6. Supervised Techniques III (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

March 16, 2021

Housekeeping

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HW1 being graded: looks good so far.

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HW2 out this week.

March 23: lab and flipped lecture will be in same session (no lab March 25).

Bias-Variance Tradeoff (Hastie et al, p38)

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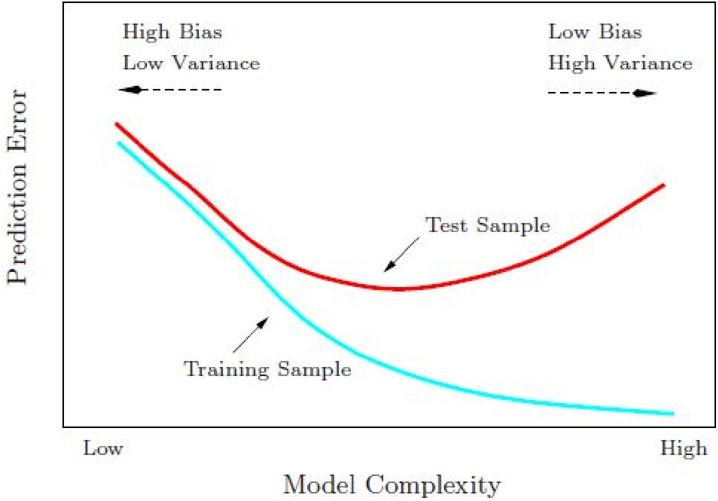

Moving left to right, what explains the training sample curve?

Moving left to right, what explains the test sample curve?

Graphically

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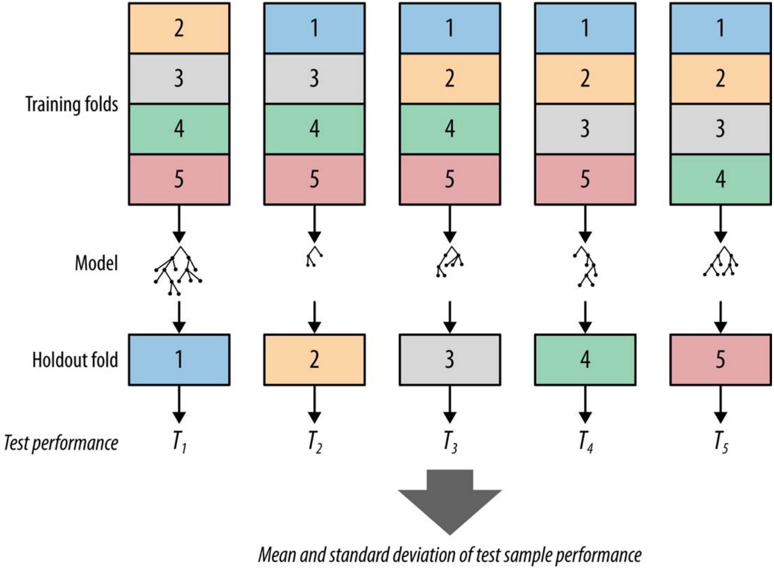

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$\rightarrow$ test set ("hold out") is used to evaluate final performance of model.

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$\Rightarrow$ lower variance

Double Descent (Nakkarin et al, 2019)

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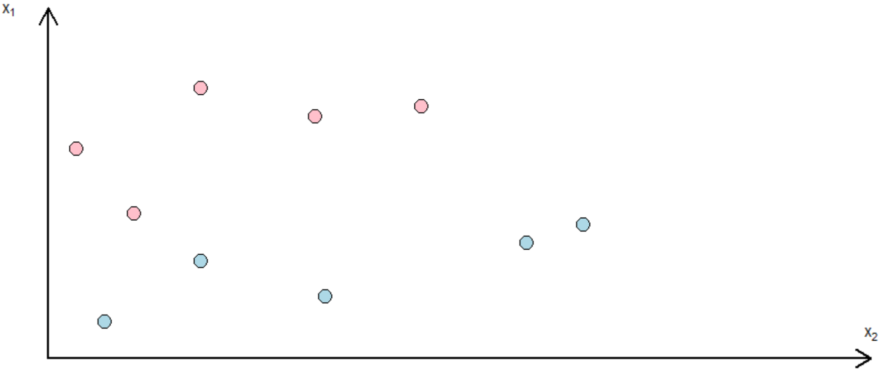

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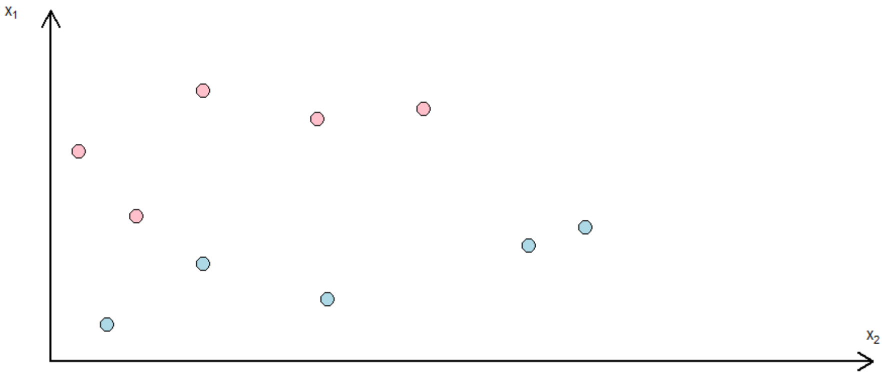

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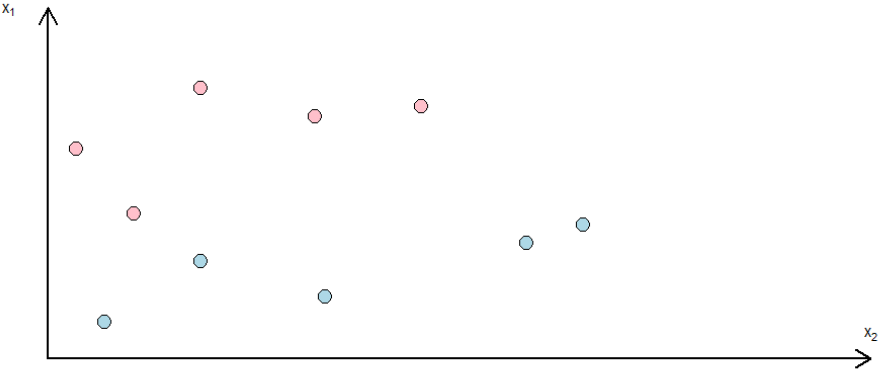

As the parties linearly separably? Where could you draw the line?

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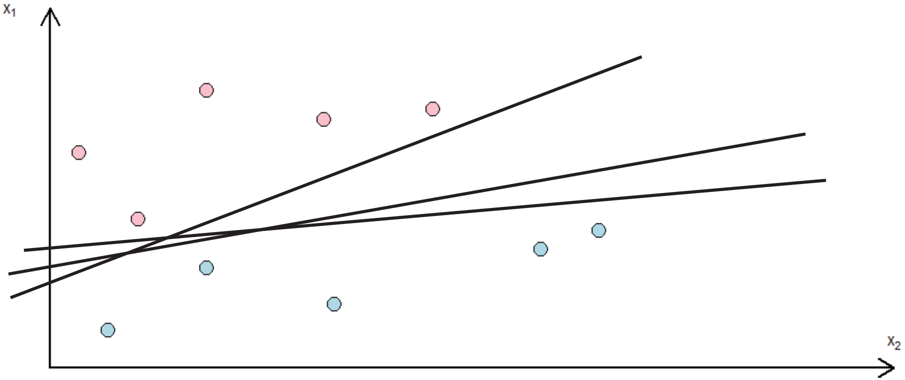

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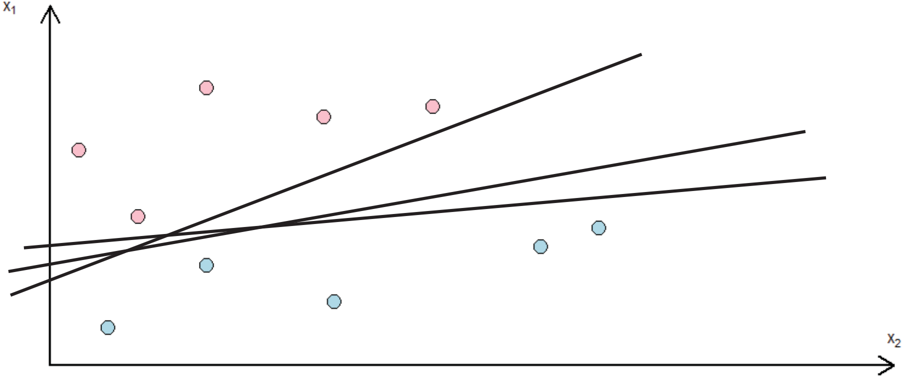

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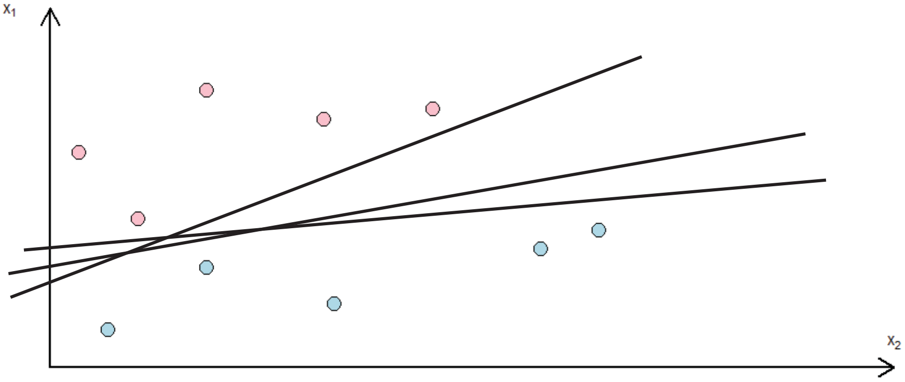

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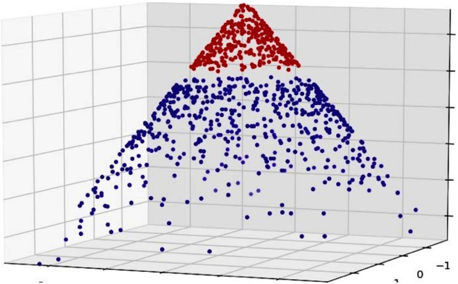
Consider the figure.

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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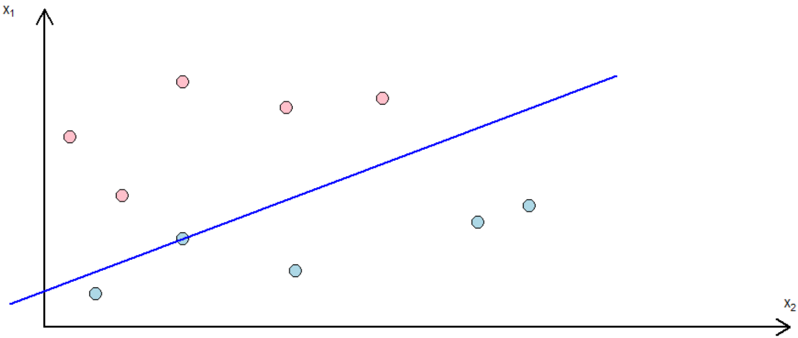

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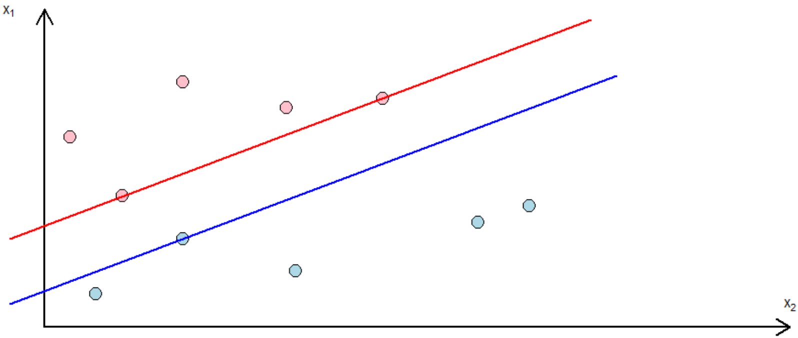

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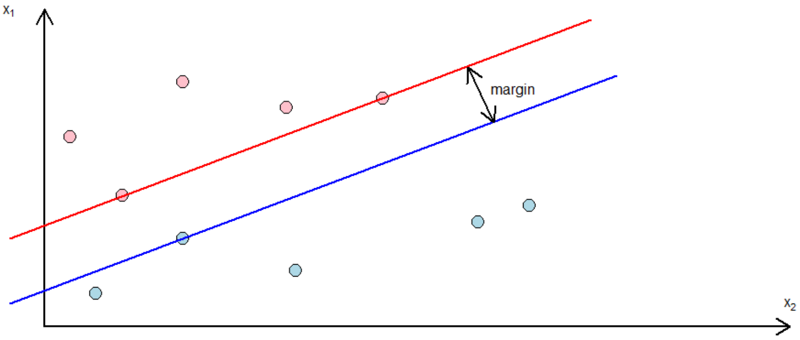

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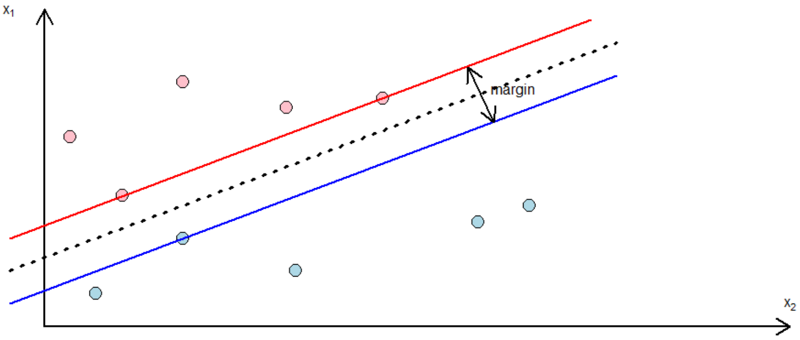

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At least one Senator is one "their" line. Why?

What name do we give to the training examples on their respective hyperplanes?

Back to Diermeier et al, 2011

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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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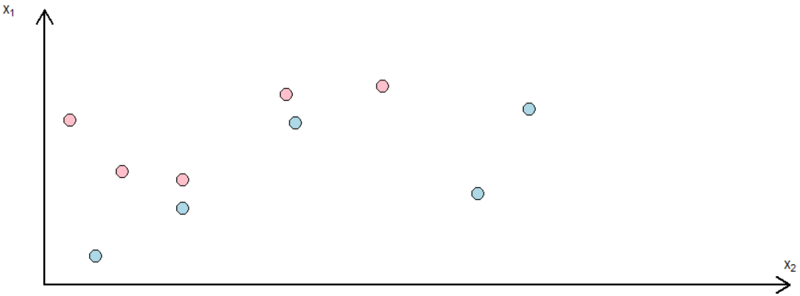
Diermeier et al's results imply that liberals use '`Handgun`' more often than conservatives.

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?

Oh dear...



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

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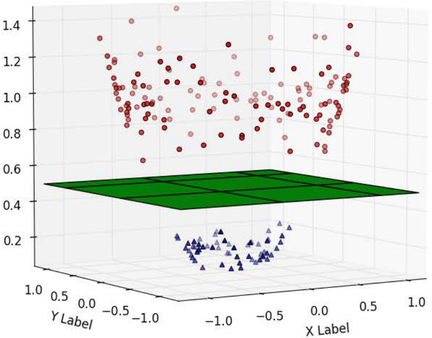
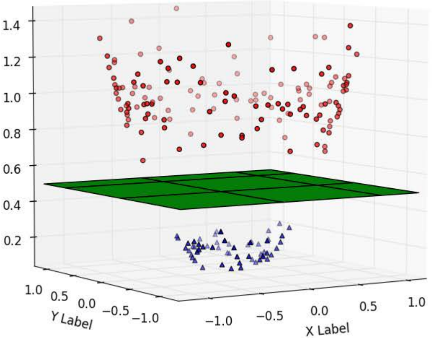
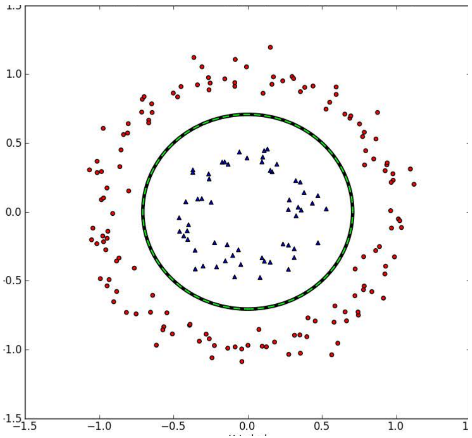
   $1 - f(x)y$ is $1 - (-2)(+1)$ in first case and $1 - (-100)(+1)$ in second case. Hinge loss larger in second case!

Kernels


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





from www.eric-kim.net

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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.

Kernel Methods in Action
(Self-indulgent Slides on Spirling, 2011)

Overview

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"establishing a firm and permanent friendship. . ."

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“That the President is hereby authorized and required, whenever in his opinion any reservation of such Indians. . . to allot the lands in said reservation. . . ”

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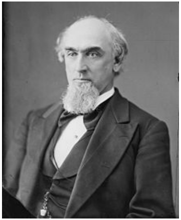
  - treaties became Congressional ‘bill-like’ entities
  - presumably different incentives (?), but do treaties look much different?



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A Treaty of Limits between the United States of America and the Chaktaw [sic] nation of Indians.

THOMAS JEFFERSON, President of the United States of America, by James Robertson, of Tennessee, and Silas Dinsmoor, of New Hampshire, agent of the United States to the Chaktaws, commissioners plenipotentiary of the United States, on the one part, and the Mingoes, Chiefs and warriors of the Chaktaw nation of Indians, in council assembled, on the other part, have entered into the following agreement, viz:

ARTICLE 1.

The Mingoes, chiefs and warriors of the Choctaw nation of Indians in behalf of themselves, and the said nation, do by these presents cede to the United States of America, all the lands to which they now have or ever had claim, lying to the right of the following lines, to say. Beginning at a branch of the Humacheeto where the same is intersected by the present Choctaw boundary, and also by the path leading from Natchez to the county of Washington, usually called M'Clarey's path, thence eastwardly along M'Clarey's path, to the east or left bank of Pearl river thence on such a direct line as would touch the lower end of a bluff on the left bank of Chickasawhay river the first above the Hiyoowannee towns, called Broken Bluff, to a point within four miles of the Broken Bluff, thence in a direct line nearly parallel with the river to a point whence an east line of four miles in length will intersect the river below the lowest

ARTICLE 4.

The Mingoes, chiefs, and warriors of the Choctaws, certify that a tract of land not exceeding fifteen hundred acres, situated between the Tombigbee river and Jackson's creek, the front or river line extending down the river from a blazed white oak standing on the left bank of the Tombigbee near the head of the shoal, next above Hobukentoopa, and claimed by John M'Grew was in fact granted to the said M'Grew by Opiomingo Hesnitta, and others, many years ago, and they respectfully request the government of the United States to establish the claim of the said M'Grew to the said fifteen hundred acres.

Done on Mount Dexter, in Pooshapukanuk, in the Choctaw country, this sixteenth day of November, in the year of our Lord one thousand eight hundred and five, and of the independence of the United States of America the thirtieth.

Commissioners:

James Robertson, [L. S.

Silas Dinsmoor, [L. S.]

Great Medal Mingos:

Pukshunnubbee. his x mark, [L. S.]

Mingo Hoomastubbee, his x mark, [L. S.]

Pooshamattaha, his x mark, [L. S.]

Chiefs and warriors:

Ookchummee, his x mark, [L. S.]

Tuskamiubbee, his x mark, [L. S.]

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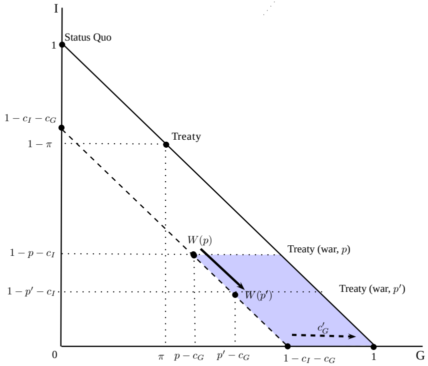

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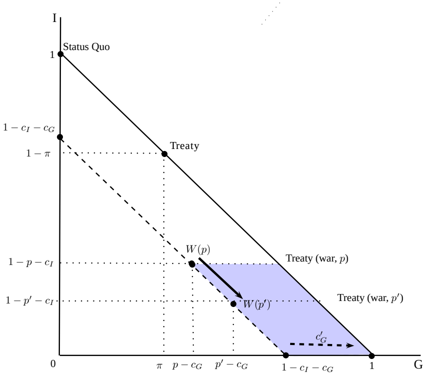

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2. `brothers not warfare now`
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but (1) and (2) share more substrings (of length 4):

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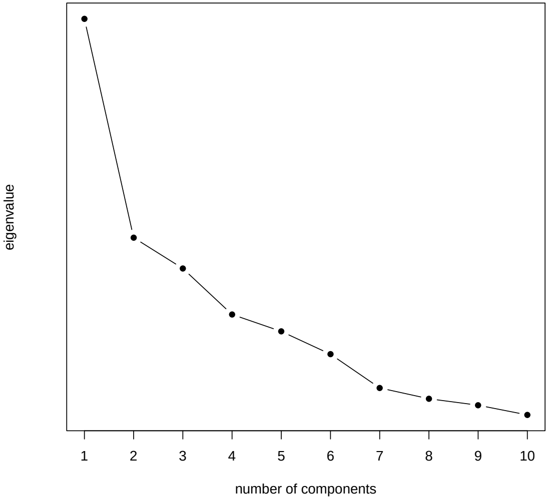
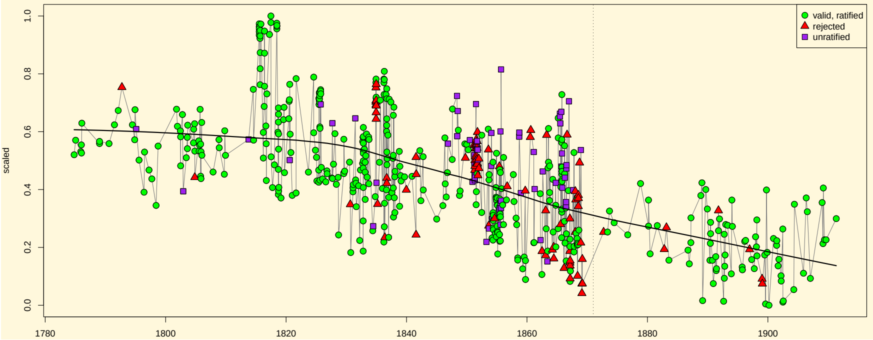


What we get, II



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?