Introduction to Information Retrieval

http://informationretrieval.org

IIR 14: Vector Space Classification

Hinrich Schütze

Center for Information and Language Processing, University of Munich

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Overview

1. Recap
2. Intro vector space classification
3. Rocchio
4. kNN
5. Linear classifiers
6. > two classes

Outline

1. Recap
2. Intro vector space classification
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Feature selection: MI for *poultry*/EXPORT

Goal of feature selection: eleminate noise and useless features for better effectiveness and efficiency

	$e_c = e_{poultry} = 1$	$e_c = e_{poultry} = 0$
$e_t = e_{\text{EXPORT}} = 1$	$N_{11} = 49$	$N_{10} = 27{,}652$
$e_t = e_{\text{EXPORT}} = 0$	$N_{01} = 141$	$N_{00} = 774{,}106$

Plug these values into formula:

$$\begin{aligned}
I(U;C) &= \frac{49}{801{,}948}\log_2\frac{801{,}948\cdot 49}{(49+27{,}652)(49+141)} \\
&+\frac{141}{801{,}948}\log_2\frac{801{,}948\cdot 141}{(141+774{,}106)(49+141)} \\
&+\frac{27{,}652}{801{,}948}\log_2\frac{801{,}948\cdot 27{,}652}{(49+27{,}652)(27{,}652+774{,}106)} \\
&+\frac{774{,}106}{801{,}948}\log_2\frac{801{,}948\cdot 774{,}106}{(141+774{,}106)(27{,}652+774{,}106)} \\
&\approx 0.000105
\end{aligned}$$

Feature selection for Reuters classes coffee and sports

Class: *coffee*

term	MI
COFFEE	0.0111
BAGS	0.0042
GROWERS	0.0025
KG	0.0019
COLOMBIA	0.0018
BRAZIL	0.0016
EXPORT	0.0014
EXPORTERS	0.0013
EXPORTS	0.0013
CROP	0.0012

Class: *sports*

term	MI
SOCCER	0.0681
CUP	0.0515
MATCH	0.0441
MATCHES	0.0408
PLAYED	0.0388
LEAGUE	0.0386
BEAT	0.0301
GAME	0.0299
GAMES	0.0284
TEAM	0.0264

Using language models (LMs) for IR

- LM = language model
- We view the document as a generative model that generates the query.
- What we need to do:
- Define the precise generative model we want to use
- Estimate parameters (different parameters for each document's model)
- Smooth to avoid zeros
- Apply to query and find document most likely to have generated the query
- Present most likely document(s) to user

Jelinek-Mercer smoothing

- $P(t|d) = \lambda P(t|M_d) + (1 - \lambda)P(t|M_c)$
- Mixes the probability from the document with the general collection frequency of the word.
- High value of λ: "conjunctive-like" search – tends to retrieve documents containing all query words.
- Low value of λ: more disjunctive, suitable for long queries
- Correctly setting λ is very important for good performance.

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- More than two classes

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Recall vector space representation

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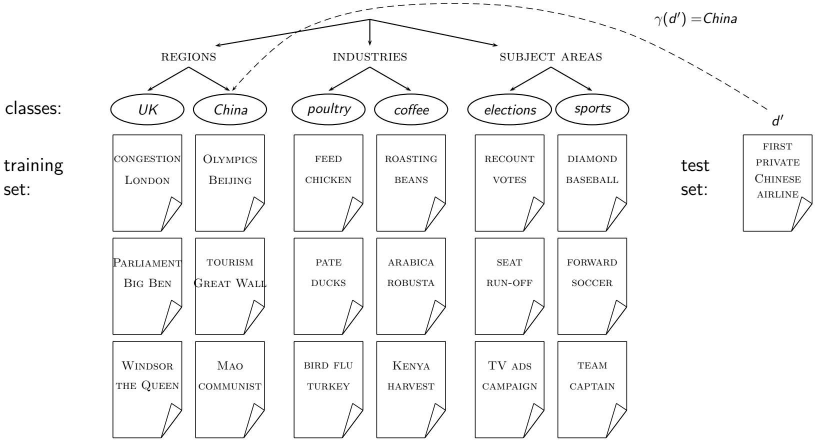
- Terms are axes.
- High dimensionality: 100,000s of dimensions
- Normalize vectors (documents) to unit length
- How can we do classification in this space?

Basic text classification setup



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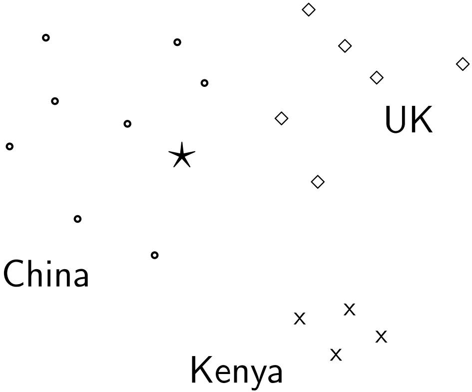
- In vector space classification, this set corresponds to a labeled set of points or vectors in the vector space.
- Premise 1: Documents in the same class form a contiguous region.
- Premise 2: Documents from different classes don't overlap.
- We define lines, surfaces, hypersurfaces to divide regions.

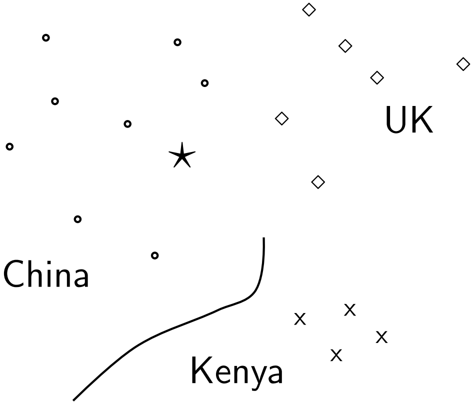
Classes in the vector space

Classes in the vector space



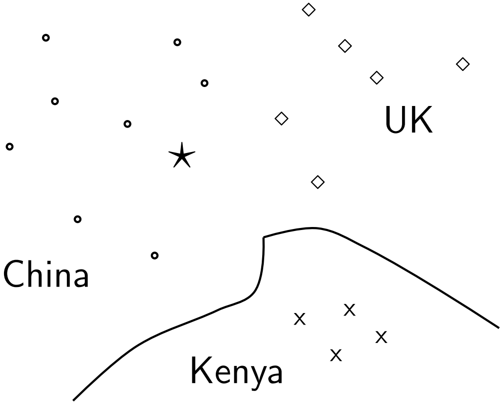
Should the document $\star$ be assigned to *China*, *UK* or *Kenya*?

Classes in the vector space



Find separators between the classes

Classes in the vector space



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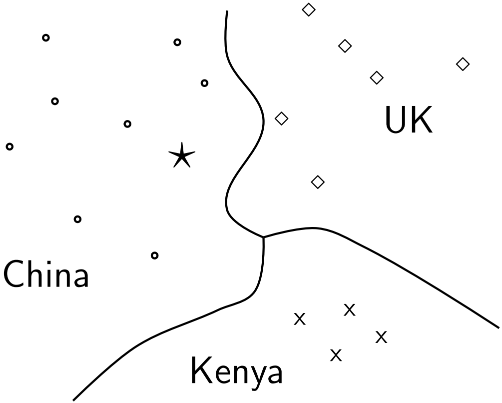

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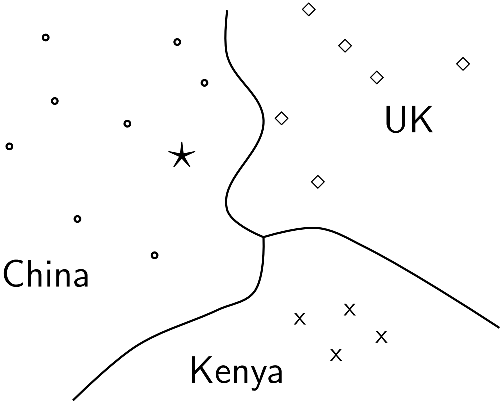
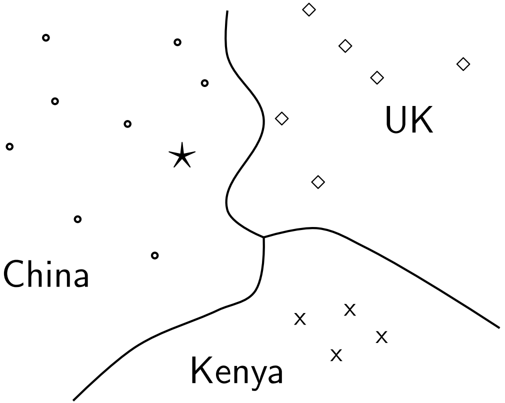


Based on these separators: $\star$ should be assigned to *China*

Classes in the vector space



How do we find separators that do a good job at classifying new documents like $\star$? – Main topic of today

Aside: 2D/3D graphs can be misleading

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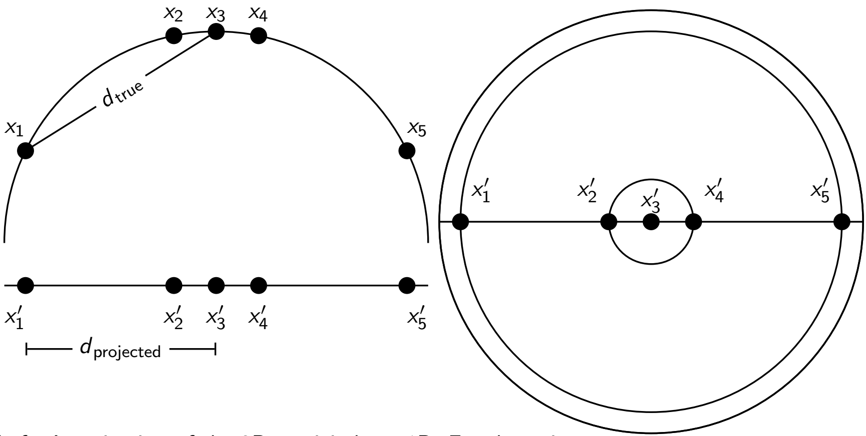

Left: A projection of the 2D semicircle to 1D. For the points x_1, x_2, x_3, x_4, x_5 at x coordinates $-0.9, -0.2, 0, 0.2, 0.9$ the distance $|x_2x_3| \approx 0.201$ only differs by 0.5% from $|x'_2x'_3| = 0.2$; but $|x_1x_3|/|x'_1x'_3| = d_{\text{true}}/d_{\text{projected}} \approx 1.06/0.9 \approx 1.18$ is an example of a large distortion (18%) when projecting a large area. *Right:* The corresponding projection of the 3D hemisphere to 2D.

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Relevance feedback

- In relevance feedback, the user marks documents as relevant/nonrelevant.
- Relevant/nonrelevant can be viewed as classes or categories.
- For each document, the user decides which of these two classes is correct.
- The IR system then uses these class assignments to build a better query ("model") of the information need ...
- ... and returns better documents.
- Relevance feedback is a form of text classification.

Using Rocchio for vector space classification

- The principal difference between relevance feedback and text classification:

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Using Rocchio for vector space classification

- The principal difference between relevance feedback and text classification:
  - The training set is given as part of the input in text classification.
  - It is interactively created in relevance feedback.

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- Compute a centroid for each class
  - The centroid is the average of all documents in the class.
- Assign each test document to the class of its closest centroid.

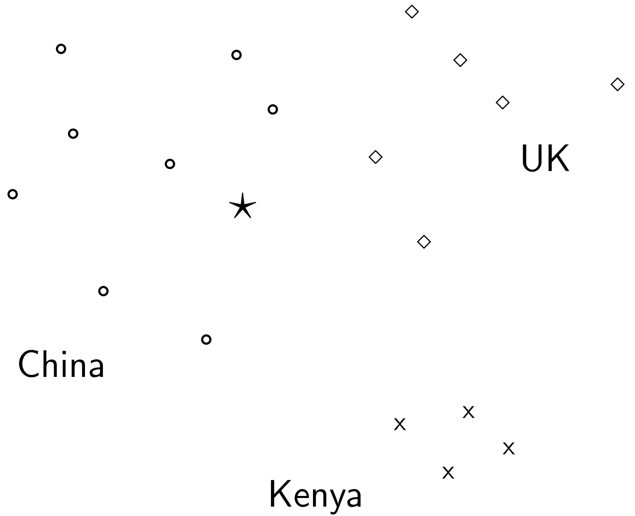
Recall definition of centroid

Recall definition of centroid

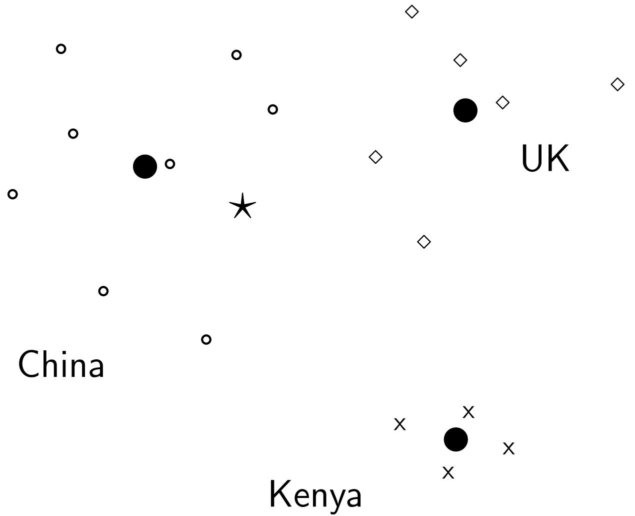
$$\vec{\mu}(c) = \frac{1}{|D_c|} \sum_{d \in D_c} \vec{v}(d)$$

where D_c is the set of all documents that belong to class c and $\vec{v}(d)$ is the vector space representation of d.

Rocchio illustrated



Rocchio illustrated



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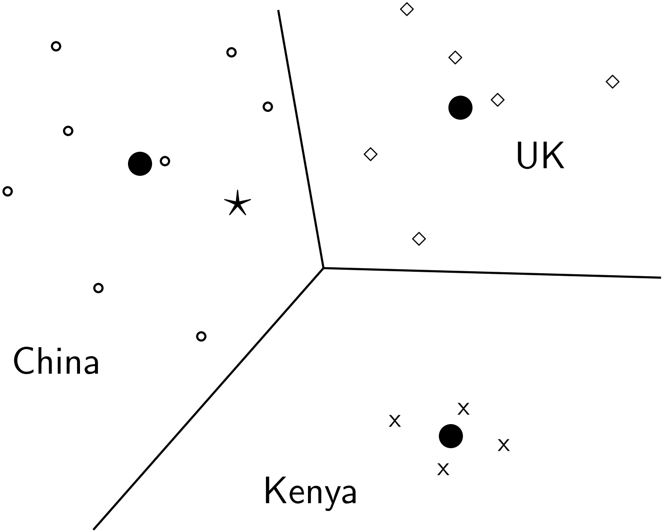

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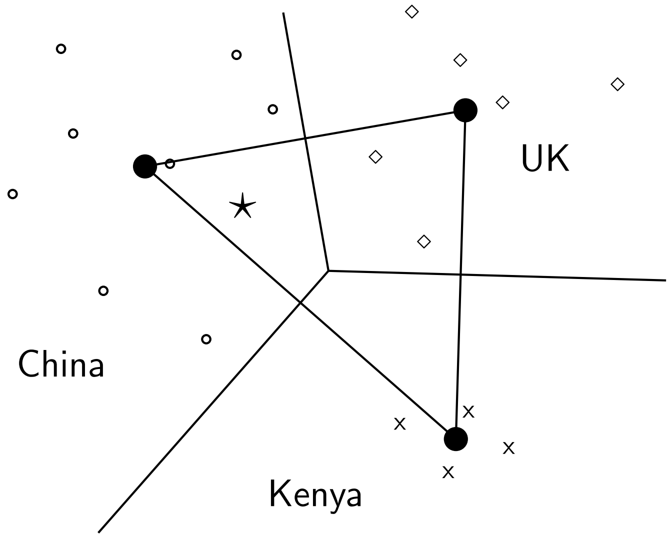

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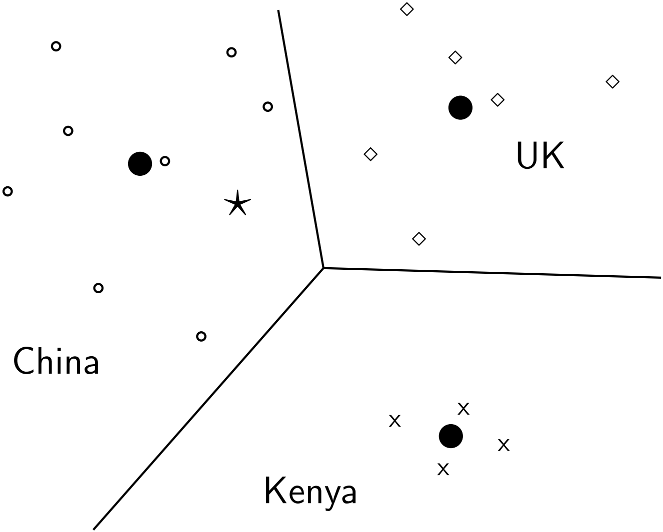
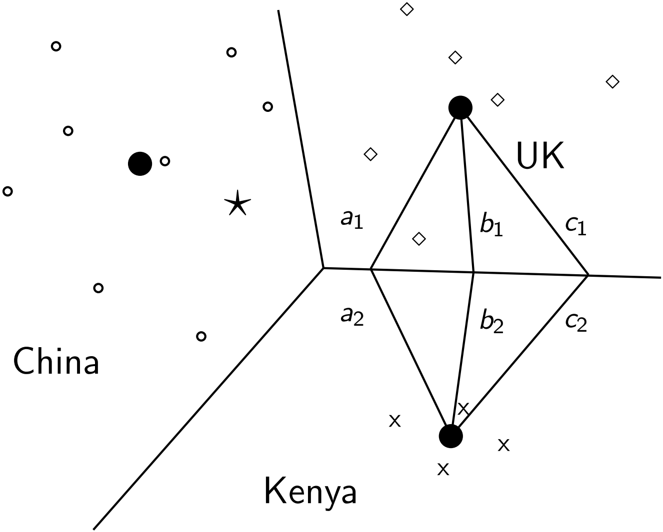


Rocchio illustrated: $a_1 = a_2, b_1 = b_2, c_1 = c_2$



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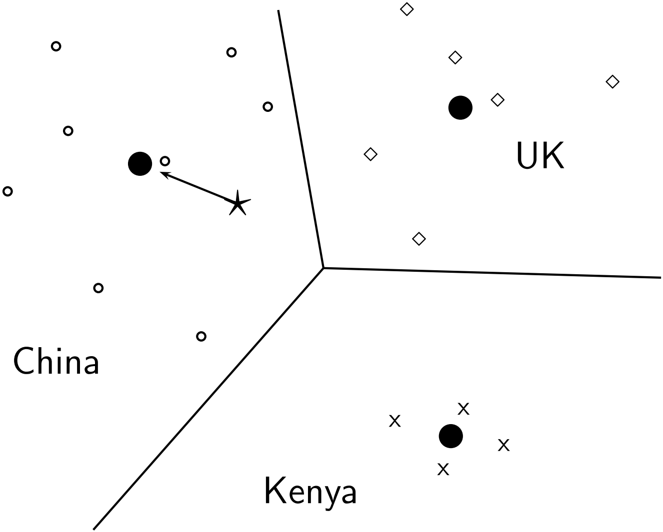

Rocchio algorithm

Rocchio algorithm

$\textsc{TrainRocchio}(\mathbb{C}, \mathbb{D})$

for each $c_j \in \mathbb{C}$
do $D_j \leftarrow \{d : \langle d, c_j \rangle \in \mathbb{D}\}$
$\quad \vec{\mu}_j \leftarrow \frac{1}{|D_j|} \sum_{d \in D_j} \vec{v}(d)$
return $\{\vec{\mu}_1, \ldots, \vec{\mu}_J\}$

$\textsc{ApplyRocchio}(\{\vec{\mu}_1, \ldots, \vec{\mu}_J\}, d)$

return $\arg\min_j |\vec{\mu}_j - \vec{v}(d)|$

Rocchio properties

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- Rocchio forms a simple representation for each class: the centroid
  - We can interpret the centroid as the prototype of the class.
- Classification is based on similarity to / distance from centroid/prototype.
- Does not guarantee that classifications are consistent with the training data!

Time complexity of Rocchio

Time complexity of Rocchio

mode	time complexity
training	$\Theta(\lvert\mathbb{D}\rvert L_{\text{ave}} + \lvert\mathbb{C}\rvert\lvert V\rvert) \approx \Theta(\lvert\mathbb{D}\rvert L_{\text{ave}})$
testing	$\Theta(L_{\text{a}} + \lvert\mathbb{C}\rvert M_{\text{a}}) \approx \Theta(\lvert\mathbb{C}\rvert M_{\text{a}})$

Rocchio vs. Naive Bayes

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- In many cases, Rocchio performs worse than Naive Bayes.

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- One reason: Rocchio does not handle nonconvex, multimodal classes correctly.

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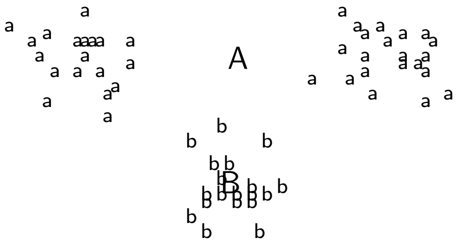

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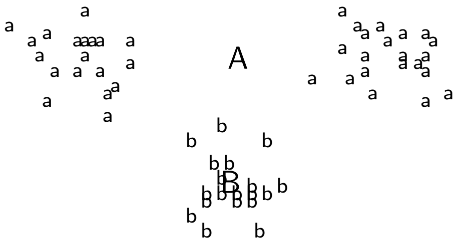

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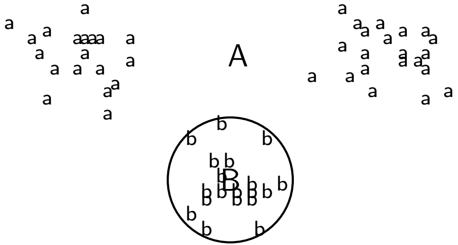

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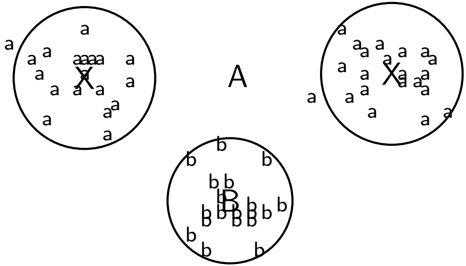

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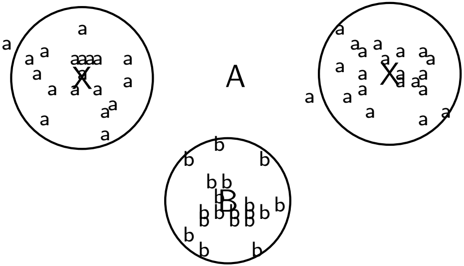

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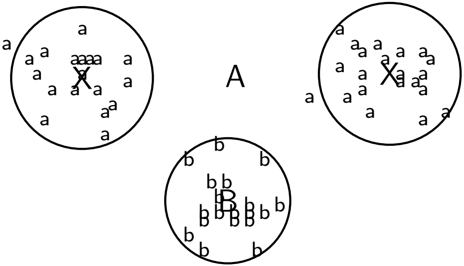

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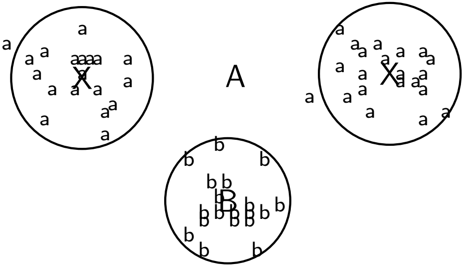

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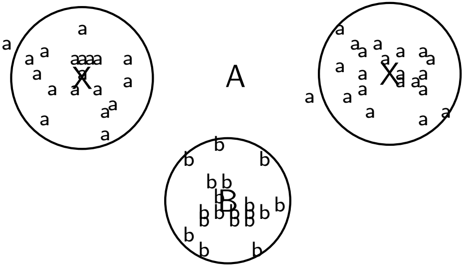

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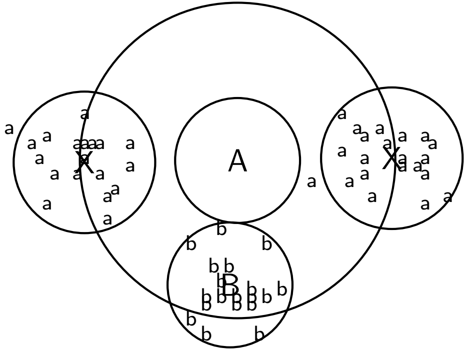

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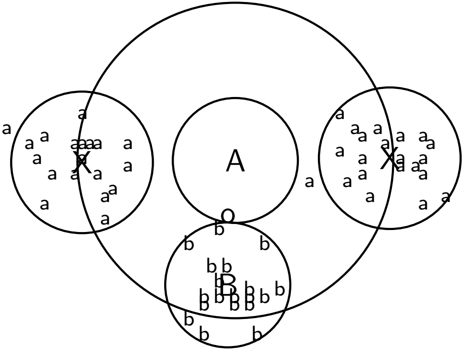

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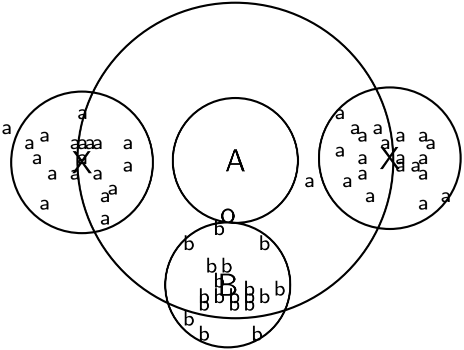

- A is centroid of the a's, B is centroid of the b's.
- The point o is closer to A than to B.
- But o is a better fit for the b class.
- A is a multimodal class with two prototypes.
- But in Rocchio we only have one prototype.

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- . . . and you don't care about efficiency that much . . .
- . . . use kNN.

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- Rationale of kNN: contiguity hypothesis
  - We expect a test document d to have the same label as the training documents located in the local region surrounding d.

Probabilistic kNN

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- Probabilistic version of kNN: $P(c|d) =$ fraction of k neighbors of d that are in c

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- kNN classification rule for probabilistic kNN: Assign d to class c with highest $P(c|d)$

kNN is based on Voronoi tessellation

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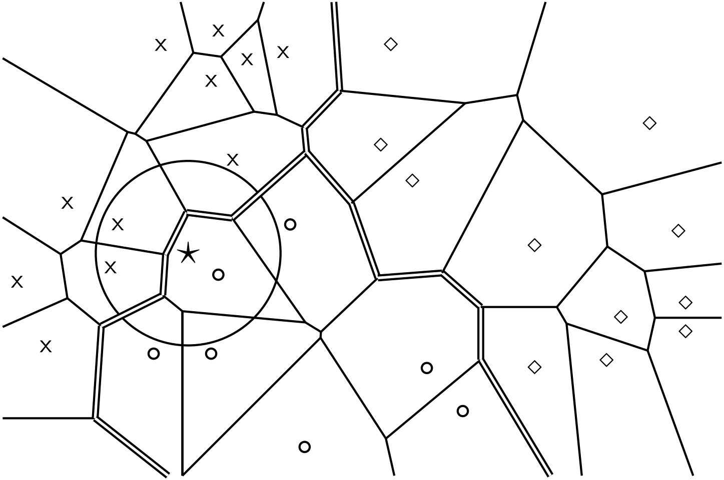

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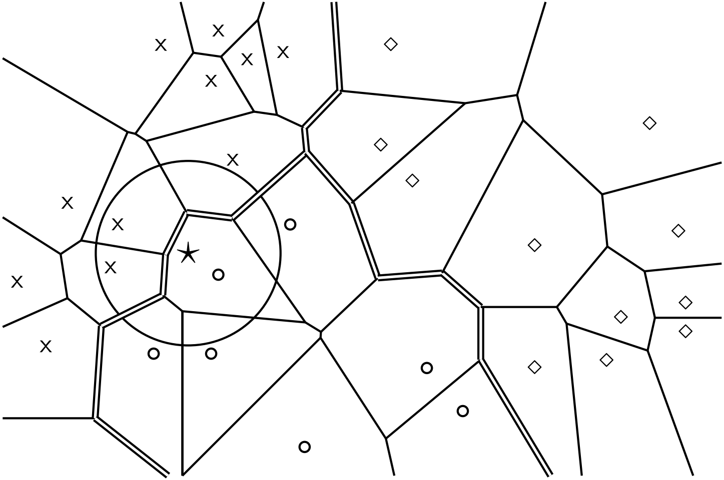


kNN algorithm

kNN algorithm

$\text{Train-kNN}(\mathbb{C}, \mathbb{D})$

$\mathbb{D}' \leftarrow \text{Preprocess}(\mathbb{D})$

$k \leftarrow \text{Select-k}(\mathbb{C}, \mathbb{D}')$

return $\mathbb{D}', k$

$\text{Apply-kNN}(\mathbb{D}', k, d)$

$S_k \leftarrow \text{ComputeNearestNeighbors}(\mathbb{D}', k, d)$

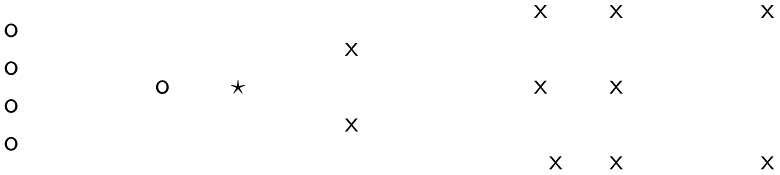
for each $c_j \in \mathbb{C}(\mathbb{D}')$

do $p_j \leftarrow |S_k \cap c_j|/k$

return $\arg\max_j p_j$

Exercise

Exercise



How is star classified by:
(i) 1-NN (ii) 3-NN (iii) 9-NN (iv) 15-NN (v) Rocchio?

Time complexity of kNN

Time complexity of kNN

kNN with preprocessing of training set

training	$\Theta(\lvert\mathbb{D}\rvert L_{\mathrm{ave}})$
testing	$\Theta(L_{\mathrm{a}} + \lvert\mathbb{D}\rvert M_{\mathrm{ave}} M_{\mathrm{a}}) = \Theta(\lvert\mathbb{D}\rvert M_{\mathrm{ave}} M_{\mathrm{a}})$

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- The larger the training set, the longer it takes to classify a test document.
- kNN is inefficient for very large training sets.

Time complexity of kNN

kNN with preprocessing of training set

training $\Theta(|\mathbb{D}|L_{\text{ave}})$

testing $\Theta(L_{\text{a}} + |\mathbb{D}|M_{\text{ave}}M_{\text{a}}) = \Theta(|\mathbb{D}|M_{\text{ave}}M_{\text{a}})$

- kNN test time proportional to the size of the training set!
- The larger the training set, the longer it takes to classify a test document.
- kNN is inefficient for very large training sets.
- Question: Can we divide up the training set into regions, so that we only have to search in one region to do kNN classification for a given test document? (which perhaps would give us better than linear time complexity)

Curse of dimensionality

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- Then

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- We see that intuition 1 (some things are close, others are distant) is not true for high dimensions.

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- Do this for each dimension, then intersect the d subsets.

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- ... unless the "true" dimensionality is much lower than d.

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- Optimality result: asymptotically zero error if Bayes rate is zero.
- But kNN can be very inaccurate if training set is small.

Outline

1. Recap
2. Intro vector space classification
3. Rocchio
4. kNN
5. Linear classifiers
6. > two classes

Linear classifiers

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- Assumption: The classes are linearly separable.

A linear classifier in 1D

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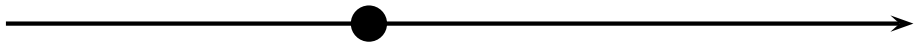
A linear classifier in 1D



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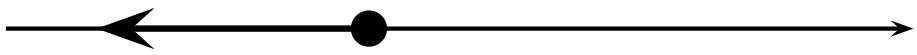

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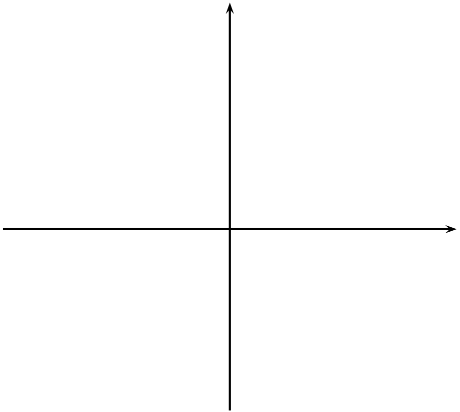

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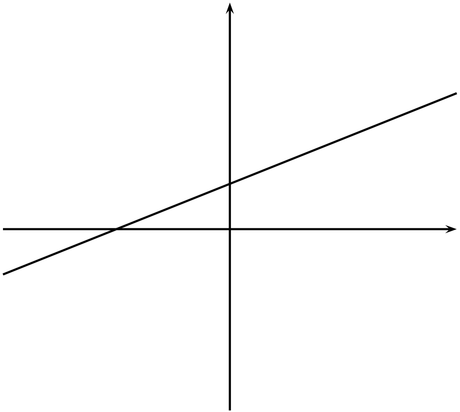

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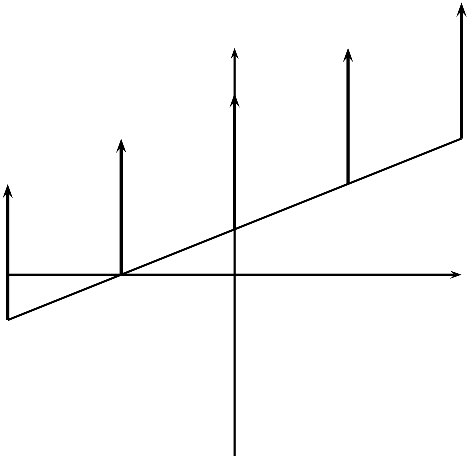

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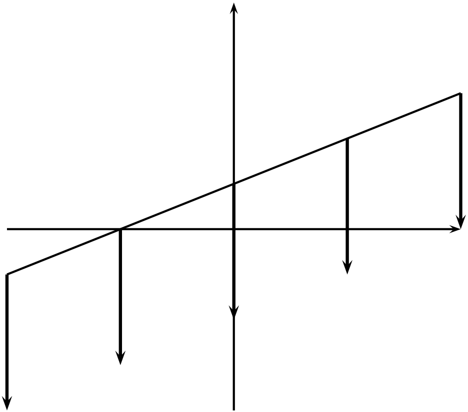

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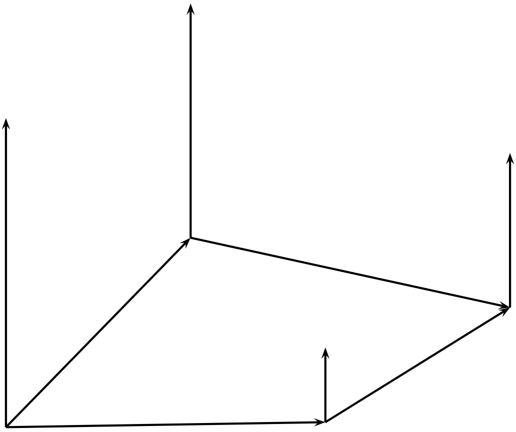

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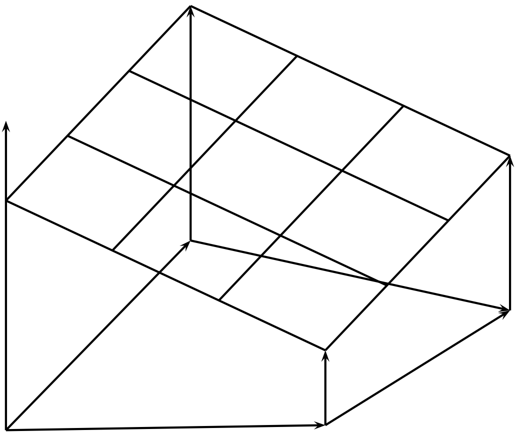

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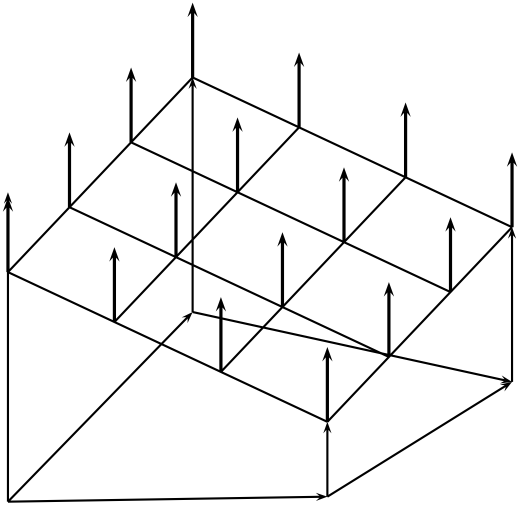

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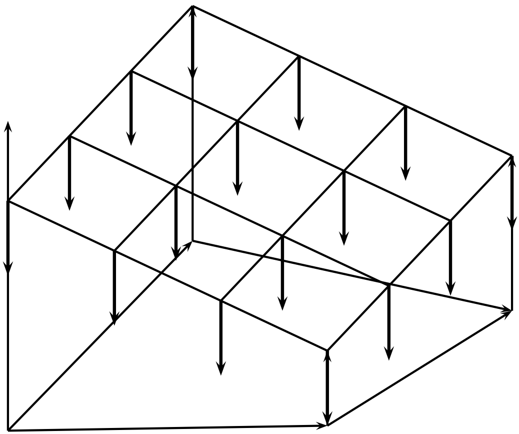

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Rocchio as a linear classifier

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- Rocchio is a linear classifier defined by:

$$\sum_{i=1}^{M} w_i d_i = \vec{w}\vec{d} = \theta$$

where $\vec{w}$ is the normal vector $\vec{\mu}(c_1) - \vec{\mu}(c_2)$ and $\theta = 0.5 * (|\vec{\mu}(c_1)|^2 - |\vec{\mu}(c_2)|^2)$.

Naive Bayes as a linear classifier

Naive Bayes as a linear classifier

Multinomial Naive Bayes is a linear classifier (in log space) defined by:

$$\sum_{i=1}^{M} w_i d_i = \theta$$

where $w_i = \log[\hat{P}(t_i|c)/\hat{P}(t_i|\bar{c})]$, $d_i =$ number of occurrences of t_i in d, and $\theta = -\log[\hat{P}(c)/\hat{P}(\bar{c})]$. Here, the index i, $1 \leq i \leq M$, refers to terms of the vocabulary (not to positions in d as k did in our original definition of Naive Bayes)

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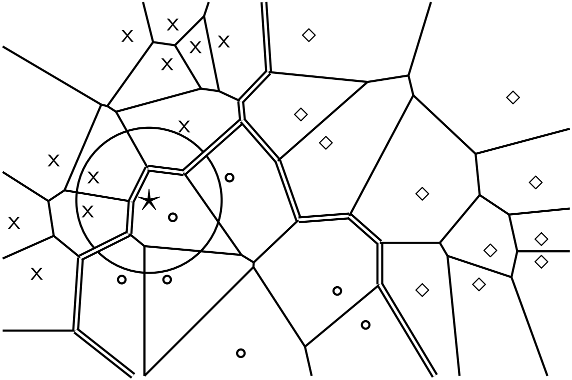

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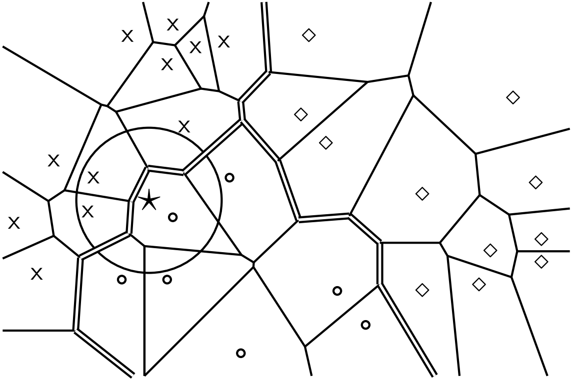

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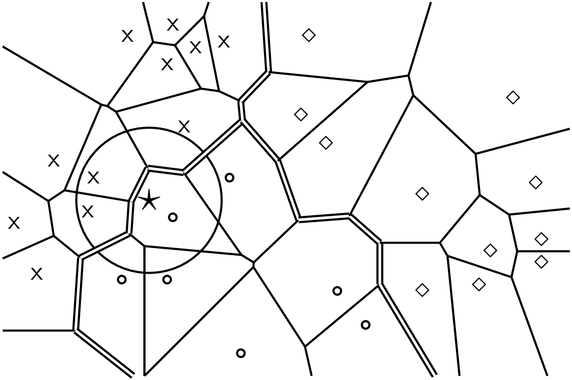

- Classification decision based on majority of *k* nearest neighbors.

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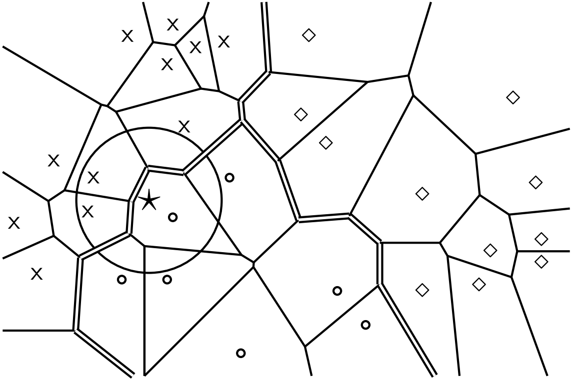

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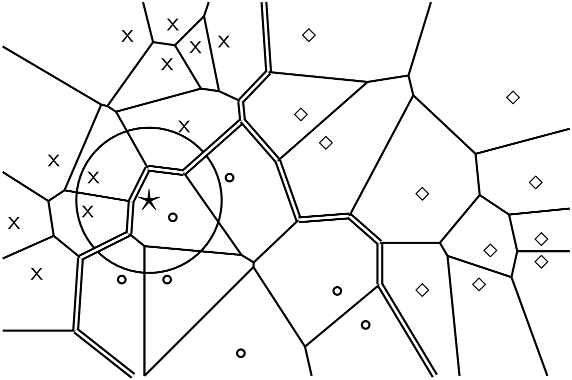

- Classification decision based on majority of k nearest neighbors.
- The decision boundaries between classes are piecewise linear ...
- ... but they are in general not linear classifiers that can be described as $\sum_{i=1}^{M} w_i d_i = \theta$.

Example of a linear two-class classifier

t_i	w_i	d_{1i}	d_{2i}	t_i	w_i	d_{1i}	d_{2i}
prime	0.70	0	1	dlrs	-0.71	1	1
rate	0.67	1	0	world	-0.35	1	0
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rates	0.60	0	0	year	-0.25	0	0
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- This is for the class *interest* in Reuters-21578.
- For simplicity: assume a simple 0/1 vector representation
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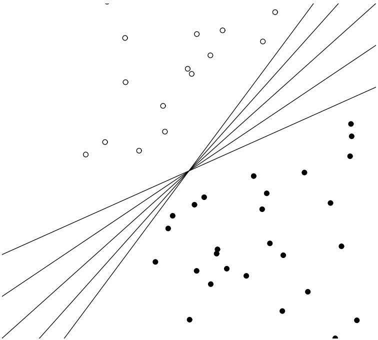
- Exercise: Which class is d_1 assigned to? Which class is d_2 assigned to?
- We assign document $\vec{d}_1$ "rate discount dlrs world" to *interest* since $\vec{w}^T\vec{d}_1 = 0.67 \cdot 1 + 0.46 \cdot 1 + (-0.71) \cdot 1 + (-0.35) \cdot 1 = 0.07 > 0 = \theta$.
- We assign $\vec{d}_2$ "prime dlrs" to the complement class (not in *interest*) since $\vec{w}^T\vec{d}_2 = -0.01 \leq \theta$.

Which hyperplane?

Which hyperplane?



Learning algorithms for vector space classification

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  - Perceptron (example available as PDF on website: http://cislmu.org)
- The best performing learning algorithms usually require iterative learning.

Perceptron update rule

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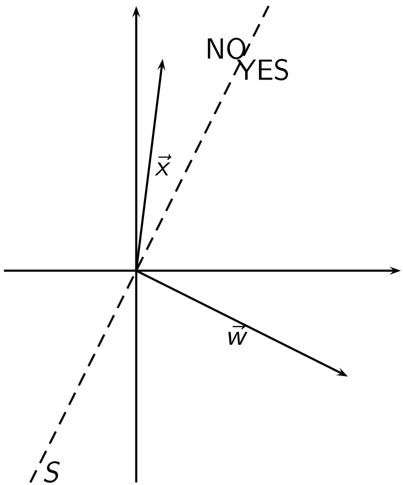
  - Otherwise: $\vec{w} = \vec{w} - \text{sign}(\vec{w}^T\vec{x})\vec{x}$

Perceptron (class of $\vec{x}$ is YES)



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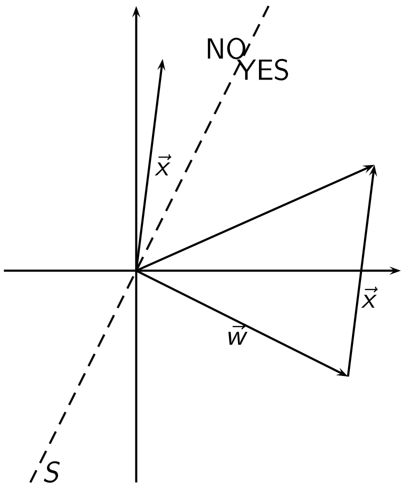

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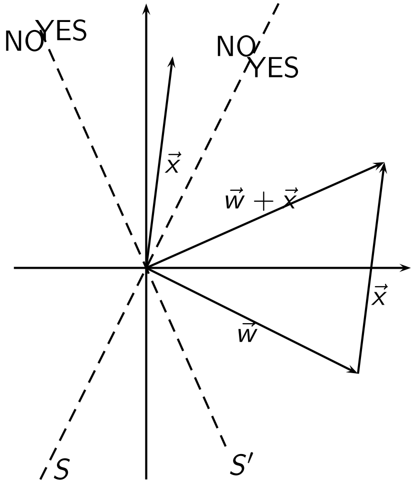

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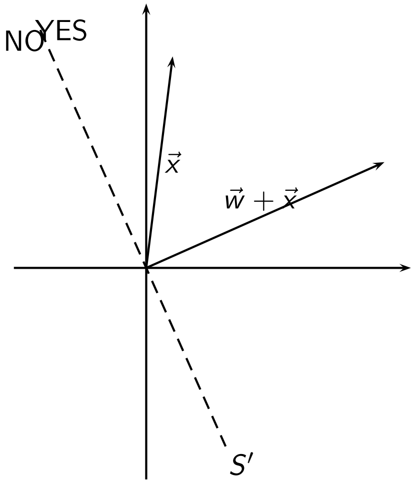

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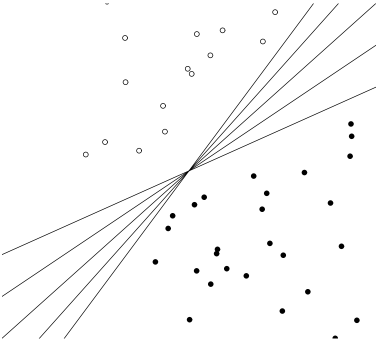

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- . . . but they behave differently on test data.
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- How do we find a low-error separator?
- Perceptron: generally bad; Naive Bayes, Rocchio: ok; linear SVM: good

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Linear classifiers: Discussion

- Many common text classifiers are linear classifiers: Naive Bayes, Rocchio, logistic regression, linear support vector machines etc.
- Each method has a different way of selecting the separating hyperplane
  - Huge differences in performance on test documents
- Can we get better performance with more powerful nonlinear classifiers?
- Not in general: A given amount of training data may suffice for estimating a linear boundary, but not for estimating a more complex nonlinear boundary.

A nonlinear problem

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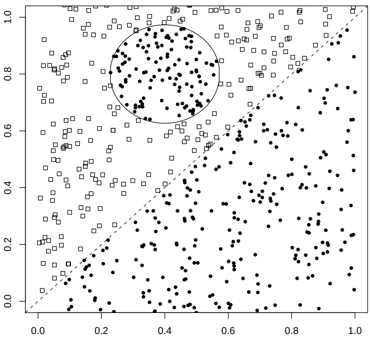

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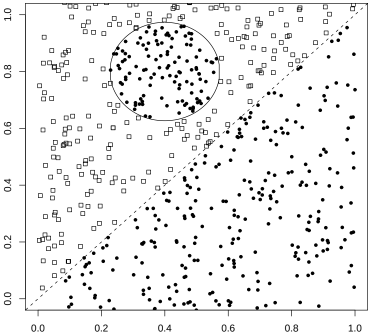

- Linear classifier like Rocchio does badly on this task.
- kNN will do well (assuming enough training data)

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  - How stable is the problem over time?
    - For an unstable problem, it's better to use a simple and robust classifier.

Outline

How to combine hyperplanes for > 2 classes?

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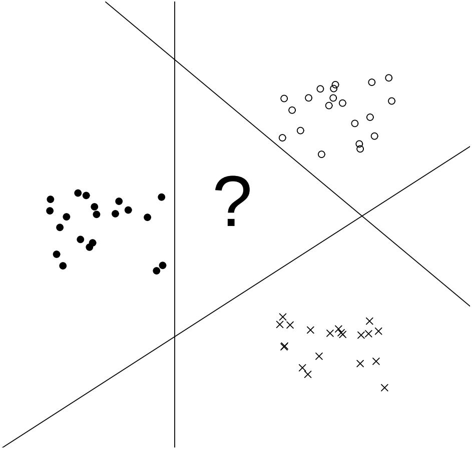

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  - Example: language of a document (assumption: no document contains multiple languages)

One-of classification with linear classifiers

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  - A type of "independence" (but not statistical independence)
  - Example: topic classification
  - Usually: make decisions on the region, on the subject area, on the industry and so on "independently"

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Any-of classification with linear classifiers

- Combine two-class linear classifiers as follows for any-of classification:
  - Simply run each two-class classifier separately on the test document and assign document accordingly

Take-away today

- Vector space classification: Basic idea of doing text classification for documents that are represented as vectors
- Rocchio classifier: Rocchio relevance feedback idea applied to text classification
- k nearest neighbor classification
- Linear classifiers
- More than two classes

Resources

- Chapter 13 of IIR (feature selection)
- Chapter 14 of IIR
- Resources at `http://cislmu.org`
  - Perceptron example
  - General overview of text classification: Sebastiani (2002)
  - Text classification chapter on decision tress and perceptrons: Manning & Schütze (1999)
  - One of the best machine learning textbooks: Hastie, Tibshirani & Friedman (2003)