Year	Model	ROUGE-1	ROUGE-2
2001	Peer T	33.03	**7.86**
	SVR	29.78	6.01
	R2N2	35.88	7.64
	NoTC	33.45	6.07
	EmSim	24.66	2.67
	SingleT	35.22	7.42
	TCSum	**36.45**	7.66
2002	Peer 26	35.15	7.64
	SVR	31.56	6.78
	R2N2	36.84	8.52
	NoTC	34.02	7.39
	EmSim	29.46	5.28
	SingleT	36.54	8.44
	TCSum	**36.90**	**8.61**
2004	Peer 65	37.88	9.18
	SVR	36.18	9.34
	R2N2	38.16	9.52
	NoTC	35.66	8.66
	EmSim	30.80	5.07
	SingleT	37.94	9.46
	TCSum	**38.27**	**9.66**

Table 2: ROUGE scores (%) of different methods.

closer look at the feature weights learned by SVR, we find the most important feature to measure sentence saliency is CF. Since we treat the documents in a topic cluster as a single document, this feature is lost in our current summarization model. It may be an important aspect that impedes the more excellent performance of TCSum.

Discussion on Summary Style Learning

We examine the ability of TCSum to learn summary styles in two ways. At first, we speculate that similar transformation matrices tend to generate summaries with similar styles. Therefore, we calculate the similarity among the transformation matrices $(\mathbf{W}_{\gamma}^{1}, \cdots, \mathbf{W}_{\lambda}^{|C|})$. Here we flatten each matrix into a vector and use the cosine similarity to measure the similarity. The scores of different transformation matrices are presented in Fig. 3. For ease of reference, we only show the results of three common categories on DUCs, i.e., Biography, Politics and Natural Disaster. As can be seen, the similarity relations of these three categories vary greatly, which matches the intuition that the large difference of the summary styles exists among these categories. For Biography, we find its transformation matrix is similar to 4 categories'. They are Business, Culture, Politics and International Relation. One possible reason is that summaries in Biography necessarily tell the career-related information of a person. Since DUC prefers choosing biographies about artists, businessmen and politicians, it is reasonable the summary style for Biography to be associated with these categories. By contrast, Natural Disaster does not present obvious similarity to any other category. We observe that summaries in Natural Disaster often contain a series of times, sites and numbers, while other categories seldom need so many details. For Politics, we find it is similar to International Relationship and Law. The former is understandable since we may use a number of terms of politics when describing international relationships. The latter may be caused by the news content. Many documents in this category are concerned with political scandals which often lead to lawsuits. Interestingly, there is an obvious negative similarity between Politics and Culture. The wordings in Politics are often thought to be serious while the documents in Culture are usually related to entertainment.

We also inspect the style change of the summaries generated according to different categories. To this end, we manually assign a category to a document cluster and then calculate the sentence saliency based on our summarization model. The salient sentences with respect to different categories are shown in Table 3. Due to the limit of space, we only display the top ranked summary sentences with the styles of three common text categories.

- "D097" is about a hurricane (Natural Disaster).
- "D066" introduces the founder of Wall-Mart (Biography).
- "D076" describes the resignation of a prime minister (Politics).

As can be seen, the salient sentences calculated by the correct categories can properly represent the main idea of the document cluster. Although "D097" and "D066" are not related to Politics, sentences selected by the corresponding transformation matrix still contain many terms of politics. It is also shown that the three Biography sentences contain either the words describing the careers (killer, mayor, founder) or the evaluative words (better, boldly). The career is a part of personal profile, and the description of main contributions of a person usually involves the evaluative words. Therefore, the corresponding transformation matrix seems to well catch the two types of needs for Biography summaries. We read the documents in "D066" and "D076" carefully, and find there is no sentence exactly matching Natural Disaster. Thus it is not surprising that the sentences selected by Natural Disaster in these two clusters are somewhat strange. However, we can see both sentences contain the date and site information. This is absolutely consistent with the style that a summary of Natural Disaster is expected to have. Moreover, both the money value and the word "bombing" can be used to describe the loss of a disaster. It appears that, the transformation matrix for Natural Disaster still works well even on a topic other than Natural Disaster, with "due diligence" to complete its own task.

Related Work

Work on extractive summarization spans a large range of approaches. Starting from unsupervised methods, one of the widely known approaches is Maximum Marginal Relevance (MMR) (**?**). It used a greedy approach to select sentences and considered the trade-off between saliency and redundancy. Good results could be achieved by reformulating it as an Integer Linear Programming (ILP) problem which was able to find the global optimal solution (**?**; **?**). Graph-based models such as Manifold (**?**) played an important role in extractive summarization because of its ability to reflect various sentence relationships. In contrast to these unsupervised methods, there are also many successful learning-based

Cluster	Category	Sentence
D097	Natural Disaster	The **storm**, packing **winds of up to 135 mph**, raged into **Charleston Thursday night**.
	Biography	“This is a dangerous, **killer** hurricane, the likes of which few people who have lived all their lives in Charleston have experienced,” warned **Mayor** Joseph P. Riley Jr.
	Politics	**Gov.** Joe Frank Harris **declared** a **state of emergency** in six counties.
D066	Biography	Sam Walton, **founder** of the Wal-Mart chain of discount supermarkets who died of cancer in April, negotiated these pitfalls much **better** than most.
	Natural Disaster	By **1991** the chain’s sales had risen to nearly **Dollars 44bn**, making it the world’s largest retailer in terms of revenues, and the Walton family probably **America**’s richest.
	Politics	Bud is a senior **vice president** and board **member** of Wal-Mart.
D076	Politics	Flamboyant former **Defense Minister** Hazeltine’s challenge to **Prime Minister** Margaret Thatcher for **leadership** of the **Conservative Party** has caused a **political** sensation in Britain.
	Biography	In the Persian Gulf crisis, she **boldly** joined with George Bush in sending troops to the Middle East.
	Natural Disaster	Among Western allies, she was alone at Ronald Reagan’s side in **1986** in supporting the U.S. **bombing** of **Libya**.

Table 3: Salient sentences selected by different categories. Sentences in the correct categories are displayed first.

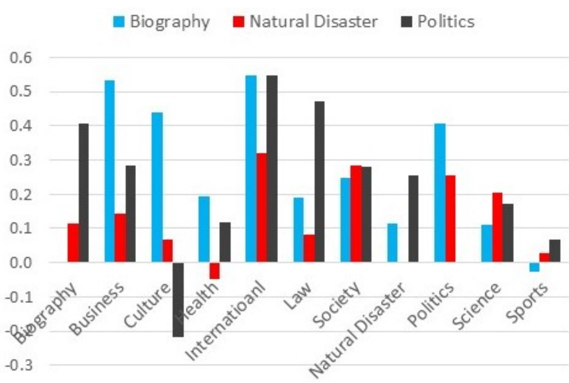

Figure 3: Similarity among the transformation matrices (we set the self similarity scores to 0).

summarization approaches. Different classifiers have been explored, including Conditional Random Field (**?**), Support Vector Regression (**?**) and Logistic Regression (**?**), etc. Recently, the application of deep neural network techniques has attracted more and more interest in the summarization research. (**?**) used unsupervised auto-encoders to represent both manual and system summaries for summary evaluation. Their method , however, did not surpass ROUGE. (**?**; **?**) tried to use neural networks to complement sentence ranking features. Although the models achieved the state-of-the-art performance, they still relied on hand-crafted features. A few researches explored to directly measure similarity based on distributed representations. (**?**) trained a language model based on convolutional neural networks to project sentences onto distributed representations. (**?**) treated single document summarization as a sequence labeling task and modeled it by recurrent neural networks. Others like (**?**) simply used the sum of trained word embeddings to represent sentences or documents. In addition to extractive summarization, deep learning technologies have also been applied to compressive and abstractive summarization (**?**; **?**).

Conclusion and Future Work

In this paper, we propose a novel summarization system called TCSum, which leverages text classification to improve the performance of summarization. Extensive experiments on DUC generic summarization benchmark datasets show that TCSum achieves the state-of-the-art performance, even without using any hand-crafted features. We also observe that TCSum indeed catches the variations of summary styles among different text categories. We believe our model can be used to other summarization tasks including query-focused summarization and guided summarization. In addition, we plan to let the model distinguish documents in a topic cluster, which is better adapted to the multi-document summarization.

Acknowledgments

The work described in this paper was supported by Research Grants Council of Hong Kong (PolyU 152094/14E), National Natural Science Foundation of China (61272291, 61672445) and The Hong Kong Polytechnic University (G-YBP6, 4-BCB5, B-Q46C). The correspondence authors of this paper are Wenjie Li and Sujian Li.

Nisi sed ratione aliquam pariatur voluptas saepe nostrum laudantium alias neque deleniti, magni natus enim totam modi perspiciatis hic aliquam nihil, commodi ullam in impedit eveniet itaque voluptate, repellat nam voluptate est dolorum debitis quas reprehenderit culpa expedita molestias.Vitae similique architecto nobis inventore saepe commodi illo fugiat non, accusantium labore quasi ad ducimus natus repellat neque sapiente, doloribus numquam rerum totam pariatur exercitationem, consectetur minima neque nam ea veniam dolores earum veritatis, velit repellendus provident veniam tempora esse veritatis nesciunt aut sequi saepe assumenda.Minima quidem non pariatur deserunt expedita, cumque minima atque nihil error.Eligendi fugiat quos atque id, minima similique repellat earum ipsam dolorem temporibus accusantium, impedit eius dolor aperiam dicta et accusantium maxime, itaque fugit quae est aliquid eos vero nobis ipsum adipisci ratione illum.Necessitatibus illo temporibus earum nobis iste minima