Evaluation of Vocational e-learning Seminars

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Abstract: The use of e-training is nowadays widely applied into various sectors such as higher education institutions (HEIs), civil society or non-profit sector, in unions of rural sector, in training banking personnel. Newly introduced data analysis methods have been applied in the field of e-learning and evaluation. Data mining has been used for finding potential areas in which data mining techniques can be applied in the field of Higher education. Within this work, a text mining method applied to analyse the text data that have been collected from replies of public sector servants, during their online training seminars. A total of 379 trainees in 26 seminars conducted by the National Centre of Public Administration between the years 2008 to 2012 and were used as input in this evaluation. The procedure of classification was following a typical text mining analysis. In order to analyse the trainee's opinion, a content analysis utilised and a more sophisticated text mining method with the use of Rapid Miner Tool was performed. This analysis resulted that among the 379 trainees appeared 446 occurrences of positive phrases, meaning 1.17 positive comments per trainee and 93 negative phrases that appeared with an average of 0.25 words per trainee. Furthermore the fraction of positive to negative opinions does not seem to be effected by the trainees' gender.

Key-Words: training, evaluation, e-learning, text mining

1. Introduction

The use of e-training is nowadays widely applied into various sectors, such as higher education institutions (HEIs) [1], civil society or non-profit sector [2], unions of rural sector [3], banks personnel training [4], traditional and emerging engineering education [5], computer science courses that incorporated the educational games concept into the learning game for C# programming language [6] and Internet Accessible Remote Laboratories [7]. In addition to that growing ICT role and adaptation implies various attempts to understand what economic benefits ICT bring to private and public sectors. The ICT impact on public sector is deeply analysed in [7] giving ICT development preconditions as well as various perspectives towards ICT economic impact evaluation. The availability of electronic and Web-enabling technologies has tremendous influence on the success of e-learning [8]. Educational communities today are rapidly increasing their interest in Web 2.0 and e-learning advancements for the enhancement of teaching practices. Web 2.0-Based E-Learning: Applying Social Informatics for Tertiary Teaching provides a useful and valuable reference to the latest advances in the area of educational technology and e-learning. [9]

Furthermore, a very important aspect in every educational and training process is the program evaluation by trainees [10]. The evaluation area of educational and training programs has been thoroughly analysed within the last decade. The e-learning and e-training comprise not necessarily identical ways of education, raising different needs, strengths and weaknesses in the educational process. This results on different needs to educational program evaluation process. [11] [12] [13]. In addition to that based on empirical studies on both developed and developing countries, shows that training costs are influenced by such factors as the technology of training, teacher costs and their determinants, programme length, extent of wastage, extent of underutilization of training inputs and scale of operation. In general, vocational/technical education is more costly than academic programmes and pre-employment vocational training is more expensive than in-service training. [14]

Particularly in public sector in [15] referred that by estimation the short-, medium-, and long-term effects of different types of government-sponsored training in West Germany using particularly rich data that allows us to control for selectivity by matching methods and to measure interesting outcome variables over eight years after a program's start. [16]. Furthermore there are a deep work on evaluation of public sector training in East Germany. In [17] attempts an evaluation of the employment and wage effects of training supported by public income maintenance outside of a firm.

Newly introduced data analysis methods have been applied in the field of e-learning and evaluation. In [18] data mining these methods have been used in order to find potential areas in which data mining techniques can be applied in the field of Higher education [19]. In particular, data mining of e-learning systems has been thoroughly examined in the work of [20]. In addition to that text mining as a relatively new method has been applied in evaluation training procedure by trainees in the field of medical training sector [21].

Sentiment analysis of text is a rapidly growing field of study in various applications. The human sensations of emotion, attitude, mood, affection, sentiment, opinion, and appeal, all contribute to the basic categories of sentiment analysis of text [22]. Initially, it was applied in the behavioral sciences field. [23]

A challenge for the analysis is robustness. Real human-produced language data that are not lean, clean and neat. New text, non-edited, differ from the language of traditional linguistic grammars. [24] Every processing model which presumes stability, order and consistency will break down when exposed to actual language use; a model intended to accommodate new text should accept that every sentence in our language, is in order as it derives, without pre-processing, re-editing, or normalisation, leaning on mechanisms keen on accepting new conventions, misspellings, non-standard usage, and code switching. Models which rely on non-trivial knowledge-intensive pre-processing (such as part-of-speech tagging, syntactic chunking, named entity recognition, language identification etc) or external resources (such as thesauri or ontologies) will always be brittle in face of real-world data. [22]

There are elements of methods aiming to approach sentiment and opinion analysis on a subject, based on a text mining approach. There are Aspect-Based Opinion Summary, Document Sentiment Classification, Classification based on Supervised Learning, Classification based on Unsupervised Learning, Sentence Subjectivity and Sentiment Classification, Opinion Lexicon Expansion, Dictionary based approach, Corpus-based approach and sentiment, Consistency, Aspect-Based Sentiment Analysis, Aspect Sentiment Classification [25].

In this paper, we apply text mining methods using the negative/positive approach, in order to analyse the text data that we have received through replies of public servants during their online training activities within National Centre of Public Administration (NCPA). We focus only on an additional and optional evaluation system with one open question, which extends the formal evaluation performed by the NCPA. This method was used to give trainees the opportunity to locate unforeseen strengths and weakness, or to propose improvement open question parts to locate unforeseen problems and reveal improvement ideas.

2. Data Description

During the years 2008 – 2012 a set of 26 seminars were conducted as asynchronous blended seminars taking part in average of 15 trainees in each one. As a part of those seminars, an additional and optional evaluation system applied using one open question in extend to the typical evaluation. This method was used to give trainees the opportunity to locate unforeseen strengths and weakness, or to propose improvements. In a selection of 26 seminars in total, taking part 379 trainees, among them 106 were male and 273 were female. All participants were higher education graduates and were public servants from various organizations thoughout Greece. The 26 programs were conducted by various regional departments of NCPA in major Greek cities, in detail 8 out of them in Athens, 4 in Thessaloniki, 4 in Patras, 2 in Larisa, 1 in Tripoli, 1 Komotini, 1 Heraklion, 1 Kerkyra, 1 Lesvos, 1 Ioannina. The subjects of the seminars were Standardization of public documents using ICT text editor and presentation methods using ICT. Program's evaluation was performed by an open question where each trainee could write his/her comments about the program as a free text. The data were collected and separated as one answer per student. The answers were filled in a form that was initially impossible to perform any type of analysis. As a result, the proper data preparation and transformation was eventually performed. All answers were collected to one csv file type, under the same format. The format of the file was simple but informative, including three fields, which were the student's evaluation, the sex of the student and the program unique code. The analysis based on trainee's diaries employed a sophisticated text mining method using RapidMiner Tool. The purpose of the analysis was to investigate mainly phrases or words that indisputably express negative or positive thoughts about the training programs as well as any possible suggestions.

3. Classification Procedure

The classification procedure based on a text mining analysis using the sophisticated software Rapid Miner. The applied process is illustrated in Figure 1 and Figure 2. The text data processed using text mining steps like *"Tokenization"* (split), *"Transform Capital Letters"*, *"Filter Stop Words"* for excluding common words, and generation of *"n-Gramms"* (finding phrases) and *"Filter Tokens by Length"* (Figure 2). [24]

The first step of the process includes the data captured by (texts from a csv file, Figure 1) using the automatic reading tool of Rapid Miner.

At the second step, the *"Nominal to Text"* operator (Figure 1) converts all nominal attributes to string attributes. Each nominal value simply used as a string value of the new attribute. If the value is missing in the nominal attribute, the new value will also be missing. The input port expects an example set. In this case, it is the output of the *"Retrieve"* operator in the attached example process. The output of other operators can also be used as input. It is essential that metadata should be attached along with the input data because attributes are specified in their metadata. The example set should have at least one nominal attribute. In case that there is no such attribute, the use of this operator does not make sense. The example set, taken as an output, is converted to text with selected nominal attributes. At this step of the procedure there is a parameter attribute filter. This parameter permits to select the attribute selection filter. In the present implementation the option of *"all"* is used, simply selecting all the attributes of the example set. Other options are used to select a subset of multiple attributes through a list of them.

The third step, concerns the operator of *"Process Documents from Data"*, getting the data from files and converting to texts for processing (Figure 1). This operator generates word vectors from string attributes. It takes as an input a word list and attributes as an output a processed word list. This step includes various options. In the present implementation the prune method was used. This method specifies whether frequent or infrequent words should be ignored for word list building and how the frequencies are specified. The available options are "*none"*, *"perceptual"*, *"absolute"*, *"by ranking"*. We used the option of *"absolute*". As a result, frequent or infrequent words ignored for word list building. In this paper, the minimum set it as 10 times, which means that the step moves away words that appear in less than 10 times. In the same way, prune above absolute ignores words that appear in more than an intended percentage and set it to 9999.

In addition to that, at the third step, the operator of process documents from data for text processing (Figure 1), illustrates a further internal analysis which constitutes the most important part of text mining, using well know text mining methods. In more details the third step consists of five sub steps, *"Tokenize", "Transform Cases", "Filter Stop Words by dictionary", "Generate n-Grams", "Filter Tokens by length"* (Figure 2).

The First Sub Step is *"Tokenization"*. Tokenize of a document means to split the text of a document into a sequence of tokens. There are a series of options to specify the splitting points. Using all non-letter characters will result in tokens consisting of one single word. This is the most appropriate option before finally building the word vector. In case of building windows of tokens or something like that, might be used split of complete sentences. This is possible by setting the split mode to specify character and enter all splitting characters. The third option allows us defining regular expressions and it appears to be the most flexible for very special cases. Each non-letter character is used as separator. As a result, each word in the text is represented by a single token. At this work the non-letters way of word tokenization is used (Figure 2).

The second sub step includes the *"Transform Cases"*, which increases the number of common words. At this work there is an effort to reveal all words with the same meaning under any typing style (lower case, upper case or mix). As a result, within the used document words "Like" and "like" are handled as equally the same, meaning that the student likes something. This resulting to add the occurrences of those two "different" words, in terms of upper/lower case. In the present implementation the cases of characters in the document transformed to lower case, using the respective *"Transform Cases"* operator (Figure 2). The second sub step (Figure 2) is considered as preparation for third sub step, which is filter stop words.

The third sub step, which is the *"Filter Stop Words"* is illustrated at Figure 2. The most important aspect of this step is to select between a case sensitive or non-case sensitive dictionary. In order to illustrate the difference, an illustrative example is provided. Let us assume that the word "Like" is in the dictionary and the word "like" is not included. This will result that this step will remove the word "Like". As described before, this work aims to reveal all words with same meaning. In this implementation, a non-case sensitive schema used for *"Filter Stop Words"* (third sub step – Figure 2). This might achieved by using as an input of the third sub step the lower case output of second sub step. A set of 54 common Greek words used as a dictionary of the third sub step *("Filter Stop Words")*.

The fourth sub step concerns the generation of *"n-Grams"*. The term of *"n-Grams"* of tokens in a document is defined as a series of consecutive tokens of length n. The term n-Grams generated by this operator consists of all series of consecutive tokens of length n. An illustrative example is a document including the phrase "like a lot" which consists of three separate words *"like"*, *"a"* and *"lot"*. Supposing that n=3, the operator will deliver in output all consecutive tokens of length 1, 2 and 3, which are all possible combinations of the three words. As a result there will be received the following six *"n-Grams": "a"*, *"lot"*, *"like"*, *"like a"*, *"a lot"*, *"like a lot"*. Those three cases of one word length, two cases of two words length and one case of three words length are extracted. In this paper the fourth sub step (Figure 2) n sets up to 5 (5-Grams) was set.

The final fifth sub step referred as *"Filters Tokens"* based on their length, in other words the number of characters that each word contains. In the present implementation used as minimum 3 characters and as maximum 9999 characters. This results some further filter common words such as *"and"*, *"or"* and other small length words that have no use within this research work.

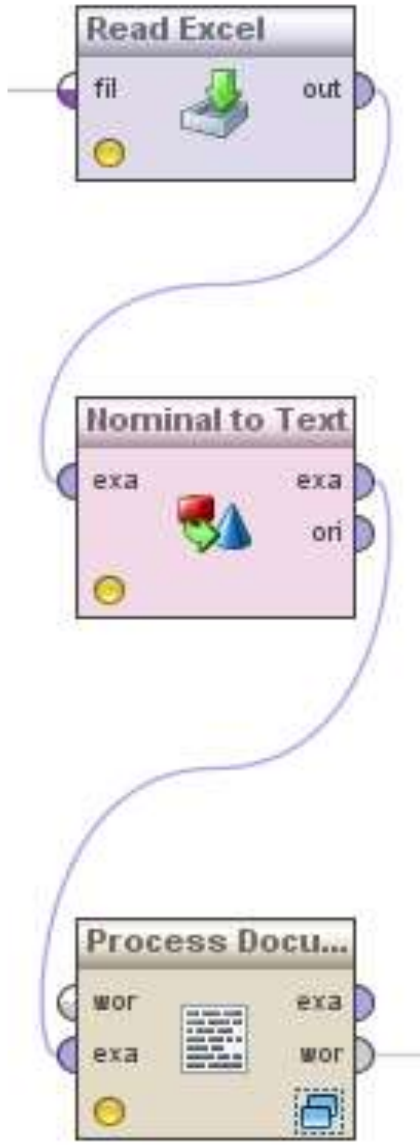

Figure 1

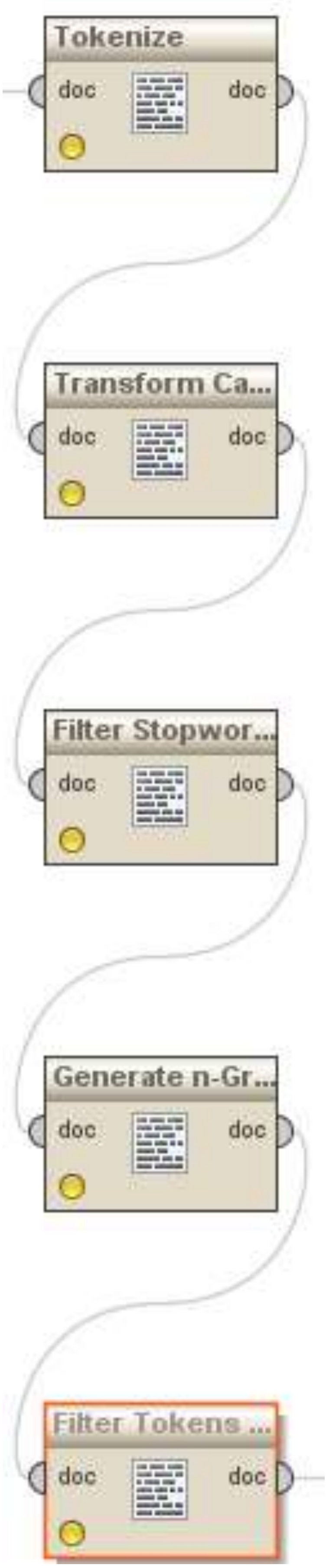

Figure 2

4. Results

After applying the prior produced method on each of the 379 trainee's replies, a set of 559 different phrases or words appeared to appeared most times. The most common word that appeared was the Greek word for *"much"*, which was appeared 400 times and the less was the Greek word for *"home*", which was appeared 10 times. Within the phrases and words that appeared, a further context analysis performed, in order to discriminate the phrases that seem important to reach to some conclusion. The phrases and words separated into two categories, the ones with positive emotion (Table 1) and the others with negative emotion (Table 2). In Table 1 and Table 2 the column Occurrences refers to the times that this phrase/word appeared within all trainee's answers, in case that someone uses twice this phrase/word, then it is counted as two times in Occurrences column. Respectively, in column Unique Occurrences, are recorded the unique appears in trainee's answers.

Table 1 – Positive Emotion

Phrases/Words	**Occurrences**	**Unique Occurrences**
Interesting	170	160
Thank you	71	70
Very good	46	43
Very Interesting	36	36
Positive	25	19
Helped me	25	25
Innovative program	25	25
Very interesting	17	17
Helps me	30	29
Very good Program	21	21
Total	**466**	**445**

Table 2 – Negative Emotion

Phrases/Words	**Occurrences**	**Unique Occurrences**
Problems	52	40
It could be	24	22
It will be good	17	16
Total	**93**	**78**

The results of Table 1 and Table 2 reveals that trainees have an opinion about e-learning seminars expressed with the phrases and words such as *"interesting*" (170 occurrences), *"very good"* (46 occurrences), *"very interesting"* (36 occurrences). The e-learning seminars getting a positive vote since they characterized as *"Innovative program"*

(25 occurrences), *"very interesting"* (17 occurrences), *"very good program"* (21 occurrences), *"helps me"* (30 occurrences). Furthermore, very interesting positive and promising comments were made such as *"thank you"* (71 occurrences). This was extracted after the application of text mining methods and the streaked context analysis to a total of 446 occurrences of positive phrases and words that appeared among the 379 trainees, which is 1.17 positive comments per trainee. On the other hand only 93 negative phrases and words appeared which means 0.25 words per trainee.

The results on Table 3 reveal that female trainees gave 349 positive answers, a percentage of 78% among the positive answers. On the contrary men gave 96 (22%) positive answers. The results on Table 4 show that female trainees gave 54 negative answers, 69% among the total negative and men gave 24 31% among the total negative. Taking into account that male trainees were 106 and female were 273, which means 28% and 72% respectively. In a percentage point of view seems that the male/female percentage of positive and negative answers is quite near the percentage of male/female population. As a result we cannot definitely conclude in any case that a positive or a negative opinion is related to gender.

Table 3 – Positive Emotion Per Gender

Phrases/Words	Unique Occurrences	Male	Female
Interesting	160	43	117
Thank you	70	14	56
Very good	43	8	35
Very Interesting	36	6	30
Positive	19	7	12
Helped me	25	3	22
Innovative program	25	5	20
Very interesting	17	4	13
Helps me	29	4	25
Very good Program	21	2	19
Total	**445**	**96**	**349**

Table 4 - Negative Emotion Per Gender

Phrases/Words	Unique Occurrences	Male	Female
Problems	40	9	31
It could be	22	10	12
It will be good	16	5	11
Total	**78**	**24**	**54**

5. Discussion and Future work

In this paper, we introduced the application of a new methodology that can be applied on further evaluation of e-training seminars offering trainees the opportunity to locate unforeseen strengths, weakness, or to propose improvements and express their view freely. The method tries to extend the typical methodology using advanced, innovative and modern technologies like text mining as well as traditional context analysis. An additional innovation of this work is that applies all those methodologies and innovations on the field of public sector training system.

Text mining is a brand new technology and e-training is a well-established area. As a result, some further applications on training should be performed in order to confirm the results. Possible future work could be concentrated in the ideas of a bigger number of trainees under e-learning programs, of an international application of the proposed methodology, as well as a more extent questionnaire, with targeted questions for positive, negative and neutral opinions. In addition to that, further work can be done related to learning analytics and *"big data"* from public sector training seminars.

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