Supporting HIV Literature Screening with Data Sampling and Supervised Learning

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Biomedical Literature Screening

- Manual screening: few documents actually kept
- Demanding, time consuming and error-prone
- Not guaranteed to be exhaustive
- Severe bottleneck in manual curation workflow

Machine Learning Approach

Automatic Text Classification

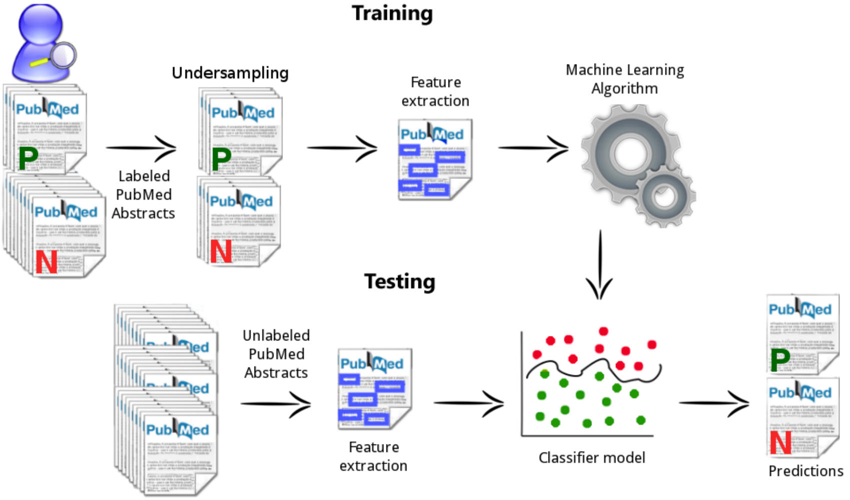
- Release the burden on scientists
- Assess more documents in less time
- Less likely to miss potential information

Goal: reduce effort by flagging candidate documents

Supervised Learning Triage

- Document collection: correct labels
- Training examples: given to classifier
- Model: used to classify new documents
- Test examples: evaluation of model

Supervised Learning Triage



Challenges: Text Classification for Biomedical Triage

1. Imbalanced Class Distribution
   - Large dataset → few relevant documents
   - Non-relevant majority introduces noise
   - Class distribution → affects performance
   - Need to reduce bias
2. Large Feature Space
   - Excessive features causes overfitting
   - Low discriminative value → poor contribution
   - More features → more computational resources
   - Need to identify best subset for the task

Data Sampling

- Selection of a specific subset of the dataset
(Chawla et al., 2002)(Japkowicz, 2000)
- Implementation → pre-processing step
- Less restrictive and less resource-demanding

Dataset Composition

SHARE Database references → http://www.hivevidence.ca

- 27,291 fully reviewed [L1]
- 1,758 included [L3]
- 26,968 unique instances (no duplicates)
- Scientific abstracts retrieved from querying PubMed

→ 18,703 unique instances with PMID

Dataset Balance

- Instances labeled as **excluded**: 17,402 (**93.05%**)

  Negative examples → Majority class

- Instances labeled as **included**: 1,301 (**6.95%**)

  Positive examples → Minority class

- Underlying distribution → real scenario of triage task
- Imbalance affects decision boundary

Dataset Statistics

Attribute	Number	%
Total number of instances	18,703	100%
Negative instances	17,402	93.05%
Positive instances	1,301	6.95%
Unique words in paper abstracts	31,632	-
Unique words in paper titles	6,821	-
Unique MeSH terms in papers	17,971	-

Methodology Overview

- Representative dataset of HIV screening task
- Study of undersampling factors
- Application of different feature settings
- Evaluation of feature selection methods
- Use of off-the-shelf classification algorithms (WEKA)
- Comparison of various supervised learning models

Imbalanced Learning Strategy

Training sets

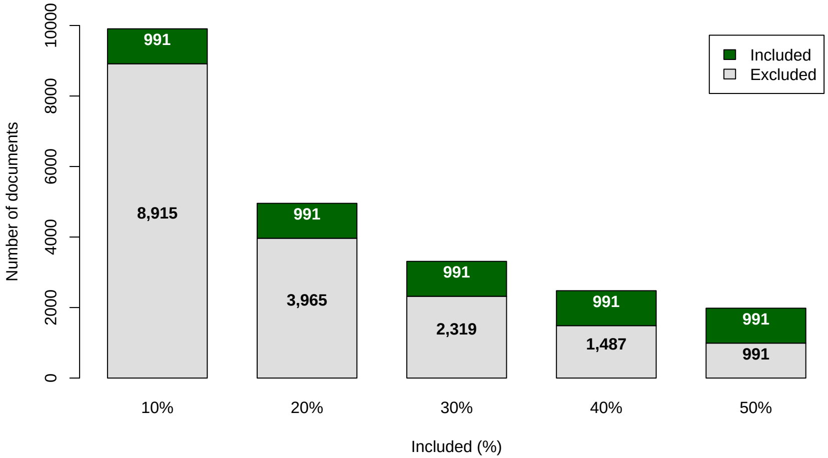
- Variety of class distributions
- Random removal of majority instances
- Progressive undersampling of 10%
- Comparison of different class balances

Test set

- 15% of the document collection
- Random selection of instances
- Real class distribution of triage task

≈7% positive and ≈93% negative instances

Undersampling Factors



Feature Extraction

<AbstractText>AIDS has emerged as a serious public health threat (...) </AbstractText>(...)

<MeshHeadingList>
<MeshHeading>
<DescriptorName (...)>Adolescent </DescriptorName>
</MeshHeading>
<MeshHeading>
<DescriptorName (...)>HIV Infections </DescriptorName>
<QualifierName (...)>etiology </QualifierName>
<QualifierName (...)>prevention control </QualifierName>
</MeshHeading>
</MeshHeadingList>

- MeSH Terms:

  [adolescent, descriptorname] [hiv infections, descriptorname]

  [etiology, qualifiername] [prevention control, qualifiername]

- Bag-Of-Words:

  [aids, 1] [emerged, 1] [serious, 1] [public, 1] [health, 1] [threat, 1]

Feature Selection Strategy

Odds Ratio (OR)

- Occurrence of features in positive class
- Confidence interval (CI) of 95% for each score
- Discard features if:
  - $\rightarrow$ CI contains the null hypothesis (1.0)
  - $\rightarrow$ OR score $<=$ null hypothesis (1.0)

Inverse Document Frequency (IDF)

- Occurrence of features in both classes
- Discard features if:
  - $\rightarrow$ IDF score $<= 1.0$ (i.e. Occurrence ratio is $>$ 10:1)

Features: Dataset Representation

- Dataset instances → feature vectors
- Feature occurrence in documents
- Training and Test sets → Feature x Document matrix

MeSH Terms vector

adolescent	*hiv infections*	*etiology*	*prevention control*	...
1	1	1	1	...

Bag-Of-Words vector

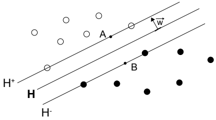
aids	*emerged*	*serious*	*public*	*health*	*threat*	...
1	1	1	1	1	1	...

Classification Algorithms

Naïve Bayes (NB)

- Baseline for triage task
- Naïve method to evaluate our approaches

Support Vector Machine (SVM)



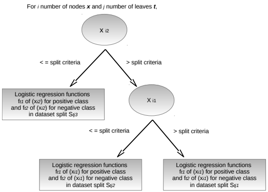
- Commonly applied in tasks with imbalanced data

(Akbani et al., 2004), (Tang et al., 2005),(Mountassir et al., 2012)

Logistic Model Trees (LMT)

- Described as suitable for imbalanced data

(Charton et al., 2013)



Experimental Settings Overview

Sets of Features

S1: Bag-Of-Words (BOW)

S2: Bag-Of-Words + MeSH Terms

S3: Domain Keywords list

Feature selection metrics

Inverse Document Frequency, Odds Ratio

Classification algorithms

NB, SVM, LMT

Undersampling Factors

From 0% USF (93%NEG 7%POS)

to $\approx$40% USF (50%NEG 50%POS)

Evaluation Metrics

- **Precision:** Correct output / all predictions

$$Precision = \frac{TP}{TP+FP}$$

- **Recall:** Correct output / class instances

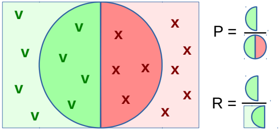
$$Recall = \frac{TP}{TP+FN}$$

- **F-measure:** Harmonic mean of Precision and Recall

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

- **F-2 score:** Emphasis on Recall measure

$$\beta = 2, \quad F_\beta = (1+\beta^2) \times \frac{Precision \times Recall}{\beta^2 \times Precision + Recall}$$



Accuracy: Correct output / all instances

$$Acc = \frac{TP+TN}{(TP+FN)+(FP+TN)}$$

Baseline Classification Model

- NB classifier
- Set of features #1: BOW of abstract and title contents

  Feature space: 22,060
- Training set with 0% USF (7% positive, 93% negative)

  Representative of the real triage task
- Performance

  Precision: 0.231 F-measure: 0.365

  Recall: 0.867 F-2 score: 0.560

Best results: HM1 model

- LMT classifier
- Set of features #2: BOW + Mesh Terms

  Feature space: 14,459
- Training set with ≈30% USF (40% positive, 60% negative)

  More balanced distribution than real scenario
- Performance

Precision: 0.467	F-measure: 0.615
Recall: 0.900	F-2 score: 0.759

Best results: HM2 model

- LMT classifier
- Set of features #2: BOW + Mesh Terms
- Feature selection: Odds Ratio

  Feature space: 2,411

- Training set with ≈30% USF (40% positive, 60% negative)

  More balanced distribution than real scenario

- Performance

Precision: 0.445	F-measure: 0.591
Recall: 0.882	F-2 score: 0.737

Model comparison

	Baseline	**HM1**	**HM2**
Balance	≈ 7% positive	≈ 40% positive	≈ 40% positive
Precision	23.1%	46.7% (+102.16%)	44.5% (+92.64%)
Recall	86.7%	90.0% (+3.81%)	88.2% (+1.73%)
F-measure	36.5%	61.5% (+68.49%)	59.1% (+61.92%)
F-2	56.0%	75.9% (+35.54%)	73.7 (+31.61%)
# features	22,060	14,459 (-34.46%)	2,411 (-89.07%)

Discussion

- Imbalanced learning strategy:

  Valuable to reduce bias effect

  Most fitting training class distribution → 40% **included**

- Set of features → MeSH Terms + BOW
- Odds Ratio → effective to narrow feature space
- Majority of **included** instances were correctly labeled

Observations

- Practical support for literature triage
- Open-source → system toolkit publicly released under MIT license
- Reproducibility:
  - → New triage models: wide-ranging annotation schemas
  - → MeSH, UMLS

`https://github.com/TsangLab/triage`

Partner Organizations

Dataparc, eHealth in Motion Ltd.

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