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Donald G. Perrin
Executive Editor

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Editorial

From Trivia Games to Performance Evaluation

Donald G. Perrin

In an effort to reduce all knowledge, skills, and attitudes in the universe to true/false, multiple-choice, and matching, we have done education a disservice. The Stanford-Binet intelligence scales invented at the beginning of the twentieth century provided the model for a plethora of assessment and evaluation devices. They produced magical numbers that determine who goes to college, gets affordable financing, or is selected for societal privileges.

The *No Child Left Behind Act* takes it a step further. It singles out schools in communities with a higher than normal percentage of minorities, disabilities, English as a Second Language, and economic distress, for punishment under Federal Law. By definition, half of the students will perform below average, and those averages are specific to parameters established by testing and measurement organizations. Educators are aware that results of these paper and pencil tests are only indicators and supplement them with other data. However, the numbers and the misnomer “objective” test, still control the outcomes.

Attempts to reform the system have come from many disciplines. Robert Mager, an engineer, suggested that objectives should be stated in terms that are observable and measurable – a description of the outcomes of learning. He even went the additional step to describe the conditions under which the performance was observed. But many teachers found such objectives laborious and difficult to write. Some even believed what they taught was so esoteric it could not be written as an objective.

Benjamin Bloom discovered that knowledge is like a pyramid with many levels, the base levels being knowledge, comprehension, and application, with analysis, synthesis, and evaluation at higher levels of learning. Academicians developed lists of action verbs ascribed to these different levels. Teachers found the system too complicated. They never caught on that if you test performance at the highest levels, it subsumes lower levels of learning. Additional pyramids for skills and attitudes were ignored.

Enter the computer. Now it was possible to measure and record every action. Powerful analysis techniques give information about learning and each individual learner that was hitherto impossible. A much broader range of performance can be measured – every response, every action, how fast, how accurately, how well! Computers are not limited to words and trivia, they can simultaneously measure, analyze, and record a full range of knowledge, skills, and attitudes through interactive multi-media, games, simulations, and real-life experience. Computer based learning management systems and learning objects are a logical extension of human abilities through machines and artificial intelligence. R2D2, the astromech droid in Star Wars, is a futuristic model of an intelligence based on the life experience of its master, Luke Skywalker.

In this issue of the Journal, Bill Gates describes areas where our commitment to education has been found lacking. The research articles that follow focus on new technologies for finding relevant information and for critical thinking to enhance the performance of teachers and learners.

Editor's Note: This speech was delivered by Bill Gates, co-founder of the Bill and Melinda Gates Foundation, to the 2005 National Education Summit on High Schools, held by the National Governors Association and Achieve, Inc. in Washington DC. Bill Gates offers a global perspective that challenges U.S. political, education and business leaders to significantly raise educational standards in science and mathematics. For more information on increasing high school graduation rates, go to http://www.gatesfoundation.org/education.

2005 National Education Summit on High Schools

William H. Gates, Co-founder
Bill & Melinda Gates Foundation

I want to thank you, Governor Warner, and your fellow governors, for your leadership in hosting this education summit on America's high schools. It is rare to bring together people with such broad responsibilities and focus their attention on one single issue. But if there is one single issue worth your focused attention – it is the state of America's high schools.

Many of us here have stories about how we came to embrace high schools as an urgent cause. Let me tell you ours.

Everything Melinda and I do through our foundation is designed to advance equity. Around the world, we believe we can do the most by investing in health – especially in the poorest countries.

Here in America, we believe we can do the most to promote equity through education.

A few years ago, when Melinda and I really began to explore opportunities in philanthropy, we heard very compelling stories and statistics about how financial barriers kept minority students from taking their talents to college and making the most of their lives.

That led to one of the largest projects of our foundation. We created the Gates Millennium Scholars program to ensure that talent and energy meet with opportunity for thousands of promising minority students who want to go to college.

Many of our Scholars come from tough backgrounds, and they could bring you to tears with their hopeful plans for the future. They reinforced our belief that higher education is the best possible path for promoting equality and improving lives here in America.

Yet – the more we looked at the data, the more we came to see that there is more than one barrier to college. There's the barrier of being able to pay for college; and there's the barrier of being prepared for it.

When we looked at the millions of students that our high schools are not preparing for higher education – and we looked at the damaging impact that has on their lives – we came to a painful conclusion:

America's high schools are obsolete.

By obsolete, I don't just mean that our high schools are broken, flawed, and under-funded – though a case could be made for every one of those points.

By obsolete, I mean that our high schools – even when they're working exactly as designed – cannot teach our kids what they need to know today.

Training the workforce of tomorrow with the high schools of today is like trying to teach kids about today's computers on a 50-year-old mainframe. It's the wrong tool for the times.

Our high schools were designed fifty years ago to meet the needs of another age. Until we design them to meet the needs of the 21st century, we will keep limiting – even ruining – the lives of millions of Americans every year.

Today, only one-third of our students graduate from high school ready for college, work, and citizenship.

The other two-thirds, most of them low-income and minority students, are tracked into courses that won't ever get them ready for college or prepare them for a family-wage job – no matter how well the students learn or the teachers teach.

This isn't an accident or a flaw in the system; it is the system.

In district after district, wealthy white kids are taught Algebra II while low-income minority kids are taught to balance a check book!

The first group goes on to college and careers; the second group will struggle to make a living wage.

Let's be clear. Thanks to dedicated teachers and principals around the country, the best-educated kids in the United States are the best-educated kids in the world. We should be proud of that. But only a fraction of our kids are getting the best education.

Once we realize that we are keeping low-income and minority kids out of rigorous courses, there can be only two arguments for keeping it that way – either we think they can't learn, or we think they're not worth teaching. The first argument is factually wrong; the second is morally wrong.

Everyone who understands the importance of education; everyone who believes in equal opportunity; everyone who has been elected to uphold the obligations of public office should be ashamed that we are breaking our promise of a free education for millions of students.

For the sake of our young people and everyone who will depend on them – we must stop rationing education in America.

I'm not here to pose as an education expert. I head a corporation and a foundation. One I get paid for – the other one costs me. But both jobs give me a perspective on education in America, and both perspectives leave me appalled.

When I compare our high schools to what I see when I'm traveling abroad, I am terrified for our workforce of tomorrow. In math and science, our 4th graders are among the top students in the world. By 8th grade, they're in the middle of the pack.

By 12th grade, U.S. students are scoring near the bottom of all industrialized nations.

We have one of the highest high school dropout rates in the industrialized world. Many who graduate do not go onto college. And many who do go on to college are not well-prepared – and end up dropping out. That is one reason why the U.S. college dropout rate is also one of the highest in the industrialized world. The poor performance of our high schools in preparing students for college is a major reason why the United States has now dropped from first to fifth in the percentage of young adults with a college degree.

The percentage of a population with a college degree is important, but so are sheer numbers. In 2001, India graduated almost a million more students from college than the United States did. China graduates twice as many students with bachelor's degrees as the U.S., and they have six times as many graduates majoring in engineering.

In the international competition to have the biggest and best supply of knowledge workers, America is falling behind.

That is the heart of the economic argument for better high schools. It essentially says: “We’d better do something about these kids not getting an education, because it’s hurting us.” But there’s also a moral argument for better high schools, and it says: “We’d better do something about these kids not getting an education, because it’s hurting them.”

Today, most jobs that allow you to support a family require some postsecondary education. This could mean a four-year college, a community college, or technical school. Unfortunately, only half of all students who enter high school ever enroll in a postsecondary institution.

That means that half of all students starting high school today are unlikely to get a job that allows them to support a family.

Students who graduate from high school, but never go on to college, will earn – on average – about twenty-five thousand dollars a year. For a family of five, that’s close to the poverty line. But if you're Hispanic, you earn less. If you’re black, you earn even less – about 14 percent less than a white high school graduate.

Those who drop out have it even worse. Only 40 percent have jobs. They are nearly four times more likely to be arrested than their friends who stayed in high school. They are far more likely to have children in their teens. One in four turn to welfare or other kinds of government assistance.

Everyone agrees this is tragic. But these are our high schools that keep letting these kids fall through the cracks, and we act as if it can’t be helped.

It can be helped. We designed these high schools; we can redesign them.

But first we have to understand that today’s high schools are not the cause of the problem; they are the result. The key problem is political will. Elected officials have not yet done away with the idea underlying the old design. The idea behind the old design was that you could train an adequate workforce by sending only a third of your kids to college – and that the other kids either couldn’t do college work or didn’t need to. The idea behind the new design is that all students can do rigorous work, and – for their sake and ours – they have to.

Fortunately, there is mounting evidence that the new design works.

The Kansas City, Kansas public school district, where 79 percent of students are minorities and 74 percent live below the poverty line, was struggling with high dropout rates and low test scores when it adopted the school-reform model called First Things First in 1996. This included setting high academic standards for all students, reducing teacher-student ratios, and giving teachers and administrators the responsibility to improve student performance and the resources they needed to do it. The district’s graduation rate has climbed more than 30 percentage points.

These are the kind of results you can get when you design high schools to prepare every student for college.

At the Met School in Providence, Rhode Island, 70 percent of the students are black or Hispanic. More than 60 percent live below the poverty line. Nearly 40 percent come from families where English is a second language. As part of its special mission, the Met enrolls only students who have dropped out in the past or were in danger of dropping out. Yet, even with this student body, the Met now has the lowest dropout rate and the highest college placement rate of any high school in the state.

These are the kind of results you can get when you design a high school to prepare every student for college.

Two years ago, I visited High Tech High in San Diego. It was conceived in 1998 by a group of San Diego business leaders who became alarmed by the city's shortage of talented high-tech workers. Thirty-five percent of High Tech High students are black or Hispanic. All of them study courses like computer animation and biotechnology in the school's state-of-the-art labs. High Tech High's scores on statewide academic tests are 15 percent higher than the rest of the district; their SAT scores are an average of 139 points higher.

These are the kind of results you can get when you design a high school to prepare every student for college.

These are not isolated examples. These are schools built on principles that can be applied anywhere – the new three R's, the basic building blocks of better high schools:

The first R is *Rigor* – making sure all students are given a challenging curriculum that prepares them for college or work;

The second R is *Relevance* – making sure kids have courses and projects that clearly relate to their lives and their goals;

The third R is *Relationships* – making sure kids have a number of adults who know them, look out for them, and push them to achieve.

The three R's are almost always easier to promote in smaller high schools. The smaller size gives teachers and staff the chance to create an environment where students achieve at a higher level and rarely fall through the cracks. Students in smaller schools are more motivated, have higher attendance rates, feel safer, and graduate and attend college in higher numbers.

Yet every governor knows that the success of one school is not an answer to this crisis. You have to be able to make systems of schools work for all students. For this, we believe we need stable and effective governance. We need equitable school choice. We need performance-oriented employment agreements. And we need the capacity to intervene in low-performing schools.

Our foundation has invested nearly one billion dollars so far to help redesign the American high school. We are supporting more than fifteen hundred high schools – about half are totally new, and the other half are existing schools that have been redesigned. Four hundred fifty of these schools, both new and redesigned, are already open and operating. Chicago plans to open 100 new schools. New York City is opening 200. Exciting redesign work is under way in Oakland, Milwaukee, Cleveland, and Boston.

This kind of change is never easy. But I believe there are three steps that governors and CEOs can take that will help build momentum for change in our schools.

> **Number 1**. Declare that all students can and should graduate from high school ready for college, work, and citizenship. How would you respond to a ninth grader's mother who said: "My son is bright. He wants to learn. How come they won't let him take Algebra?" What would you say? I ask the governors and business leaders here to become the top advocates in your states for the belief that every child should take courses that prepare him for college – because every child can succeed, and every child deserves the chance. The states that have committed to getting all students ready for college have made good progress – but every state must make the same commitment.
>
> **Number 2**. Publish the data that measures our progress toward that goal. The focus on measuring success in the past few years has been important – it has helped us realize the extent of the problem. But we need to know more: What percentage of students are dropping out? What percentage are graduating? What percentage are going on to college? And we need this data broken down by race and income. The idea of tracking low-income and minority kids into dead-end courses is so offensive to our sense of equal opportunity that the only way

> the practice can survive, is if we hide it. That's why we need to expose it. If we are forced to confront this injustice, I believe we will end it.
>
> **Number 3**. Turn around failing schools and open new ones. If we believe all kids can learn – and the evidence proves they can – then when the students don't learn, the school must change. Every state needs a strong intervention strategy to improve struggling schools. This needs to include special teams of experts who are given the power and resources to turn things around.

If we can focus on these three steps – high standards for all; public data on our progress; turning around failing schools – we will go a long way toward ensuring that all students have a chance to make the most of their lives.

Our philanthropy is driven by the belief that every human being has equal worth. We are constantly asking ourselves where a dollar of funding and an hour of effort can make the biggest impact for equality. We look for strategic entry points – where the inequality is the greatest, has the worst consequences, and offers the best chance for improvement. We have decided that high schools are a crucial intervention point for equality because that's where children's paths diverge – some go on to lives of accomplishment and privilege; others to lives of frustration, joblessness, and jail.

When I visited High Tech High in San Diego a few years ago, one young student told me that High Tech High was the first school he'd ever gone to where being smart was cool. His neighborhood friends gave him a hard time about that, and he said he wasn't sure he was going to stay. But then he showed me the work he was doing on a special project involving a submarine. This kid was really bright. It was an incredible experience talking to him – because his life really did hang in the balance.

And without teachers who knew him, pushed him, and cared about him, he wouldn't have had a chance.

Think of the difference it will make in his life if he takes that talent to college. Now multiply that by millions. That's what's at stake here.

If we keep the system as it is, millions of children will never get a chance to fulfill their promise because of their zip code, their skin color, or the income of their parents.

That is offensive to our values, and it's an insult to who we are.

Every kid can graduate ready for college. Every kid should have the chance.

Let's redesign our schools to make it happen.

About the Author

William H. Gates
Co-founder
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Chairman and Chief Software Architect
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William (Bill) H. Gates is Co-founder of the Bill & Melinda Gates Foundation, created in January 2000 to support global health and learning. Its goal is that in the 21st century, advances in these critical areas will be available for all people.

Bill Gates has won global recognition as chairman and chief software architect of Microsoft Corporation, the worldwide leader in software, services and solutions that help people and businesses realize their full potential. His late mother, Mary Gates, was a schoolteacher, University of Washington regent, and chairwoman of United Way International.

Gates attended public elementary school and the private Lakeside School. There, he discovered his interest in software and began programming computers at age 13. In 1973, Gates entered Harvard University as a freshman, where he lived down the hall from Steve Ballmer, now Microsoft's chief executive officer. While at Harvard, Gates developed a version of the programming language BASIC for the first microcomputer - the MITS Altair.

In his junior year, Gates left Harvard to devote his energies to Microsoft, a company he had begun in 1975 with his childhood friend Paul Allen. Guided by a belief that the computer would be a valuable tool on every office desktop and in every home, they began developing software for personal computers. Gates' foresight and his vision for personal computing have been central to the success of Microsoft and the software industry. Additional information on Bill Gates and Microsoft are available at http://www.microsoft.com/billgates/default.asp.

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Information on the Governor's Association Education Division and its initiatives can be found at http://www.nga.org/center/divisions/1,1188,C_ISSUE_BRIEF^D_8021,00.html

Editor's Note: Many algorithms are available to prioritize search results of web searches so the most relevant choices are listed first. These algorithms may be based on theoretical constructs, profiles, usage data, mathematical models, or combination of one or more of these aspects. In commerce, group profiles significantly improve selection; in academia, and especially in online learning systems, interactive multimedia, and simulators, learning management systems build comprehensive databases of individual learning behaviors. This enables web mining and recommender systems to make detailed profiles and analyses with greatly enhanced relevance for the individual learner. This is an important step toward the artificial intelligence of R2D2, Luke Skywalker's trusty astromech droid in Star Wars.

The Application of Web-Mining to Theme-Based Recommender Systems

Haider A Ramadhan, Jinan A Fiaidhi and Jafar M. H. Ali

Abstract

In the world of eLearning where the number of choices can be overwhelming, recommender systems help users find and evaluate items of interest. They connect users with items to "learn" (view, listen to, etc.) by associating the content of recommended items or the opinions of other individuals with the learning user's actions or opinions. Such systems have become powerful tools in variety of domains including eLearning. This article addresses the techniques used to generate recommendations and focusing on developing a theme-based web-mining application to recommend relevant Web pages to group of learners. This is achieved through automatically discovering various user access patterns from the Proxy log files, and clustering them into themes using a distance based algorithm, namely nearest neighbor algorithm. The paper also discusses experimental evaluation conducted to assess the performance of the algorithm in relation to various features extracted from documents accessed by the users.

Keywords: Web-Mining, Collaborative Filtering, Theme-Based Recommender, eLearning, Clustering.

Introduction

The term Web mining refers to a broad spectrum of mathematical modeling techniques and software tools that are used to find patterns for inferring user intentions while surfing the Web and attempting to pre-fetch documents of interests and eventually to build recommendation models. Recommender systems that incorporate Web and data mining techniques make their recommendations using knowledge learned from the actions and attributes of users. These systems are often based on the development of user profiles that can be persistent (based on demographic or keyword history data), ephemeral (based on the actions during the current session), or both. These algorithms include clustering, classification techniques, the generation of association rules, and the production of similarity graphs through techniques such as Horting's collaborative filtering.

Several prototype systems were developed in this area, which include WebWatcher (http://citeseer.nj.nec.com/armstrong97webwatcher.html), DiffAgent (Jones 1995), Alexa (Willmot 1999) and Letizia (Lieberman 1995). Several virtual universities introduced recommender systems for their learning products (e.g. myVU http://myvu.vu.edu.au/myVU/index.jsp, VURS http://vu.wu-wien.ac.at/recommender/). However, techniques followed by these systems, though novel, are considered primitive and fail to construct comprehensive models of the user profiles. For example, WebWatcher analyzes hyperlinks in the pages visited by the users and then recommends those links which the system guesses are promising in matching the goal of the session. Letizia attempts to infer user intentions by tracking his/her browsing behavior. Links found on the pages visited by the user are automatically explored by the system and are presented to the user on demand. Hence, the main goal here is to perform some degree of automatic Web exploration by anticipating future page accesses. Obviously, a more solid approach is needed to build the user model which can spell out the various access patterns of the learner.

Searching for Educational Resources

There are presently on the Web countless Learning Objects available for corporate and academic use. Despite the advantages of having access to such ever-growing object repositories, elearning now faces a more pressing challenge: how to find the most appropriate object for a given user/purpose? Common industry standards such as SCORM (Sharable Content Object Reference Model) and IMS (Instructional Management System) facilitate the location of learning objects from a repository by extended search capabilities. For example, the user can search by keyword, date, author, or any metadata field. However, since SCORM defines approximately 60 fields, average users are unlikely to completely specify their needs according to such a large number of attributes. As the granularity of the learning objects decreases and as the size of repositories increases, there will also be a need for much more fine-grained topic descriptions than either SCORM or IMS can provide. Even advanced searches can overwhelmingly return hundreds of thousands of results (Gaaster 1997). Still, this is an improvement from a simple query which could possibly return millions of results. Overall, the process may prove to be inadequate in a society that demands immediate, reliable results in order to meet the demands of their customers. We argue that software can work to alleviate such problems by trying to collaboratively “predict” what users will want rather than expect them to completely define their needs. In this direction, recommender systems research has focused recently on the interaction between information retrieval and user modeling in order to provide a more personalized and proactive retrieval experience and to help users choose between retrieval alternatives and to refine their queries

Historically recommender systems grew from the information filtering research of the late 80s and early 90s which applied information retrieval techniques for personalized information delivery. Examples of early recommender systems include Tapestry (Ki et at 1993), Group Lens (Resnick et al 1994), Fab (Balabonovic and Shoham 1997). The earliest “recommender systems” were content filtering systems designed to fight information overload in textual domains. These were often based on traditional information-filtering and information-retrieval systems. Recommender systems that incorporate information retrieval methods are frequently used to satisfy ephemeral needs (short-lived, often one-time needs) from relatively static databases. Conversely, recommender systems that incorporate information-filtering methods are frequently used to satisfy persistent information (long-lived, often frequent, and specific) needs from relatively stable databases in domains with a rapid turnover or frequent additions. Collaborative filtering (CF) is an attempt to facilitate this process of “word of mouth.” The simplest of CF systems provide generalized recommendations by aggregating the evaluations of the community at large. More personalized systems (Resnick and Varian 1997) employ techniques such as user-to-user correlations or a nearest-neighbor algorithm.

The application of user-to-user correlations derives from statistics, where correlations between variables are used to measure the usefulness of a model. In recommender systems correlations are used to measure the extent of agreement between two users (Breese et al 1998) and used to identify users whose ratings will contain high predictive value for a given user. Care must be taken, however, to identify correlations that are actually helpful. Users who have only one or two rated items in common should not be treated as strongly correlated. Herlocker et al. (1999) improved system accuracy by applying a significance weight to the correlation based on the number of co-rated items. Nearest-neighbor algorithms compute the distance between users based on their preference history. Distances vary greatly based on domain, number of users, number of recommended items, and degree of co-rating between users. Predictions of how much a user will like an item are computed by taking the weighted average of the opinions of a set of neighbors for that item. As applied in recommender systems, neighbors are often generated online on a query-by-query basis rather than through the offline construction of a more thorough model. As such, they have the advantage of being able to rapidly incorporate the most up-to-date information, but the search for neighbors is slow in large databases. Practical algorithms use heuristics to search for good neighbors and may use opportunistic sampling when faced with large populations. Both nearest-neighbor and correlation-based recommenders provide a high level of personalization in their recommendations, and most early systems using these techniques showed promising accuracy rates. As such, CF-based systems have continued to be popular in recommender applications and have provided the benchmarks upon which more recent applications have been compared. This article presents a theme based searching algorithm that enable us to analyze user access patterns, cluster them into groups representing themes or topics, and have them fed into a theme based search engine which would focus retrieving learning resources/objects that are highly relevant to the themes and avoid those objects which are not relevant to the learner topics.

While it may not be currently feasible to extract in full the meaning of an HTML document, intelligent software agents have already been developed which extract semantic features from the words or structure of the document. With the advancement of research in the area of Semantic Networks (Balabonovic and Shoham 1997), this task is expected to enjoy considerable improvement. These extracted features are then used to classify and categorize the documents. Clustering offers the advantage that a priori knowledge of categories is not needed, hence the categorization process is unsupervised. The results of clustering could then be used for various other applications such as searching for other similar documents, organization of the bookmark files, construction of user access models, automatic Web navigation, or to conduct theme based searching as opposed to current key word based searching.

Discovery of User Access Patterns and Themes

The impetus for the work reported in this paper came from our need for a complete user profile which would allow us to design a fully automatic Web navigation system and a theme based search engine. The aim of the former system is to recognize a set of learning pages which are of high interest to the user and then automatically retrieve such pages whenever a change or update is discovered in them. Recently, some work has been reported in this area which captures the pages or the user interests explicitly by asking the users to provide the URLs (Tan 2000). Next the system fetches these pages and constructs a template for each page. The system periodically fetches the pages in the background, constructs the templates, match them with the initial templates stored in the database, and notifies the users when a change in the templates is discovered. Although being a genuine improvement, explicitly capturing the user intentions may not be an efficient way to implement such important tools, an implicit way to achieve that is needed. The aim of the theme based searching is to analyze user access patterns, cluster them into groups representing themes or topics, and have them fed into a theme based search engine which would focus retrieving pages highly relevant to the themes and avoid pages which are not relevant to the user topics.

The second author proposed a framework for searching and recommending learning objects (Fiaidhi,Passi and Mohammed 2004) and currently, the first author is involved in developing two main research projects that are related to the theme-based searching. The first project aims at implicitly constructing a user profile from Proxy server logs and the browser history records. This profile is then compared with the explicit profile manually captured from the user. Both profiles are weighted and integrated to produce a final user model which is used to drive automatic Web navigation system for surfing the Web on the behalf of the user. The second project involves designing a crawler which searches the Web for pages closely relevant to the user themes automatically discovered from the Proxy log files. Our main aim here is to improve the engineering of the theme-discovery process. The purpose of this paper is to find out the optimal keyword and similarity thresholds needed to come up with more focused themes through using clustering techniques. We report the overall process of analyzing user surfing behavior and of constructing user access profile containing a set of themes. We also report an experimental evaluation on the relationship between various feature selections used for clustering the Web pages to come up with an efficient threshold.

For discovering users access patterns, two approaches have been suggested. The first approach (Cheung 1998) attempts to capture the browsing movement, forward and backward, between Web pages in a directed graph called *Traversal Oath Graph*. In this approach, a set of *maximal forward references* which represent different browsing sessions are first extracted from the directed graphs. By using *association rules*, the frequently traversed paths can be discovered. These paths represent most common traversal patterns of the user. In the second approach, user access logs are examined to discover clusters of similar pages which represent categories of common access patterns. In both cases, these patterns can be used in several applications which may include theme or topic based search tools as opposed to current keyword based searches, online catalogues for electronic commerce, and automatic Web navigation to pre-fetch pages of interest which represent user access patterns (Tan 2000).

The task of discovering user access patterns and clustering them into themes is a three-phase process. The input to the process is the user access log saved on the Web proxy server. The log file contains records for each user accessing the Web. Each record in the file represents a page request by user client machine. A typical record contains user id, client IP address, URL of the requested page, the protocol used for data transmission, the date and time of the request, the error code used, and the size of the page (Srivastava et al 1995).

In summary, the purpose of phase one is to clean up the log file and get it converted into a vector form. Each vector contains information such as user id, URL, access time and date. Irrelevant information is eliminated and total time spent on each URL is computed and added to the vector. Next, Generalization is used to consolidate all related URLs into their main home page URL. Frequency of visits and the updated total time spent are also counted and added to the vector.

In phase two, TFIDF (Term Frequency/Inverse Document Frequency (Salton 1999)**)** algorithm is used to extract keywords from the documents. Since TFIDF normally computes the weights for the words as well, some extra pre-processing was performed to strip the weights from the words. These keywords are taken from the title tag, keyword tags, header tags, meta tags, and emphasized words. According to the threshold used in the experiment (reported in the next section), a certain number of keywords are extracted and added to the initial vector produced in the previous phase. Total time spent and the visit frequency, are the two measures we use to prioritize the words in the vector.

The last phase of the discovery process is to produce the topics of interests from the term vectors. A distance based clustering technique is used to form the topics. The output is a small number of topic vectors representing themes. Each vector contains a predefined number of keywords adjusted in the order according to the time spent and the number of visits.

The distance between any two term vectors is measured by their similarity. The higher the similarity is, the smaller the distance would be. The similarity *S(VI,V2)* between two term vectors

VI and *V2* is given by the normalized inner product of VI and *V2.* When a new term vector is added to a pool of clusterized vectors, its distance from the centroid of all the clusters formed so far will be measured. The new vector will be absorbed by the closest cluster unless its distance is longer than a certain threshold (basically a number of keywords) in which case the new vector forms a new cluster by itself. The centroid of a cluster is a term vector which is the mean of all the vectors in the cluster.

The Experimental Evaluation

> *Many intelligent software agents have used clustering techniques in order to retrieve, filter, and categorize documents available on the World Wide Web. Traditional clustering algorithms either use a priori knowledge of document structures to define a distance or similarity among these documents or use probabilistic techniques, e.g. Bayesian classification. These clustering techniques use a selected set of words (features) appearing in different documents as the dimensions. Each such feature vector, representing a document, can be viewed as a point in this multi-dimensional space. Many of these traditional algorithms, however, falter when the dimensionality of the feature space becomes high relative to the size of the document space (Kurypis 1997). New clustering algorithms that can effectively cluster documents, even in the presence of a very high dimensional feature space, have recently been reported. These clustering techniques, which are based on generalizations of graph partitioning, do not require pre-specified ad hoc distance functions, and are capable of automatically discovering document similarities or associations .*

Clustering in a multi-dimensional space using traditional distance or probability-based methods has several drawbacks (Chang 1998). First, it is not trivial to define a distance measure in this space. Some words are more frequent in a document than others. Taking only the frequency of the keyword occurrence is not enough as some documents are larger than others. Furthermore, some words may occur more frequently across documents. Second, the number of all the words in all the documents can be very large. Distance-based schemes (Jain 1998), such as k-means analysis, hierarchical clustering and nearest neighbor clustering, generally require the calculation of the mean of document clusters. For sets with high dimension, randomly generated clusters may have the same mean values for all clusters. Similarly, probabilistic methods such as Bayesian classification used in AutoClass (Tiherigton 1985) do not perform well when the size of the feature space is much larger than the size of the sample set. However, in the research reported here we do not have a variable length of keywords among documents. The keyword threshold is set fixed for every experiment. In addition, the number of all words in documents is not considered as a criteria for feature selection in our experiments. Hence, it was felt that the distance based clustering would fit our need and would not need to deal with the drawbacks mentioned above.

Our proposed theme-based recommender algorithm is based on a version of the Nearest Neighbor Algorithm (Lu and Fu 1978) with an ad hoc distance similarity metrics. To illustrate the main idea behind this algorithm, we conducted Web search experiments in which a total of 218 web pages/learning objects were retrieved and grouped into four broad learning categories: news, business, finance, and economics. These pages correspond to the clustered vectors. The retrieved pages were downloaded, labeled, and archived. The labeling allowed us to easily calculate an entropy (discussed shortly). Subsequent references to any page were directed to the archive. This ensured a stable data sample since some pages are fairly dynamic in content. A total of five experiments were conducted. Documents were clustered using the Nearest Neighbor Algorithm

(NNA) referenced earlier. Only two methods of feature selection were used, namely Keyword Threshold (KT) and Similarity Threshold (ST). The KT refers to the number of words extracted from upper portions of the pages and ranged from 5, 10, 20 and 30 words. The ST ranged from 1 to 5, and was used as a measure to compare the similarity among generated clusters and to consolidate them when a given ST is satisfied. For example, with KT is set to 5 and ST to 3, only 5 keywords are used from each page and those clusters having at least 3 keywords in common are consolidated to form a single cluster.

Our objective is to find the correlation between KT and ST, and their influence on the maximum and mean sizes of the clusters produced. We also aimed at finding out total number of clusters produced across various values of KT and ST. Traditionally, it has been reported that smaller ST values tend to produce few but large clusters with less focus as far as topics are concerned, while large ST values tend to generate large number of clusters which are smaller in size and better in focus. In short, the aim was to find the relationship between dimensionality of clustering and document features. The main difference between the studies reported elsewhere and the reported in this paper has to do with the clustering technique used. Previous studies used either of the following distance based clustering techniques: Bayesian classification, hierarchical clustering, and k-means analysis. Since our near-future aim is to compare major distance based methods, we decided to use NNA. In particular, our goal is threefold:

1. To verify the inverse relationship between keyword and similarity thresholds.
2. To assess the impact of the dimensionality, i.e. KT = 5,10, 20 and 30, on the size and number of clusters produced.
3. To assess the impact of the dimensionality on the level of concentration and focus of the clusters produced.
4. To compare the performance of NNA with the other three distance based clustering algorithms mentioned above.

With the exception of point 4, all remaining three points are covered by the experiment below. It was hoped that the experiment would assist us in deciding a reasonably efficient threshold for both KT and ST to be used in our research projects which focus on the discovery of user access patterns, automatic web navigation, theme based searching, and intelligent search engines.

The entropy based analysis (kurypis 1997) was used for two main reasons. First, we plan to compare results obtained in our experiment with that reported by other distance based clustering methods referenced above using the same collection of documents used in other experiments. Comparing performance of different algorithms and validating the clustering efficiency is a complex task since it is difficult to find an objective measure of cluster quality. Hence, it was decided to proceed with using entropy as a measure of cluster goodness. Second, one of the main aims of the evaluation reported in this paper is to assess how focused the clusters are in relation to the four broad classes of the categories mentioned above. Entropy comparison is an ideal way to accomplish that.

When a cluster, for example, contains documents from one category only, the entropy value is 0 for the cluster, and when a cluster contains documents from several categories the entropy value of the cluster becomes higher. Hence, lower entropy values tend to suggest more focused clusters in their topics and vice versa. The total entropy is the average entropies of the clusters. We compare the results of the five experiments by comparing their entropies across various feature selection criteria mentioned above (i.e. ST and KT values). As stated earlier, small ST values should produce fewer clusters but with less focus, while larger ST values should produce many clusters but with more focus. This is attributed to the fact that a smaller ST value is expected to make clusters get consolidated (combined) at a higher rate since having few words in common among clusters is more typical than having large number of words in common among clusters.

As an example, assume we have three clusters C1 {x1,x3,x4,x8,x13}, C2 {x4,x7,x13,x14,x15}, and C3 {x1,x4,x8,x15}, where x refers to the keywords. With ST=3, the distance between C1 and C2 would be 2 (two words are in common), between C1 and C3 would be 3, and between C2 and C3 would be 2. As a result, the distance of 2 satisfies the ST value of 3 and hence clusters C1 and C3 would be joined in one cluster with keywords {x1,x3,x4,x8,x13,x15}. However, if ST was set to 2, then all three distances between any two clusters would satisfy the ST value and all three would be joined into one cluster containing all non-duplicate keywords in the three clusters, i.e. unionized. As a result, it would be safe to *hypothesize* that lower entropy values would be associated with lower ST values, while large ST values would be related to higher entropy values. In fact, our experimental results tend to support this claim.

Table 1: Total and size of clusters

	ST = 1				ST = 2				ST = 3				ST = 4				ST = 5			
KT	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30
Total clusters	53	39	26	19	75	61	53	44	112	83	61	30	164	151	109	79	189	158	119	62
Average	34.2				58.3				71.5				125.7				132			

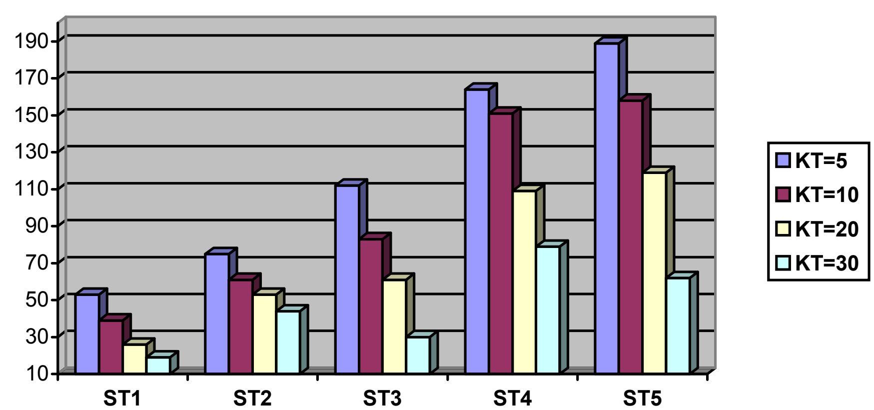

Figure 1: Total number of clusters

Figure 1 and table 1 show the relationship between various KT and ST values.

As shown in Figure 1, the number of clusters tends to increase when the threshold values are near the end of the test range. The results clearly verify the claim that smaller ST values tend to produce few but large clusters with less focus as far as topics are concerned, while large ST values tend to generate large number of clusters which are smaller in size and better in focus.

To show the percentage of overall increase in the number of clusters that is associated with the increase in the ST values, table 1 shows the weighted increase in the number of clusters across all KT values for some ST value. It is noticed that the weighted increase in the number of clusters is steady when ST values increase from 1 to 2. With ST=1, the average number of clusters is 34.2

for all KT values. When ST becomes 2, the average number of clusters produced is 58.3, an increase of 24.1 (70%) over ST=1. When ST becomes 3, average number of clusters produced is 71.5, an increase of 13.2 (23%) over ST=2. With ST=4, the average increase is noticed to be 54.2 (76%) over ST=3. Finally with ST=5, the average increase is 6.3 (5%) over ST=4.

Three main observations can be stated here. First, the number of clusters produced tends to increase across all KT values as the ST values increases. This is shown by Figure 1 and Table 1. Second, this increase is not at the same pace for different KT values. It is noticed that for any ST value, number of clusters tend to be high for smaller KT values and tend to decrease as the KT values increase. Hence, this clearly shows the inverse relationship between ST and KT values. Third, largest average increase in the number of clusters was noticed to be for ST=4 (76%). With ST=5, the average increase drastically dropped to only 5%. This may imply that the similarity threshold value of 4 is the cut off value we seek which tends to produce optimal or semi optimal number of clusters that maintain good focus.

Table 2: Maximum size of clusters

	ST = 1				ST = 2				ST = 3				ST = 4				ST = 5			
KT	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30	5	10	20	30
Max Size	65	92	123	205	52	85	111	173	39	68	106	148	19	41	87	130	5	31	79	118

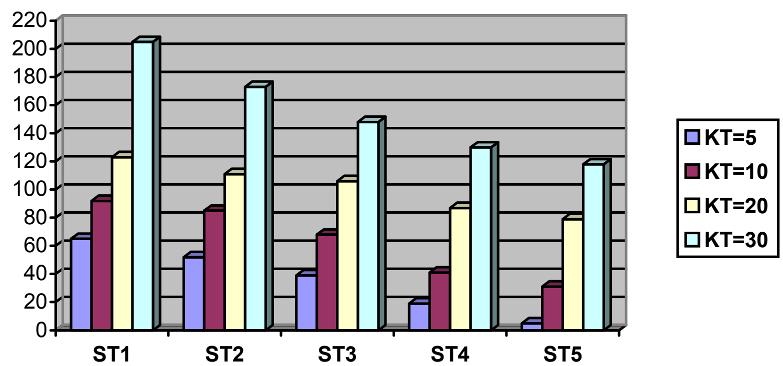

Figure 2: Maximum size of clusters

Figure 2 and Table 2 provide some insights into the maximum size of the clusters produced. Few observations can be made here. First, maximum size of the clusters across all KT values tend to decrease as ST values increase. For example, the decrease in the maximum cluster size from ST=1 to ST=5 for KT=5 is from 65 to 5, hence a reduction of 92%. The reduction, as shown in table 2, for KT=10 is 67%, for KT=20 is 36%, and for KT=30 is 42%. It may be stated that the level of reduction becomes more steady when KT=20, since the next reduction at KT=30 (6%) is not as steep as the reduction from KT=10 to KT=20 which is 31%.

Figure 3 deals with the mean size of clusters. The pattern of the above analysis regarding the maximum cluster size holds valid here as well. Average cluster size drops down as ST values increase. When ST=1, any two vectors having an overlapping keyword would be joined together, hence producing clusters with high average sizes. It can be observed that the effect of the reduction in the average cluster size is visible across all KT values. However, the level of reduction for KT values of 5, 10 and 20 seems to be more steady and stable when compared to that of KT value 30.

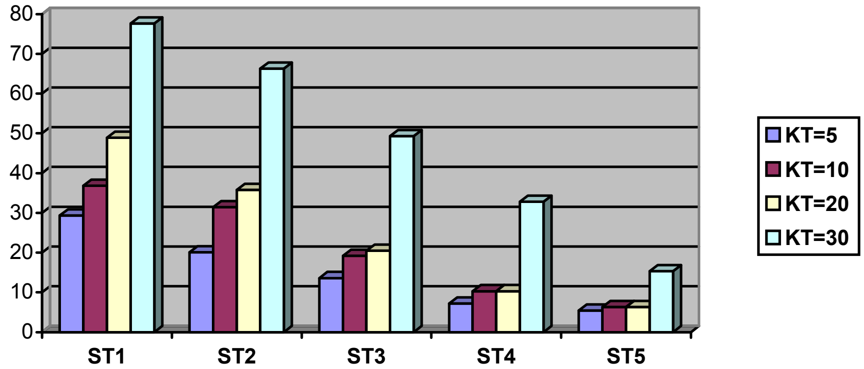

Figure 3: Mean size of clusters

Although cautiously, it could be argued that the keyword thresholds of 10 and 20 along with the similarity threshold of 4 are the cut off values that tend to be recommended by the above results. Very few studies reported on the recommended combination of both threshold values. However, it has been found that KT values of 5 and 20 tend to work best using other distance based clustering methods such as Autoclass (Tiherigton 1985) and, HAC (Duta 1973), and non-distance based methods such as Principal Component Clustering (Moore 2001). As a consequence, it is safe to state that the Nearest Neighboring Algorithm used in this study did not deviate from the path reported by others.

Figure 4 deals with using the entropy-based analysis to get some insights into the focus of the clusters produced in relation to various threshold values and the four categories mentioned earlier. As stated before, when a cluster, contains documents from one category only, the entropy value is 0 for the cluster, and when a cluster contains documents from several categories the entropy value of the cluster becomes higher. Hence, lower entropy values tend to suggest more focused clusters in their topics and vice versa. The total entropy used in the figure is the average entropies of all the clusters.

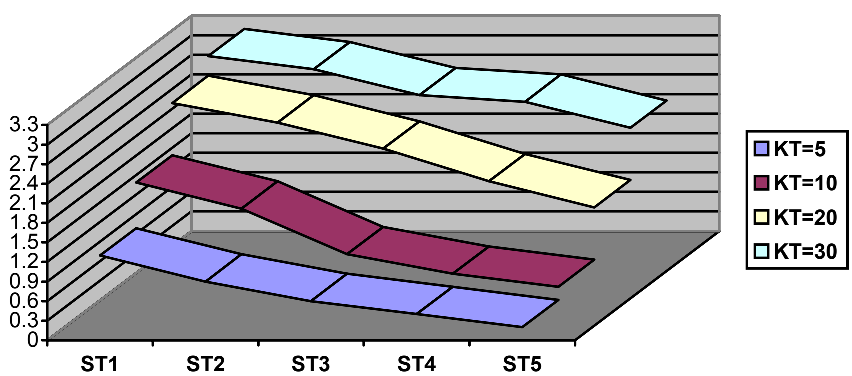

Figure 4: Entropy comparison

Few observations can be noted from the figure. First, lower ST and higher KT values tend to generate clusters with higher entropies, hence implying that such clusters are very general in their topics. This outcome makes sense since in such situation clusters tend to be large in size, and hence combining keywords from documents that belong to several categories. With high ST values, clusters tend to be small in their size mostly contain keywords from documents which come from a certain class. This observation seems to prevail even when KT values are 20 and 30. However, higher KT values still tend to generate clusters with high entropy values, implying that they contain keywords from documents belonging to more than one class, hence are of less focus in their topics. The figure also shows that the gap between entropy values is more evident when KT values change from 10 to 20, and that the gap between 20 and 30 is not as the former one. We can cautiously state that the threshold values of ST=4 and KT=5 or 10 represent the best combination of the thresholds which produce clusters with lower entropy values and hence with better focus. The study used four closely related classes, namely news, business, finance, and economy. It is possible that classes with less relevance could produce different results since un-related classes tend to have fewer keywords common among their documents. Therefore, smaller clusters with better focused keywords should be expected. It is hoped that such claim could also be formally verified.

Similar results have been recently reported but with two main differences (Moore 2001). First, the reported results considered the focus of the clusters across a range of KT values with no relationship with ST values. Second, the algorithm used in the experiment for the clustering was a non-distance based one. In this experiment, it was found that the method, i.e. the PCA algorithm referenced earlier in this paper, worked best with KT values 5 and 20. In our case, KT values 5 and 10 seemed to produce best results. Of course, the quality of the clusters can be better judged by looking at the distribution of class labels among clusters. We hope this task would be completed in the near future.

Conclusion

Recommender systems have been widely advocated as a way of coping with the problem of information overload for knowledge users. Given this, multiple recommendation methods have been developed. However, it has been shown that no one technique is best for all users in all situations. Thus we believe that effective recommender systems should incorporate a wide variety of theme based recommendations. To this end, this article, introduced two types of theme-based recommendations (Keyword Threshold (KT) and Similarity Threshold (ST)). Moreover, other issues were investigated such as the correlation between KT and ST, their influence on the maximum and mean sizes of the clusters produced, and the total number of clusters produced across various values of KT and ST. The experimental analysis shows that our theme based recommender is capable of short listing recommendations once the user themes can be clustered according the keyword threshold in relation with the similarity threshold.

References

Balabanovic M. and Shoham Fab Y. (1997). **Content-based collaborative recommendation,** *Communications of the ACM,* **40**(3): 66-72.

Breese, J., Heckerman, D., & Kadie, C. (1998). **Empirical Analysis of Predictive Algorithms for Collaborative Filtering**. In Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI-98), pp 43-52.

Chang C. (1997). **Customizable multi-engine search tool with clustering.** Proceedings of 6th International Web Conference.

Cheung D W. (1998). **Discovering user access patterns on the Web.** Knowledge Based Systems, 10, 463-470.

Duda R. (1973). **Pattern Classification and Scene Analysis,** Wiley.

Fiaidhi J., Passi K., Mohammed S., (2004). **Developing a Framework for Learning Objects Search Engine,** 2004 International Conf. on Internet Computing (IC'04) June 21-24, , Las Vegas, Nevada, USA.

Gaaster T., (1997). **Cooperative Answering through Controlled Query Relaxation**, IEEE Intelligent Systems, Vol. 12, No. 5.

Herlocker, J., Konstan, J.A., Borchers, A., and Riedl, J. (1999). **An Algorithmic Framework for Performing Collaborative Filtering.** Proceedings of the 1999 Conference on Research and Development in Information Retrieval.

Jain A. (1998). **Algorithms for Clustering Data.** Prentice Hall.

Jones D. H. (1995)**.IndustryNet: A model for Commerce on the Web,** IEEE Expert, Oct., pp 54-59.

Karypis G. (1997). **Multilevel hypergraph partitioning: Application in VLSI domain,** Proceedings of ACM/IEEE Design Automation Conference.

Lieberman H., (1995). **Letizia: An Agent that Assists Web Browsing,** International Joint Conference on Artificial Intelligence, Montreal, August http://lieber.www.media.mit.edu/people/lieber/Lieberary/Letizia/Letizia.html

Lu S. and Fu K.(1978). **A sentence-to-sentence clustering procedure for pattern analysis.** IEEE Transactions on Systems, Man, and Cybernetics, 8, 381-389.

Moore J. (2001). **Web Page Categorization and Feature Selection Using Association Rule and Principal Component Clustering**, TR 9405380, Department of Computer Science, University of Minnesota,.

Oki B. M., Goldberg D., Nichols D. and Terry D., (1992). **Using collaborative filtering to weave an information tapestry**, *Communications of the ACM,* 35(12): 61-70. Page 11/11

Resnick P., Iacovou N., Suchak M., (1994). Bergstrom and J. Riedl, GroupLens: **An open architecture for collaborative filtering of netnews,** *Proceedings of ACM CSCW'94*

Conference on Computer-Supported Cooperative Work, Sharing Information and Creating Meaning, 175-186.

Resnick, P. & Varian, H.R. (1997). Communications of the Association of Computing Machinery Special issue on Recommender Systems, 40(3):56–89.

Srivastava J., Cooley R., Deshpande M., and Tan,P.N. (2000). ***Web usage mining: Discovery and applications of usage patterns from web data*.** SIGKDD Explorations, 1(2).

Salton G. (1999). **Automatic Text Processing: The Transformation, Analysis, and Retrieval of Information by Computer,** Addison-Wesley, Reading, Mass., USA.

Tan B. (2000). **Web information monitoring for competitive intelligence,** Cybernetics and Systems, 33, 3, 225-235.

Titterington D. (1985). **Statistical Analysis of Finite Mixture Distributions**. John Wiley & Sons.

Willmot D., (1999) **Alexa**, *PC Magazine Online,* January (1999).

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Editor's Note: This paper focuses on reflection, interaction, and feedback, not only to reinforce learning, but to raise learning to higher levels of critical reflective thinking. It demonstrates the value of interaction and learning communities to enhance quality and effectiveness of online learning, especially in problem solving and critical thinking skills.

The Role of Critical Thinking in the Online Learning Environment

Kelly Bruning

Abstract

Research indicates that critically reflective learning provides students with an opportunity to evaluate concepts learned and apply them to their experiences, contemplating its affect on future learning. This process occurs in a learning community where student interaction and feedback fuels the learning process leading to a higher level of critical reflective thinking for the learner. The challenge for online instructors is how to incorporate critical thinking in the online environment in an effective manner. This paper addresses the issue of critical thinking and how it is applied in an actual online environment through an interactive exercise created by the instructor. The exercise not only fuels student learning but also creates a learning community in which students interact and share ideas. The BUS105 Create-A-Problem exercise described in this paper incorporates critical thinking in the online environment to meet the goals of developing reflective critical thinking in students and to nurture and online learning community that can be used as a model for other online instructors.

KeyWords: Critical Thinking, Online Learning, Reflective Learning, Critical Thinking Exercise, Business Math Critical Thinking

Learning Challenge

The challenge to the instructor was to develop a course that provided the fundamental knowledge on the concepts. The second was to provide usability and functionality of navigating the course. An interaction component among students needed to be incorporated into the course to foster a learning community. The instructor wanted to reinforce concepts but was faced with the challenge of how to post questions to the discussion board and encourage interaction with other learners. The last challenge was to incorporate Northwestern Michigan College's core general education outcomes into the curriculum.

Northwestern Michigan College has a campus-wide movement to incorporate five core general education learning outcomes in all classes. They are summarized as follows:

- The ability to problem solve.
- The ability to communicate with other learners.
- The ability to use the English language in communication.
- The ability to read and summarize.
- The ability to apply critical thinking concepts to course concepts.

It is the goal of Northwestern Michigan College to incorporate as many of these core competencies across the curriculum. Not only did the course need to be designed with functionality and usability in mind but it also needs to incorporate as many general education outcomes as possible. The challenge to the instructor was to gain an understanding of the online learning platform and to think of ways to incorporate the educational learning outcomes as possible. Two specific areas needed special attention: establishing interaction among students and implementing critical thinking. Critical thinking is defined in the learning outcomes handout distributed to faculty members at Northwestern Michigan College as "The ability for the student to use independent thinking and incorporate concepts learned to problem solve a realistic situation."

The unique challenge of incorporating the outcomes in the online learning environment is the lack of face-to-face communication and real time conversation. In a traditional classroom the learning community is created through natural socialization of students and designing assignments in which students work in groups. The critical thinking is stimulated when the instructor asks open-ended thought provoking questions in which student need to tap into their analytical thinking skills and apply the knowledge to the problem. Since students in the online platform work independently through the computer technology medium, the instructor needed to create a way to promote interaction among students similar to group learning in the face-to face course. The instructor also needed to create critical thinking exercises in which course concepts were reinforced but that students could also relate to.

Key Issues

Numerous authors have proposed definitions for critical thinking relative to their own disciplines. One of the earlier teams to write about critical thinking viewed it as a composite of knowledge, skills, and attitudes (Watson & Glaser, 1964). This team went on to develop the Watson-Glaser Critical Thinking Appraisal tool which is presently used by researchers of critical thinking in nursing (Hartley & Aukamp, 1994; Pless & Clayton, 1993). This tool measures skill in performing inference, recognition of assumptions, deduction, interpretation, and evaluation of arguments, all of which are used during the process of reflection. In fact, some theorists believe critical thinking is a cognitive process grounded in reflection (Jones & Brown, 1993).

In general, critical thinking is the method of evaluating arguments or propositions and making judgments that can guide the development of beliefs and taking action (Astleitner, 2002). Glister (1997) regarded critical thinking as the most important skill when using the Internet (p. 87). Reinmann-Rotmeier and Mandl (1998) as cited by Astleitner (2002), found in a Delphi-study, that experts from economy and education nominated critical thinking as the most important skill in knowledge management (p. 33). Kraak (2000) as cited by Astleitner (2002), saw critical thinking as "an important, perhaps the most important of all present time educational tasks" (p.53).

Critical thinking occupies a special place in the hearts of adult educators, particularly because of its connections to the democratic tradition that informs the field. At the heart of a strong, participatory democracy is citizens' capacity to question the actions, justifications, and decisions of political leaders, and the capacity to imagine alternatives that are more fair and compassionate than current structures and moralities. Such capacities develop as we learn to think critically. Encouraging critical thinking in adults is therefore integral to the democratic project. It is also true that critical thinking seems to hold the promise of constituting a universal theory of adult learning and, by implication, a template for adult education practice (Brookfield, 2001). If critical thinking is a uniquely adult learning process, then fostering critical thinking becomes, by implication, a uniquely adult educational process. Critical thinking can be analyzed in terms of both process and purpose, although these two elements are inevitably intertwined.

As a process, critical thinking involves adults in recognizing and researching the assumptions that undergird their thoughts and actions (Brookfield, 1987). Assumptions are the taken-for-granted beliefs about the world and our place within it that seem so obvious to us that they do not seem to need to be stated explicitly. Assumptions give meaning and purpose to who we are and what we do. In many ways we are our assumptions. So much of what we think, say, and do is based on assumptions about how the world should work and about what counts as appropriate, moral action. Yet frequently these assumptions are not recognized for the provisional understandings they really are. Ideas and actions that we regard as commonsense conventional wisdoms are often based on uncritically accepted assumptions. Some person, institution, or authority that we either trust or fear has told us that this is the way things are and we have accepted their judgment unquestioningly (Brookfield, 1987). When we think critically, we start to research these assumptions for the evidence and experiences that inform them.

Proposed Solution

Goals

1. Provide general education on concepts in the course design achieved through "helpful hints."
2. Design the course with Web usability and functionality issues in mind.
3. Incorporate as many educational outcomes as possible.
4. Foster a learning community within the classroom.
5. Create critical thinking opportunities that are fun and relevant to the student.

Strategy

- Weight course assessment tools according to importance in calculating student grades. Create-A-Problems are 20% of the student grade.
- Describe the course requirements as detailed as possible in syllabus with additional online areas that are repetitive to provide easy access to reminder information.
- Require an orientation to the course.
- Instructor comments on create-a-problems to learners via e-mail to provide positive reinforcement.
- Several core educational outcomes are incorporated throughout the course.

Required Resources

There are no other required resources for this project. The instructor must be knowledgeable in online course tools ad techniques and well as Web design. The instructor has taken Web design courses as well as courses in online teaching and training.

Providing General Knowledge

The goal of providing general knowledge to students in BUS105 was the development of "Helpful Hints" for each section of the chapter. Helpful hints provide students with brief notes on the section concepts. It is a form of mini-lecture that provides students with information and analysis of key concepts of each unit. Students were also assigned homework from their textbook. A one page summary sheet of their answers was submitted to the instructor via the instructor's drop box.

Usability and Functionality

The Blackboard platform provides a general "shell" for the course. The command buttons are all the same. It serves as a template for designing the course and provides standardization of usability and functionality of all online courses that use the Blackboard platform. To further enhance usability and functionality, the eleven chapters were divided into five modules. The components needed to complete each module were then nested within the module folder. In essence, a hierarchical filing system was developed by the instructor so that each module was self-contained. Components of each module consisted of the following: (a) helpful hints; (b) homework assignment (c) homework assignment solutions (time released after submission of the homework); (c) quizzes for the chapter in the module; and (d) create-a-problem examples.

The concept of nesting the chapters into a hierarchical file structure was developed so that students could easily find the components of the course that pertained to specific units assigned. It also provided a neat visual for students in which they would not feel overwhelmed seeing 11 different folders for each unit, in addition to a quiz folder, a create-a-problem folder, homework folder, homework solution folder, etc. The students see four folders which has been cited in student evaluations to alleviate fear of navigating the course.

Developing a Learning Community

Developing a learning community requires student interaction. The instructor was challenged with a way of promoting student interaction in a mathematics course where most solutions required only one answer. To post a question to the discussion board where students replied independently with only one answer did not meet the interaction goals desired by the instructor. Students could not really reply or build upon the previous discussion thread because only one solution is arrived at. It was the decision of the instructor to attempt to incorporate student interaction with the creation of a critical thinking exercise. This concepts is further addressed in the critical thinking section of this paper.

Incorporating Educational Outcomes

The problem solving educational outcome was in place due to the problem solving required in a mathematics course. The instructor felt that the communications core competency could be achieved by creating the interactive learning community. The writing component could be achieved through writing story problems on mathematical problems. The critical thinking could also be stimulated in the formulation of mathematical story problems using course concepts.

Critical Thinking Component

A critical thinking exercise was developed with the following goals in mind:

(a) apply the mathematical concepts learned using analytical skills

(b) have the exercise relate to the student in order to provide student interest;

(c) the ability to share the critical thinking exercise with fellow learners on the online platform to stimulate student interaction and develop a learning community.

The concept of the *Create-A-Problem* exercise was as follows:

- Students create a problem using the chapter concepts. This allowed the students to relate the problem to their life and incorporate the fundamentals of problem solving into a story problem that another student would answer.
- Students also create the detailed solution key to the problem. This also stimulates problem solving. It also prepares the student to address concerns of the student answering their problems.

- The students are paired up as partners by the instructor. The pairing changes each week to allow students to interact with each other forming a learning community.
- If Smith is paired with Jones. Smith posts the Create-A-Problems questions to Jones via the discussion thread in the course room. Jones then has a few days to prepare the answers. Jones post to the link, his solutions to Smith's problems. Smith now has the responsibility of correcting Jones' answer sheet providing feedback on incorrect problems. After a mutual understanding by the partners of the problems is met, Smith also has the responsibility of providing positive feedback to Jones on his problem solving. In this scenario, Jones in turn, is submitting his Create-A-Problems to Smith to answer and also following the sequence.
- If the partner does not post the Create-A-Problems by the due date, the student is free to answer anyone else's Create-A-Problems in the class. This alleviates the problem of students not receiving their questions from their partners on a timely basis. The partner that failed to post on time receives a markdown grade on the Create-A-Problems for not meeting the deadline.

An example of acceptable Create-A-Problems for each unit is available to students so that they understand the expectations of the caliber of Create-A-Problems expected by the instructor. The examples were written by prior students using the ruberic that appears in the following paragraph. The create-a-problem examples provided to students are based on the ruberic for the problems and incorporate concepts addressed in the research cited in the literature review of this paper regarding critical thinking theory.

The Create-A-Problems comprise 20% of the student's total grade. This gives the student the incentive to participate in the process and to formulate good, sound, problems that follow the ruberic in the course room. In addition, the instructor provides feedback to individual students regarding their Create-A-Problem assignments.

Table 1. Rubric

Comprehensive Concepts / Difficulty Level	Preparation of solutions and their detail	Responding to your partner's question(s) using the Discussion Board
1-5	1-5	1-5

Each create a problem within a set that is worth a total of fifteen points. Students receive a rating of 1-5 on the comprehensive concept of the problem. They receive a 1-5 on preparing the solutions to the problems, and they receive a 1-5 for responding and providing feedback to their partner. Late postings to the course discussion board are not be accepted for credit. If the student partner does not post to the discussion board by the due date on Wednesday evenings, students are free to answer questions posed by another learner in the classroom. This solves the problem of students not receiving their create-a-problems because their partner did not post them.

Example Problems

Section 3.1

(1) Write 1.5 as a percent. Comp. Level 1

(2) After sharing a lemon pie with my family, there is 1/8 of a pie left. What is the percent of pie left? Comp. Level 4

My brother ate 1/4 of a pie and I ate 1/8 of a pie. How much of the pie is left? Comp. Level 5

Appropriate Solution for (3) above that would score a 5 for solution detail:

1) Convert 1/4 and 1/8 to like fractions. 8 is the common denominator.
2) 2/8 + 1/8= 3/8 is consumed. 5/8 remain.
3) To find the percentage of pie convert 5/8 into a decimal by dividing the numerator by the denominator. 5 divided by 8 = .625
4) To find the percentage move the decimal point 2 placed to right and add percent sign. 62.5% of the pie is consumed.

The following solution for (3) above that would score a 1 due to lack of detail in solving the problem.

1) 62.5%

3.5 Appropriate level 5 concept:

Mr. and Mrs. Williams purchased a new home last year for $60,000. The value of the home has decreased in value 15% since last year. What is the value of the house now?

Appropriate level 5 Solution:

1) First determine how much of a decrease the home is valued at. 100%-15%=85%
2) Multiply the value of the home $60,000 by .85 (to convert % to decimal, move the decimal place two places to the left and ad a .)
3) 60,000 X .85 = $51,000
4) The home is now valued at $51,000.

Responding to partners questions via the discussion board:

No response	0
Late response	0
Incomplete response	1
Constructive Feedback	5

*Even if the answer sheet is totally correct, you must supply constructive feedback to your learning partner. (i.e. All are 100% correct, good job!)

Appropriate level 5 Feedback to question above.

(assume that the error was 8.5 (line 2 above) not .85 as it should be)

The error is in converting the percentage into a decimal.

To convert a percentage to decimal, move the decimal point 2 places to the left.

85% converts to a decimal .85

Process of Discussion Thread:

1) Step One- Student posts questions to assigned partner via the Discussion Thread.

Current Forum: CP5 Problems Read 12 times

Date: Wed Feb 19 2003 4:12 pm

Author: Kuebler, Stacy <sugarray131@yahoo.com>

Attachment: create-a-problem5,kuebler.doc (19456 bytes)

Subject: To. Milliron From. Kuebler CP5

Remove

Here are my CP questions.

5.1. Teagan makes $ 2750.92 semi-monthly. Find how much she makes weekly, biweekly, monthly, and annually.

5.2 Everett sells insurance; he makes a 5% commission on all sales he makes. On Monday he sold $ 7500, on Tuesday he sold $ 405, on Wednesday he sold $ 13000, on Thursday he sold nothing, and on Friday he sold $ 3500. What did he make this week?

5.3 Deacon makes $ 75,176 annually. How much does he pay in Social Security Tax (6.2%), Medicare tax (1.45%), and what does he make after the deductions?

5.4 Riley makes $ 2017 monthly; she is single with 3 withholding allowances. What is her withholding tax?

2) Step Two: Student has three days to respond to the questions.

Current Forum: CP5 Problems Read 13 times

Date: Thu Feb 20 2003 5:30 pm

Author: Milliron, Sara <poozar@yahoo.com>

Attachment: cp5_answer_to_kuebler.doc (25088 bytes)

Subject: To Kuebler from Milliron

Remove

Here are my answers to your Create A Problem questions.

5.1 Teagan makes $ 2750.92 semi-monthly. Find how much she makes weekly, biweekly, monthly, and annually.

Teagan makes $1269.66 weekly, $2539.31 biweekly, $5501.84 monthly, and $66022.08 annually.

5.2 Everett sells insurance; he makes a 5% commission on all sales he makes. On Monday he sold $ 7500, on Tuesday he sold $ 405, on Wednesday he sold $ 13000, on Thursday he sold nothing, and on Friday he sold $ 3500. What did he make this week?

Everett earned a gross pay of $635.25 this week.

5.3 Deacon makes $ 75,176 annually. How much does he pay in Social Security Tax (6.2%), Medicare tax (1.45%), and what does he make after the deductions?

Deacon pays $4660.91 in Social Security tax, $1090.05 in Medicare tax, and earns $69425.04 after these deductions.

5.4 Riley makes $ 2017 monthly; she is single with 3 withholding allowances. What is her withholding tax?

Found on the wage bracket method, her withholding tax is $161.
Found on the percentage method, her withholding tax is $160.65

3) Step Three: The partner responds to the solutions and provides feedback.

Current Forum: CP5 Problems Read 16 times

Date: Fri Feb 21 2003 6:37 pm

Author: Kuebler, Stacy <sugarray131@yahoo.com>

Attachment: answerscp5.doc (20480 bytes)

Subject: Re: To Kuebler from Milliron

Remove

Here are the answers I got. I think the only one we got different answers on was 5.2. Other than that you did good.

Reply

5.1

To find the monthly multiply the semi-monthly by 2. $ 2750.92 x 2 = $5501.84

To find the annual multiply the monthly by 12. $5501.84 x 12 = $ 66,022.08

To find the weekly divide the annual by 52. $ 66022.08 / 52 = $ 1269.66

To find the biweekly, multiply the weekly by 2. $ 1269.66 x 2 = $ 2539.31

5.2

Multiply Monday’s sales by the 5% commission rate. $ 7500 x .05 = $375

Multiply Tuesday’s sales by the 5% commission rate. $ 405 x .05 = $20.25

Multiply Wednesday’s sales by the 5% commission rate. $ 13000 x .05 = $650

Multiply Friday’s sales by the 5% commission rate. $ 3500 x .05 = $175

Add all the totals up. 375 + 20.25 + 650 + 175 = $1220.25

5.3

Take the amount he makes annually and multiply it by the 6.2% SST. $75,176 x .062 = $ 4660.91

Take the amount he makes annually and multiply it by the 1.45 Medicare tax. $ 75,176 x .0145 = $ 1090.05

Add the SST and the Medicare tax together. 4660.91 + 1090.05 = $5750.96

Subtract the $ 5750.96 from his annual pay. $ 75,176 – 5750.96 = $69,425.04

5.4

Check chart for a single person who is paid monthly.

Then look for the column with 3 withholdings.

$ 161

Step Four: The "ah-ha!" Response. Critical thinking has taken place! Positive feedback is given and a learning community is nurtured.

Current Forum: CP5 Problems Read 8 times

Date: Sat Feb 22 2003 2:52 pm

Author: Milliron, Sara <poozar@yahoo.com>

Subject: Re: To Kuebler from Milliron

Remove

I see where I messed up on problem 5.2 of your create a problems to me. I used $1300 instead of $13,000. Thanks for the great problems.

Here is how you did: All correct. Great Job!

Assessment Strategy

Student feedback regarding the Create-A-Problem critical thinking exercise has been quite positive. Students cite (in course evaluations) the ability to interact with other students, getting a new partner every week, and the freedom to create story problems that they can relate to as key assets of the course. They also state that the critical thinking exercises prepare them to solve he story problems that comprise the majority of the exams in business math.

Once students learn the sequence of what is expected, they look forward to a new partner every week and the ability to apply concepts learned into a fun challenging story problem that they can relate to. This is the goal of critical thinking, to stimulate the student's analytical and problem solving skills and apply concepts learned to solve realistic problems.

Insights

There are several insights I have regarding this project. First of all, I feel if I can develop a successful business mathematics course on-line, I can develop just about any course online. I have become more confident in developing and facilitation an online course. I have also learned how to develop a learning community by personalizing e-mail messages, giving frequent and feedback to students, and providing positive reinforcement. In addition, my BUS105 Business Mathematics Course has been used as an example in teaching other faculty how to incorporate the educational outcomes required by Northwestern Michigan College into the online curriculum.

The Create-a-Problem develop provides a means for fostering student interaction as well as critical thinking. In the future, I plan on using this exercise in my face-to-face course, using the Blackboard platform for students to interact to exchange their Create-A-Problems. The exercise was piloted in a face-to-face course, but the schedule of the course did not allow for frequent feedback among students (it took one week to develop questions, one week to exchange, one week to answer).

The course design is well received by students. Students make an effort to communicate to me how well they like the Create-A-Problems aspect of the course. The course is entering its one year anniversary this summer. Each class has had a capacity enrollment with a 10% attrition rate. One student commented: "I've always hated math and wasn't very good at it. The instructor has developed this class in a user-friendly ways and provides an opportunity for learners to interact with one another creating "cool" story problems that we as students can relate to. I never thought math class could be this fun. I've taken this class twice now. I am currently holding a 4.0 and hope to do well on the final exam to maintain that grade." This comment, I feel summarizes the success of the BUS105 course.

Conclusion

The instructor that recognizes the value of critical thinking will provide students with assignments that require in-depth critical thinking skills. Critical thinking is the process of taking learned theory and applying them in practice. This requires cognitive skills that require the learner to think of ways to take the concepts learned and apply them. It is considered by some researchers in the field to be on of the most critical aspects to be included in the online learning environment and the most important knowledge skill.

The role of critical thinking and reflective learning in the online environment is paramount. Critical thinking assignments provide an opportunity for learners to apply knowledge to practical application. Online instructors have the responsibility of providing this opportunity for educational growth to learners and must become creative in developing assignments and projects that foster that growth.

References

Astleitner, H. (2002). Teaching critical thinking online. *Journal of Instructional Psychology, 29,* 53-76.

Brookfield, S. (2001). Repositioning ideology critique in a critical theory of adult learning. *Adult Education Quarterly, 52,* 7-22.

Brookfield, S. Developing critical thinkers: Challenging adults to explore alternative ways of thinking and acting. San Francisco: Jossey-Bass, 1987.

Brookfield, S. (1995). *Becoming a critically reflective teacher*. SanFrancisco: Jossey-Bass, Inc.

Hartley, D., & Aukamp, V. (1994). Critical thinking ability of nurse educators and nursing students. *Journal of Nursing Education, 33*, 34-35.

Jones, S., & Brown, L. (1993). Alternative views on defining critical thinking through the nursing process. *Holistic Nurse Practitioner, 7,* 71-76.

Watson, G., & Glaser, E. (1964). *Watson-Glaser critical thinking appraisal manual*. New York: Harcourt Brace & World.

About the Author

Dr. Kelly Bruning

Dr. Kelly Bruning has been working in business, marketing, and education for over twenty years. She is now a fulltime instructor at Northwestern Michigan College. Her background consists of a broad range of business knowledge including organizational behavior, economics, marketing, finance, human relations, and information technologies.

She completed her Doctorate Degree in Business Management and Organization with a specialty in Information Technologies Management in November of 2003. She earned her MBA from Lake Superior State University.

Dr. Bruning has been active in online teaching and training since its introduction to the academic arena. She has designed content for online course and now teaches online courses at both the graduate and undergraduate level. She earned a graduate certificate in online teaching and training while writing her dissertation.

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