Multimedia Mining: Multimedia World

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Abstract – For many years, statistics have been used to analyze data in an effort to find correlations, patterns, and dependencies. However, with advancement in technology, more and more data are available, which greatly exceed the human capacity to manually analyze them. Before the 1990's, data collected by bankers, credit card companies, department stores and so on have little used. But in recent years, as computational power increases, the idea of data mining has emerged. Data mining is primarily used today by companies with a strong consumer focus - retail, financial, communication, and marketing organizations. It enables these companies to determine relationships among "internal" factors such as price, product positioning, or staff skills, and "external" factors such as economic indicators, competition, and customer demographics. Data mining software analyzes relationships and patterns in stored transaction data based on open-ended user queries. Several types of analytical software are available: statistical, machine learning, and neural networks. Data mining, the discovery of new and interesting patterns in large datasets, is an exploding field. Media mining refers to a technique whereby a user can retrieve, organize, and manage media data. Audio mining is a technique by which the content of an audio signal can be automatically analysed and searched. Video Mining is changing the way in-store insights are gathered and applied by automating the collection of shopper behavior and segmentation data. Image mining has led to tremendous growth in significantly large and detailed image databases. The discovery by computer of new, previously unknown information, by automatically extracting information from a usually large amount of different unstructured textual resources. In Text Mining, the input is free unstructured text, whilst web sources are structured. With the exponential increase in media data on personal computers and the Internet, it is critical for end users to efficiently manage metadata to find the information they are looking for. This paper is an outcome of the study on data, media, audio, video, image, text and web mining from exiting literature.

Index Terms – Data, Media, Audio, Video, Image, Text and Web Mining.

INTRODUCTION

The current age is often referred to as the information age and in this information age, it is believed that information leads to power and success. Everyone collecting tremendous amounts of information. Initially, with the advent of computers and means for mass digital storage, everyone started collecting and storing all sorts of data, counting on the power of computers to help sort through this amalgam of information. This initial chaos has led to the creation of structured databases and database management systems. The efficient database management systems have been very important assets for management of a large corpus of data and especially for effective and efficient database management systems have also contributed to recent massive gathering of all sorts of information. Today, it was far more information than can handle: from business transactions and scientific data, to satellite pictures, text reports and military intelligence. Information retrieval is simply not enough anymore for decision-making. Confronted with huge collections of data new needs to help one make better managerial choices have been created. These needs are automatic summarization of data, extraction of the "essence" of information stored, and the discovery of patterns in raw data [1]. Media-mining can help us retrieve, organize and manage the exponentially growing media data easily [5]. Image mining is more than just an extension of data mining to image domain [4]. It is an interdisciplinary endeavor that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence.

Data Mining

The various data mining definitions available from literature are:

The data mining system can automatically find and show you new patterns that will lead to fresh insight [1] - Osmar R. Zaïane
Data mining is the process of analyzing data from different perspectives and summarizing it into useful information [2] - Cipolla and Emil T.

Data mining is the process of finding correlations or patterns among dozens of fields in large relational databases [3] - Conner and Louis.

Data mining is the semi-automatic discovery of patterns, changes, associations, anomalies, and other statistically significant structures from large data sets [7] - Robert Grossman.

Data mining is a process that uses a variety of data analysis tools to discover patterns and relationships in data that may be used to make valid predictions [8,9] - Two Crows , Han, Jiawei, and Micheline Kamber.

Data mining is primarily used today by companies with a strong consumer focus - retail, financial, communication, and marketing organizations.

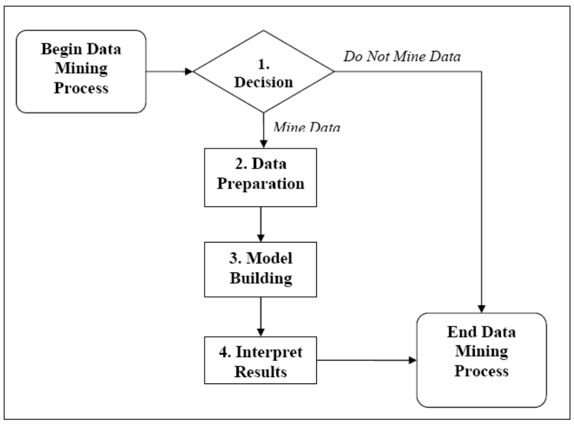

Fig 1. The Four Phases of the Data Mining Process

It enables these companies to determine relationships among "internal" factors such as price, product positioning, or staff skills, and "external" factors such as economic indicators, competition, and customer demographics. Data mining software analyses relationships and patterns in stored transaction data based on open-ended user queries. Several types of analytical software are available: statistical, machine learning, and neural networks [2, 3]. Figure 1 represents the four phases of the data mining process: decision, data preparation, model building and interpret results.

The National Basketball Association (NBA) has explored a data mining application that can be used in conjunction with image recordings of basketball games. The Advanced Scout software analyzes the movements of players to help coaches orchestrate plays and strategies. By using the NBA universal clock, a coach can automatically bring up the video clips showing each of the jump shots attempted by Williams with Price on the floor, without needing to comb through hours of video footage [6].

Issues in Data Mining

One of the key issues raised by data mining technology is not a business or technological one, but a social one. It is the issue of individual privacy. Data mining makes it possible to analyze routine business transactions and glean a significant amount of information about individuals buying habits and preferences [10].

There is in data mining can be catergorised as security issues, social issues, user interface issues, mining methodology issues, performance issues, data source issues , data integrity, diplomacy issue and ethical issues.

Security and social issues: Security is an important issue with any data collection that is shared and/or is intended to be used for strategic decision-making [12, 13]. User interface issues: The knowledge discovered by data mining tools is useful as long as it is interesting, and above all understandable by the user [12, 13].

Mining methodology issues: These issues pertain to the data mining approaches applied and their limitations [12, 13]. Performance issues: Many artificial intelligence and statistical methods exist for data analysis and interpretation [12, 13].

Data source issues: There are many issues related to the data sources, some are practical such as the diversity of data types, while others are philosophical like the data glut problem [15].

Data integrity: A key implementation challenge is integrating conflicting or redundant data from different sources [10, 11].

Diplomacy issues in data mining: A key problem that arises in any en masse collection of data is that of confidentiality. The need for privacy is sometimes due to law or can be motivated by business interests [14, 15].

Ethical Issues: The social ethical and legal implications of data mining are examined through recent case law, current public opinion, and small industry-specific examples. [16].

Media Mining

Very soon after the introduction of the notion of data-mining in the nineties, it became clear that 'knowledge discovery', a term often used for data mining techniques, was not just applicable to the digging up of more or less hidden data patterns in traditional databases [20,21].

In addition to more and better medium specific analysis tools, there is the need for analysis models that deliver features that can be integrated in a medium-independent representation and for search models that can abstract away from media-specific features [24]. Ad hoc merging of ranked lists based on word occurrence statistics and image features can be effective, but the real goal should be transformation and integration of representations into one medium-independent representation [20]. The attempt to use conceptual structures as a representation that is independent of language and modality is one of the most salient features of what has more recently become known as semantic web. And thirdly the metaphor of translation could help to clarify the difference in ambition between media crossing and media mining [22, 23].

A review three experimental approaches each illustrating the media crossing paradigm in a different way as give as *Kuper. J. and H. Saggion* [25].

With the exponential increase in media data on personal computers and the Internet, it is critical for end users to efficiently manage metadata to find the information they are looking for. Media mining refers to a technique whereby a user can retrieve, organize, and manage media data. Figure 2 represents the media mining process.

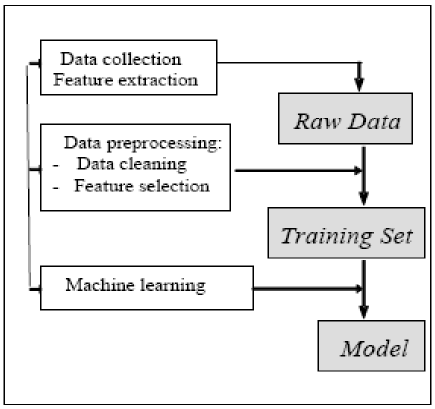

Fig. 2 Media Mining Process

MEDIA-MINING APPLICATIONS

Media mining has a huge number of emerging applications with different usage models.

Sports video analysis: Broadcast sports videos are very popular on television. Using highlights detection, consumers can quickly retrieve specific video clips without having to browse through the whole video. Sports video analytics can be viewed from the perspective of an editor. Based on a predefined semantic intention, an editor combines certain multimedia content elements and their temporal layout to achieve the desired highlighted events. Hence, detecting highlighted events is similar to a reverse process of authoring. The system framework consists of three levels: low-level audio/visual feature extraction, mid-level semantic keywords generation, and high-level event detection [26]. To minimize the semantic gap between low-level features and high-level events, he has been used mid-level semantic "keywords" followed by a classifier to infer events of interest. Our sports video analysis system can work with a multitude of sports including soccer, hockey, badminton, tennis, and diving. Given a video in a specific domain with predefined semantic intentions, the system can extract the desired events and features and interpret a summarization output video in terms of high-level semantics [26].

Personal video editing: Home videos are increasingly popular as digital video cameras become more users friendly and portable. However, because home videos for the most part are shot by amateurs, shaking, blurring, under- exposure artifacts, and redundant content are always present. Therefore, the demand for an automated home video editing system [27] is high. Such a system has to be able to recognize how many people and how many scenes are involved, mine the relationship between various people and scenes, and synthesize a short artistic video clip from a long raw video. A typical personal video editing system includes three key modules: intelligent analysis, adaptive selection, and seamless composition. The first module extracts the multi-modal and multi-level audio-visual features; the second module selects the most interesting, important, and informative content; and the third module produces a near-professional story with incidental music. The overall automated home video editing system must be easily extended to the personal video recorder and digital home entertainment system [27].

Personal video retrieval: A personal video retrieval system is a desktop application that works much like the Google desktop search to help end users manage more and more personal multimedia data from all kinds of mobility digital camera devices. In response to a user query, the personal video retrieval application finds the relevant video clips from a large video database such as from movies, TV, sports games, and home videos. Generally, a retrieval system first extracts low-level audio/visual features from videos, and then detects semantic concepts to represent the video content. Finally, a query engine returns retrieval results based on the user's query and on a similarity model. The query can be text keywords, image examples, hand-drawn sketches, or short video clips, and the output is relevant video clips ranked not only by their content similarity to the query, but also by their importance, according to a concept-link relationship analysis. To gradually improve system performance during the query procedure, the system provides user-friendly relevant feedback and active learning modules [26, 27].

Key Media-Mining Techniques

Although the above usage models are quite different from one another, the underlying technologies are common and can be extended to a broad range of media-mining applications. In this paper, four key techniques are extracted from previous usage models to show how media-mining applications are built [27].

Sports keyword detection: The mid-level module generates semantic "keywords" from the previously described low-level extraction. Listed below are some keywords in sports video analysis. These keywords are used as input for high-level event detection [28].

View type: Based on color histograms of each frame, obtain the dominant color to segment the playing field region can be obtained. Each frame is classified as a global view, medium view, close-up view, and out of view [28]. Play-field: A Hough transform from digital image processing is used to detect field boundaries and penalty box sections. Then a decision-tree-based classifier determines the play position according to the slope and position of the lines [28].

Replay: In broadcast sports videos, to capture clues for significant events, there typically is a replay following an important event. At the beginning and end of each replay, there is generally a logo flying in high speed. Logos to identify replays by discovering repeat video segments through dynamic programming [29].

Audio keywords: There are two types of audio keywords: commentator's excited speech and referee's whistle: these have a strong correlation to key events in the game such as a foul, a goal, or player entanglements. A Gauss Mixture Model (GMM) is used to detect keywords from low-level audio features including Mel frequency Cepstral coefficients (MFCC), energy, and pitch [30].

Human detection and tracking: Human detection and tracking is a significant and challenging task in many application scenarios. Different from rigid objects, humans are articulated and jointed by several human-parts, which may lead to pose variance, self-occlusion, etc. In human detection, the first problem is to select the proper features to characterize human regions/parts: Haar wavelets [31] and orientation histograms are mostly used to do this. The second problem with human detection is to use a discriminator to determine whether there are humans and here they are if they are present. The Boosting learning-based detector is preferred [31]. It is an aggressive learning algorithm that produces a strong classifier by choosing features in a family of simple classifiers and combining them linearly. Then a cascaded structure is introduced in order to quickly reject the background regions. Human tracking is essentially finding body regions or parts that correspond with successive frames by using data association and occlusion inference techniques [31].

Face detection and tracking: Face detection and face tracking have been an important technology and pre-requirement for many person-analysis relevant applications, such as face recognition/identification, emotion analysis, and cast indexing. Face detection has been studied for many years. Viola and Jones Boosting learning-based detection algorithms are the most successful algorithm to date [27]. In 2005, some improvements are proposed to enable the algorithm to handle multi-view faces more efficiently for high-quality videos [32].

Generally, Boosting-based face detection characterizes image regions by very simple Haar wavelet features, and it learns cascade detection from a training set to separate a face set from a non-face set. In the detection phase, the learned detector will slide by a window over the image to detect whether the window contains a face or not. Face tracking [33] is an extension of face detection technology, which can detect a person's continuous faces from a video sequence. Spatial and temporal constraints are employed to avoid much unnecessary calculation. Since it detects faces only in predicted face image regions, it doesn't waste time scanning all the positions of every frame [33].

Concept ontology indexing: Concept ontology indexing represents multimedia data by large-scale concept ontology for indexing and fast retrieval. There are several concept lexicons for multimedia: large-scale ontology for multimedia (LSCOM) [34] is the most popular. LSCOM currently contains about 1000 concepts that are relevant to objects, people, locations, scenes, and events. LSCOM has been successfully used by the TREC video retrieval evaluation (TRECVID) hosted by NIST [35].

Concepts are detected from more than 20 low-level MPEG-7 compatible audio/visual features, e.g., color histogram, Gabor texture, shape context, edge histogram, motion, and MFCC audio features, etc. Given these low-level features, a supervised classifier (such as an SVM) is learnt for each concept from a training set to identify whether the concept exists or not in each video shot [36]. Employing all of the concept detectors, a video shot is therefore represented and indexed by the semantic concept ontology that makes next-stage search similar to text retrieval [35, 36].

Common Characteristics in Media Mining: Three attributes of media-mining applications are given in the following paragraph:

First, a media-mining system is basically a bottom-up framework. The framework is three-layer architecture, i.e., low-level feature extraction, mid-level semantic keywords detection, and high-level concept detection. In processing, low-level visual/audio/textual features are extracted from raw media data. Then in the second layer, mid-level features or keyword concepts are detected from low-level features to bridge the semantic gap between low-level features and high-level concepts. Finally, high-level modules infer the desired concepts in the semantic keyword spaces [35].

Second, media mining is a hybrid technique of computer vision, pattern recognition, machine learning, and data mining. For example, human detection/tracking techniques involve Haar and HoG feature extraction from video frames, Boosting (cascade learning) training-based candidate detection, and associate rule learning from quite large examples to identify relationships between articulations. In these techniques, Haar and HoG features are essentially computer vision methods; Boosting is a famous machine-learning algorithm; and associate rule learning is a typical data-mining method [36].

Third, media-mining applications usually combine multiple components. For example, in the automatic home video editing application, the application needs to recognize people, mine the relationship between people, and synthesize a short artistic video clip from a long raw video [35].

Media mining has mass-market potential and is therefore quite a suitable and important proxy not only for workload analysis on future architectures, but also for developing parallel programming models for multimedia applications. Furthermore, due to its similar framework for different usage models, one technique as an example to study its computational requirements is used [35].

Multiple player detection, tracking, and classification in broadcast soccer video have been illustrated by *J. Cao and Y. Lan.*

Audio mining

Audio mining, also called audio searching, takes a text-based query and locates the search term or phrase in an audio file. This helps users by, for example, letting them quickly get to specific places in a recorded conversation or determine when a company is mentioned in a newscast. Audio indexing uses speech recognition to analyze an entire file and produce a searchable index of content bearing words and their locations. This is critical because audio content is in a binary format that is otherwise not readily searchable, explained Robert Weideman, ScanSoft's chief marketing officer. Indexing audio content thus enables searching, said Jeff Karnes, a group product manager for Virage, an audio mining vendor.

Audio mining approaches

There are two main approaches to audio mining. Text-based indexing and Phoneme-based indexing. Text-based indexing, also known as large-vocabulary continuous speech recognition, converts speech to text and then identifies words in a dictionary that can contain several hundred thousand entries. If a word or name is not in the dictionary, the LVCSR system will choose the most similar word it can find.

The system uses language understanding to create a confidence level for its findings. For findings with less than a 100 percent confidence level, the system offers other possible word matches, said Professor Dan Ellis, who leads Columbia University's Laboratory for Recognition and Organization of Speech and Audio (http://labrosa. ee.columbia.edu).

Phoneme - based indexing. Phoneme based indexing doesn't convert speech to text but instead works only with sounds. The system first analyzes and identifies sounds in a piece of audio content to create a phonetic-based index. It then uses a dictionary of several dozen phonemes to convert a user's search term to the correct phoneme string. (Phonemes are the smallest unit of speech in a language, such as the long "a" sound, that distinguishes one utterance from another. All words are sets of phonemes.) Finally, the system looks for the search terms in the index. "A phonetic system requires a more proprietary search tool because it must honeticize the query term, then try to match it with the existing phonetic string output," Weideman said. This is considerably more complex than using one of the many existing text-based search tools.

Phoneme-based searches can result in more false matches than the text-based approach, particularly for short search terms, because many words sound alike or sound like parts of other words. Thus, Ellis said, it's difficult for a phonetic system to accurately classify a phoneme except by recognizing the entire word that it is part of or by understanding that a language permits only certain phoneme sequences. However, he added, phonetic indexing can still be useful if the analysed material contains important words that are likely to be missing from a text system's dictionary, such as foreign terms and names of people and places.

How the technology works

Image Text- and phoneme-based systems operate in much the same way, except that the former uses a text-based dictionary and the latter uses a phonetic dictionary. The most important and complex component technology for audio mining is speech recognition. In these systems, explained University of Texas Assistant Professor Latifur R. Khan, "A speech recognizer converts the observed acoustic signal into the corresponding [written] representation of the spoken [words]."

Speech recognition software contains acoustic models of the way in which all phonemes are represented. Also, there is a statistical language model that indicates how likely words are to follow each other in a specific language, said William Meisel, president of TMA Associates, a speech industry market-research firm. By using these capabilities, as well as complex probability analysis, the technology can take a speech signal of unknown content and convert it to a series of words from the program's dictionary.

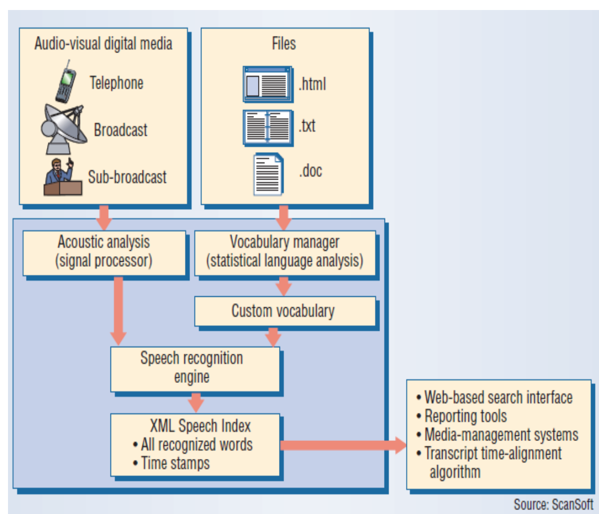

Figure 9.1. The ScanSoft Audio Mining Development System works with audio from various sources [37].

Khan noted that this process is more difficult with highly inflected languages, such as Chinese, in which tonality changes the meaning of a word. Some audio mining dictionaries are domain specific, for use by professionals in different fields, such as law or medicine. Some products, such as ScanSoft's Audio Mining Development System, shown in Figure 1, use XML's ability to tag data so that other XML-capable systems can read it, ScanSoft's Weideman noted. This lets the product export speech index information to other systems, he said.

Video mining

Video Mining can be defined as the unsupervised discovery of patterns in audio-visual content. The motivation for such discovery comes from the success of data mining techniques in discovering non-obvious patterns of shopping for example. Furthermore, surveillance video often consists of events that are not known beforehand, and is hence an obvious target for unsupervised discovery of patterns, which in this case are events. For instance, a video sequence captured by a camera trained at a crowded marketplace would defy analysis through simple motion detection [38].

Video Mining is changing the way in-store insights are gathered and applied by automating the collection of shopper behavior and segmentation data. Video Mining's patent-protected technologies and processes turn in-store video into actionable intelligence for retailers and consumer product manufacturers [39].

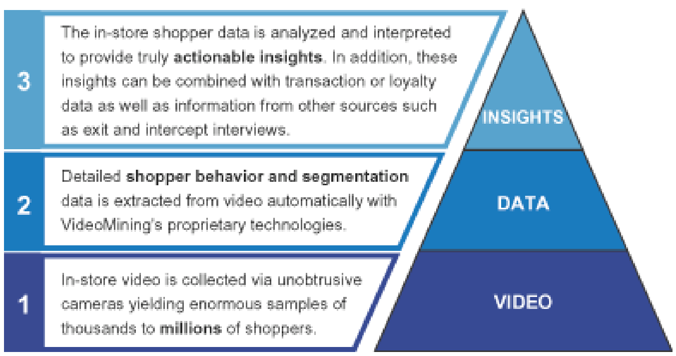

Figure 10.1. The Video Mining Process [39].

Image mining

Image mining is more than just an extension of data mining to image domain. It is an interdisciplinary endeavor that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. Advances in image acquisition and storage technology have led to tremendous growth in very large and detailed image databases [4]. These images, if analyzed, can reveal useful information to the human users. Image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images. Much knowledge can be obtained from image**s.** This process can be done in the mind by a human, and implementation of this mind processing by a system is very difficult [4].

Image mining has led to tremendous growth in significantly large and detailed image databases. The most important areas belonging to image mining are: image knowledge extraction, content-based image retrieval, video retrieval, video sequence analysis, change detection, model learning, as well as object recognition. Two different types of input data for knowledge extraction from an image collection are original image and symbolic description of the image [17].

Issues in image mining

The various issued in image mining are [18]:

1. Image Mining for Modeling of Forest Fires From Meteosat Images
2. Stochastic methods for image mining and data quality (DAQUAL)
3. In agricultural studies, topics like precision agriculture and crop modeling will be addressed
4. In environmental studies, the topic of spatial/temporal scales is still an ongoing issue for research.
5. Health issues concern the quantitative modeling of epidemics of a various kind.
6. Hydrology focuses on model-based Geostatistics for rainfall prediction.

The increasing number of image archives has made image mining an important task because of its potential to discover useful image patterns and relationships from a large set of images. A framework for extracting knowledge from a sequence of images has been proposed by Hsu, Lee and Goh. The structure of the framework composed of two modules: image analysis and knowledge processing [19].

Text Mining

Text mining is the analysis of data contained in natural language text. Text mining works by transposing words and phrases in unstructured data into numerical values which can then be linked with structured data in a database and analyzed with traditional data mining techniques [40].

Text mining is especially useful for tasks such as: Routing email to the appropriate department, teaching out information about product satisfaction from text located in disparate data stores and Analyzing open-ended survey questions. It's generally accepted that unstructured data, most of it located in text files, accounts for at least 80% of an organization's data. Text mining can be challenging because natural language text is often inconsistent. It contains ambiguities caused by semantics, slang and syntax[40].

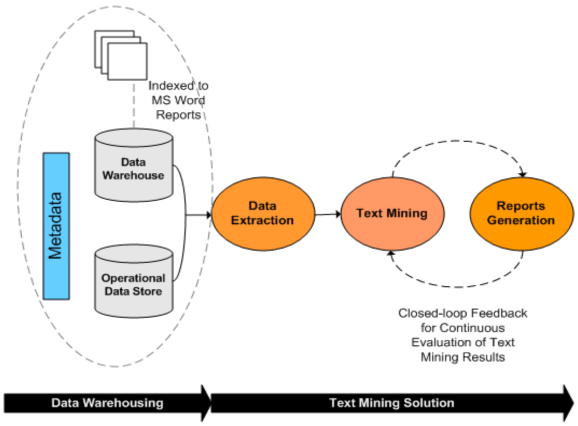

Figure 13.1. Text Mining Modules [41]

The text mining module contains the data mining scores based on historically analysis of likelihood of fraud. The algorithms were custom developed based on text entered in the claims examiner's reports and details based on the claim. This model was developed specifically for the client by DWreview. The data mining model can give the client a competitive advantage and the technical details are kept as a closely guarded corporate secret. Reports are generated on a web-based application layer. The data produced for the reports are also fed into the SAP for Insurance ERP application which is used by the client and commonly found in most of the larger insurance companies [41].

Web mining

Web mining is the application of data mining techniques to Web data. Web mining helps to solve the problem of discovering how users are using Web sites. It involves mining logs and the steps that typically have to be gone through to get meaningful data from Web logs - data collection, pre-processing, data enrichment and pattern analysis and discovery. This web site will outline the web mining process and it's applications to the real world problem of how firms can measure the contribution of their web site. Firms have made serious investments in establishing an online presence and now want to know the Return on their Investment. This web site aims to become the first port of call for anyone charged with such an exercise [42].

There are roughly three knowledge discovery domains that pertain to web mining: Web Content Mining, Web Structure Mining, and Web Usage Mining. Web content mining is the process of extracting knowledge from the content of documents or their descriptions. Web document text mining, resource discovery based on concepts indexing or agent-based technology may also fall in this category. Web structure mining is the process of inferring knowledge from the World-Wide Web organization and links between references and referents in the Web. Finally, web usage mining, also known as Web Log Mining, is the process of extracting interesting patterns in web access logs.

Web content mining is an automatic process that goes beyond keyword extraction. Since the content of a text document presents no machine-readable semantic, some approaches have suggested restructuring the document content in a representation that could be exploited by machines. The usual approach to exploit known structure in documents is to use wrappers to map documents to some data model. Techniques using lexicons for content interpretation are yet to come.

There are two groups of web content mining strategies: Those that directly mine the content of documents and those that improve on the content search of other tools like search engines.

World-wide Web can reveal more information than just the information contained in documents. For example, links pointing to a document indicate the popularity of the document, while links coming out of a document indicate the richness or perhaps the variety of topics covered in the document. This can be compared to bibliographical citations. When a paper is cited often, it ought to be important. The PageRank and CLEVER methods take advantage of this information conveyed by the links to find pertinent web pages. By means of counters, higher levels cumulate the number of artifacts subsumed by the concepts they hold. Counters of hyperlinks, in and out documents, retrace the structure of the web artifacts summarized.

Web servers record and accumulate data about user interactions whenever requests for resources are received. Analyzing the web access logs of different web sites can help understand the user behaviour and the web structure, thereby improving the design of this colossal collection of resources. There are two main tendencies in Web Usage Mining driven by the applications of the discoveries: General Access Pattern Tracking and Customized Usage Tracking.

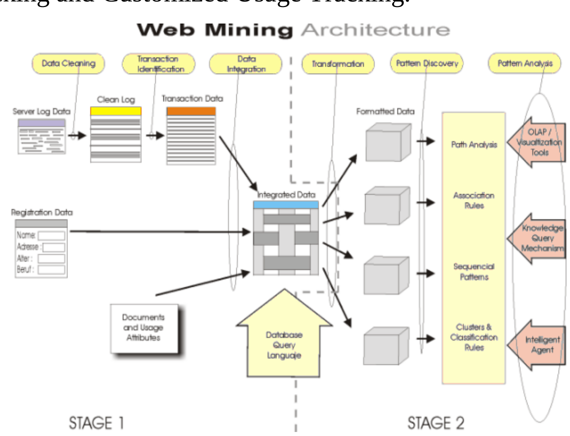

Figure 13.1. Web Mining Architecture [43]

The general access pattern tracking analyzes the web logs to understand access patterns and trends. These analyses can shed light on better structure and grouping of resource providers. Many web analysis tools existed but they are limited and usually unsatisfactory. We have designed a web log data mining tool, WebLogMiner, and proposed techniques for using data mining and OnLine Analytical Processing (OLAP) on treated and transformed web access files. Applying data mining techniques on access logs unveils interesting access patterns that can be used to restructure sites in a more efficient grouping, pinpoint effective advertising locations, and target specific users for specific selling ads. Customized usage tracking analyzes individual trends. Its purpose is to customize web sites to users. The information displayed the depth of the site structure and the format of the resources can all be dynamically customized for each user over time based on their access patterns.

While it is encouraging and exciting to see the various potential applications of web log file analysis, it is important to know that the success of such applications depends on what and how much valid and reliable knowledge one can discover from the large raw log data. Current web servers store limited information about the accesses. Some scripts custom-tailored for some sites may store additional information. However, for an effective web usage mining, an important cleaning and data transformation step before analysis may be needed [43].

CONCLUSION

In this paper, authors have highlighted the need for image mining in view of the rapidly growing amounts of image data. Authors have pointed out the various data mining definitions available from literature and briefly discussed about various issues in data mining. In addition, authors have also examined Media mining, applications and its usage models. Authors have also discussed introduction of audio mining, how audio mining technology works and it’s the unique various approaches. Authors have explained about video mining and it’s Process. In summary, image mining is a promising field for research.

Image mining research is still in its infancy and many issues remain solved. Authors have described how Text Mining module contains the data mining scores based on historically analysis of likelihood of fraud. The algorithms were custom developed based on text entered in the claims examiner's reports and details based on the claim. This model was developed specifically for the client by DWreview. However the described our Web mining is the application of data mining techniques to Web data. Web mining helps to solve the problem of discovering how users are using Web sites. Finally the authors are exploring the image mining in depth in order to propose algorithms for improving the efficiency and effectiveness of image mining.

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