machine learning for IR

some slides courtesy James Allan@umass
some slides from Chris Manning/Rada Mihalcea

Text and Machine Learning

- Information Retrieval
- Library and Information Science
  Artificial Intelligence
- Natural Language Processing
- Database Management

What is Machine Learning?

- A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E. [Mitchell '97]*

- T: Classifying Text to some category
- P: Accuracy of Classification
- E: A training set

machine learning

- Given such a dataset onemight want to:
  - Learn to put Instances into predefined classes (classification)
  - Learn relationships between attributes (association learning)
  - Groups similar instances together (clustering)

- A fictional dataset

Name	Age	Sex	…	Risk
Tom	32	M	…	Y
Mary	54	F	…	N
John	13	M	…	?
Kim	10	F	…	?
…	…	…	…	…

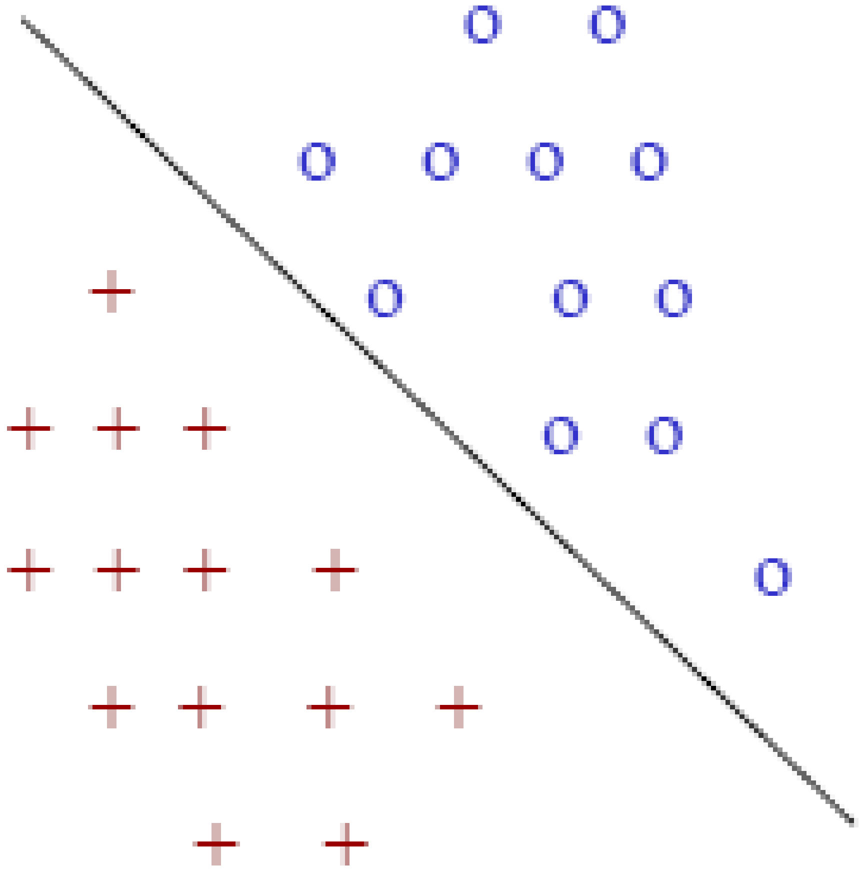
pattern classification

- Definitions:
  - Instance: Single example in the dataset (X_i)
  - Attribute: An aspect of an instance x_j
  - Value: Value that an attribute can take

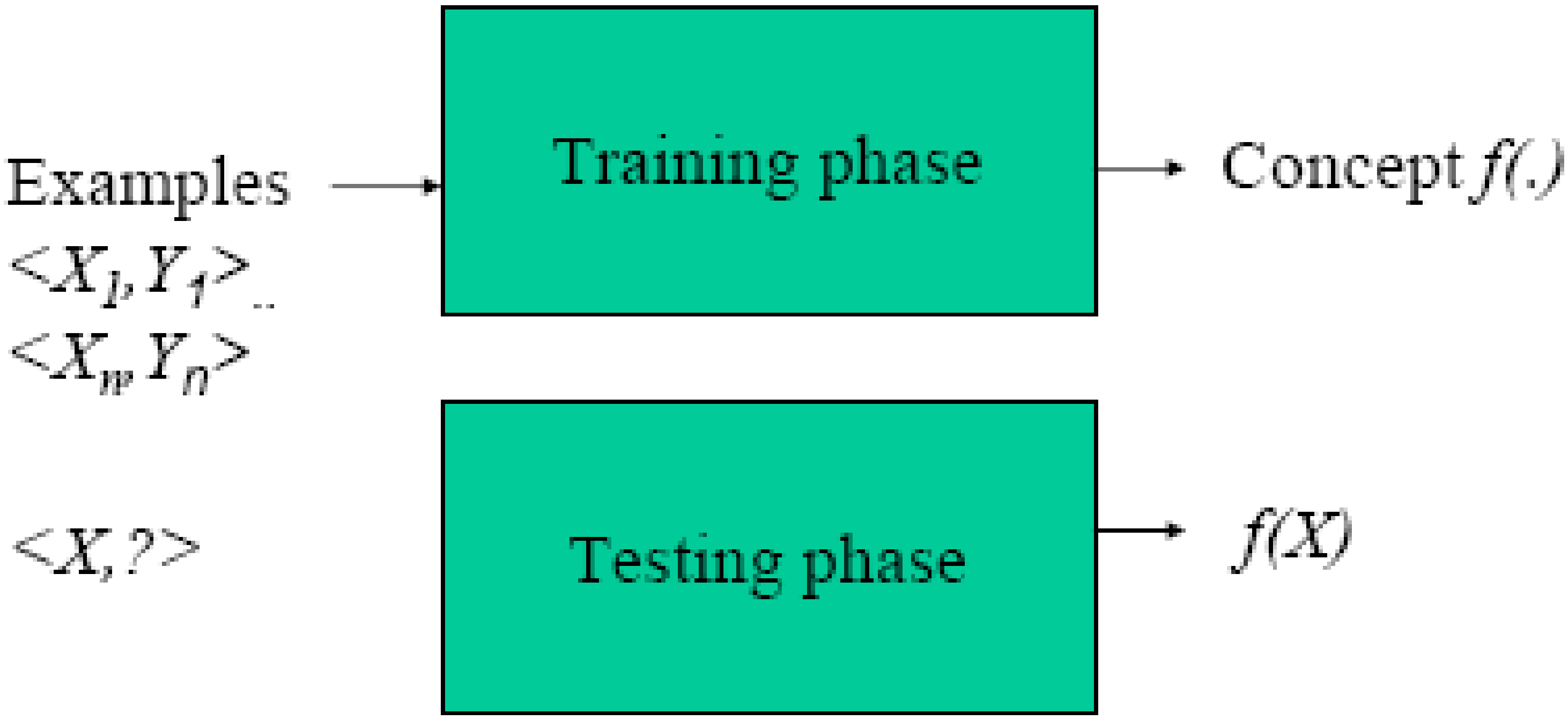
  - $X=(X_1 \ldots X_n)$, a set of d-dimensional vectors (the data)
    - $X_i = x_{1,i} \ldots x_{m,i}$
  - Y=Y˙1…Y˙m, a set of output classes
  - Concept – The thing to be learned

Name	Age	Sex	…	Risk
Tom	32	M	…	Y
Mary	54	F	…	N
John	13	M	…	?
Kim	10	F	…	?
…	…	…	…	…

example concept



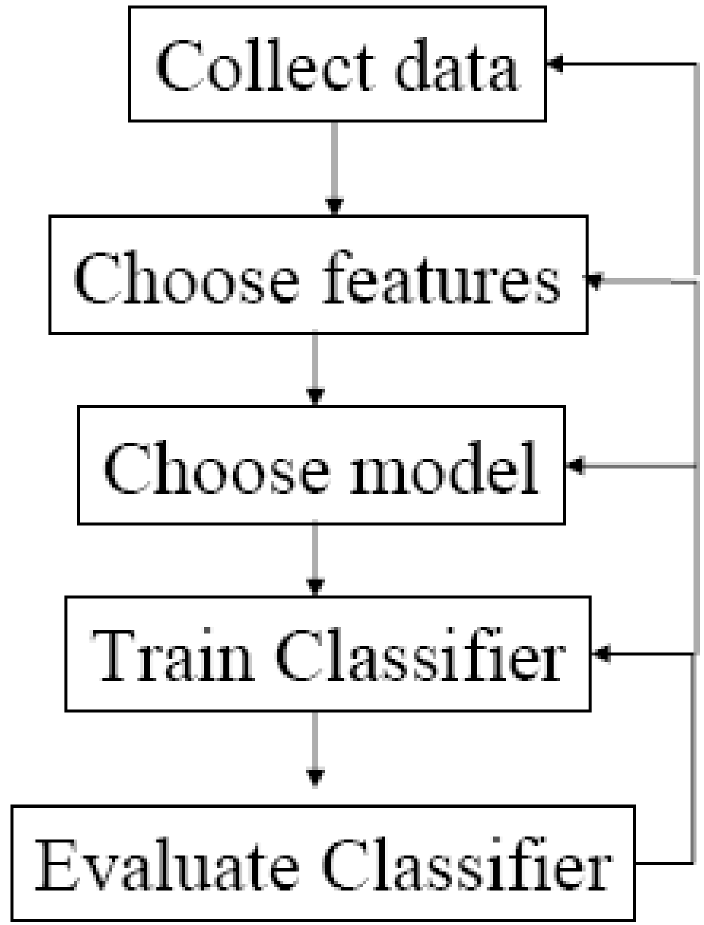
training and testing



- Document Classification
- Standard datasets:
  - Reuters: Reuters news articles in categories like earnings, acquisitions etc
  - Newsgroups: Newsgroups pages: Predict the newsgroup (comp.graphics, comp.os.mswindows.misc, rec.sport.baseball, rec.sport.hockey etc)

Features / Docs	w1	…	wn	…	Class
1					
2					
3					
4					
…		…	…	…	

classification



Cross Validation

Supervised Learning

- Supervised learning
  - learning algorithm is provided with a set of inputs for the algorithm along with the corresponding correct outputs,
  - learning involves the algorithm comparing its current
  - actual output with the correct or target outputs, so that it knows what its error is, and modify things accordingly.
- Unsupervised Learning
  - Example – regression, clustering

models

- Discriminative Models:

$$x \longrightarrow g(x)$$

- Generative models:

$$x \longrightarrow P(x|C)$$

$$P(C|x) \propto P(x|C)P(C)$$

$$g(x) = \frac{P(C|x)}{P(\bar{C}|x)}$$

naive Bayes

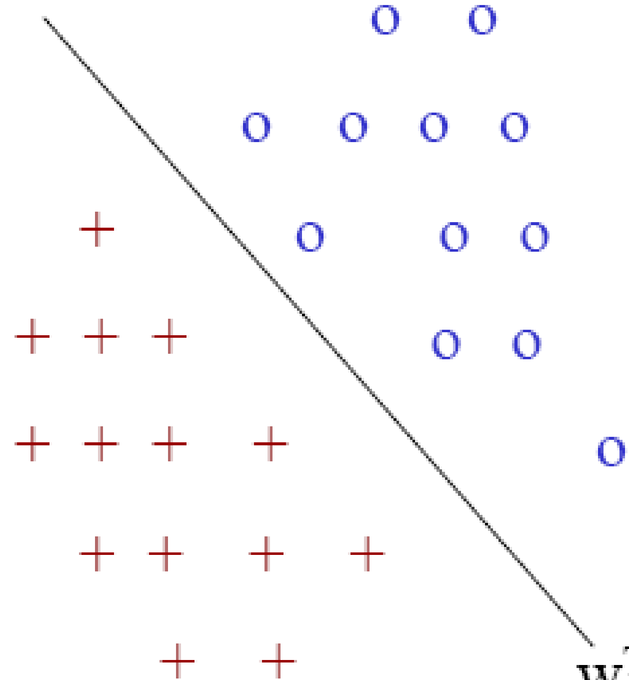
$$P(C|X) = \frac{P(X|C)P(C)}{P(X)}$$

$$P(X|C) = \prod_i^{|V|} p(x_i|C)$$

- If $P(C|X) > P(\bar{C}|X)$ then assign X to C
  - Intuitive. Also corresponds to the action where Bayes Risk is minimum
- Example of Generative Model
- Probabilities are Max likelihood with some form of smoothing

support vector machines

Find the best hyper-plane that separates the two classes



$w^Tx+b<0$

$w^Tx+b>0$

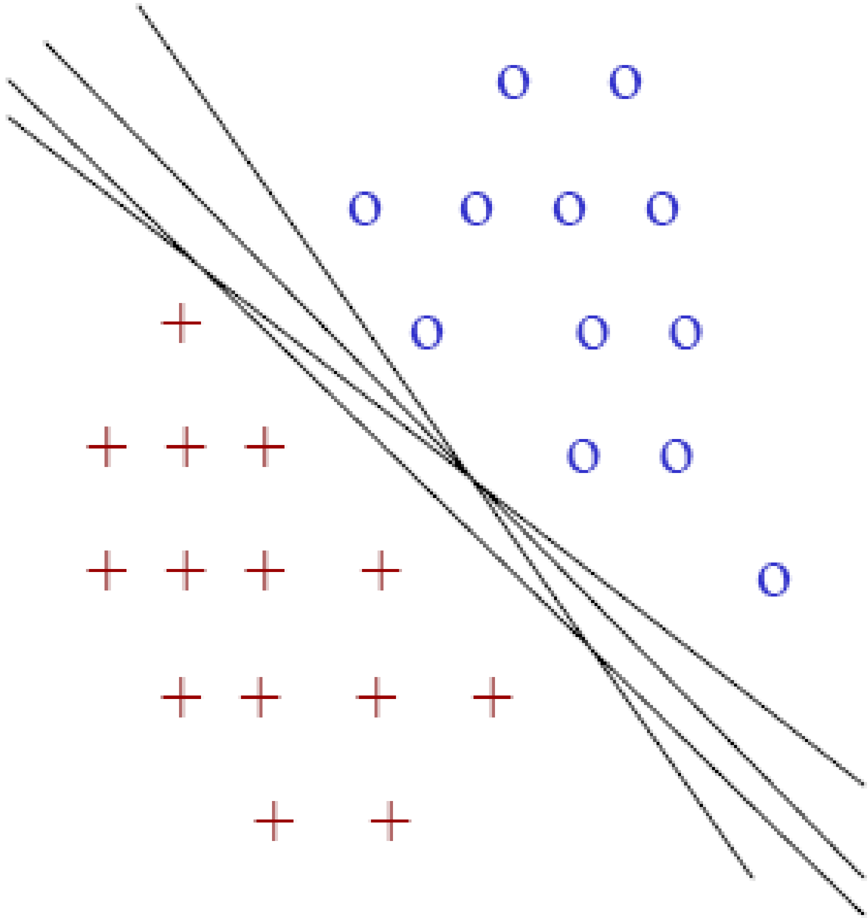
$w^Tx+b=0$

Example of a Generative Model

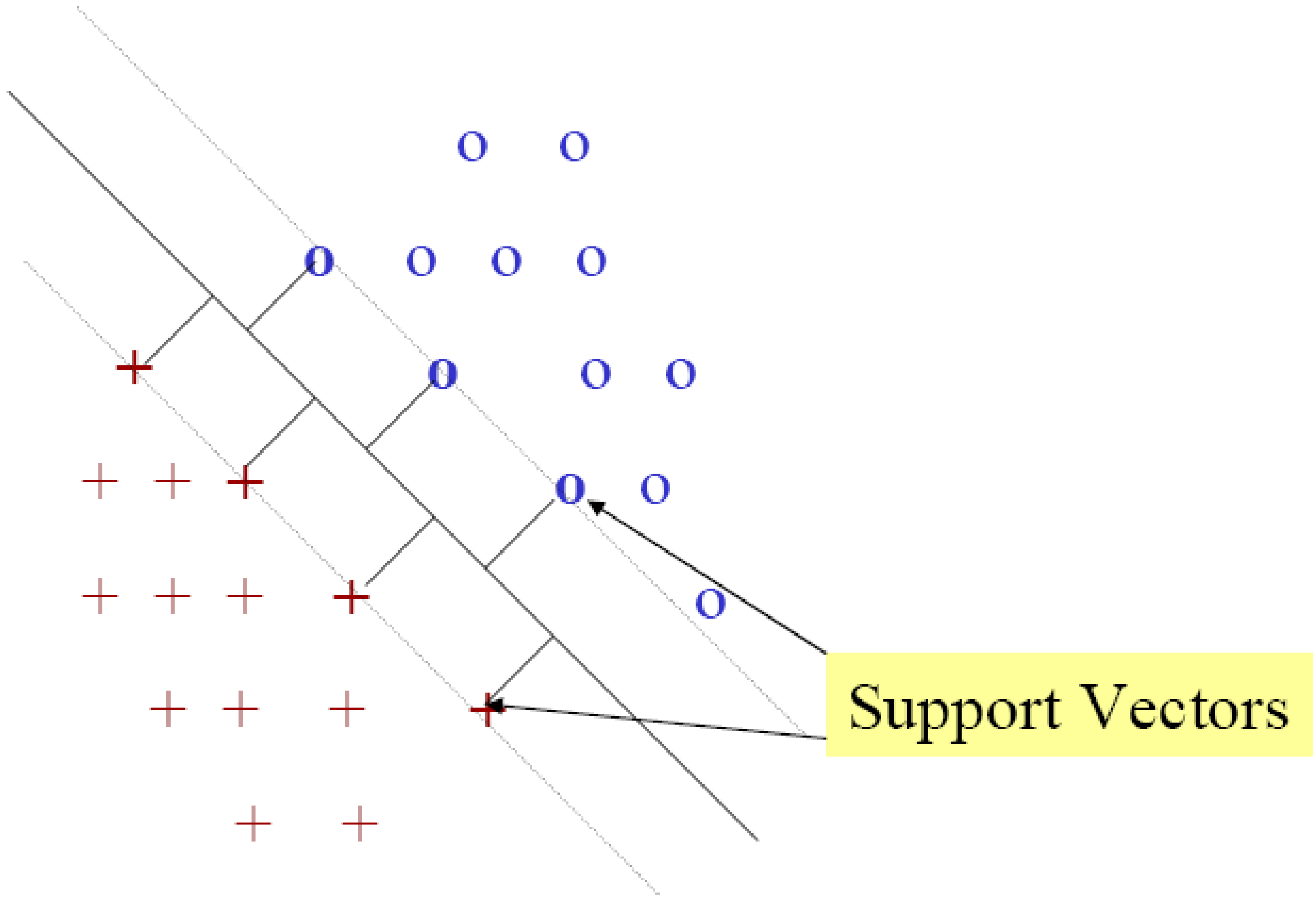
$f(x)=\mathrm{sgn}(w^Tx+b)$

support vector machines

But what is the best hyper-plane?



support vector machines

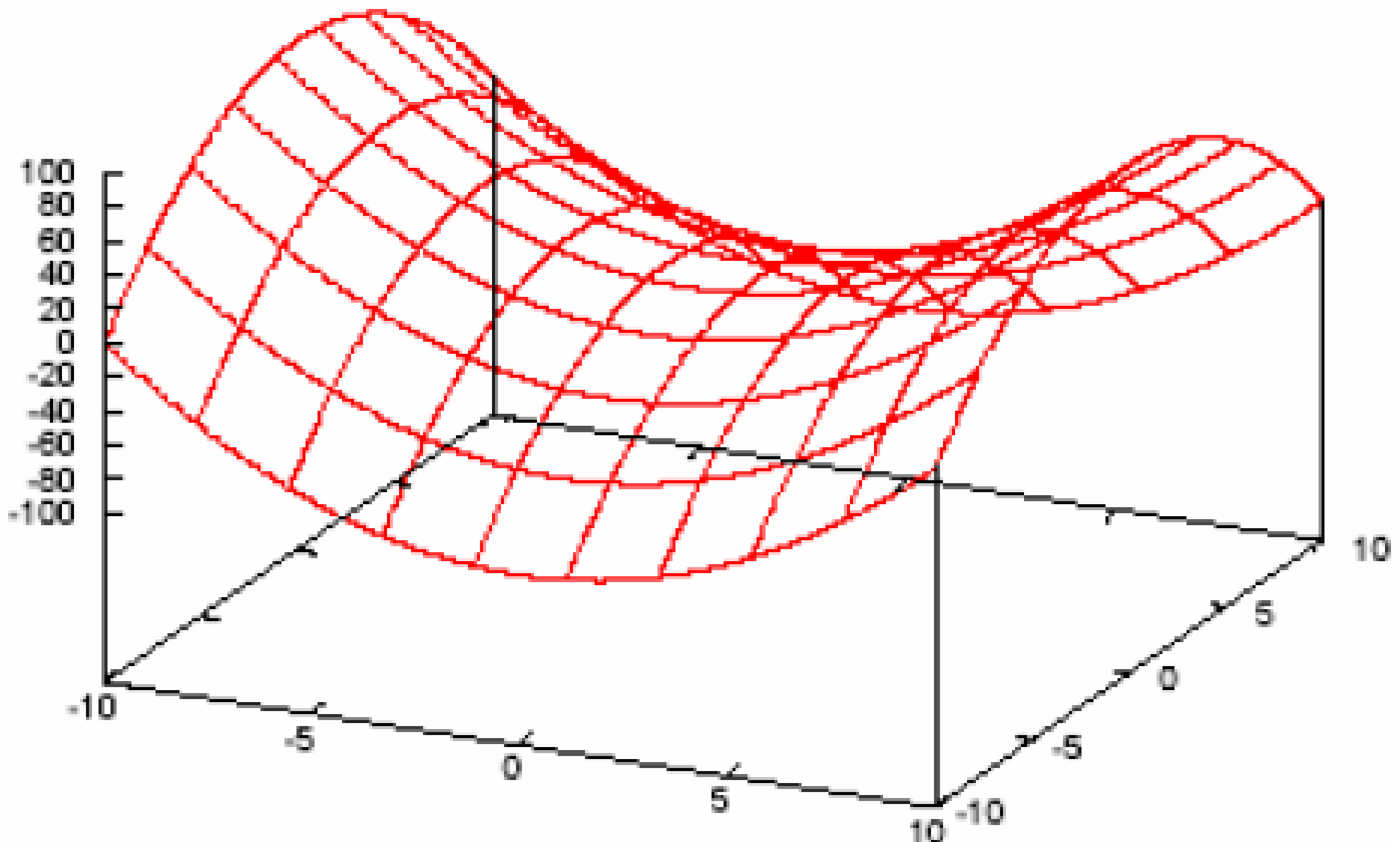


support vector machines

- optimization problem

$$(w*, b*) = argmax_{(w,b)} min_{(X_i \in X)} Y_i(w^T X_i + b)$$

Lagrange optimization



svm

- The solution is of the form

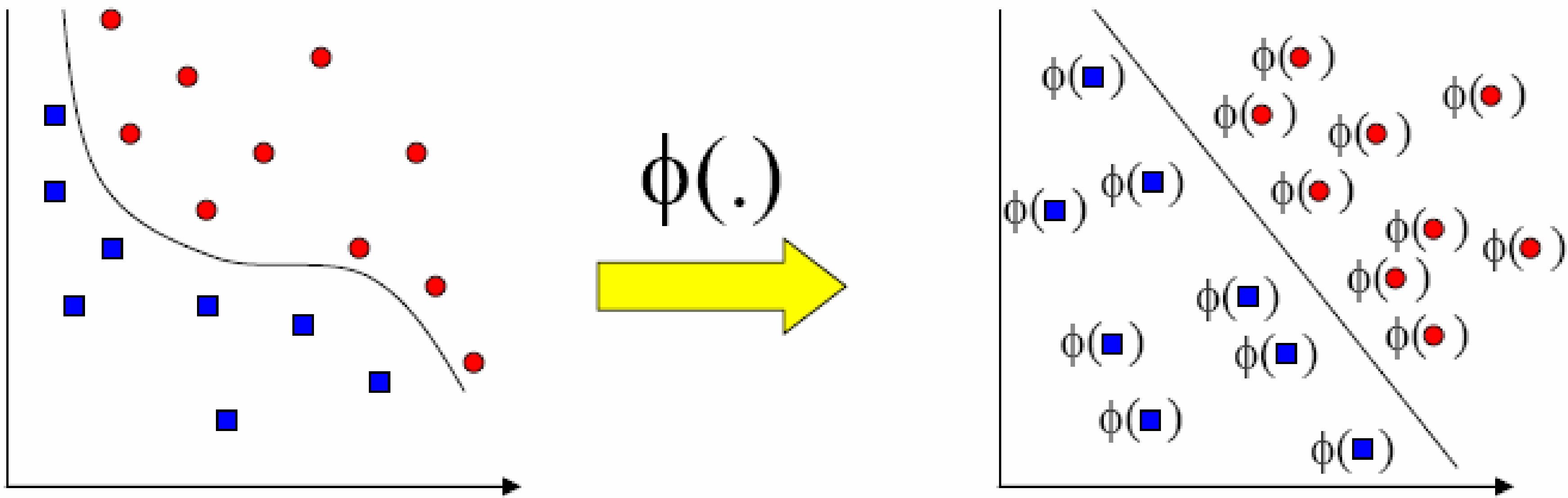
$$f(x) = sgn(\sum_{i \in SV} \alpha_i y_i x_i^T x + b^*)$$

- Support vectors are the only important data points in the training set

- Summation over number of support vectors

the kernel trick

$$K((x,y) = \phi(x)^T\phi(y)$$



IR as a Classification Problem

- Binary Classification and
- Compare with Language ModelingFramework

Probabilistic IR models as classifiers

- BIR model : A generative classifier
  - Features are binary representing the presence or absence of each word in the vocabulary
  - Uses a multiple-Bernoulli model to model the class-conditional

$$\log \frac{P(R \mid \mathbf{D})}{P(\bar{R} \mid \mathbf{D})} = \log \frac{P(\mathbf{D} \mid R)P(R)}{P(\mathbf{D} \mid \bar{R})P(\bar{R})}$$

$$= \log\left(\prod_{i:x_i=1} \frac{P(x_i = 1 \mid R)}{P(x_i = 1 \mid \bar{R})} \prod_{i:x_i=0} \frac{P(x_i = 0 \mid R)}{P(x_i = 0 \mid \bar{R})} \right)$$

Probabilistic IR models as classifiers

- Language models
  - Appear to have abandoned the notion of IR as a binary classification problem: There is no reference to the class variable R !
  - However, if we imagine each document as a unique class, language models can be considered generative!
  - Language models rank the classes (documents) for each instance (query)!

Case for Discriminative models for IR

- Theoretical considerations
  - “One should solve the (classification) problem directly and never solve a more general problem (class-conditional) as an intermediate step” [Vapnik, 1998]
  - Discriminative models tend to have a lower asymptotic error as the training set size is increased [Ng and Jordan, NIPS 2002]

Case for Discriminative models for IR

- Modeling assumptions
  - Term conditional independence assumptions in LM not strictly valid
  - Multinomial distribution fails to model burstiness of terms [Teevan and Karger, SIGIR 2003]
  - Discriminative models make very few assumptions and let the data speak for itself!

Case for Discriminative models for IR

- Case for Discriminative models for IR

- Expressiveness : advanced features
  - Proximity of query terms
  - Ordering of terms
  - Presence or absence of terms

- Hard to include such features in LMs

- Discriminative models can handle arbitrary features

Case for Discriminative models for IR

- Learning arbitrary features
  - Multiple representations of documents
    - E.g.: abstract, title, anchor text, document content
  - Query-independent features
    - E.g.: Page Rank
    - User preferences
- Language models permit both but feature weights (typically) determined empirically
- Discriminative models can learn all such features automatically

IR vs. Text Classification

- IR not same as text classification!
  - IR is much harder: training data is very sparse
  - Dynamic vs. static classes: Distribution of words in the relevant class is query-specific
    - training on words as features will not help

- Features based on query-based statistics of documents instead

Unbalanced data

- Non-relevant class is represented by much larger number of training examples than the relevant class
- Discriminative classifiers trained on unbalanced data result in trivial classifiers
- Methods used to overcoming unbalanced data problem:
  - Oversampling minority class
  - Undersampling majority class
  - Adjusting misclassification cost of one of the classes

Ad-hoc Retrieval

- Task of retrieving a ranked list of relevant documents for a given free-text query
  - 4 different TREC collections used in the experiments: each collection has a set of train and test queries and relevance judgments
  - SVM and LM
  - The models trained on each collection and tested on all 4 collections: in total we have 16 runs
  - Documents and queries are pre-preprocessed using a stop-word list and the K-stemmer

Ad-hoc Retrieval

- Used title queries in all experiments
- Dirichlet smoothing is used in LM runs: training consists of finding the best value of Dirichlet parameter
- SVMs: linear kernels proved the best
- Discriminative models trained using all relevant examples and randomly sampled non-relevant examples
- *Lemur* for LMs, *SVM-light* for SVMs

Ad-hoc Retrieval

Features used in the discriminative models

$$1.\ \sum_{i=1}^{n} \log(c(q_i, D))$$

$$2.\ \sum_{i=1}^{n} \log\left(1 + \frac{c(q_i, D)}{|D|}\right)$$

$$3.\ \sum_{i:c(q_i, D)>0} \log(idf(q_i))$$

$$4.\ \sum_{i:q_i>0} \log \frac{|C|}{c(q_i, C)}$$

$$5.\ \sum_{i=1}^{n} \log\left(1 + \frac{|D|}{c(q_i, D)} idf(q_i)\right)$$

$$6.\ \sum_{i=1}^{n} \log\left(1 + \frac{|C|}{c(q_i, C)} \frac{c(q_i, D)}{|D|}\right)$$

Out-Of-Vocab problem

- Words in test queries are mostly to have occurred in training queries.
- However, features are based not on words but on the term statistics.

adhoc retrieval

Train Test		Disk 1-2 (151-200)	Disk3 (101-150)	Disks 4-5 (401-450)	WT2G (426-450)
Disk1-2 (101-150)	LM	**0.2561 (6.75e-3)**	0.1842	0.2377 (0.80)	0.2665 (0.61)
	SVM	0.2145	0.1877 (0.3)	0.2356	0.2598
Disk3 (51-100)	LM	**0.2605 (1.08e-4)**	0.1785 (0.11)	0.2503 (0.21)	0.2666
	SVM	0.2064	0.1728	0.2432	0.2750 (0.55)
Disk4-5 (301-350)	LM	**0.2592 (1.75e-4)**	**0.1773 (7.9e-3)**	**0.2516 (0.036)**	0.2656
	SVM	0.2078	0.1646	0.2355	0.2675 (0.89)
WT2G (401-425)	LM	**0.2524 (4.6e-3)**	0.1838 (0.08)	0.2335	0.2639
	SVM	0.2199	0.1744	**0.2487 (0.046)**	**0.2798 (0.037)**

ad-hoc retrieval

- Conclusions
  - LMs, despite some inaccurate assumptions are quite robust!
  - class conditional models using a fixed distribution are relatively impervious to noise in training data
  - Simplicity helps in good generalization
    - Why use SVMs then?
  - Strength of SVMs: ability to learn relative importance of arbitrary features automatically

home page finding

- Task of retrieving the relevant document as high in the ranked list as possible.
  - Corpus is WT10G, a 10GB web collection.
  - 50 Queries for Training, 50 for development and 145 for testing
  - Evaluation
    - Mean Reciprocal Rank (MRR)
    - Success rate
    - Failure rate

home page finding

- Features used in discriminative models
  - Query-dependent features:
    - Document content
    - Anchor text
    - Title
  - Query-independent features
    - Link factor

$$\log\left(1+\frac{num-links(D)}{Avg-num-links}\right)$$

    - URL-depth: reciprocal of number of branches in the URL path of the document

home page finding

Results on the development set

SVM features	**MRR**	**Success %**	**Failure %**
Content + Anchor	0.54	73.0	5.2
Content + Anchor + Title	0.61	85.7	10.2
Content + Anchor + Title + URL	0.61	85.7	10.2
Content + Anchor + Title + URL+ link	0.61	85.7	10.2
LM baseline **SVM baseline**	**0.35** **0.33**	**52.0** **53.06**	**10.0** **12.24**

home page finding

Results on test set

– Used all query-dependent and query-independent features

Model	MRR	Success %	Failure %
Full-featured SVM	0.52	77.93	11.03
LM baseline	0.35	57.93	15.86
SVM Baseline	0.28	52.41	17.90

Different Learning Paradigms

- Inductive Learning – what you just saw
  - Learn from solved examples in a book . In-class closed book exam
- Active Learning
  - Only unsolved problems. Can ask an expert a few questions. In-class closed book exam
- Semi supervised learning
  - Book examples, back of the book questions. In-class closed book exam
- Transductive Learning.
  - Book examples. Take home exam.

Active Learning

- In *Active Learning* the learner can ask an expert the labels of some of the unlabeled instances in order to improve classification accuracy.

- The objective is to ask the expert as few questions as possible.

- Uncertainty sampling is one way of Active Learning

Active Learning

- Query by Committee [Freund, Sueng et al]
  - *They prove theoretically that if a 2 member committee can achieve information gain with +ve lower bound then error decreases exponentially in the number of queries*
- Uncertainty Sampling [Lewis and Gale]
  - *Query on those instances that the Naïve Bayes classifier is most uncertain about* $(p(Y|X) \tilde{} 0.5)$
- Optimize on expected future error[Roy,McCallum]
- Active Learning with Support Vector Machines [Tong, Koller]
  - *Pick a sample such that the knowledge of the label reduces the version space in half.*

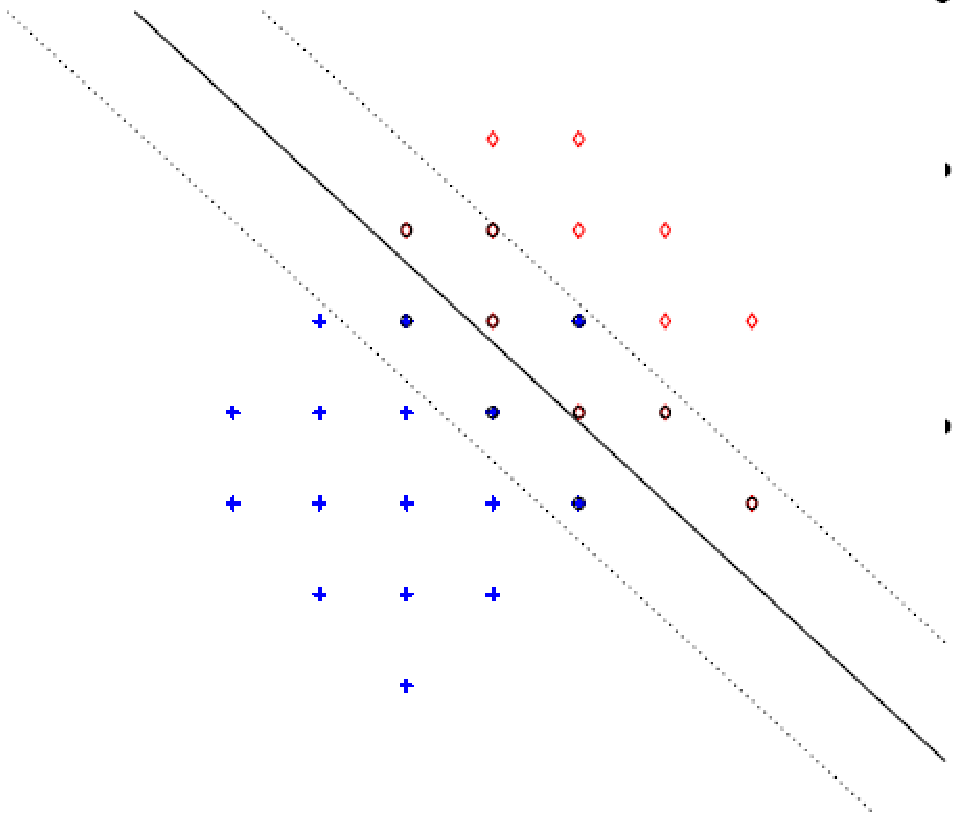
Active Learning with a Naive Bayes Classifier

- Remember the Naïve Bayes Classifier

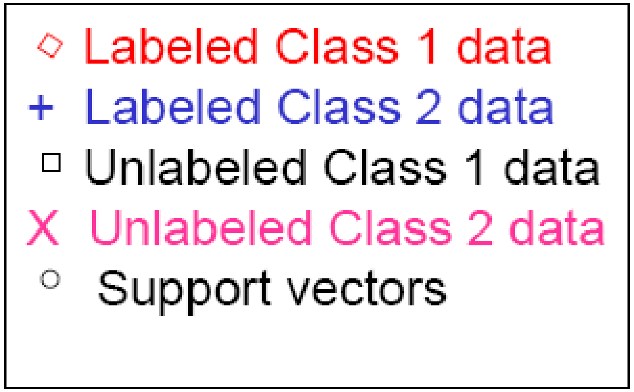
- The simplest way of uncertainty sampling is to query the user on instances with as close to 0.5 as possible.

$$\frac{P(C|D)}{P(\bar{C}|D)} = \frac{P(C)}{P(\bar{C})} \times \frac{P(D|C)}{P(D|\bar{C})}$$

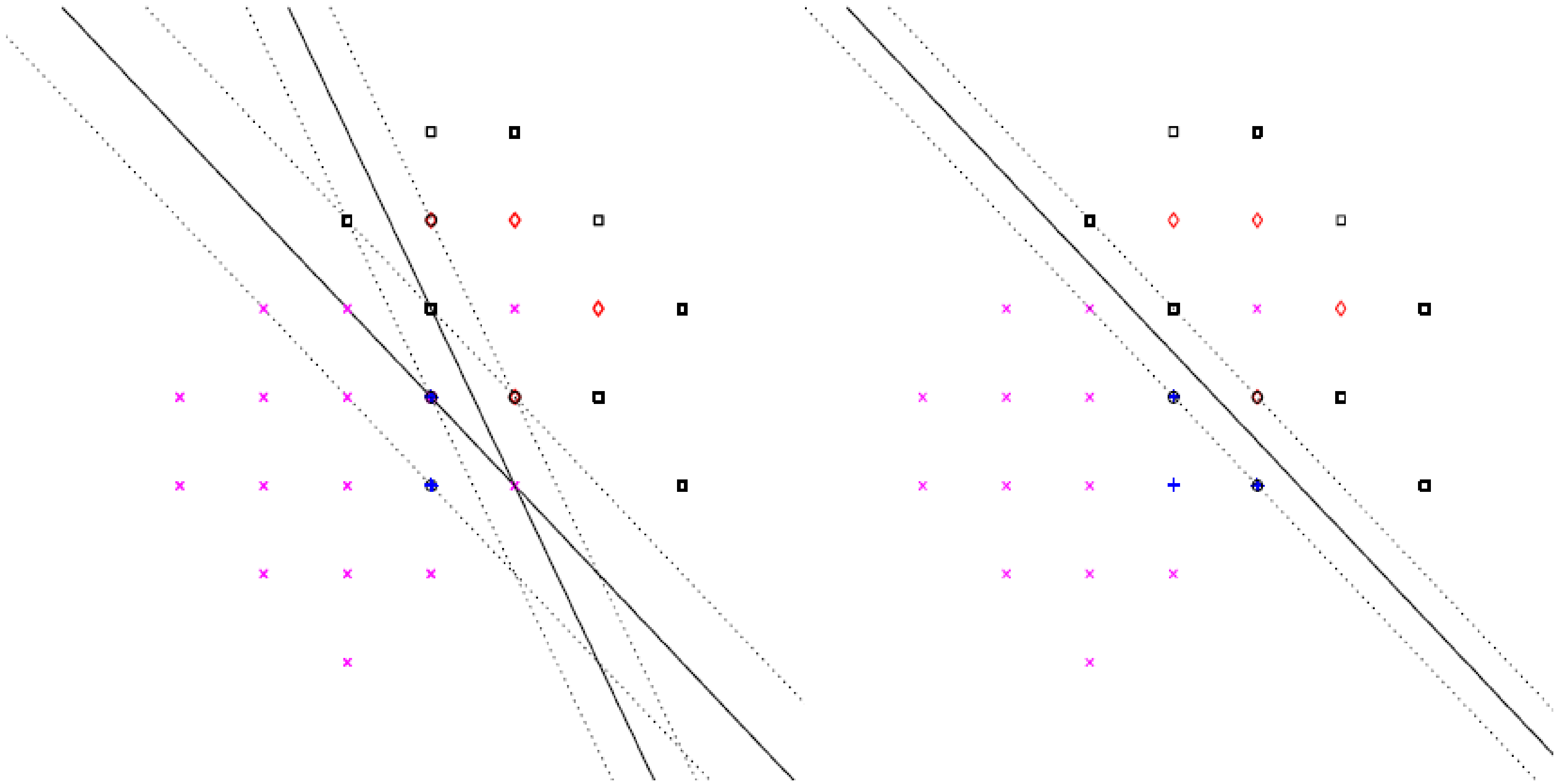
active learning with SVM



- Consider a two class problem
- The SVM tries to find the best separating hyper- plane
- When all the data is labeled it's easy.



Uncertainty Sampling



active learning and SVMs

- For each instance that you pick, you halve the hypothesis space.

- In other words you halve the number of possible concepts that fit the data

Uncertainty Sampling

Topic	SVM – Unc	Equivalent Random size
Earn	86.4	34
Acq	77.0	>100
Money	93.8	50
Grain	95.5	13
Crude	95.26	>100

Avg. test set accuracy on Reuters corpus. 2nd column is accuracy with 10 labeled instances using Uncertainty sampling with SVMs.

Maximum Likelihood Parameter Estimation

$$P(X) \sim \theta$$

- For example $\theta = \mu, \sigma$ for a normal distribution.
- Write this as: $P(X|\theta)$

$$\mathcal{D} = x_1 ... x_n$$

$$p(\mathcal{D}|\theta) = \prod_{i=1}^{n} p(x_i|\theta)$$

MLE

Log Likelihood: $l(\theta) = \log p(\mathcal{D}|\theta)$

Maximum Likelihood Estimate:

$$\widehat{\theta} = argmax_{\theta} l(\theta)$$

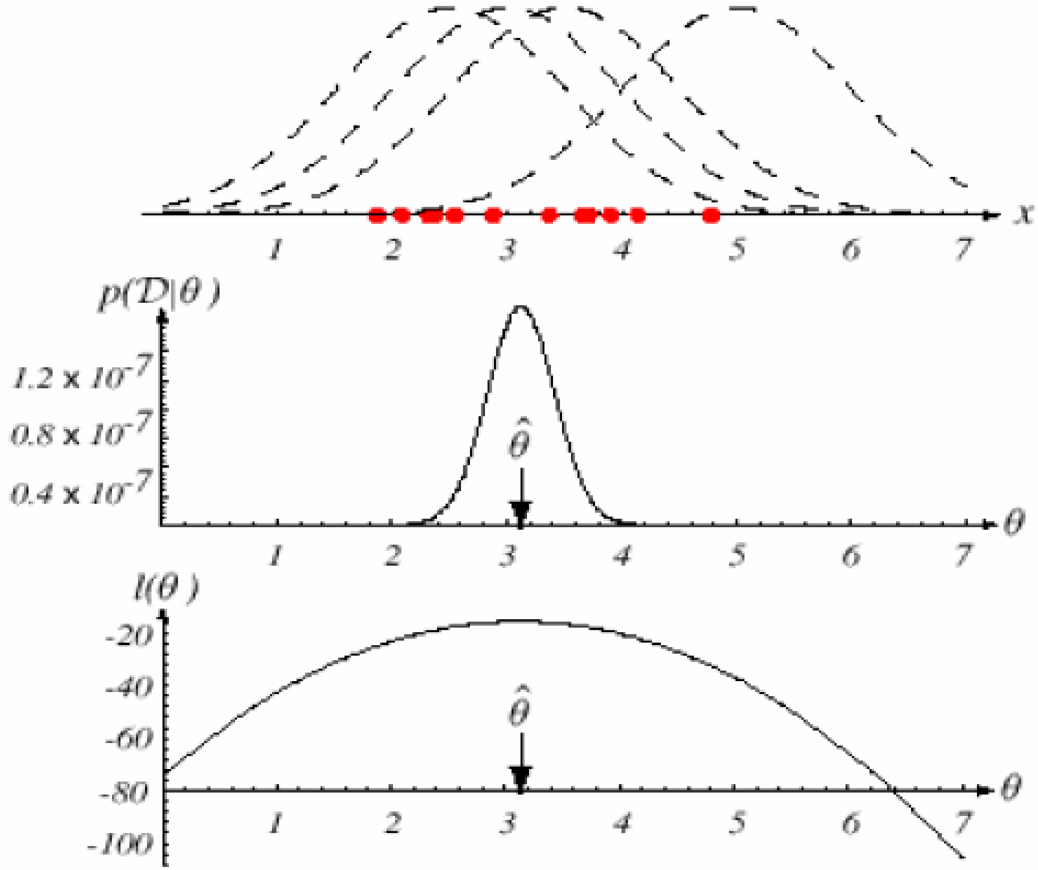


FIGURE 3.1. The top graph shows several training points in one dimension, known or assumed to be drawn from a Gaussian of a particular variance, but unknown mean. Four of the infinite number of candidate source distributions are shown in dashed lines. The middle figure shows the likelihood $p(\mathcal{D}|\theta)$ as a function of the mean. If we had a very large number of training points, this likelihood would be very narrow. The value that maximizes the likelihood is marked $\hat{\theta}$; it also maximizes the logarithm of the likelihood—that is, the log-likelihood $l(\theta)$, shown at the bottom. Note that even though they look similar, the likelihood $p(\mathcal{D}|\theta)$ is shown as a function of θ whereas the conditional density $p(x|\theta)$ is shown as a function of x. Furthermore, as a function of θ, the likelihood $p(\mathcal{D}|\theta)$ is not a probability density function and its area has no significance. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Bayesian estimation

$$P(x|\mathcal{D}) = \int p(x|\theta)p(\theta|\mathcal{D})d\theta$$

$$P(\theta|\mathcal{D}) = \frac{P(\mathcal{D}|\theta)p(\theta)}{\int p(\mathcal{D})}$$

$$P(\theta|\mathcal{D}) = \frac{P(\mathcal{D}|\theta)p(\theta)}{\int p(\mathcal{D}|\theta)p(\theta)d\theta}$$

- used for smoothing language models

text classification

Is this spam?

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 !

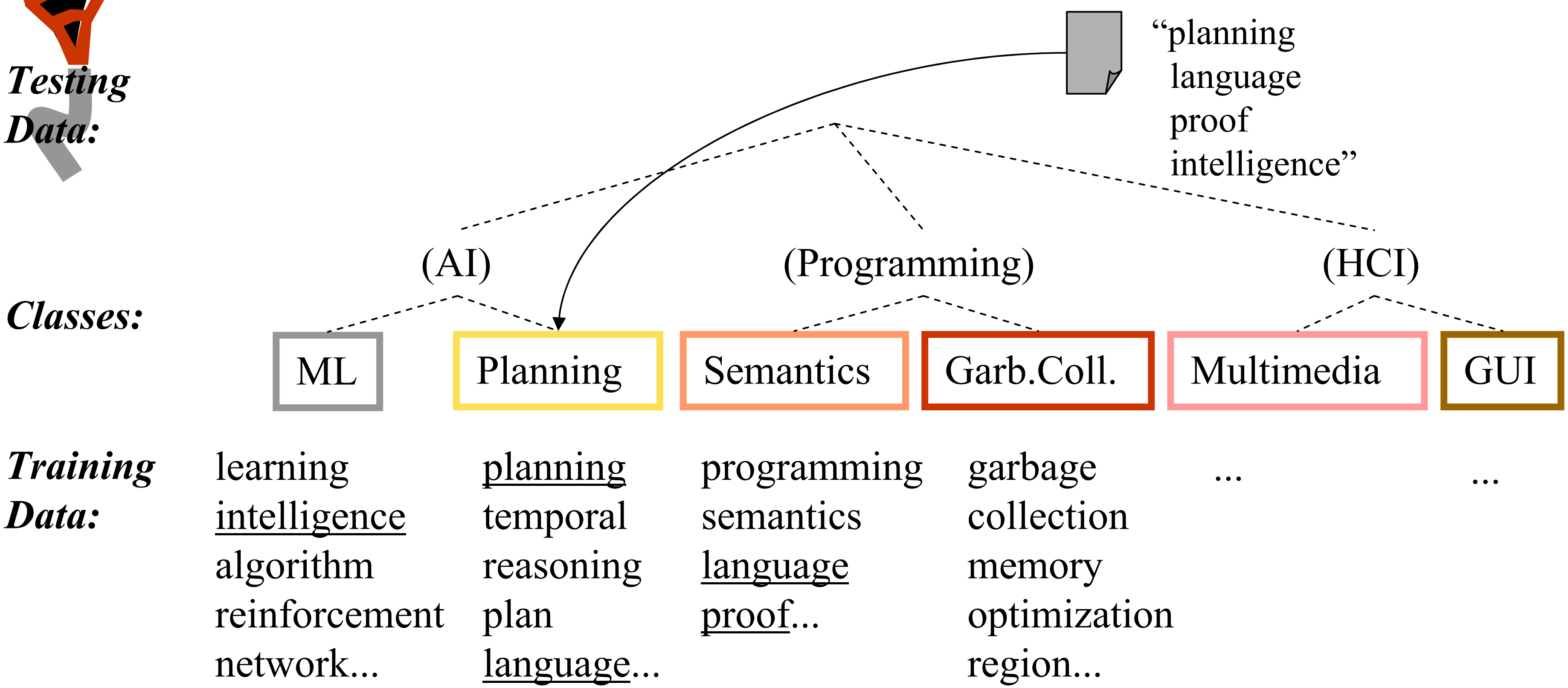
===
Click Below to order:
http://www.wholesaledaily.com/sales/nmd.htm
===

Categorization/Classification

- Given:
  - A description of an instance, $x \in X$, where X is the *instance language* or *instance space*.
    - Issue: how to represent text documents.
  - A fixed set of categories:

    $C = \{c_1, c_2, \ldots, c_n\}$
- Determine:
  - The category of x: $c(x) \in C$, where $c(x)$ is a *categorization function* whose domain is X and whose range is C.
    - We want to know how to build categorization functions ("classifiers").

Document Classification



(Note: in real life there is often a hierarchy, not present in the above problem statement; and you get papers on ML approaches to Garb. Coll.)

Text Categorization Examples

Assign labels to each document or web-page:

- Labels are most often topics such as Yahoo-categories
  e.g., ”finance,” ”sports,” ”news¿world¿asia¿business”
- Labels may be genres
  e.g., ”editorials” ”movie-reviews” ”news“
- Labels may be opinion
  e.g., “like”, “hate”, “neutral”
- Labels may be domain-specific binary
  e.g., ”interesting-to-me” : ”not-interesting-to-me”
  e.g., “spam” : “not-spam”
  e.g., “is a toner cartridge ad” :“isn’t”

Methods (1)

- Manual classification
  - Used by Yahoo!, Looksmart, about.com, ODP, Medline
  - very accurate when job is done by experts
  - consistent when the problem size and team is small
  - difficult and expensive to scale
- Automatic document classification
  - Hand-coded rule-based systems
    - Used by CS dept’s spam filter, Reuters, CIA, Verity, …
    - E.g., assign category if document contains a given boolean combination of words
    - Commercial systems have complex query languages (everything in IR query languages + *accumulators*)

Methods (2)

  - Accuracy is often very high if a query has been carefully refined over time by a subject expert
  - Building and maintaining these queries is expensive
- Supervised learning of document-label assignment function
  - Many new systems rely on machine learning (Autonomy, Kana, MSN, Verity, …)
    - k-Nearest Neighbors (simple, powerful)
    - Naive Bayes (simple, common method)
    - Support-vector machines (new, more powerful)
    - … plus many other methods
    - No free lunch: requires hand-classified training data
    - But can be built (and refined) by non-experts

Text Categorization: attributes

- Representations of text are very high dimensional (one feature for each word).
- High-bias algorithms that prevent overfitting in high-dimensional space are best.
- For most text categorization tasks, there are many irrelevant and many relevant features.
- Methods that combine evidence from many or all features (e.g. naive Bayes, kNN, neural-nets) tend to work better than ones that try to isolate just a few relevant features (standard decision-tree or rule induction)*

*Although one can compensate by using many rules

Bayesian Methods

- Learning and classification methods based on probability theory.
- Bayes theorem plays a critical role in probabilistic learning and classification.
- Build a *generative model* that approximates how data is produced
- Uses *prior* probability of each category given no information about an item.
- Categorization produces a *posterior* probability distribution over the possible categories given a description of an item.

Naive Bayes Classifiers

- Task: Classify a new instance based on a tuple of attribute values

$$\langle x_1, x_2, \ldots, x_n \rangle$$

$$c_{MAP} = \operatorname*{argmax}_{c_j \in C} P(c_j \mid x_1, x_2, \ldots, x_n)$$

$$c_{MAP} = \operatorname*{argmax}_{c_j \in C} \frac{P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)}{P(x_1, x_2, \ldots, x_n)}$$

$$c_{MAP} = \operatorname*{argmax}_{c_j \in C} P(x_1, x_2, \ldots, x_n \mid c_j) P(c_j)$$

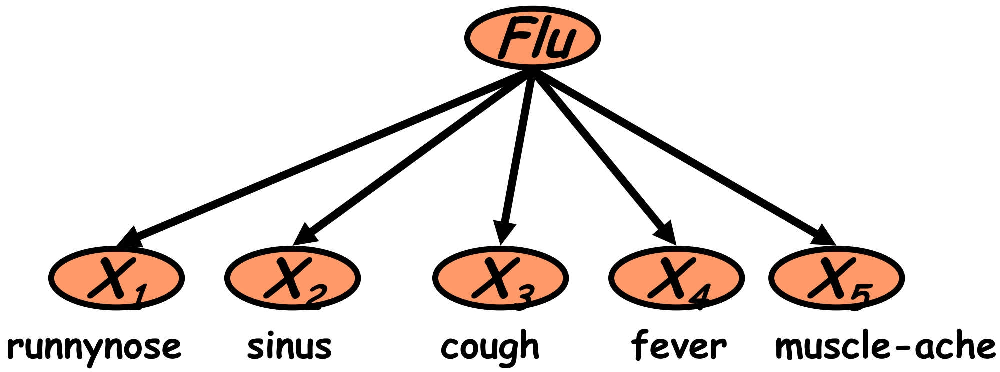
Naïve Bayes Classifier: Assumptions

- $P(c_j)$
  - Can be estimated from the frequency of classes in the training examples.
- $P(x_1,x_2,\ldots,x_n|c_j)$
  - $O(|X|^n \bullet |C|)$
  - Could only be estimated if a very, very large number of training examples was available.

Conditional Independence Assumption:

$\Rightarrow$ Assume that the probability of observing the conjunction of attributes is equal to the product of the individual probabilities.

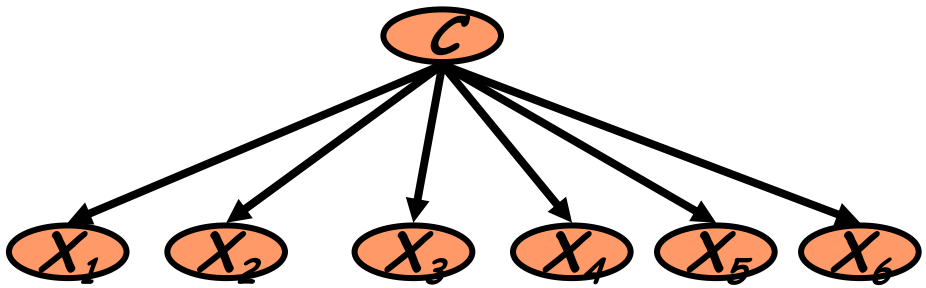
The Naïve Bayes Classifier



- Conditional Independence Assumption: features are independent of each other given the class:

$$P(X_1, \ldots, X_5 \mid C) = P(X_1 \mid C) \bullet P(X_2 \mid C) \bullet \cdots \bullet P(X_5 \mid C)$$

Learning the Model

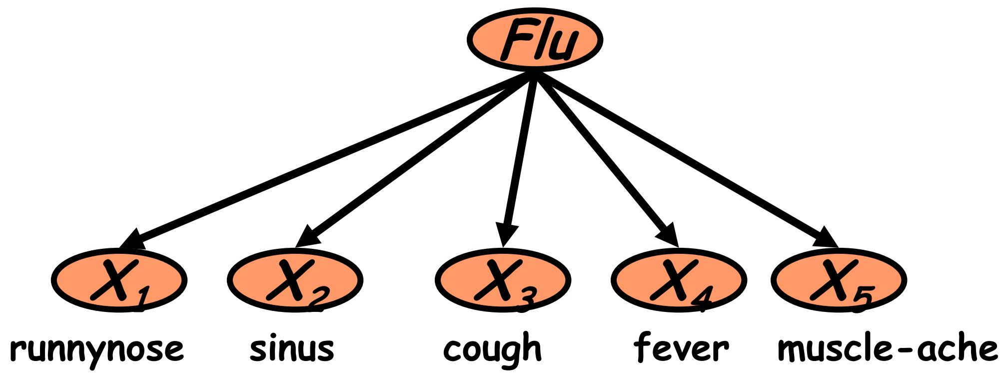


- Common practice:maximum likelihood
  - simply use the frequencies in the data

$$\hat{P}(c_j) = \frac{N(C = c_j)}{N}$$

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j)}{N(C = c_j)}$$

Problem with Max Likelihood



$$P(X_1,\ldots,X_5 \mid C) = P(X_1 \mid C) \bullet P(X_2 \mid C) \bullet \cdots \bullet P(X_5 \mid C)$$

- What if we have seen no training cases where patient had no flu and muscle aches?

$$\hat{P}(X_5 = t \mid C = nf) = \frac{N(X_5 = t, C = nf)}{N(C = nf)} = 0$$

- Zero probabilities cannot be conditioned away, no matter the other evidence!

$$\ell = \arg\max_c \hat{P}(c) \prod_i \hat{P}(x_i \mid c)$$

Smoothing to Avoid Overfitting

$$\hat{P}(x_i \mid c_j) = \frac{N(X_i = x_i, C = c_j) + 1}{N(C = c_j) + k}$$

# of values of X_i

- Somewhat more subtle version

overall fraction in data where $X_i = x_{i,k}$

$$\hat{P}(x_{i,k} \mid c_j) = \frac{N(X_i = x_{i,k}, C = c_j) + m p_{i,k}}{N(C = c_j) + m}$$

extent of "smoothing"

Naive Bayes Text Classification

- Attributes are text positions, values are words.

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}} P(c_j) \prod_i P(x_i \mid c_j)$$

$$= \underset{c_j \in C}{\operatorname{argmax}} P(c_j) P(x_1 = \text{"our"} \mid c_j) \cdots P(x_n = \text{"text"} \mid c_j)$$

- Still too many possibilities
- Assume that classification is *independent* of the positions of the words
  – Use same parameters for each position

Text Classification Algorithms: Learning

- From training corpus, extract *Vocabulary*
- Calculate required $P(c_j)$ and $P(x_k \mid c_j)$ terms
  - For each c_j in C do
    - $docs_j \leftarrow$ subset of documents for which the target class is c_j
    - $$P(c_j) \leftarrow \frac{|docs_j|}{|\text{total \# documents}|}$$
  - $Text_j \leftarrow$ single document containing all $docs_j$
  - for each word x_k in *Vocabulary*
    - $n_k \leftarrow$ number of occurrences of x_k in $Text_j$
    - $$P(x_k \mid c_j) \leftarrow \frac{n_k + 1}{n + |Vocabulary|}$$

Text Classification Algorithms: Classifying

- Return c_{NB}, where

$$c_{NB} = \underset{c_j \in C}{\operatorname{argmax}}\, P(c_j) \prod P(x_i \mid c_j)$$

General Learning Issues

- Many hypotheses are usually consistent with the training data.
  - Can derive many classification schemes
- Classification accuracy (% of instances classified correctly).
  - Measured on independent test data.
- Training time (efficiency of training algorithm).
- Testing time (efficiency of subsequent classification).

Text Categorization

- Assigning documents to a fixed set of categories.
- Applications:
  - Web pages
    - Recommending
    - Yahoo-like classification
  - Newsgroup Messages
    - Recommending
    - spam filtering
  - News articles
    - Personalized newspaper
  - Email messages
    - Routing
    - Prioritizing
    - Folderizing
    - spam filtering

Learning for Text Categorization

- Manual development of text categorization functions is difficult.
- Learning Algorithms:
  - Bayesian (naïve)
  - Neural network
  - Relevance Feedback (Rocchio)
  - Rule based (Ripper)
  - Nearest Neighbor (case based)
  - Support Vector Machines (SVM)

Using Relevance Feedback (Rocchio)

- Relevance feedback methods can be adapted for text categorization.
- Use standard TF/IDF weighted vectors to represent text documents (normalized by maximum term frequency).
- For each category, compute a *prototype* vector by summing the vectors of the training documents in the category.
- Assign test documents to the category with the closest prototype vector based on cosine similarity.

Rocchio Text Categorization Algorithm(Training)

Assume the set of categories is $\{c_1, c_2, \ldots c_n\}$

For i from 1 to n let $\mathbf{p}_i = \langle 0, 0, \ldots, 0 \rangle$ *(init. prototype vectors)*

For each training example $\langle x, c(x) \rangle \in D$

  Let **d** be the frequency normalized TF/IDF term vector for doc x

  Let $i = j: (c_j = c(x))$

  (sum all the document vectors in c_i to get $\mathbf{p}_i$)

  Let $\mathbf{p}_i = \mathbf{p}_i + \mathbf{d}$

One vector per category

Rocchio Text Categorization Algorithm (Test)

Given test document x

Let $\mathbf{d}$ be the TF/IDF weighted term vector for x

Let $m = -2$ *(init. maximum cosSim)*

For i from 1 to n:

    (compute similarity to prototype vector)

    Let $s = \text{cosSim}(\mathbf{d}, \mathbf{p}_i)$

    if $s > m$

        let $m = s$

        let $r = c_i$ *(update most similar class prototype)*

Return class r