7. Supervised $\rightarrow$ Unsupervised Techniques (flipped)

DS-GA 1015, Text as Data

Arthur Spirling

March 23, 2021

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3 Lab at 12 today (no lab on Thursday)

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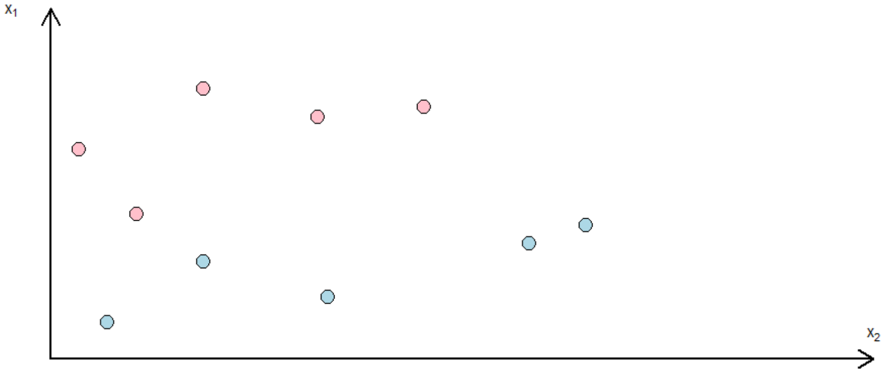

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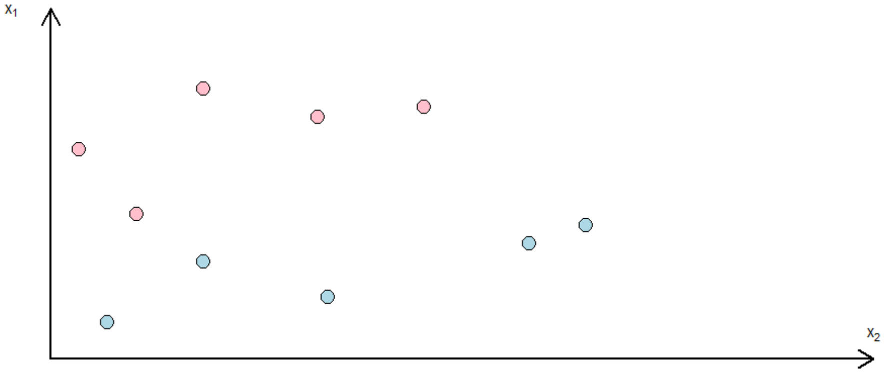

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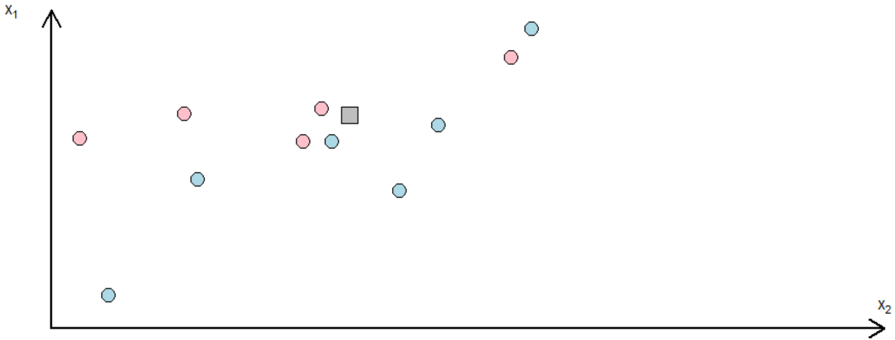
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x_2

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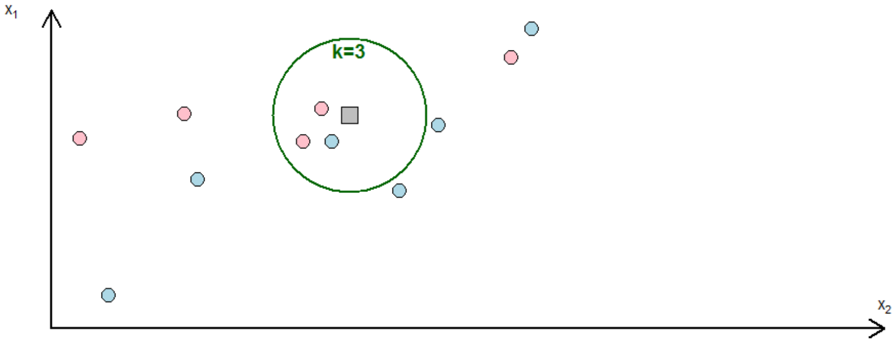
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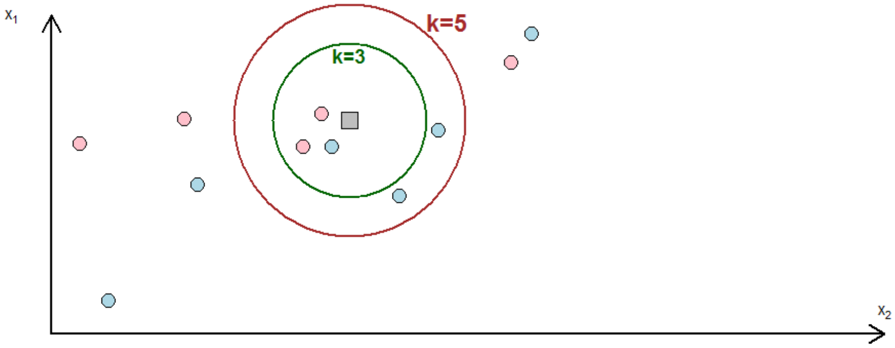

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k=5
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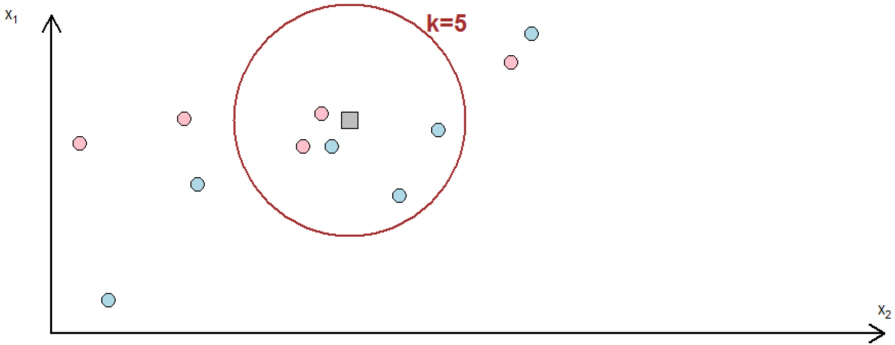
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→ Choice of k can be optimized, but generally case that noise in data causes poor classification.

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4 kNN is non-parametric: what makes it so? what are some strengths/limitations of non-parametric models?

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penalize mistakes in minority class: add a cost function.

Partitioning the Senators With Trees

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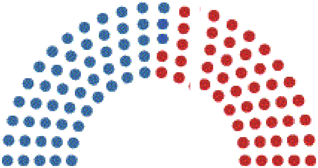

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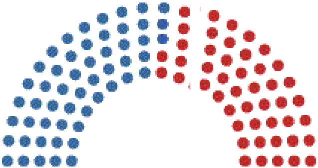

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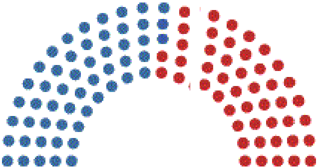

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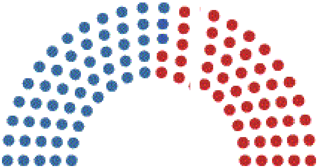

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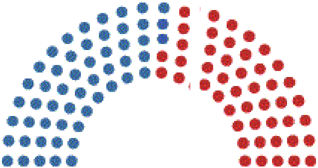

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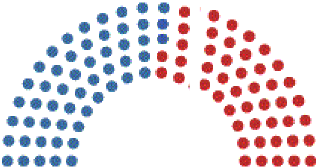

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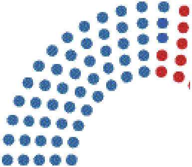

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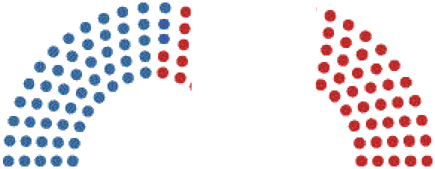

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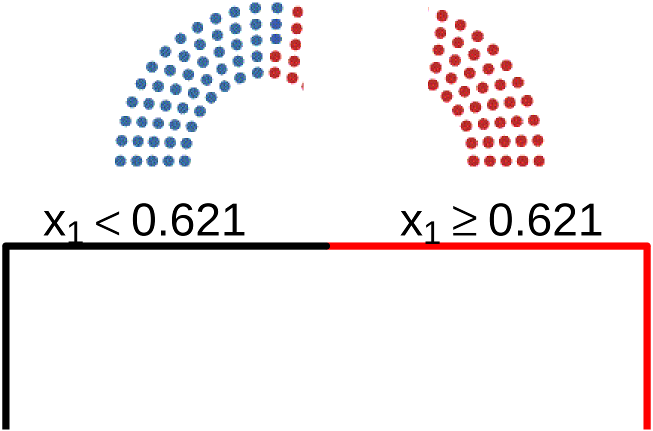

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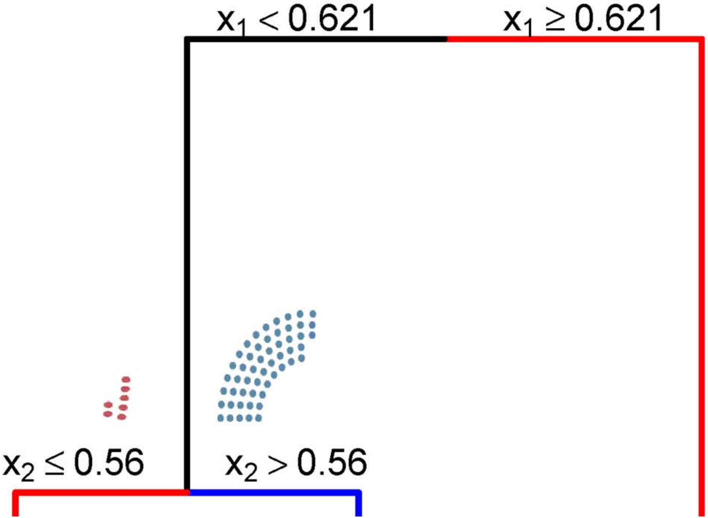

Complete Tree

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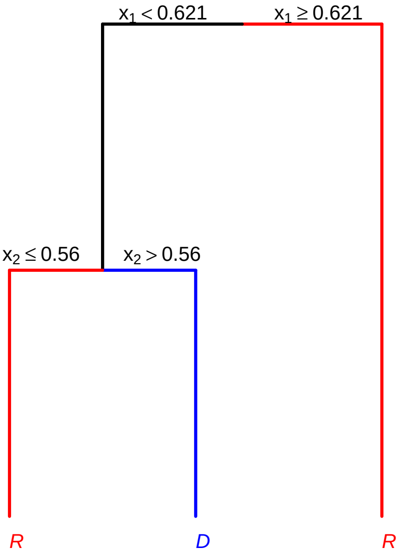

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	SVM	MaxEnt	Boostexter	Naïve Bayes	Ensemble
Major topic $N = 20$	88.7% (.881)	86.5% (.859)	85.6% (.849)	81.4% (.805)	89.0% (.884)
Subtopic $N = 226$	81.0% (.800)	78.3% (.771)	73.6% (.722)	71.9% (.705)	81.0% (.800)

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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1. In real (deep) learning problems, do we want the learners in the ensemble to be similar or diverse relative to each other (in terms of architectures, hyper-parameters etc)? Why?

2. Ensembles give us better (more accurate) predictions, but they also give us more stable predictions. Why?

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Think about how you would respond to the questions,

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Narcissistic Personality Inventory Items and Principal-Component Loadings

Items	Loadings 1	2	3	4	5	6	7
47. I would prefer to be a leader.	.83	.00	−.07	.04	−.12	.07	.22
15. I see myself as a good leader.	.83	.16	.09	−.12	.06	.03	−.14
13. I will be a success.	.67	.00	−.09	−.14	−.14	.17	.26
46. People always seem to recognize my authority.	.66	.02	.06	−.06	.06	.00	.20
2. I have a natural talent for influencing people.	.66	−.15	.02	−.02	.29	.03	−.24
16. I am assertive.	.56	.18	−.02	.22	−.02	−.03	−.27
17. I like to have authority over other people.	.56	.08	−.08	.18	.08	.05	.24
50. I am a born leader.	.35	.20	.22	.00	.09	−.14	−.01
30. I rarely depend on anyone else to get things done.	.02	.61	−.17	.04	.04	.10	−.11
23. I like to take responsibility for making decisions.	.28	.59	−.23	.23	−.12	.00	.02
53. I am more capable than other people.	−.19	.57	.16	.07	.11	.01	.20
45. I can live my life in any way I want to.	−.13	.46	.29	−.02	.05	.05	−.03
29. I always know what I am doing.	.15	.46	−.14	−.03	.30	.01	−.09
48. I am going to be a great person.	.05	.43	.39	.04	−.03	−.05	.00
54. I am an extraordinary person.	.06	.22	.69	−.07	−.06	.01	.06
7. I know that I am good because everybody keeps telling me so.	−.18	.01	.69	.00	.21	.01	.15
36. I like to be complimented.	.00	−.28	.67	.06	.00	.11	−.17
14. I think I am a special person.	.08	.16	.64	−.02	−.09	.17	−.01
51. I wish somebody would someday write my biography.	−.06	−.01	.57	.06	−.22	.09	.00
28. I am apt to show off if I get the chance.	−.04	−.02	.04	.71	−.03	.06	.06
3. Modesty doesn't become me.	−.01	.19	−.01	.69	−.16	−.06	.14
52. I get upset when people don't notice how I look when I go out in public.	−.16	.04	.10	.51	.09	.25	.17

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2 PCA is doing two things, intuitively: finding variable combinations that differ most across observations, and finding the combinations which predict the original data the best. These are equivalent: why?