Personalized Text Content Summarizer for Mobile Learning: An Automatic Text Summarization System with Relevance Based Language Model

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***Abstract*— Although millions of text contents and multimedia published on the Web have potential to be shared as the learning contents for mobile learning, effectively extracting useful information from them is an extremely difficult problem. Oft-decried information overloading is the main issue to impede this potential. Many approaches have been proposed to revise and reinforce content to provide the appropriate delivery for mobile learning. However, approaches of manually converting content to suit the mobile learning require a huge effort on the part of the teachers and the instructional designers. Automatic text summarization can reduce this cost significantly, but it may have negative impact on the understanding of the meaning conveyed, as well as the risk of producing a standard summary for all learners without reflecting their interests and preferences. In this paper, a personalized text-based content summarizer is introduced to address an approach to help mobile learners to retrieve and process information more quickly, based on their interests and preferences. In this work, probabilistic language modeling techniques are adapted to build a user model and an extractive text summarization system to generate the personalized and automatic summary for mobile learning. Experimental results have indicated that the proposed solution provides a proper and efficient approach to help mobile learners by summarizing important content quickly and adaptively.**

Keywords-component; personalized text summarization; mobile learning; content processing; relevance modelling; multiple-Bernoullio models.

I. INTRODUCTION

With the rapid growth of the mobile technology, mobile learning (m-learning) is rapidly becoming one of the mainstreams in today's e-Learning. The fast evolution of the mobile technology provides great potential to improve m-learning performance [1]. Meanwhile, this swift development makes it more possible for mobile learners to access the "on-the-fly" information. However, with millions of data available online in different forms or media types, learners find it extremely difficult to extract useful information, especially for learning purpose. In addition to this oft-decried information overloading problem, the small display screen, limited network bandwidth and storage capability of mobile devices also have potential to impede the development of the m-learning. For example, showing a large amount of text on a small screen of a mobile device requires scrolling, which is not a user-friendly task on mobile devices; also, delivering a big chunk of data across the mobile network can cost more and slow down the transaction speed significantly. Moreover, m-learners are usually willing to study using their mobile devices during their commutes. They expect to assimilate the information in a very limited time. In this case, it would be helpful if they could obtain the condensed content and important points rather than the entire learning content. Since both situations are content related, if the content size could be reduced somehow, both problems might be alleviated. However, reducing the content may have negative impact on the understanding of the meaning conveyed by it. Also, different learners may have different perspectives to the same learning content based on their learning preferences, interest, and prior knowledge. Producing one standard summary for all learners might not be good enough for an effective summarization. Thus, research on how to condense the contents properly and effectively so as to not lose the meaning yet produce personalized summary of the contents would have great potential for effective application of education technology for m-learning.

Recent research efforts in mobile learning have raised much debate about the need for small content to meet the perceived needs and expectations of learners using mobile devices. Many approaches have been proposed to revise and reinforce content to provide the appropriate delivery. For example, m-SCORM specifies and requires the content packages in m-learning to be succinct for them to be useful to more learners who enjoy accessing information anywhere [1]. However, most of these approaches involve instructional designers manually designing new content or reengineering instructional frameworks to suit the smaller screens and satisfy the 'on-the-fly' information access, such as mini learning objects based on IMS Content packaging specification and m-SCORM [1].

Researchers in m-learning have also proposed various content processing techniques in recent years. They focus on the design of presentation of the content to fit the small screen of mobile devices. These techniques include Web page adaptation techniques, a unit of information based content adaptation, and semantic web services based context-aware solutions [31, 32]. All these techniques consider changing the content layout rather than content size. They might solve the small screen issue, but they do not align well with the significant property of "on-the-fly" access to m-learning. In addition, these proposed approaches do not overcome other disadvantages of using mobile devices in learning, such as limited storage capability and network bandwidth. Also, few of these solutions consider learner's characteristics, especially the

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properties of “next generation” or “Net generation” learners. One of the most significant characteristics for next generation learners is that they like multi-tasking and have short attention span [14]. They can perform more tasks simultaneously and shift their attentions quickly from one to another, but would probably be overwhelmed or get frustrated if they are asked to read a long report for a while. In order to motivate them to engage in the learning content, more educators have supplied shorter contents in new curricula [14].

To process content effectively, many rapid authoring tools have been developed for creating mobile learning contents. However, there is no single solution to make content working for every possible mobile device due to the highly fragmented mobile technology landscape and rapidly evolving standards [16]. Some researchers have presented the idea about intelligent content strategy for automatically delivering content which is called “intelligent content” to mobile learners [17]. While ‘semantically categorized’ and ‘efficiently reusable’ are two of main concepts in this strategy, this intelligent content solution heavily relies on semantic tagging. Unfortunately, automatically putting semantic tags into the content is difficult, and hence, no significant achievement in semantic techniques is available to support automatic labeling of the content with metadata to identify the kind of content within it. Therefore, an alternative solution is considered to identify the meaning of the content.

Automatic text summarization condenses text contents into most important concepts and ideas under a particular context. This technology may be helpful to identify topics, categorize contents, and summarize documents. However, most previous work on automatic text summarization has emphasized on information abstraction and extraction. Some well-known approaches, like TFISF (term frequency and inverted sentence frequency) [4, 23], which summarizes a text based on term frequency weight that is assigned to each term, neural network system for text summarization [33], SVM [34], statistical models [2, 20, 36], and so on, usually rank sentences and select sentences with higher ranking score as the summary. These approaches have a significant drawback: they hardly combine concepts in different text spans since information in a document is often scattered across multiple sentences [29]. In addition, none of these approaches considers user’s preferences and interests within certain domain topics during the summary process. They all produce one standard summary for all users without referring to user’s preferences and interests.

Writing a summary is similar to writing other kinds of articles; it is a personal matter. A good summary is not just a condensed version of the original text; it has to express author’s deep comprehension to the content, and should reflect author’s preferences and interests. Furthermore, personalized summarization systems not only serve for simplifying the content of documents and aiding users to assimilate texts more easily, but also provide the most relevant information according to users’ preferences and interests.

In this paper, a personalized text-based content summarization system is introduced to help m-learners to retrieve and process text-based learning content more quickly both by aligning text-based content size with various mobile characteristics and by reflecting learners’ preferences and interests to the content. Similar to other language model based summarizers [18, 22], our approach adopts relevance model [35] to perform the retrieval task. Moreover, a user model is constructed using a multiple-Bernoulli distribution within a language modeling framework [11, 13]. Then, a linear approach is applied to combine these two models based on the same term indexes. After this step, documents are retrieved based on a given query. Then, top-ranked relevant documents are clustered as a group to perform the sentence similarity evaluation by the combined model. Finally a maximum similar score is used to reform the sentences into the final summary.

The rest of the paper is organized as follows: Section 2 describes related work in text summarization including personalized text summarization with probabilistic language modeling approaches. Section 3 discusses the proposed approach, focusing on relevance model for document retrieval and multiple-Bernoulli model for user modeling. This is followed by a discussion on how to combine these two models to perform the task of personalized automatic text summarization. The proposed approach is validated through an experiment and section 4 discusses the experiment with its results, followed by conclusions in Section 5.

II. RELATED WORK

Recently, researchers have proposed several approaches using structured probabilistic language models to summarize document content [2, 18, 21, 22, and 30]. Before reviewing probabilistic modeling approaches, it is worth discussing the SumBasic [4], a summarization system that exploits frequency exclusively to create summaries. In SumBasic algorithm, a sentence is assigned a score that is the sum of probabilities of words that appear in the sentence. The algorithm is based on the hypothesis that human summarizer might choose words in a summary if those words appear in documents more frequently [4]. The system SumFocus [28], built based on this algorithm, has shown the highest performance improvement in a standard ROUGE [8] evaluation at DUC 2006. Despite such achievement, this unigram distribution approach has significant disadvantages since it ignores distinction of word frequency in different documents.

Another approach, namely KLSum, uses the Kullback-Lieber (KL) divergence to measure the difference between the document distribution and the summary distribution [7]. It has circumvented some problems caused by unigram distribution, and experimental results have shown that KLSum performed better than SumBasic in DUC 2006 [28]. However, the improvement is not significant due to the natural shortcomings in the unigram model.

In order to address the shortcomings in unigram distribution, generative probabilistic language models have recently been proposed. BayeSum is a Bayesian based query-focused summarization model [18]. It applies Bayesian modeling to the query expansion technique in the language modeling framework of information retrieval [26]. This model is quite similar to the query expansion model in language modeling framework in IR, but a significant distinction between them is that BayeSum model estimates query over sentence models instead of document models. Experimental results from both TREC and DUC 2006 have shown that this approach can significantly improve performance of retrieval and document summarization. A similar approach, namely TopicSum [2], imposes Latent Dirichlet Allocation (LDA)-based topic model [12] to estimate the content distribution. Experimental results in both ROUGE [8] measurement and Document Understand Conference (DUC) manual user evaluation have shown that TopicSum can achieve similar performance as the BayeSum model.

It is worth noticing that all above mentioned approaches can produce standard summaries efficiently, but none of them consider user's interests and preferences during the summary generation. One of the reasons of including less personal information is the difficulty in building a user model that can cohere user's interests to the content summary processing. Some attempts have indeed been made to produce personalized summaries, such as modeling a user's profile as a unigram language distribution using user's information available on the web [5]. In this approach two unigram language models were generated, one for user profile and another one for text contents. Then, these two unigram models were combined linearly with two weighting parameters α and β, where summation of these two parameters was one. The extracting algorithm applied in this solution was the TFISF, which summarizes a text based on term frequency weight that is assigned to each term. Although some good performance has been achieved, the approach still suffers from the disadvantages of the unigram and the limitation of the TFISF to the multi-document summarizations. In addition, the term frequency based approaches may not identify the hidden hierarchical concepts which set behind the documents; also, there are no experimental results that have shown that the proposed user model can represent user's interests and preferences. The increased term frequency weight might come from more matching terms detected from the user profile. In order to discover the hierarchical concepts behind documents, generative probabilistic language models are adapted to build hierarchical topic models to identify sentences that contain latent concepts. Such models include BayeSum model, TopicSum model, and the collaborative topic regression (CTR) model [6]. In CTR model, user preferences and interests are modeled with topic interests, and documents are generated by LDA-based topic models in which the topic coherences are discovered from multiple documents.

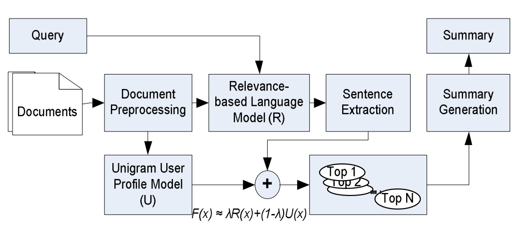

Figure 1. System architecture of the personalized text content summarizer

III. PERSONALIZED TEXT CONTENT SUMMARIZATION

A. General concept

Text summarization can be simply defined as a process in which a computer creates a condensed version of the text but still preserves most of the information presented in the original text. Normally, this process is done by ranking sentences, choosing sentences with the higher ranking score, and re-assembling them as a summary. A user specific summary might be obtained if the user's profile is considered during the sentence ranking and summary generation. Therefore, based on these processes, a high level view of the system architecture is shown in Figure 1.

B. Relevance model for automatic text summarization

Relevance model proposed by Lavrenko [35] explored word associations both in word and document layers by inferring the document relevance using a kernel-based generative model. Relevance models provide a standard solution to integrate the query reformulation techniques into language modeling framework [26]. They modify the queries using the pseudo-feedback approach which relies only on an initial ranking of the documents. The detailed discussion about algorithms of relevance model is outside of the scope of this paper. More details of this model can be found in [35]. Here, we focus on the summarization tasks.

First, using the original query, which is provided either by a user or by using the title of the document, denoted as $Q = \{q_1, q_2, ..., q_m\}$, retrieval task is performed using query-likelihood based language model (QL) with Dirichlet prior [10, 15] as smoothing approach and smoothing parameter μ set as 1000.

Second, Ponte's heuristic query expansion approach [26] is used to rank all the words (denoted as w) by using the following formula:

$$avg(w,R) = \sum_{D \in R} \log\left(\frac{p(w \mid D)}{p(w)}\right) \quad (1)$$

where R is the set of top-ranked documents (usually the top five documents are chosen) from QL model, $p(w \mid D)$ is the probability of word w in relevant document D, and $p(w)$ is the prior distribution of word w. A set of ranked words comes from this step. *k* (normally 5 based on Lavrenko's experiments [35]) highest-ranked words are then selected and added to the original query. After expended, the query is denoted as $Q' = \{q_1, q_2, ..., q_m, m_1, ...m_k\}$.

Third, the relevance model is used to rank the documents. Then, N (an experimental number that indicates the maximum number of the most relevant documents that will be selected for the final sentence extraction) highest ranked documents are selected and their probabilistic distribution is used, which is $p(w \mid D)$, for processing of the sentence extraction.

C. Personalized summarization

The main purpose of this summarization system is to provide learner specific summaries based on a learner's profile. Learner's profile is a quite general and wide concept [19], which can include learner's demographic information, self-description of the learner's learning interest, completed or currently undertaken courses, learning objectives, career objectives, and so on. In this personalized learning content summarization case, learner's learning related interests, information about currently learning content, and learning preferences are the main resources to represent a learner's profile. Based on this profile, its quantitative representation can be obtained from a statistical approach adapted from the language modeling framework. The details about this solution are described as follows.

The text content of learner's self-description for learning interest, learning objectives, and course overview description are used as the document of the learner's profile. Normally, learner's profile data can be obtained from a learning management system (LMS), like Moodle. For instance, in practical evaluation section of this paper, text contents of learner profiles of two learners, which describe learners' interests, preferences, and outline of the selected course, are obtained from Moodle learning management system. To keep learner's privacy, learner's demographic details are not considered in this modeling.

It is worth mentioning here that some learners might not provide self-description of learning interests to the LMS, or the LMS may only present learner's name and contact information in the profile. In such case, some data mining tools can be adopted to discover learner's interests and learning preferences from learning activities. In our case, learner's self-description and course overview description are available in the LMS for learner's profile modeling.

There is a hypothesis here that words or terms that have appeared in text contents of learner's profile might imply learner's interest towards certain course or study. Furthermore, terms or words that have been used in the course overview description might strongly cohere to the learning contents that will be summarized. These coherences are helpful to the relevant sentence retrieval during the summarization process. Based on this hypothesis, a user model is helpful to represent learner's interests to a particular course. In this research, a multiple-Bernoulli distribution [13] is applied to construct a user model over the text content of learner profile. The reasons for selecting the multiple-Bernoulli model to perform this task are as follows. First, the content of learner's profile usually consists of short pieces of text so that the term frequency is less important for this task [11]. Second, previous experimental results have proved that the multiple-Bernoulli models work well with small vocabulary size [3], which is the case for the course content. Third, the likelihood determined in multiple-Bernoulli models is sampled from the text content of the learner's profile over the entire vocabulary, which means that the model takes into account the non-query terms. This approach makes it possible to cover the coherence between documents and learner's profile.

Based on the Model B in the work of [13], the smoothed multiple-Bernoulli user model can be given as follows:

$$p(w_i \mid \hat{\theta}_U) = \frac{tf_{i,U} + \mu \dfrac{cf_i}{|C|}}{|U| + \dfrac{|C|}{cf_i} + \mu - 2} \tag{2}$$

where U represents the text content (of the learner profile in this case), $w_i \in U$ is the ith word in U, $tf_{i,U}$ is the number of times word w_i occurs in U, |C| is the size of the entire document collection (in this particular case, it is the number of words in the course contents without counting the stop words)), cf_i is the number of times the word w_i occurs in the entire document collection, |U| is the length of the document (which is the learner's profile here), μ is an experimental value (μ is set to 100 in this case based on [13]), and $\hat{\theta}_U$ is the MAP (maximum a posterior) multiple-Bernoulli distribution. Details about the estimation of $\hat{\theta}_U$ can be found in [13].

D. Learer specific sentence extraction

To extract the learner specific sentences, the sentence relevance to the learner profile needs to be taken into account during the sentence ranking. However, the relevance model can only determine the generic importance of the sentences over the query. It cannot find the particular relevance between sentences and the learner profile. A user model might be helpful to catch this importance that relates to the learner profile, but it might lose the sense to the natural topics of a document. Therefore, an approach is needed to combine these two models together to determine both generic and learner specific relevance of sentences.

The overall processing of the learner specific sentence extraction is described in the following steps:

First, each sentence in these top-ranked relevant documents, which have been retrieved using relevance model, is segmented and marked with order number according to its original sequence in each document.

Second, the query likelihood language model approach is used as the base model to build a learner specific sentence model for each sentence. The Jelinek-Mercer [10] smoothing approach is used here but is modified for combining sentence model and user model rather than for document only. The modified Jelinek-Mercer smoothing approach is given as the following formula:

$$\begin{aligned} &p_\lambda(w_i \mid M_s) = \\ &\lambda\{\alpha p_{ml}(w_i \mid M_s) + (1-\alpha)p(w_i \mid \hat{\theta}_U)\} \\ &+(1-\lambda)P(w_i \mid C) \end{aligned} \tag{3}$$

where M_s represents the sentence model built, which is a probabilistic distribution of words in the sentence, variable w_i represents the word in the sentence, denoted as s, $p_{ml}(w_i \mid M_s)$ is the maximum likelihood of the sentence given the word w_i, $P(w_i \mid C)$ is the general proportion of the word w_i in the entire collection of the top-ranked documents, and parameters λ and α are experimental value, where λ is set here as 0.7 for short documents based on [10], and α is 0.8. $p(w_i \mid \hat{\theta}_U)$ is the probabilistic distribution for the learner profile and its value can be calculated from equation (2).

Given $Q' = \{q_1, q_2, ..., q_m, m_1, ...m_k\}$ as the extended query, the final measure of sentence similarity can be computed using the following formula, which is adopted from Zhai's risk minimization language model [9]:

$$P(Q' \mid M_s) = \prod_{q \in Q'} P(q \mid M_s) \times \prod_{q \notin Q'} (1.0 - P(q \mid M_s)) \quad (4)$$

Then, sentences are ranked based on the value of the equation (4).

E. Summary generation

The summary generation is a straightforward process. After the candidate sentences have been ranked, the sentence generator selects the top ranked sentences until reaching the allowed size of the summary. To make the summary more readable, the original order of the sentences in the document is followed in the summary. If the order number for two or more sentences is same (since they may come from different documents but with the same position), these sentences are ordered based on the rank of the document where they belong.

IV. EXPERIMENT AND EVAULATION

In order to measure the content summarization effectiveness of the proposed approach, experiments have been performed under a mobile learning environment. A traditional e-learning course module (a computer science course, namely *Introduction to Computing and Information Systems*, which is about general concepts and basic knowledge in computing and information systems) was selected as text content to be processed in the proposed summarization system. In addition to the course content, two learner profiles have been selected to evaluate the proposed user model which provides the proportions of personalized summarization. As mentioned previously, the main purpose of the personalized summary is to assist mobile learners in capturing the main points of the learning materials with their own interests and learning preferences in a short time. Therefore, an effective personalized summary should provide the sense of the content that is being summarized with as little irrelevant information as possible, as well as infer the learner's interests and learning preferences. In our particular case, the original query comes from one of titles of the learning modules that will be summarized.

A. Performance measurement

The sentence based precision and recall ratio [24] is used to measure the summary performance. The precision is the ratio of the number of relevant sentences retrieved to the total number of sentences retrieved. It measures the correctness for the sentences in the summary. The recall is the ratio of the number of relevant sentences retrieved to the total relevant sentences in sentence collections. It measures the effectiveness of the system in generating the summary. If the recall value is 1.0, that means that all relevant sentences are retrieved by the system.

The course content in selected course module includes 82 text modules with an average of 1,460 words per module, and total 119,640 words in the entire content collection (after removing the stop words). All of them are text based contents. There are 2,401 sentences and 2,671 unique words as the vocabulary. The compression ratio of the summarization is selected as 10% (about 5 sentences on average), 25%, and 50% of the total number of sentences in original learning modules. First, several words with quite general meaning, such as 'System components hardware and software', are used as the original query to retrieve the most relevant words from these course modules. Table I lists 20 of the highest-ranked words. Top 5 words, namely 'computer', 'application', 'program', 'data', and 'file' are then selected from the list, which are then combined with original query terms for second retrieval using relevance model. Finally, 5 highest ranked modules are selected from the new generated rank list.

Based on these five learning modules, summaries are generated. To evaluate the performance of the user model, two different learner profiles are selected from the LMS for this experiment. One is *software* and *architecture* oriented and another one is *networking, hardware,* and *system* oriented. As samples, three generated summaries, namely 'General summary' that has no learner profile included, 'Learner's profile oriented to software, architecture development', and 'Learner's profile oriented to networking, hardware, and system' are listed in Figure 4, which show the differences among them with various learner profiles. The content of learner's profile was sampled from learner's self-description for his/her learning interest, which was posted on Moodle LMS, as an example (Figure 6). Three different compression ratios, namely 10%, 25%, and 50% are used in the experiment to measure the average precision and recall to evaluate the summarization performance. The interpolated average precision and average recall vs. compression ratios for three types of summaries are plotted in Figure 2 and Figure 3.

Table 1. Highest ranked words

Rank #	1,2, 3…20
Words	Compute(r), application, program, data, file, develop, communication, information, function, process, learn, access, technology, device, microcomputer, network, machine, number, storage, design.

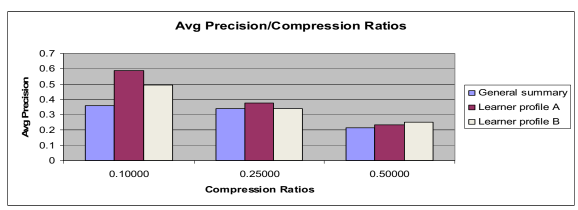

Figure 2. Interpolated Average Precision/Compression ratios for three types of summaries

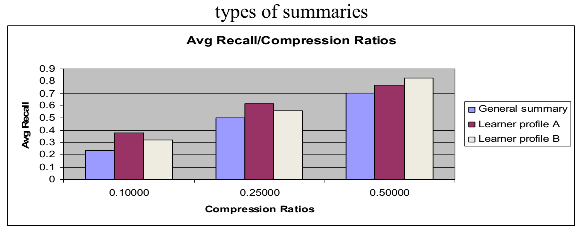

Figure 3. Interpolated Average Recall/Compression ratios for three types of summaries

B. Discussion

Based on interpolated average precision vs. compression ratios plot (Figure 2), it can be seen that the average precision improved significantly when learner profiles are included in the sentence ranking. Particularly, when the compression is high, like 10%, the average precision was increased significantly, and the overall trend of the average precisions among these three types of summaries was kept to show that the learner profile indeed improved the summarization performance. This result has also verified our hypothesis that text contents of learner's profile might imply learner's interest to the course or study, and this hint in turn can been used in the summary processing to cohere important information in the document to learner's interest.

From the plot of average recall vs. compression ratios (Figure 3), it can be seen that the average recall has also been improved significantly when learner profiles are included in the sentence ranking. This enhancement is shown in different compression ratios. In addition, the recall values increase when the value of compression ratio changes from 10% to 50%. This result has verified the recall definition, which is the proportion of retrieved relevant sentences in total relevant sentences, because more sentences are allowed in a summary, more relevant sentences will be covered. This result in turn has justified our solution is suitable for text summarization.

There is an interesting phenomenon shown in the average precision plot. The average precision decreases when the value of compression ratio increases (for example, from 10% to 50%). That is because the more retrieved sentences are allowed in the summaries, the more non-relevant sentences get included. But the average precisions of profile A and B are still greater than the one for general summary. This result has proved that our hypothesis is reasonable and our solution is appropriate for a personalized text summarization.

C. Practice in mobile environment

In order to evaluate the system in a practical scenario, the summaries of the *Introduction to Computing and Information Systems* course were generated and uploaded in the Moodle leaning system. During the experiment, iPhones were used to access the course. Most of the original learning modules had more than 1,400 words, which cannot be displayed properly on the iPhone screen, even with a very small font size (See Figure 5). After summarization, the summaries of these articles came to about 160 words (Note 10% compression ratio was used in this experiment and 5 sentences were selected as the generated summary), which can be displayed properly in about half of the visible screen (See Figure 5). Also, the summaries have reflected learner's interests towards the course although this reflection is still too coarse. In addition, the meanings of the summarized sentences are kept almost the same as the originals because the process of summary generation mainly extracts the highest ranked sentences as described previously.

General summary:

All computers require operating system (OS) software, which provides an interface for the processor, other hardware, and users. The OS enables the user to control (or operate) the computer, facilitates the running of application programs, and manages the hardware resources, activities, and connections. All this additional computing power has allowed for much more sophisticated operating systems, applications, and utility programs, all of which help make computers more flexible and easier to use. Graphical User Interface (GUI) - the evolution of interactive and intuitive user interfaces Mass-marketing of personal computers relies on the availability of a product for the workplace or home that would not require the user to undergo extensive training, which has driven software evolution in the direction of more interactive and intuitive user interfaces. In perhaps the most dramatic stage or aspect of computer development, massive growth in Internet use has spawned a whole new category of hardware and peripherals to support communication applications, and has created an entirely new marketplace and global community.

Learner's profile oriented to software, architecture development:

All computers require operating system (OS) software, which provides an interface for the processor, other hardware, and users. ***As new processing chips were developed, programmers and electronic engineers designed operating systems to use them, and these pairings led to the establishment of 'families' of PCs.*** All this additional computing power has allowed for much more sophisticated operating systems, applications, and utility programs, all of which help make computers more flexible and easier to use. Graphical User Interface (GUI) - the evolution of interactive and intuitive user interfaces Mass-marketing of personal computers relies on the availability of a product for the workplace or home that would not require the user to undergo extensive training, which has driven software evolution in the direction of more interactive and intuitive user interfaces. ***One pioneer in this was the Xerox Company, which developed a graphical interface and mouse system with which users could control operations, rather than using typed command lines or control key combinations.***

Learner's profile oriented to networking, hardware, and systems:

Of all the early microcomputers, the Apple and IBM-compatible families of machines have survived to become the major PC types in the market. What is the role of an Operating System (OS)? All computers require operating system (OS) software, which provides an interface for the processor, other hardware, and users. ***The OS enables the user to control (or operate) the computer, facilitates the running of application programs, and manages the hardware resources, activities, and connections.*** All this additional computing power has allowed for much more sophisticated operating systems, applications, and utility programs, all of which help make computers more flexible and easier to use. Graphical User Interface (GUI) - the evolution of interactive and intuitive user interfaces Mass-marketing of personal computers relies on the availability of a product for the workplace or home that would not require the user to undergo extensive training, which has driven software evolution in the direction of more interactive and intuitive user interfaces.

Figure 4. Generated summaries under different learner profiles

V. Conclusions and Future Work

In this paper, a text summarization system has been developed to produce a personalized summary for learning contents in mobile learning environment. The experimental results have demonstrated that the system is able to generate learner specific summaries effectively from a large size of learning contents. As discussed previously, this good performance is due to the higher relevant topics and keywords explored by the relevance model and the specific information provided by the user model. Although many relevant topics and keywords are retrieved, there are still a few irrelevant terms picked by this model. This irrelevance brings 'noise' to the retrieval processing and eventually affects the effectiveness of the summarization. This would be one of main limitations of the system, which provides a direction for the future improvements.

For future work, the system can be improved by integrating it with statistical topic modeling approaches in machine learning that provide certain learning capability to the system for a better summarization where the summarizing patterns are expected to match the ones in human generated summaries. In addition, to impose more advanced statistic modeling approaches in the system, an automatic summary evaluation, like ROUGE [8], will be applied to further evaluate the effectiveness of the summarization.

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References

[1] A. DeGani, G. Martin, G. Stead, and F. Wade (2010). "Mobile Learning Shareable Content Object Reference Model (m-SCORM) Limitations and Challenges [N09-35]," retrieved Feb 12, 2012 from http://www.m-learning.org/knowledge-centre/research.

[2] A. Haghighi and L. Vanderwende, (2009). "Exploring content models for multi-document summarization," in Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, May 31-June 05, 2009, Boulder, Colorado, pp. 362–370.

[3] A. Mccallum and K. Nigam. (1998). "A comparison of event models for naive bayes text classification," in Proceedings of AAAI/ICML-98 Workshop on Learning for Text Categorization, pp. 41–48. AAAI press.

[4] A. Nenkova and L. Vanderwende, (2005). "The impact of frequency on summarization," Technical report, Microsoft Research.

[5] C. Kumar, P. Pingali, V. Varma. (2008). "Generating personalized summaries using publicly available web documents," in Proceedings of the 2008 IEEE/WIC/ACM international conference on web intelligence and international conference on intelligent agent technology, pp. 103–106.

[6] C. Wang and D. Blei. (2011). "Collaborative topic modeling for recommending scientific articles," Knowledge Discovery and Data Mining, 2011.

[7] C. Y. Lin, G. Cao, J. Gao, and J. Y. Nie, (2006). "An information-theoretic approach to automatic evaluation of summaries," in Proceedings of the HumanLanguage Technology Conference of the NAACL, Main Conference, pp. 463–470.

[8] C. Y. Lin, (2004). "Rouge: A package for automatic evaluationof summaries," in Processdings of ACL workshop on Text Summarization Branches Out.

[9] C. Zhai, (2002). "Risk Minimization and Language Modeling in Text Retrieval," PhD Thesis, Carnegie Mellon University, 2002.

[10] C. Zhai and J. Lafferty, (2001). "A Study of Smoothing Methods for Language Models Applied to Ad Hoc Information Retrieval," in Proceedings of the 24th ACM SIGIR, pp. 334-342.

[11] D. E. Losada. (2005). "Language modeling for sentence retrieval: A comparison between multiple-Bernoulli and multinomial models," in Information Retrieval and Theory Workshop, Glasgow, United Kingdom.

[12] D. M. Blei, A. Y. Ng, and M. J. Jordan, (2003). "Latent Dirichlet Allocation," Journal of Machine Learning Research, 3, 993-1022. ISSN 1532-4435.

[13] D. Metzler, V. Lavrenko, and W. B. Croft. "Formal multiple bernoulli models for language modeling," in SIGIR 2004, pp.540–541.

[14] D. G. Oblinger, and J. L. Oblinger, (2005). "Educating the net generation," retrieved November, 24, 2011 from http://www.educause.edu/educatingthenetgen

[15] D. MacKay and L. Peto, (1995). "A hierarchical dirichlet language model," Natural Language Engineering, 1(3): pp. 289-307.

[16] G. Hartmann, G. Stead, and A. DeGani. (2011). "Cross-platform mobile development," retrieved Dec 4, 2011 http://www.mole-project.net/images/documents/deliverables/WP4_crossplatform_mobile_development_March2011.pdf

[17] G. William. (2009) "The Emergence of Intelligent Content," White Paper for Intelligent Content Conference, Palm Springs, CA. Retrieved Feb 27th, 2012 http://jgollner.typepad.com/files/the-emergence-of-intelligent-content-jgollner-jan-2009.pdf

[18] H. Daumé III and D. Marcu, (2006). "Bayesian query-focused summarization," in Proceedings of the Conference of the Association for Computational Linguistics (ACL).

[19] H. Liu, B. Salem, M. Rauterberg (2009). "A survey on user profile modeling for personalized service delivery systems," in Proceedings of IADIS International Conference on Interfaces and Human Computer Interaction 2009 (pp.45-51): ISBN: 978-972-8924-85-0.

[20] I. Mani, G. Klein, D. House, L. Hirschman, T. Firmin, and B. Sundheim, (2002). "SUMMAC: A Text Summarization Evaluation," Natural Language Processing, vol. 8, pp. 43-68.

[21] J. Eisenstein and R. Barzilay, (2008). "Bayesian unsupervised topic segmentation," in Proceedings of the Conference on Empirical Methods in Natural Language Processing, Oct 25-27, 2008, Honolulu, Hawaii.

[22] J.-C. Ying, S.-J. Yen, Y.-S. Lee, Y.-C. Wu, J.-C. Yang, (2007). "Language Model Passage Retrieval for Question-Oriented Multi Document Summarization," in Proceedings of the Document Understanding Conference (DUC), 2007.

[23] J. L. Neto, A. A. Freitas, and C. A. A. Kaestner, (2002). "Automatic Text Summarization Using a Machine Learning Approach," in Proceedings of the 16th Brazilian Symposium on Artificial Intelligence: Advance in Artificial Intelligence, London.

[24] J. Makhoul, F. Kubala, R. Schwartz, and R. Weischedel, (1999). "Performance Measures for Information Extraction," in Proceedings of DARPA Broadcast News Workshop, 1999.

[25] J. P. Callen, (1994). "Passage-level evidence in document retrieval," in Proceedings of the Seventeenth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 302-310.

[26] J. Ponte, and W. B. Croft, (1998). "A Language Modeling Approach to Information Retrieval," in Proceedings of the 21st ACM SIGIR Conference on Research & Development on Information Retrieval, pp. 275-281.

[27] J. Reynar, A. Ratnaparkhi, (1997). "A maximum entropy approach to identifying sentence boundaries," in Proceedings of the Fifth Conference on Applied Natural Language Processing, pp. 16–19.

[28] L. Vanderwende, H. Suzuki, C. Brockett, and A. Nenkova, (2007). "Beyond sumbasic: Task-focused summarization with sentence simplification and lexical expansion," Information Processing and Management an International Journal, Vol. 43, No. 6(2007), pp. 1606-1618

[29] M. Witbrock and V. Mittal, (1999). "Ultra-summarization: A statistical approach to generating highly condensed non-extractive summaries," in Proceedings of the 22nd International Conference on Research and Development in Information Retrieval (SIGIR-99), Poster Session, Berkeley, CA (1999), pp. 315–316.

[30] R. Barzilay, L. Lee, (2004). "Catching the drift: Probabilistic content models, with applications to generation and summarization," in Proceedings of Human Language Technology Conference and North American Chapter of the Association for Computational Linguistics(HLT-NAACL), pp. 113-120, 2004.

[31] S. J. H. Yang, J. Zhang, N. W. Y. Shao, & R. C. S. Chen. (2007). "A UOI-based content adaptation method for improving web content accessibility in the mobile internet," ETRI Journal, 29(6), pp. 794–807.

[32] S. J. H. Yang, J. Zhang, and A. F. M. Zhang, (2008). "Applying Web Page Adaptation Technique to the Augmentation of Mobile Learning," Research and Practice in Technology Enhanced Learning, vol. 3, pp. 253-273, doi: 10.1142/S1793206808000574.

[33] S. P. Yong, Ahmad I. Z. Abidin and Y. Y. Chen, (2005). "A Neural Based Text Summarization System," in Proceedings of the 6th International Conference of DATA MINING, Greece, 2005.

[34] T. Joachims, (1998), "Text Categorization with SupportVector Machines: Learning with Many Relevant Features," in European Conference on Machine Learning (ECML).

[35] V. Lavrenko and W. B. Croft, (2001). "Relevance-Based Language Models," In the 24th ACM SIGIR Conference on Research & Development on Information Retrieval, pp. 120-127.

[36] Y. Yamauchi and M. Mukaidono, "Probabilistic inference and bayesian theorem on rough sets," in Rough Sets and Current Trends in Computing, ser. LNCS, vol. 2005, 2000, pp. 73–81.

Figure 5. Examples of an iPhone that accesses one of learning contents and their summaries with or without learner profiles. The first screen-shot is the original content shown in iPhone. The second one is the summary without learner profile involved. The third and forth ones are summaries with different learner profiles.

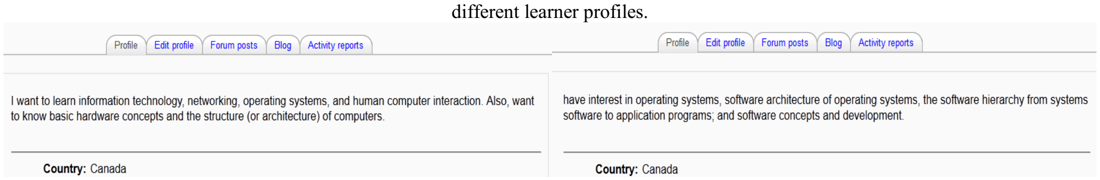

Figure 6. Learner profiles: Networking, hardware, and system oriented profile is in the left-side; the software and architecture oriented profile is in the right-side.