6. Supervised Techniques III

DS-GA 1015, Text as Data
Arthur Spirling

March 12, 2019

Housekeeping

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2. Class will not meet on March 19 (Spring break) or April 2 (work on final papers).

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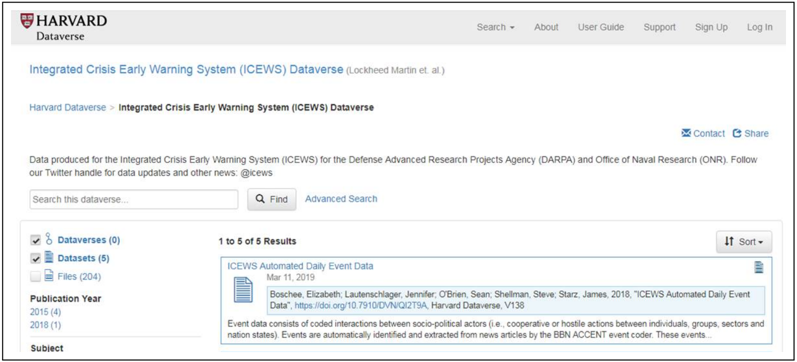

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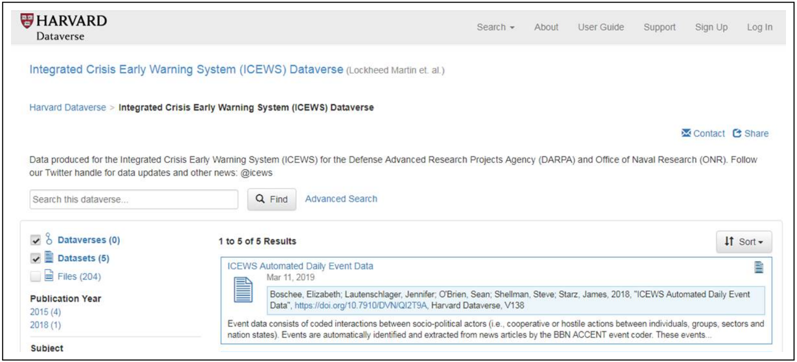

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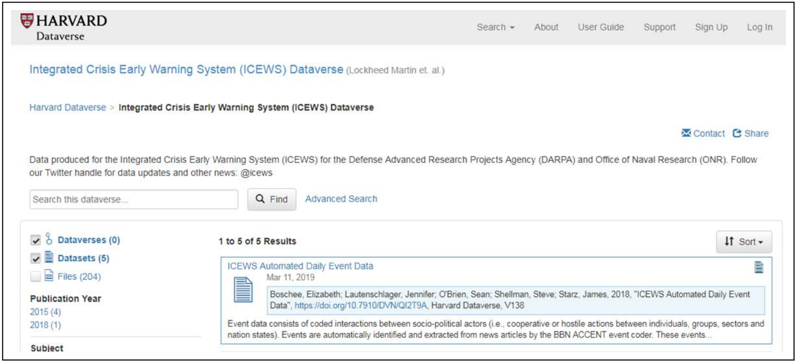

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Cons: Asia focussed, doesn't cover US, proprietary code-book

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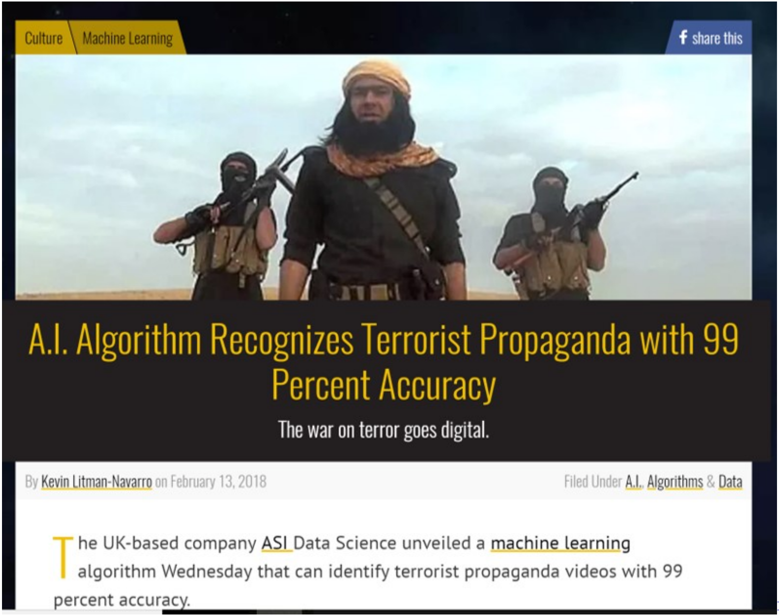
Culture | Machine Learning

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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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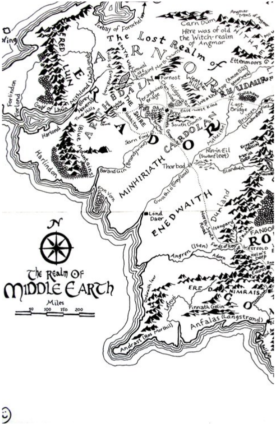
The Realm of
Middle Earth
Miles
50 100 150 200
N
The Lost Realm of Arnor
Here was of old
the Witch-realm
of Angmar
Carn Dûm
Angmar
Icebay of Forochel
Ered Luin
Eriador
Forlindon
Forlond
Gulf of Lhûn
Mithlond (Grey Havens)
Lhûn (Lune)
Harlond
Harlindon
Blue Mountains
Tower Hills
Emyn Uial
Nenuial (Lake Evendim)
North Downs
Fornost
Arthedain
The Shire
Hobbiton
Brandywine Bridge
Weather Hills
Weathertop (Amon Sûl)
Ettenmoors
Rhudaur
Trollshaws
Last Bridge
East-West Road
Bree
South Downs
Bruinen (Loudwater)
Mitheithel
Cardolan
Sarn Ford
Baranduin (Brandywine)
Minhiriath
Tharbad
Nîn-in-Eilph (Swanfleet)
Glanduin
Moria Gate
Gwathlo (Greyflood)
Eryn Vorn
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



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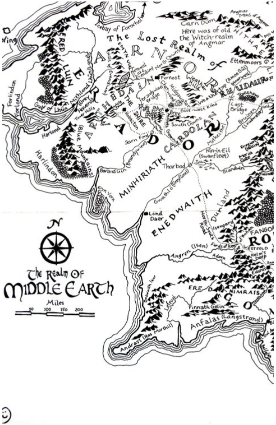

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These techniques involve some important decisions about the bias-variance tradeoff, and the use of (cross) validation in checking model performance and selecting the best model.

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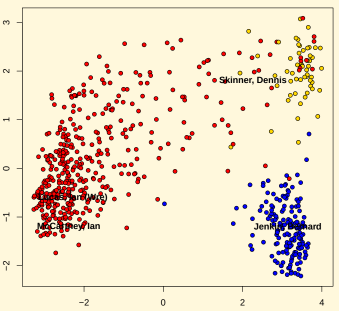

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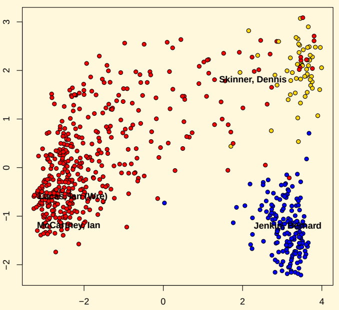

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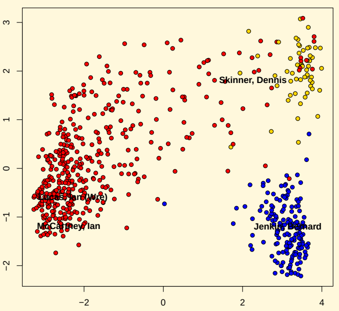

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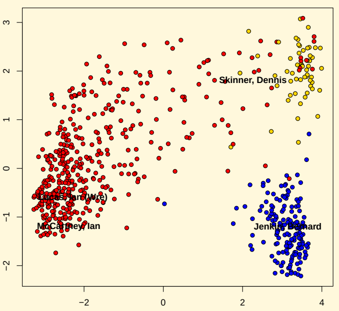

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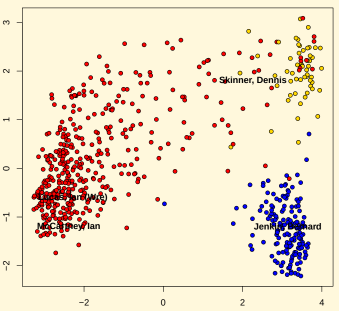

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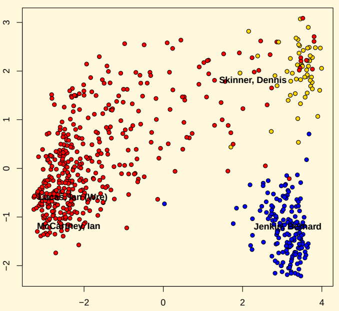

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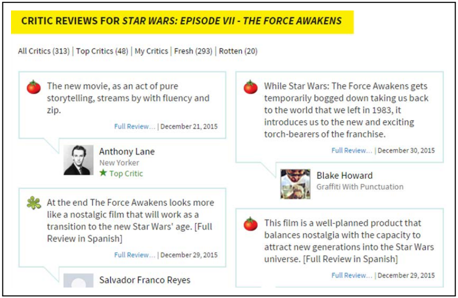

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So techniques may require careful tuning of *regularization parameters* to obtain good performance.

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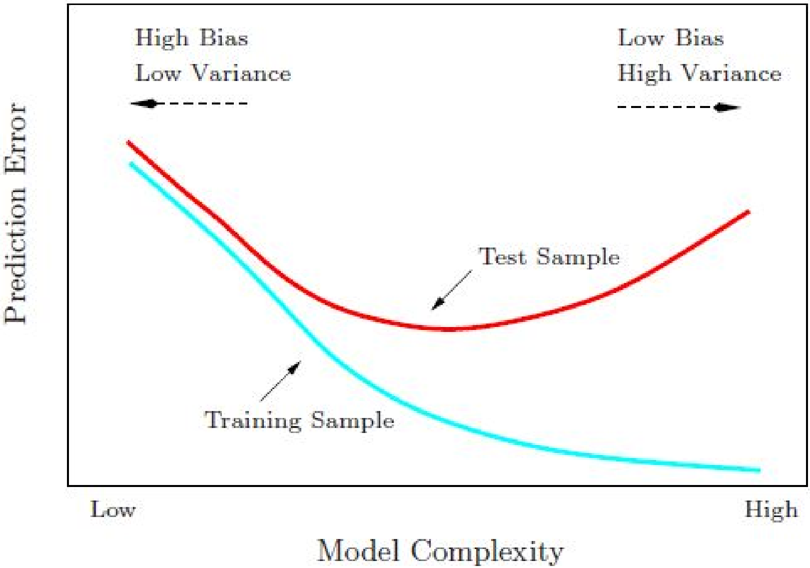
Bias-Variance Tradeoff (Hastie et al, p38)



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→ Can follow same steps for models of different specifications; variant on this approach can be used for model selection, directly.

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→ Can follow same steps for models of different specifications; variant on this approach can be used for model selection, directly.

Graphically

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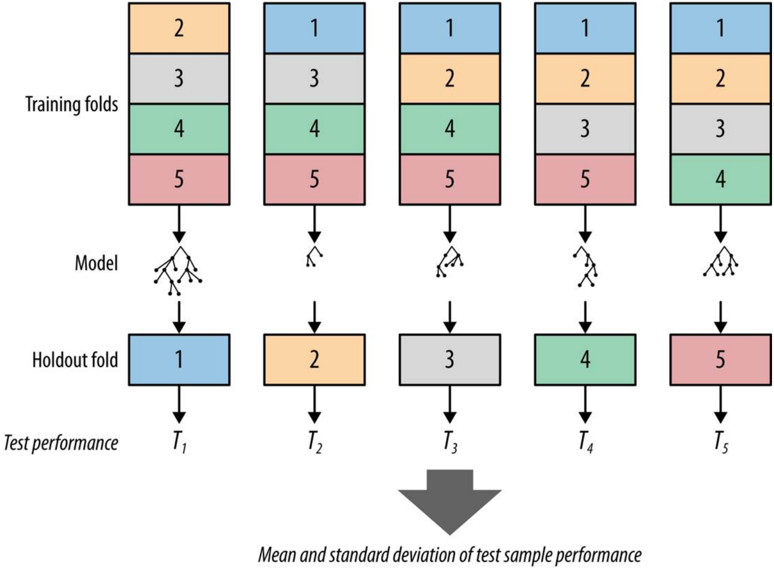

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Have the (stemmed, stopped, weighted etc) speech term matrix for each Senator as X.

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What method to use?

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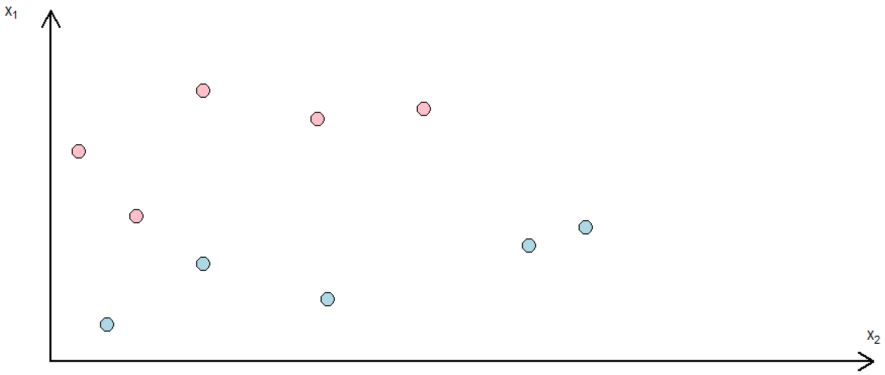

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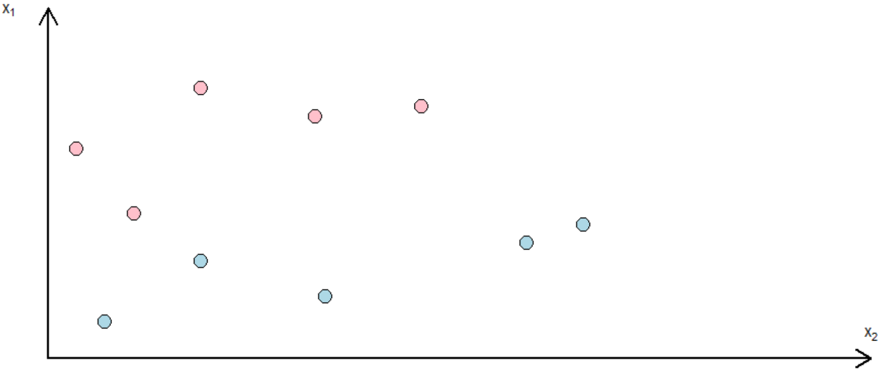

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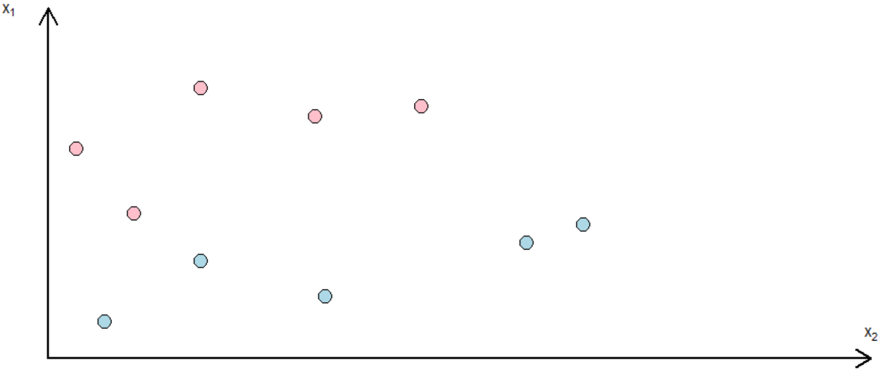

As the parties linearly separably? Where could you draw the line?

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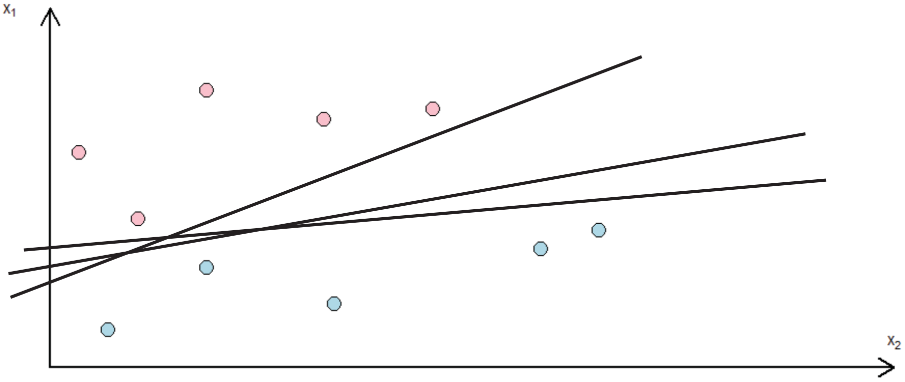

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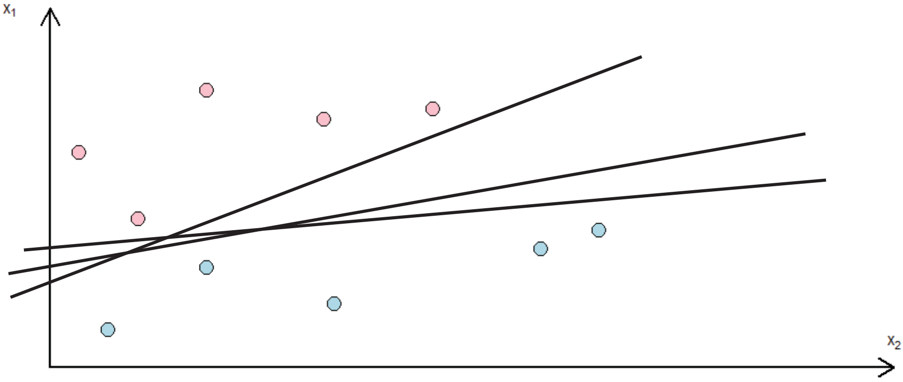

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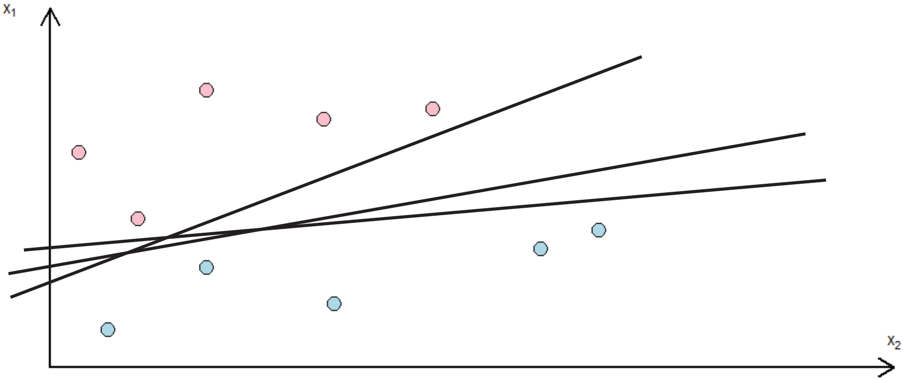

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$\rightarrow$ That optimal line—the separating hyperplane—is the maximum margin hyperplane. It will maximize the margin of the training data.

Partner Exercise

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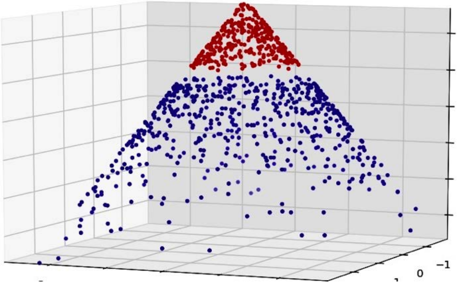
Consider the figure.

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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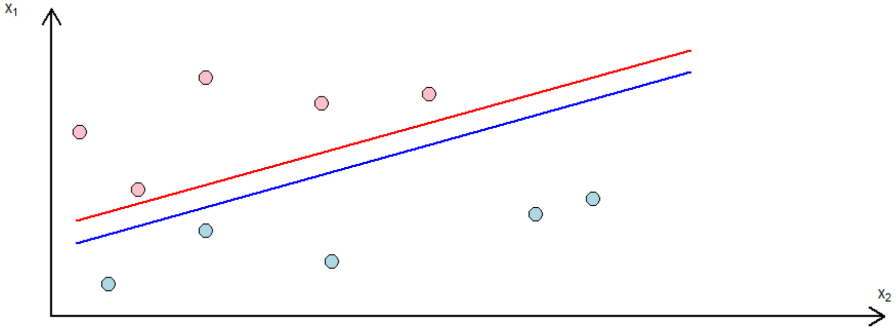

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NB The hyperplane cannot be anywhere other than equidistant because then it will break the rule about ensuring the largest minimum distance.

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

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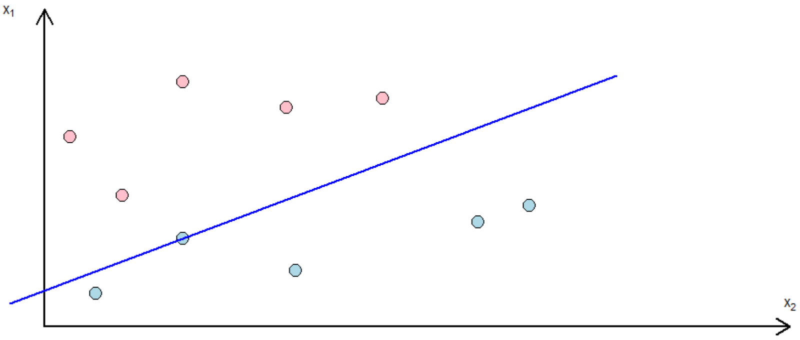

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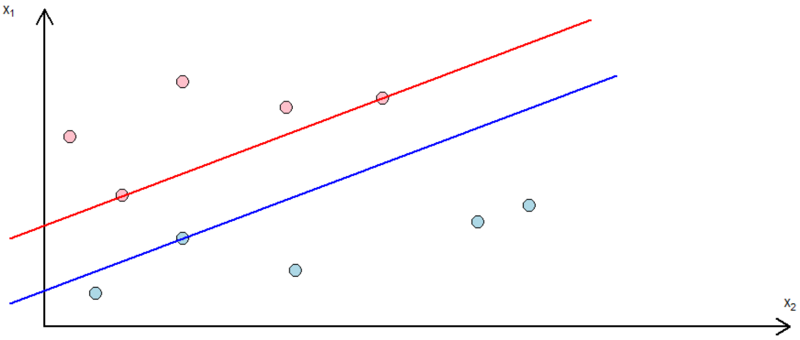

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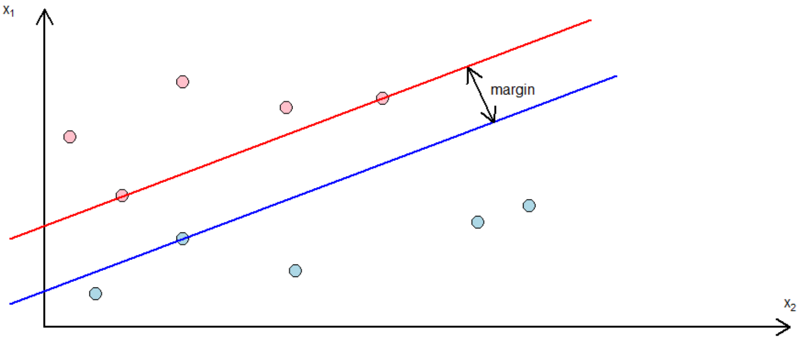

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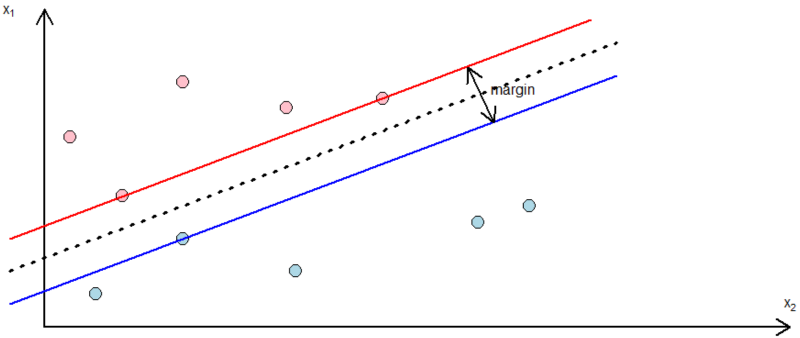

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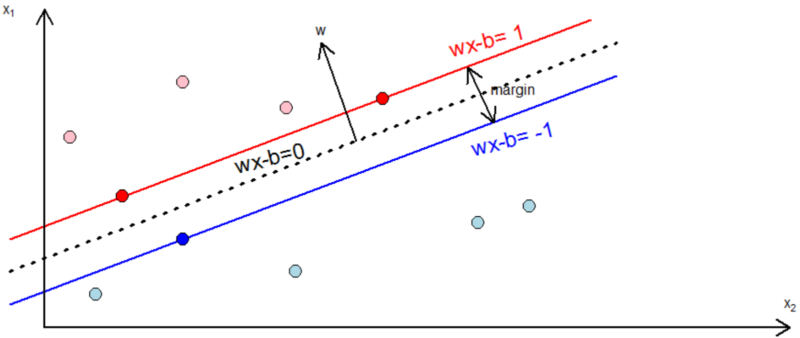

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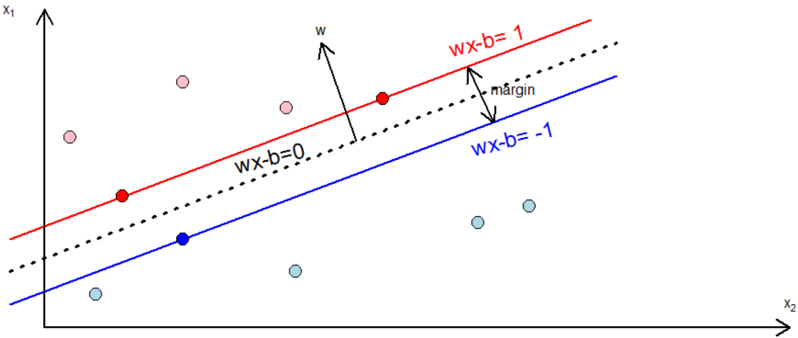

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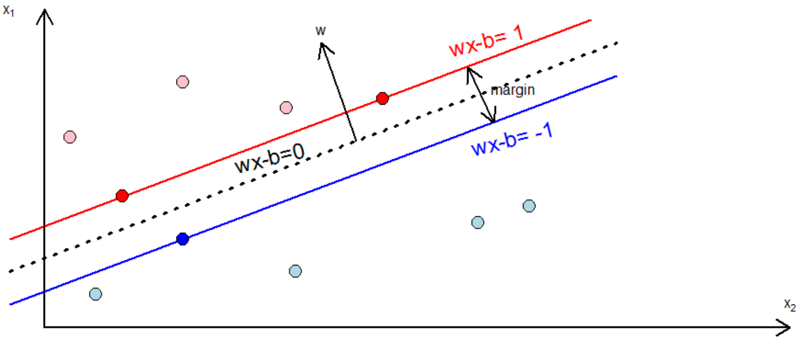

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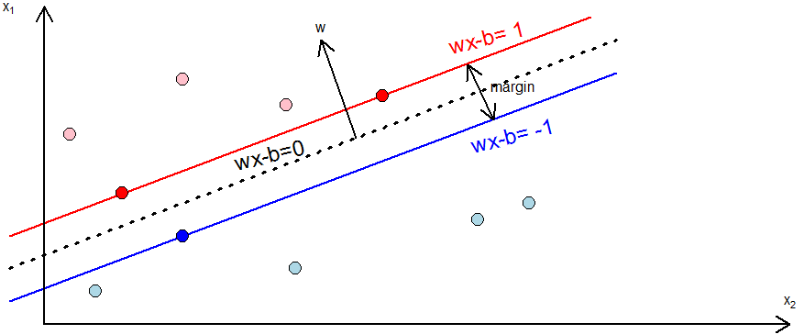

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Words			
Liberal		Conservative	
FAS: −199.49	SBA: −113.10	habeas: 193.55	homosexual: 103.07
Ethanol: −198.92	Nursing: −109.38	CFTC: 187.16	everglades: 102.87
Wealthiest: −159.74	Providence: −108.73	surtax: 151.81	tower: 101.67
Collider: −142.28	Arctic: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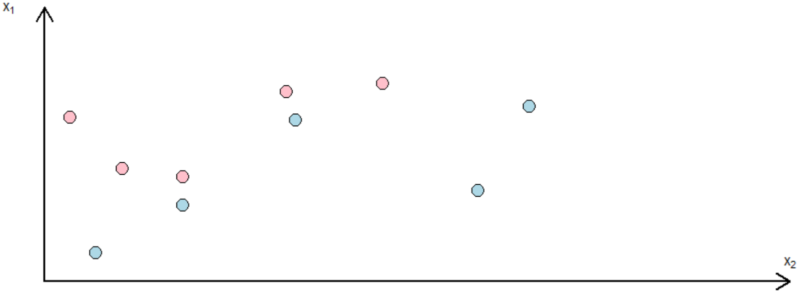

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Hyperplane(s) will be drawn in way that is more sensitive to 'bigger' mistakes in classification.

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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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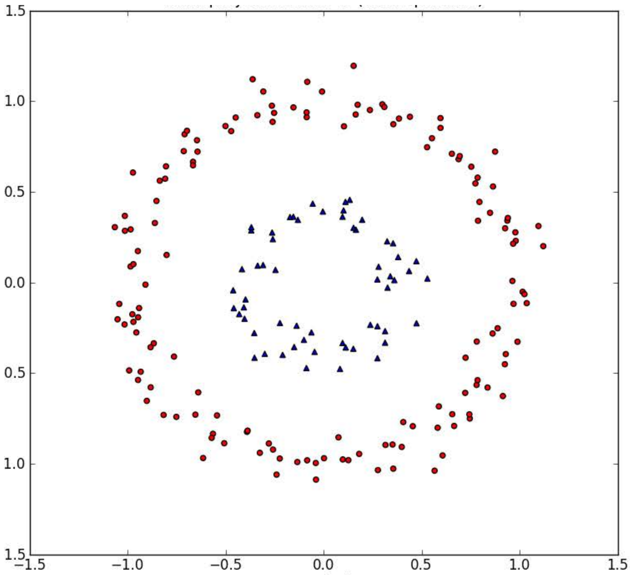

from www.eric-kim.net

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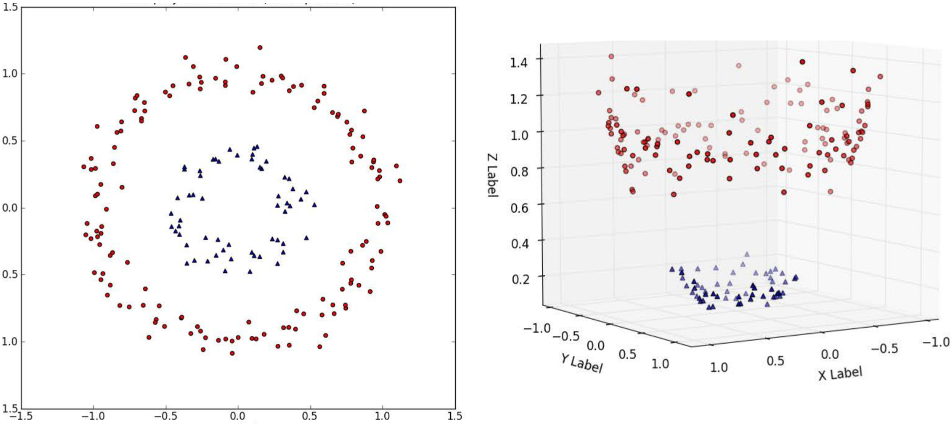
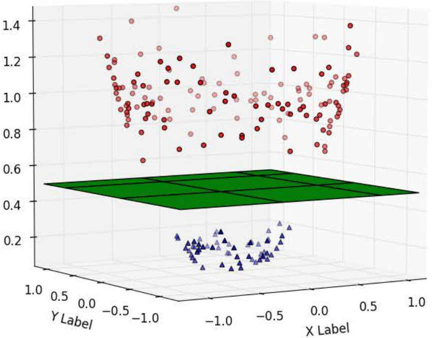
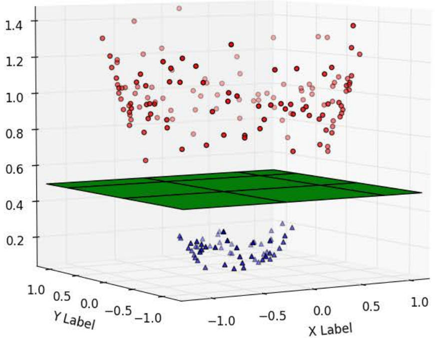
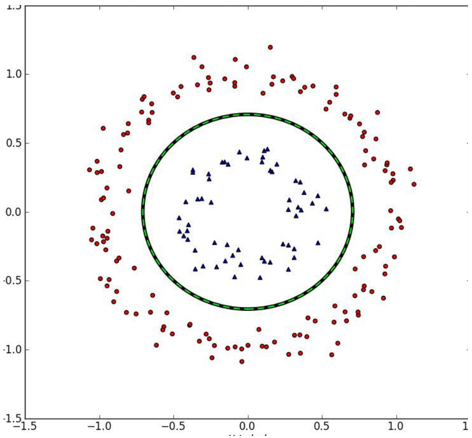


from www.eric-kim.net


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?