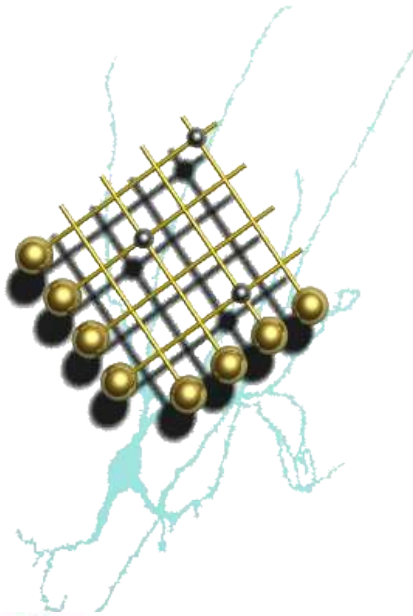


# Winnow: Software to replace journal table of contents alerts



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# The problems with email tables of contents alerts

- Small fraction of articles relevant
- Hence alerts go unread
- To read abstracts and articles, researcher has to deal with a variety of journal-specific interfaces
- Setting up tables of contents alerts requires dealing with multiple websites too

# Winnow: a solution

- Collects the latest journal tables of contents from a database (Pubmed)
- Classifies the articles as interesting or boring using Naïve Bayes
- Learns from the user which articles are interesting or boring
- Displays abstracts; easy access to PDFs
- Can save references in BibTeX

# Implementation

- Winnow is a Java application
- It interacts with PubMed, hosted by the National Center for Biotechnology Information (NCBI)
- Search and retrieval of data is via the E-Utilities, a set of HTTP tools
- Results are returned in XML format

# Data Sources

- Considerations:
  - Protocol (e.g. Z39.50)
  - Authentication
  - Availability of full text and abstracts
- Z39.50 gives access to:
  - ZETOC (comprehensive coverage; titles only; no authentication)
  - BIOSIS
  - Perhaps Web of Knowledge in the future

# Naïve Bayes Algorithm

Class  $C$  can be  $c_1$  (good)  $c_2$  (bad)

Document  $d$  comprises  $N_t$  instances of word  $t$  ( $w_t$ )  
out of a vocabulary of  $V$

Likelihood of generating document  $d$  given  $C = c_j$ :

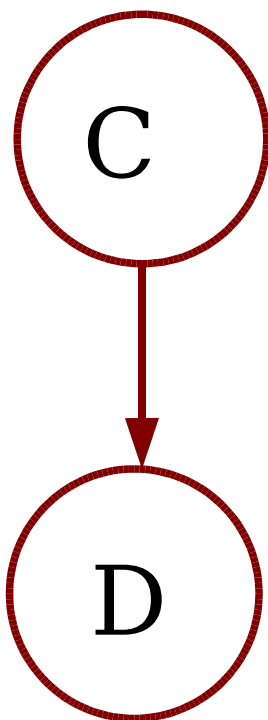
$$P(D=d|C=c_j) \propto \prod_{t=1}^V \frac{P(w_t|c_j)^{N_t}}{N_t!}$$

(Multinomial formula ; independence ; bag of words)

$$\text{Bayes: } P(C=c_j|D=d) = \frac{P(D=d|C=c_j) P(C=c_j)}{\sum_{k=1}^2 P(D=d|C=c_k) P(C=c_k)}$$

$$\text{Posterior ratio } L = \frac{P(C=c_1|D=d)}{P(C=c_2|D=d)} = \frac{P(C=c_1)}{P(C=c_2)} \prod_{t=1}^V \left( \frac{P(w_t|c_1)}{P(w_t|c_2)} \right)^{N_t}$$

$$P(C=c_1|D=d) = \frac{1}{1 + 1/L}$$



# Training Naïve Bayes

$$P(C=c_j) = \frac{1+m_j}{2+m_1+m_2} \propto 1+m_j$$

where  $m_j$  is no. articles seen of each class

$$P(w_t|C=c_j) = \frac{1+n_{tj}}{\sum_{t=1}^V (1+n_{tj})}$$

where  $n_{tj}$  is no. occurrences of word  $t$  in class  $j$  counted over all documents,  $d_i$  i.e.

$$n_{tj} = \sum_i N_{it} P(c_j|D=d_i)$$

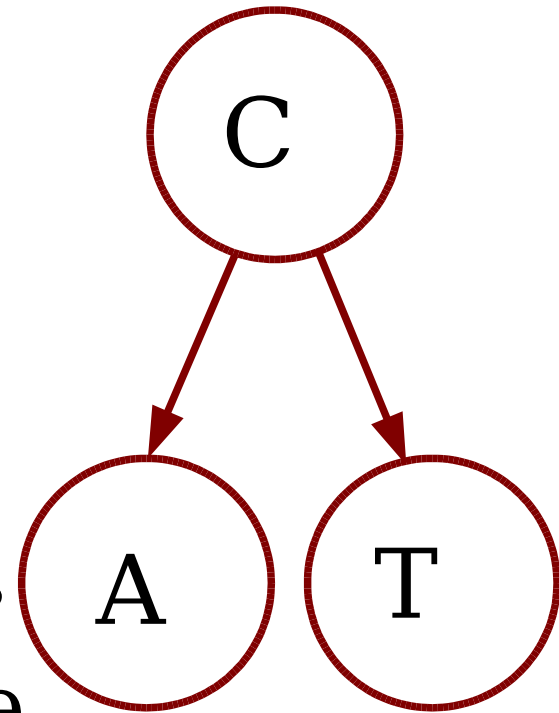
where  $P(C=c_j|D=d_i)$  is the user's rating (0 or 1)

Stored in “good” and bad hashtables of words and counts.

Increment count for word in appropriate hash when training

# Different Fields

- Titles, abstract and authors contain different types of information
- Some articles contain only title & author information
  - e.g. Nature N&V, ZETOC alerts
- Hence have combine separate conditional probability tables
  - Bayesian chain rule

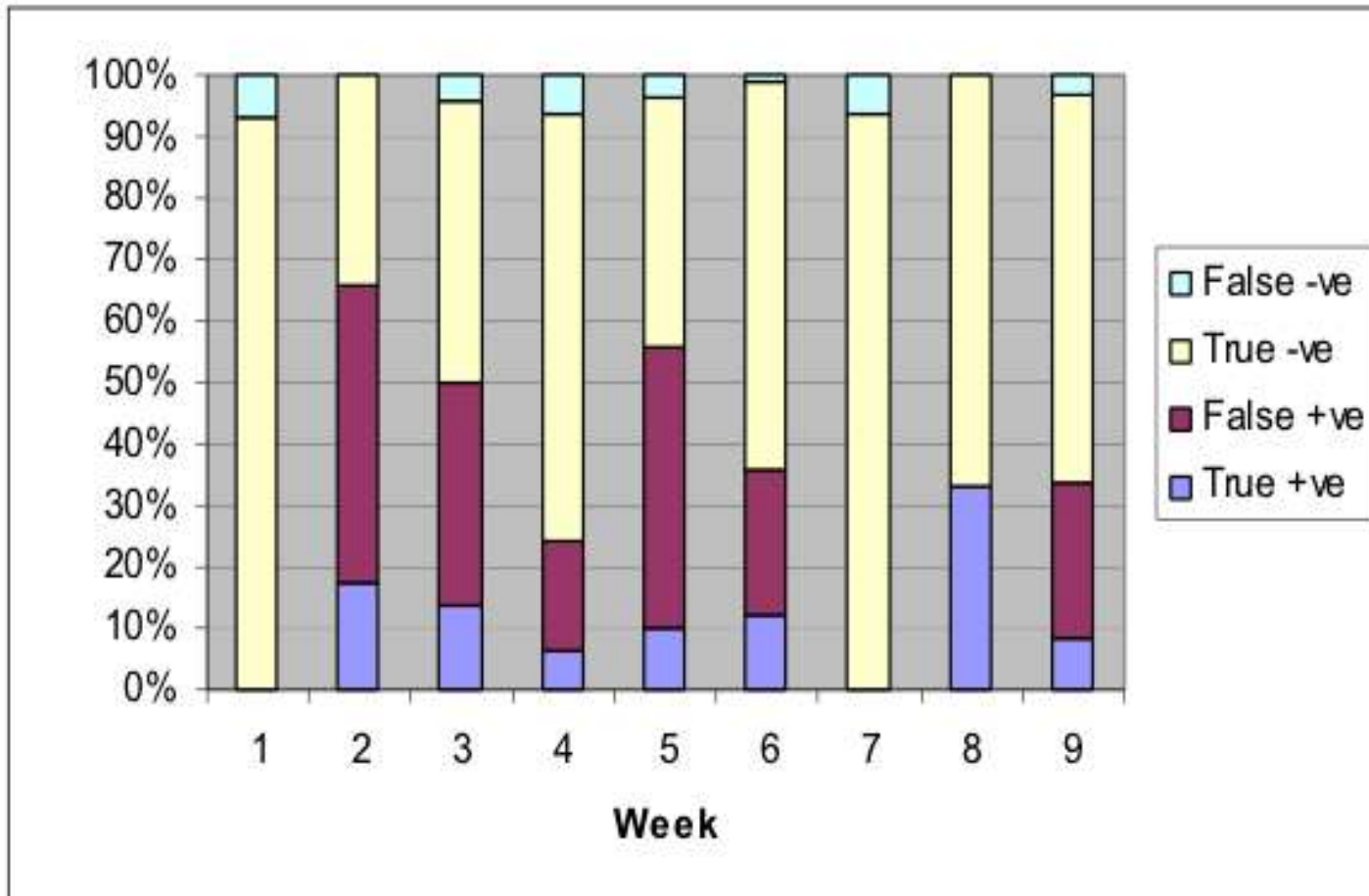




# Performance

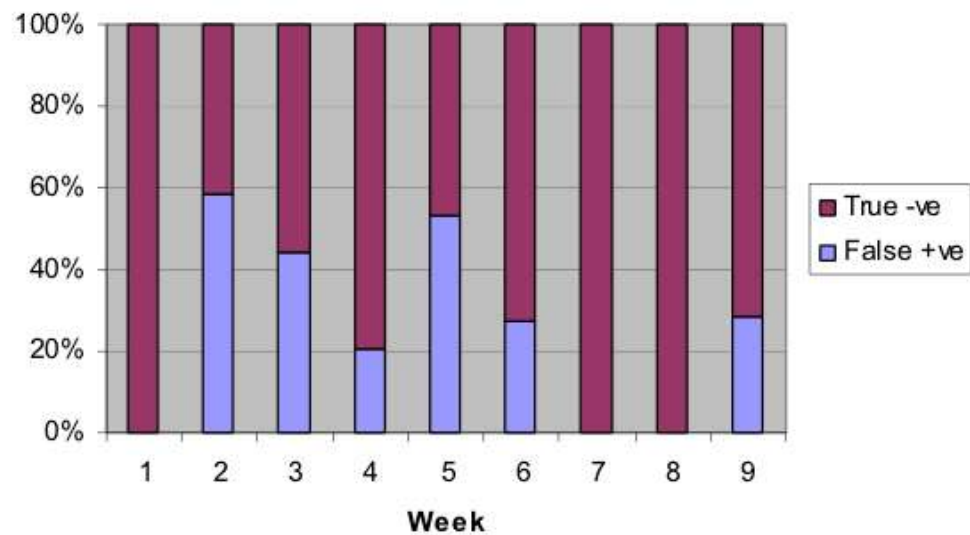
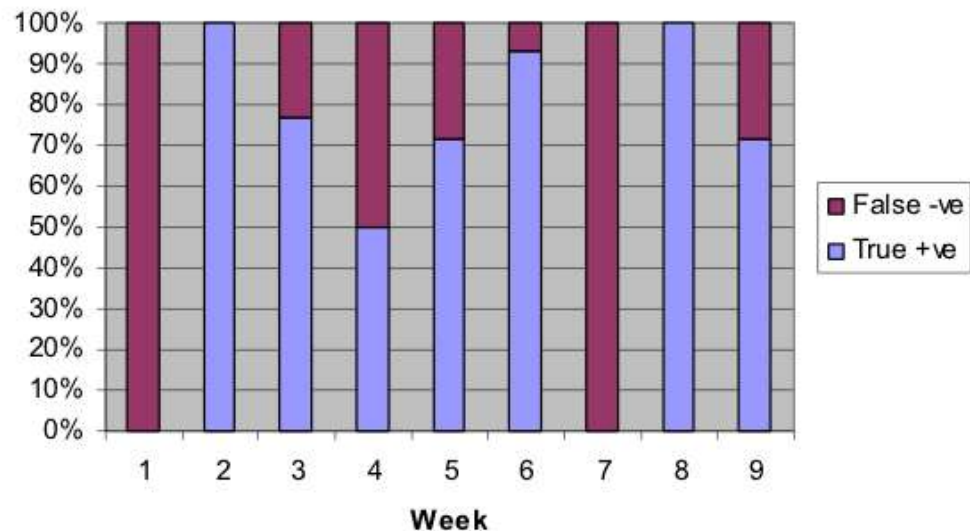
- Software tested by user over 10 weeks
- Classification based on title and abstract lumped together
- Training on every example – even if classified correctly
- 906 articles

# Classification



About 10% positives

# Interesting and uninteresting articles



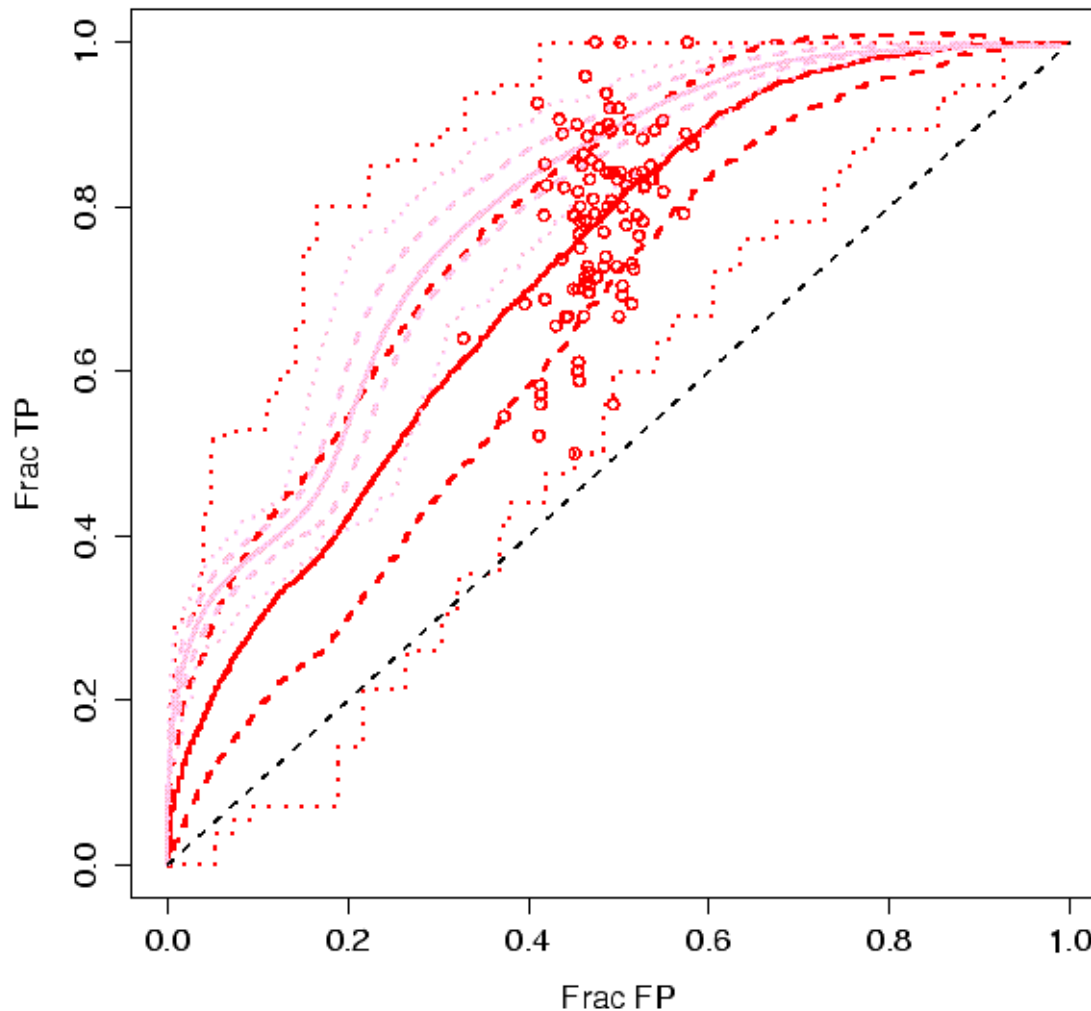
- Overall 72% of interesting articles classified correctly
- 68% of uninteresting articles classified correctly
  - i.e would have seen 32% of possible false positives

# Crossvalidation study

- Corpus of 2662 articles, 1047 with empty abstracts
- 218 interesting articles, 2444 boring
- Ten by tenfold crossvalidation procedure
- Naïve Bayes (ifile implementation) and CRM114 (another mail filter; more complex algorithm)

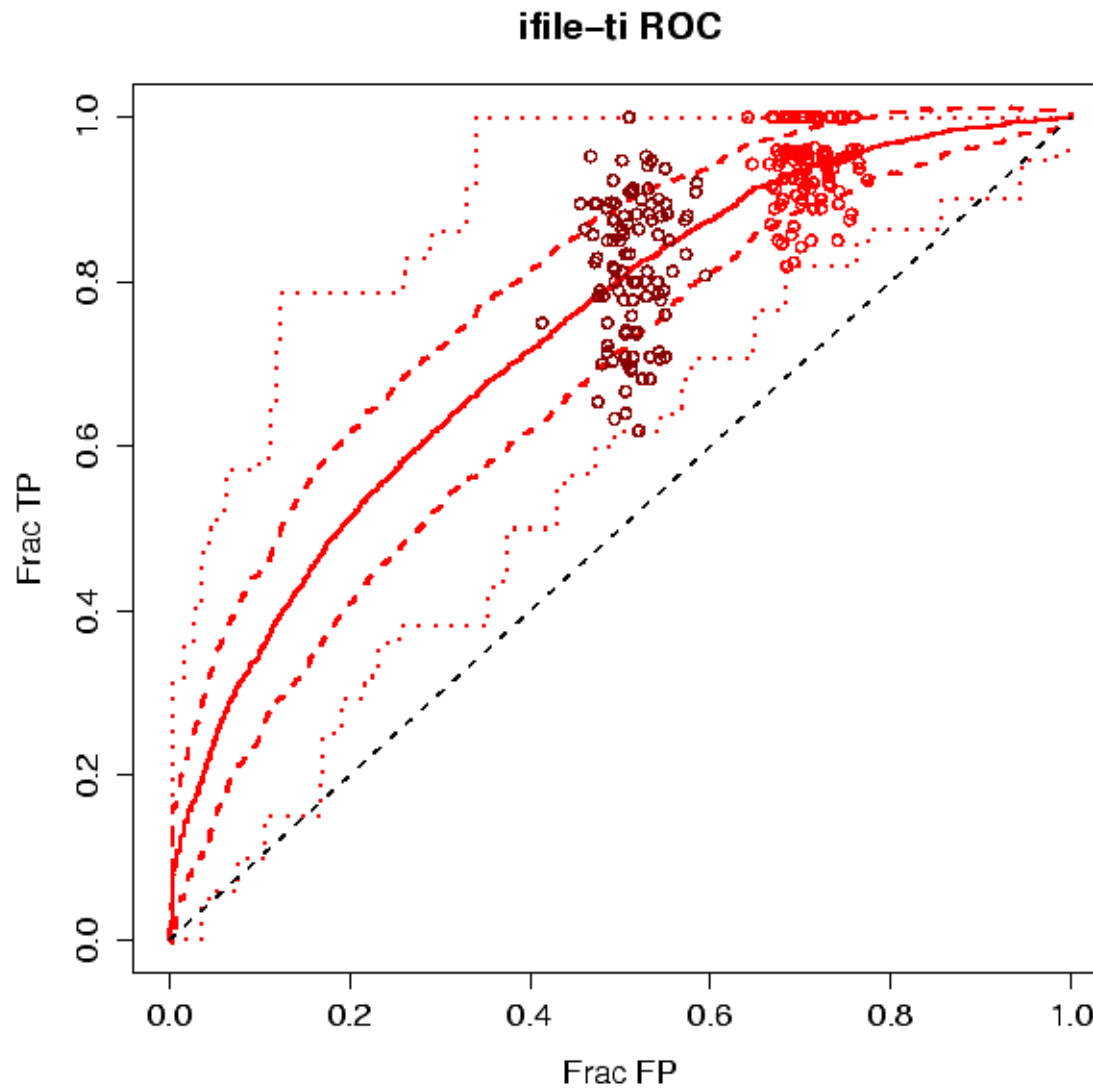
# Naïve Bayes: title and abstract (lumped together)

ifile-ti-ab ROC



$48 \pm 4\%$  FP  
 $78 \pm 11\%$  TP

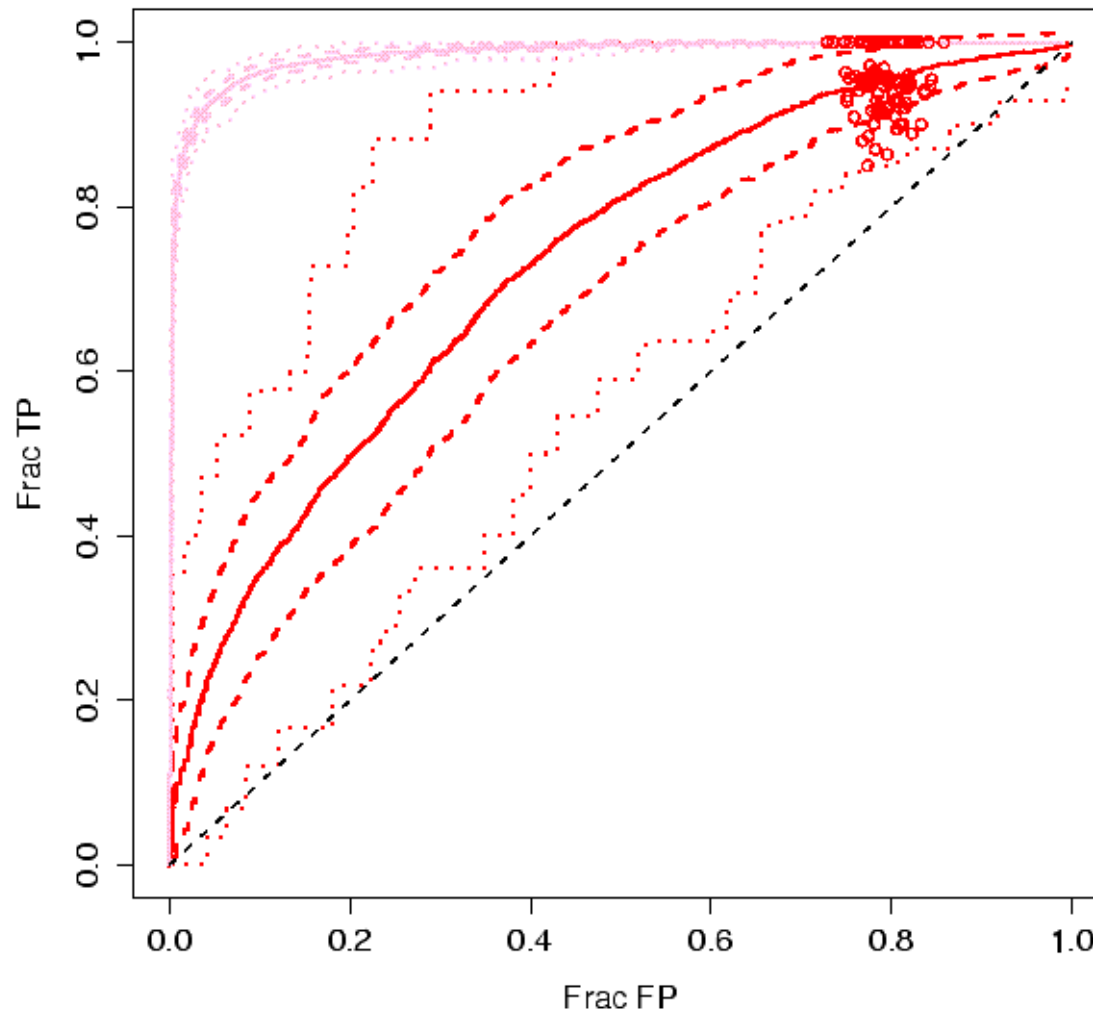
# Naïve Bayes – titles only



$71 \pm 3\%$  FP  
 $94 \pm 5\%$  TP

# Naïve Bayes – titles and authors

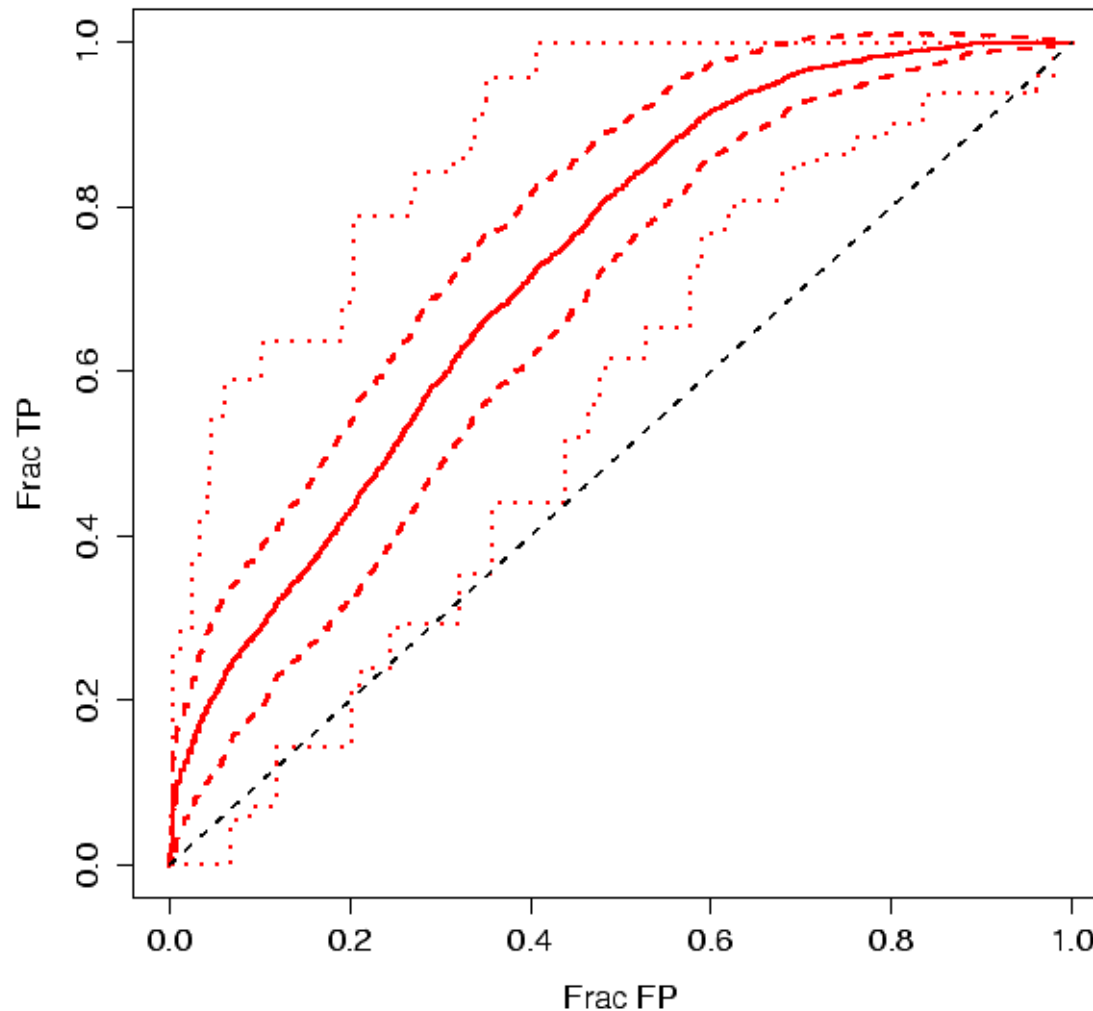
ifile-ti-au-chain ROC



$79 \pm 2\%$  FP  
 $96 \pm 4\%$  TP

# Naïve Bayes – Abstracts and Titles

ifile-ti-ab-chain ROC

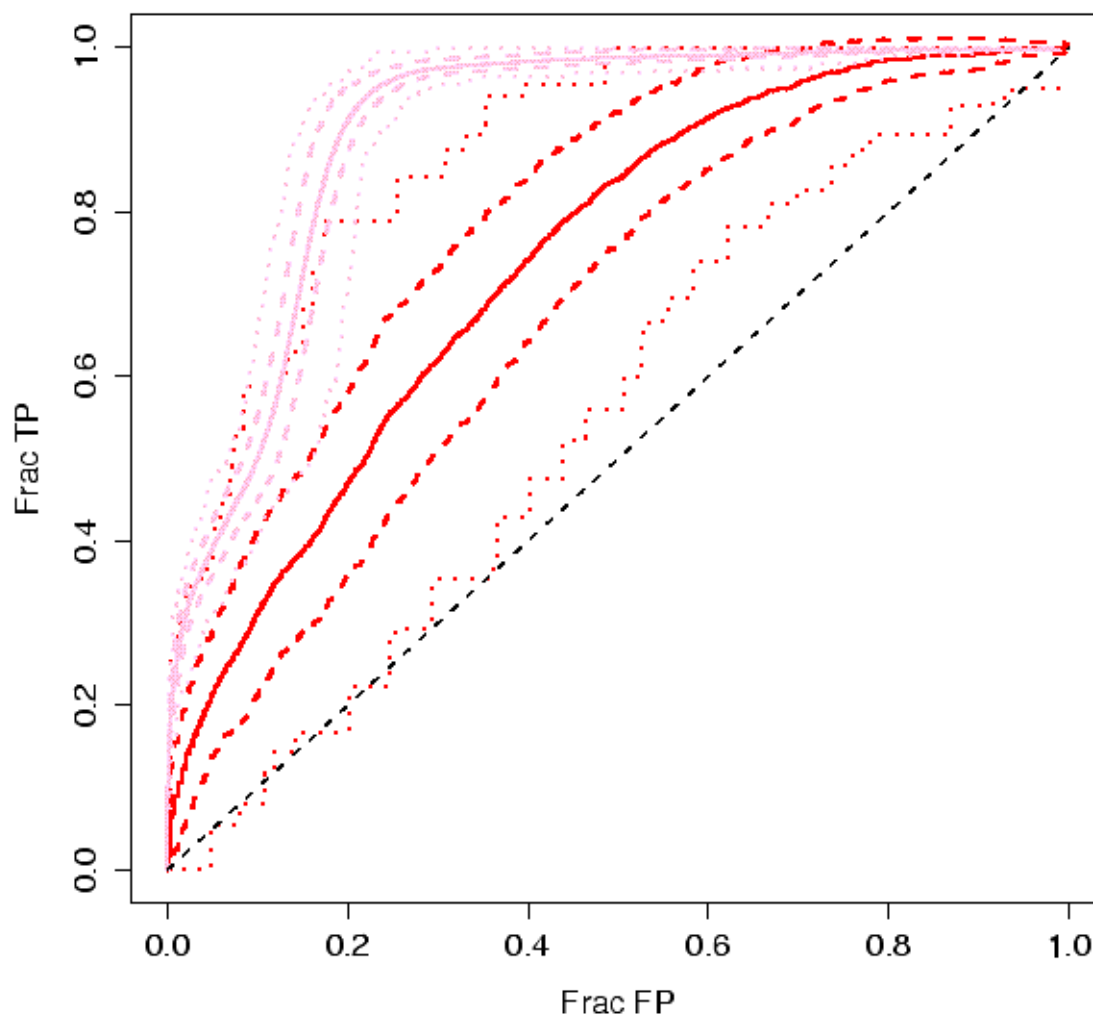


$59 \pm 4\%$  FP  
 $90 \pm 7\%$  TP



# NB Titles + Abstracts + Authors

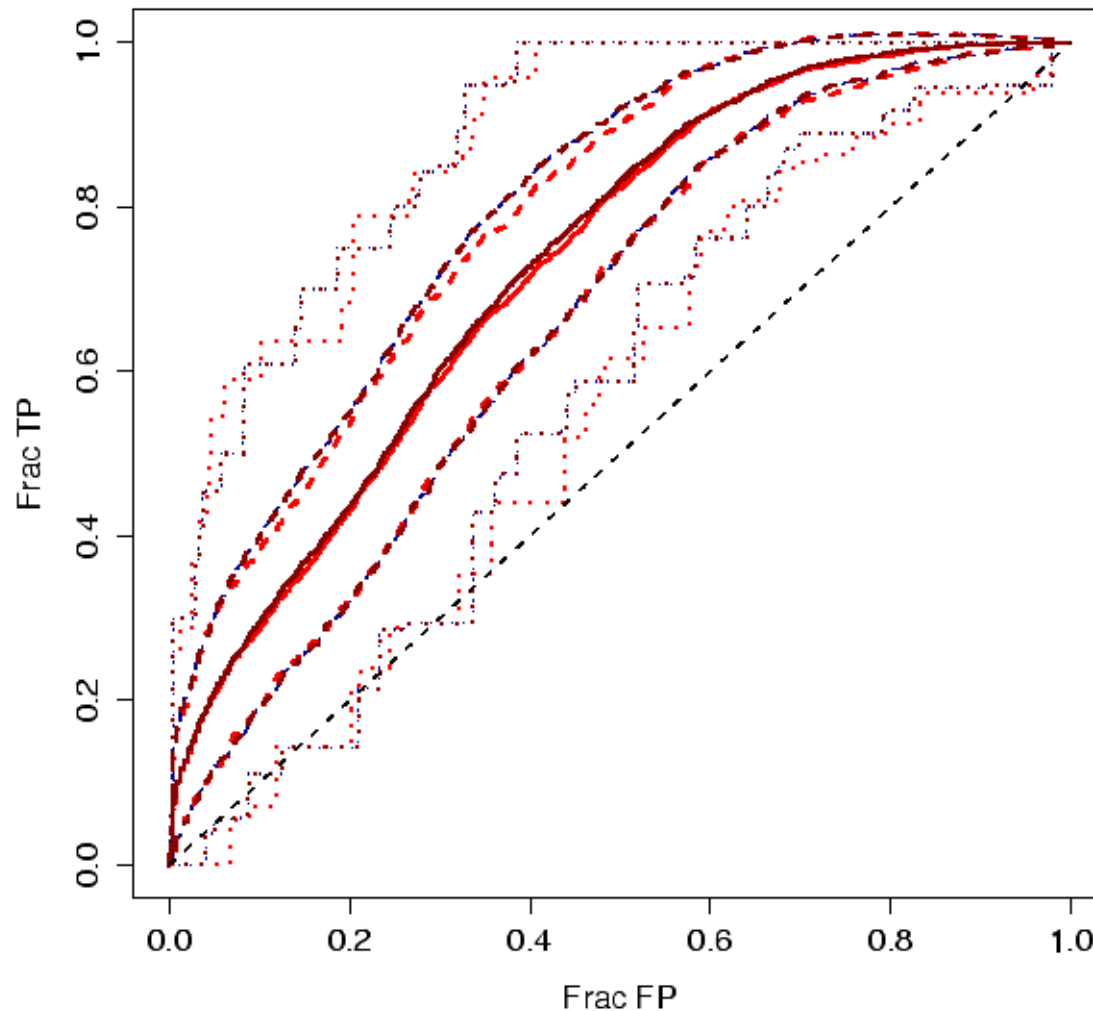
ifile-ti-ab-au-chain ROC



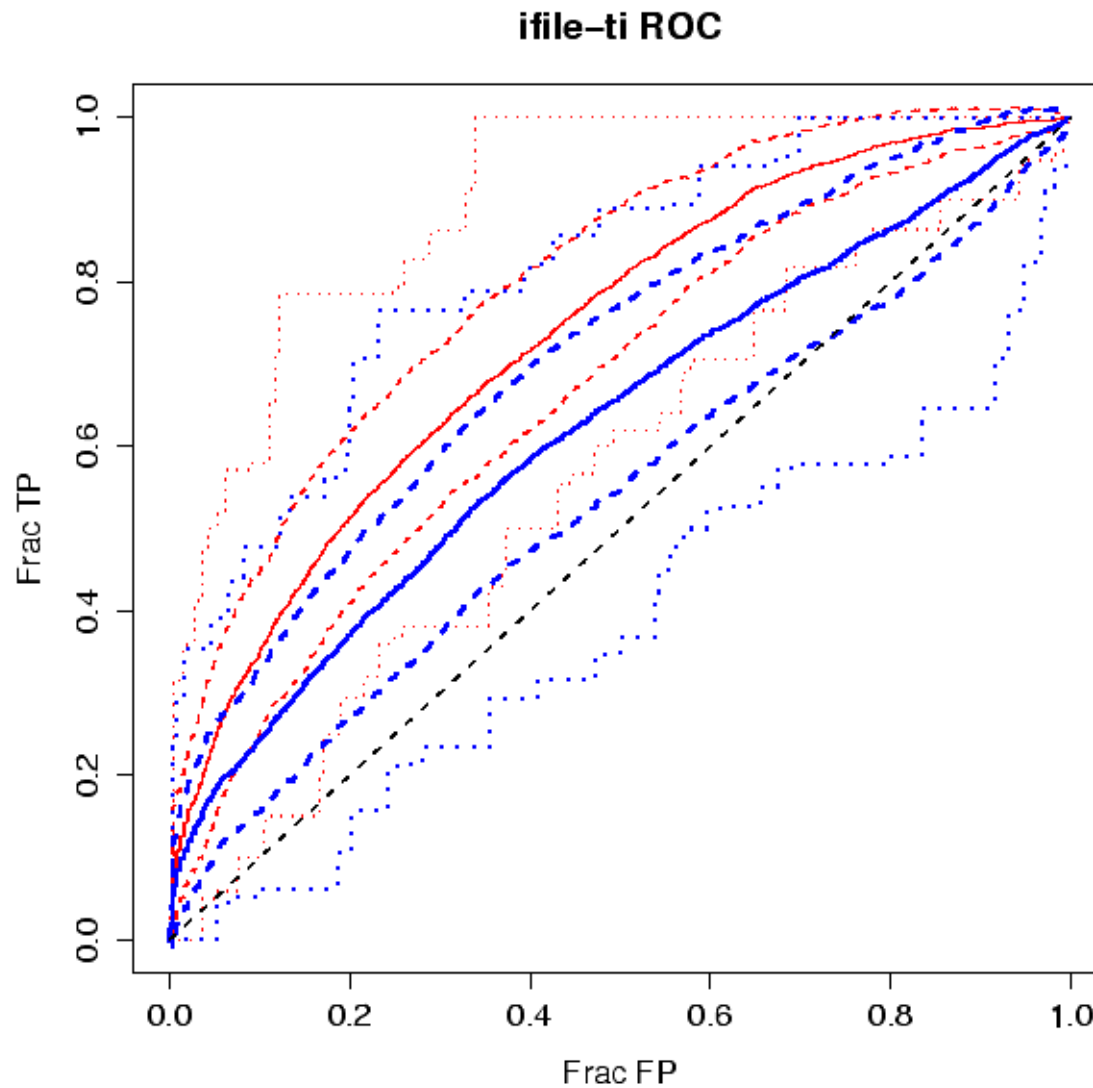
$64 \pm 4\%$  FP  
 $93 \pm 6\%$  TP

# Naïve Bayes – occurrence vs counts

ifile-ti-ab-chain-occ ROC



# CRM titles vs NB titles



# Conclusions

- The algorithm does cut down on the number of uninteresting articles to be skimmed for finding a given fraction of interesting articles
  - But performance is not great
- Performance on titles is comparable with title + authors/abstracts
- A more complex algorithm doesn't do as well
  - Overfitting?

# The future

- Improve algorithm
  - star rating system?
- Performance improvements
- More data sources
- Corpus collection tool?
- Open source project