Computational Methods for Data Analysis

Vector Space Categorization; (On Text)

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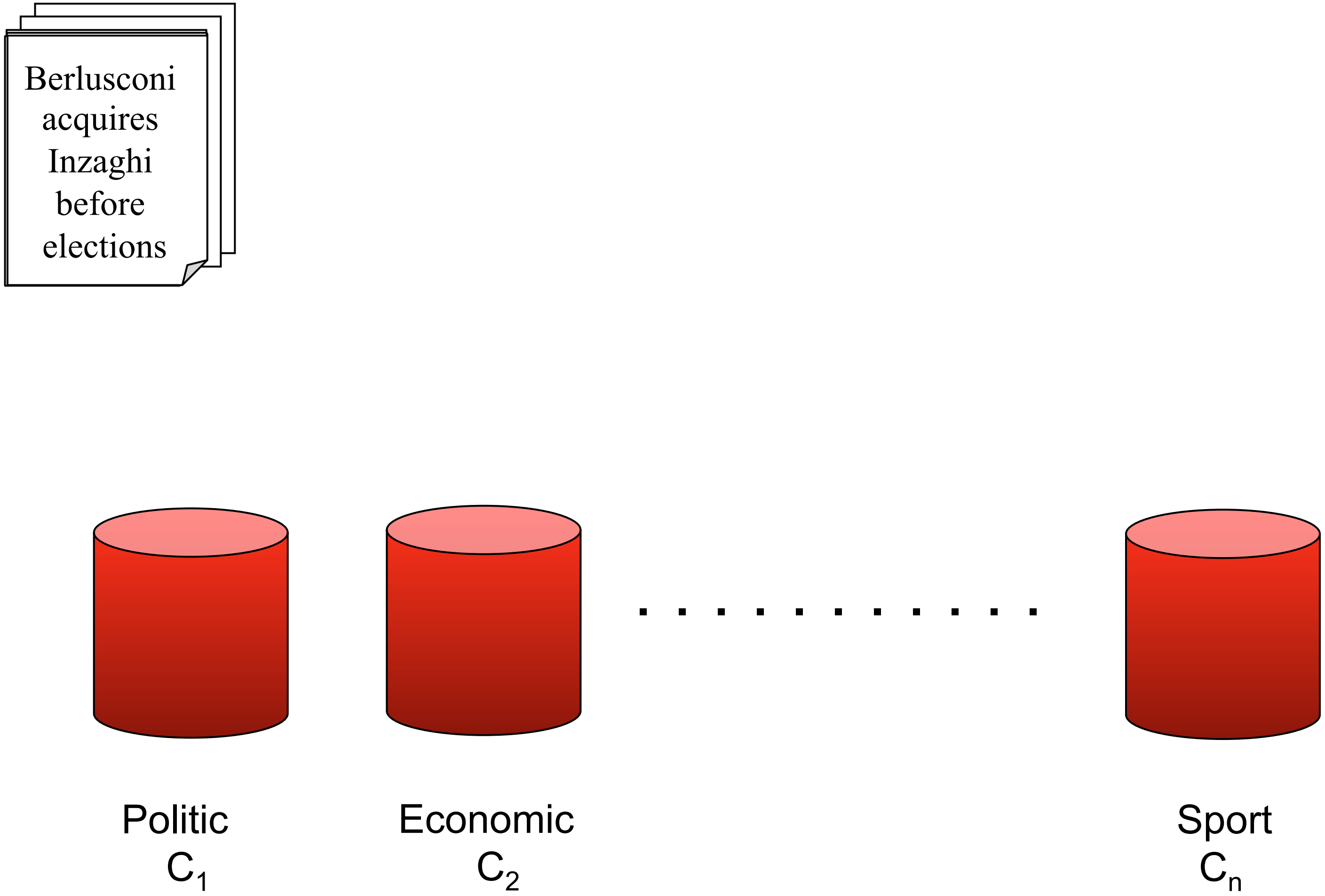
Outline

- Text Categorization and Optimization
  - TC Introduction
  - TC designing steps
  - Rocchio text classifier
  - Support Vector Machines
  - The Parameterized Rocchio Classifier (PRC)
  - Evaluation of PRC against Rocchio and SVM

Introduction to Text Categorization



Berlusconi acquires Inzaghi before elections

. . . .

Politic C_1

Economic C_2

Sport C_n

Text Classification Problem

- Given:
  - a set of target categories: $C = \{ C^1,..,C^n \}$
  - the set *T* of documents,

  define

$$f : T \rightarrow 2^C$$

- VSM (Salton89')
  - Features are dimensions of a Vector Space.
  - Documents and Categories are vectors of feature weights.
  - *d* is assigned to C^i if

$$\vec{d} \cdot \vec{C}^i > th$$

The Vector Space Model

d_1: Politic

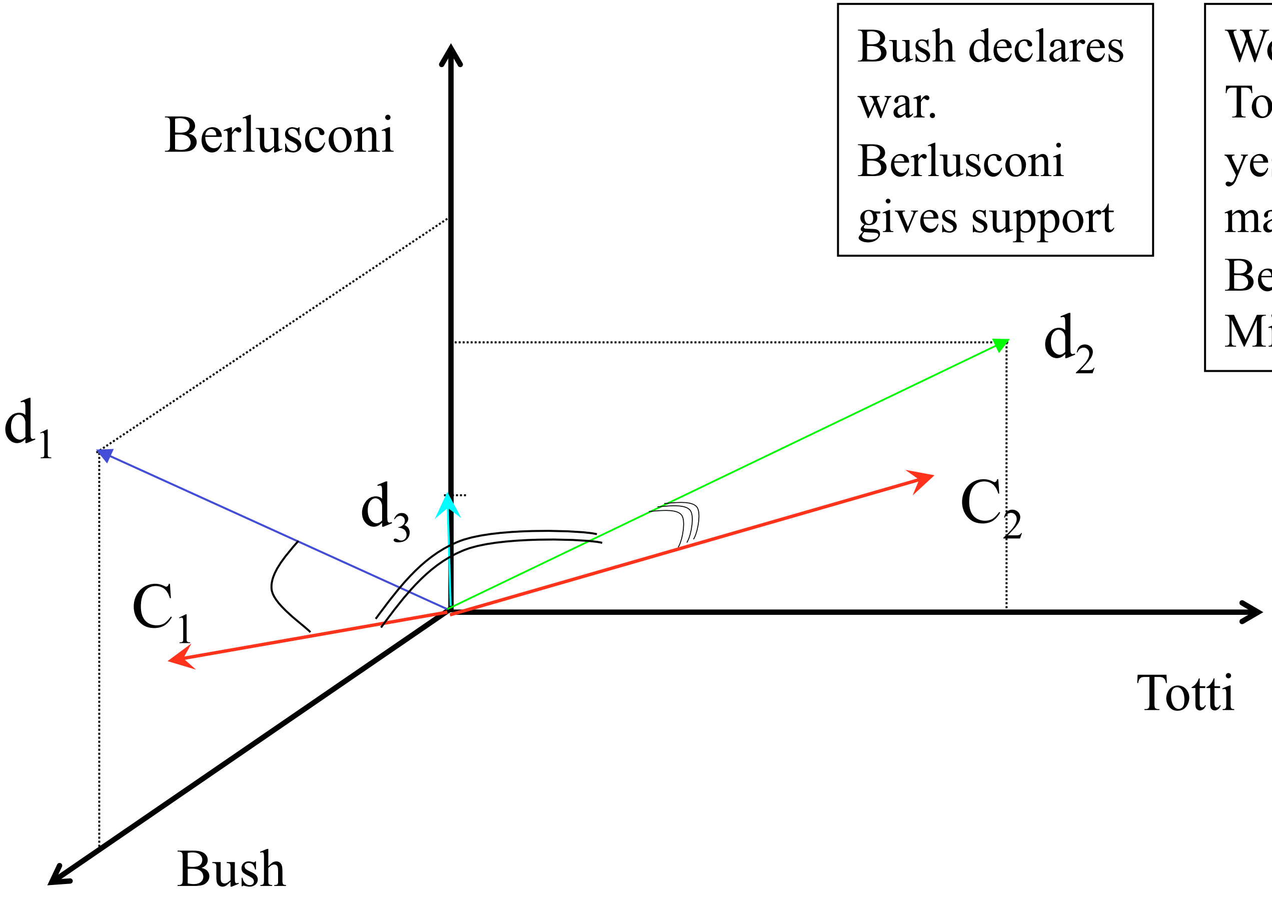
Bush declares war.
Berlusconi gives support

d_2: Sport

Wonderful Totti in the yesterday match against Berlusconi's Milan

d_3:Economic

Berlusconi acquires Inzaghi before elections



C_1 : Politics Category

C_2 : Sport Category

Automated Text Categorization

- A corpus of pre-categorized documents
- Split document in two parts:
    - Training-set
    - Test-set
- Apply a supervised machine learning model to the training-set
    - Positive examples
    - Negative examples
- Measure the performances on the test-set
    - e.g., Precision and Recall

Feature Vectors

- Each example is associated with a vector of *n* feature types (e.g. unique words in TC)

$$\vec{x} = (0,\ ..,1,..,0,..,0,\ ..,1,..,0,..,0,\ ..,1,..,0,..,0,\ ..,1,..,0,..,\ 1)$$

acquisition buy market sell stocks

- The dot product $\vec{x} \cdot \vec{z}$ counts the number of features in common

- This provides a sort of *similarity*

Text Categorization phases

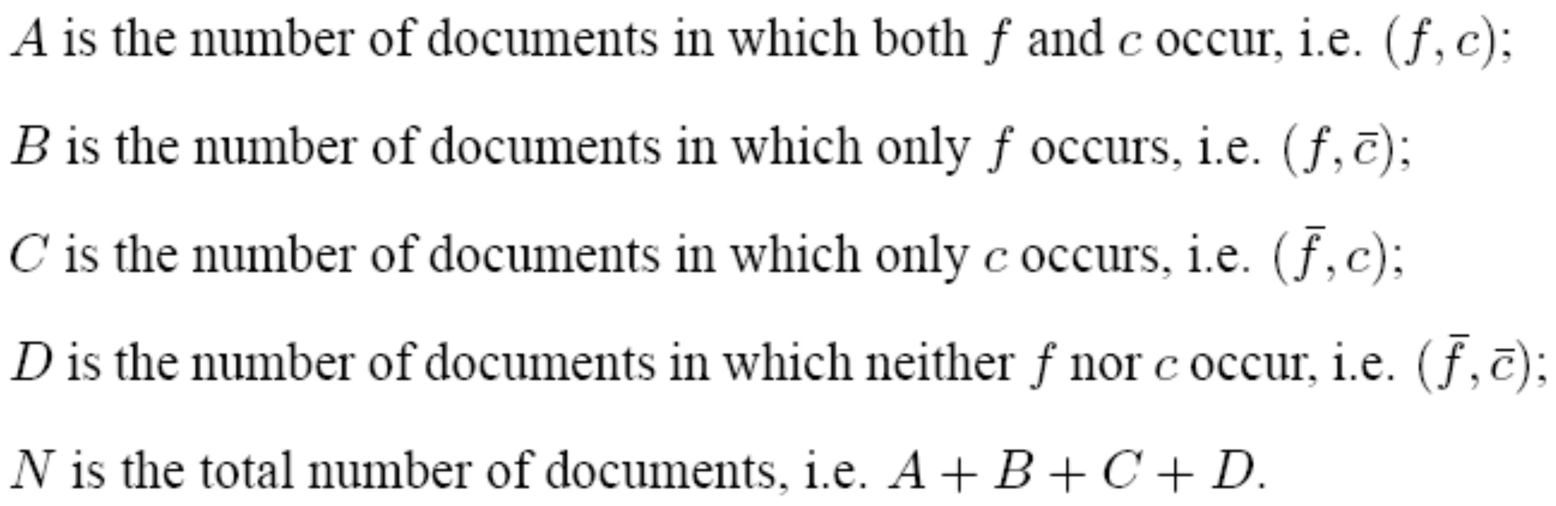
- Corpus pre-processing (e.g. tokenization, stemming)
- Feature Selection (optionally)
  - Document Frequency, Information Gain, χ_2 , mutual information,...
- Feature weighting
  - for documents and profiles
- Similarity measure
  - between document and profile (e.g. scalar product)
- Statistical Inference
  - threshold application
- Performance Evaluation
  - Accuracy, Precision/Recall, BEP, f-measure,..

Feature Selection

- Some words, i.e. features, may be irrelevant
- For example, “function words” as: “the”, “on”,”those”…
- Two benefits:
  - efficiency
  - Sometime the accuracy
- Sort features by relevance and select the *m*-best

Statistical Quantity to sort feature

- Based on corpus counts of the pair <feature,category>



- A is the number of documents in which both f and c occur, i.e. (f, c);
- B is the number of documents in which only f occurs, i.e. $(f, \bar{c})$;
- C is the number of documents in which only c occurs, i.e. $(\bar{f}, c)$;
- D is the number of documents in which neither f nor c occur, i.e. $(\bar{f}, \bar{c})$;
- N is the total number of documents, i.e. $A + B + C + D$.

Statistical Selectors

- Chi-square, Pointwise MI and MI

$$\chi^2(f,c) = \frac{N \times (AD - CB)^2}{(A+C)(B+D)(A+B)(C+D)}$$

$$PMI(f,c) = log\frac{P(f,c)}{P(f) \times P(c)}$$

$$\begin{aligned} MI(f) \quad &= -\sum_{c\in\mathcal{C}} P(c)log(P(c)) + P(f)\sum_{c\in\mathcal{C}} P(c|f)log(P(c|f)) \\ (f,C) \quad &\quad +P(\bar{f})\sum_{c\in\mathcal{C}} P(c|\bar{f})log(P(c|\bar{f})) \end{aligned}$$

Chi-Square Test

$$\mathrm{X}^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i},$$

- O_i = an observed frequency;
- E_i = an expected (theoretical) frequency, asserted by the null hypothesis;
- n = the number of cells in the table.

Just an intuitions from Information Theory of MI

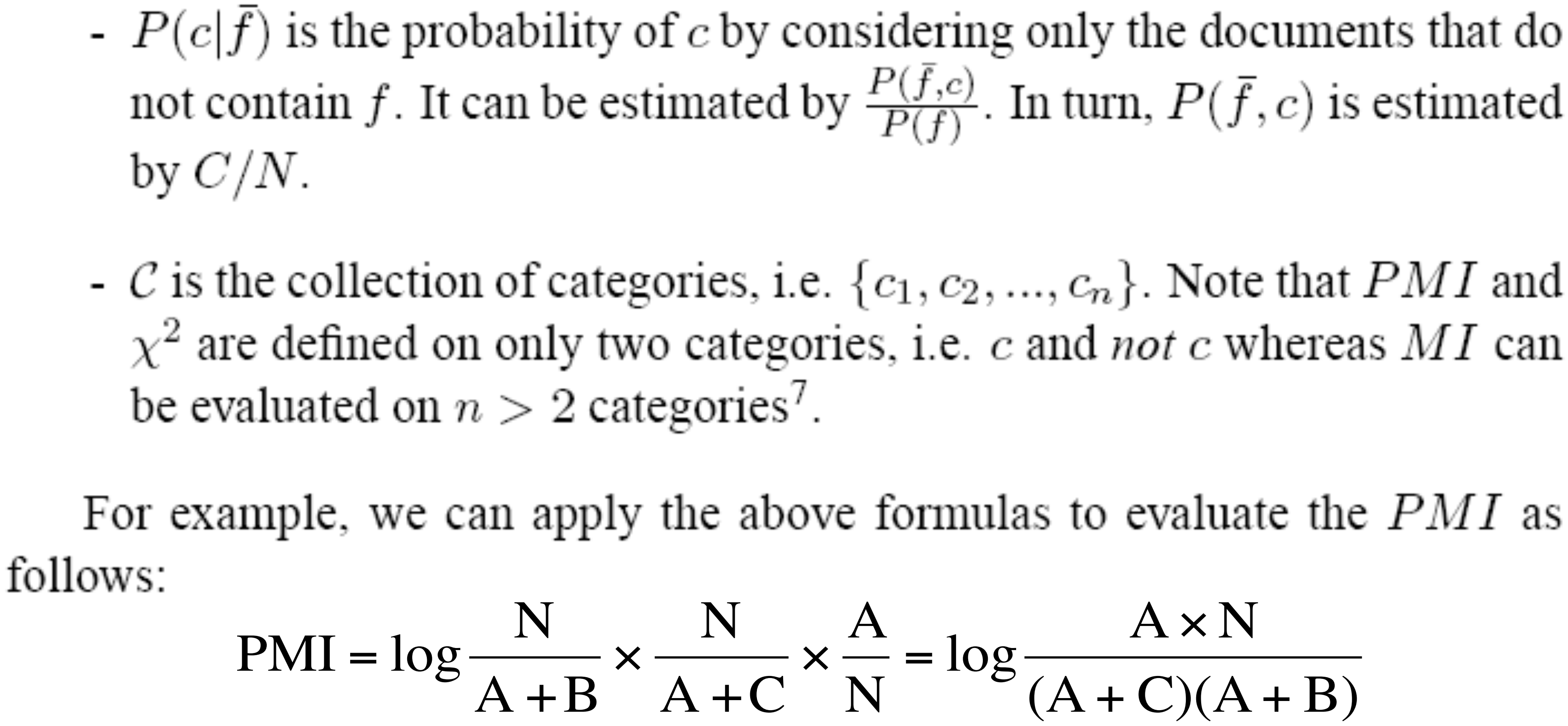
- MI(X,Y) = H(X)-H(X|Y) = H(Y)-H(Y|X)
- If X very similar to Y, H(Y|X) = H(X|Y) = 0

⇒ MI(X,Y) is maximal

Probability Estimation

- $P(f, c)$ is the probability that f and c co-occurs and can be estimated by A/N;
- $P(f)$ is the probability of f, estimated by $(A + B)/N$;
- $P(c)$ is the probability of c, estimated by $(A + C)/N$;
- $P(c|f)$ is the probability of c by considering only the documents that contain f. It can be estimated by $\frac{P(f,c)}{P(f)}$.
- $P(\bar{f})$ is the probability that f does not occur, estimated by $(C + D)/N$;

Probability Estimation (con't)



- $P(c|\bar{f})$ is the probability of c by considering only the documents that do not contain f. It can be estimated by $\frac{P(\bar{f},c)}{P(\bar{f})}$. In turn, $P(\bar{f},c)$ is estimated by C/N.

- C is the collection of categories, i.e. $\{c_1, c_2, ..., c_n\}$. Note that PMI and χ^2 are defined on only two categories, i.e. c and *not* c whereas MI can be evaluated on $n > 2$ categories[7].

For example, we can apply the above formulas to evaluate the PMI as follows:

$$\mathrm{PMI} = \log \frac{\mathrm{N}}{\mathrm{A}+\mathrm{B}} \times \frac{\mathrm{N}}{\mathrm{A}+\mathrm{C}} \times \frac{\mathrm{A}}{\mathrm{N}} = \log \frac{\mathrm{A} \times \mathrm{N}}{(\mathrm{A}+\mathrm{C})(\mathrm{A}+\mathrm{B})}$$

Global Selectors

$$PMI_{max}(f) = \max_{c \in \mathcal{C}} \ \mathrm{PMI}(f, c)$$

$$PMI_{avg}(f) = \sum_{c \in \mathcal{C}} P(c) \times \mathrm{PMI}(f, c)$$

$$\chi^2_{max}(f) = \max_{c \in \mathcal{C}} \quad \chi^2(f, c)$$

$$\chi^2_{avg}(f) = \sum_{c \in \mathcal{C}} P(c) \times \chi^2(f, c)$$

Document weighting: an example

- N, the overall number of documents,
- N_f, the number of documents that contain the feature *f*
- o_f^d the occurrences of the features *f* in the document *d*
- The weight *f* in a document is:

$$\omega_f^d = \left(\log\frac{N}{N_f}\right)\times o_f^d = IDF(f)\times o_f^d$$

- The weight can be normalized:

$$\omega'^{d}_{f} = \frac{\omega_f^d}{\sqrt{\sum_{t\in d}(\omega_t^d)^2}}$$

Profile Weighting: the Rocchio's formula

- ω^d_f, the weight of *f* in *d*
  - Several weighting schemes (e.g. TF * IDF, Salton 91')

- $\vec{C}^i_f$, the profile weights of *f* in C_i:

$$\vec{C}^{\,i}_{f} = \max\left\{ 0,\ \frac{\beta}{|T_i|}\sum_{d\in T_i}\omega^d_f - \frac{\gamma}{|\overline{T}_i|}\sum_{d\in \overline{T}_i}\omega^d_f \right\}$$

- T_i, the training documents in C^i

Similarity estimation

- Given the document and the category representation

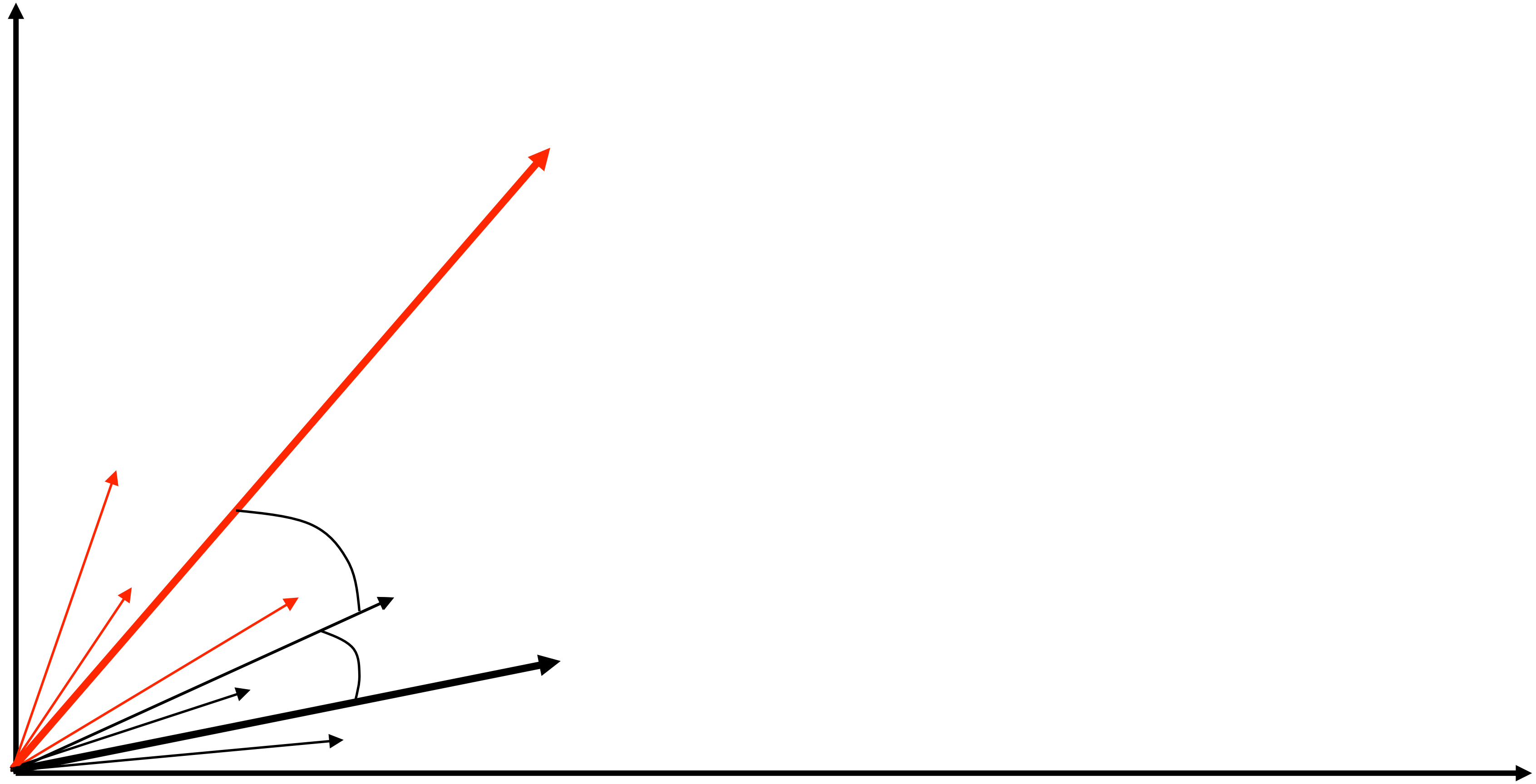
$$\vec{d} = \left\langle \omega^{d}_{f_1}, \ldots, \omega^{d}_{f_n} \right\rangle, \quad \vec{C}_{i} = \left\langle \Omega^{i}_{f_1}, \ldots, \Omega^{i}_{f_n} \right\rangle$$

- It can be defined the following similarity function (cosine measure

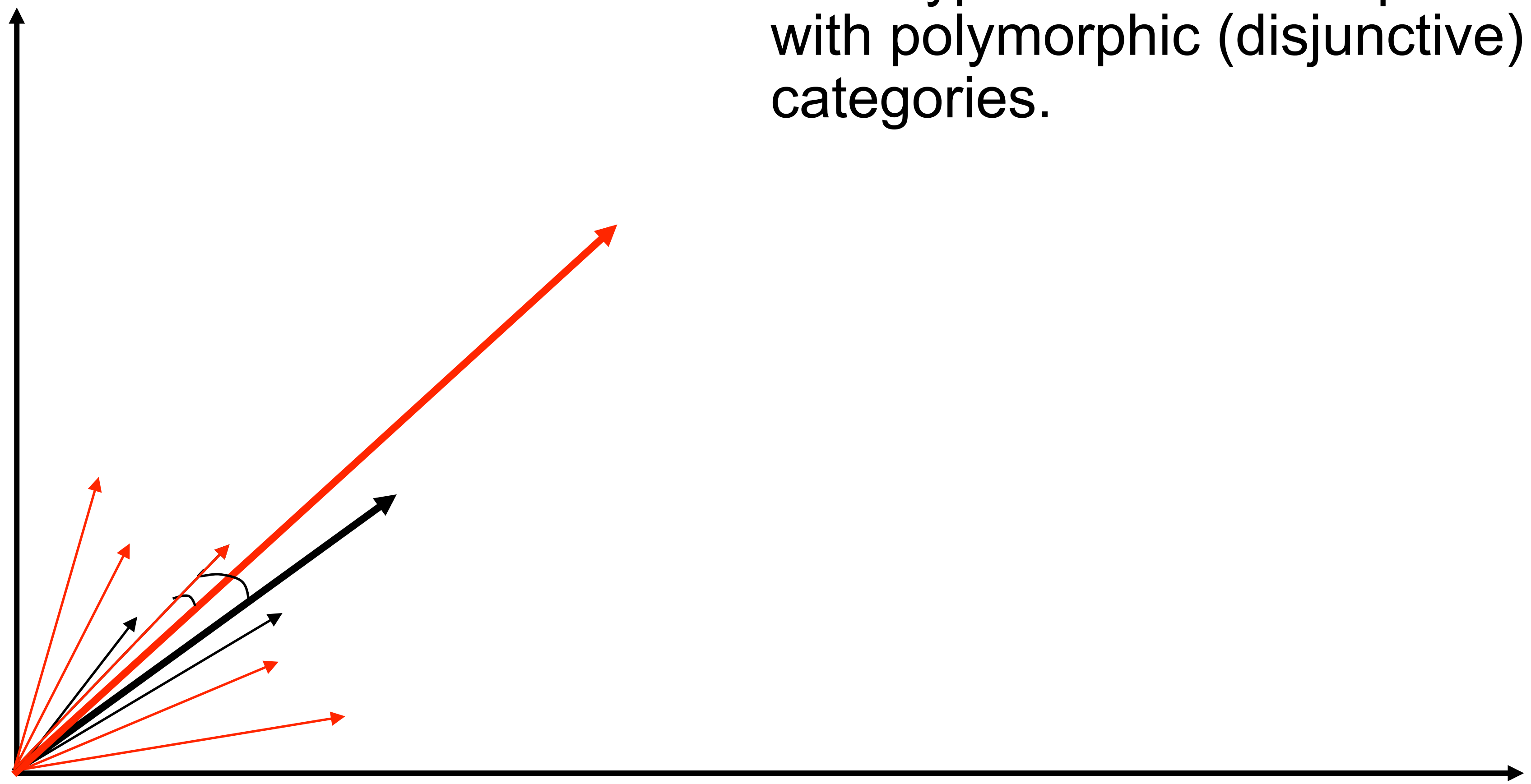
$$s_{d,i} = \cos(\vec{d}, \vec{C}_{i}) = \frac{\vec{d} \cdot \vec{C}^{i}}{\left\| \vec{d} \right\| \times \left\| \vec{C}_{i} \right\|} = \frac{\sum_{f} \omega^{d}_{f} \times \Omega^{i}_{f}}{\left\| \vec{d} \right\| \times \left\| \vec{C}_{i} \right\|}$$

- *d* is assigned to C^{i} if $\vec{d} \cdot \vec{C}^{i} > \sigma$

Bidimensional view of Rocchio categorization



Rocchio problems



- Prototype models have problems with polymorphic (disjunctive) categories.

The Parameterized Rocchio Classifier (PRC)

- Which pair values for β and γ should we consider?
- Literature work uses a bunch of values with β > γ (e.g. 16, 4)
- Interpretation of positive (β) vs. negative (γ) information

- Our interpretation [Moschitti, ECIR 2003]:
- One parameter can be bound to the threshold

- By rewriting $\vec{C}^i \cdot \vec{d} > \sigma$ as

Binding the β parameter

$$\left(\frac{\beta}{|C|}\sum_{\vec{d}\in C}\vec{d}-\frac{\gamma}{|\bar{C}|}\sum_{\vec{d}\in\bar{C}}\vec{d}\right)\cdot\vec{d}\geq\sigma$$

and dividing by β,

$$\left(\frac{1}{|C|}\sum_{\vec{d}\in C}\vec{d}-\frac{\gamma}{\beta|\bar{C}|}\sum_{\vec{d}\in\bar{C}}\vec{d}\right)\cdot\vec{d}\geq\frac{\sigma}{\beta}\Rightarrow\left(\frac{1}{|C|}\sum_{\vec{d}\in C}\vec{d}-\frac{\rho}{|\bar{C}|}\sum_{\vec{d}\in\bar{C}}\vec{d}\right)\cdot\vec{d}\geq\tilde{\sigma}.$$

Rocchio parameter interpretation

$$\vec{C}^{\,i}_{f} = \max\left\{ 0, \quad \frac{1}{|T_i|}\sum_{d \in T_i} \vec{d}_f - \frac{\rho}{|\overline{T}_i|}\sum_{d \in \overline{T}_i} \vec{d}_f \right\}$$

- 0 weighted features do not affect similarity estimation
- A ρ increase causes many feature weights to be 0

⇒ ρ is a feature selector and we can find a maximal value ρ_{max} (all features are removed)

- This interpretation enabled $\gamma >> \beta$

Feature Selection interpretation of Rocchio parameters

- Literature work uses a bunch of values for β and γ
- Interpretation of positive (β) vs. negative (γ) information
- ⇒ value of β > γ (e.g. 16, 4)

- Our interpretation [Moschitti, ECIR 2003]:
- Remove one parameters

$$\vec{C}_f^i = \max\left\{ 0, \ \frac{1}{|T_i|} \sum_{d \in T_i} \vec{d}_f - \frac{\rho}{|\bar{T}_i|} \sum_{d \in \bar{T}_i} \vec{d}_f \right\}$$

- 0 weighted features do not affect similarity estimation
- increasing ρ causes many feature to be set to 0 ⇒ they are removed

Feature Selection interpretation of Rocchio parameters (cont'd)

- By increasing ρ:
  - Features that have a high negative weights get firstly a zero value
  - High negative weight means very frequent in the other categories
  - ⇒ zero weight for irrelevant features
- If ρ is a feature selector, set it according to standard feature selection strategies [Yang, 97]
- Moreover, we can find a maximal value ρ_{max} (associated with all feature removed)
- This interpretation enabled $\gamma >> \beta$

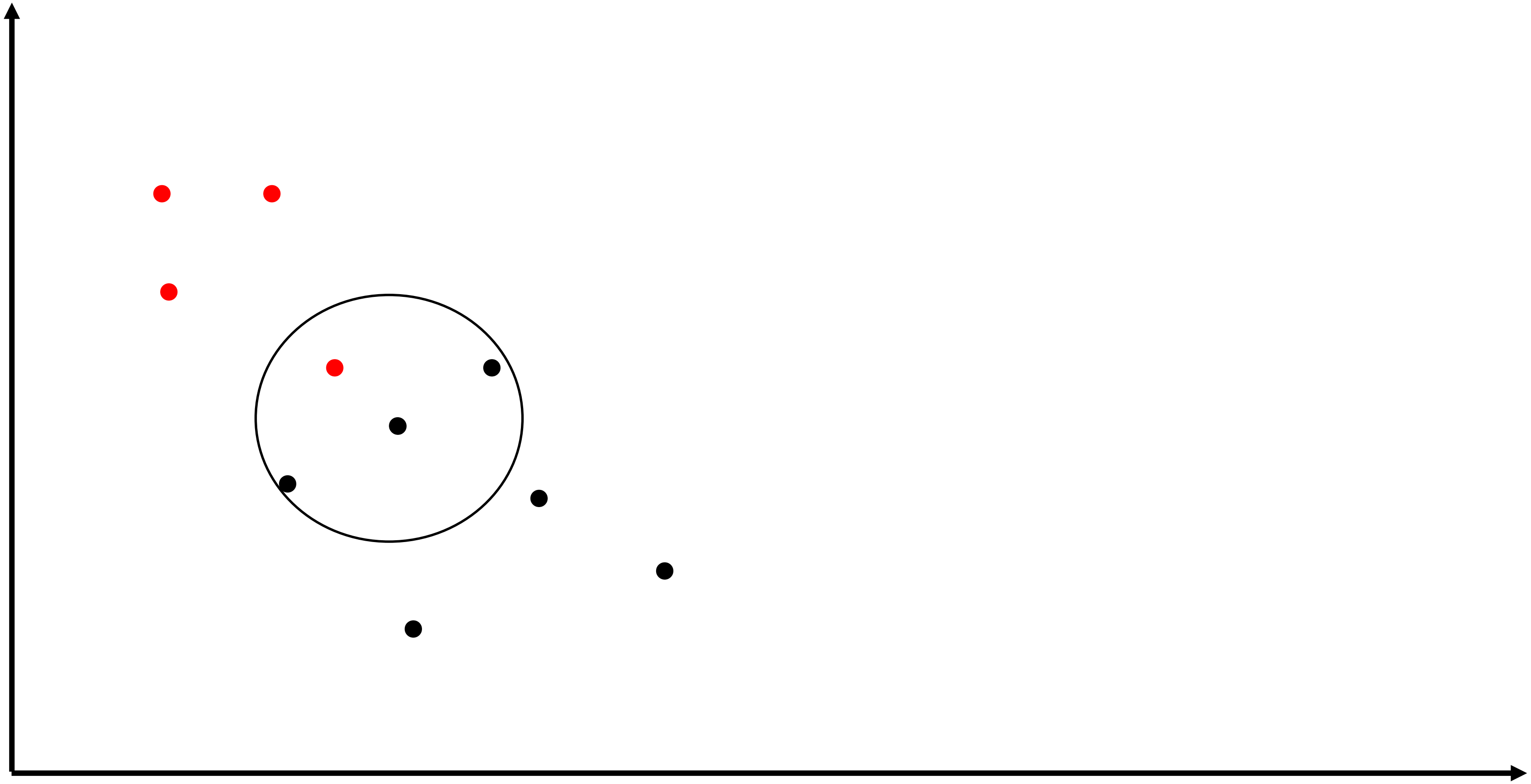
Nearest-Neighbor Learning Algorithm

- Learning is just storing the representations of the training examples in *D*.
- Testing instance *x*:
  - Compute similarity between *x* and all examples in *D*.
  - Assign *x* the category of the most similar example in *D*.
- Does not explicitly compute a generalization or category prototypes.
- Also called:
  - Case-based
  - Memory-based
  - Lazy learning

K Nearest-Neighbor

- Using only the closest example to determine categorization is subject to errors due to:
  - A single atypical example.
  - Noise (i.e. error) in the category label of a single training example.
- More robust alternative is to find the *k* most-similar examples and return the majority category of these *k* examples.
- Value of *k* is typically odd, 3 and 5 are most common.

3 Nearest Neighbor Illustration (Euclidian Distance)



K Nearest Neighbor for Text

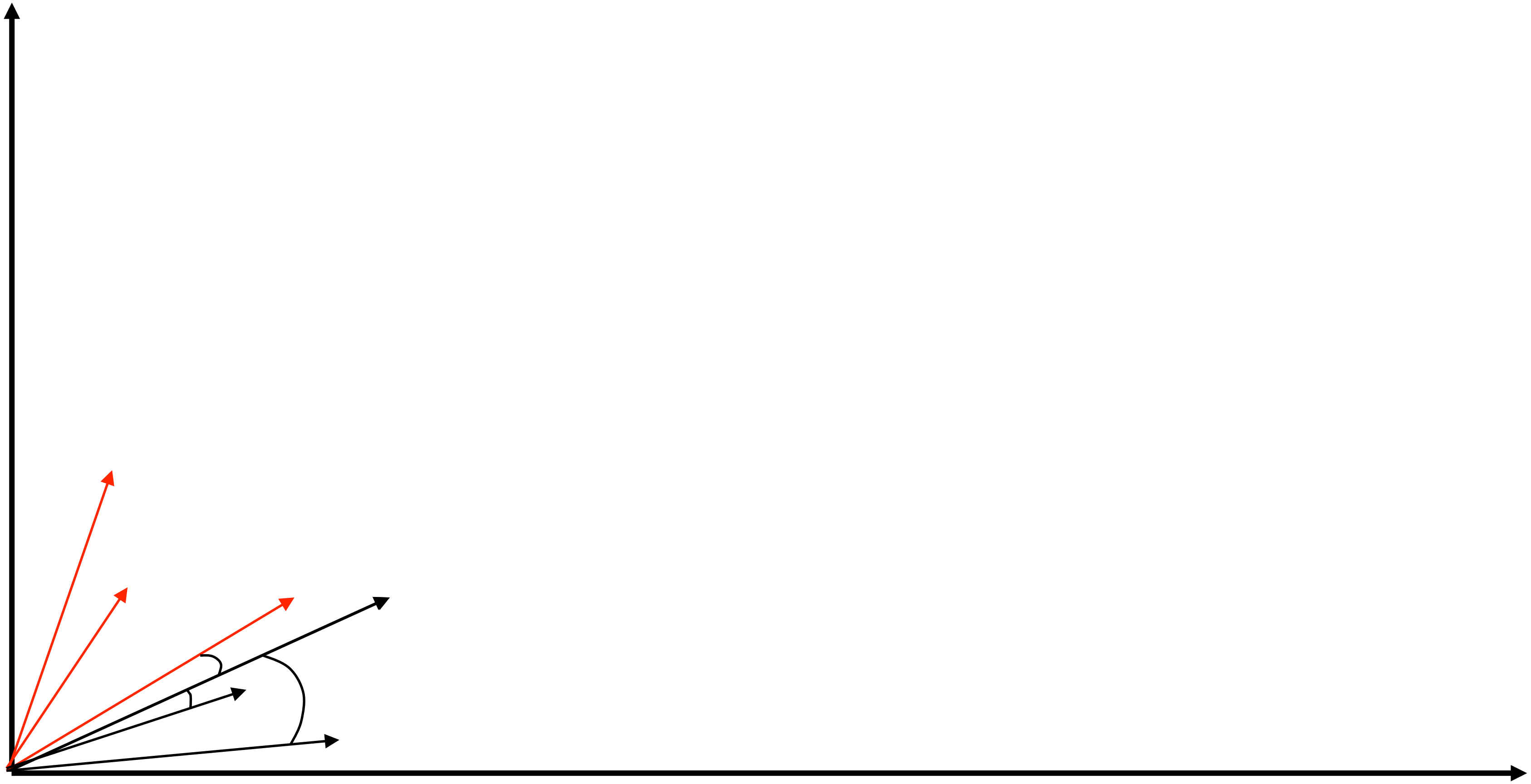
Training:

```
For each each training example <$x$, $c(x)$> $\in D$
    Compute the corresponding TF-IDF vector, $\mathbf{d}_x$, for document $x$
```

Test instance *y*:

```
Compute TF-IDF vector $\mathbf{d}$ for document $y$
For each <$x$, $c(x)$> $\in D$
    Let $s_x = \text{cosSim}(\mathbf{d}, \mathbf{d}_x)$
Sort examples, $x$, in $D$ by decreasing value of $s_x$
Let $N$ be the first $k$ examples in D.     (get most similar neighbors)
Return the majority class of examples in $N$
```

Illustration of 3 Nearest Neighbor for Text



A state-of-the-art classifier: Support Vector Machines

- The Vector $\vec{C}^i$ satisfies:

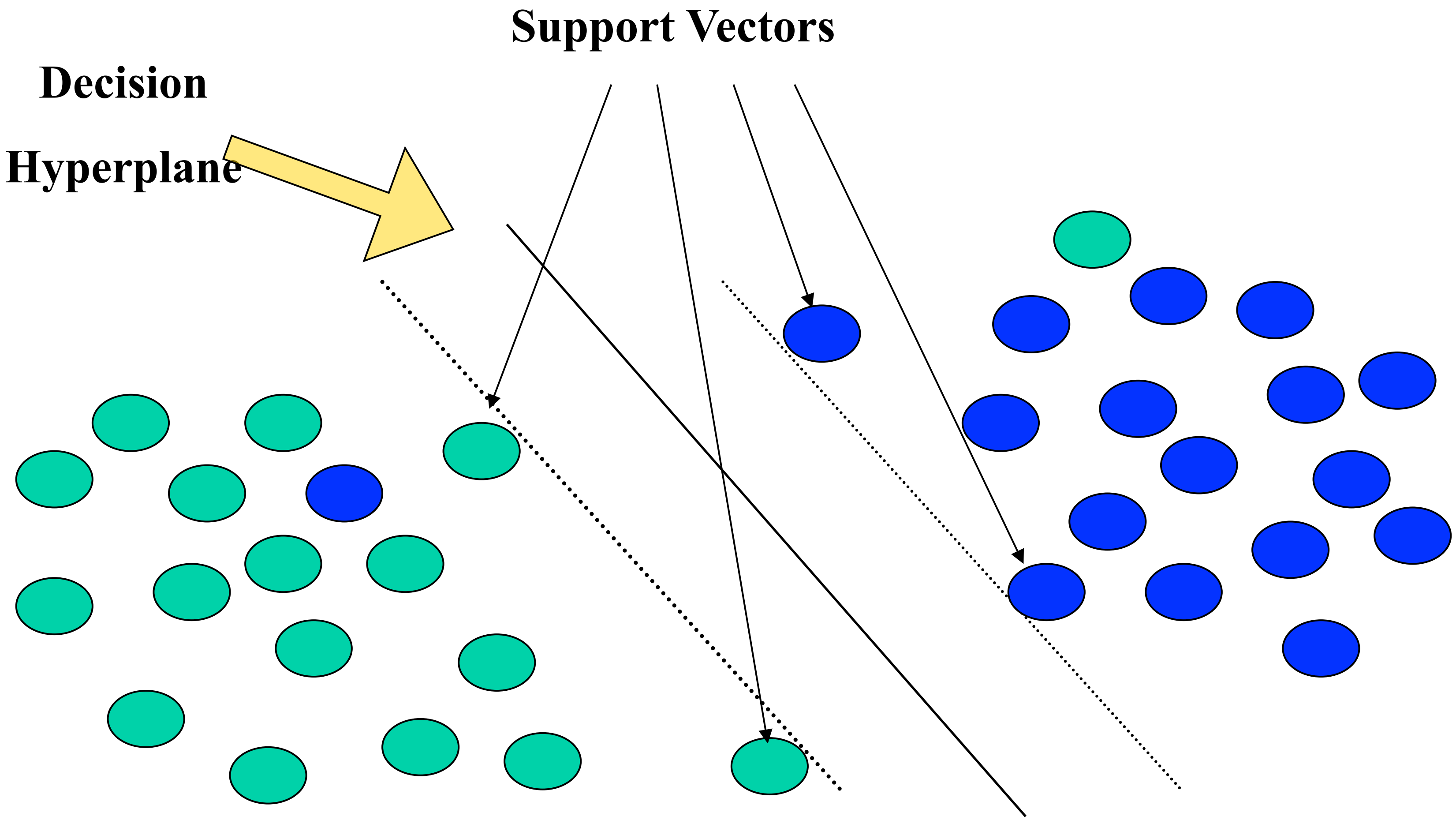
$$\min\left|\vec{C}^i\right|$$

$$\vec{C}^i \times \vec{d} - th \geq +1,\ \text{ if } d \in T_i$$

$$\vec{C}^i \times \vec{d} - th \leq -1, \text{ if } d \notin T_i$$

- *d* is assigned to C^i if $\vec{d} \times \vec{C}^i > th$

SVM



Other Text Classifiers

- *RIPPER* [Cohen and Singer, 1999] uses an extended notion of a profile. It learns the contexts that are positively correlated with the target classes, i.e. words co-occurrence.
- EXPERT uses as context nearby words (sequence of words).
- *CLASSI* is a system that uses a neural network-based approach to text categorization [Ng *et al.*, 1997]. The basic units of the network are only perceptrons.
- *Dtree* [Quinlan, 1986] is a system based on a well-known machine learning model.
- *CHARADE* [I. Moulinier and Ganascia, 1996] and *SWAP*1 [Apt´e *et al.*, 1994] use machine learning algorithms to inductively extract Disjunctive Normal Form rules from training documents.

Experiments

- Reuters Collection 21578 Apté split (Apté94)
  - 90 classes (12,902 docs)
  - A fixed splitting between training and test set
  - 9603 vs 3299 documents
- Tokens
  - about 30,000 different
- Other different versions have been used but …

  most of TC results relate to the 21578 Apté
  - [Joachims 1998], [Lam and Ho 1998], [Dumais et al. 1998], [Li Yamanishi 1999], [Weiss et al. 1999],

    [Cohen and Singer 1999]…

A Reuters document- Acquisition Category

CRA SOLD FORREST GOLD FOR 76 MLN DLRS - WHIM CREEK

SYDNEY, April 8 - <Whim Creek Consolidated NL> said the consortium it is leading will pay 76.55 mln dlrs for the acquisition of CRA Ltd's <CRAA.S> <Forrest Gold Pty Ltd> unit, reported yesterday.

CRA and Whim Creek did not disclose the price yesterday.

Whim Creek will hold 44 pct of the consortium, while <Austwhim Resources NL> will hold 27 pct and <Croesus Mining NL> 29 pct, it said in a statement.

As reported, Forrest Gold owns two mines in Western Australia producing a combined 37,000 ounces of gold a year. It also owns an undeveloped gold project.

A Reuters document- Crude-Oil Category

FTC URGES VETO OF GEORGIA GASOLINE STATION BILL

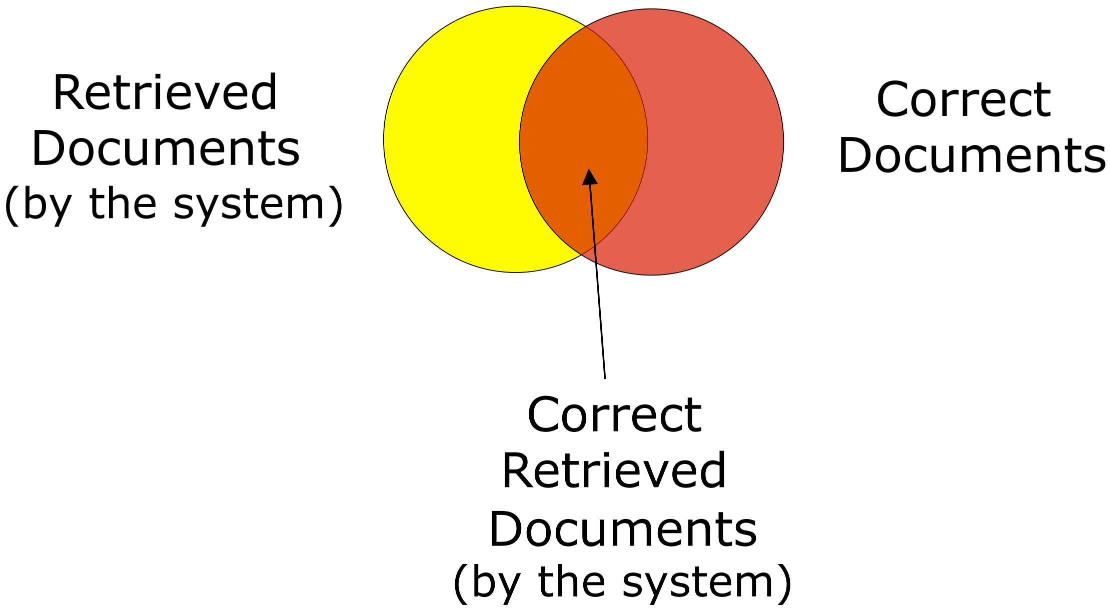
WASHINGTON, March 20 - The Federal Trade Commission said its staff has urged the governor of Georgia to veto a bill that would prohibit petroleum refiners from owning and operating retail gasoline stations.

The proposed legislation is aimed at preventing large oil refiners and marketers from using predatory or monopolistic practices against franchised dealers.

But the FTC said fears of refiner-owned stations as part of a scheme of predatory or monopolistic practices are unfounded. It called the bill anticompetitive and warned that it would force higher gasoline prices for Georgia motorists.

Performance Measurements

- Given a set of document *T*
- Precision = # Correct Retrieved Document / # Retrieved Documents
- Recall = # Correct Retrieved Document/ # Correct Documents



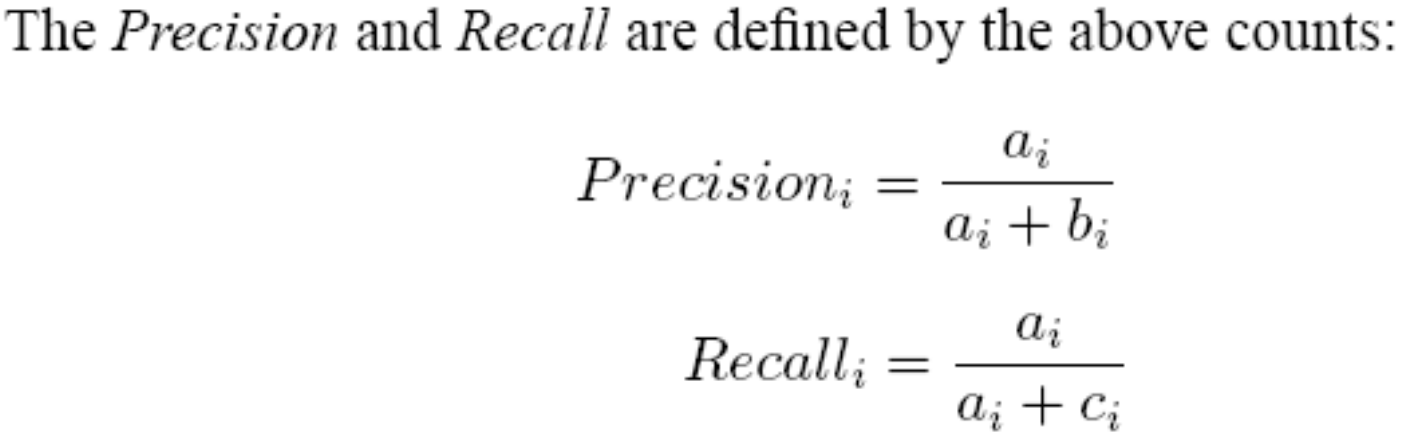
Retrieved Documents (by the system)

Correct Documents

Correct Retrieved Documents (by the system)

Precision and Recall of C_i

- a, corrects
- b, mistakes
- c, not retrieved



The *Precision* and *Recall* are defined by the above counts:

$$Precision_i = \frac{a_i}{a_i + b_i}$$

$$Recall_i = \frac{a_i}{a_i + c_i}$$

Performance Measurements (cont'd)

- Breakeven Point
  - Find thresholds for which

    Recall = Precision
  - Interpolation
- f-measure
  - Harmonic mean between precision and recall
- Global performance on more than two categories
  - Micro-average
    - The counts refer to classifiers
  - Macro-average (average measures over all categories)

F-measure e MicroAverages

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

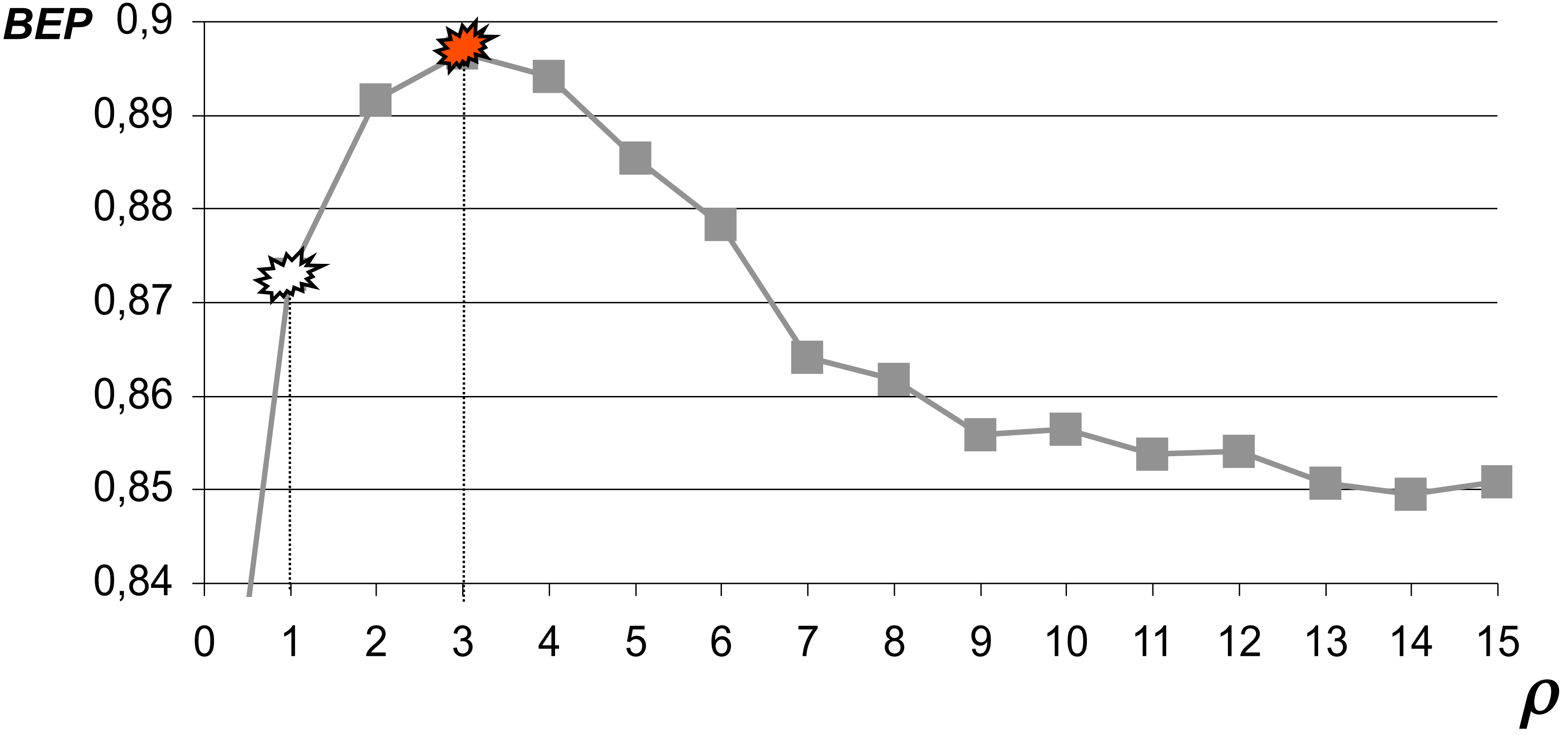
$$\mu Precision = \frac{\sum_{i=1}^{n} a_i}{\sum_{i=1}^{n} a_i + b_i}$$

$$\mu Recall = \frac{\sum_{i=1}^{n} a_i}{\sum_{i=1}^{n} a_i + c_i}$$

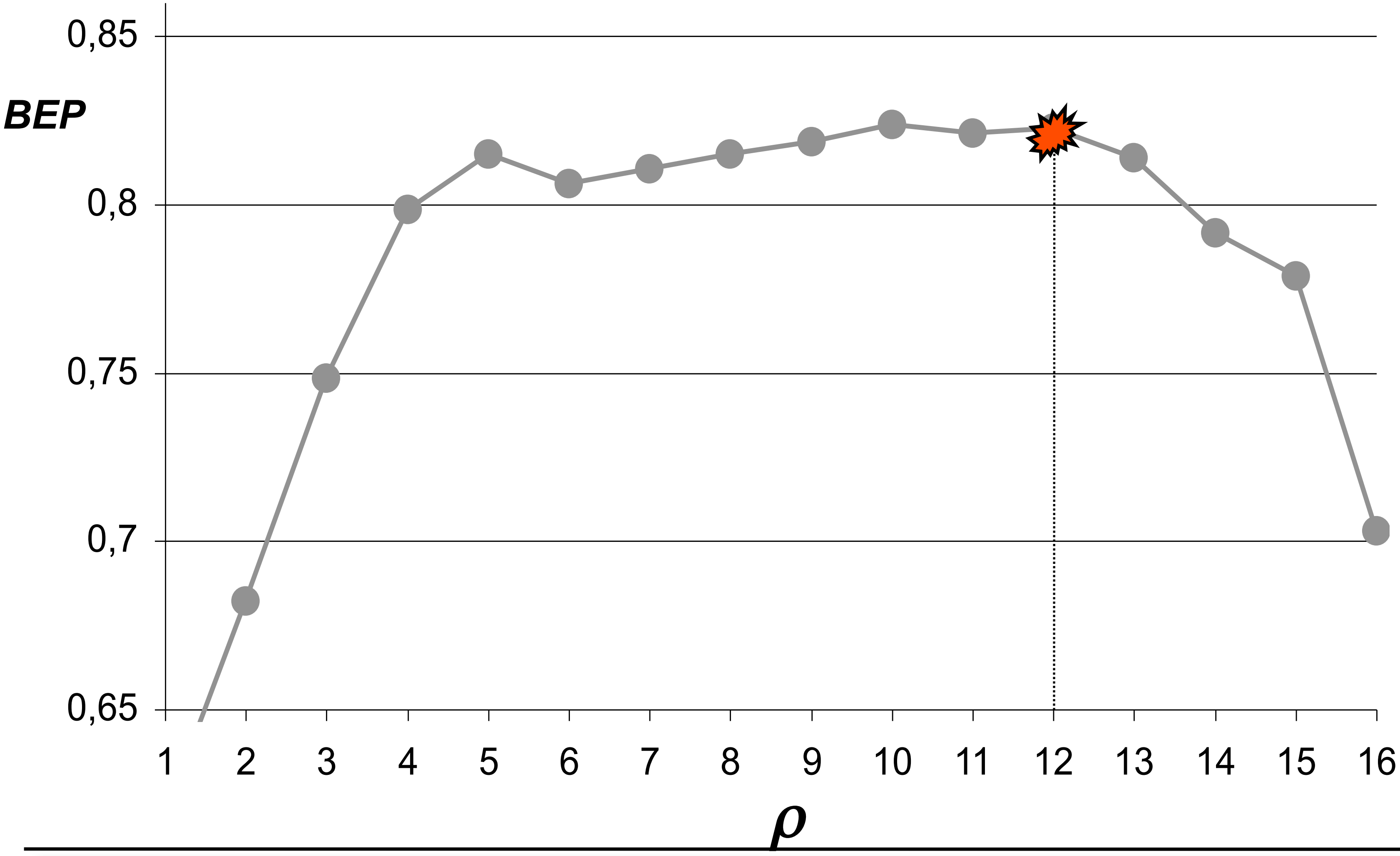
$$\mu BEP = \frac{\mu Precision + \mu Recall}{2}$$

$$\mu f_1 = \frac{2 \times \mu Precision \times \mu Recall}{\mu Precision + \mu Recall}$$

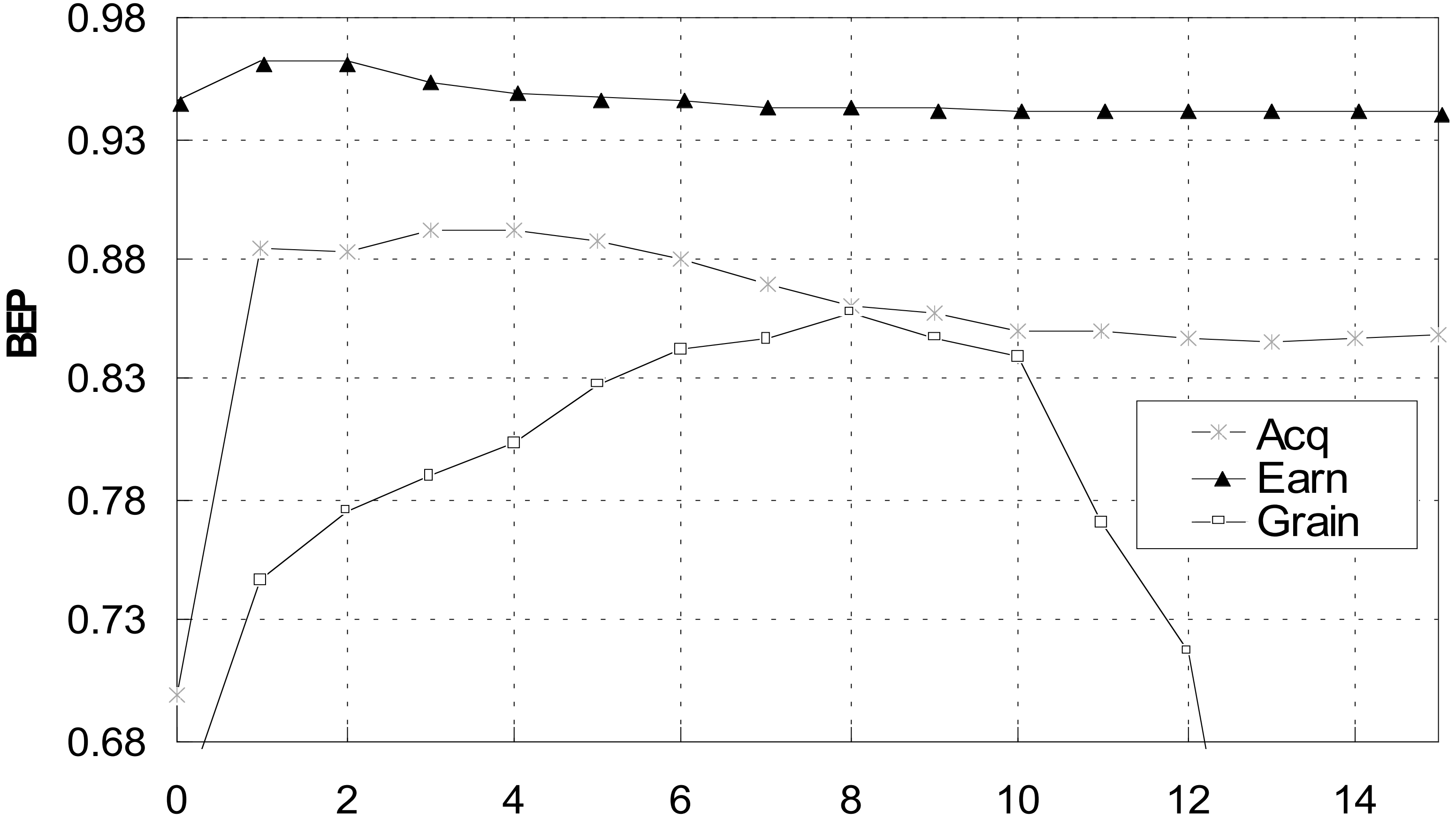
The Impact of ρ parameter on Acquisition category



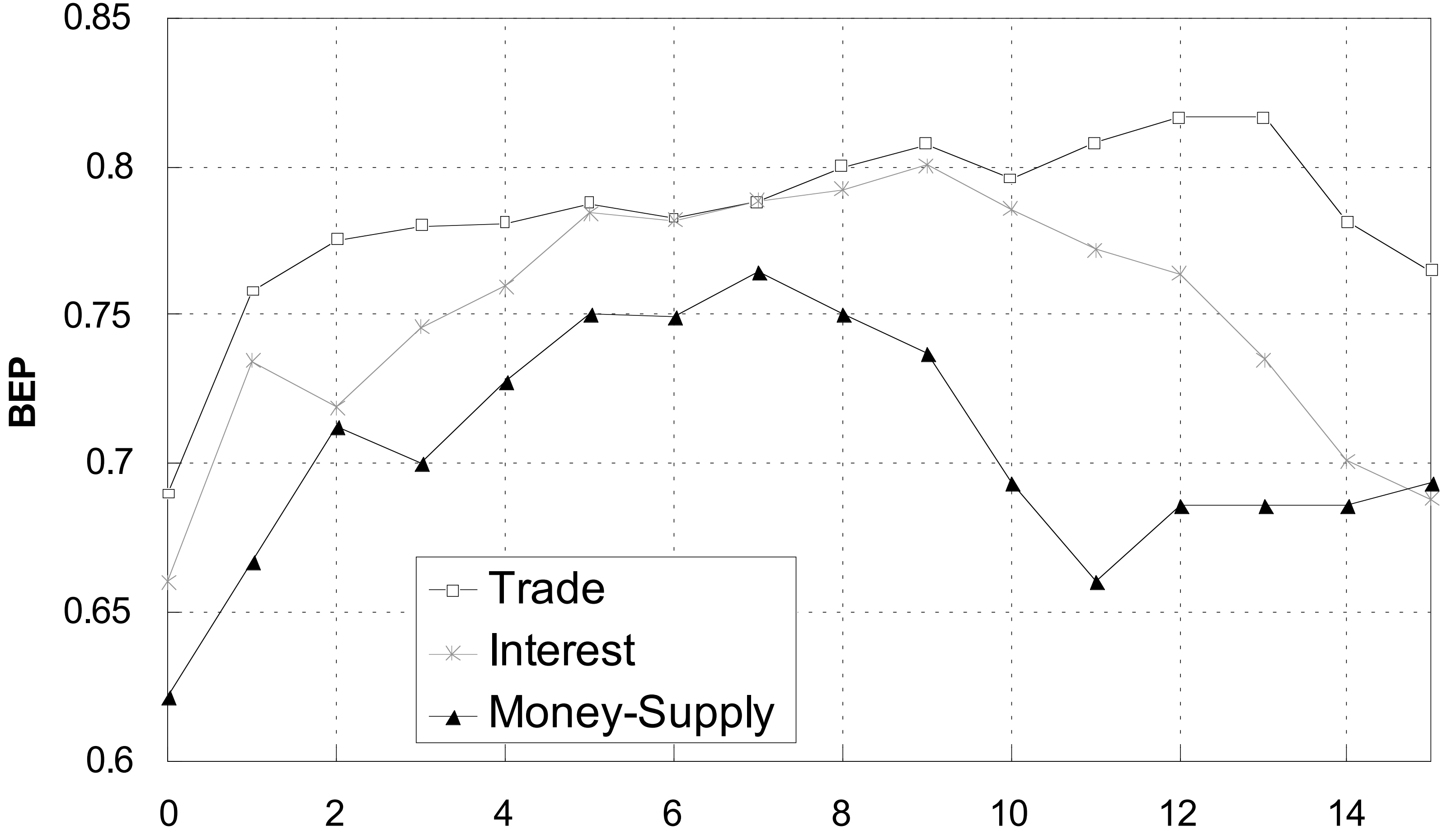
The impact of ρ parameter on Trade category



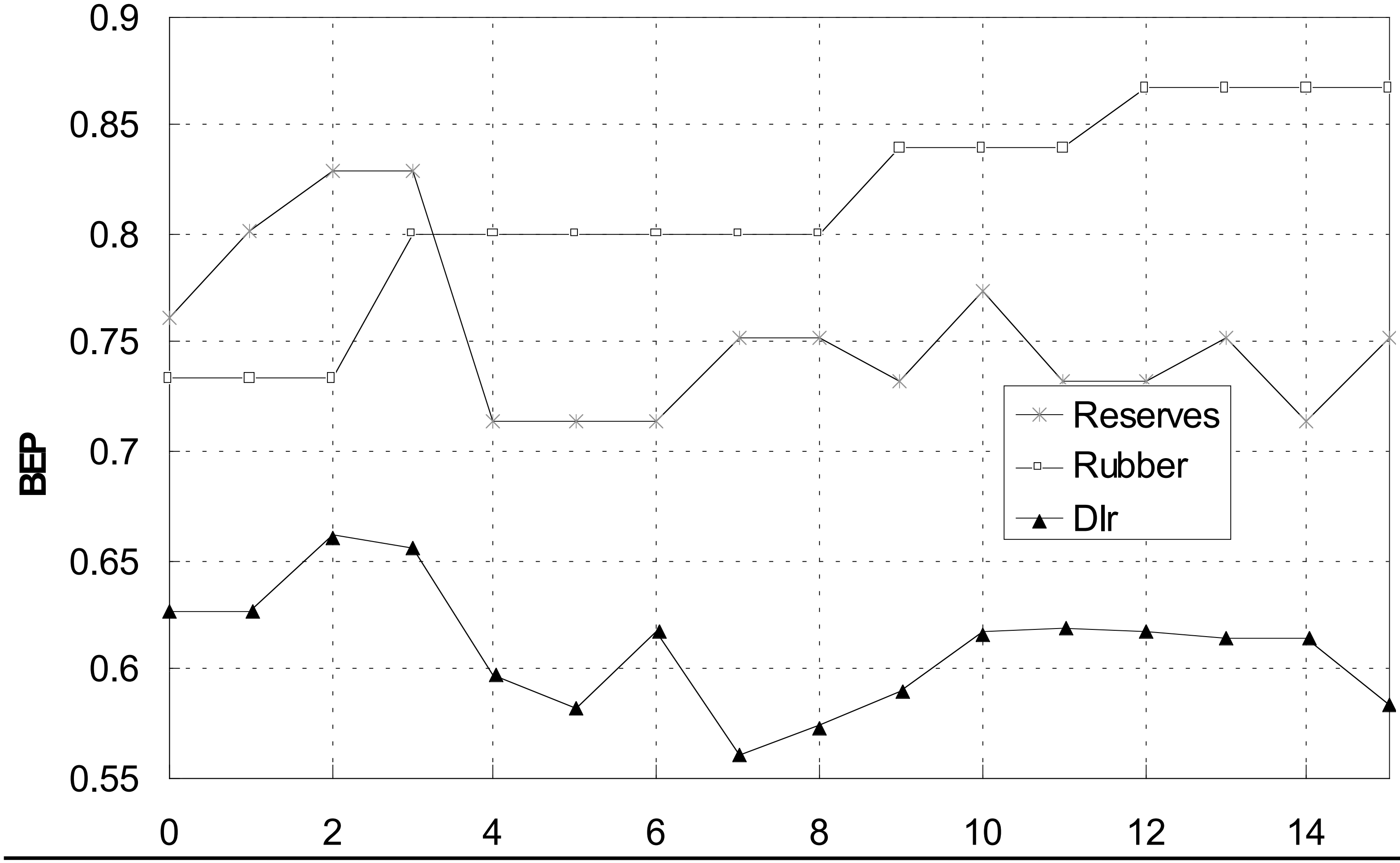
Mostly populated categories



Medium sized categories



Low size categories



Parameter Estimation Procedure

- Validation-set of about 30% of the training corpus
- for all $\rho \in [0,30]$
  - TRAIN the system on the remaining material
  - Measure the BEP on the validation-set
- Select the ρ associated with the highest *BEP*
- re-TRAIN the system on the entire training-set
- TEST the system based on the obtained parameterized model
- For more reliable results:
  - 20 validation-sets and made the ρ average
- The Parameterized Rocchio Classifier will refer to as PRC

Comparative Analysis

- Rocchio literature parameterization
  - $\rho = 1$ ($\gamma = \beta=1$) *and* $\rho = \frac{1}{4}$ ($\gamma = 4, \ \beta=16$)
- Reuters fixed test-set
  - Other literature results
- SVM
  - To better collocate our results
- Cross Validation (20 samples)
  - More reliable results
- Cross corpora/language validation
  - Reuters, Ohsumed (English) and ANSA (Italian)

Results on Reuters fixed split

Feature Set (~30.000)	PRC	Std Rocchio (γ = ¼ β or γ = β)	SVM
Tokens	82.83 %	72.71% - 78.79 %	85.34 %
Literature (stems)	-	75 % - 79.9%	84.2 %

- Rocchio literature results (Yang 99’, Choen 98’, Joachims98’)
- SVM literature results (Joachims 98’)

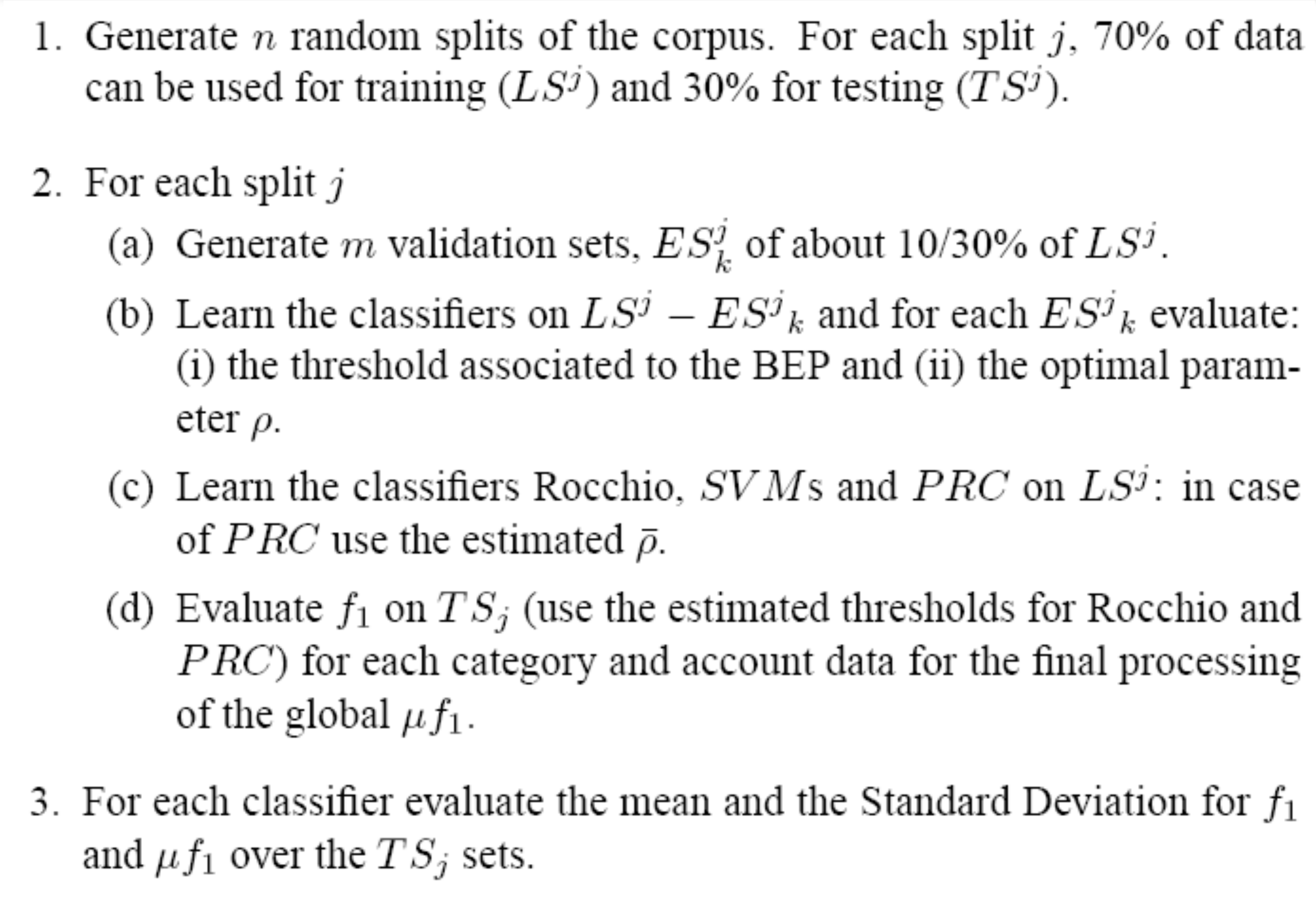
Breakeven points of widely known classifiers on Reuters

SVM	**PRC**	KNN	RIPPER	CLASSI*	Dtree
85.34%	82.83%	82.3%	82%	80.2%	79.4%

SWAP1*	CHARADE*	EXPERT	Rocchio	Naive Bayes
80.5%	78.3%	82.7%	72%-79.5%	75 % - 79.9%

* Evaluation on different Reuters versions

Cross-Validation



1. Generate n random splits of the corpus. For each split j, 70% of data can be used for training (LS^j) and 30% for testing (TS^j).

2. For each split j
   (a) Generate m validation sets, ES^j_k of about 10/30% of LS^j.
   (b) Learn the classifiers on $LS^j - ES^j{}_k$ and for each $ES^j{}_k$ evaluate: (i) the threshold associated to the BEP and (ii) the optimal parameter ρ.
   (c) Learn the classifiers Rocchio, $SVMs$ and PRC on LS^j: in case of PRC use the estimated $\bar{\rho}$.
   (d) Evaluate f_1 on TS_j (use the estimated thresholds for Rocchio and PRC) for each category and account data for the final processing of the global μf_1.

3. For each classifier evaluate the mean and the Standard Deviation for f_1 and μf_1 over the TS_j sets.

N-fold cross validation

- Divide training set in *n* parts
  - One is used for testing
  - *n-1* for training
- This can be repeated *n* times for *n* distinct test sets
- Average and Std. Dev. are the final performance index

Cross-Validation on Reuters (20 samples)

	Rocchio				PRC		SVM	
	RTS		TS^{σ}		RTS	TS^{σ}	RTS	TS^{σ}
	ρ=.25	ρ=1	ρ=.25	ρ=1				
earn	95.69	95.61	92.57±0.51	93.71 ±0.42	95.31	94.01 ±0.33	98.29	97.70 ±0.31
acq	59.85	82.71	60.02±1.22	77.69 ±1.15	85.95	83.92 ±1.01	95.10	94.14 ±0.57
money-fx	53.74	57.76	67.38±2.84	71.60 ±2.78	62.31	77.65 ±2.72	75.96	84.68 ±2.42
grain	73.64	80.69	70.76±2.05	77.54 ±1.61	89.12	91.46 ±1.26	92.47	93.43 ±1.38
crude	73.58	80.45	75.91±2.54	81.56 ±1.97	81.54	81.18 ±2.20	87.09	86.77 ±1.65
trade	53.00	69.26	61.41±3.21	71.76 ±2.73	80.33	79.61 ±2.28	80.18	80.5 7±1.90
interest	51.02	58.25	59.12±3.44	64.05 ±3.81	70.22	69.02 ±3.40	71.82	75.74 ±2.27
ship	69.86	84.04	65.93±4.69	75.33 ±4.41	86.77	81.86 ±2.95	84.15	85.97 ±2.83
wheat	70.23	74.48	76.13±3.53	78.93 ±3.00	84.29	89.19 ±1.98	84.44	87.61 ±2.39
corn	64.81	66.12	66.0 4±4.80	68.21 ±4.82	89.91	88.32 ±2.39	89.53	85.73 ±3.79
MicroAvg. 90 cat.	72.61	78.79	73.87±0.51	78.92 ±0.47	82.83	83.51 ±0.44	85.42	87.64 ±0.55

Ohsumed and ANSA corpora

- Ohsumed:
  - Including 50,216 medical abstracts.
  - The first 20,000 documents year 91,
  - 23 *MeSH diseases* categories [Joachims, 1998]

- ANSA:
  - 16,000 news items in Italian from the ANSA news agency.
  - 8 target categories,
  - 2,000 documents each,
  - e.g. Politics, Sport or Economics.

- Testing 30 %

An Ohsumed document:
Bacterial Infections and Mycoses

Replacement of an aortic valve cusp after neonatal endocarditis.
Septic arthritis developed in a neonate after an infection of her hand.
Despite medical and surgical treatment endocarditis of her aortic valve developed and the resultant regurgitation required emergency surgery.
At operation a new valve cusp was fashioned from preserved calf pericardium.
Nine years later she was well and had full exercise tolerance with minimal aortic regurgitation.

Cross validation on Ohsumed/ANSA (20 samples)

	Rocchio		PRC	SVM
Ohsumed	BEP		f1	f1
MicroAvg.	ρ=.25	ρ=1		
(23 cat.)	54.4 ± .5	61.8 ±.5	65.8±.4	68.37±.5

	Rocchio		PRC
ANSA	BEP		f1
MicroAvg.	ρ=.25	ρ=1	
(8 cat.)	61.76 ±.5	67.23 ±.5	71.00 ±.4

Computational Complexity

- PRC
  - Easy to implement
  - Low training complexity: $O(n*m\ log\ n*m)$
    - (n = number of doc and m = max num of features in a document)
  - Low classification complexity:

    $min\{O(M), O(m*log(M))\}$ (M is the max num of features in a profile)
  - *Good accuracy: the second top accurate classifier on Reuters*
- SVM
  - More complex implementation
  - Higher Learning time > $O(n^2)$ (to solve the quadratic optimization problem)
  - Actually is linear for linear SVMs
  - Low complexity of classification phase (for linear SVM) =

    $min\{O(M), O(m*log(M))\}$

From Binary to Multiclass classifiers

- Three different approaches:
- **ONE-vs-ALL (OVA)**
  - Given the example sets, {E1, E2, E3, …} for the categories: {C1, C2, C3,…} the binary classifiers: {b1, b2, b3,…} are built.
  - For b1, E1 is the set of positives and E2∪E3 ∪… is the set of negatives, and so on
  - For testing: given a classification instance x, the category is the one associated with the maximum margin among all binary classifiers

From Binary to Multiclass classifiers

- **ALL-vs-ALL (AVA)**
  - Given the examples: {E1, E2, E3, …} for the categories {C1, C2, C3,…}
    - build the binary classifiers:

      {b1_2, b1_3,…, b1_n, b2_3, b2_4,…, b2_n,…,bn-1_n}
    - by learning on E1 (positives) and E2 (negatives), on E1 (positives) and E3 (negatives) and so on…
  - For testing: given an example x,
    - all the votes of all classifiers are collected
    - where b_{E1E2} = 1 means a vote for C1 and b_{E1E2} = -1 is a vote for C2
  - Select the category that gets more votes

From Binary to Multiclass classifiers

- **Error Correcting Output Codes** (ECOC)
  - The training set is partitioned according to binary sequences (codes) associated with category sets.
    - For example, 10101 indicates that the set of examples of C1,C3 and C5 are used to train the C_{10101} classifier.
    - The data of the other categories, i.e. C2 and C4 will be negative examples
  - In testing: the code-classifiers are used to decode one the original class, e.g.

    $C_{10101} = 1$ and $C_{11010} = 1$ indicates that the instance belongs to C1

That is, the only one consistent with the codes

References

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