Automatic Classification of Accounting Literature

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Abstract: Literature taxonomization is a key element of understanding the knowledge about disciplines. The procedure traditionally used for this classification effort entails a set of manual processes that can be very time consuming and may lead to inconsistent classification. This paper explores the possibilities of using semantic parsing, information retrieval and data mining techniques to develop a methodology for automatic classification of academic articles in accounting based on different criteria. A two-phase experimentation on automatic classification processes has been done in the area of "Treatment", "Accounting Area" and "Mode of Reasoning" (Vasarhelyi et al. 1984, 1988, Brown and Vasarhelyi 1985, Brown et al. 1987). The results from the first phase indicate that using only keywords for classification of accounting literature is not effective. Findings from the second phase indicate that using the full abstract for classification is more successful than using only the keywords. The best results are obtained by using Complement Naïve Bayes (CNB) and Evolving Non-Determinism (END) algorithms which provide accuracy at 81.67%. We discuss the potential path for this preliminary research that seems to be very promising and have several collateral benefits and applications.

I Introduction and Background

Overview

The purpose of this study is to develop a methodology for automatically classifying academic publication texts. The literature taxonomization process has been a critical element for understanding the development and evolution of knowledge and research areas in various disciplines (Brown et al. 1987, 1989, Vasarhelyi et al. 1988, Brinberg and Shields 1989, Meyer and Rigsby 2001, Heck and Jensen 2007). Traditionally, the taxonomization performed in this branch of research has been performed manually (Vasarhelyi et al. 1984, Brown et al. 1985, 1989, and Badua 2005).

As online databases for academic publications expand, the appropriateness of the methodology applied in investigating the nature, attributes and development of academic research contribution has been challenged and encountered potential limitations due to its relatively time-consuming process and the possibility of inconsistent classification results (Nobata 1999). Literature in the Information Science discipline has reported that the emergence and popularize of online academic databases indicates the existing challenges encountered by professionals to access information in a timely and efficient form (Nobata 1999). These difficulties, however, can be addressed and most likely resolved by developing a methodology that automatically classifies and tags publications.

This paper builds on the literature by exploring the possibilities of using information retrieval and data mining techniques to develop a methodology to achieve consistent and efficient classification results for academic articles. Specifically, the "Treatment", "Accounting Area" and "Mode of Reasoning" taxons, three of the twelve taxonomic categories founded in the Rutgers University Accounting Research Database have been adopted in the preliminary analysis for automating the article classification process. Treatment taxon identifies the major factor or other accounting phenomenon associated with the information content of the research article, e.g. the main predictor variable in the regression model of an empirical study falls under the treatment taxon. Accounting area identifies the major accounting field under which this paper falls, and Mode of Reasoning identifies the technique used to formally arrive at the conclusions of the study, either by quantitative or qualitative analysis (Vasarhelyi 1984, 1988, Badua 2005).

This article is the initial study that adopts automatic classification method in categorizing accounting literature by the taxonomy classes developed in prior research (Brown et al. 1985, Vasarhelyi and Berk 1984). Our results contribute to both the accounting and accounting information system literature by improving the research methodology applied in areas that analyzes accounting literature development and evolution and extends the usefulness of automatic text classification methods in the literature.

Motivation and Research Questions

In attempt to cope with the challenges and improve potential limitations (e.g. time-consuming process and ineffective classification results) encountered in manually performed literature research taxonomization, a better developed automatic classification method of information retrieval and data mining techniques is needed. This study aims to assist the entire classification literature process and approaches the objective by analyzing the keywords and abstracts of articles while comparing the automatic classification results under different data mining approaches at the end. The following are our e three main research questions 1) Can we automate the classification process (of accounting literature) using only keywords from academic journal articles? 2) Can we automate the classification process (of accounting literature) using the abstracts of academic journal articles? 3) Do results vary depending on which elements we use to automate the literature classification process and to what extent do they differ?

The next section of this study reviews prior research that performs either manual or automatic classification techniques and then leads to our experiment and adopted methodology. The latter part of this study discusses our analyses, results and conclusions.

II Prior Research

Literature on Accounting Studies Classification-The Manual Method

The scope of accounting research has expanded in many ways. There is a stream of accounting research that examines the characteristics and contribution of published accounting articles within a certain time period for either a particular journal, a specific accounting area or multiple accounting journals that represent accounting research as a whole.

Studies in this area typically perform publication and content analysis in a traditional approach, i.e., manually collecting and classifying the accounting articles that represents the main and core knowledge of the accounting discipline to better understand the nature and attributes of the development of accounting research. The following discusses the secondary review studies that have involved manual research and analysis. Chatfield (1975) studied the historical research development process in the first fifty years of *The Accounting Review* and according to his analysis there exist four distinct stages of the evolution of articles published in TAR. Dyckman and Zeff (1984) researched on the contribution of Journal of Accounting Research (JAR) within 1963 to 1982 and showed that publication in JAR improved the development of empirical studies in accounting, especially in capital markets and behavioral research areas. Brown, Gardner and Vasarhelyi (1987) studied the research contributions of Accounting, Organizations and Society (AOS) between 1976 and 1984 by applying classification and citation analysis methods to evaluate whether AOS has achieved its research objectives. Their findings suggest that AOS draws substantially more of its research from psychology, multiple-disciplinary, management and sociology/political science than TAR or JAR and that AOS achieved its aims and scope while acting as a complement outlet for research involving the international, behavioral, organizational and social aspects of accounting. A more recent article by Heck and Jensen (2007) focused on the evolution of research contributions made by TAR between year 1926 and 2005. They illustrated the research evolution in various aspects including research methods, accounting topics, authorship, as well as the accounting practice issues that influence academia research.

There also exist several studies that perform manual classification of articles in specific subcategories or a certain school of thought in accounting research. Ijiri, Kinard and Putney (1968) surveyed the budgeting literature and classified articles in that area. Felix and Kinney (1982) surveyed the audit literature. Hofstedt (1975, 1976) classified behavioral accounting research. Research methods and content in Behavioral Accounting Research were also studied by Meyer and Rigsby (2001), who focused on the content, research methods, and contributors by applying both the taxonomies developed by Birnberg and Shields (1989) and citation analysis method for the first ten years of BRIA (1989- 1998).

Gonedes and Dopuch(1974) focused on manually classifying articles based on research methodology. Ashton (1982) and Libby and Lewis (1977, 1982) have reviewed the information processing literature and while Ball (1971) and Hakansson (1973) have surveyed the empirical research literature. Vasarhelyi (1988) researched four taxonomies: foundation discipline, school of thought, research methods, and mode of reasoning and examines journals for article publication frequency, dominant taxonomies and trends within those taxonomies. Sampling a similar time period, Fleming, Graci, and Thompson (2000) examined the evolution of accounting publications by analyzing the research methods, financial accounting subtopics, citation analyses, length, and author background in The Accounting Review (TAR) between 1966 and 1985 and also provided a comparison of results with two additional periods 1926-1945 and 1946-1965.

Four attribute dimensions of accounting studies were explored and analyzed in another study by Brown, Gardner and Vasarhelyi (1989). The study performed manual classification, publication counts and citation analyses for over 1100 accounting articles, focusing on attributes including accounting area, research method, school of thought, and geographic focus that have impacted contemporary accounting literature (AOS, TAR, JAE, and JAR) from 1976 to 1984. The level of publication and impact along the attribute dimensions were also predicted and results suggested that the importance of publications can be predicted with considerable more success than the relative amount of future publication in an attribute area and that papers published in new areas tend to be more influential than papers published in the established areas. In summary, the aforementioned surveys involved manual literature classification processes and concentrated on a variety of aspects of accounting research. Studies on the automatic classification process of accounting publication has been largely absent from the literature which providing an opportunity for this study to exploring this research branch.

Development of Taxonomy Classes

The taxons used for preliminary automatic classification analysis including "Treatment", "Accounting Area", and "Mode of Reasoning" were developed by Vasarhelyi and Berk (1984). Several follow up studies evolved the taxonomy classes and enlarged the scope of research, for example, Badua (2005) examined the development of accounting thought by summarizing 12 taxonomic and citation characteristics of several major accounting journals and developing an evaluative metric to analyze the contribution to accounting research from each paradigm. The Accounting Research Directory (ARD) contains classification results for twelve accounting journals within 1963 to 1993 by adopting the taxonomy classes.

According to Vasarhelyi (1988) and Badua (2005), the 12 taxonomy classes include Research Method, Inference Style, Mode of Reasoning, Mode of Analysis, School of Thought, Information, Treatment, Accounting Area, Geography, Objective, Applicability and Foundation Discipline. Each of these 12 classes contains several subclasses (see Appendix I), the following elaborates the detail definition of all classes as in ARD and Badua (2005).

1. Research Method- identifies which type of study underlies the research article. There are three main areas: analytical, archival, and empirical. Analytical studies apply either internal logic or simulations. Archival studies utilize sources either from primary or secondary records. Empirical studies can be carried out as case, field, lab experiments or opinion surveys.

2. Mode of Reasoning- identifies the technique used to formally arrive at the conclusions of the study, either by quantitative or qualitative analysis. The quantitative subcategory includes various items, e.g. descriptive statistics, regression, ANOVA, factor analysis, non-parametric, correlations, and analytical.

The major contribution of this paper is the development of a methodology for automatically classifying academic accounting articles. The technique of automatically classifying text or information retrieval have been developing in information science research areas but has not yet been adopted for categorizing academic publications very successfully. The following reviews literature on automatic classification methods. Crawford (1979) used all of the documents that contain a given term to represent the environment in which the term was used. Crouch (1990) developed a method of automatic thesaurus construction based on the term discrimination value model. Both Crouch (1990) and

3. School of Thought- indicates which major area of accounting research the article contributes to. Major areas include behavioral, statistical modeling, accounting theory, accounting history, institutional, agency theory, and expert systems.

4. Information- identifies the accounting phenomenon and content the research is trying to address. If the article includes an empirical study, the information taxon will likely be the dependent variable in the regression model. Major subcategories are financial statements, internal information, external information, and market based information.

5. Treatment- identifies the major factor or other accounting phenomenon associated with or causes the information taxon. The treatment taxon will be the main predictor variable in the regression model in an empirical study. Main subcategories are financial accounting methods, auditing, managerial and other.

6. Accounting Area- identifies the major accounting field under which this paper falls. The major fields are tax, financial, managerial, audit, and information systems.

7. Geography- differentiates whether the geographic context is US, non-US, or both.

8. Objective- indicates the type of business entity examined in the study: profit, not-for-profit, regulated, or all of the above.

9. Foundation Discipline- identifies the underlying academic area that the research is based upon. Disciplines include psychology, sociology, political science, philosophy, economics and finance, engineering, mathematics, statistics, law, accounting and management.

The three remaining taxons are the inference style, mode of analysis, and applicability, which identify whether there are hypotheses tested in the research, differentiate normative and descriptive studies, and indicate the applicable term (immediate, medium, and long term) of the studies, respectively.

Literature on Accounting Studies Classification-The Automatic Method

Crouch and Yang (1992) showed that automatic classification method produces useful thesaurus classes which improves information retrieval when used to supplement query terms. Chen and Lynch (1992) applied algorithmic approaches to the generation of a concept network and Chen, Yim, & Fye (1995) used this approach to automatically generate a thesaurus and to evaluate it for the Worm Community System (WCS).

Similar techniques were created for domain-specific thesaurus for Drosophilia information (Chen, Schatz, Martinez, and Ng 1994) and for computing a knowledge base for Worm classification system (Chen and Lynch 1992). A more recent study by Wu and

Gangolly (2000) researched on the feasibility of automatically classifying financial accounting concepts. They statistical analyzed the frequencies of terms in financial accounting standards and decreased the dataset dimensionality via principal components analysis method. Clusters of concepts are then derived by the agglomerative nesting algorithm.

Nobata (1999) explores the identification and classification of biology terms by applying generalizable information extraction methods to the 100 biological abstracts from MEDLINE. The specific techniques adopted for classifying the terms include statistical and decision tree method. The techniques used for term candidate identification are shallow parsing, decision trees, and statistical identification methods. The study found that utilizing statistical and decision tree methods for automating the classification process based on wordlists provide results that vary and with its own strengths for different term class types which suggest the need for future studies on refining the applied algorithms for automating the classification process to achieve more accurate results.

While there has clearly been development of automatic text classification method in the information science literature, the method has seems limited expansion to accounting or accounting information system literature. The objective of achieving an effective output of research results is still under progress, providing opportunity for this study to fill the gap and make initial contribution in this research area.

III Methodology

Sample Collection

Three hundred and fifty eight articles published in accounting journals were downloaded manually, the following details the data collection and filtering processes. Articles were collected from different journals as shown in table 1. Among the three hundred fifty eight articles, only one hundred and eighty six were used in the first phase of keywords classification process due to the unavailability of keywords for the remaining articles. In the second phase of analysis, full abstracts of accounting articles were collected from both Business Resource Premier and the Social Science Research Network databases via Rutgers University's online library and three hundred and fifty six articles were utilized for analysis.

Table 1: Selected Accounting Journals for Articles Collection

Journals used for Articles Collection	
AOS	Accounting, Organizations and Society
AUD	Auditing: A Journal of Practice and Theory
CAR	Contemporary Accounting Research
TAR	The Accounting Review
JAAF	Journal of Accounting, Auditing and Finance
JAE	Journal of Accounting and Economics
JAPP	Journal of Accounting and Public Policy
JAR	Journal of Accounting Research
JETA	Journal of Emerging Technologies in Accounting
JIS	Journal of Information Systems

The Two-Phase Experiment of Automatic Literature Classification

The automatic classification experiment contains two main phases (Figure 1), Phase I uses the keywords for analysis, while Phase II utilizes the full abstract of collected academic articles.

The first step in the automatic classification process was to develop a parsing tool which could be used to extract keywords from the articles in the first phase and extract full abstract for the second phase of analysis. Parsing is a technique that has been developed in the linguistic and computer science literature to analyze the given text by reasoning out the grammatical structure applied in the text, also known as 'syntactic analysis.' In terms of performing language analysis, which is part of the Natural Language Processing (NLP) along with information retrieval and machine translation, Semantic Parsing is a method to serve this objective. Parsing function also allows one to create customized language for specific objectives.

Prior to performing the data mining process, we applied the semantic parsing technique to the collected academic accounting articles in the two-phase experiment. To eliminate unwanted words, a combination of two stop words list is used. The function of a stop word list is to eliminate frequently occurring words that do not have any semantic bearing. The first stop word list contains 571 words and was built by Gerard Salton and Chris Buckley for the experimental SMART information retrieval system at Cornell University The second stop word list was obtained from the Onix Text Retrieval Toolkit. Table 2 provides examples of the words used for the experiment.

After eliminating the stop words a word count is done on the remaining list of words. This essentially shows how many times a particular word or a phase occurs in a particular journal article. Following this we calculate the term frequencies. Term frequency signifies in how many journals a certain word or phrase occurs out of the full list of journal articles. Finally a document-term matrix is created using the term frequency data as a reference point. A document-term matrix is a mathematical matrix that describes the frequency of terms that occur in a collection of documents. In a document-term matrix, rows correspond to documents in the collection and columns correspond to terms.

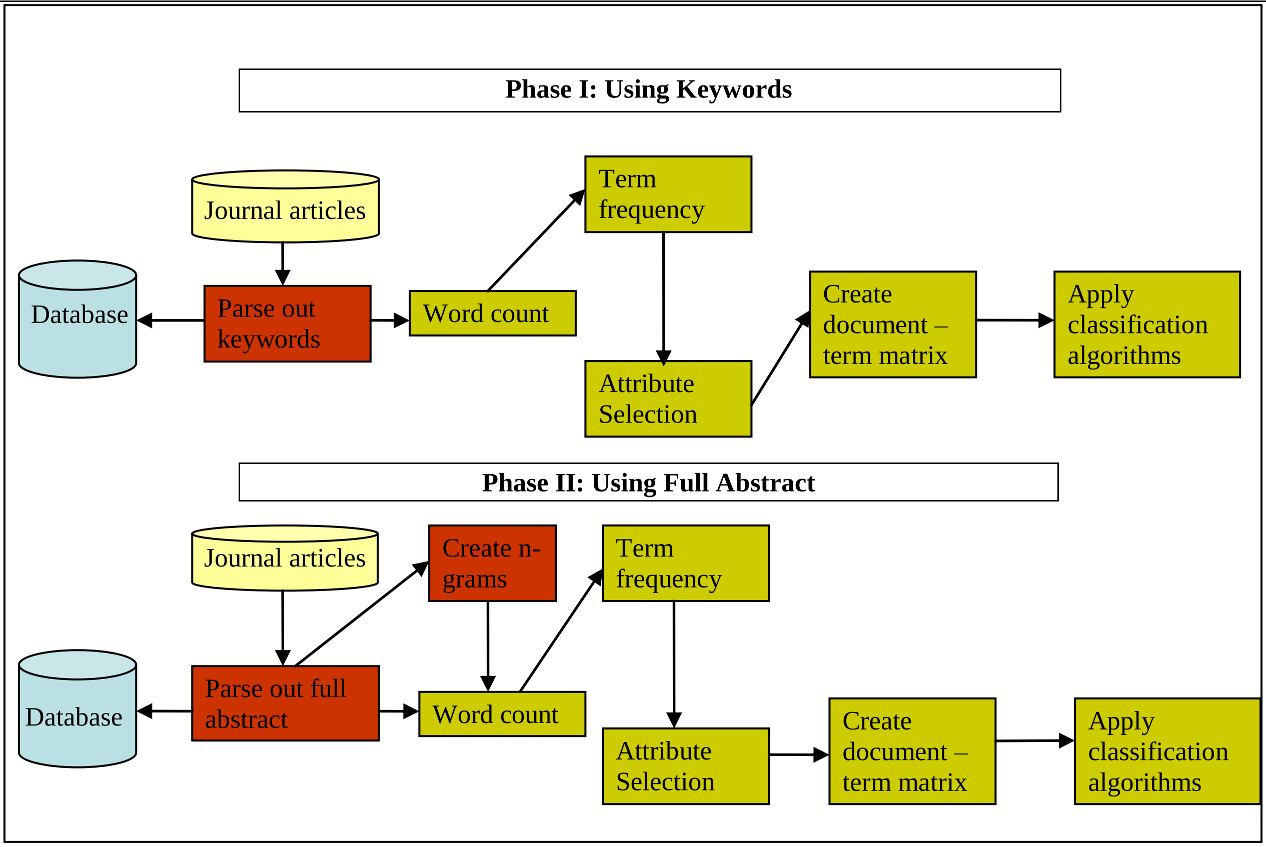

Figure 1: Two-Phase Experiment Process Diagram. The First Phase uses Keywords and the Second Phase uses the Full Abstracts of all Collected Articles.

Table 2: Examples of Keywords used for Treatment Taxon Classification

Treatment Classes	**Examples of Words from Full Abstracts**
Auditing	CLIENT ACCEPTANCE, AUDIT PARTNERS, HYPOTHESIS GENERATION, AUDIT-SCOPE.
Managerial	DECISION MAKING, MEASURE, COMPARE, EFFICIENCY, EVALUATION.
Financial	MARKET REACTIONS, NEWS, SPECULATION, ACCRUALS.

Treatment Classes	**Examples of Keywords**
Auditing	AUDITOR INDEPENDENCE, RISK EVALUTION, RISK ADAPTATION, COST OF CONTINUOUS AUDITS, MATERIALITY.
Managerial	DECISION PERFORMANCE, INCENTIVES COMPENSATION, MENTAL MODELS, PERFORMANCE MEASUSURES.
Financial	RESIDUAL INCOME VALUATION MODEL, ECONOMIC RENTS, EARNINGS EXPECTATIONS.

Fig.2 is an example of a document-term matrix. The first column “File” is the number of the journal article. The column headings from the second column onward show the words that occur in different journal articles. Each cell in the matrix indicates how many times a certain word occurred in a document. For example the word “materiality” occurs two times in the document named 31.txt

File	Residual Income	Audit-scope	Materiality	Performance Measure
31.txt	6	2	2	1
1400.txt	3	0	2	0
6732.txt	4	0	2	0
8902.txt	0	3	2	1
4569.txt	3	0	0	2
8726.txt	0	4	0	1
7239.txt	7	1	0	0
543.txt	4	1	2	3

Figure 2 An Example of Document-term Matrix

In the final step data mining algorithms are applied to this document-term matrix. Four broad categories of data mining algorithms have been used. There are supervised learning algorithms, rule based classifiers, decision trees and some other miscellaneous algorithms. A detailed list of the different algorithms used and corresponding results are shown in Appendix II.

As shown in Fig. 1 the basic steps for Phase I and Phase II are identical. However in case of Phase II the full abstract is extracted whereas in case of Phase I only the keywords are extracted. Following the extraction of words from the full abstract word bi-grams and tri-grams are created with the objective of creating meaningful phrases that are being used in the articles. The steps that follow are essentially the same as in Phase II. A count of the phases, frequency of the phrases followed by creation of the document-term matrix and finally applying data mining algorithms to the document-term matrix complete the whole procedure.

Validation and Taxonomy Classes

The validation process for the experiment was carried out by using 1) a five-fold cross validation and 2) a 66% keywords split for the training set and the remaining 37% for the test dataset. The five-fold cross validation first divides the keywords and abstracts into five subsets and then uses one subset as test set while the other subsets as training sets altogether. This process will then continue by using the second subset as test set and the remaining ones as training set repetitively for five times.

The specific taxons used in this study to automate the literature classification process are the "Treatment", "Accounting Area" and the "Mode of Reasoning" taxons. The "Treatment" taxon include financial accounting, auditing, and managerial subcategories and identifies the major factor or accounting phenomenon associated with the information content of the research article (Vasarhelyi 1984, 1988, Badua 2005), e.g. the main predictor variable in the regression model of an empirical study will be classified under the treatment taxon. The "Accounting Area" taxon contains subcategories as tax, financial, managerial, audit, and information systems. This taxon categorizes the major accounting field that an article belongs to. The "Mode of Reasoning" taxon identifies the technique used to formally arrive at the conclusions of the article, the technique used is either by quantitative or qualitative analysis.

The next section discusses the automatic classification results of our two-phase experiment for the aforementioned three taxons.

IV Results

Analysis of Treatment Taxon

Phase I: Keywords Analysis with all Subclasses

This section demonstrates the automatic classification results of four data mining algorithms of analysis including supervised learning, decision trees, rule-based classifiers, and o. Table 3 shows the results for using only keywords for classification. Detailed results can be seen in Table of Appendix III. Of the four classification methods, applying Complement Naïve Bayes algorithm belonging to the supervised learning method gives the highest level of classification accuracy (51.43%) followed by Ridor algorithm (49.65%), a rule based classifier method. Results of applying decision trees and other miscellaneous algorithms indicate that the SimpleCart algorithm (47.86%) and the Classification Via Regression algorithm (45%) appear to provide the most accurate level of classification among other miscellaneous algorithms.

The overall classification accuracy for all algorithms seems quite insignificant. However, the best performer only reached fifty percent. Further analysis is carried out for Phase I in attempt to improve the accuracy level.

Table 3: Results of Phase I Keywords Experiment- Treatment Taxon- All Subclasses Included

Algorithm group	Correctly Classifies
Supervised Learning	51.43%
Decision Trees	47.86%
Rule Based Classifier	49.65%
Miscellaneous	45%

Phase I: Keywords Analysis with Five-fold Cross Validation

Results shown in Table 3 indicate the limited success of classification accuracy reached by using keywords for automating the classification process for all subclasses in Treatment taxon. In light of these results, the manual classification process and adopted classification classes were reconsidered for the analysis. In the Treatment taxon, articles are classified to the fourth subclass titled "Other" when they are not classified into any of the other three classes (Financial, Managerial, and Auditing) As this may complicate the analysis for this study, articles which had been assigned to the "Other" class were removed from the data corpus and were not included in the rest of the experiments.

After limiting the classes for analysis, the number of articles used in the analysis came down to 98 with a list of 358 keywords. Two different methods of validation were applied and the results demonstrate that the greatest accuracy level was obtained from the Decision Trees classification method using the Simple Cart algorithm which classifies the articles with approximately 60%.The algorithms that result in the second highest accuracy level of classification are the Bayes net and DMNB Tex from Supervised classification method and ND algorithm from amongst other miscellaneous algorithms with 59.2% level of automatic classification accuracy. Results in this section are demonstrated in Table 4.

Table 4: Results of Phase I Keywords Experiment- Treatment Taxon with Five-fold Cross Validation

Algorithm Group	Correctly Classifies
Supervised Learning	59.2%
Decision Trees	60.25%
Rule Based Classifier	59.18%
Miscellaneous	59.2%

Phase I: Keywords Analysis with Percentage Split (66%)

Results in this section reports the accuracy level with 66% percentage split of keywords and demonstrates very similar accuracy level across all four classification methods. For each classification method, the algorithms that indicate the highest classification accuracy are all at the 51.51% level followed by algorithms with 45.45% level of accuracy. The accuracy level results obtained from the 66% percentage split validation method are similar to the ones in the all subclasses analysis of phase I (Table 3) which both demonstrates nearly 50% accuracy

Table 5: Results of Phase I Keywords Experiment- Treatment Taxon- Percentage Split Validation

Algorithm Group	Correctly Classifies
Supervised Learning	51.51%
Decision Trees	51.51%
Rule Based Classifier	51.51%
Miscellaneous	51.51%

Phase II: Full Abstracts Analysis with Five-fold Cross Validation

The second phase of the experiment utilizes all the text in the full abstract as opposed to using only the keywords for classification analysis. A parsing program was developed to parse out the full abstract from each article and a list of stop words were used to eliminate unused text in each article. In addition to using a stop word list to screen out text, a manual observation of the terms or phrases was performed to remove irrelevant words as well. The attributes for the classification process include a list of 263 words at the end.

Classification results for utilizing the full abstract of articles are demonstrated in shown in Table 6. The findings show that Complement Naïve Bayes algorithm provide the most accurate level of automatic classification at 74.01%, followed by NaiveBayes Multinomial algorithm at 72.88%. Both algorithms are under the classification method of supervised learning with wordlists**.**

Table 6: Results of Phase II Full Abstract Experiment- Treatment Taxon- Five-fold Cross Validation

Algorithm Group	Correctly Classifies
Supervised Learning	74.01%

Decision Trees	**71.75%**
Rule Based Classifier	**70.05%**
Miscellaneous	**66.67%**

Phase II: Full Abstract Analysis with Percentage Split (66%)

Findings for full abstract after the 66% percentage split demonstrates that the most accurate level for automatic classification can be reached by using the ComplementNaiveBayes algorithm in the Supervised Learning method and END algorithm amongst other miscellaneous algorithms both result in 81.67% accuracy. The DecisionTable algorithm in Rule based classifier method and REPTree algorithms in Decision Trees method result in 80% accuracy.

Table 7: Results of Phase II Full Abstract Experiment- Treatment Taxon - Percentage Split Validation

Algorithm Group	**Correctly Classifies**
Supervised Learning	**81.67%**
Decision Trees	**80%**
Rule Based Classifier	**80%**
Miscellaneous	**81.67%**

Analysis in Accounting Area Taxon

After the experiment on Treatment taxon, the classification process was applied to the Accounting Area taxon as well to determine whether the proposed method of classification works effectively in cases other than Treatment taxon. The experiment was carried out in two phases. Table 8 and Table9 show details of the result. Table 8 shows the results of using only the keywords. In general, most effective results are obtained by applying the supervised learning algorithms. In particular, applying the Naïve bayes, Naïve Bayes Multinomial and Naïve Bayes Multinomial Updateable classifiers achieves 69.12% accuracy.

Table 8: Results of Phase I Keywords Experiment-Accounting Area Taxon

Algorithm Group	**Correctly Classifies**
Supervised Learning	**69.12%**
Decision Trees	**68%**
Rule Based Classifier	**61.32%**

Table 9 shows the results for the second phase of the experiment where the full abstract is used. In general, the better results are obtained by applying the Supervised Learning algorithms. In particular, applying the Complement Naïve bayes algorithm concedes the best result with an accuracy level at85%.

Table 9: Results of Phase II Full Abstract Experiment- Accounting Area Taxon

Algorithm Group	**Correctly Classifies**
Supervised Learning	**85.31%**
Decision Trees	**74%**
Rule Based Classifier	**74.33%**

Analysis of subclasses in Mode of Reasoning Taxon

Results of applying the classification process to the Mode of Reasoning taxon are shown in Table 10 and Table 11. Table 10 shows the Phase I results of the experiment where only the keywords are applied for classification. The general results are quite weak for this particular taxon, demonstrating accuracy at approximately 50%. None of the algorithms was able to carry out particularly effective result.

Table 10: Results of Phase I Keywords Experiment- Mode of Reasoning

Algorithm Group	**Correctly Classifies**
Supervised Learning	**54.62%**
Decision Trees	**56.11%**
Rule Based Classifier	**56.62%**
Miscellaneous	**53.33%**

Results of using the full abstract (Phase II) to create a wordlist and classify the articles are shown in Table 11. Unlike the case in prior twotaxons (Treatment and Accounting area) where using the full abstract improves the results in general, the accuracy level in Mode of Reasoning taxon deteriorated in Phase II in comparison with Phase I.

The inability to classify the Mode of Reasoning taxon with higher accuracy could be explained to a certain extent due to the larger number of subclasses (11) as compared to the three and six subclasses under Treatment and Accounting area, respectively. For these classes there is a non-uniform representation of data. For example, out of the three hundred and fifty six articles examined only seven articles used Factor analysis/Probit/Discriminant analysis whereas one hundred and eight articles performed Regression analysis.

The articles in the database will have to be updated with fairly uniform representation from different classes of the taxons to be extracted for future research. In order to improve the results, the database needs to be expanded further. It is necessary that the training dataset be comprehensive and should include articles that belong to all the subclasses listed under the different taxons.

Table 11: Results of Phase II Full Abstract Experiment- Mode of Reasoning

Algorithm Group	Correctly Classifies
Supervised Learning	48.12%
Decision Trees	42.35%
Rule Based Classifier	43.45%

Results of Phase I and Phase II Experiments- A Comparison

Table 11: Comparison of Results

Taxon	Experiment	Best Performance Methods	Accuracy
Treatment	Phase II	Supervised Learning	81.67%
Accounting Area	Phase II	Supervised Learning	85.31%
Mode of Reasoning	Phase I	Rule Based	56.26%

In the first phase of the experiment, keywords analysis provides limited success for effectively classifying the articles with the highest accuracy level at approximately 60% in the five-fold cross validation analysis stage and the two other analyses only reached around fifty percent of accuracy level. The second phase of experiment that utilizes article's full abstract, on the other hand, indicates that both Complement Naïve Bayes (CNB) and Evolving Non-Determinism (END) algorithms provide the highest level of accuracy for automatic literature classification at 81.67% for the Treatment taxon. For both Accounting Area and Treatment taxons the accuracy level of classification is highest when Supervised learning algorithms are applied using full abstract of articles. However the results are not satisfactory for Mode of Reasoning taxon. As discussed before one of the reasons for this could be absence of sufficent data representation from all the classes.

This study adopted four main classification methods including supervised learning, decision trees, rule based classifier and other miscellaneous algorithms. Specific algorithms belonging to each of these classes have been used. A detailed listing of such algorithms could be found in Appendix II Our analyses indicates that it is much more effective to analyze full abstracts than to limit analysis to keywords alone.

V Conclusion

The main contribution of this study is the development of an automated accounting literature classification process to explore the research contributions of articles published in various accounting journals as well as evolution of accounting research branch. This study adopts semantic parsing and data mining techniques to explore the possibilities of developing a methodology for classifying academic articles in accounting automatically on the basis of various criteria and taxons. Two phases of the classification process were carried out for the "Treatment", "Accounting Area" and "Mode of Reasoning" taxons of accounting literature with the first phase using keywords and the second utilizing full abstracts.

In terms of classification accuracy, results of "Treatment" and "Accounting Area" indicate that utilizing full abstracts for the automatic literature classification process obtains more effective and successful outputs than using keywords. Furthermore, the classification method that allow the literature to be automatically classified with the highest level of accuracy is the supervised learning method, in which the Complement Naïve Bayes (CNB) and the Evolving Non-Determinism (END) algorithms performs best for "Treatment" and "Accounting Area" taxons.

Taxonomization of literature has been a useful research branch in various disciplines. However, prior literature have been performing the classification process manually which appears to be a time consuming process and may lead to inconsistent classification results. The findings of this preliminary study seem promising and indicate that the aforementioned limitations could be improved by automatically classifying literature. Future research can continue to build on this study by exploring the automation of the classification process for other criteria or taxons of accounting literature, investigating and developing techniques with higher precision, and/or benefiting other disciplines by applying automatic taxonomization to publications in their research areas to sharpen the tool for analyzing research evolution, contribution and directions of academic disciplines. An integral part of developing similar classification processes for different taxons, with several subclasses, would be to build a training dataset that has a uniform representation from different classes. It would also be interesting to explore whether any new areas of research are developing meaning whether a new class needs to be added to the taxons. Developing an automated method for this kind of exploration could be useful.

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Appendix I Taxonomy Classes

A. RESEARCH METHOD

1. Analytical Internal Logic
2. Analytical Simulation
3. Archival Primary
4. Archival Secondary
5. Empirical Case
6. Empirical Field
7. Empirical Lab
9. Opinion Survey
10. Mixed

B. INFERENCE STYLE

1. Inductive
2. Deductive
3. Both

C. MODE OF REASONING

1. Quantitative.: Descriptive Statistics
2. Quantitative: Regression
3. Quantitative: Anova
4. Quantitative: Factor .Analysis, MDS, Probit, Discriminant
5. Quantitative: Markov
6. Quantitative: Non-Parametric
7. Quantitative: Correlation'
8. Quantitative: Analytical'
10. Mixed
90. Qualitative

D. MODE OF ANALYSIS

1. Normative
2. Descriptive
3. Mixed

E. SCHOOL OF THOUGHT

1. Behavioral - Hips
2. Behavioral - Other
3. Statistical Modeling - EMH
4. Statistical Modeling- Time Series
5. Statistical Modeling- Information Economics
6. Statistical Modeling- Mathematical Programming
7. Statistical Modeling- Other
8. Accounting Theory
9. Accounting History
10. Institutional
11. Other
12. Agency Theory
13. Expert Systems

F INFORMATION

100. Financial Statements
    101. Net Income or EPS
    102. Income Statement
    103. Balance Sheet
    104. Cash Flows, Etc
    105. Other Fin. Statement
    106. Financial Ratios
    107. Combination 1-2
    108. Quarterly Reports
    109 Foreign Currency
    110. Pension'
    112. Debt Covenants
200. Internal Information
    201. Performance Measure5
    202. Personality Measures
    203. Auditor Behavior
    204. Manager Behavior
    205. Decision Making
    206. Internal Controls
    207. Costs
    208. Bud6ets
    209. Group Behavior
    210. Pricin6

211. Compensation
300. External Information
301. Footnotes
302. Sec Info, (10 K)
303. Forecasts
304. Audit Opinion
305. Bond Rating
309. Other
400. Market Based Info
401. Risk
402. Security Prices or Return
403. Security Trading
404. Options
405. All of The Above-Market
500. Mixed

G. TREATMENT

100. Financial Accountin6 Methods
101. Cash
102. Inventory
103. Other Current Assets
104. Property Plant & Equip / Depr
105. Other Non-Current Assets
106. Leases
107. Lon6 Tern Debt
108. Taxes
109. Other Liabilities
121. Valuation (Inflation)
122. Special Items
131. Revenue Recognition
132. Accounting Changes
133. Business Combinations
134. Interim Reporting
135. Amortization / Depletion
136. Segment Reports
137. Foreign Currency
141. Dividends-Cash
143. Pension (Funds)
150. Other -Financial Accounting
160. Financial Statement Timin6'
170. R & D
171. Oil & Gas
200. Auditing
201. Opinion
202. Sampling
203. Liability
204. Risk
205. Independence
206. Analytical Review
207. Internal Control
208. Timing
209. Materiality
210. EDP Auditing
211. Or6anization
212. Internal Audit
213. Errors
214. Trail
215. Jud6ement
216. Planning
217. Efficiency - Operational
218. Audit Theory
219. Confirmations
300. Managerial
301. Transfer Pricing
302. Breakeven
303. Bud6etin6 & Plannin6
304. Relevant Costs
3o5. Responsibility Accounting
306. Cost Allocations
307 Capital Bud6eting
308. Tax (Tax Planning)
309. Overhead Allocations
310. HRA / Social Accounting
311. Variances
312. Executive Compensation
400. Other
401. Submissions To The FASB Etc
402. Manager Decision Characteristics
403. Information Structures (Disclosure)
404. Auditor Training
405. Insider Trading Rules
406. Probability Elicitation
407. International Differences
408. Form Of Organization. (Partnership)
409. Auditor Behavior
410. Methodology
411. Business Failure
412. Education
413. Professional Responsibilities
414. Forecasts
415. Decision Aids
416. Organization & Environment
417. Litigation
418. Governance;

H. ACCOUNTING AREA

1. Tax
2. Financial
3. Managerial
4. Audit
5. Information Systems
6. Mixed;

I. GEOGRAPHY

1. Non-USA
2. USA
3. Both

J. OBJECTIVE

1. Profit
2. Not for Profit
3. Regulated
4. All

K. APPLICABILITY

1. Immediate
2. Medium term
3. Long Term

L. FOUNDATION DISCIPLINE

1. Psychology
2. Sociology, Political Science, Philosophy
3. Economics & Finance
4. Engineering, Communications & Computer Sciences
6. Mathematics, Decision Sciences, Game Theory
7. Statistics
8. Law
9. Other Mixed
10. Accounting
11. Management

Appendix II Data Mining Algorithms

Classification 1: Supervised Learning

Algorithms
Bayesnet
DMNB Tex
Naïve Bayes
Naïve Bayes Multinomial
Naïve Bayes Multinomial Updateable
Naïve Bayes Updateable
Complement Naïve Bayes

Classification 2: Decision Trees

Algorithms
J48
J48graft
LADTree
RandomForest
RandomTree
REPTree
SimpleCart

Classification 3: Rule Based Classifier

Algorithms
ZeroR
Ridor
PART
OneR
JRip
DecisionTable

Classification 4: Other miscellaneous algorithms

Algorithms
ClassificationVia
Regression
Multiclass Classifier
SimpleLogistic
SMO
AttributeSelected
Classifier
Bagging
ClassificationVia
Clustering
CVParameterSelection
Dagging
Decorate
END
EnsembleSelection
FilteredClassifier
Grading
LogitBoost
EnsembleSelection
FilteredClassifier
Grading
LogitBoost
MultiBoostAB
EnsembleSelection
FilteredClassifier
Grading
LogitBoost
MultiBoostAB
MultiScheme
ND

Appendix III Detailed Classification Results in Treatment, Accounting Area and Mode of Reasoning Taxons

Table 3: Results of Phase I Keywords Experiment- Treatment Taxon -All Subclasses Included

3.1 Classification 1: Supervised Learning

Algorithm	Correctly Classified
Bayesnet	46.07%
ComplementNaiveBayes	51.43%
DMNBTex	45%
NaiveBayes	42.5%
NaiveBayesMultinomial	49.26%
NaiveBayesMultinomial Updateable	49.28%
NaiveBayesUpdateable	42.5%

3.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	39.64
J48graft	41.07
LADTree	47.85
RandomForest	45.36
RandomTree	37.86
REPTree	47.5
SimpleCart	47.86

3.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	36.43%
Ridor	49.65%
PART	38.57%
OneR	48.57%
JRip	46.78%
DecisionTable	45.71%
ConjunctiveRule	46.07%

3.4 Classification 4: Miscellaneous

Algorithm	Correctly Classified
ClassificationVia Regression	45%
AttributeSelected Classifier	43.93%
Multiclass Classifier	35.36

Table 4: Results of Phase I Keywords Experiment –Treatment Taxon-after Modification and with Five-fold Cross Validation

4.1 Classification 1: Supervised Learning

Algorithm	Correctly Classified
Bayesnet	59.2%
ComplementNaive Bayes	29.6%
DMNBTex	59.2%
NaiveBayes	58.16%
NaiveBayes Multinomial	56.12%
NaiveBayes Multinomial Updateable	56.12%
NaiveBayes Updateable	58.16

4.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	56.12%
J48graft	56.12%
LADTree	57.14%
RandomForest	57.14%
RandomTree	55.1%
REPTree	59.18%
SimpleCart	60.25%
LMT	56.12%
NBTree	59.18%

4.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	59.18%
Ridor	59.18%
PART	55.1
OneR	56.12%
JRip	57.14%
NNge	46.94%
DecisionStump	57.14%
FT	54%

4.4 Classification 4: Miscellaneous

Algorithm	Correctly Classified
Logistic	58.16%
SimpleLogistic	56.12%
SMO	57.14

KStar	57.14
LWL	57.14
AttributeSelected Classifier	57.14
Bagging	59.18%
ClassificationVia Clustering	59.18%
ClassificationVia Regression	59.18%
CVParameterSelection	59.18%
Dagging	59.18%
Decorate	56.12%
END	59.18%
EnsembleSelection	59.18%
FilteredClassifier	59.18%
Grading	59.18
LogitBoost	55.1%
MultiBoostAB	57.14%
MulticlassClassifier	57.14%
MultiScheme	59.18%
NestedDichotomies ClassBalancedND	57.14%
DataNearBalancedND	59.18%
ND	59.2%
OrdinalClassClassifier	59.18%
RacedIncremental LogitBoost	59.18%
RandomCommittee	58.16%
RandomSubSpace	59.18%
RotationForest	57.14%
Stacking	59.18%
StackingC	59.18%
Vote	59.18%

Table 5: Results of Phase I Keywords Experiment –Treatment Taxon-after Modification and with 66% Percentage Split Validation

5.1 Classification 1: Supervised Learning

Algorithm	**Correctly Classified**
Bayesnet	51.51%
ComplementNaive Bayes	15.15%
DMNBTex	51.51%
NaiveBayes	51.51%
NaiveBayes Multinomial	45.45%
NaiveBayes Multinomial Updateable	45.45%
NaiveBayes Updateable	51.51%

5.2 Classification 2: Decision Trees

Algorithm	**Correctly Classified**
J48	45.45%
J48graft	45.45%
LADTree	45.45%
RandomForest	51.51%
RandomTree	51.51%
REPTree	51.51%
SimpleCart	51.51%
NBTree	51.51%
BFTree	45.45%
DecisionStump	45.45%
FT	45.45%

5.3 Classification 3: Rule Based Classifier

Algorithm	**Correctly Classified**
ZeroR	51.51%
Ridor	51.51%
PART	45.45%
OneR	45.45%
JRip	51.51%
DecisionTable	51.51%
ConjunctiveRule	51.51%
NNge	39.39%

5.4 Classification 4: Miscellaneous

Algorithm	**Correctly Classified**
SimpleLogistic	45.45%
SMO	51.51%
AttributeSelected Classifier	45.45%
Bagging	51.51%
ClassificationVia Clustering	51.51%

ClassificationVia Regression	51.51%
CVParameter Selection	51.51%
Dagging	51.51%
Decorate	45.45%
END	51.51%
EnsembleSelection	51.51%
FilteredClassifier	51.51%
Grading	51.51%
LogitBoost	45.45%
MulticlassClassifier	45.45%
MultiScheme	51.51%
AdaBoostM1	45.45%

Table 6: Results of Phase II – Treatment Taxon-Full Abstract Experiment

6.1 Classification 1: Supervised Learning with Wordlists

Algorithm	**Correctly Classified**
BayesNet	69.5%
ComplementNaive Bayes	74.01%
DMNBText	68.36%
NaiveBayes	54.23%
NaiveBayes Multinomial	72.88%
NaiveBayes Updateable	54.24
SMO	58.75
DecisionTable	70.05

6.2 Classification 2: Decision Trees

Algorithm	**Correctly Classified**
J48	66.67%
J48graft	71.75%
LADTree	65%
RandomForest	69.5%
RandomTree	51.41%
REPTree	65.54%
SimpleCart	70.05%
BFTree	70.06%
FT	63.84%

6.3 Classification 3: Rule Based Classifier

Algorithm	**Correctly Classified**
ZeroR	48.6%
Ridor	63.28%
PART	62.71%
OneR	65.54%
JRip	63.28%
DecisionTable	70.05%
ConjunctiveRule	65.54%
NNge	58.76%
DecisionStump	65.54%

6.4 Classification 4: Miscellaneous

Algorithm	**Correctly Classified**
SimpleLogistic	66.67%
SMO	58.76%

Table 7: Results of Phase II – Treatment Taxon-Full Abstract Experiment with Percentage Split (66%)

7.1 Classification 1: Supervised Learning with Wordlists

Algorithm	**Correctly Classified**
BayesNet	80%
ComplementNaive Bayes	81.67%
DMNBText	68.33%
NaiveBayes	63.33%
NaiveBayes Multinomial	80%
NaiveBayes Updateable	63.34%
NaiveBayes Multinomial Updateable	80%

7.2 Classification 2: Decision Trees

Algorithm	**Correctly Classified**
J48	65%
J48graft	73.33%
LADTree	50%
RandomForest	70%
RandomTree	38%
REPTree	80%
SimpleCart	75%
BFTree	64%
FT	65%

DecisionStump	76.7%
LMT	70%

7.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	53.33%
Ridor	61.67%
PART	68.33%
OneR	77%
JRip	52%
DecisionTable	80%
NNge	60%

7.4 Classification 4: Miscellaneous

Algorithm	Correctly Classified
ClassificationVia Regression	78.33%
Multiclass Classifier	43.33%
SimpleLogistic	70%
SMO	56.67%
AttributeSelected Classifier	78.33%
Bagging	78.33%
ClassificationVia Clustering	51.67%
CVParameter Selection	53.33%
Dagging	68.33%
Decorate	78.33%
END	81.67%
EnsembleSelection	78.33%
FilteredClassifier	80%
Grading	54%
LogitBoost	73.4%
MultiBoostAB	76.67%
MultiScheme	53.33%

Table 8: Results of Phase I – Accounting Area- Keywords Experiment

8.1 Classification 1: Supervised Learning

Algorithm	Correctly Classified
Bayes net	60.33%
Naïve Bayes	69.116
Naïve Bayes Multinomial	69.116
Naïve Bayes Multinomial	69.116%
Updateable	
Complement Naïve Bayes	45.35%

8.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	68%
J48graft	68%
Random Forest	65.51%
Random Tree	65.51%
Simple CART	64.43%

8.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	60%
PART	52%
JRip	61.32%
Decision Table	60.2762%
Conjunctive Rule	60.8287%
Ridor	54%

Table 9: Results of Phase II- Accounting Area- Full Abstract Experiment

9.1 Classification 1: Supervised Learning with Wordlists

Algorithm	Correctly Classified
Bayes Net	83.2%
ComplementNaive Bayes	85.31%
NaiveBayes	80.42%
NaiveBayes Multinomial	71.36

9.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	74%
J48graft	74%
RandomForest	73%
RandomTree	57%

9.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	73%
Ridor	71.36%
PART	71.36%
OneR	71.36%
JRip	74.33%

Table 10: Results of Phase I- Mode of reasoning Keywords Experiment

10.1 Classification 1: Supervised Learning

Algorithm	Correctly Classified
Bayes net	50.32%
Naïve Bayes	53.32%
Naïve Bayes Multinomial	51.02%
Naïve Bayes Multinomial Updateable	54.62%
Complement Naïve Bayes	27%
DMNB Text	53.32%

10.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	56.11%
J48graft	56.11%
Random Forest	53.89%
Random Tree	48.89%
Simple CART	54.44%
BFTree	55.55%
Decision Stump	55.55%
REP Tree	53.33%

10.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	53.33%
PART	54.44%
JRip	54.16%
Decision Table	54.16%
Conjunctive Rule	56.42%
Ridor	52.22%
OneR	56.62%

Table 11:Results of Phase II- Mode of reasoning Full Abstract Experiment

11.1 Classification 1: Supervised Learning with Wordlists

Algorithm	Correctly Classified
Bayes Net	40%
ComplementNaive Bayes	48.12%
NaiveBayes	46.69%
NaiveBayes Multinomial	47.05%
DMNB Text	48.13%
Naïve Bayes Multinomial Updateable	47.05%
Naïve Bayes Updateable	46.69%

11.2 Classification 2: Decision Trees

Algorithm	Correctly Classified
J48	35.45%
J48graft	36.61%
RandomForest	42.35%
RandomTree	31.58%
Simpel CART	39.85%

11.3 Classification 3: Rule Based Classifier

Algorithm	Correctly Classified
ZeroR	40.21%
Ridor	33.02%
PART	34.46%
JRip	43.45%
Conjunctive Rule	40.93%