COMP 631: Introduction to Information Retrieval

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https://cs.rice.edu/~xh37/index.html

Today's topic

- Text Classification 1

Introduction to

Standing queries

- The path from IR to text classification:
  - You have an information need to monitor, say:
    - Unrest in the Niger delta region
  - You want to rerun an appropriate query periodically to find new news items on this topic
  - You will be sent new documents that are found
    - I.e., it's not ranking but classification (relevant vs. not relevant)
- Such queries are called standing queries
  - Long used by "information professionals"
  - A modern mass instantiation is Google Alerts
- Standing queries are (hand-written) text classifiers

Spam filtering
text classification task

From: "" <takworlld@hotmail.com>
Subject: real estate is the only way... gem oalvgkay

Anyone can buy real estate with no money down

Stop paying rent TODAY !

There is no need to spend hundreds or even thousands for similar courses

I am 22 years old and I have already purchased 6 properties using the methods outlined in this truly INCREDIBLE ebook.

Change your life NOW !

==========
Click Below to order:
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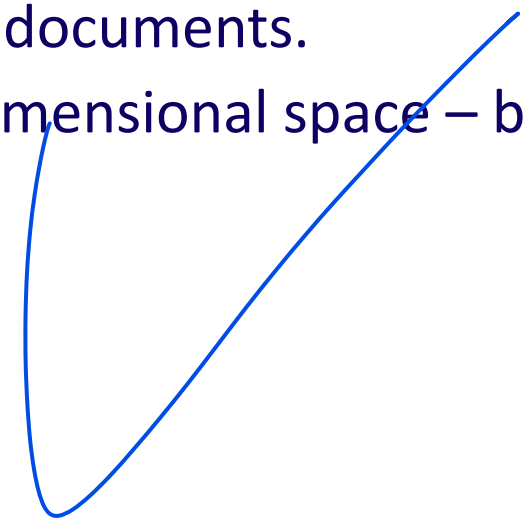
==========

Categorization/Classification

- Given:
  - A representation of a document *d*
    - Issue: how to represent text documents.
    - Usually some type of high-dimensional space – bag of words
  - A fixed set of classes:

    $C = \{c_1, c_2, \ldots, c_J\}$
- Determine:
  - The category of *d*: $\gamma(d) \in C$, where $\gamma(d)$ is a classification function
  - We want to build classification functions ("classifiers").

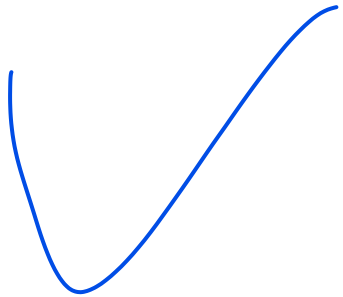


Classification Methods (1)

- Manual classification
  - Used by the original Yahoo! Directory
  - Looksmart, about.com, ODP, PubMed
  - Accurate when job is done by experts
  - Consistent when the problem size and team is small
  - Difficult and expensive to scale
    - Means we need automatic classification methods for big problems

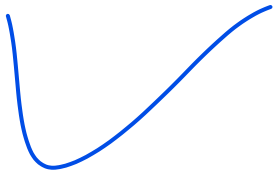
Classification Methods (2)

- Hand-coded rule-based classifiers
  - One technique used by news agencies, intelligence agencies, etc.
  - Widely deployed in government and enterprise
  - Vendors provide "IDE" for writing such rules



Classification Methods (2)

- Hand-coded rule-based classifiers
  - Commercial systems have complex query languages
  - Accuracy is can be high if a rule has been carefully refined over time by a subject expert
  - Building and maintaining these rules is expensive



A Verity topic
A complex classification rule: art

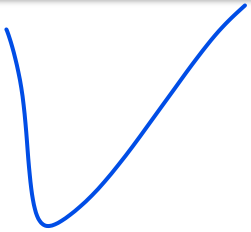
```
comment line          # Beginning of art topic definition
top-level topic       art ACCRUE
                          /author = "fsmith"
topic definition modifiers
                          /date   = "30-Dec-01"
                          /annotation = "Topic created
                                         by fsmith"
subtopic topic        * 0.70 performing-arts ACCRUE
  evidence topic      ** 0.50 WORD
  topic definition modifier
                          /wordtext = ballet
  evidence topic      ** 0.50 STEM
  topic definition modifier
                          /wordtext = dance
  evidence topic      ** 0.50 WORD
  topic definition modifier
                          /wordtext = opera
  evidence topic      ** 0.30 WORD
  topic definition modifier
                          /wordtext = symphony
subtopic              * 0.70 visual-arts ACCRUE
                      ** 0.50 WORD
                          /wordtext = painting
                      ** 0.50 WORD
                          /wordtext = sculpture
subtopic              * 0.70 film ACCRUE
                      ** 0.50 STEM
                          /wordtext = film
subtopic              ** 0.50 motion-picture PHRASE
                      *** 1.00 WORD
                          /wordtext = motion
                      *** 1.00 WORD
                          /wordtext = picture
                      ** 0.50 STEM
                          /wordtext = movie
subtopic              * 0.50 video ACCRUE
                      ** 0.50 STEM
                          /wordtext = video
                      ** 0.50 STEM
                          /wordtext = vcr
                      # End of art topic
```

Note:

- maintenance issues (author, etc.)
- Hand-weighting of terms

[Verity was bought by Autonomy, which was bought by HP ...]

Classification Methods (3): Supervised learning



- Given:
  - A document *d*
  - A fixed set of classes:

    $C = \{c_1, c_2, \ldots, c_J\}$
  - A training set *D* of documents each with a label in *C*
- Determine:
  - A learning method or algorithm which will enable us to learn a classifier γ
  - For a test document *d*, we assign it the class

    $\gamma(d) \in C$

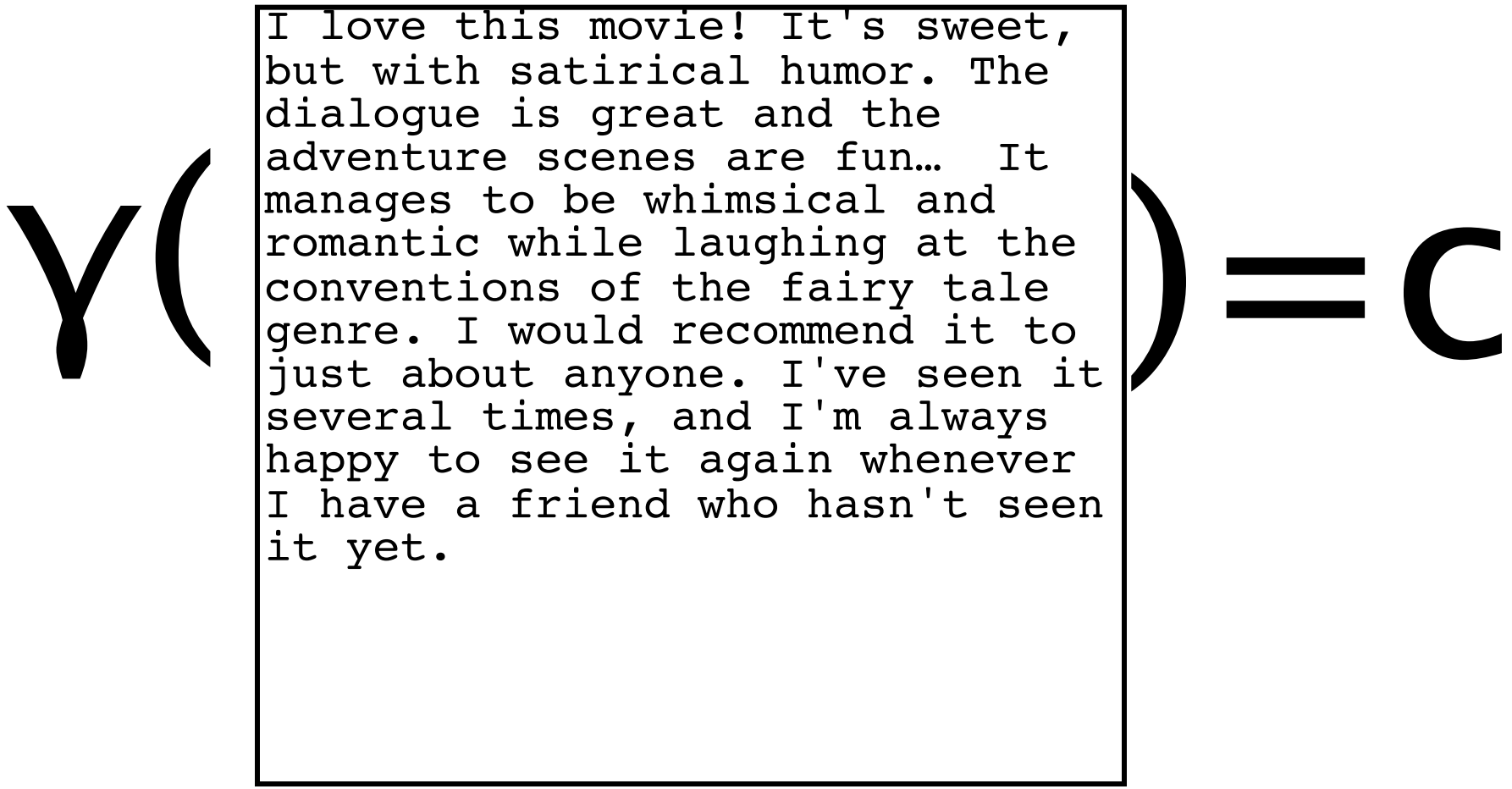
Classification Methods (3)

- Supervised learning
  - Naive Bayes (simple, common) – see video
  - k-Nearest Neighbors (simple, powerful)
  - Support-vector machines (newer, generally more powerful)
  - … plus many other methods
  - No free lunch: requires hand-classified training data
  - But data can be built up (and refined) by amateurs
- Many commercial systems use a mixture of methods

Features

- Supervised learning classifiers can use any sort of feature
  - URL, email address, punctuation, capitalization, dictionaries, network features
- In the simplest bag of words view of documents
  - We use only word features
  - we use all of the words in the text (not a subset)

The bag of words representation



The bag of words representation

Feature Selection: Why?

- Text collections have a large number of features
  - 10,000 – 1,000,000 unique words … and more
- Selection may make a particular classifier feasible
  - Some classifiers can't deal with 1,000,000 features
- Reduces training time
  - Training time for some methods is quadratic or worse in the number of features
- Makes runtime models smaller and faster
- Can improve generalization (performance)
  - Eliminates noise features
  - Avoids overfitting

Feature Selection: Frequency

- The simplest feature selection method:
  - Just use the commonest terms
  - No particular foundation
  - But it make sense why this works
    - They're the words that can be well-estimated and are most often available as evidence
  - In practice, this is often 90% as good as better methods
  - Smarter feature selection

Naïve Bayes

- Classify based on prior weight of class and conditional parameter for what each word says:

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} \left[\log P(c_j) + \sum_{i \in positions} \log P(x_i \mid c_j) \right]$$

- Training is done by counting and dividing:

$$P(c_j) \leftarrow \frac{N_{c_j}}{N} \qquad P(x_k \mid c_j) \leftarrow \frac{T_{c_j x_k} + \alpha}{\sum_{x_i \in V} [T_{c_j x_i} + \alpha]}$$

- Don't forget to smooth

Bayes Theorem

- A probabilistic approach for solving classification problems
- Conditional Probability: $P(Y \mid X) = \frac{P(X,Y)}{P(X)}$

$$P(X \mid Y) = \frac{P(X,Y)}{P(Y)}$$

- Bayes theorem:

$$P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)}$$

Example of Bayes Theorem

- Given:
  - A doctor knows that meningitis causes stiff neck 50% of the time
  - The probability that a patient has meningitis is 1/50,000
  - The probability that a patient has stiff neck is 1/20

- If a patient has stiff neck, what's the probability he/she has meningitis?

$$P(M \mid S) = \frac{P(S \mid M)P(M)}{P(S)} = \frac{0.5 \times 1/50000}{1/20} = 0.0002$$

Joint Probability Distribution

- An example of two Boolean variables

	Toothache	!Toothache
Cavity	0.04	0.06
!Cavity	0.01	0.89

- Observations: mutually exclusive and collectively exhaustive
- What are P(Cavity), P(Cavity v Toothache), P(Cavity|Toothache)?

Using Bayes Theorem for Classification

- Consider each attribute and class label as random variables

- Given a record with attributes (X_1, X_2,…, X_d)
  - Goal is to predict class Y
  - Specifically, we want to find the value of Y that maximizes P(Y| X_1, X_2,…, X_d)

- Can we estimate P(Y| X_1, X_2,…, X_d) directly from data?

Using Bayes Theorem for Classification

- Approach:
  - Compute posterior probability $P(Y \mid X_1, X_2, \ldots, X_d)$ using the Bayes theorem

$$P(Y \mid X_1 X_2 \ldots X_d) = \frac{P(X_1 X_2 \ldots X_d \mid Y) P(Y)}{P(X_1 X_2 \ldots X_d)}$$

  - Choose Y that maximizes

    $P(Y \mid X_1, X_2, \ldots, X_d)$

  - Equivalent to choosing value of Y that maximizes

    $P(X_1, X_2, \ldots, X_d \mid Y)\ P(Y)$

- How to estimate $P(X_1, X_2, \ldots, X_d \mid Y)$?

Conditional Independence

- **X** and **Y** are conditionally independent given **Z** if P(**X**|**YZ**) = P(**X**|**Z**)

- Example: Arm length and reading skills
  - Young child has shorter arm length and limited reading skills, compared to adults
  - If age is fixed, no apparent relationship between arm length and reading skills
  - Arm length and reading skills are conditionally independent given age

Naïve Bayes Classifier

- Assume independence among attributes X_i when class is given:
  - $P(X_1, X_2, \ldots, X_d \mid Y_j) = P(X_1 \mid Y_j)\, P(X_2 \mid Y_j) \ldots P(X_d \mid Y_j)$
  - $P(X_i \mid Y_j)$ can be estimated for all X_i and Y_j from data
  - A new point is classified to Y_j if $P(Y_j) \prod P(X_i \mid Y_j)$ is maximal.

Estimate Probabilities from Data

Tid	Refund	Marital Status	Taxable Income	Evade
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

- Class: $P(Y) = N_c/N$
  - e.g., P(No) = 7/10, P(Yes) = 3/10

Let's work out all P(X|Y)

- For discrete attributes:

$$P(X_i \mid Y_k) = |X_{ik}| / N_c$$

  - where $|X_{ik}|$ is number of instances having attribute value X_i and belonging to class Y_k
  - Examples:

P(Status=Married|No) = 4/7
P(Refund=Yes|Yes)=0

Estimate Probabilities from Data

- For continuous attributes:
  - Discretization: Partition the range into bins:
    - Replace continuous value with bin value
  - Probability density estimation:
    - Assume an attribute follows a normal distribution
    - Use data to estimate parameters of distribution (e.g., mean and standard deviation)
    - Once probability distribution is known, use it to estimate the conditional probability $P(X_i|Y)$

Estimate Probabilities from Data

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10	No	Single	90K	Yes

- Normal distribution:

$$P(X_i \mid Y_j) = \frac{1}{\sqrt{2\pi\sigma_{ij}^2}} e^{-\frac{(X_i - \mu_{ij})^2}{2\sigma_{ij}^2}}$$

  - One for each (X_i, Y_i) pair

- For (Income, Class=No):
  - If Class=No
    - sample mean = 110
    - sample variance = 2975

$$P(Income = 120 \mid No) = \frac{1}{\sqrt{2\pi}(54.54)} e^{-\frac{(120-110)^2}{2(2975)}} = 0.0072$$

Example of Naïve Bayes Classifier

Given a Test Record:

$$X = (\text{Refund} = \text{No}, \text{Married}, \text{Income} = 120\text{K})$$

naive Bayes Classifier:

P(Refund=Yes|No) = 3/7
P(Refund=No|No) = 4/7
P(Refund=Yes|Yes) = 0
P(Refund=No|Yes) = 1
P(Marital Status=Single|No) = 2/7
P(Marital Status=Divorced|No)=1/7
P(Marital Status=Married|No) = 4/7
P(Marital Status=Single|Yes) = 2/3
P(Marital Status=Divorced|Yes)=1/3
P(Marital Status=Married|Yes) = 0

For taxable income:
If class=No: sample mean=110
sample variance=2975
If class=Yes: sample mean=90
sample variance=25

- P(X|Class=No) = P(Refund=No|Class=No)
  × P(Married| Class=No)
  × P(Income=120K| Class=No)
  = 4/7 × 4/7 × 0.0072 = 0.0024

- P(X|Class=Yes) = P(Refund=No| Class=Yes)
  × P(Married| Class=Yes)
  × P(Income=120K| Class=Yes)
  = 1 × 0 × 1.2 × 10^{-9} = 0

Since P(X|No)P(No) > P(X|Yes)P(Yes)

Therefore P(No|X) > P(Yes|X)

=> Class = No

SpamAssassin

- Naïve Bayes has found a home in spam filtering
  - Paul Graham's A Plan for Spam
  - Widely used in spam filters
  - But many features beyond words:
    - black hole lists, etc.
    - particular hand-crafted text patterns

SpamAssassin Features:

- Basic (Naïve) Bayes spam probability
- Mentions: Generic Viagra
- Regex: millions of (dollar) ((dollar) NN,NNN,NNN.NN)
- Phrase: impress ... girl
- Phrase: 'Prestigious Non-Accredited Universities'
- From: starts with many numbers
- Subject is all capitals
- HTML has a low ratio of text to image area
- Relay in RBL, http://www.mail-abuse.com/enduserinfo_rbl.html
- RCVD line looks faked
- http://spamassassin.apache.org/tests_3_3_x.html

Naive Bayes is Not So Naive

- Very fast learning and testing (basically just count words)
- Low storage requirements
- Very good in domains with many equally important features
- More robust to irrelevant features than many learning methods
  - Irrelevant features cancel out without affecting results

Naive Bayes is Not So Naive

- More robust to concept drift (changing class definition over time)
- Naive Bayes won 1st and 2nd place in KDD-CUP 97 competition out of 16 systems
  - Goal: Financial services industry direct mail response prediction: Predict if the recipient of mail will actually respond to the advertisement – 750,000 records.
- A good dependable baseline for text classification (but not the best)!

Evaluating Categorization

- Evaluation must be done on test data that are independent of the training data
  - Sometimes use cross-validation (averaging results over multiple training and test splits of the overall data)
- Easy to get good performance on a test set that was available to the learner during training (e.g., just memorize the test set)

Evaluating Categorization

- Measures: precision, recall, F1, classification accuracy
- Classification accuracy: r/n where n is the total number of test docs and r is the number of test docs correctly classified

Recall: Vector Space Representation

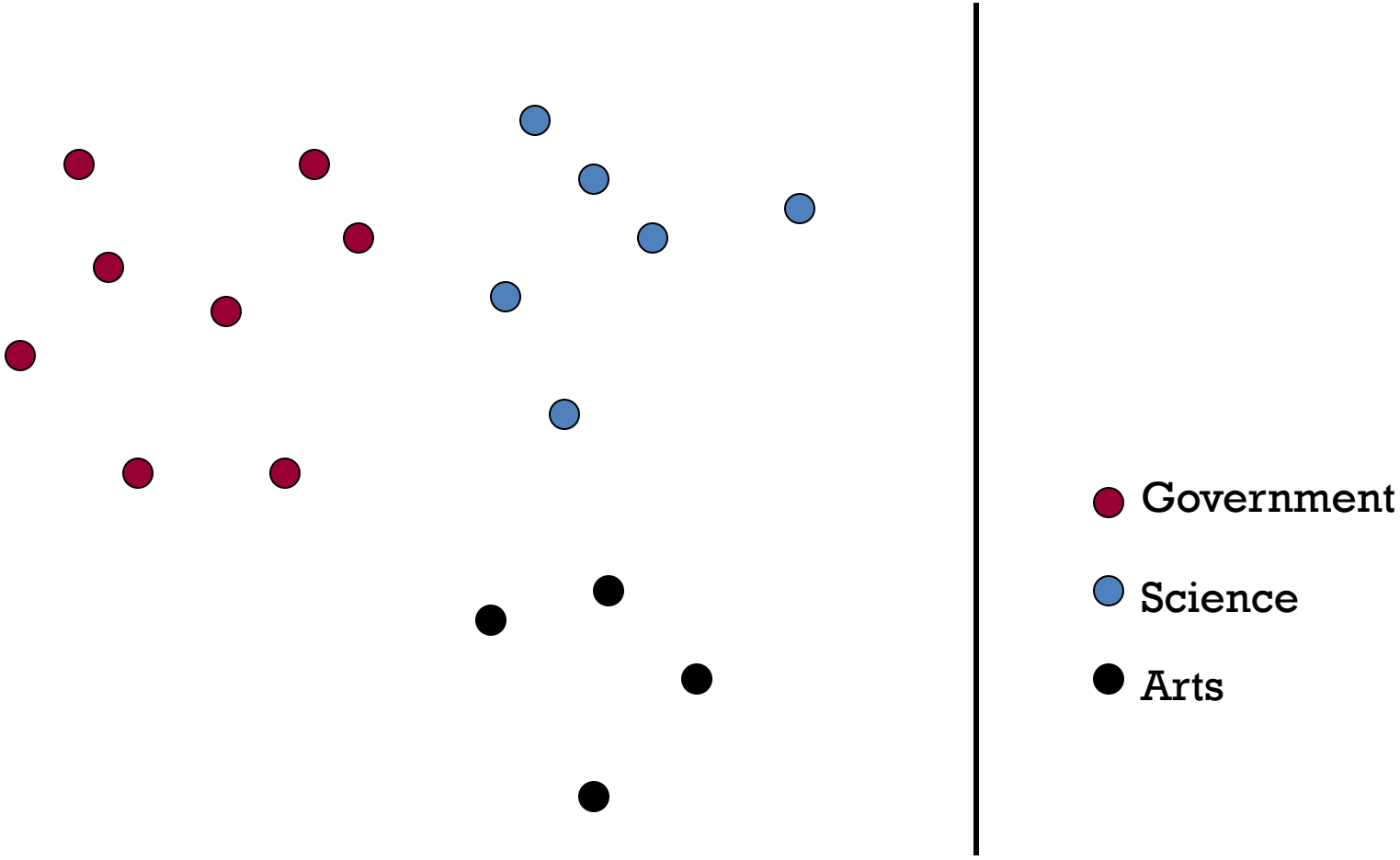
- Each document is a vector, one component for each term (= word).
- Normally normalize vectors to unit length.
- High-dimensional vector space:
  - Terms are axes
  - 10,000+ dimensions, or even 100,000+
  - Docs are vectors in this space

- How can we do classification in this space?

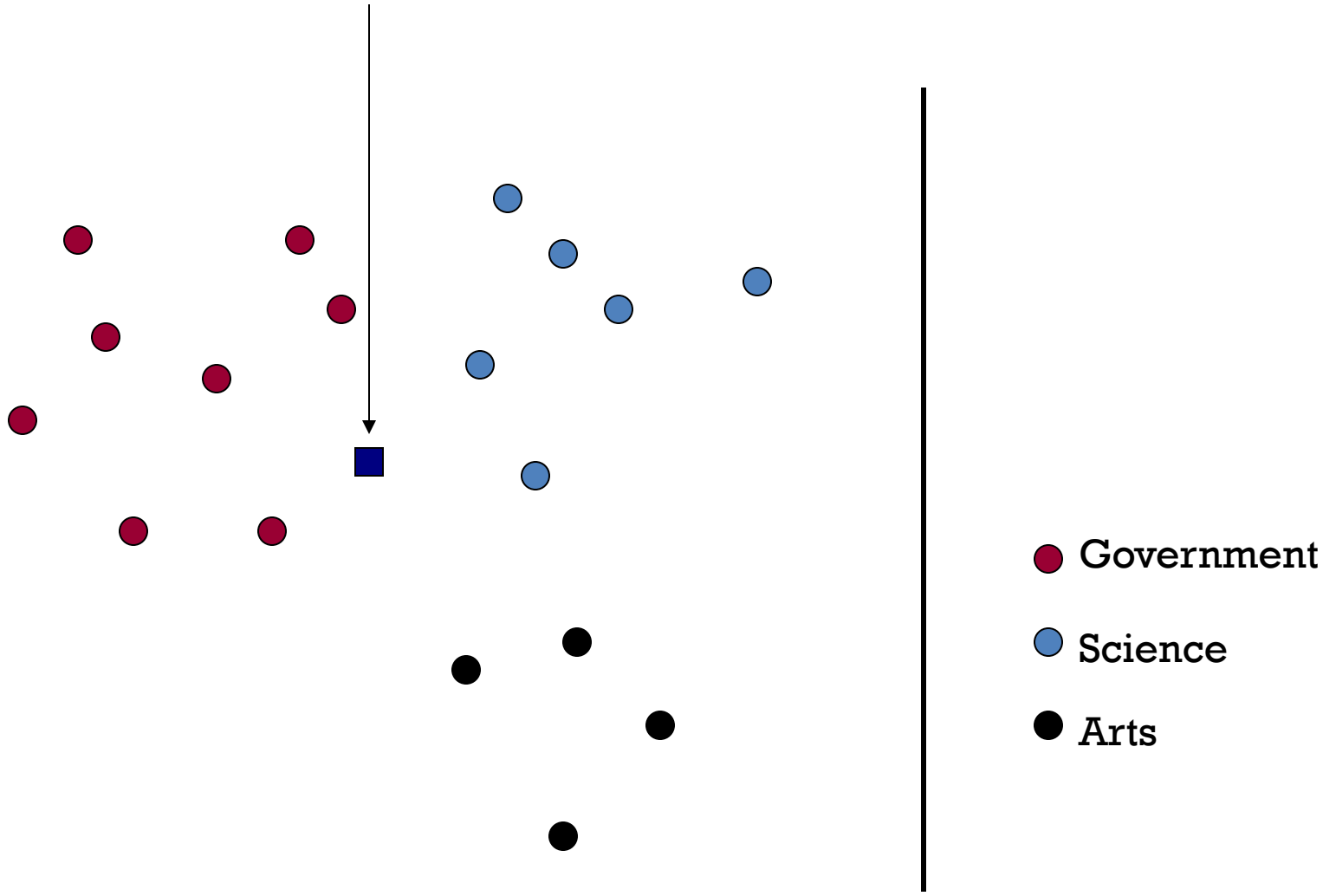
Classification Using Vector Spaces

- In vector space classification, training set corresponds to a labeled set of points (equivalently, vectors)
- Premise 1: Documents in the same class form a contiguous region of space
- Premise 2: Documents from different classes don't overlap (much)
- Learning a classifier: build surfaces to delineate classes in the space

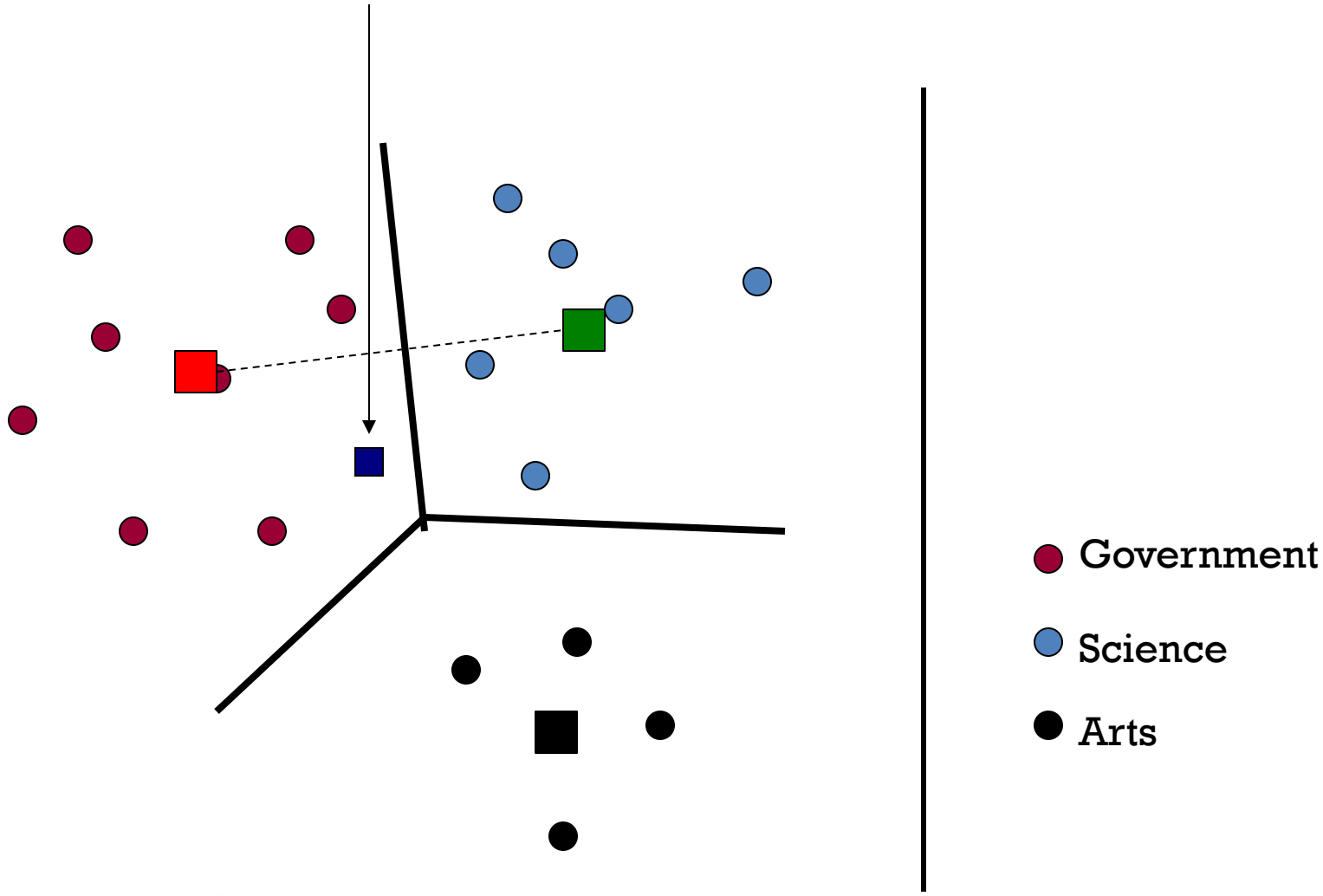
Documents in a Vector Space



Test Document of what class?



Test Document = Government



Our focus: how to find good separators

Definition of centroid

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

- Where Dc is the set of all documents that belong to class c and v(d) is the vector space representation of d.

- Note that centroid will in general not be a unit vector even when the inputs are unit vectors.

Rocchio classification

- Rocchio forms a simple representative for each class: the centroid/prototype
- Classification: nearest prototype/centroid
- It does not guarantee that classifications are consistent with the given training data

Why not?

Two-class Rocchio as a linear classifier

- Line or hyperplane defined by:

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

- For Rocchio, set:

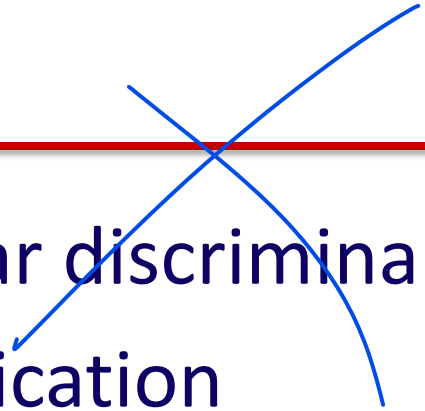
$$\vec{w} = \vec{\mu}(c_1) - \vec{\mu}(c_2)$$

$$\theta = 0.5 \times (|\vec{\mu}(c_1)|^2 - |\vec{\mu}(c_2)|^2)$$

Linear classifier: Example

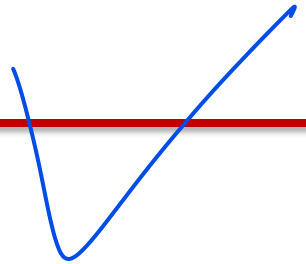
- Class: "interest" (as in interest rate)
- Example features of a linear classifier
w_i	t_i	w_i	t_i
0.70	prime	−0.71	dlrs
0.67	rate	−0.35	world
0.63	interest	−0.33	sees
0.60	rates	−0.25	year
0.46	discount	−0.24	group
0.43	bundesbank	−0.24	dlr
- To classify, find dot product of feature vector and weights

Rocchio classification



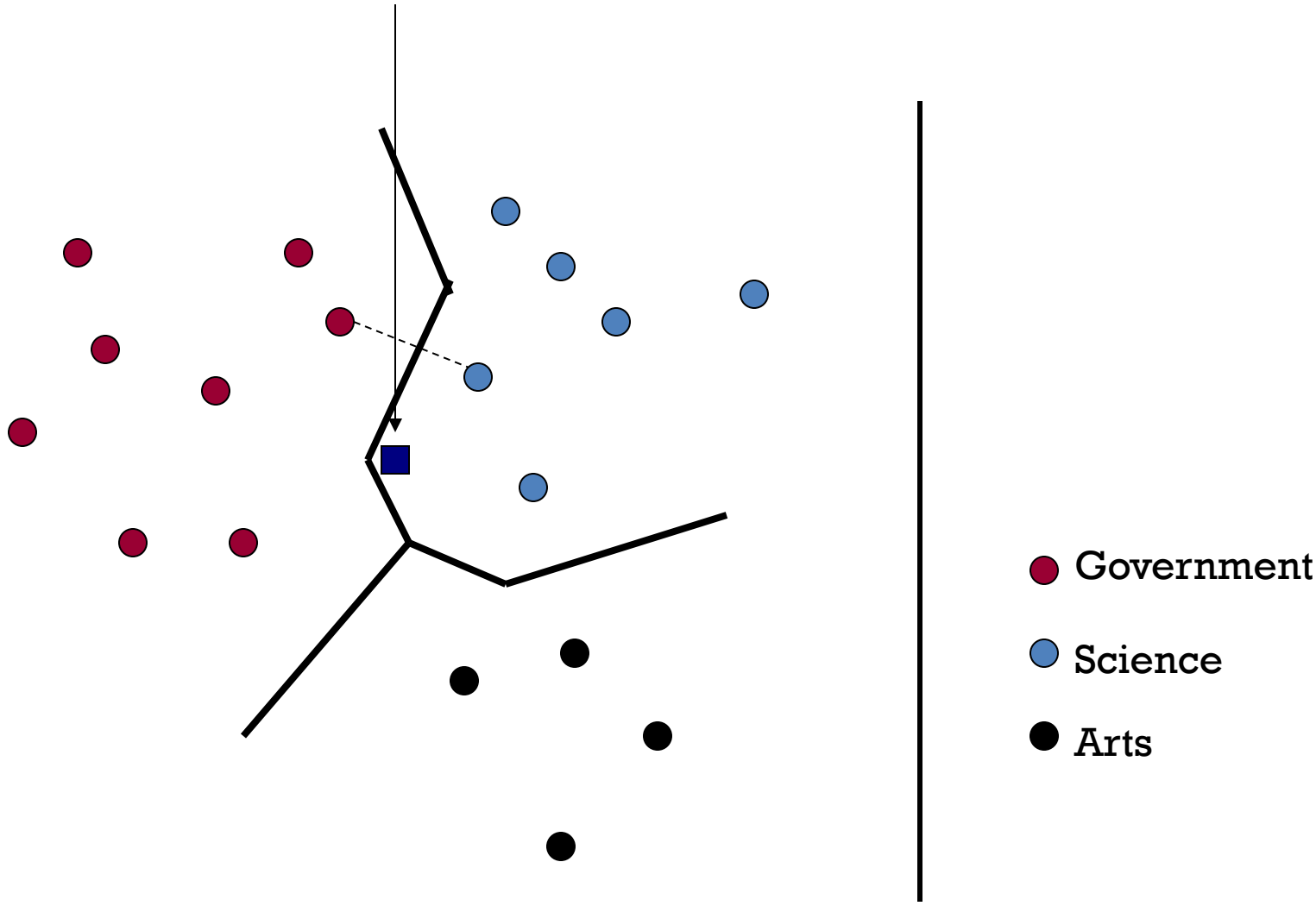
- A simple form of Fisher's linear discriminant
- Little used outside text classification
  - It has been used quite effectively for text classification
  - But in general worse than Naïve Bayes
- Again, cheap to train and test documents

k Nearest Neighbor Classification



- kNN = k Nearest Neighbor
- To classify a document d:
- Define k-neighborhood as the k nearest neighbors of d
- Pick the majority class label in the k-neighborhood
- For larger k can roughly estimate P(c|d) as #(c)/k

Test Document = Science



Voronoi diagram

Nearest-Neighbor Learning

- Learning: just store the labeled training examples D
- Testing instance x (under 1NN):
  - Compute similarity between x and all examples in D.
  - Assign x the category of the most similar example in D.
- Does not compute anything beyond storing the examples
- Also called:
  - Case-based learning
  - Memory-based learning
  - Lazy learning
- Rationale of kNN: contiguity hypothesis

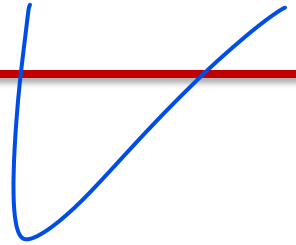
k Nearest Neighbor

- Using only the closest example (1NN) subject to errors due to:
  - A single atypical example.
  - Noise (i.e., an error) in the category label of a single training example.
- More robust: find the k examples and return the majority category of these k
- k is typically odd to avoid ties; 3 and 5 are most common

Nearest Neighbor with Inverted Index

- Naively finding nearest neighbors requires a linear search through $|D|$ documents in collection
- But determining k nearest neighbors is the same as determining the k best retrievals using the test document as a query to a database of training documents.
- Use standard vector space inverted index methods to find the k nearest neighbors.
- Testing Time: $O(B|V_t|)$ where B is the average number of training documents in which a test-document word appears.
  - Typically $B << |D|$

kNN: Discussion



- No feature selection necessary
- No training necessary
- Scales well with large number of classes
  - Don't need to train *n* classifiers for *n* classes
- Classes can influence each other
  - Small changes to one class can have ripple effect
- Done naively, very expensive at test time
- In most cases it's more accurate than NB or Rocchio

Bias vs. capacity – notions and terminology

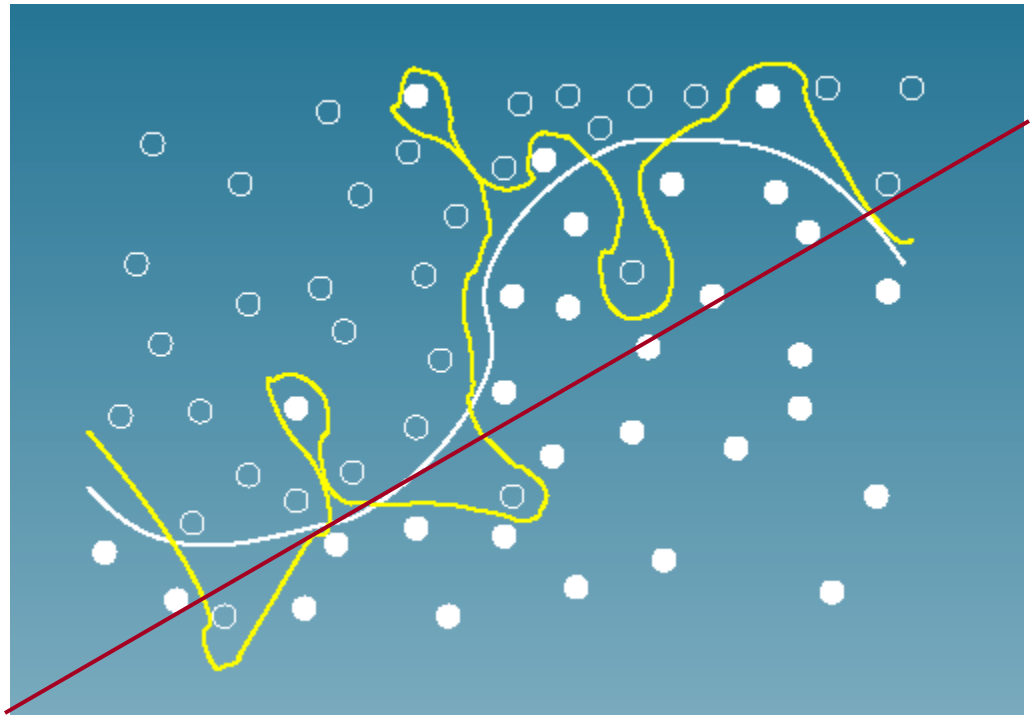
- Consider asking a botanist: Is an object a tree?
  - Too much *capacity*, low *bias*
    - Botanist who memorizes
    - Will always say "no" to new object (e.g., different # of leaves)
  - Not enough capacity, high bias
    - Lazy botanist
    - Says "yes" if the object is green
  - You want the middle ground

(Example due to C. Burges)

kNN vs. Naive Bayes

- Bias/Variance tradeoff
  - Variance ≈ Capacity
- kNN has high variance and low bias.
  - Infinite memory
- Rocchio/NB has low variance and high bias.
  - Linear decision surface between classes

Bias vs. variance: Choosing the correct model capacity



Summary: Representation of Text Categorization Attributes

- Representations of text are usually very high dimensional
  - "The curse of dimensionality"
- High-bias algorithms should generally work best in high-dimensional space
  - They prevent overfitting
  - They generalize more
- For most text categorization tasks, there are many relevant features and many irrelevant ones

Which classifier do I use for a given text classification problem?

- Is there a learning method that is optimal for all text classification problems?
- No, because there is a tradeoff between bias and variance.
- Factors to take into account:
  - How much training data is available?
  - How simple/complex is the problem? (linear vs. nonlinear decision boundary)
  - How noisy is the data?
  - How stable is the problem over time?
    - For an unstable problem, it's better to use a simple and robust classifier.