7A. Supervised Techniques IV

DS-GA 1015, Text as Data
Arthur Spirling

March 23, 2021

Where Are We?

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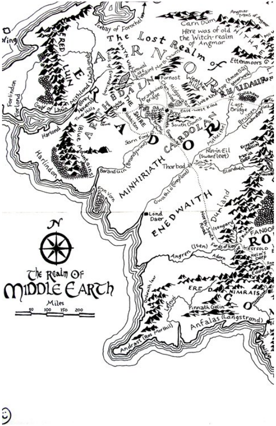

The Realm of
MIDDLE EARTH
Miles
50
100
150
200
The Lost Realm of
ARNOR
Here was of old
the Witch-realm
of Angmar
Carn Dûm
Angmar
Icebay of Forochel
ERED LUIN
Forlindon
Forlond
Gulf of Lhûn
Mithlond
(Grey Havens)
Lhûn (Lune)
Harlond
Harlindon
Tower Hills
(Blue Mountains)
ERIADOR
ARTHEDAIN
THE SHIRE
Hobbiton
Nenuial
(Lake Evendim)
North Downs
Fornost
Brandywine Bridge
Old Forest
Bree
Midgewater
Weather Hills
Weathertop
(Amon Sûl)
Ettenmoors
RHUDAUR
Trollshaws
Last Bridge
East-West Road
South Downs
Bruinen
(Loudwater)
Mitheithel
CARDOLAN
Sarn Ford
Baranduin (Brandywine)
MINHIRIATH
Tharbad
Nîn-in-Eilph
(Swanfleet)
Glanduin
Moria Gate
Eryn Vorn
Gwathló (Greyflood)
Lond Daer
ENEDWAITH
Dunland
North-South Road
Isengard
FANGORN
ROHAN
WESTFOLD
Fords of Isen
Angren (Isen)
Adorn
Helm's Deep
Edoras
ERED NIMRAIS
GONDOR
Pinnath Gelin
Anfalas (Langstrand)
Andrast (Ras Morthil)
Lefnui

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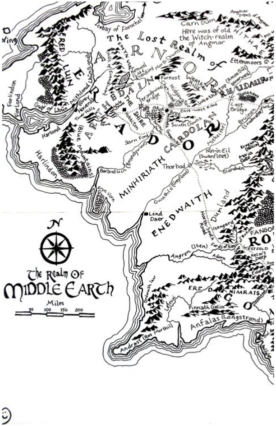

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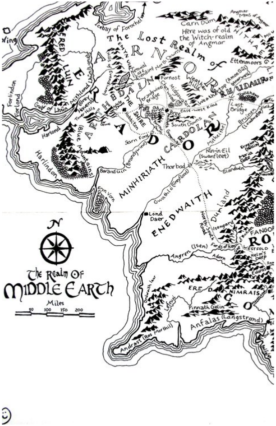

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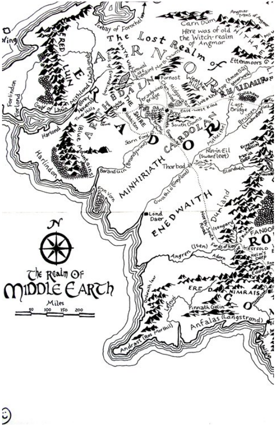

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Plus ways to combine those techniques: ensembles.

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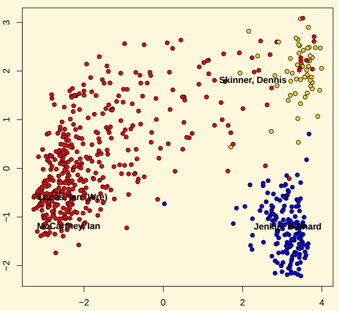

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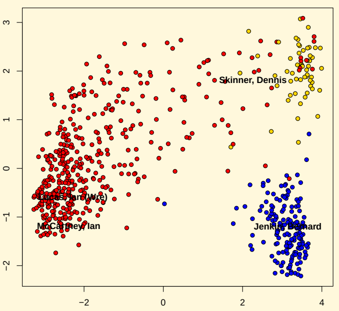

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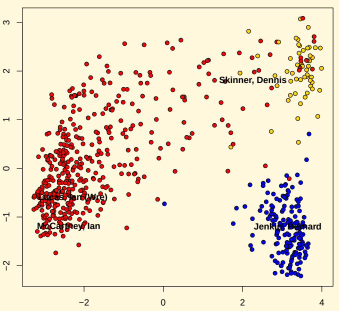

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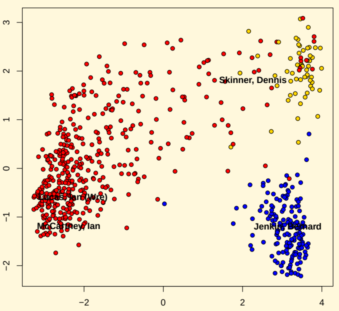

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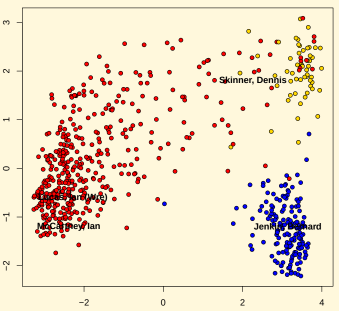

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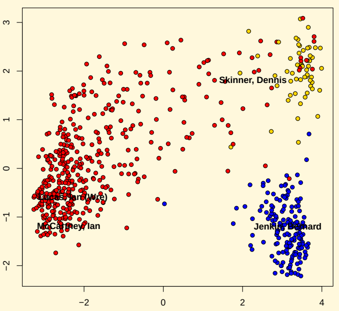

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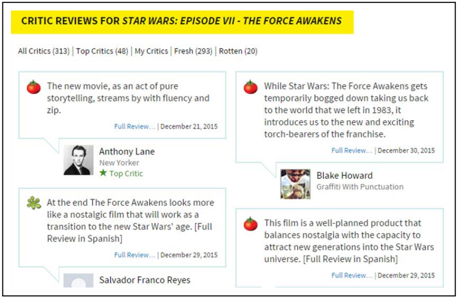

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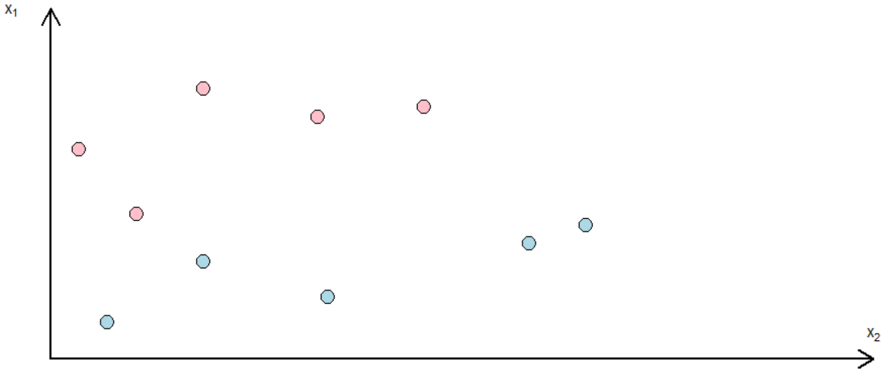

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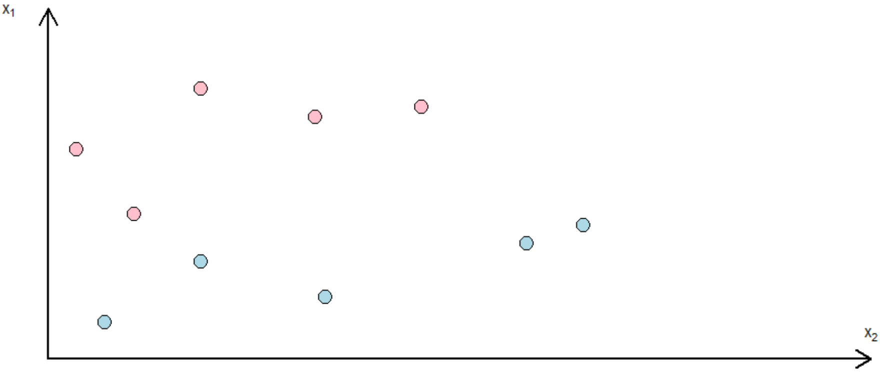

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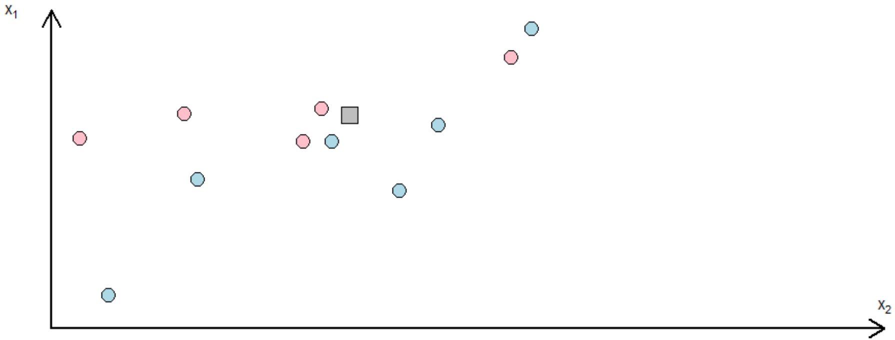

x1
x2

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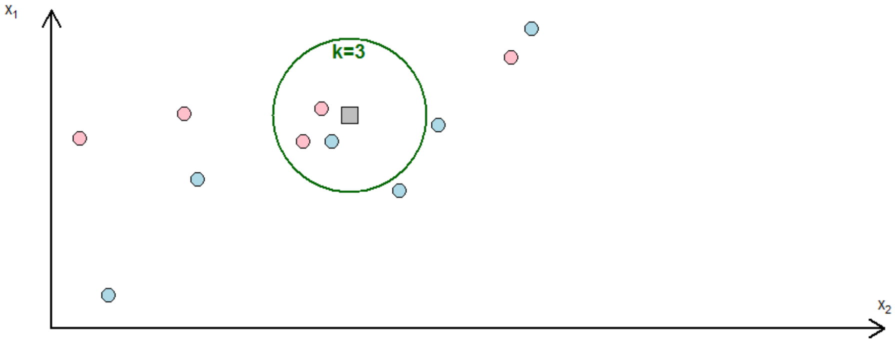

x_1
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x_2

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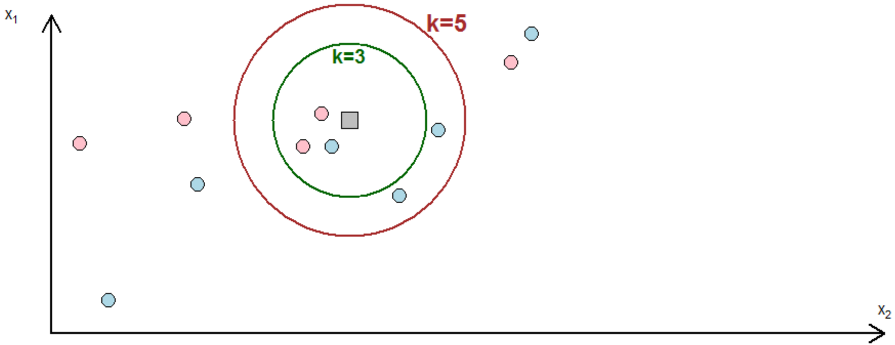
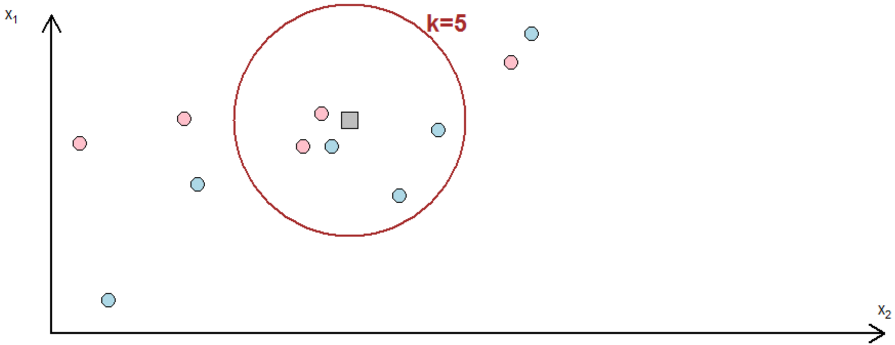

x1
k=5
k=3
x2



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→ Choice of k can be optimized, but generally case that noise in data causes poor classification.

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Works with any types of features, though typically requires rescaling (normalizing) to ensure that one unit of one variable is not treated same as one unit of another (e.g. gender vs income: male is more different to female than \$10,000 is to \$10,001)

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Trees and Forests

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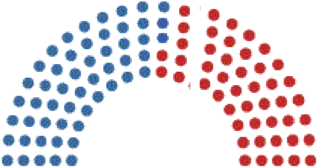

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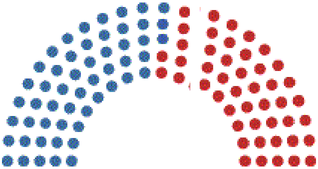

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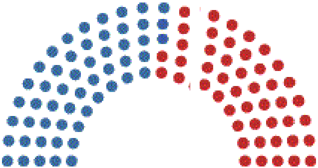

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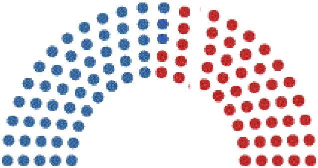

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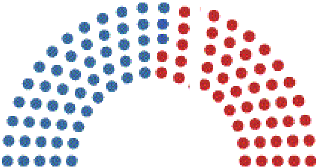

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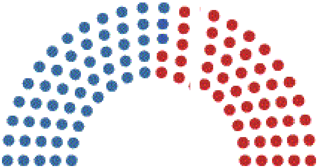

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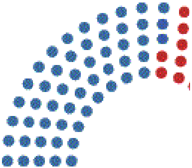

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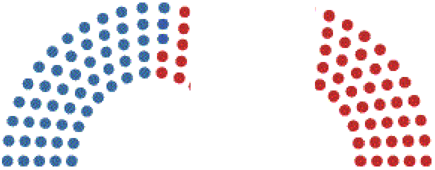

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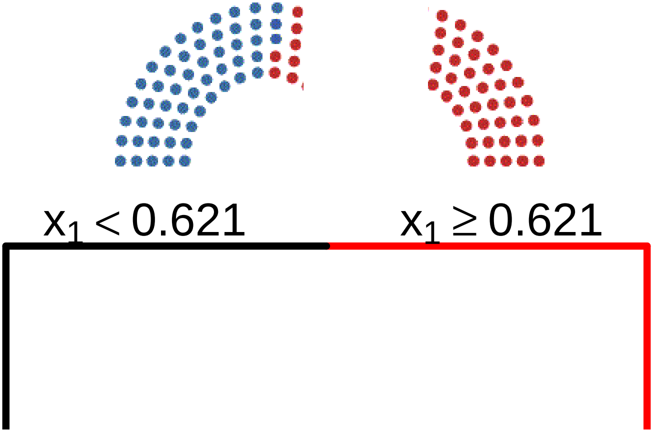

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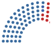

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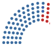

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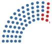

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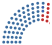

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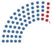

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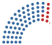

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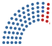

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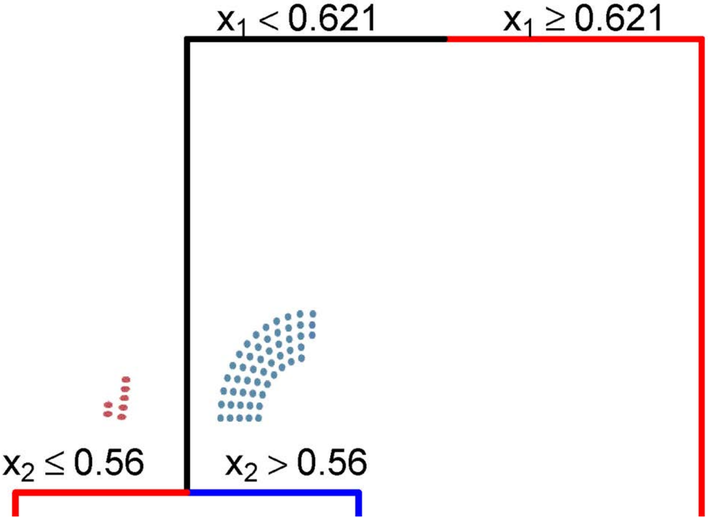

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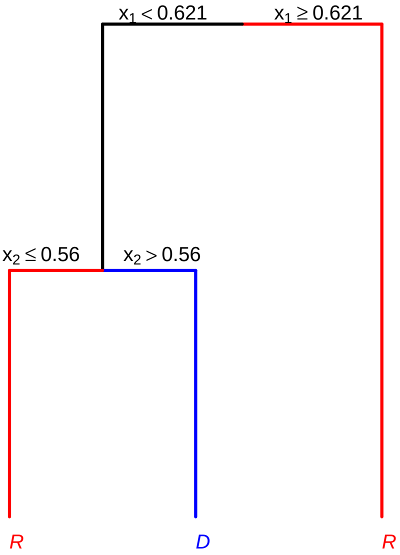

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- In practice, there are parameters to control depth of trees, and overall learning rate.

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- priors control how much each tree affects the outcome surface (basically our $\hat{y}$ prediction, conditioned on X), in way that ensures no tree dominates
- by MCMC we obtain posterior sample of M trees, and thus sample of $Y_i|X_i$: draws give measure of uncertainty over X relationship with Y.

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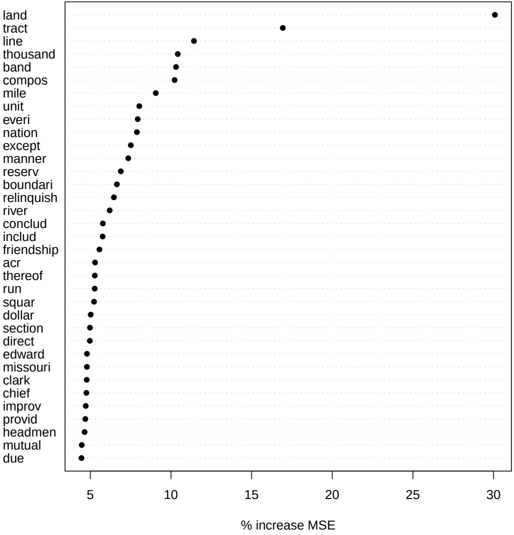

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stem	appearance	common phrasing (frequency)	ρ
friendship	friendship	"A treaty of peace and friendship" (15)	0.504
mutual	mutually	"shall be mutually forgiven and forgot" (19)	0.255
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`cession`	cession	"In consideration of the foregoing cession" (15)	-0.205
`relinquish`	relinquish	"cede and relinquish to the United States" (4)	-0.208
`boundari`	boundary	"land included within the following boundaries" (4)	-0.214
`tract`	tract	"One tract," (14)	-0.442
`dollar`	dollars	"forty dollars" (11)	-0.457
`land`	lands	"one section of land" (29)	-0.567
`reserv`	reservation	"one other reservation" (5)	-0.622

Ensembles

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Q Can they use supervised learning to do better? (better in terms of time: assume humans are accurate)

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In subtopic stage, use SVM (as best performer).

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	SVM	MaxEnt	Boostexter	Naïve Bayes	Ensemble
Major topic $N = 20$	88.7% (.881)	86.5% (.859)	85.6% (.849)	81.4% (.805)	89.0% (.884)
Subtopic $N = 226$	81.0% (.800)	78.3% (.771)	73.6% (.722)	71.9% (.705)	81.0% (.800)

Note. Results are based on using approximately 187,000 human-labeled cases to train the classifier to predict approximately 187,000 other cases (that were also labeled by humans but not used for training). Agreement is computed by comparing the machine's prediction to the human assigned labels. (AC1 measure presented in parentheses).

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