**Chapter Six**

**Optimization and Evaluation**

* 1. **Introduction**

Optimization is a continuous process that happens iteratively and recursively to achieve better: addressing and understanding the problems in hand, presenting different proposed solutions, optimizing the selected solution, applying the optimized and enhanced solution, evaluating the applied solution, and then back to the beginning of the optimization lifecycle. Optimization lifecycle is presented in figure 6.1. In this chapter, we review what we have presented through the dissertation quickly and focus on evaluation and optimization aspects of the proposed Adaptive e-Learning Models and Intelligent Services.

**Figure 6.1: Optimization Lifecycle**

* 1. **Addressing Problems**

Proposed Adaptive e-Learning Models addressed two problems categories: Technical and Pedagogical problems.

* + 1. **Pedagogical Problems**

Reviewing current e-Learning status shows that current Blended Learning Model Paradigm faces many challenges; mainly pedagogical. To take a closer look at the problem, we conducted a pilot study for fourth year Information Systems department students at the faculty of Computers and Information Sciences in Mansoura University, Egypt, later at 2008. The good thing is that students believe in the efficiency of e-Learning and they are willing to use e-Learning and participate in e-Learning experiments, however there were problems. Pedagogical problems include:

* Students don’t use internet as their source of information although Internet is the main updated source of information and needs to be integrated in the learning environment.
* Most Students don’t know what “Tutorials” is. That means they haven’t utilized an online learning resources in a sequenced manner that helps them learn new topics at the end of a certain stage.
* Most students don’t access internet via their mobile phones, and they are not willing to participate in mobile learning experiments. They even believe mobile learning will not become popular in the near future.
* Students agreed that we utilize different forms of e-Learning. Though the faculty of the authors does not provide an official site for e-Learning, any online courses, assessment site or any other form of e-Learning other than the authors’ attempts, students still believe that e-Learning is efficient - even if they have not experienced it at all.

For more details about the pilot study, the reader can refer to chapter 3.

* + 1. **Technical Problems**

Integrating University Management Information Systems (UMIS) and Learning Management Systems (LMS) is a need to achieve better e-Learning systems. Different software architecture patterns can be utilized in integrating both systems. Studying and analyzing many of the available software architectures has led to the realization of efficiency and effectiveness of utilizing Service Oriented Architecture (SOA) however it has led to different challenges. Challenges include the lack of performance efficiency when transmitting large amount of data. Besides, efforts of presenting adaptive and intelligent features of e-Learning have been spent without integration and presentation in current e-Learning systems. Web Service Software Factory design pattern as an example of Web services design patterns that builds everything within systems as Web services will yield to big performance degradation to proposed integrated e-Learning systems. Another technical optimization includes utilizing another integration technologies rather than Web services.

* 1. **Presenting Proposed Solutions**

Keeping the focus on Web and Desktop applications and shifting away from mobile learning is a direct result of students’ unwillingness to experience and participate in mobile learning experiences. The pedagogical solutions focus on introducing adaptive and intelligent features in e-Learning to reach personalized environment. While the technical solutions focus on utilizing SOA in presenting those features. However, we still provide capability to integrate mobile learning activities using SOA.

* + 1. **Pedagogical Solutions**

Different adaptive and intelligent pedagogical e-Learning solutions are presented to enable personalized e-Learning environment that will enhance students’ e-Learning experience. The need for a personalized e-Learning system that incrementally and gradually takes students through an e-Learning experience is clear from the problems in hands section.

* + - 1. **Adaptive Pedagogical Solutions**

There are four main approaches that can be used to give a historical overview of Adaptive e-Learning. They are *Macro Adaptive*, *Aptitude-Treatment Interaction* (ATI), *Micro-Adaptive* and *Constructivistic-Collaborative* approaches. Proposed adaptive e-Learning model proposed in chapter three addresses those different adaptive e-Learning approaches and utilizes all of them. The four addressed approaches are:

* **Macro Adaptive Approach:** The proposed model addresses this capability by testing the student profile and learning preferences before establishing learning material.
* **Aptitude-Treatment Interaction (ATI) Approach:** The proposed model addresses allows the students to choose among the topics to learn (within the constraints of the pre-requisites). This gives them the partial control experience. Also, the proposed model provides the capability to arrange meetings between the instructors and students that have issues with certain learning topics. Students are given the chance to self-study the subjects and attend the exams 3 times. If the student fails to pass the exam 3 times, a meeting must be arranged between the instructor and the student to submit a repost by the instructor to the student profile, so the student can continue the learning process again in the adaptive way. This sort of blended learning gives strength to the proposed model.
* **Micro-Adaptive Approach:** The proposed model addresses this approach by providing the capability to calculate the required time to study for each learning topic.
* **Constructivistic-Collaborative Approach:** Online forum, wiki and blog services will be available to students to enhance collaborate and help each other. Facilities to enable online study groups - like chatting applications - can be made available. Arguments around the effectiveness of Web 2.0 features in e-Learning are taking place all around.
  + - 1. **Intelligent Pedagogical Solutions**

Intelligent techniques are presented to empower the proposed Adaptive e-Learning Models. Proposed models shed lights on supporting e-Learning with intelligent features. One of the main features supported by our model is supervised intelligent curriculum sequencing to present adaptive e-Learning fine-tuned by the instructor. Nine intelligent services that can be utilized in different e-Learning functionalities were presented. These intelligent services are grouped into two categories based on their aims: *Instructor Services* and *Student Services*.

The Instructor Intelligent Services are: *Intelligent Learning Object (LO) Classifier service, Intelligent Online Lecture LOs Advisor, Intelligent Student Performance Tracker and Intelligent Cheating Depressor.* The Student Intelligent Services are: *Intelligent Time-to-Learn Topic Calculation, Intelligent Study Plan Advisor, Intelligent Agenda Study Time Planner, Intelligent Meeting Manager for Suspended Students and Intelligent LOs Recommender.*

Fuzzy Logic is the intelligent technique used in different aspects of the services to enable different functionalities as presented in chapter four.

* + 1. **Technical Solutions**

Combining both Business Process Management (BPM) and Service Oriented Architecture (SOA) is proven to achieve numerous advantageous features for systems. Presenting adaptive and intelligent features as services with standard interfaces will allow different e-Learning systems to adopt them, so they will be reusable and newly introduced information systems will not have to redo the work again, besides, wrapping adaptive and intelligent features with standard interfaces will present a separation of interests that help adaptive and intelligent features’ researchers and developers to focus more on their target and transfer the responsibility of utilizing those features in different information systems to information systems specialists. Presented Adaptive e-Learning Models presented an adaptive learning process that adaptively changes based on students’ performance. Proposed model composing services can be categorized in the following layers:

* **Orchestration Layer:** holds services responsible for maintaining learning process logic and activities. It includes services that utilize both composite services’ layer services, and data services’ layer services.
* **Composite Services:** are services that hold other services and don’t complete functioning unless all composing services execute successfully; however it is not controlling them.
* **Data Services Layer (Information as a Service “IaaS”):** is the layer that holds services responsible for transforming Meta-data into meaningful information to other utilizing information systems, instructors, and students.
* **Model Layer (Database):** it is the database layer that holds data tables.

Though Web services provide technology neutral interface to be utilized online through standard URL, J2EE Connector Architecture (JCA) connects Java based applications in an enhanced performance measures when compared to XML Web services. Another technical optimization point includes using emerging protocols that are designed for Web. The Open Data Protocol (OData) is a web protocol for querying and updating data. OData applies web technologies such as HTTP, Atom Publishing Protocol (AtomPub) and JSON to provide access to information from a variety of applications, services, and stores. OData is being used to expose and access information from a variety of sources, including but not limited to relational databases, file systems, content management systems, and traditional web sites.

* 1. **Optimizing Selected Solution**

Applying the presented solution yielded some challenges and bottlenecks that need optimization. Optimization in this phase focuses on the system performance. Intelligent LOs Recommender is the one of the core services and lies in the heart of the proposed Adaptive e-Learning Models. It is utilized in different intelligent services. However, upon deployment, Intelligent LOs Recommender met challenges that affected its performance and efficiency. Optimizing it will affect the presented models overall performance. Intelligent LOs Recommender is evaluated from Performance perspective in order to accelerate overall system performance.

* + 1. **Intelligent LOs Recommender Challenges**

To empower the presented adaptive e-Learning models, we designed and built the Intelligent LOs Recommender. Intelligent LOs Recommender was tested on different files (221) and online LOs (342). Files LOs generated 7388 tokenized Term Frequencies (TF) and online LOs generated 169876 TFs. Challenges in designing and implementing the Intelligent LOs Recommender include:

1. **Identifying Seeds:** with the increasing number of online content, defining seeds for the crawler is an important task.
2. **Identifying Online and Offline Phases:** identifying bottlenecks in the Intelligent LOs Recommender performance is an important issue to avoid dead ends and long times of processing that affects systems.
3. **Evaluating Accuracy of Generated Terms:** generated terms shall be evaluated to avoid non-related terms.

Unleashing an online crawler to collect different LOs available online, and storing meta-data about them in an offline database, with URLs made available for later visits of the Intelligent LOs Recommender service was the first task achieved in building this service. Visiting those URLs later, retrieving the LOs, tokenizing and stemming, calculating Term Frequencies, and storing calculated Term Frequencies in the database for later matching with course objectives. Random LOs group of the crawlers results are used as the test set with capacity of 254 LOs. Reading time in seconds for each of those LOs are presented in Figure 6.2. Table 6.1 presents summary of the main statistical measures of LOs reading times in seconds.

**Figure 6.2: Learning Objects Reading Time in Seconds**

**Table 6.1: Summary of the Main Statistical Measures of Learning Objects Reading Times in Seconds**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0.819568872 | **Mean** | 5.108815395 |
| **Max.** | 38.5457058 | **Mode** | N/A |
| **Range** | 37.72613692 | **Median** | 3.159333944 |

Reading times fall in an average time of five seconds in retrieving the LO. Optimizing LOs retrieval can be done through increasing network bandwidth and the servers’ memory that affects window sizing. Tokenization duration for retrieved LOs is presented in Figure 6.3 followed by Table 6.2 summarizing the main statistical measures of tokenizing LOs times in seconds. Tokenization duration falls below half a second at its worst case, and it is believed that tokenization is in an optimized form.

**Figure 6.3: Learning Objects Tokenization Duration in Seconds**

**Table 6.2: Main Statistical Measures of Learning Objects Tokenization Times in Seconds**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0.000496149 | **Mean** | 0.051718733 |
| **Max.** | 0.461540937 | **Mode** | N/A |
| **Range** | 0.461044788 | **Median** | 0.026743531 |

Term Frequencies calculation time for each LO is presented in Figure 6.4 followed by Table 6.3 that highlights a summary of the main statistical measures of Learning Objects Term Frequencies calculation time in seconds. TF processing ranges are from fractions of milliseconds to less than three seconds for the LO. TF processing is efficient enough to be utilized in the recommendation process.

**Figure 6.4: Learning Objects Term Frequencies Calculation Times in Seconds**

**Table 6.3: Main Statistical Measures of Term Frequency Calculation Time in Seconds**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 6.48499E-05 | **Mean** | 0.095572824 |
| **Max.** | 2.913298845 | **Mode** | 0.001230955 |
| **Range** | 2.913233995 | **Median** | 0.015192032 |

The first performance bottleneck appears in extracted terms database insertion times. Figure 6.5 presents LOs keywords insertion time in seconds. As summarized in Table 6.4, average keywords insertion time for LO is 373 seconds, with worst cases exceeding 2536 seconds. Such performance issue is not accepted and leading to dead ends in the system. It takes a lot of time to insert keywords in the database for later recommendation processing.

**Figure 6.5: Learning Objects Keywords Insertion Times in Seconds**

**Table 6.4: Main Statistical Measures of Learning Objects Keywords Insertion Time in Seconds**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 4.576031208 | **Mean** | 373.0938357 |
| **Max.** | 2536.919661 | **Mode** | N/A |
| **Range** | 2532.34363 | **Median** | 260.3440971 |

Figure 6.6 compares the percentage that tokenized number of words and the total number of words contributes to the total. Tokenized number of words when compared to total number of words doesn’t exceed 15% by anyhow. One challenge with online LOs is the tremendous amount of Hyper Text Markup Language (HTML) used for web based user interface. Tokenization process is responsible for handling this challenge. Regular Expressions (RE) are used to extract text from online LOs. Tables 6.5 and 6 present statistical measures about total and tokenized number of words respectively.

**Figure 6.6: Learning Objects Tokenized No. of Words vs. Total No. of Words**

**Table 6.5: Main Statistical Measures of Learning Objects Original No. of Words Count**

|  |  |  |  |
| --- | --- | --- | --- |
| **For Total Learning Object Words** | | | |
| **Min.** | 5 | **Mean** | 7238.443137 |
| **Max.** | 66491 | **Mode** | 1085 |
| **Range** | 66486 | **Median** | 3803 |

**Table 6.6: Main Statistical Measures of Learning Objects Tokenized Number of Words Count**

|  |  |  |  |
| --- | --- | --- | --- |
| **For Tokenized Words** | | | |
| **Min.** | 0 | **Mean** | 912.6745098 |
| **Max.** | 9737 | **Mode** | 121 |
| **Range** | 9737 | **Median** | 469 |

Though tokenized number of words percentage when compared to total number of words doesn’t exceed 15%, there is still a challenge facing our proposed Intelligent LOs Recommender which is the tremendous amount of extracted keywords that is not related to course objectives. Processing books for example, is a big challenge. One of the processed books was read in less than 0.25 a second with 12522837 original words number, generated 258457 tokenized words (1.6 MB of data) in 2188 seconds for tokenization processing, and Term Frequency calculation of 521 seconds. Such processing never finished uploading extracted keywords into the database.

Situation changes a lot when adding the course objectives into inputs. Course objectives extracted keywords and expanded by WordNet to increase system's efficiency percentage when compared to number of tokenized words and total number of words is presented in Figure 6.7. Handling more than the really needed keywords yields a big performance degradation that we can get rid of by presenting a design solution and taking the decision of including course objectives as an input parameter, thus coming over the performance bottleneck. Figure 6.8 followed by Table 6.7 presents the optimization gained in insertion.



**Figure 6.7: Course Objectives Extracted and Expanded Keywords vs. Tokenized No. of Words vs. Total No. of Words**

**Figure 6.8: Learning Objects Optimized Keywords Insertion Times in Seconds**

**Table 6.7: Main Statistical Measures of Learning Objects Keywords Insertion Time in Seconds**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0 | **Mean** | 124 |
| **Max.** | 132 | **Mode** | N/A |
| **Range** | 132 | **Median** | 74 |

* + 1. **Intelligent LOs Recommender Optimization Techniques and Comments on Results**

Optimizing and Enhancing the Intelligent LOs Recommender can be done through different design decisions:

* **Taking course objectives into consideration while determining crawler seeds:** a preprocessing step that processes course objectives and generate search keywords that are used to find related web sites using one of the many internet search engines helps in finding more near and accurate seeds for the crawler. In our proposed model, we developed a java based crawler that takes course objectives keywords as input, uses Google search engine to invoke the search query, loops through search results, and stores meta-data about found URLs in the database.
* **Query Expansion:** to increase the accuracy of search terms resulting from processing course objectives and specifications, query expansion methods can be utilized. WordNet is a lexical database for the English language that groups English words into sets of synonyms to provide short, general definitions, and records the various semantic relations between these synonym sets. Extracted keywords are expanded by WordNet synonyms and then passed to the crawler when seeking seeds.
* **Taking course objectives into consideration while calculating Term Frequencies for Learning Objects:** the main objective of Intelligent LOs Recommender is to intelligently contribute in personalizing the learning experience for the student by recommending the most accurate LOs, not indexing the online LOs. So, there is no need to get stuck in analyzing what doesn’t matter for the recommendation process. Enhanced solution will not calculate frequencies for terms that don’t exist in curse objectives and will not store term frequencies at all. The processing time and cost is much cheaper when compared to storage cost.
  1. **Evaluating Optimized Solution**

Presented Adaptive e-Learning Models and Intelligent Services shall be evaluated from different perspectives. Evaluation perspectives include:

1. **User Satisfaction:** Users here are both students and instructors.
2. **Information Retrieval** Evaluation of Intelligent LOs Recommender.
3. **Intelligent LOs Classifier** Evaluation.

Following sections present those three evaluation aspects and results.

* 1. **User Satisfaction Evaluation**

Preparing a Computer Networks Course and presenting it to students in the form of the presented Adaptive e-Learning Models and experiencing it, resulted in the following satisfaction measures. Table 6.8 presents summary of students’ opinion about presented features and how they evaluate the need for it and its performance. Presented Adaptive e-Learning Model was tested on sample of 10 students. Table 6.9 presents summary of instructors’ thoughts about presented features and how they evaluate the need for it and its performance and behavior.

**Table 6.8: Summary of Students’ Evaluation of Presented Adaptive e-Learning Models Features**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Feature | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **Learning Preferences** | 90% | 10% | -- | -- | -- |
| **Learning Profile** | 85% | 15% | -- | -- | -- |
| **Customizing Course within Rules** | 80% | 10% | 10% | -- | -- |
| **Separate Groups** | 30% | 10% | 10% | 25% | 25% |
| **Exams Check Points** | 30% | 10% | 10% | 30% | 20% |
| **LVQ** | 90% | 5% | 5% | -- | -- |
| **Video LOs** | 90% | 5% | 5% | -- | -- |
| **Intelligent LOs Recommender** | 70% | 20% | -- | 5% | 5% |
| **Intelligent Agenda Study Time Planner** | 63% | 17% | 5% | 8% | 7% |
| **Intelligent Study Plan Advisor** | 65% | 30% | -- | 5% | -- |
| **Intelligent Meeting Manager for Suspended Students** | 40% | 10% | 8% | 2% | 40% |

**Table 6.9: Summary of Instructors’ Evaluation of Presented Adaptive e-Learning Models Features**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Feature | Strongly Agree | Agree | Neutral | Disagree | Strongly Disagree |
| **Learning Preferences** | 90% | 10% | -- | -- | -- |
| **Learning Profile** | 90% | 10% | -- | -- | -- |
| **Customizing Course within Rules** | 90% | 10% | -- | -- | -- |
| **Separate Groups** | 70% | 20% | 10% | -- | -- |
| **Exams Check Points** | 70% | 15% | 15% | -- | -- |
| **LVQ** | 90% | 5% | 5% | -- | -- |
| **Video LOs** | 90% | 5% | 5% | -- | -- |
| **Intelligent LOs Recommender** | 70% | 20% | 10% | -- | -- |
| **Intelligent Online Lecture LOs Advisor** | 73% | 17% | 10% | -- | -- |
| **Intelligent Cheat Depressor** | 50% | 10% | 10% | 20% | 10% |
| **Intelligent Student Tracker** | 80% | 20% | -- | -- | -- |

**6.5.2 Information Retrieval Evaluation**

One of the fundamental problems in Information Retrieval (IR) is the ranking problem, ordering the results of a query such that the most relevant results show up first. Ranking algorithms employ scoring functions that assign scores to each result of a query at hand. So, ranking the results of a query consists of assigning a score to each result and then sorting the results by score, from highest to lowest. Many performance measures are used by IR community to evaluate the effectiveness of ranking functions.

In order to measure the relevance of the Ranked Recommended LOs list, three performance measures are used namely: Precision, Recall, and F-measure. The first performance measure used is Precision. Precision measures the ratio of relevant documents within a given number of documents returned to the number of returned documents. The second performance measure is Recall. Recall is defined as the number of relevant documents retrieved by a search divided by the total number of existing relevant documents (which should have been retrieved). The Recall measure quantifies what fraction of all the relevant results was ranked to fall within the first k documents. Precision and Recall scores are not discussed in isolation. Instead, both may be combined into a single measure, such as the F-Measure. F-Measure is the weighted harmonic mean of precision and recall. Figure 6.9 shows the precision measures of the proposed Intelligent LOs Recommender followed by Table 6.10 highlighting a summary of the main statistical measures. Figure 6.10 shows the recall measures of the proposed Intelligent LOs Recommender followed by Table 6.11 highlighting a summary of the main statistical measures. Figure 6.11 shows the F-Measure of the proposed Intelligent LOs Recommender followed by Table 6.12 highlighting a summary of the main statistical measures.

**Figure 6.9: Precision Evaluation of Proposed Intelligent LOs Recommender**

**Table 6.10: Summary of the Main Statistical Measures of Precision**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0.333333333 | **Mean** | 0.700674926 |
| **Max.** | 0.909090909 | **Mode** | 0.727272727 |
| **Variance** | 0.008883086 | **Median** | 0.727272727 |

**Figure 6.10: Recall Evaluation of Proposed Intelligent LOs Recommender**

**Table 6.11: Summary of the Main Statistical Measures of Recall**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0.434782609 | **Mean** | 0.31440623 |
| **Max.** | 0.434782609 | **Mode** | 0.347826087 |
| **Variance** | 0.005640442 | **Median** | 0.347826087 |

**Figure 6.11: F-Measure Evaluation of Proposed Intelligent LOs Recommender**

**Table 6.12: Summary of the Main Statistical Measures of F-Measure**

|  |  |  |  |
| --- | --- | --- | --- |
| **Min.** | 0 | **Mean** | 0.308731541 |
| **Max.** | 0.588235294 | **Mode** | 0.470588235 |
| **Variance** | 0.04558944 | **Median** | 0.441176471 |

**6.5.3 Intelligent LOs Classifier Evaluation**

Presented Intelligent LOs Classifier is evaluated to check its accuracy and capability to classify unclassified documents. Intelligent LOs Classifier implements Naïve-Bayes classifier algorithm. The following training set was given to the classifier. Table 6.13 presents categories and documents for each document that the classifier was trained on. Table 14 presents the results of testing. Testing set is presented to the trained classifier. Intelligent LOs Classifier resulted in 100% accuracy.

**Table 6.13: Summary of Intelligent LOs Classifier Training Set**

|  |  |
| --- | --- |
| Category | Training Document |
| Bioinformatics | |
|  | Biologically Inspired Computation |
|  | Dynamical Systems in Neuroscience |
|  | Molecular Analysis of Cancer |
|  | Probabilistic Models of the Brain Perception and Neural Function |
| BPM | |
|  | BPM Success: How a Travel Giant Turned its Ship Around CIO |
| Computer Networks | |
|  | Interconnecting CISCO network devices Part 1 |
|  | Interconnecting CISCO network devices Part 2 |
|  | Portable Command Guide |
| e-Learning | |
|  | 101 free e-Learning tools |
|  | Adaptive and Personal LMS |
|  | E-Learning Technologies |
|  | Questionmark-Tools-Effective-Assessments |
|  | SCROM-v1 |
| English | |
|  | New interchange 1-key |
|  | New interchange 1-student book |
|  | New interchange 1-workbook |
|  | Intro Workbook 3rd edition |
| Programming | |
|  | ASPNet in VB |
|  | ASPnet MVC |
|  | Applied Numeric Methods using Matlab |
|  | Essential Matbal for Engineers and Scientists |
|  | Visual Basic 2008 |
| SOA | |
|  | SOA Description |
|  | SOA Lab Setup Guide |
|  | SOA Release Notes |
|  | SOA Design Patterns |
|  | SOA Instructor Exercises Guide |
|  | SOA Lab Setup Guide Classroom |
|  | SOA Lab Setup Guide Online |
|  | SOA Student Exercises |
|  | SOA Student Book |

**Table 6.14: Summary of Intelligent LOs Classifier Testing Set**

|  |  |  |
| --- | --- | --- |
|  | | |
| Document | **e-learning by design** | |
| Class Percentage |  |  |
|  | English | NaN |
|  | e-Learning | -17510.210584564997 |
|  | Bioinformatics | -20216.649226425725 |
|  | BPM | -17698.0930699629 |
|  | Computer Networks | -20366.694928274974 |
|  | SOA | -19893.456729741945 |
|  | Programming | -22055.679402138958 |
| Decision | **e-Learning** | |
|  | | |
| Document | **effective e-Learning environment personalization using web usage mining technology** | |
| Class Percentage |  |  |
|  | English | NaN |
|  | e-Learning | -21879.011486226136 |
|  | Bioinformatics | -25730.60082626081 |
|  | BPM | -25055.906020316877 |
|  | Computer Networks | -25432.70422899807 |
|  | SOA | -25199.419281366278 |
|  | Programming | -28851.363753332593 |
| Decision | **e-Learning** | |
|  | | |
| Document | **CCNP2\_SLM\_v50** | |
| Class Percentage |  |  |
|  | English | NaN |
|  | e-Learning | -769103.2978993196 |
|  | Bioinformatics | -839262.6497608843 |
|  | BPM | -695368.4959748124 |
|  | Computer Networks | -610877.2165053524 |
|  | SOA | -784774.4069853874 |
|  | Programming | -855032.0508602582 |
| Decision | **Computer Networks** | |
|  | | |
| Document | **forrester\_bpm\_wave** | |
| Class Percentage |  |  |
|  | English | NaN |
|  | e-Learning | -83003.91116782578 |
|  | Bioinformatics | -94739.36297244373 |
|  | BPM | -78479.22990639707 |
|  | Computer Networks | -89490.77817552155 |
|  | SOA | -84576.42321484128 |
|  | Programming | -101919.05505022638 |
| Decision | **BPM** | |
|  | | |
| Document | **Network\_Fundamentals\_2D\_IRG** | |
| Class Percentage |  |  |
|  | English | NaN |
|  | e-Learning | -31300.31339492937 |
|  | Bioinformatics | -33352.432161580524 |
|  | BPM | -29577.875485405537 |
|  | Computer Networks | -29199.402824383295 |
|  | SOA | -32654.278796223974 |
|  | Programming | -36143.44494075163 |
| Decision | **Computer Networks** | |
|  | | |
| Document | **Prentice.Hall.SOA.Principles.of.Service.Design.Jul.2007** | |
| Class Percentage |  |  |
|  | **English** | **NaN** |
|  | **e-Learning** | **-810529.5972492553** |
|  | **Bioinformatics** | **-991026.2503207972** |
|  | **BPM** | **-962086.7346663276** |
|  | **Computer Networks** | **-933969.3054615034** |
|  | **SOA** | **-730561.9506475903** |
|  | **Programming** | **-1049997.9439706628** |
| Decision | **SOA** | |

* 1. **Summary**

This chapter presents the optimization activity we have been through this dissertation and highlights the optimization concepts have been focused on. Helping e-Learning in presenting new Adaptive e-Learning Models that enhances the e-Learning experience, presenting new Intelligent Services to provide advanced functionalities that cannot be achieved using standard methods, and enhancing the presented services are the activities that form the complete lifecycle of optimization. Optimization is an iterative and recursive operation that shall take place all the time, in order to enhance systems.

Optimized Solution shall be evaluated from different perspectives. To evaluate the Adaptive e-Learning Models, we surveyed the two target categories of the models: Students and Instructors. Both of them showed interest in the presented Adaptive e-Learning Models and feel that it can enhance the e-Learning experience greatly. Students have issues with the repeated exams process, and grouping students in smaller groups. However, they liked the adaptivity features presented. Instructors suspected the applicability of intelligent cheat depressor service, however they still agree to use it as an indicator, and the final decision remains their decision of course. The second perspective to evaluate the optimized Adaptive e-Learning Models and Intelligent Services from is Information Retrieval (IR). Information retrieval measures of proposed Intelligent LOs Recommender shows an achievement in precision measure, with challenges at Recall and F-Measure due to the increased number of relevant learning objects as a result of including the course objectives at the crawling phase. That means, almost all of the Learning Objects stored in the database is already relevant. Future work includes expanding the proposed Intelligent LOs Recommender automatic annotation of media LOs.

Finally, optimized Adaptive e-Learning Models and Intelligent Services evaluated another service that is: Intelligent LOs Classifier. Presented Intelligent LOs Classifier uses Naïve-Bayes Classifier, and it showed 100% classification capability.