LITERATURE SUMMARY REVIEW:

These topics discuss the work done by the various authors, students and researchers in brief under the domain of classification and pre-processing the textual data.

| SR .no | Title of paper, publisher /event | Autor of public ation | Proble m they solved | Technolo gy they used | Metho dology used | Input provid ed | Output obtained | Summary of work | Future work proposed/ possible extension of work |
|-----------|--|----------------------------------|---|-----------------------------|---|-----------------------|--|--|---|
| | Text Categoriz ation with Support Vector Machines : Learning with Many Relevant Features | Thorst en Joachi ms | Classifi cation of Text Docum ent | Polynom ial and RBF kernels | SVM | Text Docu ment | Text classificati on based on predefined categories | It uses Support Vector Machine for the text classification. They are fully Automated and eliminate the need of manual parameter turing. The document may fall in multiple, one or not any of the categories. The representation of each category is treated as separate binary classification. With the information retrival system, the documents are transformed into representable format for the learning algo and classification task. Ordering of the words doesn't matter so it generates the category for the corresponding word in the set including its number of repetition. It has a very high dimensional feature sets which doesn't over-fit the feature set for classification and also generalizes the accuracy. | SVMs do not require any parameter tuning, since they can nd good parameter settings automaticall y. All this makes SVMs a very promising and easy-to-use method for learning text classifiers |
| 2 | Interactio n of Feature Selection Methods | Janez Brank , Mark o | Classifi cation of Text Docum ent | Tensorflo w | SVM, differ ent classif ier ie. | Text Docu ment | Text classificati on based on predefined | The method SVM and other classifier for better accuracy. The Naïve Bayes Classifier, Perceptron-I, Linear | Expand the study to additional classifiers, linear and |

| | | G 1 | | | 37.0 | | | CYD 6: 1 1 | 1. |
|---|------------|--------|----------|--------|-----------|-------|------------|--------------------------|---------------|
| | and | Grobe | | | Naïve | | categories | SVM is used as the | non-linear, |
| | Linear | lnik | | | Bayes | | | classifier. One of the | and |
| | Classifica | | | | , | | | classifier's weaknesses | diversify |
| | tion | | | | Perce | | | can be hindered by | the feature |
| | Models | | | | ptron- | | | another. Using this | scoring |
| | | | | | I, | | | concept, the | algorithms |
| | | | | | Linear | | | classification is done. | to include |
| | | | | | SVM | | | Here the feature | those that |
| | | | | | | | | selection is done in two | possibly |
| | | | | | | | | ways. One is using full | include |
| | | | | | | | | features set and second | information |
| | | | | | | | | one is using selected | of feature |
| | | | | | | | | features set and study | dependencie |
| | | | | | | | | them for future | s or similar |
| | | | | | | | | references for linear | characteristi |
| | | | | | | | | classification. Feature | cs, leading |
| | | | | | | | | selection is based on | to more |
| | | | | | | | | score of the feature. | sophisticate |
| | | | | | | | | Top ranked are kept | d data |
| | | | | | | | | while other are | modeling. |
| | | | | | | | | discarded. | 8 |
| | | | | | | | | It has seen the SVM has | |
| | | | | | | | | outperformed | |
| | | | | | | | | perceptron- based and | |
| | | | | | | | | Naïve Bayes- based | |
| | | | | | | | | classifiers for the text | |
| | | | | | | | | categorization. | |
| 3 | An | Ana | Classifi | ModApt | Latent | Messa | Assigning | The classification is | We plan to |
| | Empirical | Cardo | cation | e | Sema | ges | one or | based on the messages, | investigate |
| | Comparis | soCac | of Text | | ntic | and | more | newsgroups and | if further |
| | on of | hopo | Docum | | Analy | News | number of | categorized into 10 | improveme |
| | Text | and | ent | | sis | group | Text | different sections. Both | nts can be |
| | Categoriz | Arlind | CIIt | | (LSA) | group | Categoriza | the inputs are used for | applied to |
| | ation | 0 | | | (LSA) | | tion | comparing the SVM | the SVMs |
| | Methods | Limed | | | , SVM, | | tion | and LSA results. Pre- | and k-NN |
| | Wichious | e | | | KNN | | | processing of dataset is | LSA |
| | | Olivei | | | IXININ | | | done by removing | models. If |
| | | | | | | | | words with length | possible, |
| | | ra | | | | | | smaller than 3 or | this would |
| | | | | | | | | | further |
| | | | | | | | | greater than 20. | enhance the |
| | | | | | | | | Removed numbers, | |
| | | | | | | | | made the upper and | superiority |
| | | | | | | | | lower cases same. The | of these |
| | | | | | | | | tf-idf (term frequency – | methods |
| | | | | | | | | inverse document | observed in |
| | | | | | | | | frequency) is used for | this |
| | | | | | | | | computing the index | experiments |
| | | | | | | | | term weight of a | |
| | | | | | | | | document. The LSA | |
| | | | | | | | | then lowers the | |

| | Integratin | Dimit | Classifi | ModApt | FIS | Text | Text | dimension of the original set of vectors with the new ones which comprises mostly a generalized word or class for the document. It is seen that k-NN LSA shows more promising classification than any other used method. Most of the time feature | Can be |
|---|---|---|---|--|----------------------------------|----------------------|--|---|--|
| 4 | g Feature and Instance Selection for Text Classifica tion | ris Frago udis,D imitris Meret akis, Spiros Likot hanaS sis | cation of Text Docum ent | e- training- test, Newsgro up, Reuters | (Feature and Instance Selection) | Document | classificati on based on predefined categories | selection does the job of reducing the dataset. Thus the FIS algorithm pre-processes the dataset by selecting the features and instances then dataset is provided to algorithm. Naïve Bayes, TAN and LB classifier has produced better results with resultant dataset of FIS algorithm. Also provides best result compared to SVM. The results were compared between MI (Mutual Information) and FIS dataset classifier. It was observed that FIS had more promising results than MI. Naïve Bayes, TAN and LB algorithm used the data set which was the resultant dataset of the MI and FIS. Among which FIS had more accurate results. | extend FIS for dealing with multiclass problems and to apply it to structured data in addition to text. |
| 5 | Pruning Training Corpus to Speedup Text Classifica tion | Jihon g Guan, Shuig eng Zhou | Classifi cation of Text Docum ent | VC++ 6.0 under Windows 2000, PC with P4 1.4GHz CPU and 256MHz memory | KNN | Text Docu ment | Text classificati on based on predefined categories | The method is based on the pruning of dataset by clustering method. The classification is done by using the KNN and Linear classifier. They both alone are not efficiently producing results as they can by | Improves by the factor of larger than 4, with less than 3% degradation of micro- averaging |

| 6 | Accuracy improve ment of automatic | Xuexi an Han Guow | Classifi cation of Text Docum | ModApt e-training-test, | Euclid ean distan ce, | Text Docu ment | Text classificati on based on | doing both. Firstly the clustering calculates the difference between the documents vector as corresponding to features selected. By treating each training class as a distinctive cluster, then using a genetic algorithm to select a subset of document features such that the difference among all clusters is maximized. The pruning method has dataset of document D. A document d also has other documents in its classified class. The features and similarities score of the document is tallied with the Class in Dataset D. Thus we are pruning the dataset For further classification based on the score of a document and selecting only the class which has the score near to the document. The procedure of the automatic text classification consists of four general steps for feature vector. | performanc e. So can be put to use where unnecessary features are bulk or irrelevant. Can be used where biased dataset |
|---|--|-------------------------------------|--|----------------------------|--|----------------------|-------------------------------|--|---|
| | text classifica tion based on feature transform ation and Multi- classifier combinat ion | ei Zu, Watar u Ohya ma1 | ent | Newsgro up, Reuters. | SVM- Linear , Linear discri minan t functi on, | | predefined categories | feature vector generation, dimension reduction, learning and classification. The study done in this report tells us that the use of multiple classifiers can be done for better and efficient classification of documents. The classifiers alone are not efficient enough but the working together it overcomes each- others | comes into picture with multiple dimensional ity. |

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|---|------------|--------------|----------|-----------|--------|------|--------------|--|--------------|
| | | | | | | | | drawback. Based on the | |
| | | | | | | | | score of the document's | |
| | | | | | | | | feature, dataset can be | |
| | | | | | | | | reduced dimensionally | |
| | | | | | | | | if the feature doesn't | |
| | | | | | | | | have the needed count. | |
| | | | | | | | | Among all the | |
| | | | | | | | | classifiers, the SVM- | |
| | | | | | | | | Linear had the best | |
| | | | | | | | | outcome with reduced | |
| | | | | | | | | dimensionality. | |
| 7 | Combini | Yongg | Classifi | ModApt | K- | Text | Text | It uses basic K- nearest | Multiple |
| | ng | uang | cation | e- | neares | Docu | classificati | neighbour for the | reducts to |
| | Multiple | Bao | of Text | training- | t | ment | on based | classification. Alone K- | improve the |
| | K- | and | Docum | test, | Neigh | | on | nearest neighbour is | performanc |
| | Nearest | Naohi | ent | Newsgro | bour, | | predefined | sufficient so multiple | e of the k- |
| | Neighbou | ro | | up, | KNN | | categories | feature set has been put | nearest |
| | r | Ishii | | Reuters. | Classi | | | to use. It combines | neighbor |
| | Classifier | | | | fier, | | | multiple KNN | classifier |
| | s for Text | | | | RkNN | | | classifiers. To select the | which is |
| | Classifica | | | | | | | feature of the subset, | easiest |
| | tion by | | | | | | | the MFS were build on | classifier. |
| | Reducts | | | | | | | trail and error. To | So future |
| | | | | | | | | overcome this problem, | use might |
| | | | | | | | | random selection of | be |
| | | | | | | | | MFS was done. This | restricted. |
| | | | | | | | | made the problem NP- | 1080110000. |
| | | | | | | | | hard. The multiple | |
| | | | | | | | | reducts can be | |
| | | | | | | | | formulated precisely | |
| | | | | | | | | and in a unified way | |
| | | | | | | | | within the framework | |
| | | | | | | | | of Rough Sets theory. | |
| | | | | | | | | This theory generates | |
| | | | | | | | | multiple reducts which | |
| | | | | | | | | improves the | |
| | | | | | | | | | |
| | | | | | | | | performance of KNN classifier. | |
| 8 | Feature | Jana | Classifi | Reuters | Naive | Text | Text | In text classification, | Many areas |
| 0 | Selection | Novo | cation | IXCUICIS | Bayes | Docu | classificati | usually a document | of future |
| | using | vicov | of Text | | Classi | ment | on based | representation using a | work |
| | Improved | | Docum | | fier, | ment | on | bag-of-words approach | remain. |
| | Mutual | a , Anton | ent | | Best | | predefined | is employed. This | Ongoing |
| | Informati | on | Ciit | | indivi | | categories | representation scheme | work |
| | on for | Malik | | | dual | | categories | | includes |
| | | and | | | | | | leads to very high dimensional feature | |
| | Text | | | | featur | | | | comparison |
| | Classifica | Pavel | | | es(BI | | | space. A predefined | on the other |
| | tion | Pudil | | | F), | | | number of the best | text |
| | | | | | Seque | | | features are taken to | classifiers, |
| | | | | | ntial | | | form the best feature | for |

| | | | | | 1 | | | <u>, </u> | |
|---|------------|--------|----------|---------|---------|------|--------------|--|--------------|
| | | | | | forwa | | | subset. Scoring of | example, |
| | | | | | rd | | | individual words can be | support |
| | | | | | selecti | | | performed. Best | vector |
| | | | | | on | | | individual features | machines |
| | | | | | (SFS) | | | (BIF) methods evaluate | and k- |
| | | | | | (212) | | | all the n words | nearest |
| | | | | | | | | individually according | neighbor. |
| | | | | | | | | | neighbor. |
| | | | | | | | | to a given criterion, sort | |
| | | | | | | | | them and select the best | |
| | | | | | | | | k words. Sequential | |
| | | | | | | | | forward selection (SFS) | |
| | | | | | | | | methods firstly select | |
| | | | | | | | | the best single word | |
| | | | | | | | | evaluated by given | |
| | | | | | | | | criterion. Then, add one | |
| | | | | | | | | word at a time until the | |
| | | | | | | | | number of selected | |
| | | | | | | | | words reaches desired k | |
| | | | | | | | | words. r SFS methods | |
| | | | | | | | | do not result in the | |
| | | | | | | | | optimal words subset | |
| | | | | | | | | but they take note of | |
| | | | | | | | | dependencies between | |
| | | | | | | | | words as opposed to the | |
| | | | | | | | | BIF methods. Therefore | |
| | | | | | | | | SFS often give better | |
| | | | | | | | | results than BIF. | |
| 9 | D: ': : | D. | C1 'C | D 4 | A 1 D | T. 4 | Tr. 4 | | A 1 D 4 |
| 9 | Discretizi | Pio | Classifi | Reuters | AdaB | Text | Text | Based on the idea of | AdaBoost. |
| | ng | Nardi | cation | and | oost | Docu | classificati | adaptive boosting, a | MH is in |
| | Continuo | ello, | of Text | newsgro | | ment | on based | version of boosting in | the |
| | us | Fabriz | Docum | up | | | on | which members of the | restricted |
| | Attribute | 10 | ent | | | | predefined | | lot of the |
| | s in | Sebast | | | | | categories | sequentially generated | peak text |
| | AdaBoos | iani, | | | | | | after learning from the | categorizati |
| | t for Text | and | | | | | | classification mistakes | on |
| | Categoriz | Aless | | | | | | of previously generated | performers |
| | ation | andro | | | | | | members of the same | nowadays, a |
| | | Sperd | | | | | | committee, | lot where |
| | | uti | | | | | | AdaBoost.MH is a | the margins |
| | | | | | | | | realization of the well- | for |
| | | | | | | | | known AdaBoost | performanc |
| | | | | | | | | algorithm, which is | e |
| | | | | | | | | specifically aimed at | improveme |
| | | | | | | | | multi-label TC4, and | nt are |
| | | | | | | | | which uses decision | slimmer and |
| | | | | | | | | trees composed of a | slimmer. |
| | | | | | | | | root and two leaves | Simmici. |
| | | | | | | | | only as weak | |
| | | | | | | | | 1 | |
| | | | | | | | | hypotheses. Algorithms | |
| | | | | | | | | attempt to optimally | |

| 10 | A comparat ive study on feature selection in text categoriz ation | Yamin g Yang, Jan O Peder son | Classifi cation of Text Docum ent | Reuters, OHSUM ED | KNN, Linear Least Squar e Fit (LLS F), Docu ment freque ncy, | Text Docu ment | Text classificati on based on predefined categories | split the interval on which these attributes range into a sequence of disjoint subintervals. This split engenders a new vector (binary) representation for documents, in which a binary term indicates that the original nonbinary weight belongs or does not belong to a given sub-interval Document Frequency (DF) Threshold is the simplest for vocabulary reduction. Easily scales to very large corpus. Due to widely received assumption of info retrival, DF is not used. The Information Gain (IG) measures the bit of information and obtains | Eases the computation and power over the application used for high level performanc e. From Neural Network to |
|----|---|--|---|-------------------------|--|----------------------|--|--|---|
| | | | | | Information gain, Chitest | | | the category of the document by the presence or absence of terms. With each term Information gain is calculated and few are discarded which has less value than already predefined threshold. Thus conditional probability is put to use for term <i>t</i> and category <i>c</i> . The Chi-test measures the lack of independence between the term <i>t</i> and category c and can be compared to Chi square distribution with one degree of freedom. Thus the IG or DF combined with KNN or LLSF gives us efficient results for the classification. | Text categorizati on The methods can be used significantly . |

| 11 | "Text | Machi | Classific | linear | SVM | Text | text | In this we study about | In future |
|----|-------------------------|-----------------|-----------------|------------------------|--------------|--------------|------------------------|---|----------------------------|
| | Categoriz ation with | ne Learni | ation of text | kernel, 2nd order | | docum ent | classificatio n, | (SVM) support vector machines . | work we want to see if |
| | Support | ng, 46, | docume | polynomi | | | lemmatizati | The SVM are capable of | the results |
| | Vector Machines. | 423– 444, | nt | al kernel, Gaussian | | | on, stemming | effectively processing feature vectors of some 10 | can be generalized |
| | wiaciiiies. | 2002 | | rbf-kernel | | | stemming | 000 dimensions, given | to other |
| | | c | | TOT KETHET | | | | that these are sparse. | languages |
| | | ,2002 | | | | | | And also support vector | i.e. Slavic, |
| | | Kluwe | | | | | | machines provide a fast | romance, and |
| | | r | | | | | | and effective means for | non-Indo- |
| | | Acade | | | | | | learning text classifier's | Europeans. If |
| | | mic Publis | | | | | | from examples we study different | the results were |
| | | hers. | | | | | | mappings of frequencies | positive, a |
| | | Manuf | | | | | | to input space, and | generic |
| | | acture | | | | | | combine these mappings | algorithm |
| | | d in | | | | | | with different kernel | would be |
| | | The | | | | | | functions | found that |
| | | Nether lands | | | | | | | worked well |
| | | lanus | | | | | | | on nearly any language. |
| 12 | 1. | Ke H., | They | salton | Conce | Text | Classified | They uses the vector | This method |
| | Text | Shaop | find that | | pt | docum | data on | space model and feature | for put |
| | categoriza | ing M | this | | indexi | ent | | selection of the text | forwarded in |
| | tion | | algorith | | ng, | | | document is represented | the paper is |
| | based on Concept | 2002 | m can effective | | princi | | | by a vector and all subsequent calculation | meaningfull to online text |
| | indexing | | ly | | ple | | | based, many ML | categorisatio |
| | and | | reduce | | comp | | | technology have been | n, application |
| | principal | | dimensi | | onent | | | successfully applied to | of more |
| | componen | | onality | | analys | | | text categorization. | machine |
| | t analysis. | | without | | is, Vsm,K | | | Concept indexing is | learning. |
| | | | sacrifici ng | | NN,Ba | | | simple and effective way to reduce dimension. For | |
| | | | categori | | ysean | | | effective in data | |
| | | | zation | | classifi | | | compression and feature | |
| | | | accurac | | er. | | | extraction we use | |
| | | | у. | | | | | PCA,they applied pca to | |
| 13 | "Improvin | Clairv | Classific | Corpora, | SVM | Text | automatic | ci subspace. In general, support vector | the proposed |
| 13 | g SVM | oyance | ation of | threshold | D V IVI | docum | process for | machines (SVM), when | thresholding |
| | Text | Corpor | text | adjusting | | ent | adjusting | applied to text | approach is |
| | Classificat | ation, | docume | algorithm | | | the | classification provide | independent |
| | ion | 5001 | nt | | | | thresholds | excellent precision, but | of the learnt |
| | Performan | Baum | | | | | of generic | poor recall. | model, using |
| | ce through Threshold | Boule vard, | | | | | SVM which | So to improve Recall we customizing | it in conjunction |
| | Adjustme | Suite | | | | | incorporate | SVMs. | with other |
| | nt" | 700, | | | | | s a user | Customizing Means to | types of |
| | | Pittsbu | | | | | utility | adjust the threshold | models will |
| | | rgh, | | | | | model, an | associated with an SVM. | also form an |
| | | PA | | | | | integral | We describe an automatic | interesting |
| | | 15213- 1854, | | | | | part of an information | process for adjusting the | aspect of future work. |
| | | 1034, | | | | | miormation | thresholds of generic | ruture work. |

| | 1 | **C * | 1 | T | I | <u> </u> | | CYD 6 1111 | |
|----|-------------|-------------|-----------|------------|------------|--------------|-----------|--|----------------|
| | | USA | | | | | manageme | SVM which incorporates a user utility model, an | |
| | | | | | | | nt system | integral part of an | |
| | | | | | | | | information management | |
| | | | | | | | | system | |
| 14 | "Feature | Pedro | Classific | Tensorflo | multi- | huge | Improve | In this we use the feature | for |
| - | Selection | A. C. | ation of | w | agents | networ | Document | selection algorithms were | improving |
| | Algorithm | Sousa | text | | system | k | | evaluated in order to | documents' |
| | s | 1, João | docume | | s, | infrast | | improve documents' | classification |
| | to | Paulo | nt | | | ructure | | classification performance | performance. |
| | Improve | Piment | | | feature | s and | | _ | |
| | Document | ão1, | | | selecti | new | | | |
| | S | Bruno | | | on, | inform | | | |
| | Classificat | René | | | Inform | ation, | | | |
| | ion | D. | | | ation | text | | | |
| | Performan | Santos | | | retriev | docum | | | |
| | ce" | 2, and | | | al, | ent | | | |
| | | Fernan | | | text | | | | |
| | | do Moura | | | learnin | | | | |
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| | "An | Yimin | Classific | Corpus, | KNN, | Text | Improve | This paper is a | for |
| 15 | evaluation | g | ation of | categoriza | LLSF | docum | Text | comparative study of text | improving |
| | of | Yang | text | tion | ,neural | ents, | | categorization methods. | documents' |
| | statistical | yiming | docume | methods | networ | previo | | Fourteen methods are | classification |
| | approache | @cs.c | nt | | k and | usly | | investigated, based on | performance. |
| | s to text | mu.ed | | | WOR | publis | | previously published | |
| | categoriza | u April | | | D, | hed | | results and newly | |
| | tion." | 10, | | | cross | results | | obtained results from | |
| | | 1997 | | | metho d | and newly | | additional experiments. Corpus biases in | |
| | | | | | evalua | obtain | | commonly used document | |
| | | | | | tion | ed | | collections are examined | |
| | | | | | tion | results | | using the performance of | |
| | | | | | | | | three classifiers. Problems | |
| | | | | | | | | in previously published | |
| | | | | | | | | experiments are analyzed, | |
| | | | | | | | | and the results of flawed | |
| | | | | | | | | experiments are excluded | |
| | | | | | | | | from the cross-method | |
| | | | | | | | | evaluation. As a result, | |
| | | | | | | | | eleven out of the fourteen | |
| | | | | | | | | methods are remained. A | |
| | | | | | | | | k-nearest neighbor (kNN) classifier was chosen for | |
| | | | | | | | | the performance baseline | |
| | | | | | | | | on several collections; on | |
| | | | | | | | | each collection, the | |
| | | | | | | | | performance scores of | |
| | | | | | | | | other methods were | |
| | | | | | | | | normalized using the | |
| | | | | | | | | score of kNN. This | |
| | | | | | | | | provides a common basis | |
| | | | | | | | | for a global observation | |

| 16 | Text categoriza tion based on Concept indexing and principal componen t analysis. | Ke H., Shaop ing M 2002 | They find that this algorith m can effective ly reduce dimensi onality without sacrifici ng categori zation accurac y. | salton | Conce pt indexi ng, princi ple comp onent analys is, Vsm,K NN,Ba ysean classifi er. | Text docum ent | Classified data on | on methods whose results are only available on individual collections. Windrow-Hoff, k-nearest neighbour, neural networks and the Linear Least Squares Fit mapping are the topperforming classifiers, while the Roccio approaches had relatively poor results compared to the other learning methods. KNN is the only learning method that has scaled to the full domain of MEDLINE categories, showing a graceful behaviour when the target space grows from the level of one hundred categories to a level of tens of thousands An Evaluation of Statistical Approaches to Text They uses the vector space model and feature selection of the text document is represented by a vector and all subsequent calculation based, many ML technology have been successfully applied to text categorization. Concept indexing is simple and effective way to reduce dimension. For effective in data compression and feature extraction we use PCA, they applied pca to ci subspace. | This method for put forwarded in the paper is meaningfull to online text categorisation, application of more machine learning. |
|----|---|--|--|--------------------|---|-----------------------------|--------------------|---|--|
| 17 | A Comparis on of Word- and Sense- based Text Categoriz ation | Kehag ias A., Petrid is V., Kabur lasos V., Fragk ou P | : (a) in compar ing the merit of words and senses as classifi cation | Wordnet lexical | MAP, ML,v erson space, KNN, Recur sive Versio n of the | Lexica l databa se | Classified data | They work with WordNet lexical database and distinction between the word and senses. It contains the large number of noun ,verb etc of English language .WordNet provide carefully worked out word and sense vocabularies for English | Nevertheless, in a practical classification task the senses would have to be obtained by a disambiguati on step which, in all probability, |

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|-----|---------------------|--------|--------------|-----------|---------|------|--------------|-------------------------------|----------------|
| | Using | 2003 | features | | MAP | | | language, as well as the | would |
| | Several | | and | | algorit | | | membership of each word | introduce a |
| | Classificat | | (b) in | | hm, | | | into a number of | significant |
| | ion | | testing | | Maxi | | | senses.the document they | error |
| | Algorithm | | several | | mum | | | have used in their text | |
| | S. | | classific | | Likeli | | | categorisation experiment | |
| | | | ation | | hood | | | use a subset of the brown | |
| | | | algorith | | (ML) | | | corpus .for document | |
| | | | ms on | | Classi | | | representation they used | |
| | | | the | | | | | 4 document | |
| | | | Brown | | ficatio | | | representation two are | |
| | | | Corpus | | n | | | word based and two are | |
| | | | | | | | | sense based. And classify | |
| | | | | | | | | algorithm uses are | |
| | | | | | | | | Maximum a posteriori | |
| | | | | | | | | (MAP) classification, | |
| | | | | | | | | batch version, recursive | |
| | | | | | | | | version of MAP | |
| | | | | | | | | algorithm, maximum | |
| | | | | | | | | Likelihood classification | |
| | | | | | | | | and FLNMAP with | |
| 17 | | B. | | Computat | Corpu | Text | Classified | voting. They first linguistic | This theory |
| 1 / | Automotio | | Thorr | ional | _ | data | data on | research on genre that | used in |
| | Automatic detection | Kessl | They propose | linguists | S | uata | basis of | uses quantitative method | application |
| | of text | er, G. | a theory | iniguists | logisti | | linguistics. | then identify the genres: | of genre |
| | genre. | Nunb | of | | C | | imgaistics. | genetic cues, these cues | classification |
| | genre. | erg, | genres | | Regre | | | that have figured | to tagging, |
| | | and | as | | ssion, | | | prominently in previously | summarizatio |
| | | H. | bundles | | Neura | | | work on genre.then | n. |
| | | Schut | of | | 1 | | | applied method like | |
| | | ze. | facets, | | Netw | | | corpus, logistic | |
| | | | which | | ork, | | | Regression, Neural | |
| | | | correlate | | | | | Network. For each genre | |
| | | | with | | | | | facet, it compare our | |
| | | 1997 | various | | | | | result using surface cues. | |
| | | | surface | | | | | _ | |
| | | | cues, | | | | | | |
| | | | and | | | | | | |
| | | | argue | | | | | | |
| | | | that | | | | | | |
| | | | genre | | | | | | |
| | | | detectio | | | | | | |
| | | | n based | | | | | | |
| | | | on | | | | | | |
| | | | surface | | | | | | |
| | | | cues is | | | | | | |
| | | | as | | | | | | |
| | | | successf | | | | | | |
| | | | ul as | | | | | | |
| | | | detectio | | | | | | |
| | | | n based | | | | | | |
| | | | on | | | | | | |
| | | | deeper | | | | | | |

| | | | structura | | | | | | |
|----|----------------|--------|-----------------|----------|---------|-------|---------------|---|-------------------------|
| | | | 1 | | | | | | |
| | | | properti | | | | | | |
| | | | es. | | | | | | |
| 19 | | Karl- | In this | Search | Rule | Text | Classified | Here they used text | The main |
| | Technique | Micha | they | engine, | induct | docum | clustered | document data then then | contribution |
| | s for | el | demonst | web | ion, | ent | document | classifying these data by | of this paper |
| | Improving | Schne | rate that | kernel | Naïve | | | the help of naïve bays | is our novel |
| | the | ider | simple | | bays, | | | classifier, in these | feature |
| | Performan | | modific | | decisi | | | Bayesian text | scoring |
| | ce of Naive | 2002 | ation are | | on | | | classification uses a | function, which is able |
| | Bayes for | | able to improve | | tree,su | | | parametric mixture model to model the generation of | to distinguish |
| | Text | | the | | pport | | | document.to make the | features that |
| | Classificat | | perform | | vectr | | | estimation of parameters | improve the |
| | ion | | ance of | | machi | | | tractable, we make the | clustering of |
| | | | Naïve | | ne, | | | Naïve Bayes assumption | the training |
| | | | Bayes | | cluste | | | that the basic units are | documents |
| | | | for text | | ring | | | distributed independently. | (and thus are |
| | | | classific | | Img | | | For the highly | useful for |
| | | | ation | | | | | classification accuracy | classification |
| | | | significa | | | | | than binary independence |) from |
| | | | ntly. | | | | | model on text document | features that |
| | | | | | | | | because it model word | degrade the |
| | | | | | | | | occurrence frequency one | clustering |
| | | | | | | | | can see that for longer | quality (and |
| | | | | | | | | document the | thus should |
| | | | | | | | | classification scores | be removed) |
| | | | | | | | | dominated by the word | |
| | | | | | | | | probabilities and the | |
| | | | | | | | | probabilities hardly affect the classification. Feature | |
| | | | | | | | | selection is commonly | |
| | | | | | | | | regarded as a nessarry | |
| | | | | | | | | step in text classification. | |
| | | | | | | | | By taking logarithms and | |
| | | | | | | | | dividing by the length of a | |
| | | | | | | | | document, instead of | |
| | | | | | | | | multiplying conditional | |
| | | | | | | | | probabilities they | |
| | | | | | | | | calculate their geometric | |
| | | | | | | | | mean and thus account for | |
| | | | | | | | | the impact of wrong | |
| | | | | | | | | independence | |
| | | | | | | | | assumptions under | |
| | | | | | | | | varying document | |
| | | | | | | | | lengths. Furthermore, by | |
| | | | | | | | | adding the entropy of (the | |
| | | | | | | | | probability distribution | |
| | | | | | | | | induced by) the | |
| | | | | | | | | document, we account for | |
| | | | | | | | | varying document complexities. | |
| 20 | | Klopo | . The | Natural | ETC | Large | Classificati | In these work they used | empirical |
| | Very | Ixiopo | paper | language | | data | on of input | ETC described in details, | evaluation of |
| Ц | · J | 1 | Labor | 154450 | 1 | | 311 31 IIIput | _ = 1 C CCCCTTCCC III details , | 3.22344311 01 |

| T + | | T | ı . | 1 | 111 | | | |
|-------------|--------|-----------|-----------|----------|--------|-------------|--|-------------|
| Large | tek M. | presents | possessin | algorit | like | large data. | it constructs a tree-like | a Bayesian |
| Bayesian | and | results | g task. | hm, | search | | Bayesian network but | multinet |
| Networks | Woch | of | | naïve | engine | | contrary to the Chow/Liu | classifier |
| in Text | M. | empirica | | bays | , | | algorithm it does not | based on a |
| Classificat | | 1 | | classif | langua | | need to compare all | new method |
| ion | | evaluati | | ier, e | ge | | variables with each other | of learning |
| | | on of a | | Chow | text, | | so that it saves much | very large |
| | | Bayesia | | | petent | | calculations of so-called | tree-like |
| | | n | | /Liu | databa | | DEP-measure. They | Bayesian |
| | | multinet | | algorit | ses. | | estimate also the fitness of | network |
| | | classifie | | hm | | | ETC to the data bye | |
| | | r based | | | | | determining the log | |
| | | on a | | | | | likelihood for the | |
| | | new | | | | | artificial test and test data. | |
| | | method | | | | | The goal was to check the | |
| | | of | | | | | quality of the structure of | |
| | | learning | | | | | a Bayesian network | |
| | | very | | | | | obtained using ETC | |
| | | large | | | | | algorithm for various | |
| | | tree-like | | | | | DEP functions. Then they | |
| | | Bayesia | | | | | compared ETC based | |
| | | n | | | | | multi-net classifier | |
| | | network | | | | | accuracy with Naive | |
| | | S | | | | | Bayes accuracy (NB). On | |
| | | | | | | | the one hand, though NB | |
| | | | | | | | is not a particularly good | |
| | | | | | | | one, it scales quite well | |
| | | | | | | | for tasks with dozens of | |
| | | | | | | | thousands of attributes, | |
| | | | | | | | ETC exhibits a bit higher | |
| | | | | | | | stability than NB. | |
| | | | | | | | Standard error values are | |
| | | | | | | | usually slightly lower | |
| | | | | | | | than those for NB | |
| | | | | | | | classifier, though the | |
| | | | | | | | differences are not | |
| | | | | | | | striking. It turns out that | |
| | | | | | | | in spite of the possibility | |
| | | | | | | | of generation of different | |
| | | | | | | | trees in case of different | |
| | | | | | | | sequences of variables the | |
| | | | | | | | quality of the Bayesian | |
| | | | | | | | networks obtained is | |
| | | | | | | | similar they also | |
| | | | | | | | investigated the | |
| | | | | | | | complexity of ETC is | |
| | | | | | | | nlog(N) .then they reduce | |
| | | | | | | | the ETC complexity, the | |
| | | | | | | | popular words should be removed from the | |
| | | | | | | | | |
| | | | | | | | dictionary. But in some | |
| | | | | | | | cases this may deteriorate | |
| | | | | | | | the accuracy of the classification. | |
| | | | | <u> </u> | | | Classification. | |