6. Supervised Techniques III

DS-GA 3001, Text as Data
Arthur Spirling

March 6, 2018

Housekeeping

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

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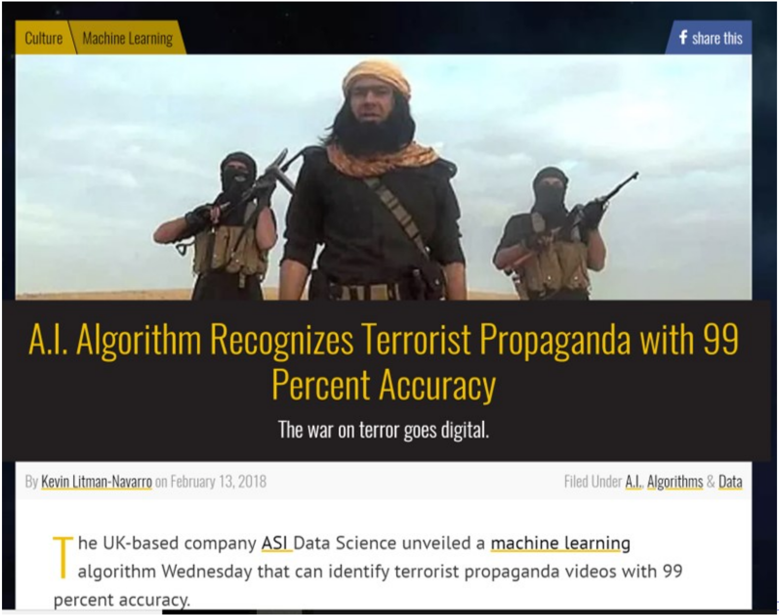

Culture | Machine Learning

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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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The Lost Realm of Arnor
Here was of old the Witch-realm of Angmar
Carn Dûm
Ettenmoors
Fornost
Weather Hills
Weathertop (Amon Sûl)
Rhudaur
Last Bridge
East-West Road
Bree
South Downs
The Shire
Hobbiton
Sarn Ford
Cardolan
Eriador
Gulf of Lhûn
Mithlond (Grey Havens)
Harlond
Harlindon
Forlindon
Forlond
Ered Luin
Blue Mountains
Minhiriath
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
Gwathló (Greyflood)
Enedwaith
Dunland
Lond Daer
North-South Road
Isengard
Fangorn
Fords of Isen
Westfold
Helm's Deep
Edoras
Angren (Isen)
Adorn
Ered Nimrais
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Lefnui
The Realm of Middle Earth
Miles
50
100
150
200

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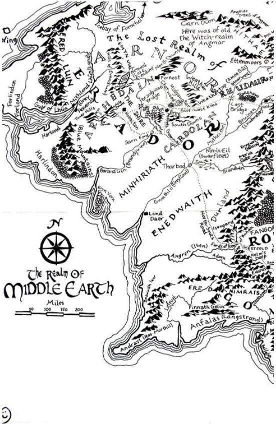

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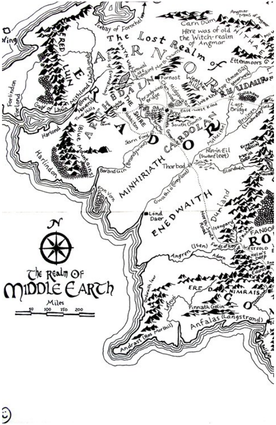

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These techniques involve some important decisions about the bias-variance tradeoff, and the use of (cross) validation in checking model performance and selecting the best model.

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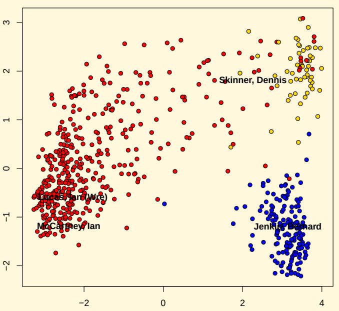

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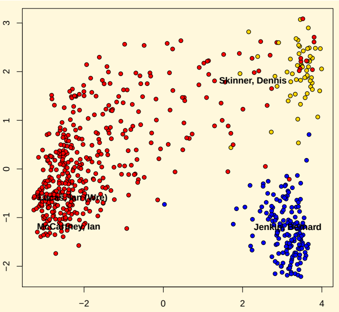

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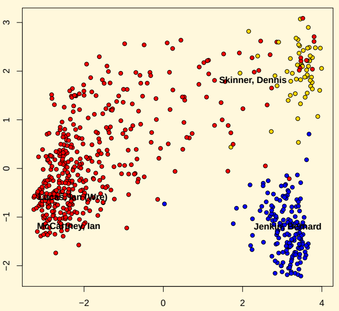

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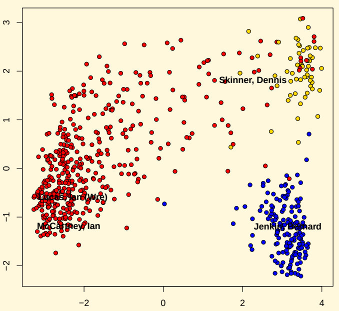

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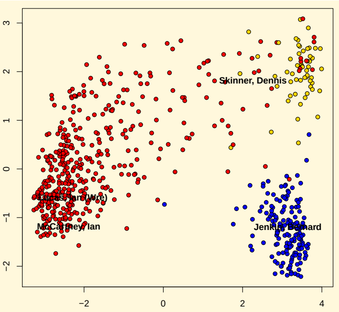

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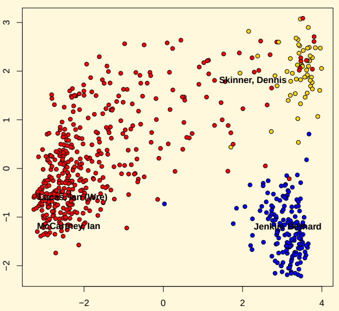

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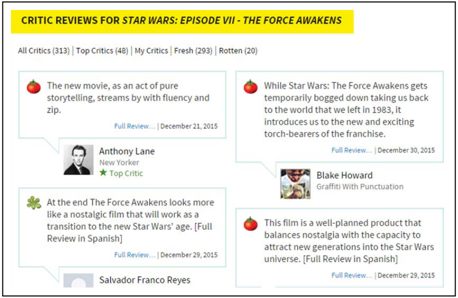

CRITIC REVIEWS FOR *STAR WARS: EPISODE VII - THE FORCE AWAKENS*

All Critics (313) | Top Critics (48) | My Critics | Fresh (293) | Rotten (20)

The new movie, as an act of pure storytelling, streams by with fluency and zip.

Full Review... | December 21, 2015

Anthony Lane
New Yorker
★ Top Critic

While Star Wars: The Force Awakens gets temporarily bogged down taking us back to the world that we left in 1983, it introduces us to the new and exciting torch-bearers of the franchise.

Full Review... | December 30, 2015

Blake Howard
Graffiti With Punctuation

At the end The Force Awakens looks more like a nostalgic film that will work as a transition to the new Star Wars' age. [Full Review in Spanish]

Full Review... | December 29, 2015

Salvador Franco Reyes

This film is a well-planned product that balances nostalgia with the capacity to attract new generations into the Star Wars universe. [Full Review in Spanish]

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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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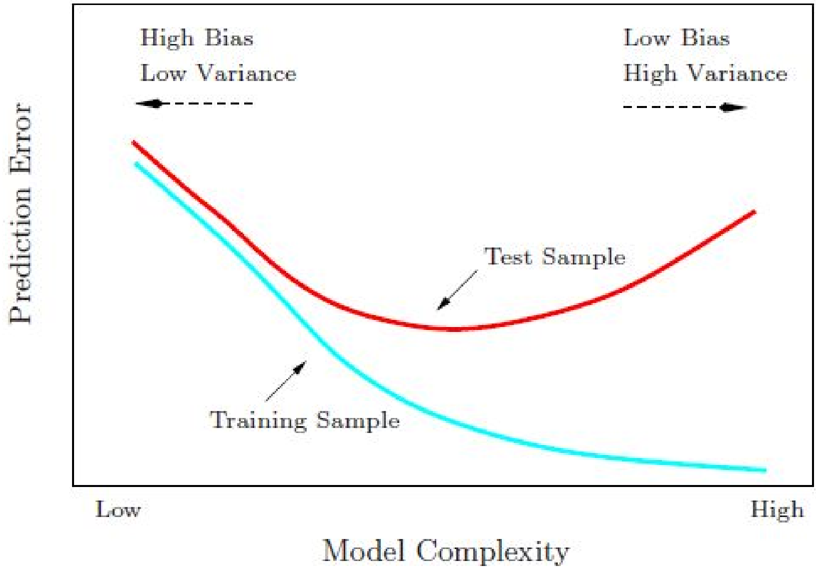

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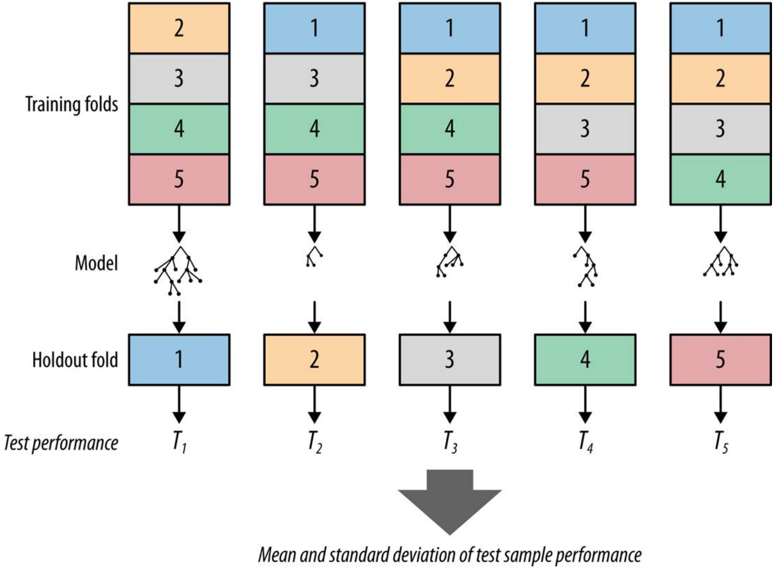

Motivating Example Diermeier et al, 2011

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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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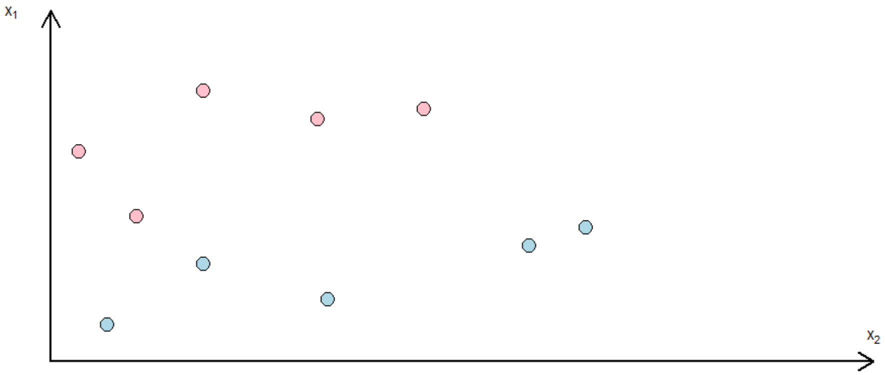

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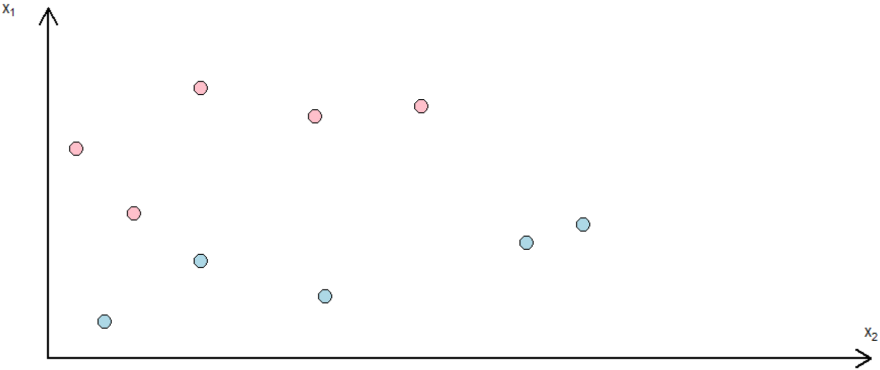

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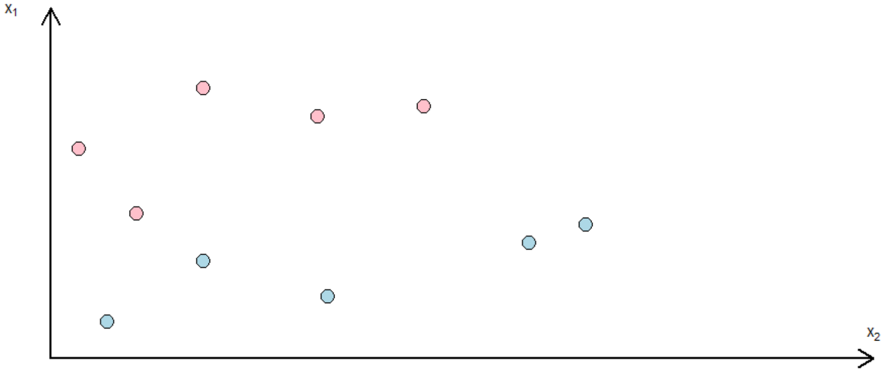

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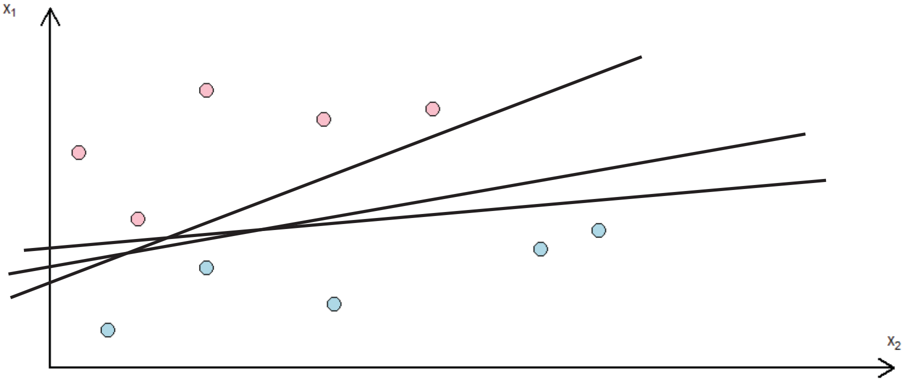

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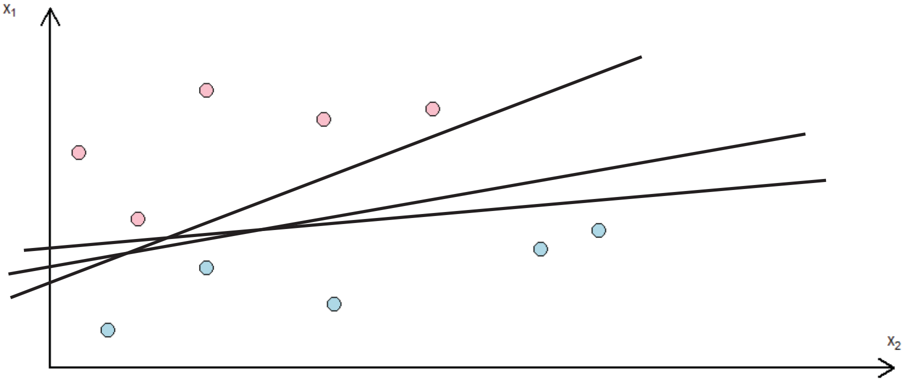

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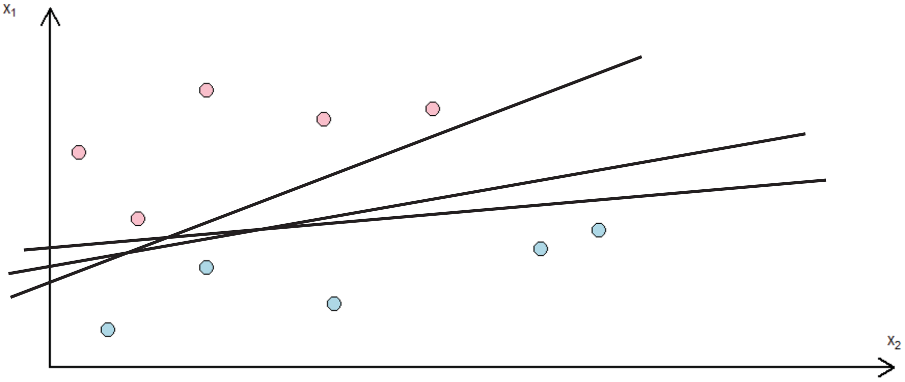

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$\rightarrow$ That optimal line—the separating hyperplane—is the maximum margin hyperplane. It will maximize the margin of the training data.

Partner Exercise

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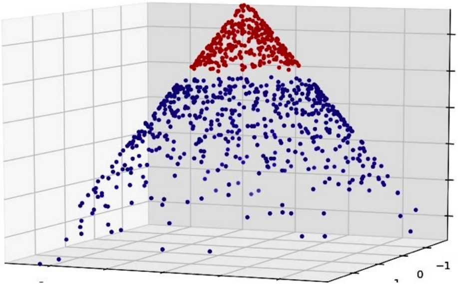
Consider the figure.

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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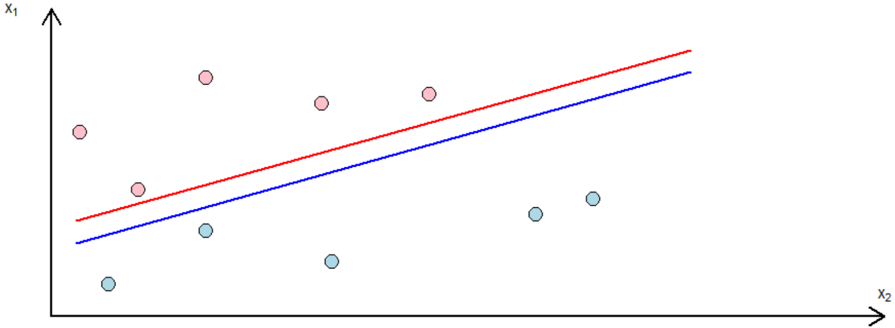

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NB The hyperplane cannot be anywhere other than equidistant because then it will break the rule about ensuring the largest minimum distance.

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

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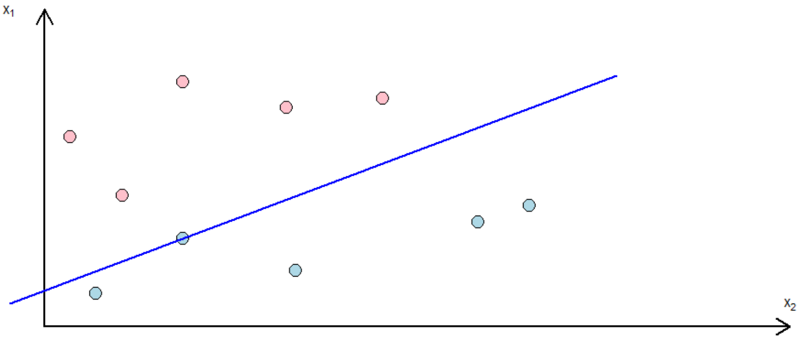

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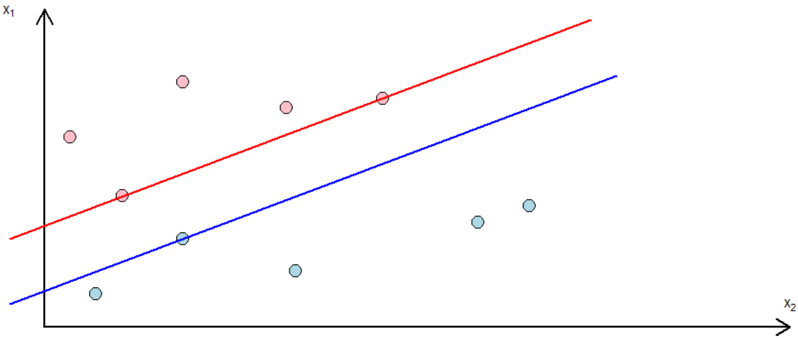

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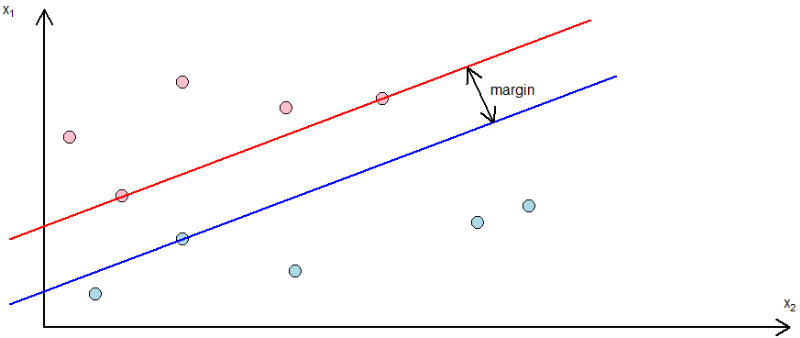

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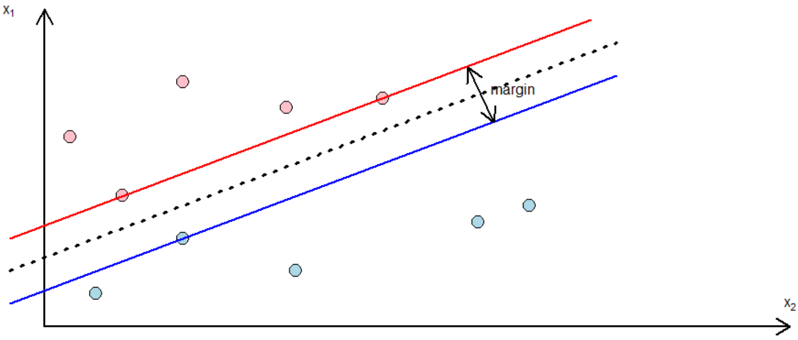

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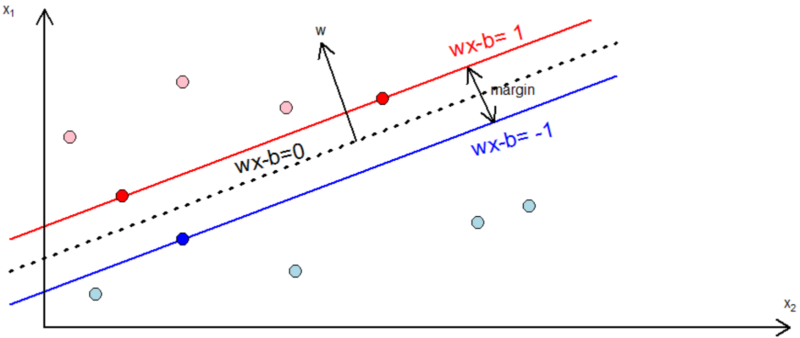

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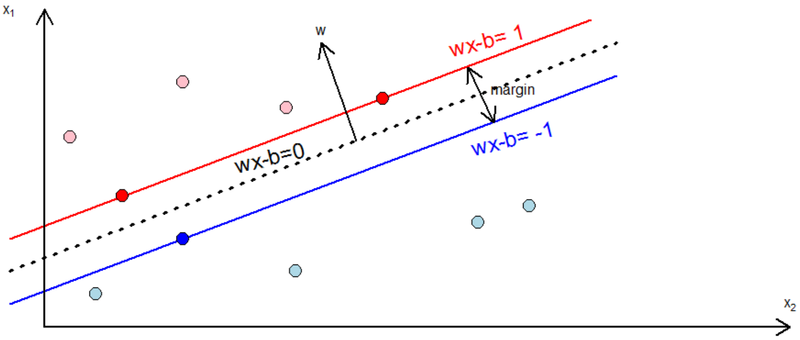

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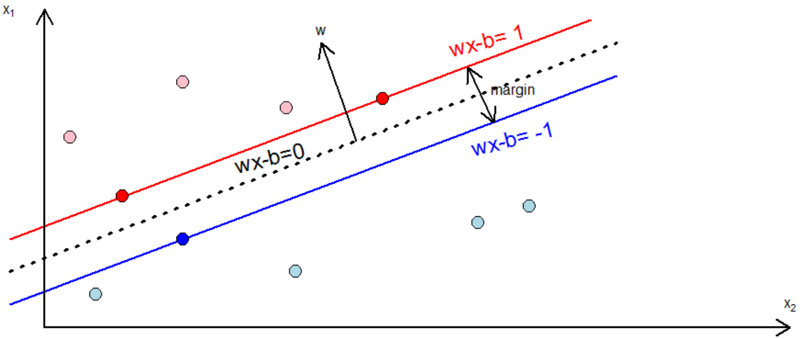

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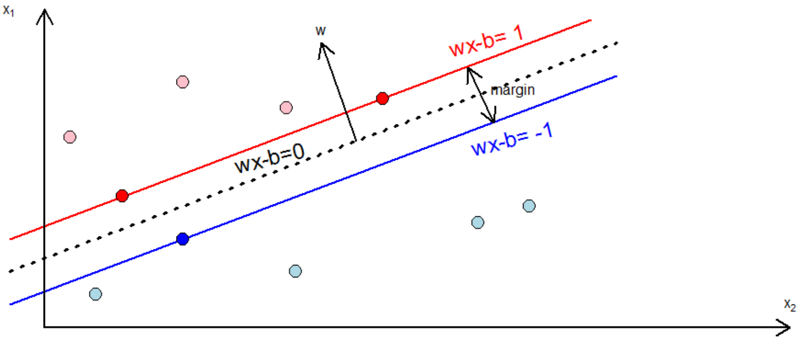

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Liberal		Conservative	
FAS: −199.49	SBA: −113.10	habeas: 193.55	homosexual: 103.07
Ethanol: −198.92	Nursing: −109.38	CFTC: 187.16	everglades: 102.87
Wealthiest: −159.74	Providence: −108.73	surtax: 151.81	tower: 101.67
Collider: −142.28	Arctic: −108.30	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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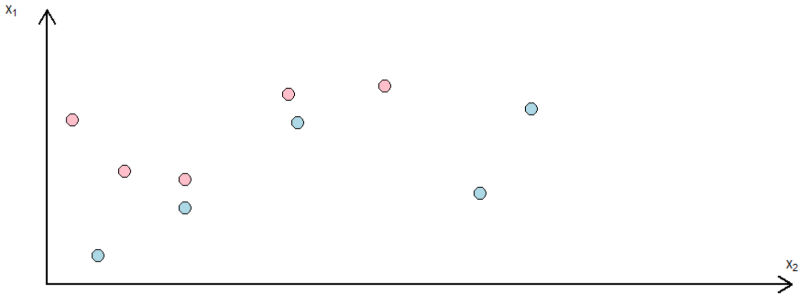

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Hyperplane(s) will be drawn in way that is more sensitive to 'bigger' mistakes in classification.

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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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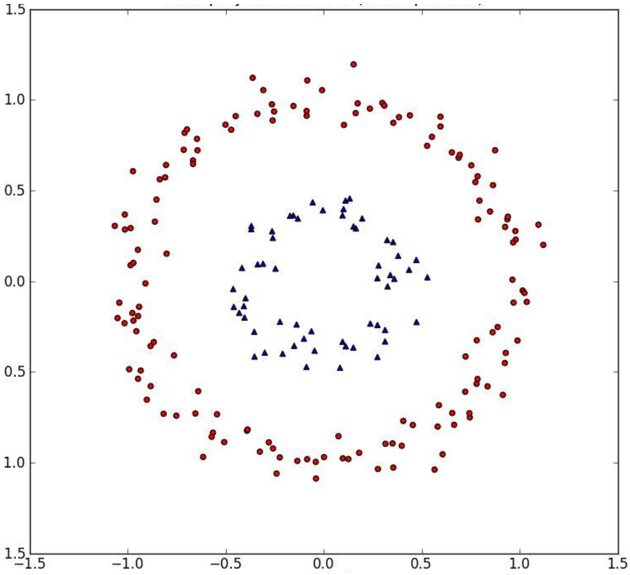

from www.eric-kim.net

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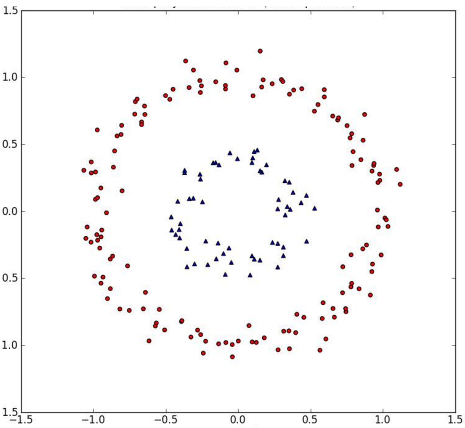
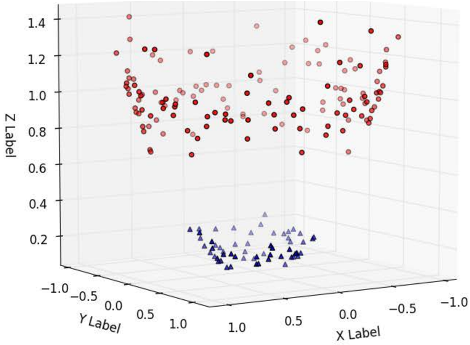
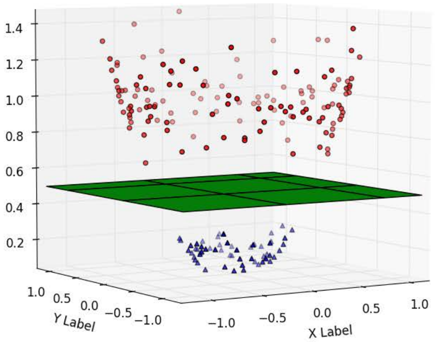
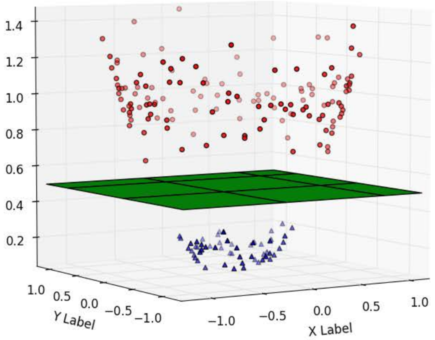
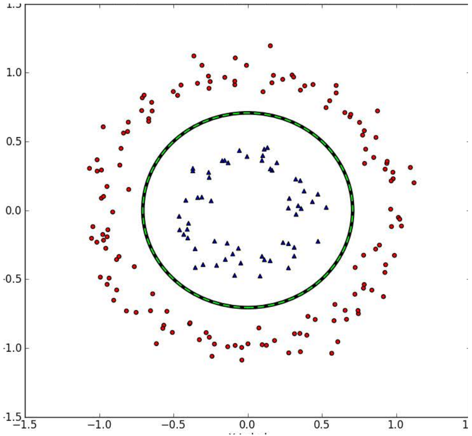




from www.eric-kim.net


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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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?