Extraction of Relevant Figures and Tables for Multi-document Summarization

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Abstract. We propose a system that extracts the most relevant figures and tables from a set of topically related source documents. These are then integrated into the extractive text summary produced using the same set. The proposed method is domain independent. It predominantly focuses on the generation of a ranked list of relevant candidate units (figures/tables), in order of their computed relevancy. The relevancy measure is based on local and global scores that include direct and indirect references. In order to test the system performance, we have created a test collection of document sets which do not adhere to any specific domain. Evaluation experiments show that the system generated ranked list is in statistically significant correlation with the human evaluators' ranking judgments. Feasibility of the proposed system to summarize a document set which contains figures/tables as their salient units is made clear in our concluding remark.

Keywords: Multi-document summarization, Figures, Tables, Ranked list, Local scoring, Global scoring.

1 Introduction

Document summarization is a fairly mature research area with wide applicability [1]. The field of summarization encompasses an extreme variety of methodologies, which usually, fall into two categories, namely, extractive and abstractive techniques. Amongst these, extractive techniques have far-reaching potential in emulating domain independent summarization as it refrains from using natural language generation. Thus the system need not be aware of domain specific vocabulary. Generation of a single extractive summary from multiple, topically related documents is a common practice and is frequently applied in various domains. Past several years have resulted in a steady improvement of digital document summarization but failed to achieve the desired effectiveness [2].

The ability to condense information cohesively and coherently is an essential issue of any summarization system and is particularly crucial to the generation of an effective summary. This ability can be further enhanced by incorporating relevant figures/tables at appropriate places in the summarized text. Noticeably, the major advancements in this field deal with text summarization only [3]. Very few research works address the utility of other document components e.g. tables, pictures, figures, etc. towards the generation of a better summary [4-7].

Figures/Tables are generally introduced into the documents either to elucidate the textual components or to express the information which cannot be well represented in the text form. Human beings tend to understand ideas more easily when expressed in the form of a diagram or a table. Additionally, the figures/tables convey a large chunk of information in relatively condensed form [8]. Hence, these units characterize an excellent choice as components in a summary. Given such significance, one must find a way to extract important figures and tables for effective summarization of digital documents.

As the proliferation of digital content continues, information extraction becomes increasingly complex; in particular, extraction of the most relevant figures/tables [9]. It is further complicated by the fact that the automatic analysis of visual features at very large scale is computationally intensive and more importantly, not much effective [10].

In view of the above stated complexity, we propose a system which extracts important figures and tables from topically related documents by exploiting their association with the textual component. Typically, any figure or table can be associated with its corresponding text using a direct reference or an indirect reference. Direct references (E.g. Fig. 2.1, Table 3.1 etc.) are usually found in scientific documents but not in newspaper articles or magazines. Therefore, in addition to direct references, indirectly referring sentences are also taken into account while computing relevancy score. Our system essentially prepares a ranked list of all the figures/tables, which is ordered, based on their computed relevancy. Given a text-only summary of a document set, the proposed system provides a mechanism to extract the relevant figures/tables from the same set to integrate them into the summary. This integration is assisted by the generated ranked list of the units (figures/tables) and must be done in a way that improves the cohesion and the coherence of the extractive text summary. The system builds on the previous works of text-only multi document summarization [11], further enhancing its capability to summarize documents having figures/tables as their key elements.

The rest of the paper is organized as follows. In Section 2, we discuss related work. We present our proposed method and its implementation in Section 3. In Section 4, we describe evaluation methods. We perform evaluation experiments and discuss the major findings in Section 5. We conclude our paper and discuss future work in Section 6.

2 Related Work

Summarization has been a field of vast research [3]. It has recently started exploring importance of non-textual components in regard to document summarization [1]. Robert P. Futrelle, et al [4-5] discussed issues and problems involved in figure summarization. He focused on biological articles and mainly studied content based features of figures. Hong Yu and Minsuk Lee [6] worked on summarization of figures in documents from the biological domain. In their approach, the abstracts of the biological articles were related with the images present in them. Their hypothesis was that the images can be summarized based on the sentences present in the document. In another approach, Shashank Agarwal and Hong Yu [7] summarized figures by using sentences from each of the four rhetorical categories – Introduction, Methods, Results and Discussion (IMRaD). Ahmet Aker, et al [12], also worked on a domain specific approach for summarizing documents containing information related to geo-referenced images. They used a query based approach for summarization, which performed better than generic ones but lacked information that was selected by human evaluators.

Sumit Bhatia and Prasenjit Mitra [13] referred to the figures and tables present in the documents as document-elements and applied approaches to generate a summary of sentences about these entities (created a synopsis of document elements). Hong Yu, et al [14] developed an approach for figure ranking in full text biomedical articles to help in figure searching. They ranked figures based on their contribution to knowledge discovery. Their hypothesis states that most important figure should be the focus of the article. Hong Yu, et al [15] further explored the applications of figure summarization. Above approaches were mainly directed towards figure summarization. We have applied methods to augment the text summary with figures/tables. Our hypothesis is that importance of figures/tables can be measured in accordance with importance of associated sentences. This hypothesis is inspired from that of Hong Yu and Minsuk Lee [6]. We have also incorporated domain independent methods to extract sentences associated with figures/tables. The related approaches are directed towards extracting information about figures and tables from their document only. We incorporated effects of all the documents in data-set on the importance of figures/tables, from summarization point of view (through global scoring measures).

3 Methodology

As the focus of our paper is on the extraction of relevant figures/tables and their integration with the multi document text-summary, our text summarization module is just an implementation of a well-known extractive technique. The technique is outlined in the papers [11,16], which discuss the major principles of a multi-document summarizer named, MEAD. The text summarization module of MEAD consists of three components - a feature extractor, a sentence scorer and a sentence re-ranker. Sentences are added to the summary beginning with the highest scoring sentence. A sentence is added only if its calculated similarity with all the sentences which are already added is above a predetermined threshold.

Given this text only summarizer, we now discuss our method to incorporate figures/tables contained in digital documents into their summary.

In order to gather information about figures/tables of the document set, different components from the documents need to be analyzed. For this purpose, extraction of these components is done as a part of preprocessing, which are further utilized to compute the relevancy score of figures/tables present in that document. A text-only summary is generated using the textual component of the documents. List of figures and tables are ranked based on their computed score and finally, integrated to the text summary. Fig. 1 shows a graphical representation of the methodological steps.

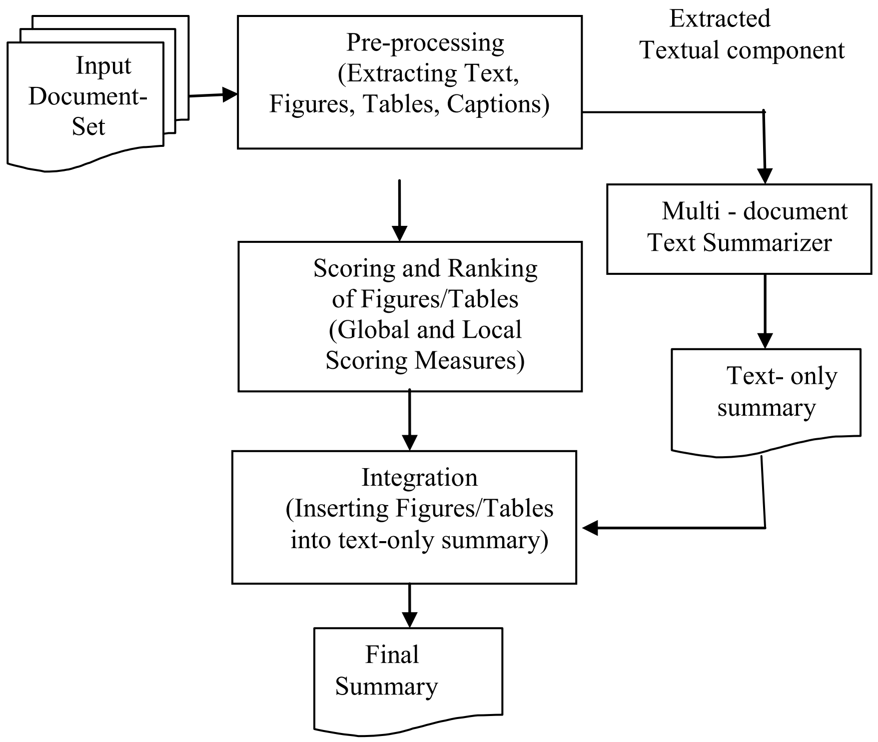

Fig. 1. Overview of the proposed system.

3.1 Pre-processing

Document-components Extraction. In our implementation of the proposed system, the input documents are of OpenDocument format [17], which is an XML-based open-standard document format. This format allows us to extract figures of a document in a separate directory. The input documents are then converted into html format using an open source utility [18]. This step is done so that text, figures and tables come under different standard tags. Due to this, the extraction of text and search of other components' position within this text, become standard and easier. By looking at the corresponding html tags, text is extracted and the positions of figures and tables are marked in the text. The extracted texts of multiple documents are stored into separate text files, which are used to generate text-only summary using the multi-document text summarizer module.

Caption Extraction. The caption of any figure or table carries significant information about it. We now identify the captions for all the figures and tables from the extracted text in which figure/table positions have already been marked. We look for the presence of words and symbols like fig, figure, diagram, diag, table, ':' inside the preceding and succeeding sentences of the figure/table in the document. Stop-word removal and stemming are then performed on the extracted caption for its future use in subsequent stages.

3.2 Figure/Table Scoring & Ranking

To generate a ranked list of figures/tables, we give them a score based on their relationship with the text in the documents and importance of that corresponding text in the summary. The figures/tables to be selected for final summary can be prioritized according to this ranked list. Primarily the stop words are removed from the documents and then the key terms viz. stem of all the remaining words are extracted. Now, the evolved documents are used in the further steps of scoring.

For the scoring of figures/tables, we require two complimentary measures, one based on its local importance within the document and the other based on its global importance within the set of documents.

Local measure. For local scoring of a figure/table, related sentences within the document containing the figure/table are categorized under two labels - direct reference and indirect reference.

Direct reference. We analyze the caption to extract the part which is used as a referent to the figure/table. This part is then used to find sentences where the figure/table is cited (using the same referent). These sentences act as direct reference. Their count forms a component (m) of local score.

$$\text{m} = \text{number of direct references} \;. \tag{1}$$

Indirect reference. We find the cosine similarity (equation 2) of the caption with each sentence in the document. Those sentences that have high similarity (we have obtained an empirical value of 0.3) act as indirect reference. Indirect references are sentences assumed to be explaining the concept portrayed by the caption of the corresponding figure/table.

Mathematically, cosine similarity could be illustrated as:

$$cs = \cos(\theta) \;\; ; \text{where, } \theta = \cos^{-1}\left(\frac{a.b}{|a||b|}\right) \;. \tag{2}$$

where, a and b are the d-dimensional vectors representing the two sentences whose cosine similarity is to be calculated; d is the number of terms in vocabulary set of all the source documents.

Let the value of the cosine similarity for j^{th} sentence in a total of n indirect references be cs(j) for the figure F. Sum of cosine similarities (CS) of indirect references with caption form another component for local score, which can be calculated (using equation 2) as:

$$\mathrm{CS} = \sum_{j=1}^{n} cs(j) \ . \qquad (3)$$

Global measure. In our text summarization module, the importance of text in relation to the summary is calculated from the viewpoint of entire document set. In a similar way, while calculating relevancy score of any figure/table to be inserted in this text, we should involve the whole document set, in addition to the local references mentioned earlier. To reflect the same into the relevancy measure, we introduce a global component based on a score (equation 4) calculated for each referring sentence. This score includes the usage frequency of all the terms present in the sentence.

For scoring the sentences, a term frequency matrix is created over the vocabulary of the document set. We believe that the introductory sentences in the documents convey a lot about it, hence the terms appearing in the introductory section are also more important. Frequency of a term present in the introduction is incremented by a weight of 1.2 rather by 1. This matrix is then used to score sentences by adding up the frequency of all the terms appearing in the sentence.

$$\mathrm{scs} = \sum_{k=0}^{n} \mathrm{w_j} \ . \qquad (4)$$

where, scs is the score of sentence containing n words with frequency w_j of jth word. This score is utilized during final calculation of score for indirect (equation 6) and direct (equation 7) references.

3.3 Final score

The final score of a figure/table consists of two scores, one is for direct references and the other is for indirect references denoted by DR and IR respectively. For every figure/table, the sentence scores for directly and indirectly referring sentences are included into the DR and IR as a global measure.

Mathematically, for the figure F, the final score S can be calculated as described in the following. The contribution of the direct references can be calculated as:

$$DR = m * \sum_{i=1}^{m} scs_i \ . \qquad (5)$$

where m is the number of direct references (equation 1) and scs_i is the score of i^{th} direct reference (equation 4).

The contribution of the indirect references can be calculated as:

$$IR = CS * \sum_{j=1}^{n} scs_j \ . \qquad (6)$$

where CS is the sum of cosine similarity score of caption with indirect references (equation 3) and scs_j is the score of j^{th} indirect reference (equation 4).

$$\text{Final Score, S} = \text{IR} + \text{DR} \ . \qquad (7)$$

This process is followed for all the figures and tables in document set.

3.4 Ranking

After scoring all the figures and tables on the basis of above method, two ranked lists, one for the figures and the other for the tables, are generated. The ranked lists are in descending order of the scores of units. This ranking reflects the relative importance of a figure/table from the summarization point of view.

3.5 Figure/Table Integration

The ranking step is followed by the integration of ranked units into the summary. It is done in two different ways, depending on the type of sentence occurring in the textual summary. All the figures/tables which correspond to any direct reference in the summary–text are unconditionally selected for integration. For the rest of the units, we select a pre-defined percentage (in proportion to text summary produced by text summarization module) of their total count. Figures/Tables referred by indirect references are selected, prioritized by ranked list i.e. higher ranked ones are integrated first till their number exceeds the above percentage.

These units are extracted from different documents and need to be integrated into a single document (i.e. summary). A unique referent is created for each unit. We modified the referent of the direct references in the summary accordingly. Figures/Tables are positioned in the summary after the paragraph that contains its reference (direct or indirect).

4 Evaluation

To assess the performance of the proposed system, we devise an experimental evaluation where multiple human evaluators were involved to judge the system ranking of figures/tables. Each human evaluator was asked to generate an expected ranked list which is ordered based on their potential significance to achieve an effective summary after integration.

In essence, our evaluation objective is to evaluate the system generated list based on the gold standard lists proposed by different human evaluators. Kendall's τ coefficient and Spearman's rank correlation coefficient are widely used to compare two ordered lists. We calculate the coefficient values for each pair of the system ranking and an evaluator's judgment. However, to effectively reflect agreements and disagreements among multiple gold standards we use the methods named weighted correlation aggregation (WCA), rank-based aggregation (RBA) proposed by the Kim et al. [19]. These two methods address the issue of trustworthiness of different evaluators.

4.1 Evaluation methods

Let $D = \{d_1, ..., d_k\}$ be a set of k figures/tables to be ranked. 'n' number of human evaluators ranked the above k items in their individual ranked lists, denoted as $R_1, ..., R_n$, where, $R_i = (d_{i1}, ..., d_{ik})$ is a ranked-list obtained from i^{th} human evaluator. Similarly, $R = (d_1, ..., d_{k},)$ is a system generated ranked-list.

Scoring function $S(R;R_1, ..., R_n)$ is used as an evaluation measure for evaluating system ranking R based on multiple gold standard lists i.e. $R_1,.....R_n$.

Two scoring functions are used to evaluate our present system as follows:

Weighted Correlation Aggregation (WCA). In this approach, the weighted average of correlation values obtained from multiple evaluators is considered as overall score for the system ranking being evaluated. The weight for a particular evaluator is calculated on the basis of agreement with all other evaluator's judgment i.e. average correlation with all other evaluators. Formally,

$$S_{WCA}(R; R_1,...,R_n) = \frac{\sum_i^n w_i C(R,R_i)}{\sum_i^n w_i} . \quad (8)$$

$$\text{Where, } w_i = \frac{1}{n-1} \sum_{j=1, j \neq i}^{n} C(R_i, R_j) . \quad (9)$$

Here, the two list correlation measure C(R,Rj), can be either Kendall's τ coefficient or Spearman's rank correlation coefficient. These two variants are denoted as WCA- τ and WCA-Sp respectively.

Rank-based Aggregation (RBA). Ranks assigned by all the evaluators are summarized in the form of consensus order list formed by reordering of elements according to their combined ranking score.

Combined Ranking Score of the i^{th} item is given by

$$\text{Rank}_{\text{new}}(d_i) = \sum_{j=1}^{n} \text{Rank}_j(d_i) . \quad (10)$$

where, $Rank_j(d_i)$ is the rank of d_i in R_j i.e. ranked list of jth human evaluator.

The generated Consensus order list can now be evaluated using Kendall's τ coefficient or Spearman's rank correlation. Based on which coefficient is being used, we get two variants of the method, denoted by RBA- τ and RBA-Sp.

The two scoring methods described in the subsections of 4.1 are basically aggregation of correlation coefficients. We either use Kendall's τ coefficient or Spearman's rank correlation, both lie in the range of [-1, 1]. A correlation value of +/-1 implies perfect correlation, while positive correlation value suggests positive association and negative value indicates negative association. A correlation value nearly zero means no association between the two lists.

5 Experimental Results

To support the evaluation experiments, limited scale document collections were prepared from different domains. Five human evaluators were involved in the experiment to generate the gold standards for each document collection.

Table 1. Description of the Document Collections.

Document Collection	Domain/Topic	No. of Documents	No. of elements Figures	Tables
Doc-Set 1	Scientific (Artificial Neural Network)	5	7	0
Doc-Set 2	Medical (Effect of the Sun on Skin)	3	2	8
Doc-Set 3	Geography (Nile River)	4	12	0

5.1 Data-set

Three document collections which were created to carry out experiments contain on-average 4 articles and are judged by 5 evaluators. Table 1 contains a brief description about these collections. Human evaluators were asked to rank the elements (figures/tables) based on their relative importance for the summarized text. Ranks assigned do not contain tied values i.e. no two units can be ranked at the same level.

The gold standards shown in the tables 2, 3, 4 correspond to Doc-set 1, Doc-set 2 and Doc-set 3 respectively. E1, E2, E3, E4, E5 are the judgments gleaned from the five evaluators.

Table 2. Gold standards gathered in response to the Doc-Set 1.

Document Number	Figure Number	System Ranks	Evaluators' Rankings E1	E2	E3	E4	E5
5	3	1	6	4	2	1	1
3	1	2	1	3	1	4	3
5	1	3	3	2	4	2	2
2	1	4	2	1	3	6	6
4	1	5	5	6	6	5	4
5	2	6	4	5	5	3	5
1	1	7	7	7	7	7	7
Spearman's rank correlation coefficient			0.39	0.60	0.89	0.67	0.85
Kendall's τ coefficient			0.33	0.33	0.71	0.52	0.71

Table 3. Gold standards gathered in response to the Doc-Set 2.

Document Number	Table Number	System Ranks	Evaluators' Rankings				
			E1	E2	E3	E4	E5
1	5	1	1	3	2	1	2
1	1	2	5	1	1	2	1
1	3	3	2	2	3	5	4
1	4	4	6	5	6	4	3
1	7	5	3	4	5	3	6
1	6	6	4	6	4	6	5
1	2	7	7	7	7	7	7
2	1	8	8	8	8	8	8
Spearman's rank correlation coefficient			0.73	0.90	0.88	0.90	0.92
Kendall's τ coefficient			0.64	0.78	0.71	0.78	0.78

Table 4. Gold standards gathered in response to the Doc-Set 3.

Document Number	Figure Number	System Ranks	Evaluators' Rankings				
			E1	E2	E3	E4	E5
1	1	1	4	8	7	6	2
3	2	2	2	1	4	4	5
2	1	3	1	3	6	10	7
2	3	4	8	2	3	1	1
4	2	5	7	5	2	3	3
1	4	6	3	7	5	2	8
4	3	7	5	6	1	8	9
4	1	8	6	4	8	7	10
1	2	9	9	11	9	5	8
3	1	10	11	9	10	11	11
1	3	11	10	10	12	9	4
2	2	12	12	12	11	12	12
Spearman's rank correlation coefficient			0.82	0.73	0.66	0.54	0.67
Kendall's τ coefficient			0.64	0.57	0.45	0.39	0.56

5.2 System Performance

Spearman's rank correlation coefficient and Kendall's τ coefficient have been calculated [20] for each pair of system ranking and an evaluator's judgment. An aggregated score using these correlation values is calculated for each dataset using methods WCA and RBA as described in the previous section.

The major findings of the experiments are summarized in the table below:

Table 3. Scores for the system rankings.

Document Collection	WCA-τ Score	WCA-Sp Score	RBA-τ Score	RBA-Sp Score
Doc-Set 1	0.767	0.848	0.952	0.982
Doc-Set 2	0.759	0.839	0.878	0.951
Doc-Set 3	0.871	0.935	0.964	0.988

It has been clearly shown in [19] that RBA Scores are more effective and robust than WCA scores. Values of scores obtained for different document sets are considerably close to the perfect correlation value. Our experimental results demonstrate the effectiveness of our proposed system to extract the most relevant figures/tables of the document set from various domains.

6 Conclusion

In this paper, we have presented a system that can be used to identify relevant figures/tables from a document set, in order to generate a better summary of it. Evaluation experiments have been performed on document sets from different domains. System performance is reasonably good on all the document sets. This system thus, appears to be especially promising for the summarization of documents having figures/tables as their key elements irrespective of their domain, for example, scientific journals, geographical descriptions etc. However, the resulting set of relevant units still contains some relevant but redundant figures/tables. Furthermore, the figures and the tables can also be pruned to keep only the important portions in them. These are the most challenging issues that need to be resolved and require a new insight and potentially, a new strategy. We plan to address these issues in our future work. It is hoped that the effectiveness of the present system will be improved after resolving these issues.

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7 References

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