Scalable Term Selection for Text Categorization

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Abstract: By involving the target dimensionality as a parameter, a new term selection criterion is constructed via controlling the average vector length, whose expected value can be given by an empirical formula.
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1. Introduction

1.1. Text Categorization

Common TC phases:

- document vectorization
- dimensionality reduction (term selection)
- classifier learning
- classification and evaluation

Related definition:

\( D \) — the training document set
\( d_j \) — a document in \( D \)
\( T \) — the term set
\( t_i \) — a term in \( T \)
1.2. Term Selection

Term selection is necessary for

- removing *irrelevant* terms and *redundant* terms
- considerations on computational cost

Why not general feature selection techniques?

- Domain specific (ad hoc) ones are always better.
- TC has the special *sparseness* problem (which is supposed to cause the low performance at low dimensionalities).

The current technique ($\chi^2$, IG, BNS, ...):

- a single criterion $\circ(t_i)$ $\rightarrow$ a single rank list
- implicitly considered the *discriminability* and the *coverage* of $t_i$
  (correspond to the *specificity* and the *exhaustivity* of the term set $T$).
## 2. Experiment Settings

**Document collections:**

|                      | CE     | 20NG   | Comment                                      |
|----------------------|--------|--------|----------------------------------------------|
| Language             | Chinese| English|                                              |
| Num of categories    | 55     | 20     |                                              |
| Num of documents     | 71,674 | 18,821 |                                              |
| Split                | 9 : 1  | 6 : 4  |                                              |
| Num of terms, $|T|\rangle$ | 1,067,717 | 30,220 | $df(t_i) \geq 2$ in the training set |

**Other settings:**

Term selection: $\chi^2$ (baseline), STS

Term weighting: $tfidf(t_i, d_j) = \log(tf(t_i, d_j) + 1) \cdot \log \left(\frac{df(t_i) + 1}{N_d}\right)$

Classifier: linear kernel SVMs

Evaluation: $F_1$-measure
Section 3: Average Vector Length (AVL)

3. Average Vector Length (AVL)

Observation:

▶ Sparseness is the main reason of the low performance at low dimensionalities.
Section 3: Average Vector Length (AVL)

The basic idea:

- **vector length**: measures the sparseness of a document
- **average vector length**: measures the “sparseness of a term set”

Estimating AVL by training set:

\[ |d_j| \] — number of different terms in \( T \) contained by \( d_j \).

- More plausible:
  \[
  \exp \left( \frac{\sum \log |d_j|}{|D|} \right)
  \]

- Faster to compute (while \( T \) varies):
  \[
  \frac{\sum |d_j|}{|D|} = \frac{\sum df(t_i)}{|D|}
  \]

So we define

\[
AVL_T = \frac{\sum_{t_i \in T} df(t_i)}{|D|}
\]
4. Scalable Term Selection (STS)

The basic idea: STS should automatically accommodate its favor of high coverage to different target dimensionalities.

4.1. Measuring Coverage and Discriminability

The metrics of coverage and discriminability should:

- not be highly positively correlated
- have a slight negative correlation, intuitively

**coverage:**

\[ \log df(t_i) \]
Section 4: Scalable Term Selection (STS)

**discriminability:**

**probability ratio:**

\[
PR(t_i, c) = \frac{P(t_i|c_+)}{P(t_i|c_-)} = \frac{df(t_i, c_+)/df(c_+)}{df(t_i, c_-)/df(c_-)}
\]

\[\log PR_{\text{max}}(t_i) = \log \max_c \{PR(t_i, c)\}, \text{ in which } c \text{ is a category.}\]
4.2. The Combined Criterion

$$\zeta(t_i; \lambda) = \left( \frac{\lambda}{\log(\text{PR}(t_i))} + \frac{1 - \lambda}{\log(\text{df}(t_i))} \right)^{-1}, \quad \lambda \in [0, 1]$$

The optimal $\lambda$ is a function of the target dimensionality $k$:

$$\lambda^*(k) = \arg \max_{\lambda} F_1(k)$$

There is a corresponding optimal AVL:

$$\text{AVL}^*(k) \longleftrightarrow \lambda^*(k)$$

Is there an empirical formula to estimate $\lambda^*$ or AVL$^*$?

$$\text{AVL}^*(k) \approx \text{AVL}^*(k)$$
5. Experiments and the Final Algorithm

1. For each dimensionality $k$, we manually search $AVL^*(k)$ in integers.
2. For each $AVL$, search the corresponding $\lambda$; $AVL(\lambda; k)$ is monotone and fast to compute.
Observations:

- $F_1(k)$ is not very sensitive to small $\Delta AVL(k)$ near $AVL^*(k)$.

- $\gamma = \frac{\log(AVL^*(k))}{\log(AVL_T)} \log(k) \approx 0.085$

  $(AVL_{T_{CE}} = 898.53, AVL_{T_{20NG}} = 82.16)$
Final formulas:

The empirical estimation of $AVL^*(k)$ is

$$AVL^*(k) = \exp(\gamma \log(AVL_T) \cdot \log(k)) = AVL_T^{\gamma \log(k)}$$

and the final STS criterion is

$$\zeta(t_i, k) = \zeta(t_i; \lambda(AVL^*(k))) = \zeta \left( t_i; \lambda \left( AVL_T^{\gamma \log(k)} \right) \right)$$

in which $\lambda(AVL)$ is still computed by search.
6. Further Observation and Discussion

Comparing the selection results of STS and $\chi^2$:

• For most $\lambda$, the Spearman’s rank correlation coefficient between $\eta(t_i; \lambda)$ and $\chi^2(t_i)$ is bigger than 0.999.

• Selection areas on (coverage, discriminability) of CE and 20NG:

![Graph showing data points and contour lines for STS and $\chi^2$]
About sparseness:

- *collection sparseness*: too few training samples. This backroom factor might lead to the different behaviors of STS on CE and 20NG.
- *document sparseness*: this study.

Adaptability:

- Performance
- Computational cost: depends on AVL or $k$

plots