

Graph Based Text Classification

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ABSTRACT

In this paper, a graph based classifications model is proposed on the basis of the word semantic space. This model can solve the problems of vector space model, such as the order or words, the boundary between sentences and phrases, etc. Different feature selection methods are also explained in this paper.

Keywords – Feature Selection, Graph based model, K-NN algorithm, Preprocessing, Semantic Space, Text Classification, and Vector Space Model

1. INTRODUCTION

With the development of internet, a large amount of data in any organization needs efficient classification. The traditional text classification techniques have been based on vector space model which ignored the structural information of the document that is word order and co-occurrence of the words in the document. Therefore the paper has used graph based technique which takes into account the structural information of the document.

The Graph based technique has been recently developed by Schenker A. and Zhaotao et al. More work on graph based technique has been done by Wei Jin, Rohini k and Maul and Alexander. Word semantic space has been proposed by Zhao et al [1] in 2010 Graph based text classification has been introduced by Whang and Liu [2] in 2010.

2. FEATURE SELECTION AND PREPROCESSING

The text classification begins with preprocessing which includes the stop word removal and stemming of the document. The stemming algorithm that the paper has used is porter stemmer. After preprocessing the next phase is feature selection. The feature selection that the paper has used are MI[3] with Chi, RMI[4] with Chi [5] and WT .

RMI

Regularized mutual information measures the relevance of a term in a category. It is effective than mutual information and do not takes into account the numerical values.

$$RMI = 2MI(t, c) / H[t] + H[c]$$

Weight Of Terms

It is formed by replacing the IDF [inverse document frequency] in TF-IDF. It is used to measure the weight of terms appearing frequently as well as rarely in the document.

$$WT = TF(t).MI(t, c)/MI$$

It is used to measure the mutual dependence of the two terms in a paragraph or in whole document.

$$I(t, c) = \log P(t, c) / P(t/c) * P(t)$$

$$I(t, c) = \log P(t/c) - \log P(t)$$

Where $P(t, c)$ is the probability of the term t in the category c , $P(t)$ is the probability of the term t and $P(c)$ is the probability of the category c .

Chi Square Statistics

It is used to measure the lack of independence between the term t and the category c .

$$CHI(w, c) = N * (P(w, c) * P(\bar{w}, \bar{c}) - P(w, \bar{c}) * P(\bar{w}, c)) / (P(w) * P(\bar{w}) * P(c) * P(\bar{c}))$$

$P(w)$ is the probability of w in the document d and $P(c)$ is the probability when the text belong to category c . $P(\bar{w}, c)$ is the probability that word do not occur in the category, $P(\bar{w}, \bar{c})$ is the probability that word w and category do not appear .similarly the meaning of rest of the terms can be known.

3. GRAPH BASED TEXT CLASSIFICATION

After the feature selection step the whole text converted into graph based on the features selected.

3.1. Graph Based Text Representation Model [7]

A graph is 3 tuple $G = (V, E, F, W, M)$, where V is a set of nodes, E is a collection of weighted edges connecting nodes. FWM (Feature Weight Matrix) [8] is defined as the feature weight matrix of the edges.

- Node:

Unique feature terms obtained from the train set using feature selection methods.

- Edges:

Constructed based on order and co-occurrences relationship between feature words.

- Feature Weight Matrix:

Here every document is represented as incidence matrix. The weight w of the edge indicates the degree of constraint between the two features related to the edge. The weight between the two features is semantic measure which is defined as

$$W_{AB} = 1 / (\text{num}(B) - \text{num}(A))$$

Where $\text{num}(B)$ is the order of the feature A in the document, $\text{num}(A)$ is the order number of the feature B in the document. If the two feature terms appear one after another in the document and A appears before B , then in the picture G there is directed edge from A to B and the weight is 1. this phenomenon is called A directly restrict B or B is directly restricted by A . if the feature A and B are not adjacent and A appears before B , then in the graph G there is a directed edge, and its weight can be computed through the formula (5). This is called A indirectly restrict B or B is indirectly restricted by A .

4. IMPROVED KNN CLASSIFICATION BASED ON GRAPH

As a graph consists of nodes, edges and the weight of the edges, we can define the similarity measure of two graphs by those elements. Three different algorithms [8] have been used for classification. First has been used to convert the text into graph and then two improved classification measures have

been used in calculating the similarity between two graphs and finally classifying the document.

First of all the document will be converted into graph based representation with the help of following matrix

$$T = [t_1, t_2, \dots, t_n]$$

$$M = \begin{pmatrix} a_{11} & a_{12} & \dots & \dots & a_{1,n-1} & a_{1n} \\ a_{21} & a_{22} & \dots & \dots & a_{2,n-2} & a_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n-1,1} & a_{n-2,2} & \dots & \dots & a_{n-1,n-1} & a_{n-1,n} \\ a_{1n} & a_{n2} & \dots & \dots & a_{n,n-1} & a_{nn} \end{pmatrix}$$

In the above, T is the set of features; t_i is the Feature for $i = 1, 2, \dots, n$. M is the incidence matrix of the features; a_{ij} is the relevance degree between the features t_i and t_j ($1 < i < j < n$). If some word A restricts another word B several times, then the nearest constraint (the maximal constraint) between them is considered. According to the definition 1, the maximal constraint is 1 and the matrix U is obtained:

$$U = \begin{pmatrix} u_{11} & u_{12} & \dots & \dots & u_{1,n-1} & u_{1n} \\ u_{21} & u_{22} & \dots & \dots & u_{2,n-1} & u_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ u_{n-1,1} & u_{n-1,2} & \dots & \dots & u_{n-1,n-1} & u_{n-1,n} \\ u_{n1} & u_{n2} & \dots & \dots & u_{n,n-1} & u_{nn} \end{pmatrix}$$

The Matrix U need to be normalized.

$$\text{Let } W_{ij} = U_{ij} / \sum_k U_{ki}$$

where $I, j, k, l = 1, 2, \dots, n$. Then normalized matrix w is as follows

$$W = \begin{pmatrix} W_{11} & W_{12} & \dots & \dots & W_{1,n-1} & W_{1n} \\ W_{21} & W_{22} & \dots & \dots & W_{2,n-2} & W_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ W_{n-1,1} & W_{n-1,2} & \dots & \dots & W_{n-1,n-1} & W_{n-1,n} \end{pmatrix}$$

$W_{n1} \quad W_{n2} \quad \dots \quad W_{n,n-1} \quad W_{n,n}$

Input :

Training set $D=\{d_1, d_2, \dots, d_i, \dots, d_n\}$ D_i is a text after segment and stop words filtering $D_i = \{f_1, f_2, \dots, f_i, \dots, f_m\}$, f_i is the i -th word of text $f_i =$ Feature selected, $N_i =$ Node $w_i =$ Weight

Output :

Training set $G=\{g_1, g_2, \dots, g_i, \dots, g_n\}$ g_i is the i -th text represented by graph

Procedure:

1. For each d_i in D
 2. Initialize the node set N_i , edge set E_i and Feature Weight Matrix FWM_i to be empty.
 3. For each f_i in d_i
 4. If($f_i \in N_i$)
 5. create a new node n_i representing f_i ,
 6. add n_i to N_i , set $w_{ii}=1$ // w_{ii} is defined in (3)
 7. End If
 8. End for
 9. For each f_i in d_i
 10. Create a new edge e_i connecting f_i and f_{i+1}
 11. find the node n_k which representing f_i
 12. If($e_i \in E$)
 13. add e_i to E_i , set weight $e_i = 1$
 - 14 w_{kk++} ; // w_{kk} represents the frequency of n_k
 15. Else If($e_i \in E_i$)
 16. weight $e_i ++$;
 17. w_{kk++}
 18. End If
 19. End For
- Algorithm1. Text to graph conversion

FW(feature weight): It describes the similarity between two graphs by weight of both nodes and edges appear in both two graphs. It can be calculated as follows.

Testing set graphs $G=\{g_1, g_2, \dots, g_i, \dots, g_n\}$
 Training set graphs $CG=\{cg_1, cg_2, \dots, cg_i, \dots, cg_n\}$ $w_{ij} =$ weight of the edge

$F_w =$ Feature Weight

Procedure:

1. For each edge in g_i
2. If edge in cg_i
3. If($w_{ij}(g_i) \geq w_{ij}(cg_i)$) // w_{ij} is the weight of edge
4. If($j > i$)

5. $F_w += \alpha w_{ij}(cg_i)$
6. Else if($j=i$)
7. $F_w += w_{ij}(cg_i)$
8. End if
9. Else If($w_{ij}(g_i) < w_{ij}(cg_i)$)
10. If($j > i$)
11. $F_w += \alpha w_{ij}(g_i)$
12. Else if($j=i$)
13. $F_w += w_{ij}(g_i)$
14. End if
15. End if
16. End if
17. End for

Algorithm 2. Calculation of feature weight

The following algorithm has been used for the final classification of the document into its category. **Input:** Testing set graphs $G=\{g_1, g_2, \dots, g_i, \dots, g_n\}$, value $k=5$ Training set graphs $CG=\{cg_1, cg_2, \dots, cg_i, \dots, cg_n\}$
 $Nfp =$ Node Fit Percent
 $Efp =$ Edge Fit Percent
 $F_w =$ Featured Weight

Output :

Result set $R=\{r_1, r_2, \dots, r_i, \dots, r_n\}$

Procedure:

- 1 For each g_i in G
2. Initial List RL to store F_w and text category (length is K)
- 3 For each cg_i in CG
4. If $Nfp(g_i, cg_i) > \alpha$ && $Efp(g_i, cg_i) > \alpha$
5. Calculate Feature weight $F_w(g_i, cg_i)$
- 6 If RL is not full
- 7 Add $F_w(g_i, cg_i)$ and category of cg_i to RL
- 8 Else If RL is full
- 9 If $F_w(g_i, cg_i) > \min(F_{wi} \text{ in RL})$
- 10 Replace F_{wi} in RL with $F_w(g_i, cg_i)$
- 11 End if
- 12 End if
- 13 End if
- 14 . End For
- 15 the category of g_i is the category appears most in RL
- 16 add the category of g_i to the Result Set R.
- 17 End For

Algorithm 3. Classification of document

5. CONCLUSION

In this paper semantic space method had been proposed with the graph based method so as to have a better and

efficient classification. This can be further combined with different classifier to have efficient classification.

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