CS347

Lecture 9

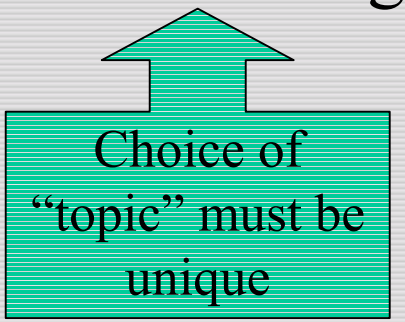
May 11, 2001

Today's topic

- Automatic document classification
  - Rule-based classification
  - Supervised learning

Classification

- Given one or more topics, decide which one(s) a given document belongs to.
- Applications
  - Classification into a topic taxonomy
  - Intelligence analysts
  - Routing email to help desks/customer service



Step back

- Manual classification
  - accurate when done by subject experts
  - consistent when done by a small team
  - difficult to scale
  - used by Yahoo!, Looksmart, about.com, ODP
    - hundreds of subject editors maintain thousands of topics
    - (topics organized in a tree-like navigation structure)

Supervised vs. unsupervised learning

- Unsupervised learning:
  - Given corpus, infer structure implicit in the docs, without prior training.
- Supervised learning:
  - Train system to recognize docs of a certain type (e.g., docs in Italian, or docs about religion)
  - Decide whether or not new docs belong to the class(es) trained on

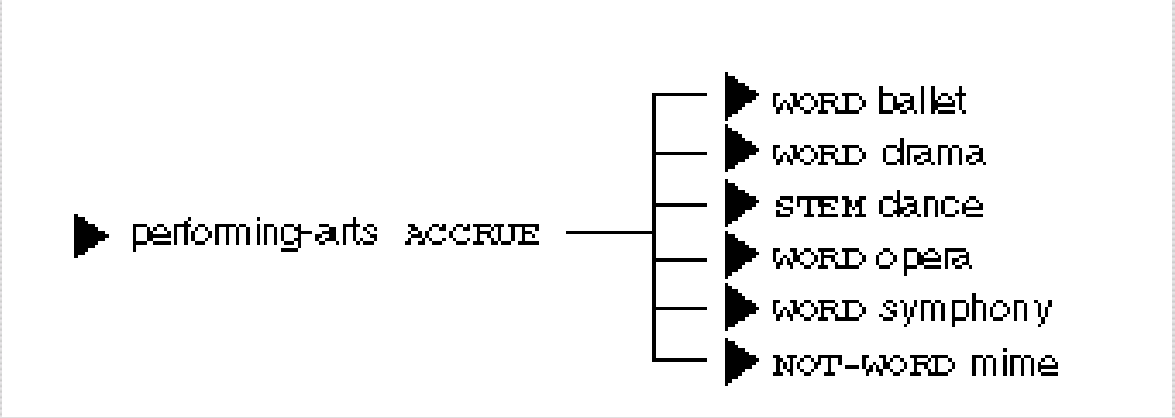
Challenges

- Must teach machine a model of each topic
- Given new doc, must measure fit to model(s)
- Evaluation: how well does the system perform?
- Threshold of pain: how confident is the system's assessment?
  - Sometimes better to give up.

Teaching the system models

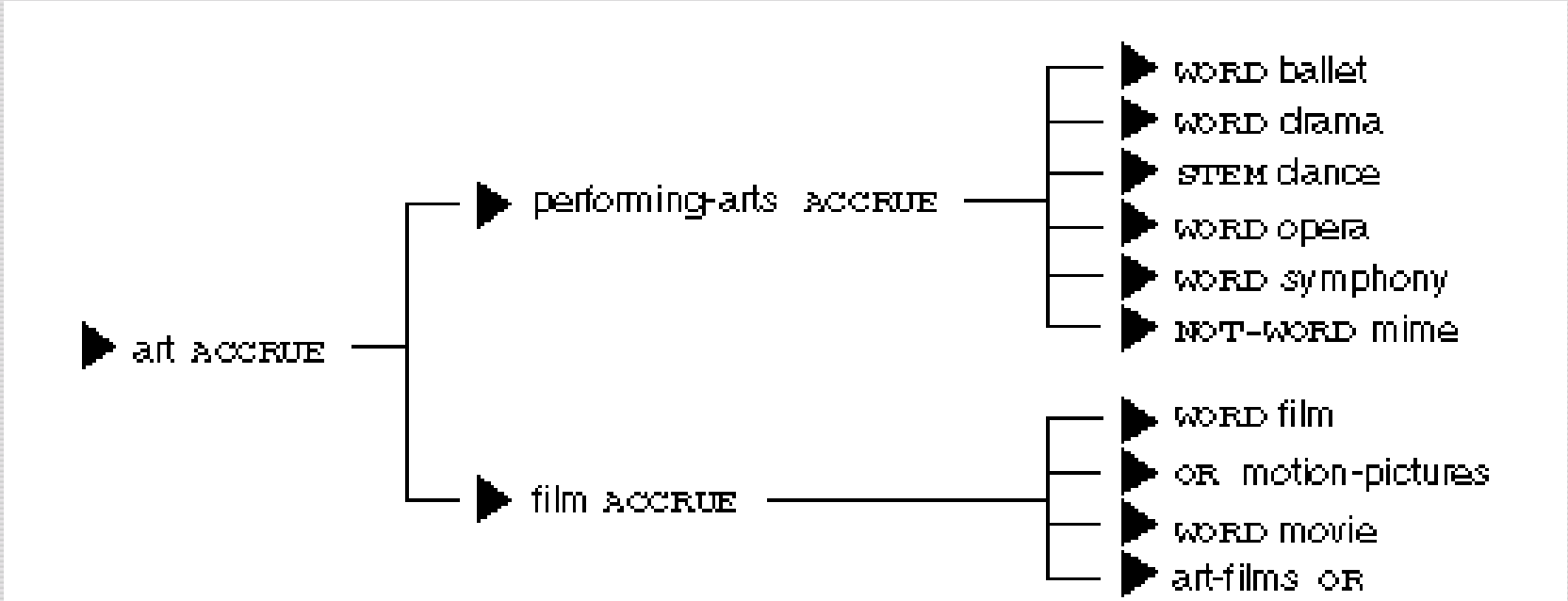
- Through an explicit query
- Through exemplary docs
- Combination

Explicit queries



- For the topic “Performing Arts”, query accrues evidence from stemmed and non-stemmed words.
- Query built by a subject expert.
- New doc scored against query:
  - if accrued evidence exceeds some threshold, declare it to belong to this topic.

Explicit queries



Topic queries can be built up from other topic queries.

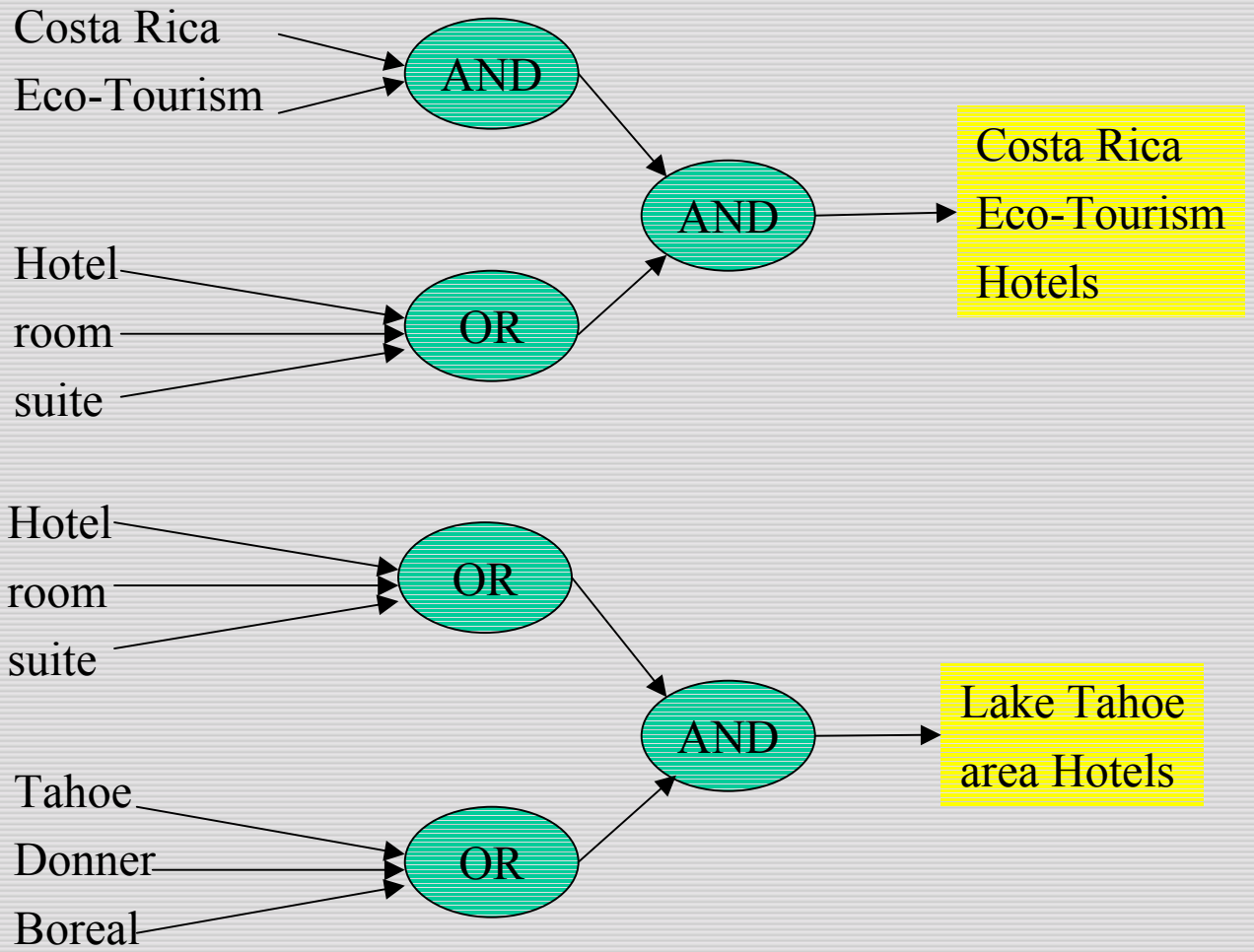
Large scale applications

- Document routing
- Customer service
- Profiled newsfeeds
- Spam/porn filtering

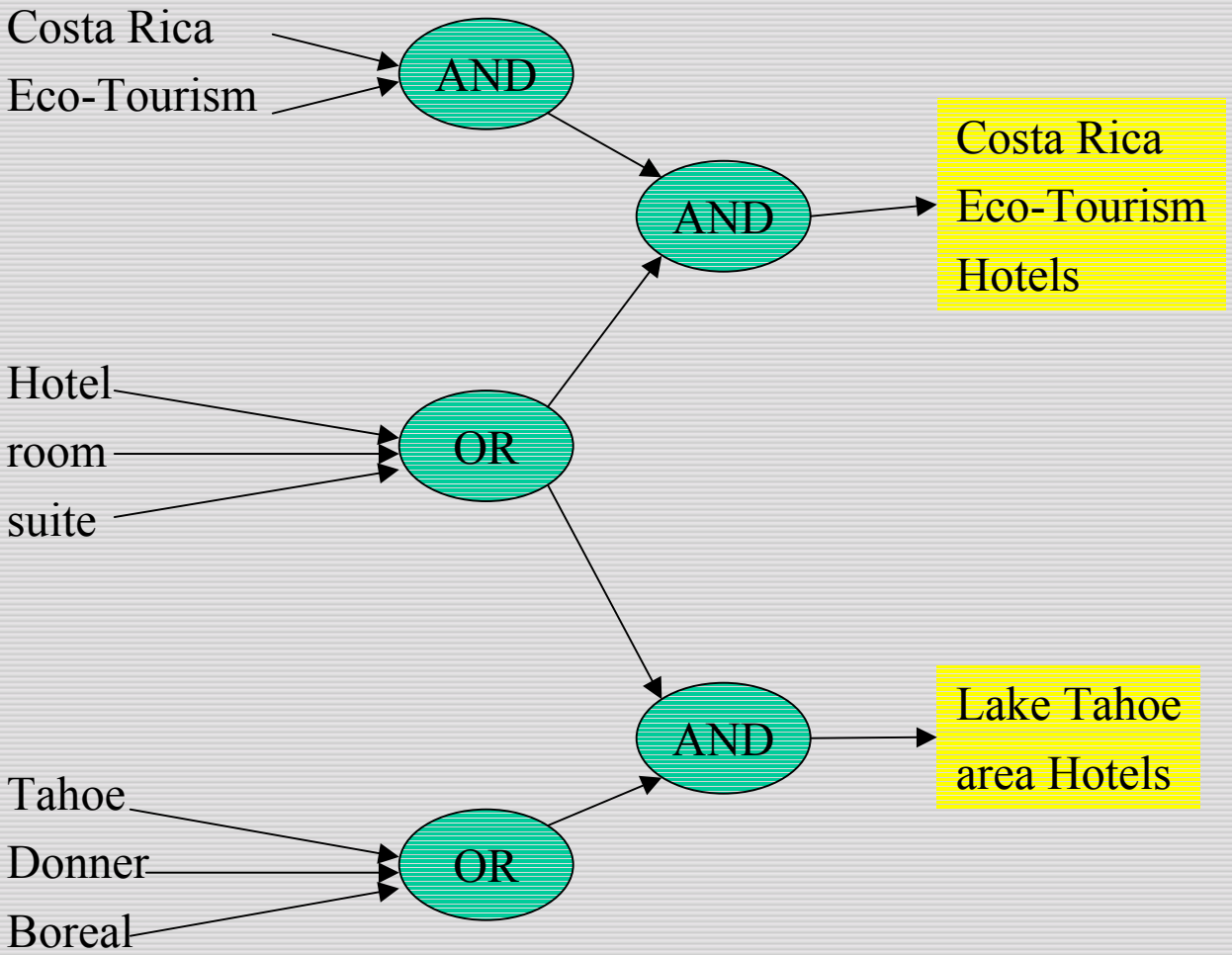
Typical example

- Dow Jones
  - Over 100,000 standing profiles
  - A profile can have >100 atomic terms
  - Common sub-expressions shared by different topics
  - Optimizing this sharing is a hard problem.

Example of sharing



Example of sharing



Measuring classification

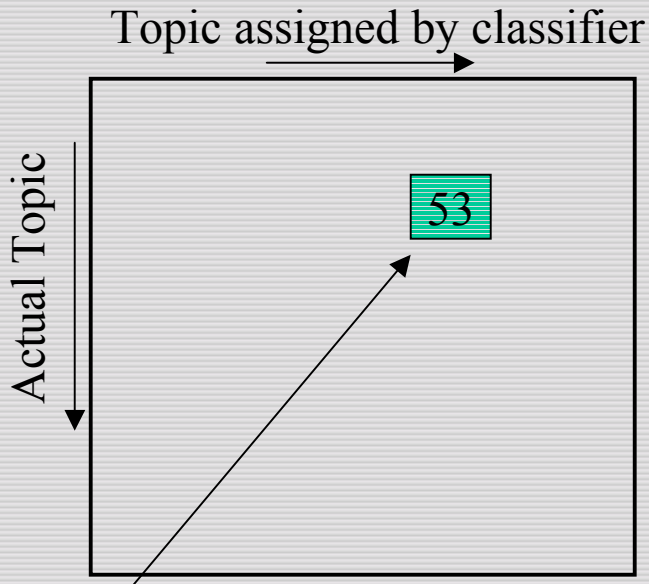
- Figures of merit include:
  - Accuracy of classification (more below)
  - Speed of classification (docs/hour)
  - Effort in training system (human hours/topic)

Factors affecting measures

- Documents
  - size, length
  - quality/style of authorship
    - uniformity of vocabulary
- Accuracy measurement
  - need definitive judgement on which topic(s) a doc belongs to
    - usually human

Accuracy measurement

- Confusion matrix



This (i, j) entry means 53 of the docs actually in topic i were put in topic j by the classifier.

Confusion matrix

- Function of classifier, topics and test docs.
- For a perfect classifier, all off-diagonal entries should be zero.

Confusion measures

- Fraction of docs in topic *i* classified correctly:

$$\frac{c_{ii}}{\sum_j c_{ij}}$$

- Fraction of docs assigned topic *i* that are actually about topic *i*:

$$\frac{c_{ii}}{\sum_j c_{ji}}$$

- Fraction of docs classified correctly:

$$\frac{\sum_i c_{ii}}{\sum_j \sum_i c_{ij}}$$

Classification by exemplary docs

- Feed system exemplary docs on topic (*training*)
- Positive as well as negative examples
- System builds its model of topic
- Subsequent *test* docs evaluated against model
  - decides whether test is a member of the topic

More generally, set of topics

- Exemplary docs for each
- Build model for each topic
  - differential models
- Given test doc, decide which topic(s) it belongs to

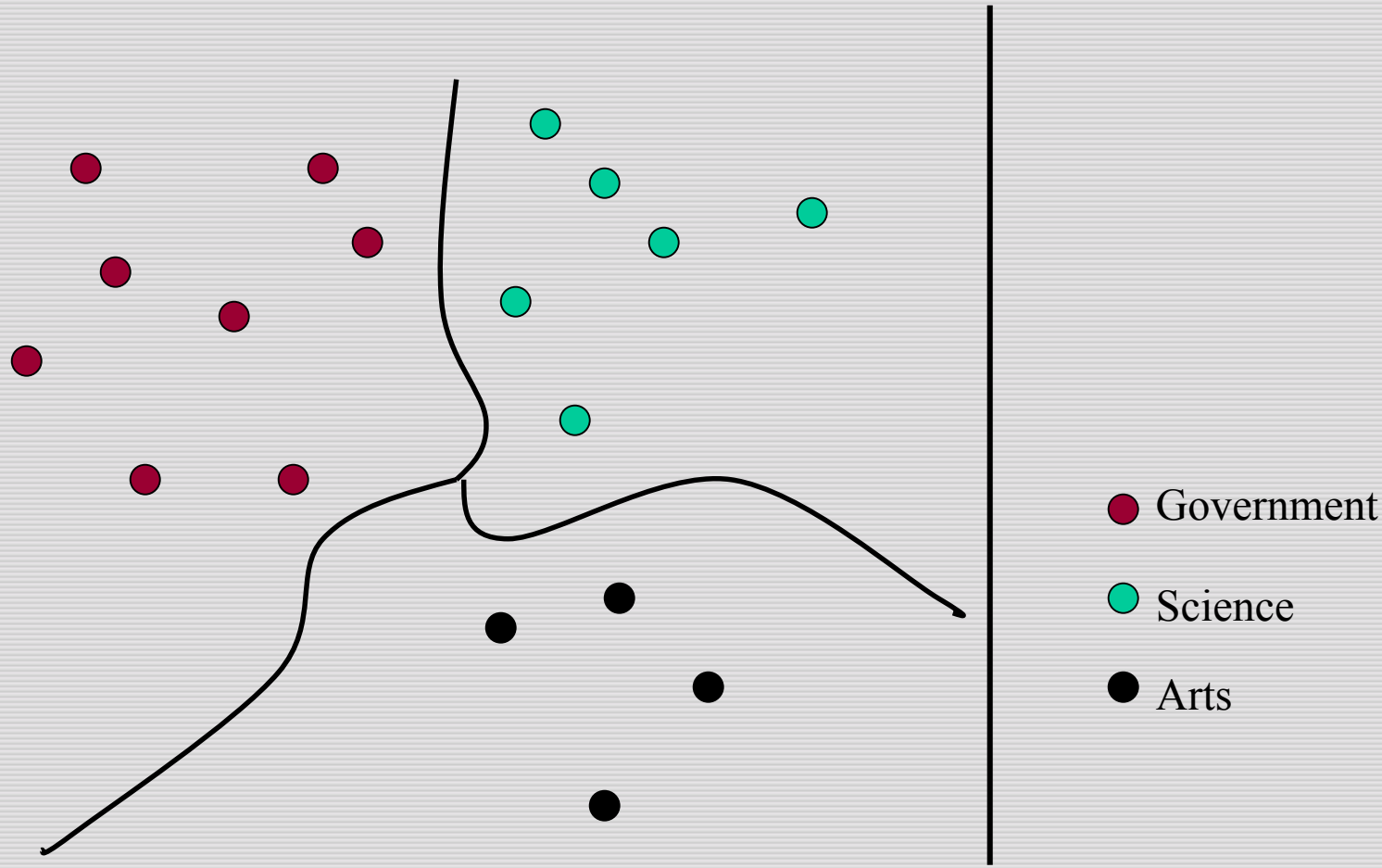
Recall doc as vector

- Each doc *j* is a vector, one component for each term.
- Normalize to unit length.
- Have a vector space
  - terms are axes
  - *n* docs live in this space
  - even with stemming, may have 10000+ dimensions

Classification using vector spaces

- Each training doc a point (vector) labeled by its topic
- Hypothesis: docs of the same topic form a contiguous region of space
- Define surfaces to delineate topics in space

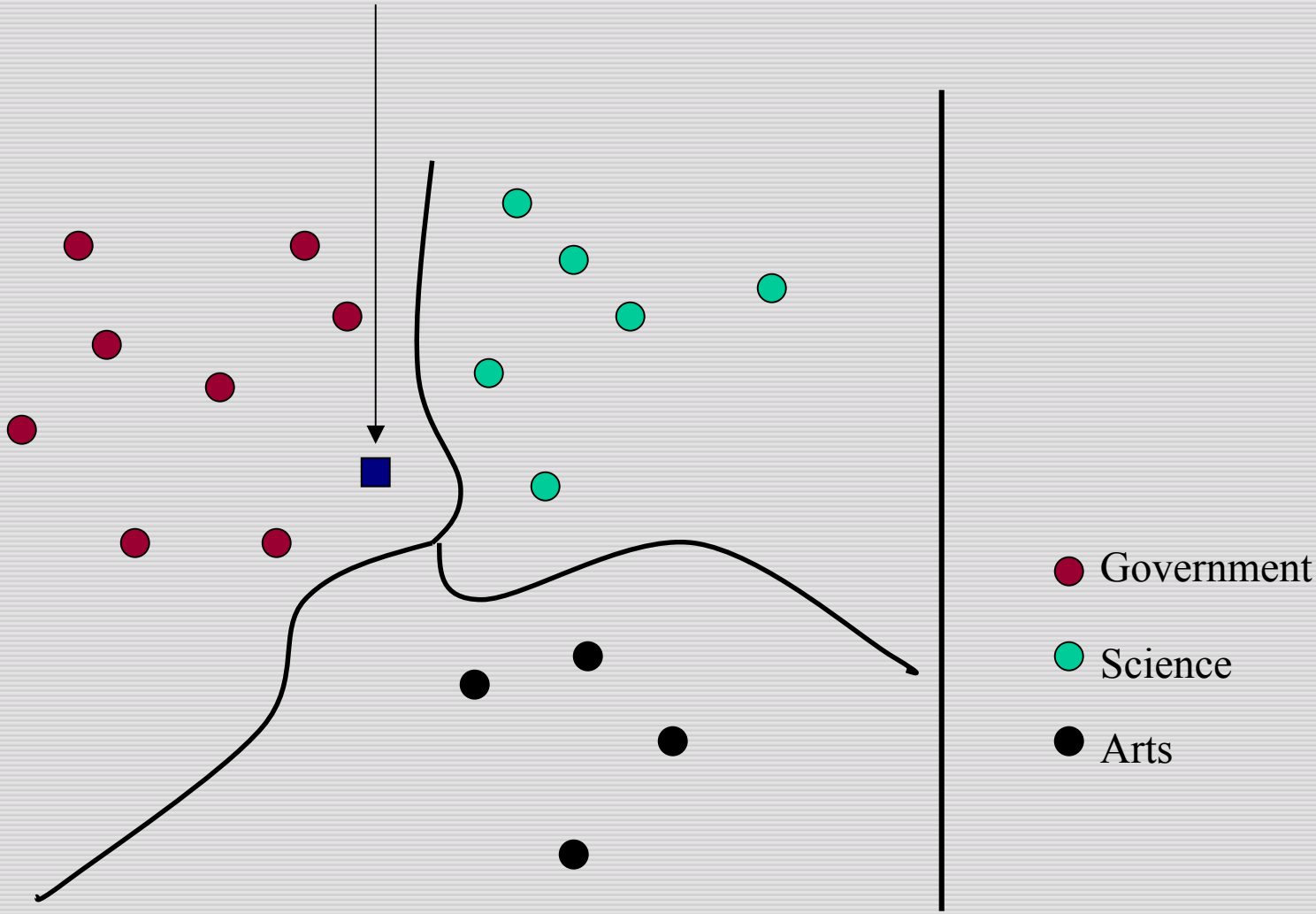
Topics in a vector space



Given a test doc

- Figure out which region it lies in
- Assign corresponding topic

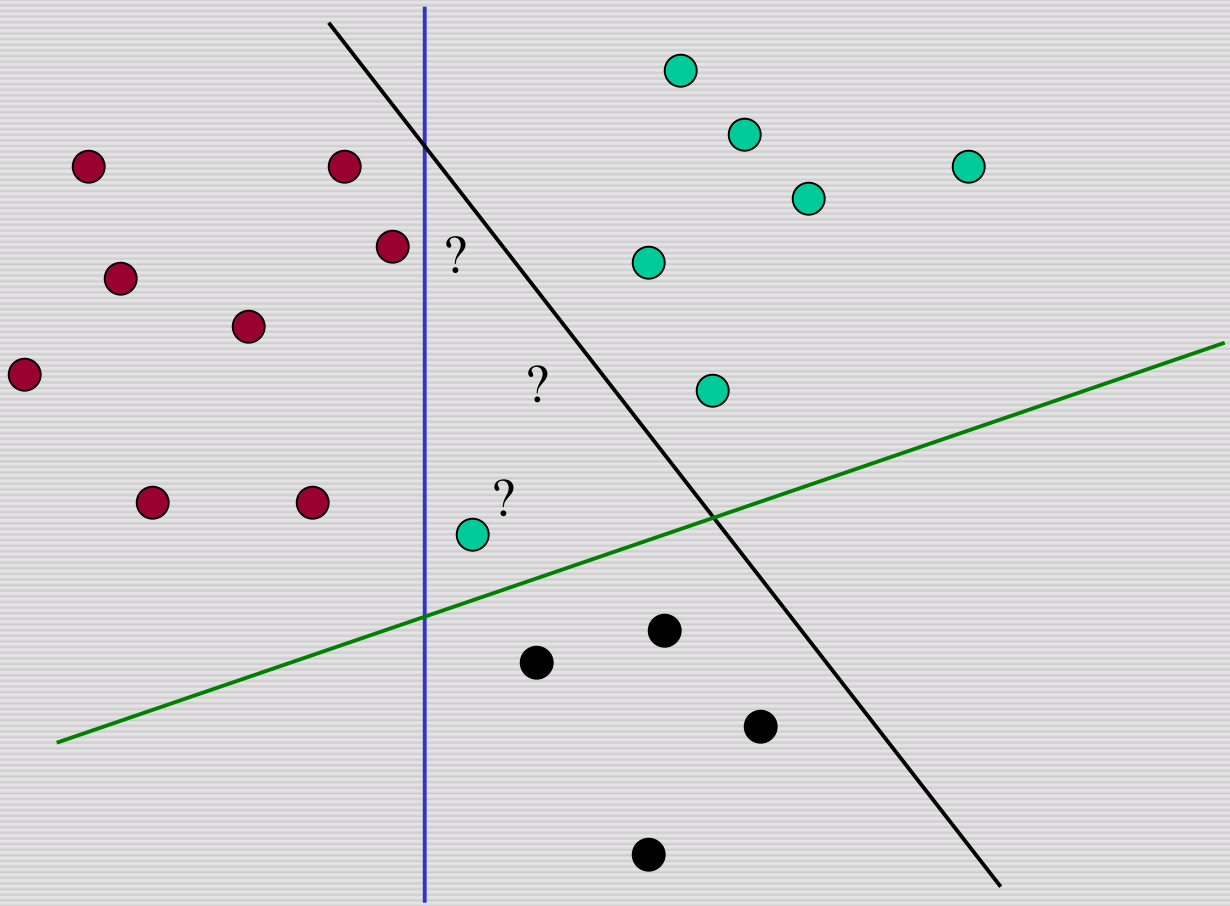
Test doc = Government



Issues

- How do we define (and find) the separating surfaces?
- How do we compose separating surfaces into regions?
- How do we test which region a test doc is in?

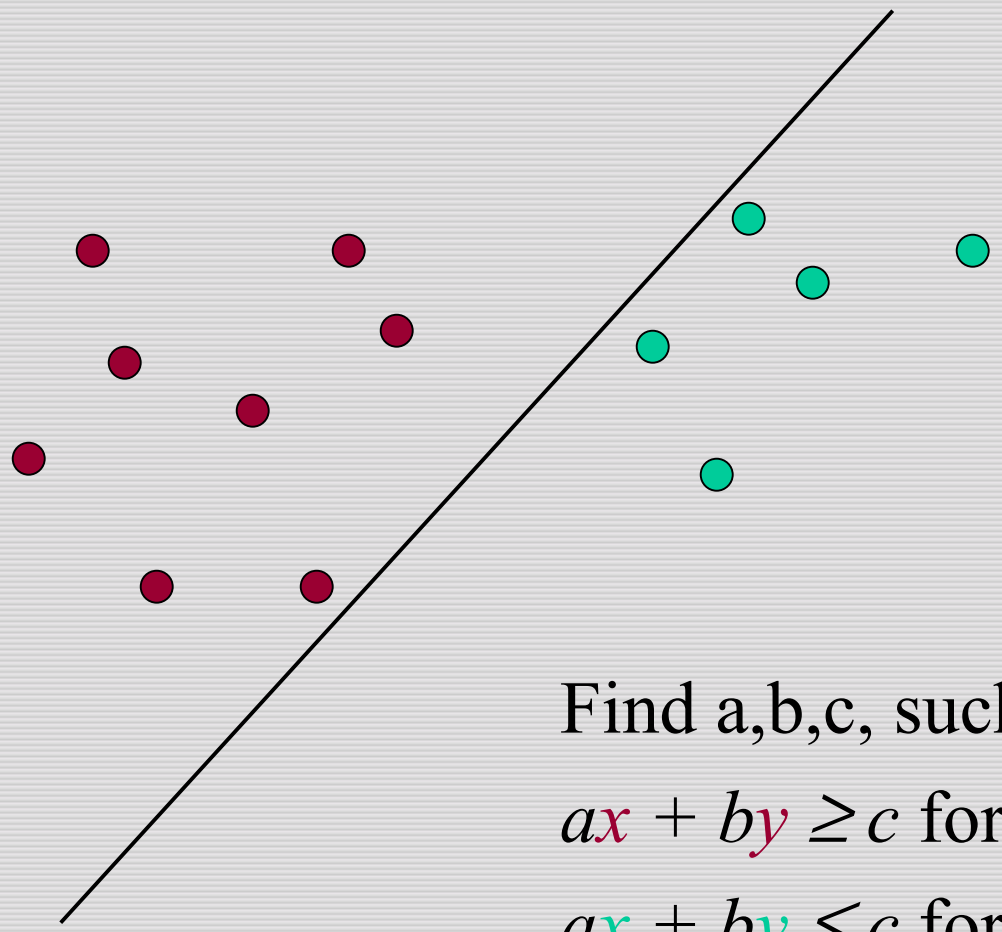
Composing surfaces: issues



Separation by hyperplanes

- Assume *linear separability* for now:
  - in 2 dimensions, can separate by a line
  - in higher dimensions, need hyperplanes.
- Can find separating hyperplane by *linear programming:*
  - separator can be expressed as $ax + by = c$;

Linear programming

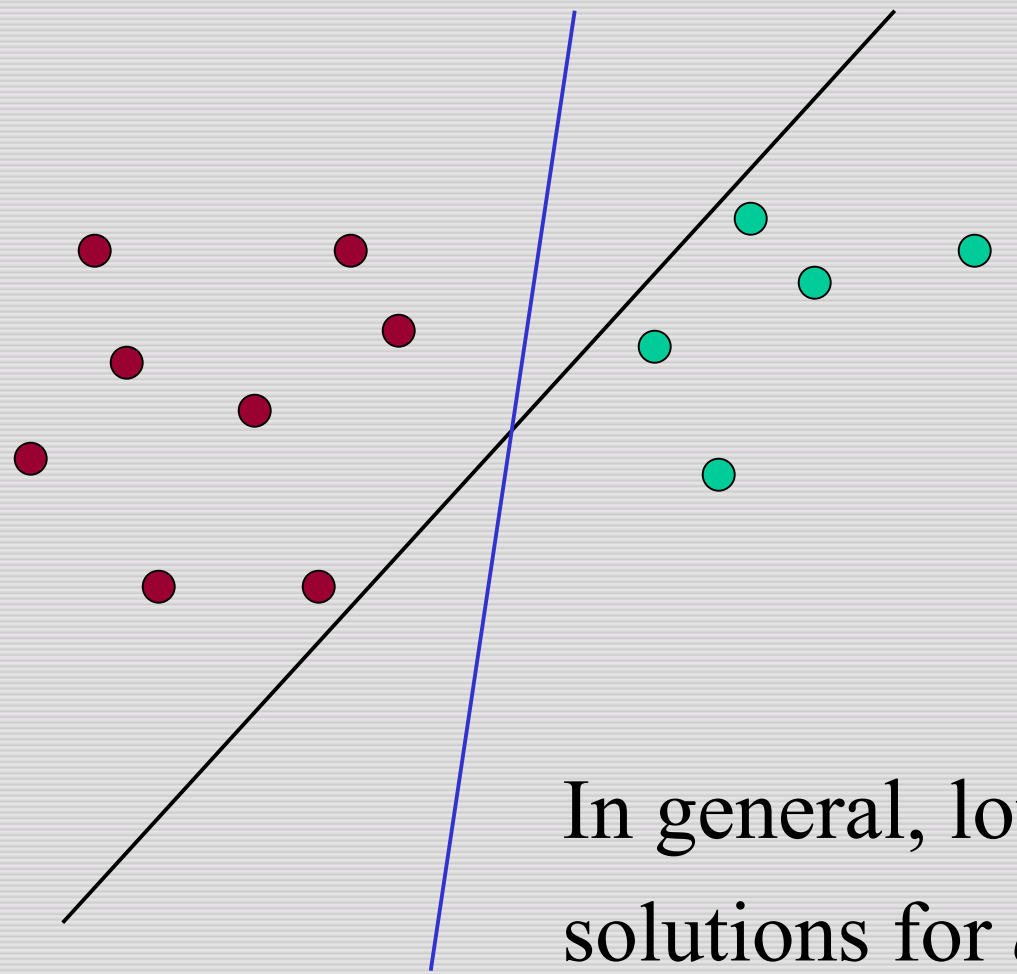


Find a,b,c, such that

$ax + by \geq c$ for red points

$ax + by \leq c$ for green points.

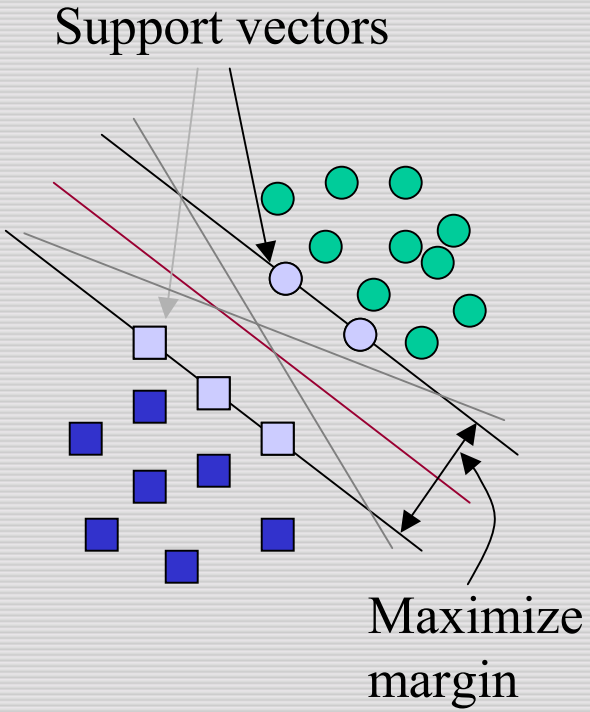
Which hyperplane?



In general, lots of possible solutions for *a,b,c*.

Support Vector Machine (SVM)

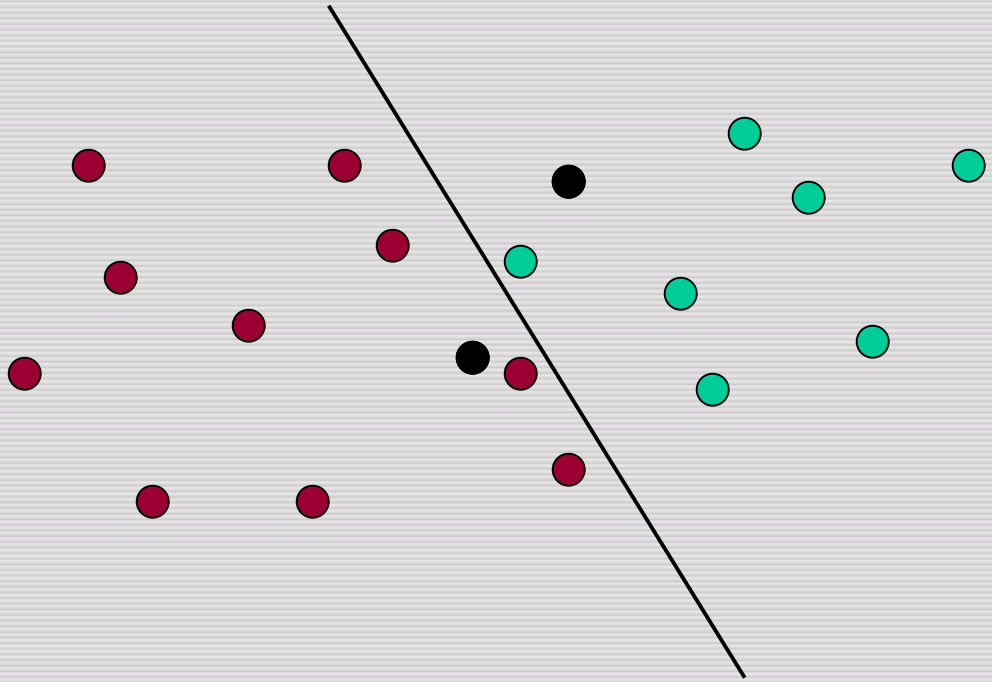
- *Quadratic programming* problem
- The decision function is fully specified by training samples which lie on two parallel hyper-planes



Building an SVM classifier

- Now we know how to build a separator for two linearly separable topics
- What about topics whose exemplary docs are not linearly separable?
- What about >2 topics?

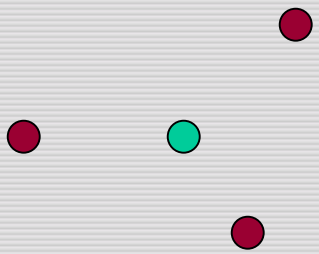
Not linearly separable



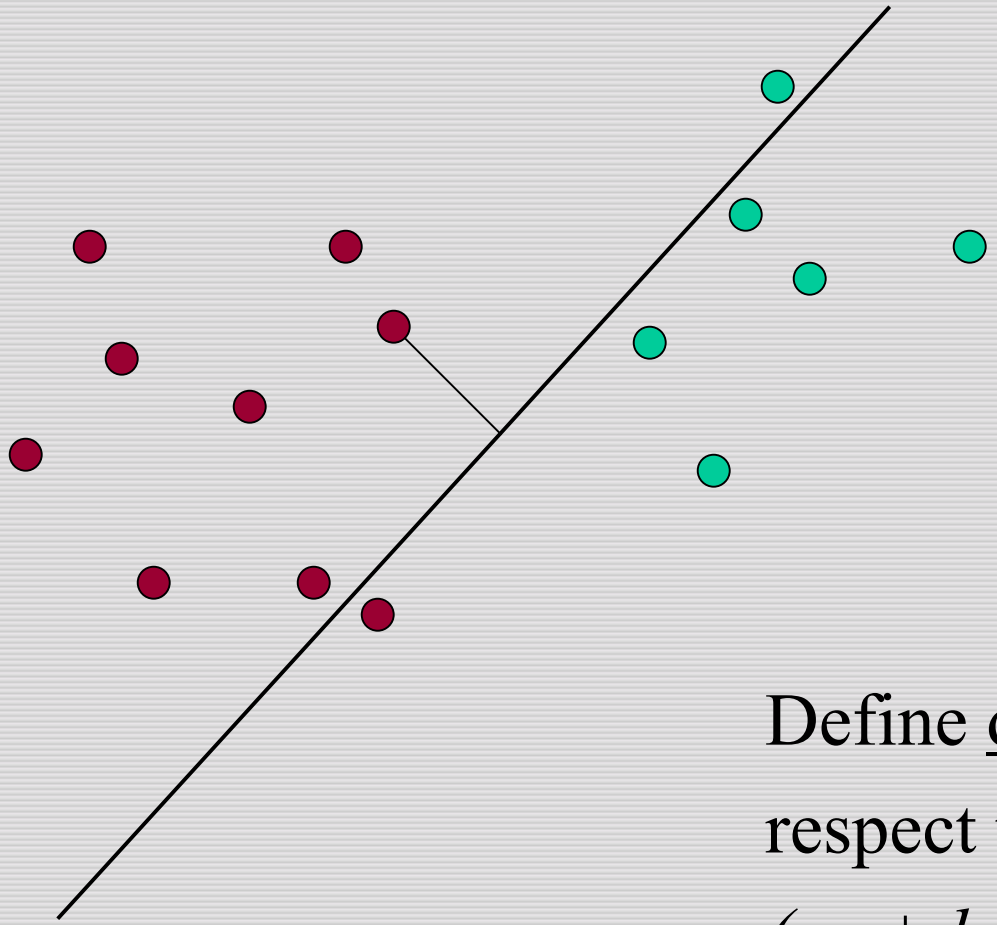
Find a line that penalizes points on “the wrong side”.

Exercise

- Suppose you have n points in d dimensions, labeled red or green. How big need n be (as a function of d) in order to create an example with the red and green points not linearly separable?
- E.g., for $d=2$, $n \geq 4$.



Penalizing bad points



Negative for bad points.

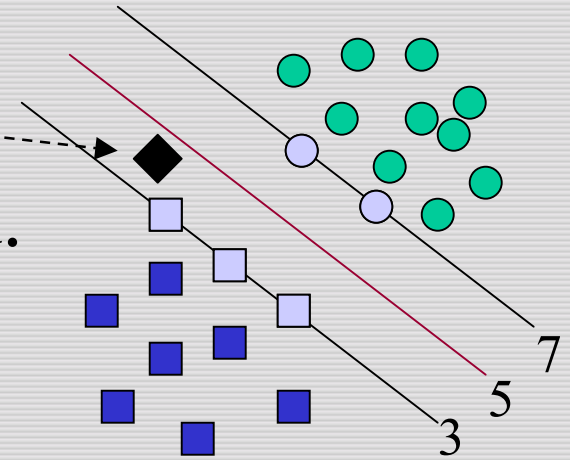
Define distance for each point with respect to separator $ax + by = c$:

$(ax + by) - c$ for red points

$c - (ax + by)$ for green points.

Solve quadratic program

- Solution gives "separator" between two topics: choice of a,b.
- Given a new point (x,y), can score its proximity to each class:
  - evaluate $ax+by$.
  - Set confidence threshold.



Category: Interest

- **Example SVM features**
- 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
• 0.43 baker	• -0.24 january

Separating multiple topics

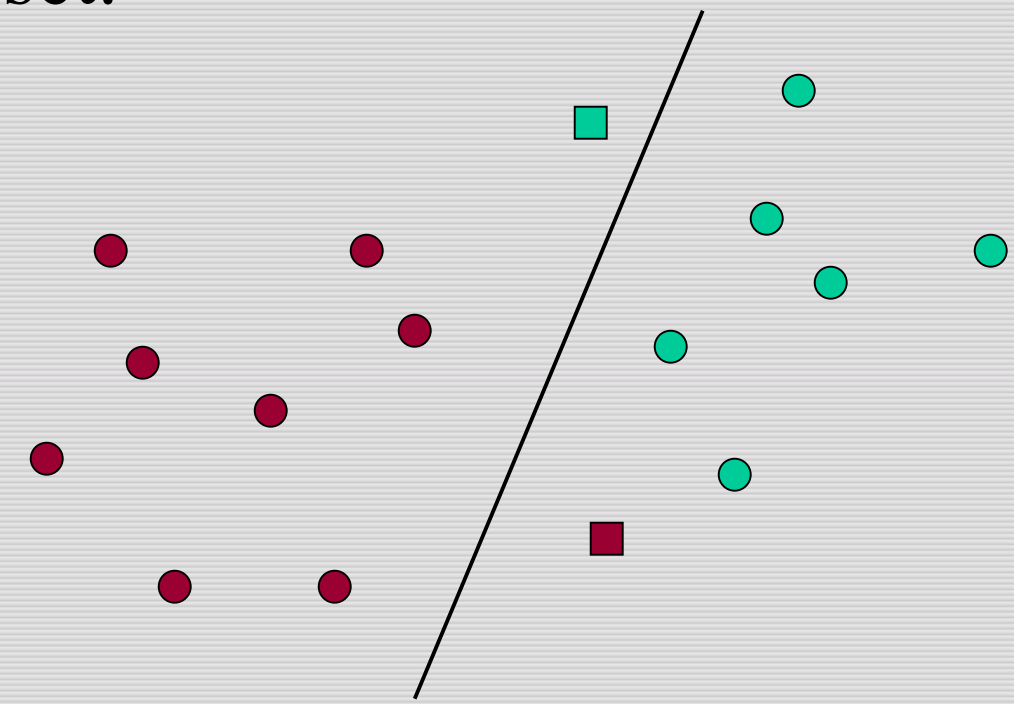
- Build a separator between each topic and its complementary set (docs from all other topics).
- Given test doc, evaluate it for membership in each topic.
- Declare membership in topics above threshold.

Negative examples

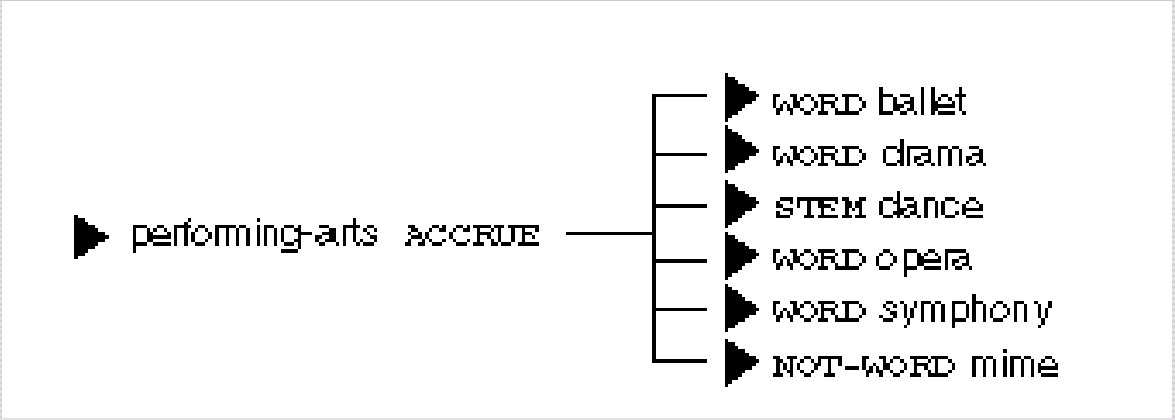
- Formulate as above, except negative examples for a topic are added to its complementary set.

○ Positive examples

□ Negative examples



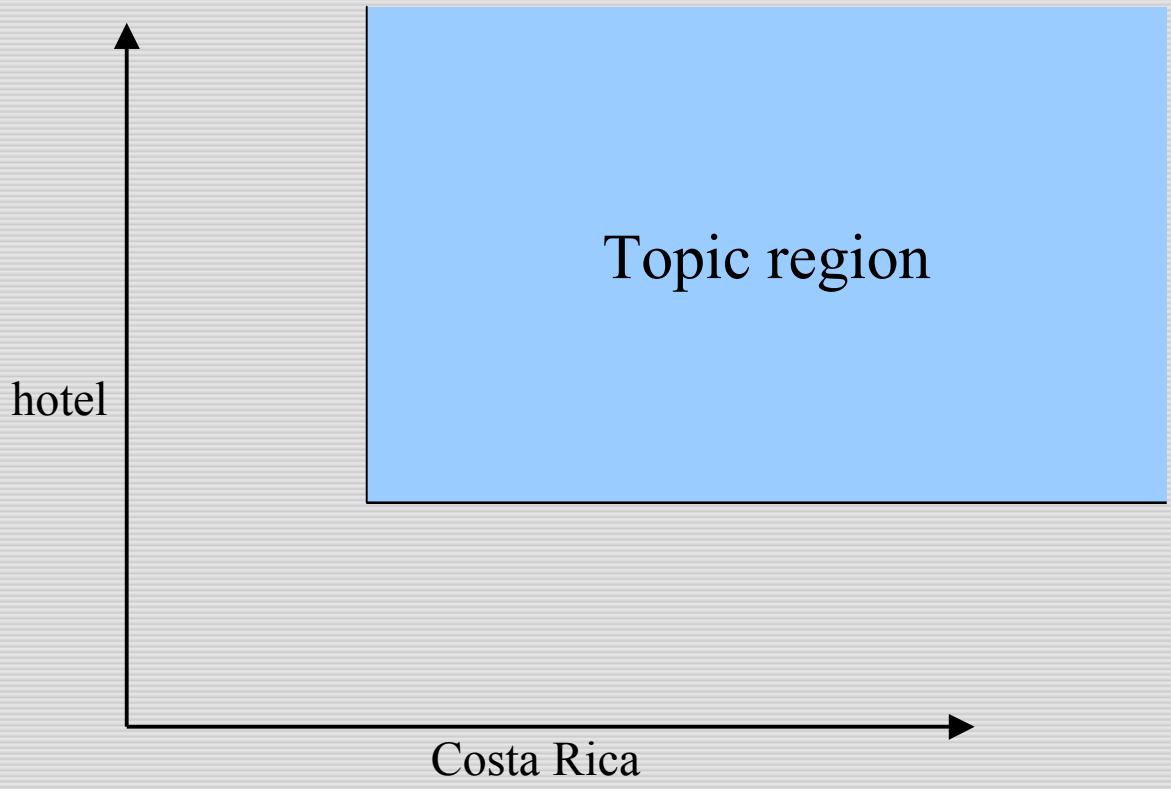
Recall explicit queries



- Can be viewed as defining a region in vector space.
- No longer linear separators.

Simple example

- Query = ***Costa Rica*** *AND* ***hotel***



Challenge

- Combining rule-based and machine learning based classifiers.
  - Nonlinear decision surfaces vs. linear.
  - User interface and expressibility issues.

UI issues

- Can specify rule-based query in the interface.
- Can exemplify docs.
- What is the representation of the combination?

Classification - closing remarks

- Can also use Bayesian nets to formulate classification
  - Compute probability doc belongs to a class, conditioned on its contents
- Many fancy schemes exist for term weighting in vectors, beyond simple *tf*×*idf* .

Resources

- R.M. Tong, L.A. Appelbaum, V.N. Askman, J.F. Cunningham. Conceptual Information Retrieval using RUBRIC. Proc. ACM SIGIR 247-253, (1987).
- S. T. Dumais, Using SVMs for text categorization, IEEE Intelligent Systems, 13(4), Jul/Aug 1998.