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An Efficient,Effective and High Probability Clustering Based Algorithm For Feature Selection

Niharika Ankam
B.Tech Student,
Department of CSE,
TKR College of Engineering & Technology.

Pravallika Boddu
B.Tech Student,
Department of CSE,
TKR College of Engineering & Technology.

Vinay Chary Cholleti
B.Tech Student,
Department of CSE,
TKR College of Engineering & Technology.

Mr.China Paga.Ravi
Associate.Professor,
Department of CSE,
TKR College of Engineering & Technology.

Abstract:

In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features for use in model construction. The central assumption when using a feature selection technique is that the data contains many redundant or irrelevant features. Redundant features are those which provide no more information than the currently selected features, and irrelevant features provide no useful information in any context. Feature subset clustering is a powerful technique to reduce the dimensionality of feature vectors for text classification.

In this paper, we propose a similarity-based self-constructing algorithm for feature clustering with the help of K-Means strategy. The words in the feature vector of a document set are grouped into clusters, based on similarity test. Words that are similar to each other are grouped into the same cluster, and make a head to each cluster data sets. By the FAST algorithm, the derived membership functions match closely with and describe properly the real distribution of the training data. Besides, the user need not specify the number of extracted features in advance, and trial-and-error for determining the appropriate number of extracted features can then be avoided. Experimental results show that our FAST algorithm implementation can run faster and obtain better-extracted features than other methods

Keywords:

Feature selection, Subset, K-Means, FAST, Clustering, Redundant data, Text classification, Rule mining.

Introduction:

Feature selection techniques are a subset of the more general field of feature extraction. Feature extraction creates new features from functions of the original features, whereas feature selection returns a subset of the features. Feature selection techniques are often used in domains where there are many features and comparatively few samples (or data points).

The archetypal case is the use of feature selection in analysing DNA microarrays, where there are many thousands of features, and a few tens to hundreds of samples. Feature selection techniques provide three main benefits when constructing predictive models:

- improved model interpretability,
- shorter training times,
- enhanced generalisation by reducing overfitting.

Feature selection is also useful as part of the data analysis process, as it shows which features are important for prediction, and how these features are related.

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Subset selection:

Subset selection evaluates a subset of features as a group for suitability. Subset selection algorithms can be broken up into Wrappers, Filters and Embedded. Wrappers use a search algorithm to search through the space of possible features and evaluate each subset by running a model on the subset. Wrappers can be computationally expensive and have a risk of over fitting to the model. Filters are similar to Wrappers in the search approach, but instead of evaluating against a model, a simpler filter is evaluated.

Embedded techniques are embedded in and specific to a model.Many popular search approaches use greedy hill climbing, which iteratively evaluates a candidate subset of features, then modifies the subset and evaluates if the new subset is an improvement over the old. Evaluation of the subsets requires a scoring metric that grades a subset of features. Exhaustive search is generally impractical, so at some implementor (or operator) defined stopping point, the subset of features with the highest score discovered up to that point is selected as the satisfactory feature subset.

The stopping criterion varies by algorithm; possible criteria include: a subset score exceeds a threshold, a program's maximum allowed run time has been surpassed, etc.Alternative search-based techniques are based on targeted projection pursuit which finds low-dimensional projections of the data that score highly: the features that have the largest projections in the lower-dimensional space are then selected.

Search approaches include:

- Exhaustive
- Best first
- Simulated annealing
- Genetic algorithm
- Greedy forward selection
- Greedy backward elimination
- Targeted projection pursuit
- Scatter Search
- Variable Neighborhood Search

Two popular filter metrics for classification problems are correlation and mutual information, although neither are true metrics or 'distance measures' in the mathematical sense, since they fail to obey the triangle inequality and thus do not compute any actual 'distance' – they should rather be regarded as 'scores'. These scores are computed between a candidate feature (or set of features) and the desired output category.

The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The actual data mining task is the automatic or semi-automatic analysis of large quantities of data to extract previously unknown interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection) and dependencies (association rule mining). This usually involves using database techniques such as spatial indices. These patterns can then be seen as a kind of summary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics.

For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting are part of the data mining step, but do belong to the overall KDD process as additional steps.

The related terms data dredging, data fishing, and data snooping refer to the use of data mining methods to sample parts of a larger population data set that are (or may be) too small for reliable statistical inferences to be made about the validity of any patterns discovered. These methods can, however, be used in creating new hypotheses to test against the larger data populations.

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Data mining involves six common classes of tasks:

Anomaly detection (Outlier/change/deviation detection) – The identification of unusual data records, that might be interesting or data errors that require further investigation.

Association rule learning (Dependency modeling) – Searches for relationships between variables. For example a supermarket might gather data on customer purchasing habits. Using association rule learning, the supermarket can determine which products are frequently bought together and use this information for marketing purposes. This is sometimes referred to as market basket analysis.

Clustering – is the task of discovering groups and structures in the data that are in some way or another "similar", without using known structures in the data.

Classification – is the task of generalizing known structure to apply to new data. For example, an e-mail program might attempt to classify an e-mail as "legitimate" or as "spam".

Regression – attempts to find a function which models the data with the least error.

Summarization – providing a more compact representation of the data set, including visualization and report generation.

Existing System:

The embedded methods incorporate feature selection as a part of the training process and are usually specific to given learning algorithms, and therefore may be more efficient than the other three categories. Traditional machine learning algorithms like decision trees or artificial neural networks are examples of embedded approaches. The wrapper methods use the predictive accuracy of a predetermined learning algorithm to determine the goodness of the selected subsets, the accuracy of the learning algorithms is usually high. However, the generality of the selected features is limited and the computational complexity is large.

The filter methods are independent of learning algorithms, with good generality. Their computational complexity is low, but the accuracy of the learning algorithms is not guaranteed. The hybrid methods are a combination of filter and wrapper methods by using a filter method to reduce search space that will be considered by the subsequent wrapper. They mainly focus on combining filter and wrapper methods to achieve the best possible performance with a particular learning algorithm with similar time complexity of the filter methods.

Disadvantages:

1.The generality of the selected features is limited and the computational complexity is large.

2.Their computational complexity is low, but the accuracy of the learning algorithms is not guaranteed.

Proposed System:

Feature subset selection can be viewed as the process of identifying and removing as many irrelevant and redundant features as possible. This is because irrelevant features do not contribute to the predictive accuracy and redundant features do not redound to getting a better predictor for that they provide mostly information which is already present in other feature(s). Of the many feature subset selection algorithms, some can effectively eliminate irrelevant features but fail to handle redundant features yet some of others can eliminate the irrelevant while taking care of the redundant features. Our proposed FAST algorithm falls into the second group. Traditionally, feature subset selection research has focused on searching for relevant features.

A well-known example is Relief which weighs each feature according to its ability to discriminate instances under different targets based on distance-based criteria function. However, Relief is ineffective at removing redundant features as two predictive but highly correlated features are likely both to be highly weighted. Relief-F extends Relief, enabling this method to work with noisy and incomplete data sets and to deal with multiclass problems, but still cannot identify redundant features.

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Advantages:

1. Good feature subsets contain features highly correlated with (predictive of) the class, yet uncorrelated with each other.

2.The efficiently and effectively deal with both irrelevant and redundant features, and obtain a good feature subset.

Scope :

We main aim of this project is Get the Search Details Very fastly and Accurasly.Traditionally, feature subset selection research has focused on searching for relevant features. A well known example is Relief , which weighs each feature according to its ability to discriminate instances under different targets based on distance-based criteria function. However, Relief is ineffective at removing redundant features as two predictive but highly correlated features are likely both to be highly weighted. extends Relief, enabling this method to work with noisy and incomplete data sets and to deal with multi-class problems, but still cannot identify redundant features.

Implementation:

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective.The implementation stage involves careful planning, investigation of the existing system and it's constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

Main Modules:

1.User Module :

In this module, Users are having authentication and security to access the detail which is presented in the ontology system. Before accessing or searching the details user should have the account in that otherwise they should register first.

2.Distributed Clustering :

The Distributional clustering has been used to cluster words into groups based either on their participation in particular grammatical relations with other words by Pereira et al. or on the distribution of class labels associated with each word by Baker and McCallum .

As distributional clustering of words are agglomerative in nature, and result in suboptimal word clusters and high computational cost, proposed a new information-theoretic divisive algorithm for word clustering and applied it to text classification. proposed to cluster features using a special metric of distance, and then makes use of the of the resulting cluster hierarchy to choose the most relevant attributes.

Unfortunately, the cluster evaluation measure based on distance does not identify a feature subset that allows the classifiers to improve their original performance accuracy.Furthermore, even compared with other feature selection methods, the obtained accuracy is lower.

3.Subset Selection Algorithm:

The Irrelevant features, along with redundant features, severely affect the accuracy of the learning machines. Thus, feature subset selection should be able to identify and remove as much of the irrelevant and redundant information as possible. Moreover, "good feature subsets contain features highly correlated with (predictive of) the class, yet uncorrelated with (not predictive of) each other. Keeping these in mind, we develop a novel algorithm which can efficiently and effectively deal with both irrelevant and redundant features, and obtain a good feature subset.

4.Time Complexity :

The major amount of work for Algorithm 1 involves the computation of SU values for TR relevance and F-Correlation, which has linear complexity in terms of the number of instances in a given data set. The first part of the algorithm has a linear time complexity in terms of the number of features m. Assuming features are selected as relevant ones in the first part, when k ¼ only one feature is selected.

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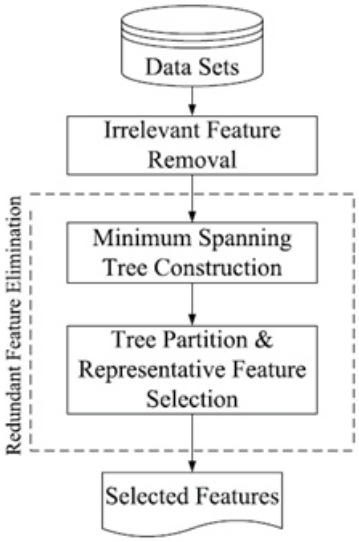
Architecture :



Conclusion:

For the entire Fast algorithm in hands with association rule implementation gives flexible results to users, like removing irrelevant features from the Original Subset, and constructing a minimum spanning tree from the relative subset whatever present in the data store. By partitioning the minimum spanning tree we can easily identify the text representation from the features. Association Rule Mining gives ultimate data set with header representation as well as FAST algorithm with applied K-Means strategy provides efficient data management and faster performance. The revealing regulation set is significantly smaller than the association rule set, in particular when the minimum support is small. The proposed work has characterized the associations between the revealing regulation set and the non-redundant association rule set, and discovered that the enlightening regulation set is a subset of the non-redundant association rule set.

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