VisualSum: An Interactive Multi-Document Summarization System Using Visualization

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ABSTRACT

Given a collection of documents, most of existing multi-document summarization methods automatically generate a static summary for all the users. However, different users may have different opinions on the documents, thus there is a necessity for improving users' interactions in the summarization process. In this paper, we propose an interactive document summarization system using information visualization techniques.

Categories and Subject Descriptors: H.3.3[Information Storage and Retrieval]: Information Search and Retrieval; H.5.2[User Interfaces]: Interaction styles.

General Terms: Algorithms, Experimentation, Performance

Keywords: Multi-Document Summarization, visualization

1. INTRODUCTION

With huge volume of text resources on the Internet, document summarization has been receiving a lot of attentions. Existing document summarization methods usually involve natural language processing and machine learning techniques. However, most of these methods exclude human from the summarization process, which is efficient in terms of reducing users' workload, but is not desired since the generated summaries are identical for all the users, contradicting to the subjective nature of summarization [6].

To address the issue that people with diverse interests may expect dynamic summaries based on their own preference, we develop VisualSum, an interactive visualized document summarization system, to help users select their preferred sentences to form the summaries.

The summarization process of VisualSum is performed in an iterative manner as illustrated in Figure 1. It starts with all the sentences in the documents, and stops when a satisfactory summary is obtained by a user. Each sentence selection iteration includes three steps as follows. **Step (1)**: The system generates a 2-D view graph of current sentences, in which each node represents a sentence, and the location and color of the sentence are determined by the layout and clustering algorithms respectively. **Step (2)**: The user selects a sentence based on the visualization results in Step (1). **Step (3)**: The system removes the sentence clusters of the selected sentences from the current sentence set.

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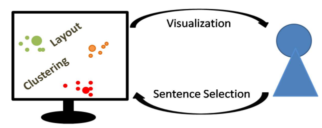

Figure 1: The diagram of user interactive summarization

Experiments and a user study demonstrate the effectiveness of the VisualSum system.

2. METHODOLOGY

In this section, we introduce the components of VisualSum including sentence graph representation, layout and clustering algorithms, and user interaction function.

2.1 Sentence Graph Representation

Given a collection of documents, we first decompose them into sentences. An undirected graph $G = (V, E)$ is then constructed to represent the relationships among the sentences, where V is the vertex set and E is the edge set. Each vertex in V is a sentence, and each edge in E is associated with the cosine similarity between two sentences (vertices). Two vertices are connected if their cosine similarity is greater than 0.

2.2 Linlog Layout Algorithm

Here, we use Linlog, a popular energy-based layout algorithm[7], to display the sentence relationships. The energy function in Linlog is

$$E(p) = \sum_{\{u,v\}:u\neq v} (\omega_{\{u,v\}}\|p_u - p_v\| - d_v d_u ln\|p_u - p_v\|)$$

Where $\omega_{\{u,v\}}$ is the weight of the edge connecting vertices u and v, and d_u and d_v are the degrees of u and v respectively. The optimal positions p of all the vertices are obtained by minimizing E.

2.3 Clustering with Maximum Modularity

The node (sentence) positions displayed by the energy-based layout algorithm are consistent with the clustering results obtained by maximizing graph modularity [2, 7]. Modularity can be defined as

$$\sum_{c\in C\in}[\frac{w_c}{w_C} - (\frac{d(c)^2}{d(C)^2})]$$

where w_c, w_C are the sum of edge weights in cluster c and

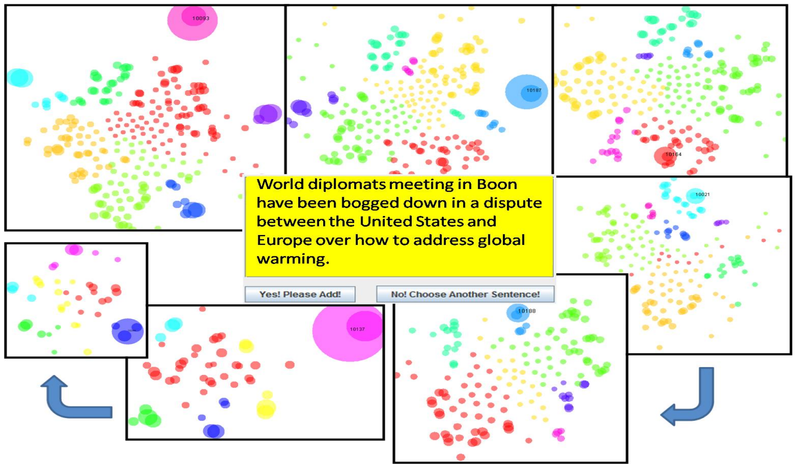

Figure 2: An example visualization and summarization by VisualSum

cluster set C respectively, and $d(c)$ and $d(C)$ are the sum of node degrees for all the nodes in cluster c and cluster set C.

The clustering results can be easily obtained by a bottom-up algorithm, in which each sentence is treated as a singleton cluster at the beginning and then successively merge pairs of clusters until the maximum modularity is reached.

2.4 User Interaction

Now we show how VisualSum assists users to interactively select sentences to create summaries. The visualization in VisualSum clearly illustrates the following information for users. (1) Each node is a sentence and the color of the node indicates the cluster it belongs to. (2) The radius of each node is determined by the sentence's degree. The larger the node, the more important the corresponding sentence. (3) Important sentences in the largest cluster are labeled by their sentence IDs and recommended to users as candidates. (4) Large nodes in the overlapping area of two clusters may be the transition sentences between the clusters. (5) The larger the distance between two clusters, the dissimilar the two topics.

Since the visualization process clearly shows the relationships among the sentences, users can easily select the important sentences they are interested in to form the summary. Figure 2 shows an example of the visualization and sentence selection procedure.

3. EXPERIMENTS

3.1 Automatic Summarization

First of all, we examine the summarization performance of VisualSum using DUC 2006 dataset. Since the DUC evaluation is not personalized, we select the largest sentence node in the largest cluster at each iteration, until the required length of summaries is reached. Table 1 shows the evaluation results using ROUGE toolkit [5] (intuitively, the higher the scores, the better the performance). We compare VisualSum with four widely used baseline summarizers. From Table 1, we observe that the summarization performance of VisualSum outperforms LeadBase and Random and is comparable with NMF and LSA. Note that the motivation of VisualSum is not to build an automatic summarizer, but to help users to create their desired summaries using visualization. Thus in this experiment, we just demonstrate the comparable performance of VisualSum for automatic document summarization.

Systems	R-1	R-2	R-L	R-W	R-SU
VisualSum	**0.332**	**0.055**	**0.308**	**0.113**	**0.107**
LeadBase [1]	0.320	0.052	0.297	0.110	0.104
Random	0.317	0.049	0.294	0.108	0.101
NMF [4]	0.324	**0.055**	0.300	**0.113**	0.106
LSA [3]	0.331	0.050	0.305	0.112	0.102

Table 1: Summarization performance comparison.

3.2 User Study

To better evaluate the summarization results of VisualSum, we conduct a user survey. The subjects of the survey are fifteen students at different levels and from various majors at Florida International university. Each participant randomly selects a set of news documents, and uses VisualSum to form a summary. Then they are asked to assign a score of 1 (the least satisfaction) to 10 (the highest satisfaction), according to their satisfaction of the use of VisualSum. The average scores of VisualSum and the baseline summarizers are 8.07, 7.5 respectively, which demonstrate the effectiveness of VisualSum.

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