method to use?

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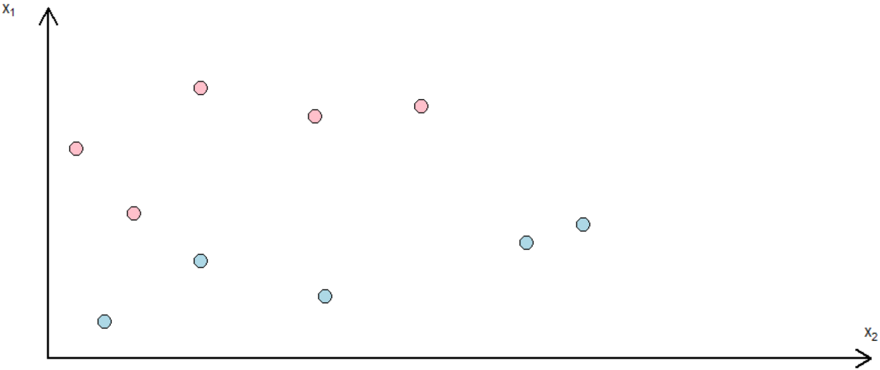

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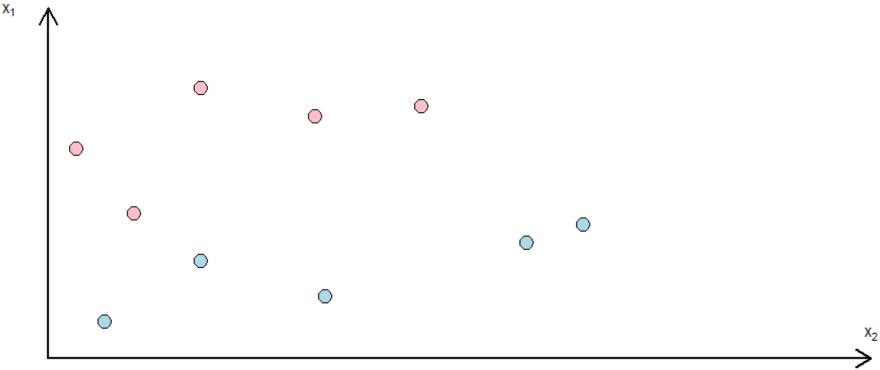

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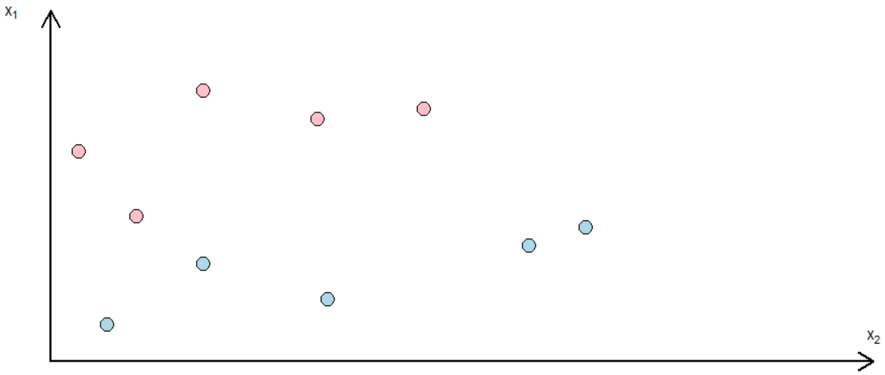

As the parties linearly separably? Where could you draw the line?

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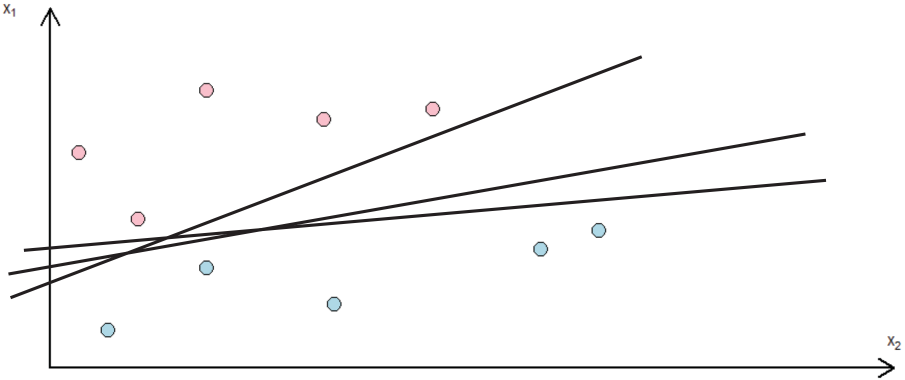

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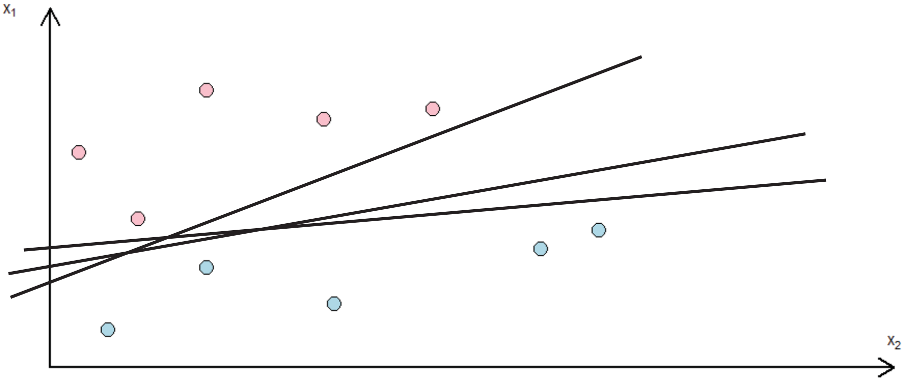

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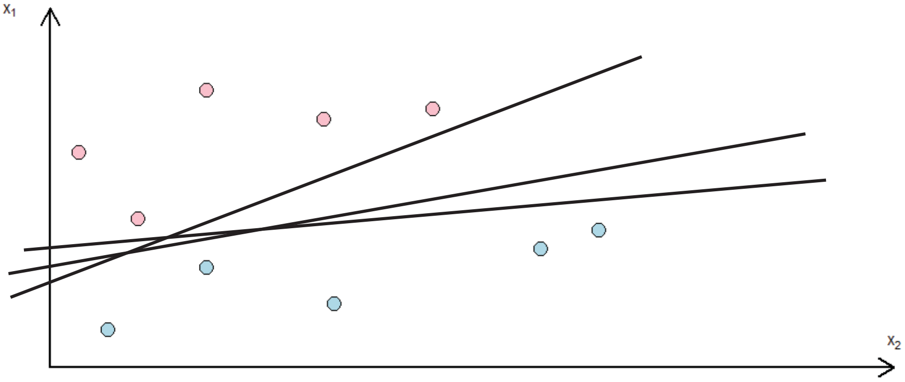

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$\rightarrow$ That optimal line—the separating hyperplane—is the maximum margin hyperplane. It will maximize the margin of the training data.

Partner Exercise

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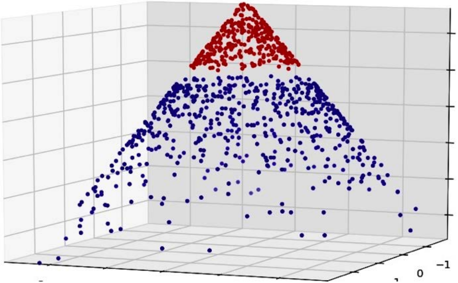
Consider the figure.

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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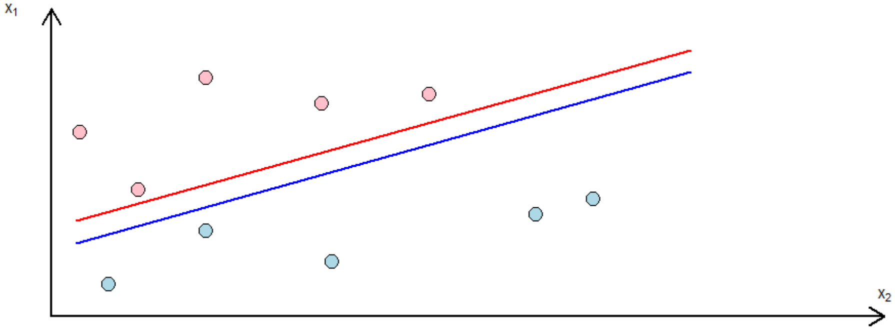

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NB The hyperplane cannot be anywhere other than equidistant because then it will break the rule about ensuring the largest minimum distance.

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

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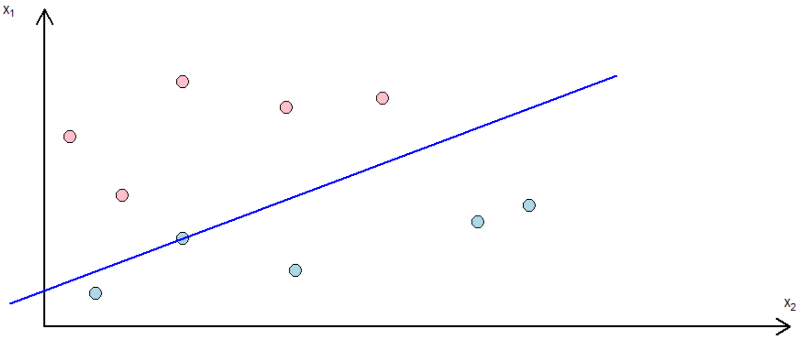

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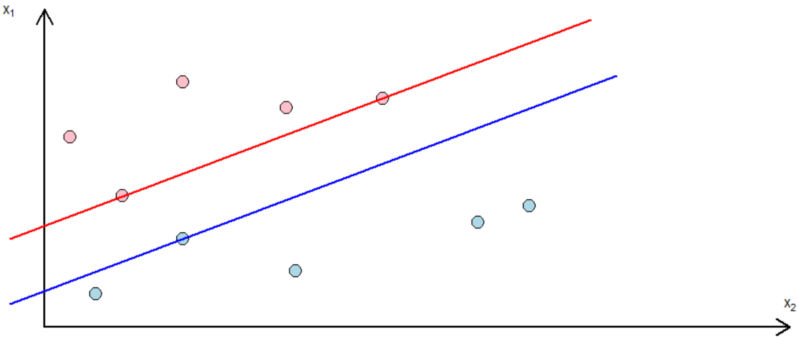

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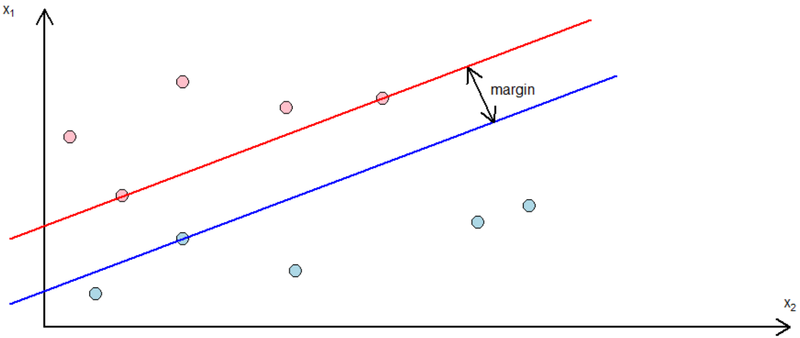

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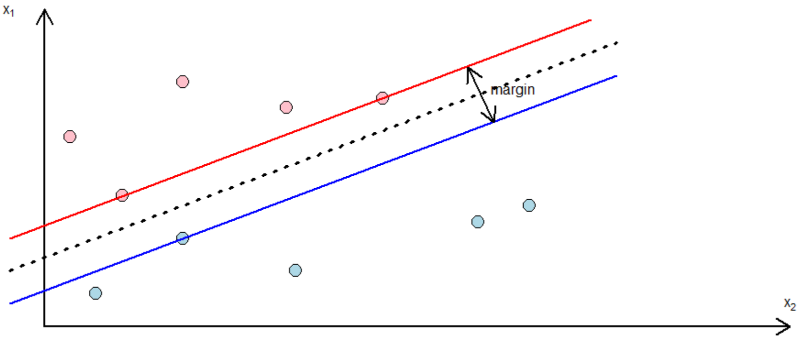

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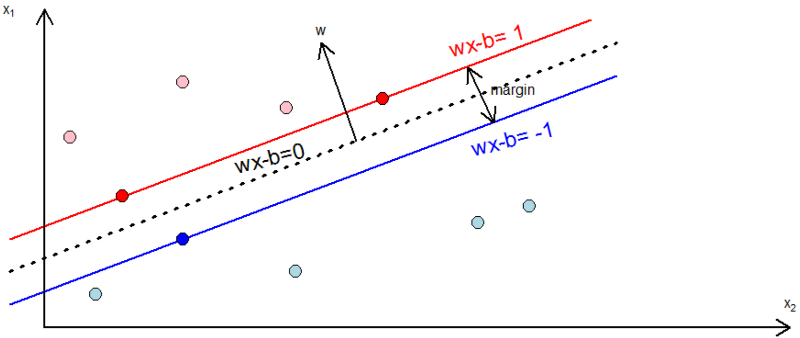

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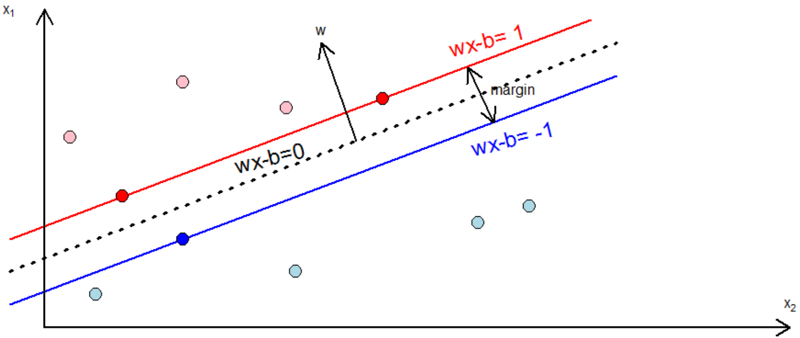

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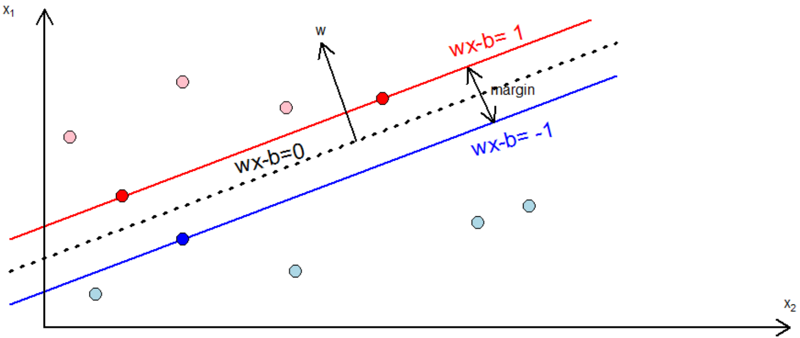

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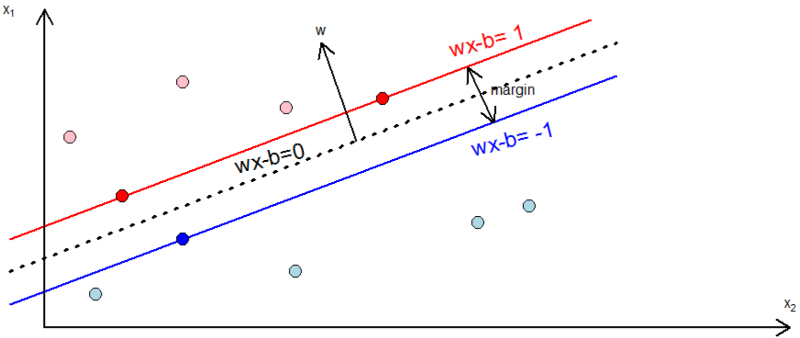

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Words			
Liberal		Conservative	
FAS: −199.49	SBA: −113.10	habeas: 193.55	homosexual: 103.07
Ethanol: −198.92	Nursing: −109.38	CFTC: 187.16	everglades: 102.87
Wealthiest: −159.74	Providence: −108.73	surtax: 151.81	tower: 101.67
Collider: −142.28	Arctic: −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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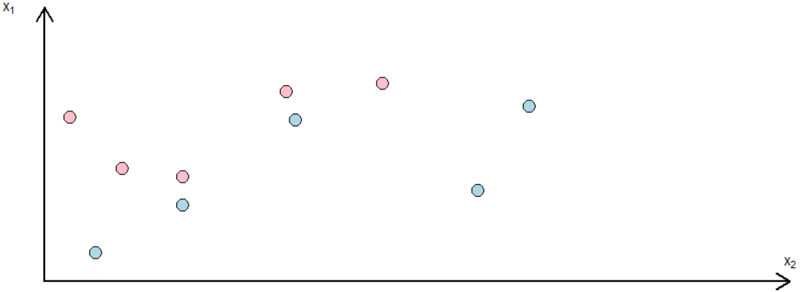

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Hyperplane(s) will be drawn in way that is more sensitive to 'bigger' mistakes in classification.

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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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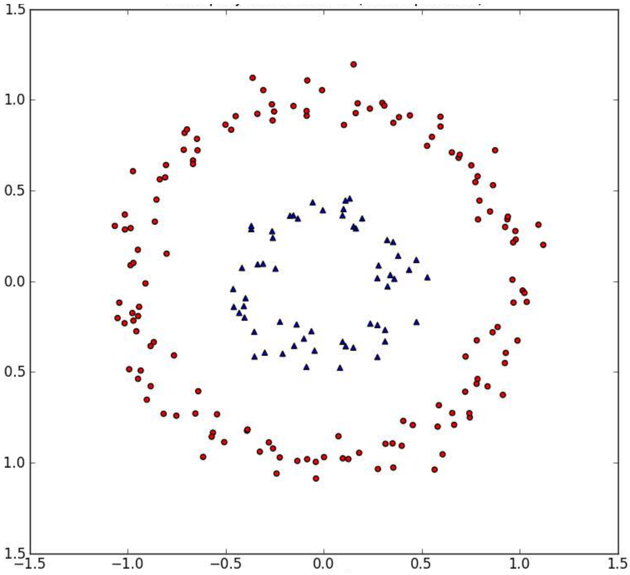

from www.eric-kim.net

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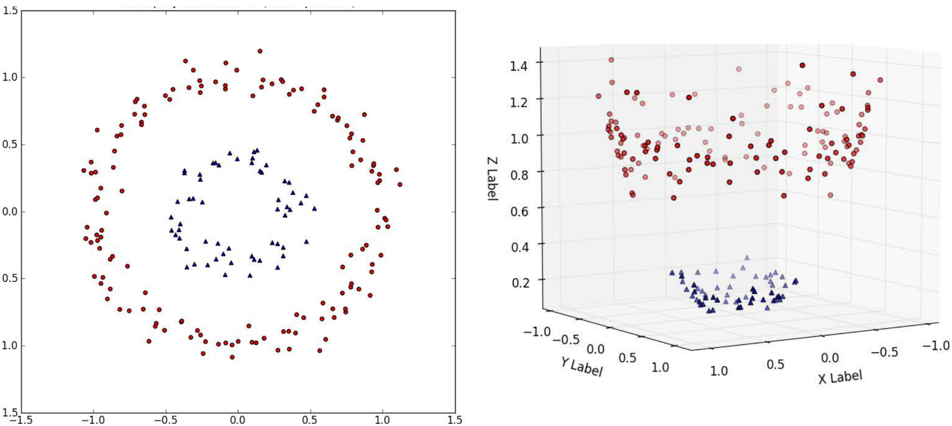
$\rightarrow$ Results in a non-linear hyperplane once back in 2 dimensions.



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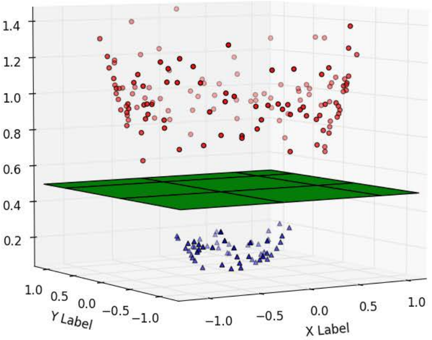
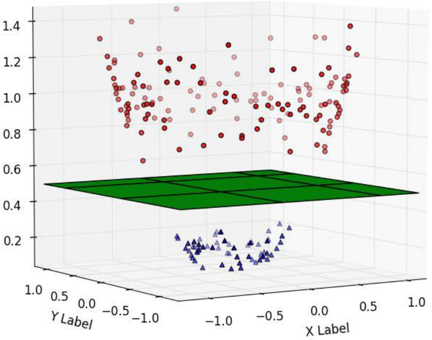
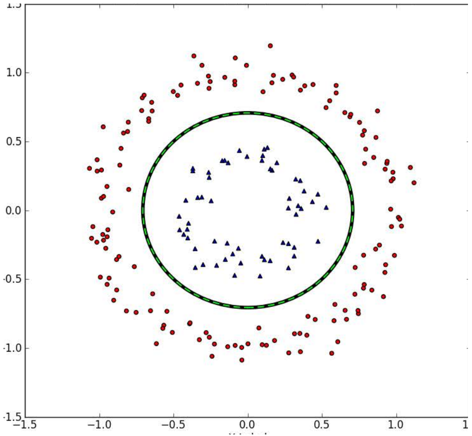

1.4
1.2
1.0
0.8
0.6
0.4
0.2
1.0 0.5 0.0 −0.5 −1.0
Y Label
−1.0 −0.5 0.0 0.5 1.0
X Label





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Kernel Methods

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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?