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Personalized Summaries Generation: An Approach based on Learning Styles

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Abstract. The increasing information that can be found on the Internet makes very difficult to read and understand all this information in a short period of time. Automatic text summarization aims to address the problem of information overload by extracting the most important information from a document. This allows the reader to make decisions to determine the relevance of the information. This article presents a method for the automatic generation of personalized summaries in Spanish. The personalization is based on the VAK learning styles model. We focus an extractive approach based on heuristics to select the relevant parts of the source content. Our proposed method has been evaluated with junior high school students in a Turing Test experiment with encouraging results.

Keywords: Automatic summarization, learning styles, Turing test, VAK model.

1 Introduction

Today, digital information is growing exponentially, which has caused difficulties in processing and understanding all that information in little time. In this way summaries can help to manage the increasing information. Summarization is the process of converting a text into a shorter version, keeping the essence, meaning and informational elements of the original text. Since the manual summarization represents a time expensive and generally laborious process, the automatic text summarization is a promising research field and is gaining attention from researchers in computer science. Research on automatic text summarization began more than five decades ago with the earlier works of Edmundson [1]. Since then, various theories have been proposed ranging from text linguistics to artificial intelligence.

The main approaches in automatic text summarization are extractive and abstractive. The extractive summaries are generated from the selection of sentences considered outstanding in the source text. Sentences are literally extracted, freely joined, and presented as the summary of the text [2, 3, 4].

The abstractive summaries are created by regenerating new content from the source text; that is, the sentences are reformulated through processes of merging, combining, or deleting terms. In this way, sentences are obtained that, in principle, were not in the source text [5, 6, 7, 8].

Our proposal attempts to provide a solution to the generation of personalized extractive summaries in Spanish, considering the learning style of those who require a summary. Learning styles refers to the fact that each person uses their own method or strategies to learn. The people develop certain preferences or global trends that define a learning style. In this research work, Neurolinguistics Programming Model of Bandler and Grinder [9] was used; this model is also called VAK model for the learning styles it includes: Visual, Auditory and Kinesthetic. The VAK model argues that the people use a series of textual terms in their language and communication system according to their learning style.

Our extractive approach is based on four heuristics to select the relevant sentences to be included in the summary. These heuristics are based on the work of Acero and colleagues [22].

We aim to apply this proposal in educational field. In the academic field, students need to read many research documents in order to conduct their work and in order to have success in their studies. In this context, personalized summaries would be beneficial for students. Therefore, we propose to integrate the proposed summarization model in intelligent learning environment, in this way, the personalization process is based on a student model.

The rest of the paper is organized as follows: Section 2 presents some background concepts on automatic text summarization and learning styles models; Section 3 presents our proposal for personalized text summarization; Section 4 describes the evaluation experiments and results. Finally, Section 5 presents conclusions and outline some future work.

2 Background

2.1 Automatic Text Summarization

Automatic text summarization is the process of shortening digital content documents, to create a summary that represents the most important information within the original content. Research on automatic summarization began with the work of Luhn [11] and Edmundson [1]. To generate summaries without human intervention, they applied the frequency of the words and the position of sentences in the document. Nowadays, several approaches for automatic text summarization can be found in literature; for example, statistical learning [13], machine learning [14, 15], text connectivity [16, 17], conceptual graphs [7, 18], algebraic reduction [19], clustering and probabilistic models [20] and reader-adaptive methods [21].

Automatic summarization can produce a summary of a single document or from multiple documents. The summarization process largely depends on the goals of the user, for example, the summary can be the result of a specific query of the user or it can include a summary of the full information [12].

There are two main ways to generate a summary automatically: the extractive summarization and the abstractive summarization. The extractive approach consists of selecting and extracting the most important sentences or phrases from the original content; then combining all the selected sentences to generate the summary. The abstractive approach consists of generating new sentences based on the original content but keeping the points as they are exposed in the original content.

2.2 Learning Styles Model

Learning theories describe proposals about how the people learn new concepts and abilities; several learning theories have been proposed, all of them state different, and sometimes, contrasting points of view; for example, the dispute between proposals focused on the student and proposals focused on the teachers. The learning styles theory relies on the hypothesis where everyone has a particular way to learn including strategies and preferences, emphasizing that individuals perceive and process information in different ways. Consequently, learning styles theory states learning of individuals has more to do with a process focusing the learning style than with the intelligence of the individuals. Several learning styles models have been proposed, such as the Felder-Silverman Learning Styles Model [31], Kolb Model [32] and the VAK Model [9] among others.

The Felder-Silverman Learning Styles Model proposes four categorizations for learning styles: sensing-intuitive, visual-verbal, active-reflective, and sequential-global. The Kolb Model works on two levels: a four-stage cycle of learning and four separate learning styles: diverging, assimilating, converging, and accommodating. This theory is concerned with internal cognitive processes of learners. The Visual Auditory Kinesthetic, VAK, Model proposed by Bandler and Grinder is based on Neuro-Linguistic Programming.

3 Automatic Generation of Personalized Summaries

The automatic generation of summaries of text is the process of extracting important information from the original text, producing a summary [5]. The summaries according to their purpose can be classified into generic, domain-specific, and query-based. Besides, according to their output the summaries can be abstractive or extractive [10].

We propose a method for generating text summaries using a student model and a learning styles model, which allowed the summaries to be personalized. The model generates domain-specific extractive summaries of documents in Spanish. Fig. 1 shows the architecture of our proposal. This architecture contains several processes and resources to carry out the generation of personalized summaries.

The external resources are composed by a student model, a collection of words VAK, and a collection of proper nouns. The student model contains a representation of the state of the users including their VAK learning style obtained from the Neurolinguistics Programming Test [34]. This information allows us to generate personalized summaries according to the learning style of each user.

The collection of VAK words is composed of words related with each one of the VAK learning styles as proposed by Bandler and Grinder [9].

They argue that people use a learning style which determine their language and their communication system. The proposed set of VAK words is composed by 67 words: 22 visual words, 24 auditory words and 21 kinesthetic words). In order to enriched this set of VAK words, we conducted an analysis of words and their synonyms as result of this study, the collection of VAK words is composed for 1132 new words: 380 visual words, 392 auditory words and 360 kinesthetic words. In Table 1 some examples for the VAK words are presented.

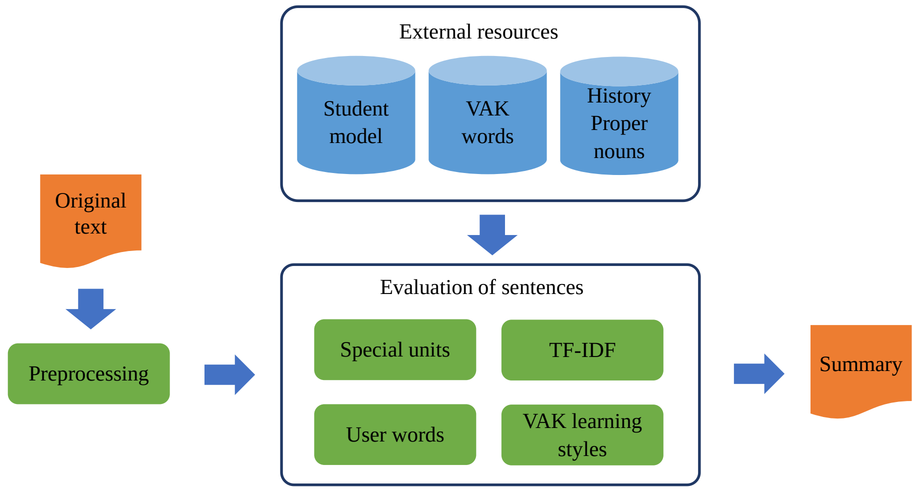

Fig. 1. The architecture of our proposal of generation of automatic summaries of texts.

Table 1. Words related to each learning style according to the Visual Auditory and Kinesthetic Model.

Learning style	Spanish word	English translation
Visual	Obviamente Claro Perspectiva Ilustrar	Obviously Clear Perspective To illustrate
Auditory	Grito Armonía Hablar Sonoro	Scream Harmony To talk Sonorous
Kinesthetic	Pesado Sentir Calor Frialdad	Heavy To feel Hot Coldness

To build the collection of proper nouns, an analysis of official books for History I and History II for junior high school was conducted. The study looked for all the nouns that designated a person, place, company, or things with a singular name.

This study was conducted in a manual way. This set is composed by 244 proper nouns. Table 2 shows some examples of proper nouns.

In preprocessing stage, a plain text document is transformed into an object with minimal linguistic characteristics such as words and sentences. In our proposal, the following basic preprocessing tasks were carried out: segmentation, tokenization, noise elimination, and stop-words elimination.

Table 2. Examples of proper nouns included in the collection of proper nouns.

Word type	Spanish proper nouns	English translation
Thing	Plan de Ayutla	Ayutla Plan
Country	Trinidad y Tobago	Trinidad and Tobago
Historical figure	Benito Juárez	Benito Juarez
Historical figurer	Alejandro Magno	Alexander the Great

Then, the sentences of the text are evaluated according to four heuristics to provide weight for each of the sentences of the text to be summarized and to select the most relevant ones and to be included in the summary. These heuristics are based on the work of Acero and colleagues [22].

The first heuristic, special units, consists of giving a weight to the sentences that contain one or more special units found in that sentence. Special units are acronyms, numbers and proper nouns included in the collection of History proper nouns. The sentence is given to a weight *N* according to the number of special units identified in the sentence.

The second heuristic, TF-IDF, consists of identifying the most relevant words from the text and checking how many of these relevant words are found in each sentence. The relevant words are identified calculating the TF-IDF statistic of words in the sentences. In this way, a high weight is assigned to sentences that contain a greater number of relevant words. The weight is obtained according with the number of relevant words that the sentence contains. Sentences that do not contain any relevant word are assigned a weight of zero.

The third heuristic, user terms, consists of enhancing those sentences that have a greater relevance for the user. The user provides some important words to be included in the summary, which are kept in the student model, to personalize the generated summary. The weight of the sentences in this heuristic is oriented to the similarity with the preferences of the user. Sentences that contain one or more words that the user has considered in their interests are given the weight of 1. If the sentence does not contain any words of interest to the user, they are given the weight of zero.

The fourth heuristic, learning styles, consists of identifying the words that are related to the learning style of the user according to the VAK model. The sentence weight is assigned according to the number of words related to the VAK learning style of the user found in each sentence. Sentences do not contain any term from the VAK words according to the learning style of the user are assigned to zero.

After, the evaluation of the sentences, the four weights for each sentence is used to obtain a single weight for the sentences. The final weight is calculated by means of Eq. 1. Four external parameters, *a*, *b*, *c*, *d,* are included to estipulate the importance of each heuristic. Thus, prioritizing one heuristic over another and being able to perform the tests. The sentences with highest weight are selected.

$$Sentence\ weight = \frac{(a*H1)+(b*H2)+(c*H3)+(d*H4)}{a+b+c+d}. \quad (1)$$

4 Experiments and Results

For many years, to evaluate the quality of automatically produced summaries has been a challenge for research groups within this area. The evaluation of a summary becomes a very subjective task because there is no ideal summary to compare an automatically generated summary and neither to evaluate its customization. To evaluate our proposal, the automatic generation of extractive summaries, we conducted a study based on the Turing Test [35] as proposed by Molina and Torres [36].

In the study 210 second-year junior high school students participated, whose ages range from 11 to 16 years. They are students from a village near to Mexico City. The participants filled in the Neurolinguistics Programming Test [34], thus we can know their VAK learning style. Within this learning style classification, they were randomly selected as judges or summarizer students. A group of 45 participants were designated as judges (15 visual judges, 15 auditory judges and 15 kinesthetic judges) and 6 participants were designated as summarizer students (2 visual students, 2 kinesthetic students, and 2 auditory). As part of the experiments, we built a collection of 45 Spanish text documents from books of History I and History II from junior high school. This collection was provided to students in order to they can elaborate the summaries.

This experiment consisted of evaluating the quality of the summaries based on the Turing test [35] and consists of having a group of human judges, which must identify the origin, human or automatic, of a series of summaries. The results are validated with a statistical hypothesis test.

For the generation of summaries by humans, each of the 6 summarizer students were assigned with two randomly selected documents from the collection of text documents, thus, they must make two summaries. Since we are evaluating extractive documents, they were asked to decide in each given text document, which sentence is relevant to be included in the summary. On the other hand, for the generation of automatic summaries made by a software system, we used our proposal to generate 6 summaries: 2 visual summaries, 2 auditory summaries and 2 kinesthetic summaries. All the summaries are from different text documents.

Once the summaries were generated by the students and by the software system. Each one of the 45 judges was assigned with the 12 summaries. The sole instruction given to the judges was to determine if they believed that the summary was made by a human or generated by a machine, this is by a summarizer software system.

To evaluate the significance of the results, the experiment *Lady Tasting Tea* proposed by Fisher was conducted. In that experiment, Ronald A. Fisher developed an exact statistical test based on counting the number of successes and failures by means of a contingency table [37]. According to the results of the 45 judges, contingency tables were created for each judge.

The validation of the summaries was carried out through the approach of two hypotheses: the null hypothesis, H_0, which states there is no relation between the responses of the judges and the origin of the summary; and the alternative hypothesis,

H_1, which states there is a positive relation in the response of the judges. We use the Fisher Test function from the R programming language to calculate the *p-values*. We used the standard test setup: two tails with a 95% confidence interval. From the 45 judges, only two judges presented a statistically significant result (*p-value*<0.05). While the remaining 43 judges cannot affirm that their result is significant in distinguishing the true origin of the summaries. Therefore, we argue that the 43 judges found the same quality in the summaries made by humans as in the summaries generated by our proposal.

5 Conclusions and Future Work

In this paper, we presented an extractive approach for personalized automatic summarization. The personalization is based on the learning style of the user. We used the Neurolinguistics Programming Model, also called VAK model. This model proposes a set of words related to each learning style. We strengthen including more words for the three learning styles. We argue people would better understand a summary that includes words related with their learning styles.

We evaluated the quality of the summaries base on the Turing Test. The results obtained from the experiment carried out allowed us to demonstrate that the summaries developed with the presented heuristics had the same quality as those summaries carried out by the group of high school level students manually.

Currently, we are working in the evaluation of the personalization of summaries, trying to know whether including the VAK learning style produces learning gains in the understanding of the summaries, and also we want to know whether user selected words and VAK words make a difference in the quality of the summaries and whether there is a correlation between students competences and their judgements.

References

1. Edmundson, H.P.: New Methods in Automatic Extracting (1969)
2. Pembe, F.C., Güngör, T.: Automated query-biased and structure-preserving text summarization on web documents. In: Proceedings of the International Symposium on Innovations in Intelligent Systems and Applications (2007)
3. Chatterjee, N., Sahoo, P.K.: Random indexing and modified random indexing based approach for extractive text summarization. Computer Speech and Language, pp. 33–44 (2015)
4. Ferreira, R., Freitas, F., de Souza, L., Dueire, R., Lima, R., Simske, S.J., Favaro, L.: Context based text summarization system. In: 11th IAPR International Workshop on Document Analysis Systems (2014)
5. Banerjee, S., Mitra, P., Sugiyama, K.: Multi-document abstractive summarization using ilp based multi-sentence compression. In: Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, pp. 1208–1214 (2015)
6. Gaikwad, D.K., Mahender, C.N.: A review paper on text summarization. International Journal of Advanced Research in Computer and Communication Engineering, pp. 154–160 (2016)

7. Miranda-Jiménez, S., Gelbukh, A., Sidorov, G.: Generación de resúmenes por medio de grafos conceptuales. Revista Signos. Estudios de Lingüística, pp. 463–485 (2014)
8. Rawat, P., Ganpatrao, N.G., Gupta, D.: Text summarization using abstractive methods. Journal of Network Communications and Emerging Technologies (JNCET), pp. 26–29 (2017)
9. Bandler, R., Grinder, J.: De sapos a príncipes: Santiago de Chile. Cuatro Vientos (1982)
10. Kumar, Y.J., et al.: A review on automatic text summarization approaches. J. Comput. Sci., 4, pp. 178–190 (2016)
11. Luhn, H.P.: A statistical approach to mechanized encoding. IBM Journal of research and development, pp. 309–317 (1957)
12. Vilca, G.C.: Generación automática de resúmenes abstractivos mono documento utilizando análisis semántico y de discurso. Universidad Católica de Perú (2017)
13. Jeong, H.: Efficient keyword extraction and text summarization for reading articles on smartphone. Papers of Department of Computer Science and Engineering, 34, pp. 779–794 (2015)
14. Wong, K.F., Wu, M., Li, W.: Extractive summarization using supervised and semi-supervised learning. Association for Computational Linguistics, 1, pp. 985–992 (2008)
15. Fattah, M.A.: A hybrid machine learning model for multi-document summarization. Applied Intelligence, 4, pp. 592–600 (2014)
16. Pal, R., Maiti, P.K., Saha, D.: An approach to automatic text summarization using simplified lesk algorithm and wordnet. International Journal of Control Theory and Computer Modeling, 4, pp. 15–23 (2013)
17. Atkinson J., Munoz. R.: Rhetorics-based multi-document summarization. Expert Systems with Applications, 11, pp. 4346–4352 (2013)
18. Martinez-Romo, J., Araujo, L., Fernandez, A.D.: SemGraph: Extracting keyphrases following a novel semantic graph-based approach. J. Assoc. Inf. Sci. Technol., 67(1), pp. 71–82 (2016)
19. Lee, J.H., Park, S., Ahn, Ch.M., Kim, D.: Automatic generic document summarization based on non-negative matrix factorization. Information Processing and Management, 45(1), pp. 20–34 (2009)
20. Mei, J.P., Chen, L: SumCR: A new subtopic based extractive approach for text summarization. Knowledge and Information Systems, 31(3), p. 527–545 (2012)
21. Kumar, C., Pingali, P., Varma, V.: Generating personalized summaries using publicly available web documents. IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, pp. 103–106 (2008)
22. Acero, I., Alcojor, M., Díaz, A., Gómez, J.M., Maña, M.J.: Generación automática de resúmenes personalizados. Procesamiento del Lenguaje Natural, 27 (2001)
23. Amigó, E., Gonzalo, J., Peñas, A., Verdejo, F.: Qarla: a framework for the evaluation of text summarization systems. In: 43rd Annual Meeting of the Association for Computational Linguistics (ACL'05), pp. 280–289 (2005)
24. Mani, I., House, D., Klein, G., Hirschman, L., Firmin, T., Sundheim, B.: The tipster summac text summarization evaluation. In: Ninth conference on European chapter of the Association for Computational Linguistics, pp. 77–85 (1999)
25. Saggion, H., Lapalme, G.: Concept identification and presentation in the context of technical text summarization. In: ANLP/NAACL Workshop on Automatic Summarization (2000)
26. Orasan, C., Hasler, L.: Computer-aided summarisation: How much does it really help. In: Proceedings of Recent Advances in Natural Language Processing, pp. 437–444 (2007)
27. Molina, A., Torres-Moreno, J.M., da Cunha, I., SanJuan, E., Sierra, G.: Sentence compression in Spanish driven by discourse segmentation and language models. Cornell University, Computation and Language (cs.CL) Information Retrieval (2012)
28. Lin, Ch.Y.: ROUGE: A package for automatic evaluation of summaries. In: Workshop Text Summarization Branches Out (ACL'04) (2004)

29. Molina, A.: Compresión automática de frases: un estudio hacia la generación de resúmenes en español. Inteligencia Artificial, 16(51), pp. 41–62 (2013)
30. Molina, A., da Cunha, I., Torres-Moreno, J.M., Velazquez-Morales, P.: La compresión de frases: un recurso para la optimización de resumen automático de documentos. Linguamática, 2(39), pp. 13–27 (2010)
31. Constante, M.A., Guevara, P.D.: Los estilos de aprendizaje son características identitarias o rasgos cognitivos, afectivos. Revista Publicando, 4(12), pp. 181–196 (2017)
32. Kolb, D.A.: Experiential learning: experience as the source of learning and development. Englewood Cliffs, NJ: Prentice Hall (1984)
33. Felder, R., Silverman, L.: Learning and teaching styles in engineering education: Engineering education, pp. 674–681 (1988)
34. De la Parra, E.: Herencia de vida para tus hijos. Crecimiento integral con técnicas PNL, pp. 88–95 (2004)
35. Turing, A.M.: Computing machinery and intelligence. Mind, 59(236), pp. 433–460 (1950)
36. Molina, A., Torres-Moreno, J.M.: The Turing test for automatic text summarization evaluation. Linguamática, 7(2), pp. 45–55 (2015)
37. Agresti, A.: Categorical data analysis. Wiley Interscience, 359 (2002)