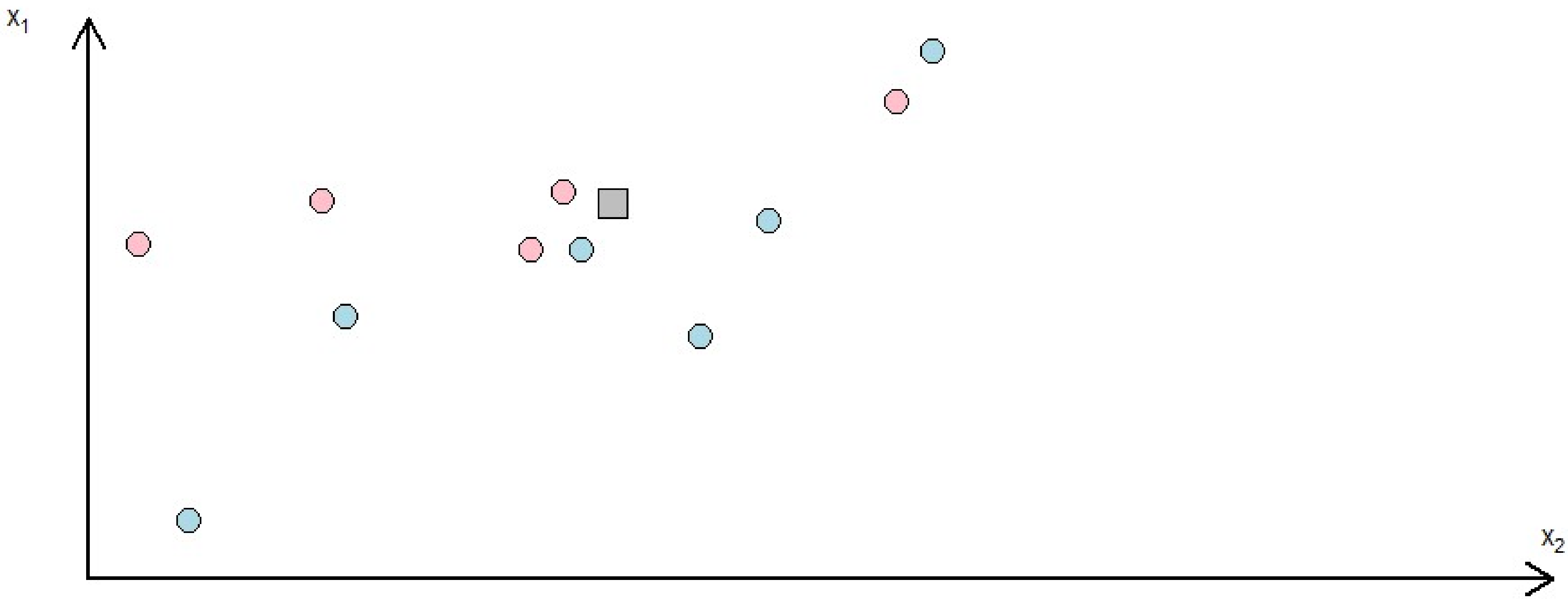
x_1
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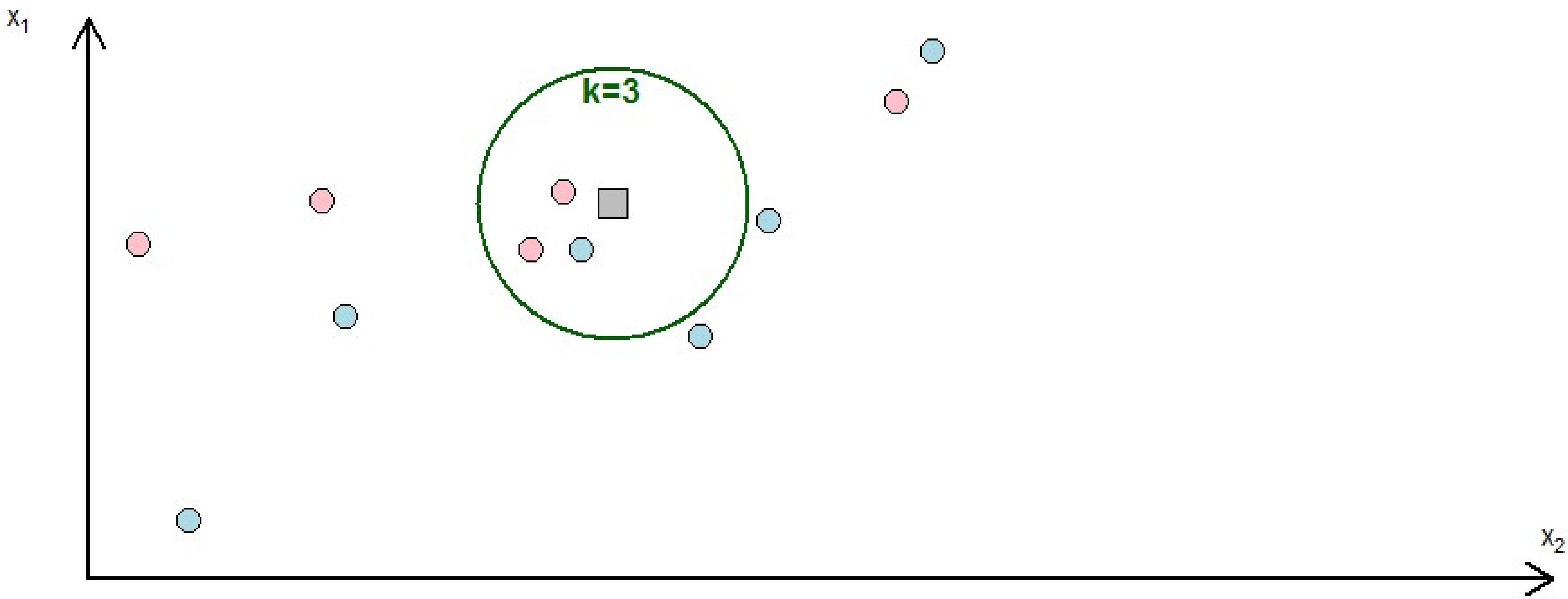
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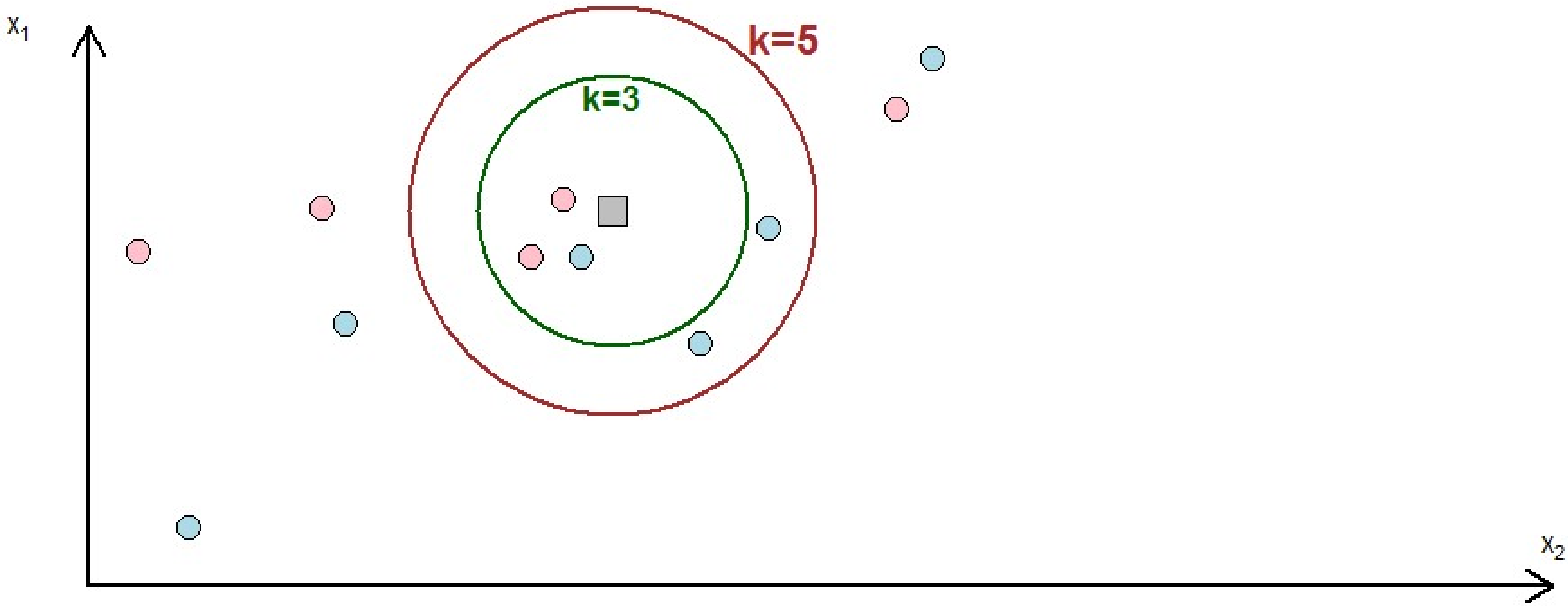
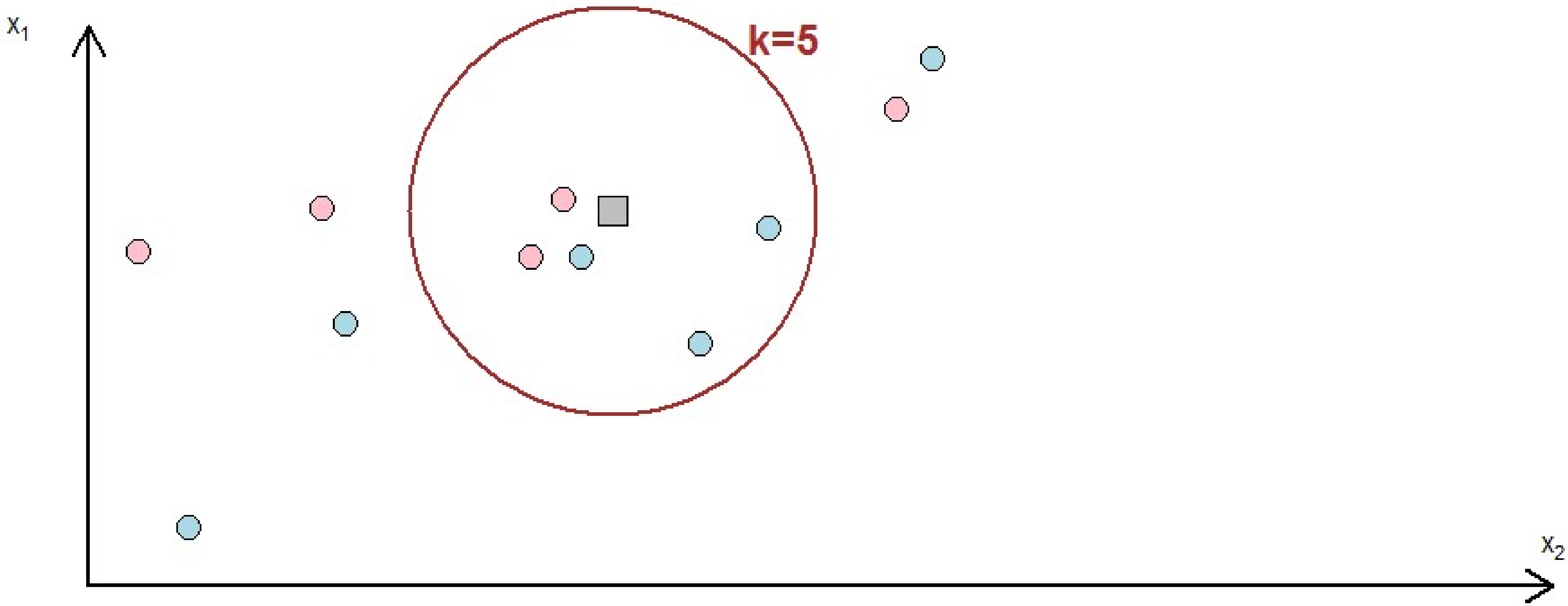

x1
k=5
k=3
x2



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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

Partitioning the Senators With Trees

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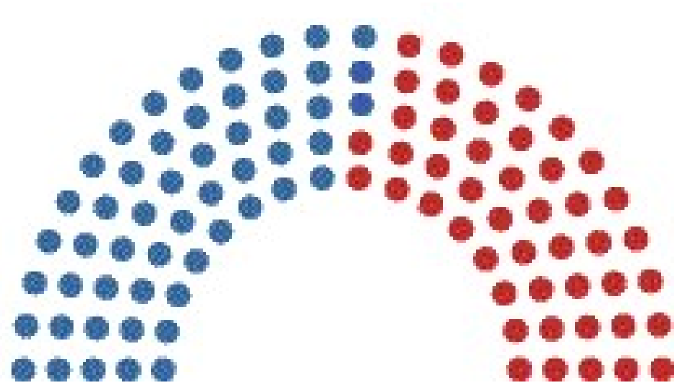

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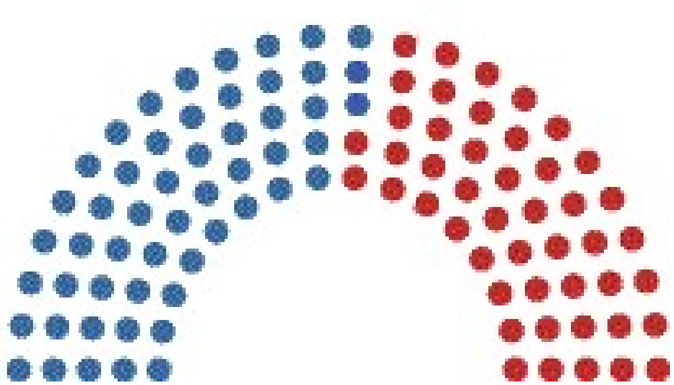

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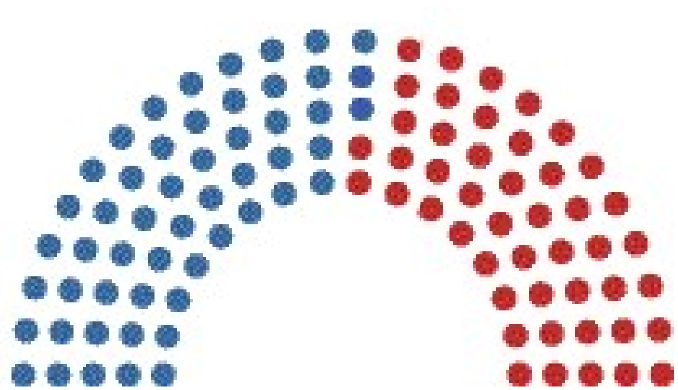

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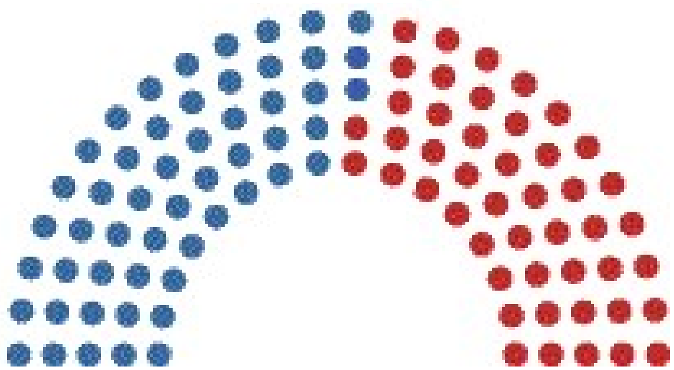

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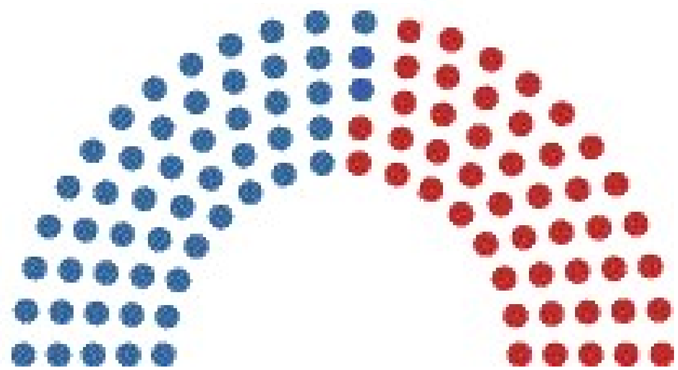

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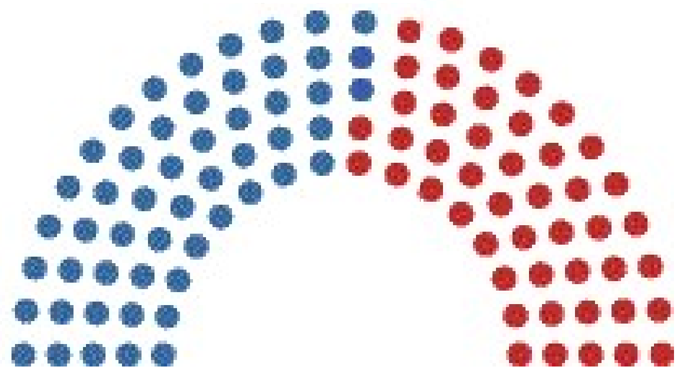

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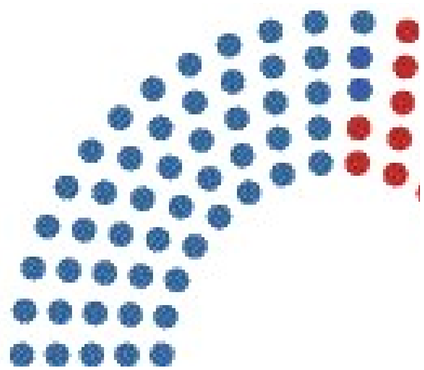

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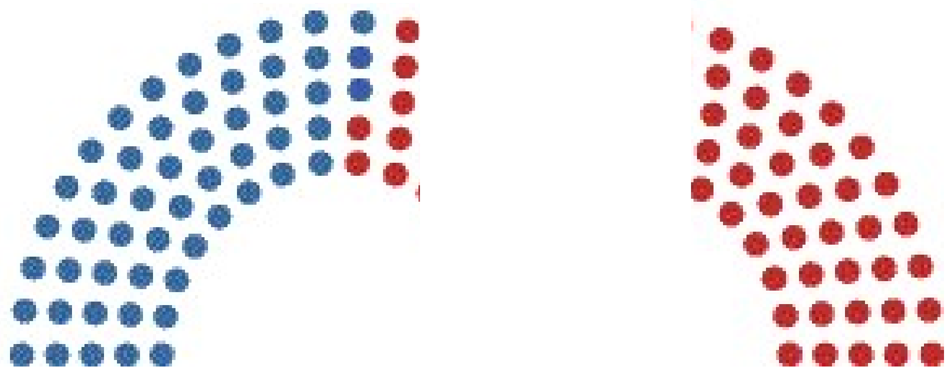

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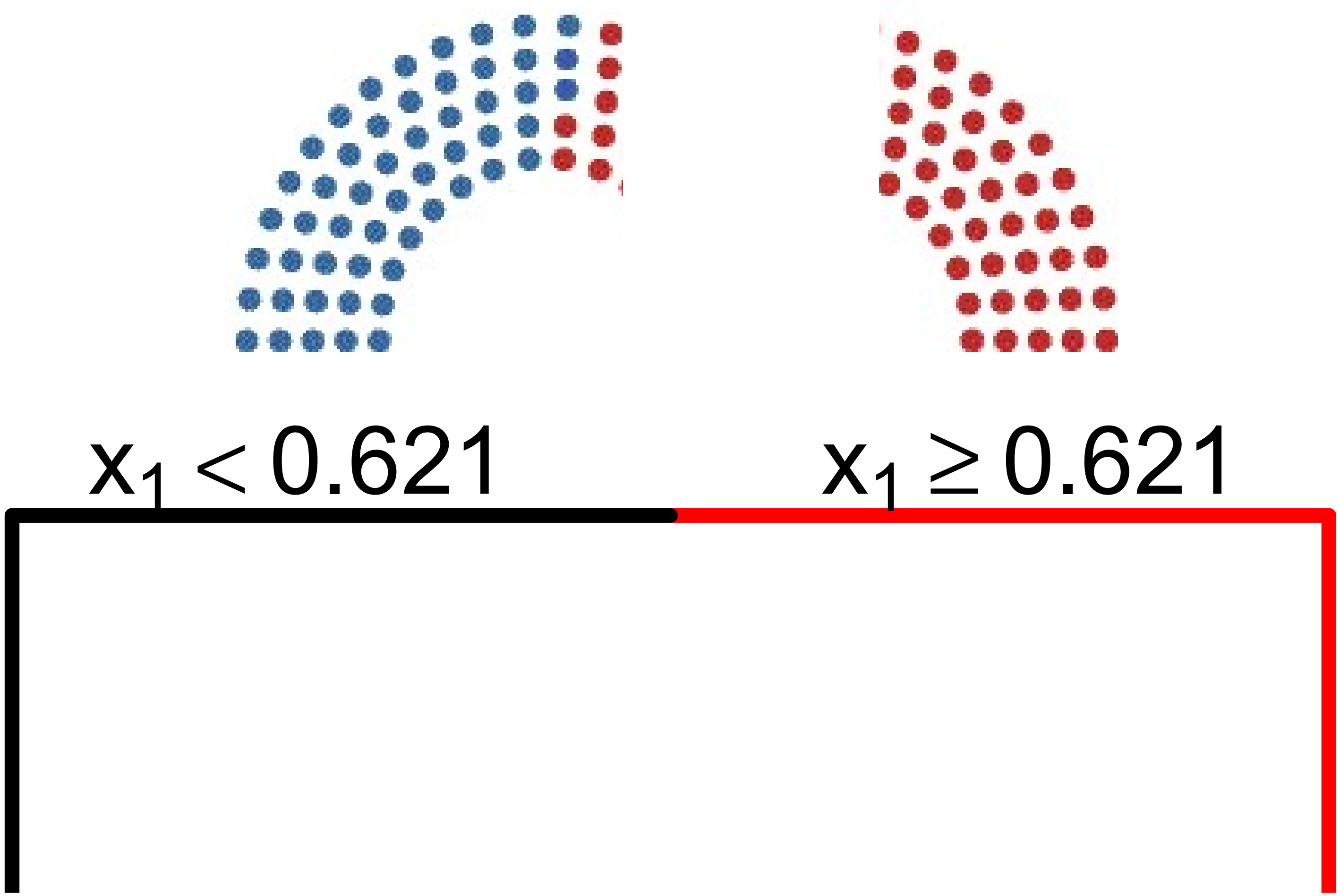

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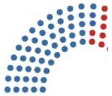

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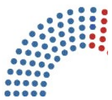

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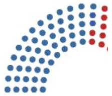

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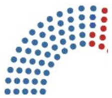

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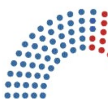

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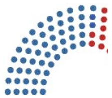

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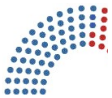

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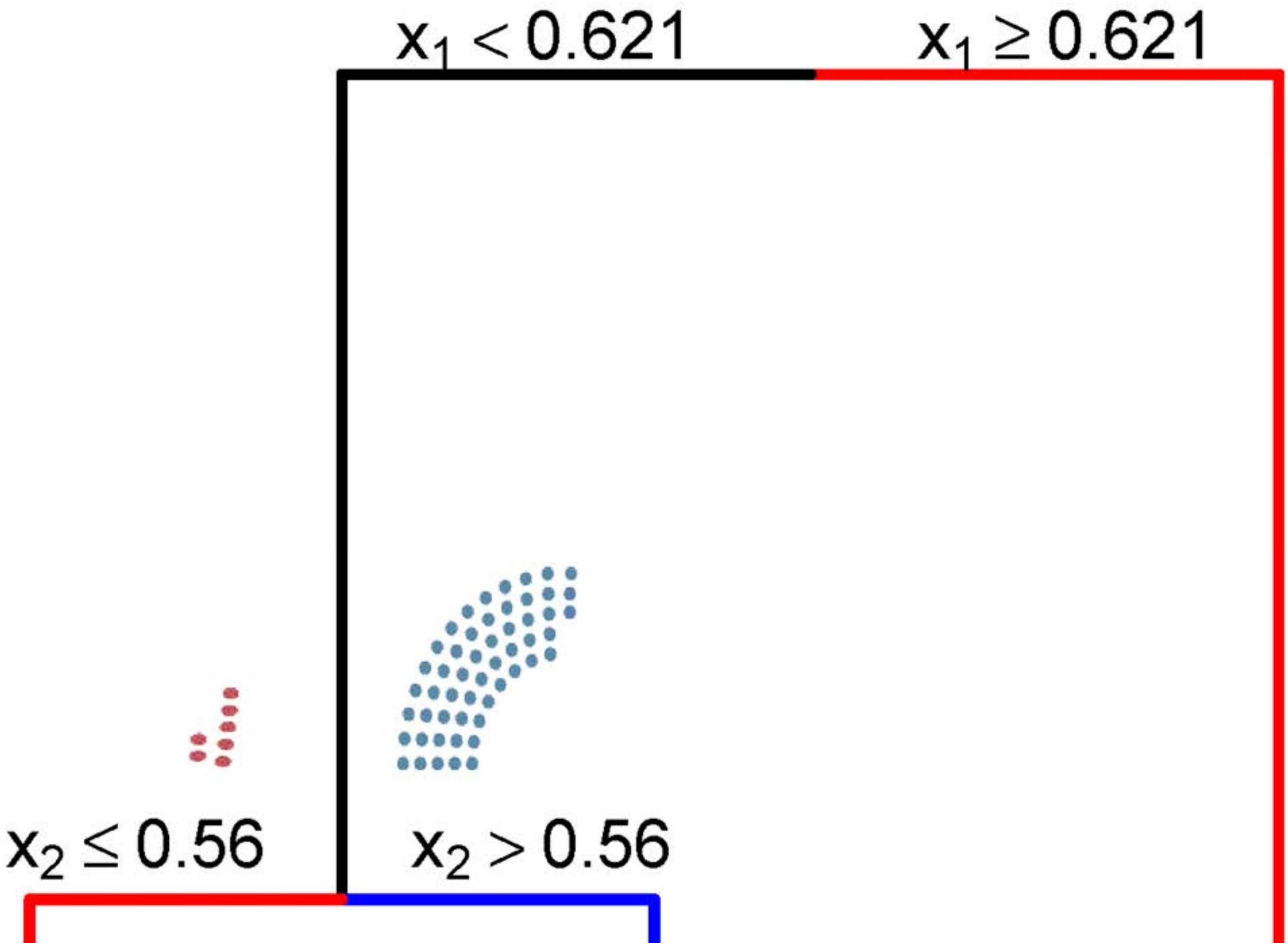

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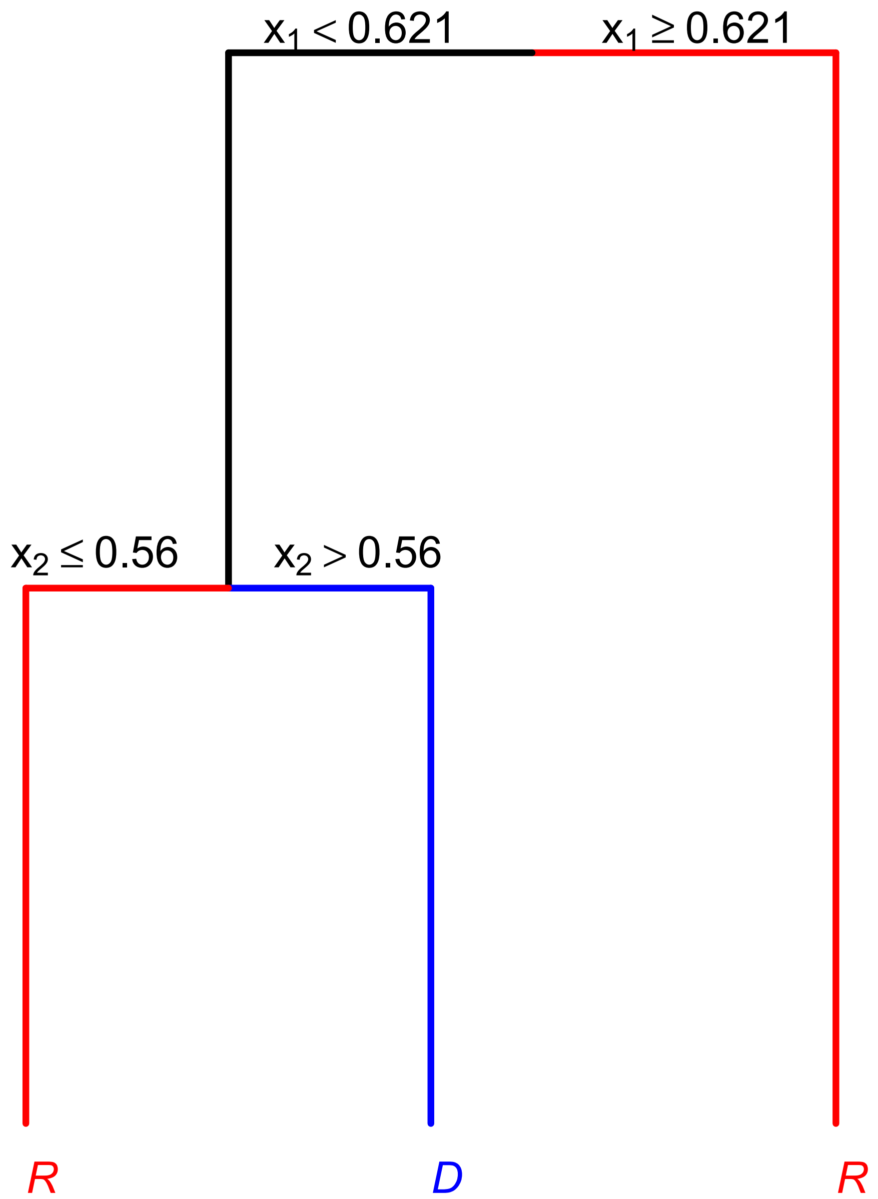

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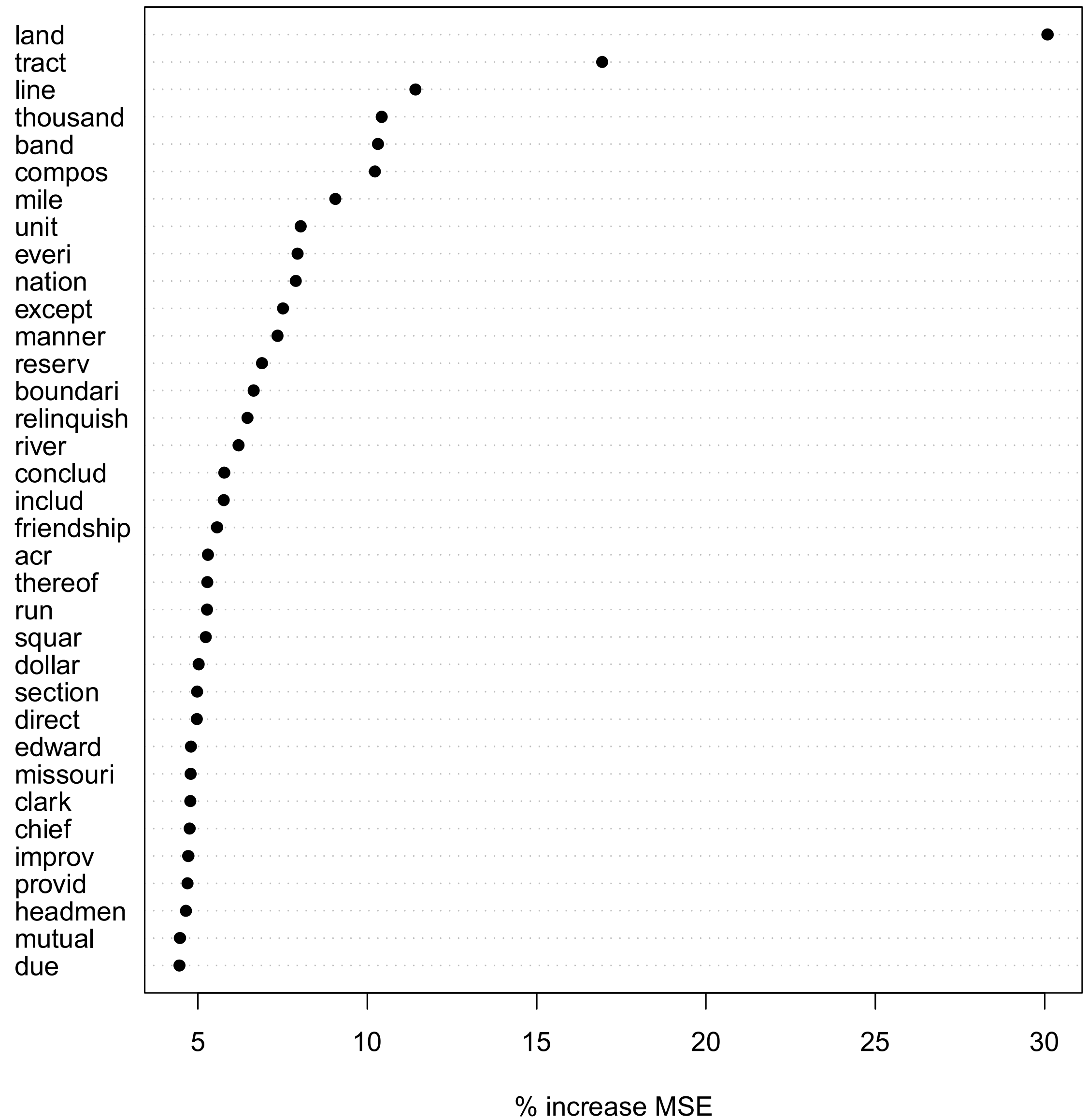

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stem	appearance	common phrasing (frequency)	ρ
`friendship`	friendship	“A treaty of peace and friendship” (15)	0.504
`mutual`	mutually	“shall be mutually forgiven and forgot” (19)	0.255
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cession	cession	"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

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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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	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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Imagine you apply the model from the 2015 data to 2016, and then every year thereafter: 2017, 2018...2024, 2025. Would you expect it to get more or less accurate over time? Why?