I.J. Information Technology and Computer Science, **2020, 4, 19-27**
Published Online August 2020 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijitcs.2020.04.03

Enhancement of Single Document Text Summarization using Reinforcement Learning with Non-Deterministic Rewards

K. Karpagam[1]
[4] Dr. Mahalingam College of Engineering & Technology, Pollachi
E-mail: karpagam80@gmail.com

A. Saradha [2], **K. Manikandan**[3], **K. Madusudanan**[4]
[2] Institute of Road Transport and Technology, Erode
[3] Vellore Institute of Technology, Vellore
[4] Dr. Mahalingam College of Engineering & Technology, Pollachi
E-mail: saradha.irtt@gmail.com, kmanikandan@vit.ac.in,tptmadhu@gmail.com

Received: 07 February 2020; Accepted: 16 March 2020; Published: 08 August 2020

Abstract: A text summarization system generates short and brief summaries of original document for given user queries. The machine generated summaries uses information retrieval techniques for searching relevant answers from large corpus. This research article proposes a novel framework for generating machine generated summaries using reinforcement learning techniques with Non-deterministic reward function. Experiments have exemplified with ROUGE evaluation metrics with DUC 2001, 20newsgroup data. Evaluation results of proposed system with hypothesis of automatic summarization from given datasets prove that statistically significant improvement for answering complex questions with f- actual vs. critical values.

Index Terms: Complex Question answering system, Non deterministic Rewards, Reinforcement learning, Machine Learning, Text summarization

1. Introduction

The traditional IR keyword-based methods tedious the user by displaying large list of documents and less appropriate answer for the complex /analytical questions. Sample complex questions are How India was affected by tsunami?, Which is the best school for studies in south India? , Differentiate between volatile and non volatile memory. Complex questions will be answered by summary list of unique sentences to provide appropriate answers. The quality of summarization is reached by analyzing the semantic & syntactic similarity of sentence and words. In order to extract related sentences associated areas of text mining such as Question Answering System (QAS), multimedia information retrieval, topic detection with terms and single document summarization will help to satisfy the user needs.

The challenges of complex questions is addressed by applying techniques such as machine learning, deep learning and reinforcement learning in machine generating summaries. Reinforcement learning works through the problem on its own by self learning in situations. In order to maximize system performance, it allows machines and software agents to learn on specific context using learning models that trains the system through reward, agent, action, state, policy, value and environment [3, 20].

Reinforcement learning agents can be of two types, passive and active. If agent is passive, it will have a fixed policy and learns on its own in executing policy. Alternatively, an active agent changes its policy whenever needed at the real run and learns its way. Early reinforcement learning algorithms such as TD (λ), SARSA with feature set, action space and delayed reward are used for document summarization. The query focused rewards can be given by balancing preferences for selecting textual units related to query. Learning agent receives rewards and penalties based on their performance. The deterministic and non-deterministic numeric reward with policy is used to generate accurate wide range of summaries.

2. Literature Review

The background study of summarization need arises explore existing system techniques, several researchers proposed techniques for document/ text summarization with different perspective for efficiency. The study is carried out in this regard. In paper [1], an automatic extractive Arabic single document summarizing method for producing a informative summary from documents. It also uses two summarizing techniques score-based and supervised machine learning for generating summaries. It evaluates each sentence based on statistical and semantic features using precision, recall, ROUGE and F-score metrics .In paper [2] discusses on extractive document summarization approach based on a Deep Q-Network with Q-value approximation policy. The system trained and tested using CNN/Daily corpus, DUC 2002 dataset and the DUC 2004 dataset and evaluated using Rouge metric. In paper [3] considers single document for extracting and ranking sentences by Extractive Summarization method with Reinforcement Learning. The learning algorithm uses CNN and Daily Mail datasets for experimenting and evaluated though ROUGE evaluation metric.

The framework for answering complex questions by using reinforcement learning model with help of training bye set of complex questions, a list of relevant documents per question, and human-generated summaries. Performance is measured with DUC 2004 and compares with ROUGE scores [4, 7].The system that combines interactive user interface and reinforcement learning which helps in active participation of user extracting related answers and feedback [9]. This system is claimed as a best user centered design for recommended system on many real time scenarios. In paper [14] developed a novel complex question answering system which focuses on automatic machine-generated summaries by reinforcement learning model. It was trained and tested with benchmark datasets 20newsgroup and DUC2001. The experiments carried out and evaluated with standard metrics s ROUGE.

ROUGE metrics a package for automatic text summarization using extractive methods and evaluation with metrics such as ROUGE-N, ROUGE-L, ROUGE-W, ROUGE-S, and ROUGE-SU. It also focuses on the goal of evaluation, analyzes and relates to the selection of appropriate metric [3, 10 & 15]. Benefits of text summarization are reached in different domains such as news articles, legal proceedings, medical, tourism and web pages. In paper [16] proposed a text summarization model for hotel reviews and reaches its efficient performance level.

The study of related works states that machine generated summaries uses non deterministic rewards function for consolidating unique sentence. Despite of current efforts on text summarization techniques formulating a accurate summary with respective features. The research gap found that the state of art of non deterministic reward consideration leads to reduce false negatives and increases the true positive sentences. The related works shows that existing system not considers this issue to the fullest extent. To achieve this ,non deterministic rewards of unique sentences are consider for summary generation.

The main research objective is to bridge the research gap, proposed system first focuses on generating automatic summaries with non deterministic rewards. It considers lexical features such as Skip gram, longest common subsequence, unigram, bigram. The proposed architecture description and results are discussed in following sections.

3. Proposed System Architecture

Proposed system describes various phases involved in complex QA system development are question type processing, constructions of reinforcement learning for answer generation. Architecture of Complex Intelligent Question Answering System (IQAS) is shown in Fig 1.

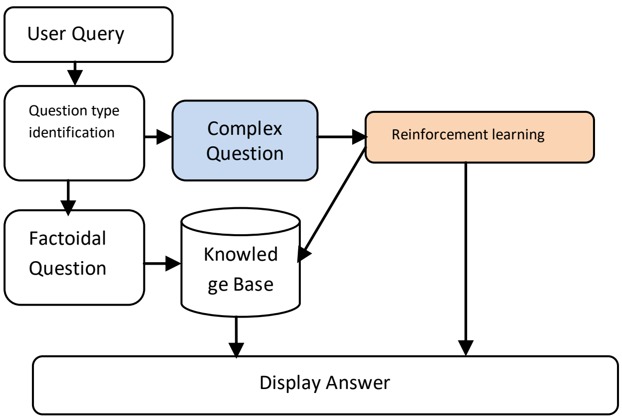

Fig.1. Architecture of Complex IQAS

Question processing phase gets the user query input through interface in natural language. User query is pre-processed using tokenization, stop words removal and stemming to extricate keywords [17, 18, and 19]. The trained question classifier using Stanford Part-of-speech parser of the proposed system identifies the question types as evaluative question, choice question, hypothetical question, confirmative/rhetorical question and complex question using question pattern template. After identifying the question type, if question is Factoidal /simple question, answer is extracted from knowledgebase. The knowledge base is developed from the benchmark dataset DUI 2001, Yahoo! Answers, 20newsgroup, TREC-9QA and Quora track for answer generation. If the question type is complex question, needs a descriptive answer by combining multiple sentences from related documents. Reinforcement learning supports in appropriate machine summary generation.

Qas Using Reinforcement Learning Model

Complex question needs deep analysis and wide prospection for efficient results. In QAS, answer generation for user queries is the classical task. Sequence of related sentences has to be identified and extracted from single documents for machine generated summaries. The system is trained to find user question type using Part –of –speech tagger question template. For instance complex question 'Tell about Gandhiji' is defined as Tell VB | about IN | Gandhiji NNP. It should produce answer summary instead of single sentence to satisfy the user requirements. It is required to summarize about Gandhiji which includes his birth place, family members, studies, freedom fight activities etc.

In QAS, answer for complex questions are generated using necessary information such as comparison, descriptions, opinion and discussions. To mitigate this, the relevant sentences are combined together which should be unique, related and informative. It is concerned with how software agents take actions and react in an environment to maximize cumulative reward. It uses computer algorithms to make the machine to develop optimal solutions through actions. Training for learning model is provided with training dataset which contains human generated summaries by experts, complex questions and list of related document. The single-document summarization is evaluated using DUC (document understanding conference) with DUC 2001, 2002 which checks for summary length and relevancy analyzed by Rouge evaluation metrics. After the formation of the machine generated summaries, quality of answer has been evaluated with various features such as avoiding redundancy sentences, identifying the word overlap sentences etc [21,22].

Hidden Markov Model (HMM) is used to define the process of text summarization using reinforcement learning techniques. It consists of Set of states s, Set of actions a, Reward function r (positive reward or negative reward), Policy π , Agent A and Value V. Next state is calculated by S ~ S + A. The parameters are denoted as s_t, a_t, v_t, r_t with discrete time t. The only feedback received is whether desired summarized output is reached or not. Next state probability is reached out by P (s_t+1 | s_t, a_t). Rewards and actions are determined by single policy is obtained by equation

$$Q(s_t, a_t) = r_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) \tag{1}$$

Where reward function r is for calculating the redundancy and relevance of the sentences in state s_{t+1} and action a_{t+1}. Policy deciding the agent behaviour and mapping its states for action is given by

$$\prod : S \to A a_t = \prod(s_t) \tag{2}$$

The reward probability p (r_t+1 | s_t , a_t) is maximized by choosing the correct policy. For each policy, there is a V∏ (s_t) and the optimal policy is found in such a way that

$$V^*(S_t) = \max_{\Pi} V^{\Pi}(S_t), \forall S_t \tag{3}$$

The proposed system uses a reward function that measures the relatedness of the machine generated summary with human generated answers. Numeric rewards will be maximized by choosing correct policy which has mapping between state and action in a non-deterministic manner. Non-deterministic rewards compute the values based on the nature of sentence. If the agent while in a given state of arranging the sentences repeats for a given action, it moves the same next state by receiving different reward value. Rewards function value should be positive for appropriate sentences and negative reward for non-appropriate sentences.

The reward function is calculated by the empirical formula as follows

$$r = w\, X\; relevance(a) - (1-w) X\; reduncany(a) \tag{4}$$

Where w is the weight parameter, $relevance(a)$ is the similarity between abstract summary from the user and selected sentence and $redundancy(a)$ is the similarity between the current sentences in the answer list and the selected sentences. The action process is for choosing relevant sentence of user query from the document.

Highest score sentence is considered for answer pool. Initially answer states is denoted as NULL, the learning model is processed for each iteration a related sentence is added to the answer state list. The comparison ratio can also be specified in auto-summarizer range varies from 10% to 30%.

After training stage of learning model, the candidate summaries are analysed with reward function and store related feature weights consequently. Based on the feature weights related sentences are selected for answer pool list. Summarizer arranges the sentences in chronological order with 250 words, and then it terminates process of action and state.

The flow model of algorithm with pseudo code is shown in fig 2. The answers rated by the users are collected as a list. From the list generated, more likely answers are chosen from the user's perspective. The answers are chosen and stored with user history for further processing. After the process of receiving the answers from crowd users, proposed User Choice - Specific Reinforced Learning (UCS-RL) algorithm has been used to get feedback rating for validate answers . Updated answer list is stored for further references and in reduction of time. The answers are displayed to user through user interface.

```
User choice-specific reinforced learning (UCS-RL) algorithm
Let R_list  be the list of answers provided to the user.
Show R_list  to the user.
Get options to choose the best answer from the user point of view.
Let the Ans_Choosen ←Best (R_list)
If Ans_Choosen from the R_list
            Update  user_history ←Ans_Choosen
            Rank answer for the question based on the Ans_Choosen
            Update Ans_Choosen as the best the answer for the question
Else
             Get answer from the user,
            Validate the answer
            Update the answer list
End if
```

Fig.2. Pseudo code of UCS-RL algorithm

To reduce the response time, knowledge base is updated with similar questions and the answer. The similar questions with corresponding answers generation is described in next sections.

4. Results and Discussion

The result obtained from reinforcement learning and crowdsourcing techniques for complex questions with bench mark datasets are discussed below.

Datasets

The benchmark datasets such as TREC-9 QA, 20newsgroup (UCI repository) and DUC 2001 from AQUAINT are used to build knowledgebase. By using open source OpenNLP toolkit (https://opennlp.apache.org), original data are pre-processed into small text segments for answer retrieval. The 20newsgroup dataset consist of 5 domains such as sports, entertainment, business, politics etc for easy retrieval of data. TREC -9 QA consists of newspaper and newswire documents collection from various sources such as APnewswire, financial times, Los Angeles times etc. It consists of attributes such as question id, question, and document id and judgment answer string. It also deals with semantic similarity for keyword terms using WordNet on answer tagging with major class labels such as name, time, number, entities and human etc. AQUAINT program is generated to solve the text related question answering considering the relevant topic, semantically similar words from huge data collections (David Graff 2002& 2008).Text summarization is evaluated with DUC2001 corpus which consists of 45 topics, where each topic contains 25 documents. Human summaries are generated and evaluated with the machine generated summaries with quality and responsiveness. The controlling parameters for answer extraction problem for the dataset are shown in Table 1.

Table 1. Dataset Description

Dataset Parameters	Size	
	20newsgroup	DUC 2001
Data source	UCI	AQUAINT
No .of clusters	50	45
No. of documents in each clusters	25	25
Average no. of sentence /documents	35	30
Maximum no. of sentence /documents	75	80
Summary length (in words)	250	250

5. Performance Evaluation

The evaluative measure for text summarization is categorized into intrinsic and extrinsic. The intrinsic measure deals with the text quality and content based evaluation. Text quality measure checks for grammar, non-redundancy, structure of summary, coherent summaries for readability etc. Extrinsic measure deals with the task based evaluation for document categorization, information retrieval and question answering. In order to get desirable answer this system used both type of evaluative measures.

ROUGE (Recall-Oriented Understudy) a software package introduced by Lin in 2004 is widely used for content based evaluation of automatic text summarization. The proposed system evaluates quality of machine generated summaries by unigrams , bigrams , ROUGE-N (N-gram based co-occurrence statistics), ROUGE-L (Longest Common sentence Subsequence), and ROUGE-S (Skip-bigram-based co-occurrence statistics)[15].

ROUGE-N is used for finding n-gram in machine summaries divided by sum of the number of n-grams occurring at the human summaries. The recall related measure of ROUGE-N is computed as follows:

$$ROUGE-N=\frac{\sum_{S\in \mathrm{Re}renceSummaries}\sum_{gram_n\in S}Count_{match}(gram_n)}{\sum_{S\in \mathrm{Re}reneceSummaries}\sum_{gram_n\in S}Count(gram_n)} \tag{5}$$

Where N denotes for length of N-gram, $Count_{match}$ (N-gram) is maximum number of N-grams co-occurring in a machine summary (reference summary) and human summaries, Count (N-gram) is the number of N-grams in machine summary.

ROUGE-L (sentence level of longest common sequence) is estimated with F-measure to find the similarity between two summaries X of length m and Y of length n, where X is a human-generated summary sentence and Y is a machine-generated summary sentence. It is calculated by the empirical formula given below:

$$R_{lcs}=\frac{LCS(X/Y)}{m} \tag{6}$$

$$P_{lcs}=\frac{LCS(X,Y)}{n} \tag{7}$$

$$F_{lcs}=\frac{(1+\beta^2)R_{lcs}P_{lcs}}{R_{lcs}+\beta^2P_{lcs}} \tag{8}$$

Where LCS(X, Y) denotes the length of longest common subsequence of X and Y.

ROUGE-S (Skip-bigram-based co-occurrence statistics) is a measure that overlaps skip bigrams between a machine translation and a set of human translations. To compute skip-bigram-based F-measure by formula is given below:

$$R_{skip2}=\frac{SKIP2(X,Y)}{C(m,2)} \tag{9}$$

$$P_{skip2}=\frac{SKIP2(X,Y)}{C(n,2)} \tag{10}$$

$$F_{skip2}=\frac{(1+\beta^2)R_{skip2}P_{skip2}}{R_{skip2}+\beta^2P_{skip2}} \tag{11}$$

Where $SKIP2(X,Y)$ is the number of skip-bigram matches between X and Y.

The result shows that the proposed system outperforms when reinforcement learning involves QA corpus, user interaction for rating. The Table 2 & Table 3 shows the ROUGE evaluation measure attained from various systems such as baseline, reinforcement learning and reinforcement learning with QA corpus (proposed) for benchmark dataset.

Table 2. ROUGE scores on 20newsgroup at limited 250 words summary

Systems	Baseline summary	Human summary	Reinforcement Learning
ROUGE-N	0.0649	0.0863	0.0871
ROUGE-L	0.1265	0.1347	0.1389
ROUGE-S	0.1127	0.1365	0.1373

Table 3. ROUGE scores on DUC 2001 at limited 250 words summary

Systems	Baseline Summary	Human summary	Reinforcement Learning
ROUGE-N	0.0459	0.0963	0.0471
ROUGE-L	0.1245	0.1847	0.1689
ROUGE-S	0.1337	0.1765	0.1173

The following Table 4 shows the performance analysis of machine-generated summary with the golden standard summary generated by human [1]. Standard Classifiers such as Support Vector Machines (SVM), Naïve Bayes, Neural Networks are considered for evaluation. The evaluation of efficiency is computed using the precision, recall, F1-score and Mathew correlation. Precision deals with the true positive on number of overlapping words with the total words occur in machine summary which reduces false positives. Recall deals with the number of overlapping words with the total words occur in reference summary which reduces false negatives. Mathew correlation coefficient checks for quality of summarizer using binary classifier with a value range from -1 to 1.

Table 4. Performance of machine generated summary using standard classifiers

Reference Summaries	Classifiers	ROUGE -N			
		Precision	Recall	F1-score	Mathew Correlation
Machine generated summary (proposed)	SVM	0.5000	0.3191	0.3896	0.0394
	Naïve Bayes	0.6000	0.3830	0.4675	0.1705
	Neural Network	0.7333	0.3860	0.5057	0.2160
Gold Standard Summary	SVM	0.9333	0.4590	0.6154	0.4340
	Naïve Bayes	0.6333	0.4043	0.4935	0.2142
	Neural Network	0.8333	0.4386	0.5747	0.3482

Text summary from a single document can be done with the training of human summaries. The following table shows sample for "Why Apple iPod is the most popular gadget?" from dataset is given in the following table. System summary is framed as, the details in iPod is available from 0.40.txt in the 20newsgroup dataset. The related sentence is available at 3 positions and 13 positions from the total 52 sentences. Table 5 shows the comparison between human summary and system summary.

Table 5. Comparison of Human generated summary and System generated summary

Question: Why Apple iPod be the most popular gadget?	
Document : 20newsgroup\Technology\040.txt	
Sentence	System summary
3/52	Apple iPod family expands market in digital music players with 6 GB gold colored and their prices have been cut by an average of £40.
13/ 52	the Apple iPod, is at number 12 in the list while the first Sony transistor radio is at number 13
	Human Summary
1	iPod touch is ultra-thin and colorful, plays music and video, rules games. To get the greatest graphics performance out of the A8 chip to obtain high quality.
2	The rank of Apple iPod is 12 than Sony transistor at number 13.

6. Statistical Significance Test

In proposed work, ANOVA (ANalysis Of VAriance), a statistical test for significance is chosen to compare summarizers that there is any significant difference in framing text summaries for a given user query. Using ANOVA test, the parameter values are calculated for sum of square (ss), mean square (ms), F-value for mean square, P- values and degree of freedom (df) associated with source etc[13].

Null hypothesis for ANOVA test is stated as significant difference in summarized answers and alternate hypothesis is there is no significant difference in summarized answers. Rank of the summarizers is determined based on the relevance content generated with highest relevancy score. Performance differences of the summarizers are identified with the significance of 95% confidence level for each mean and 0.05% tolerance level for quality.

The accuracy analysis is done by comparing F values. If actual F-value is less than tabulated F- value then null hypothesis is rejected and alternate hypothesis is accepted. In the proposed system, null hypothesis is accepted; this implies that there is a significant difference between existing and proposed summarizers. The significant performance of the summarizers is shown as in Table6 & Fig 3.

Table 6. ANOVA test for 20newsgroup dataset

Source	ss	df	ms	F	Prob> F
Columns	330.08	4	82.52	0.45	0.7708
Error	8224.8	45	182.773		
Total	8554.88	49			

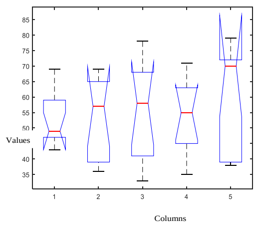

Fig 3. Box plot view of ANOVA test for 20newsgroup dataset

7. Conclusion & Future Work

The proposed work developed a novel framework for answering complex question through machine generated summaries using reinforcement learning with Non-deterministic reward. Learning model was trained by human generated summaries and list of complex questions. Proposed system efficiency outer performs than existing system. The system generated summaries are compared with human generated summaries, made extensive evaluation with benchmark datasets using standard metrics such ROUGE. The limitation of system is not to handle abbreviated and single word questions. Future improvement is to apply deep learning for natural language understanding and automatically generate answers according to the previous scenario.

References

[1] Aziz Qaroush , Ibrahim Abu Farha, Wasel Ghanem, Mahdi Washaha, Eman Maali.," An efficient single document Arabic text summarization using a combination of statistical and semantic features", Journal of King Saud University - Computer and Information Sciences ,Elsevier, 2019.

[2] Kaichun Yao, Libo Zhang, Tiejian Luo, Yanjun Wu, "Deep reinforcement learning for extractive document summarization", Neuro computing, Elsevier, pp. 52– 62, 2018.

[3] Shashi Narayan, Shay B. Cohen, Mirella Lapata , June," Summarization with Reinforcement Learning", Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1, Pages: 1747–1759, 2018.

[4] Yalias Chali, Sadid A. Hasan & Mustapha Mojahid, "Reinforcement Learning Formulation to the Complex Question Answering Problem", Information Processing & Management, Elsevier, 2015, vol. 51, Issue no 3, pp. 252-272, 2015.

[5] Rasmita Rautray, Rakesh Chandra Balabantaray& Anisha Bhardwaj ,"Document Summarization using Sentence Features", International Journal of Information Retrieval Res(IJIRR), Volume 5 Issue 1, pp.36-47,2015.

[6] Ming Tan, Cicero dos Santos, Bing Xiang & Bowen Zhou," Improved Representation Learning for Question Answer Matching", Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, August, pp. 7-12,2016.

[7] SeonggiRyang & Takeshi Abekawa ," Framework of Automatic Text Summarization using Reinforcement Learning', In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing & Computational Natural Language Learning, EMNLP- CoNLL Jeju Island, Korea pp. 256–265,2012.

[8] Denis Savenkov & Eugene Agichtein, "CRQA: Crowd- Powered Real-Time Automatic Question Answering System", Proceedings, The Fourth AAAI Conference on Human Computation & Crowdsourcing , Association for the Advancement of Artificial Intelligence, pp.189 -198,2016.

[9] Dorota Gowacka, Tuukka Ruotsalo, Ksenia Konyushkova , Kumaripaba Athukorala, Samuel Kaski& Giulio Jacucci, " Directing Exploratory Search: Reinforcement Learning from User Interactions with Keywords", IUI'13, Copyright ACM, pp.117-127,2013.

[10] Chin-Yew Lin, "ROUGE: A Package for Automatic Evaluation of Summaries", In Proceedings of Workshop on Text Summarization branches out, Post- Conference Workshop of Association for Computational Linguistics, Barcelona, Spain , pp. 74–81, 2004,.

[11] Al-Radaideh, Q.A., Bataineh, D.Q, ," A hybrid approach for arabic text summarization using domain knowledge and genetic algorithms", Cognitive Computer, 2018.

[12] Rautray, R., Balabantaray, R.C. , ,An evolutionary framework for multi-document summarization using cuckoo search approach, Mdscsa. Application Computer Information, volume 14,issue 2, pp.134–144, 2018.
[13] Smucker, M.D., Allan, J. and Carterette, B.,"A comparison of statistical significance tests for information retrieval evaluation", In Proceedings of the sixteenth ACM conference on Conference on information and knowledge management, ACM, 623-632,2007.
[14] Karpagam.K & Saradha.A, "Text Summarization using Machine Learning Approaches for Question Answering System", International Journal of Advances in Computer and Electronics Engineering, ISSN: 2456 - 3935, Volume 4, Issue 2, pp.1–5,2019.
[15] Gunnar Schröder, Maik Thiele &Wolfgang Lehner , 'Setting Goals & Choosing Metrics for Recommender System Evaluations ', 5th ACM Conference on Dresden University of Technology Recommender Systems Chicago, October 23th, 2011.
[16] Hua, Y.H., Chenb, Y.L., Chou, H.L," Opinion mining from online hotel reviews a text summarization approach", Information Process Management 53 (2), pp.436–449,2017.
[17] Abdelkrime, A., Djamel Eddine, Z., Khaled Walid, H. ,"All summarizer system at multilingual single and multi-document summarization" Proceedings of the SIGDIAL 2015 Conference,pp.237–244, 2015.
[18] Litvak, M., Vanetik, N., Last, M., Churkin, E.. Museec," A multilingual text summarization tool", pp. 73–78,2016,.
[19] Thomas, S., Beutenmüller, C., de la Puente, X., Remus, R., Bordag, S,,., "Extractive text Summarizer", Proceedings of the SIGDIAL 2015 Conference, pp. 260–269,2015.
[20] Jan Frederik Forst, Anastasios Tombros& Thomas Roelleke, 'Less Is More: Maximal Marginal Relevance as a Summarization Feature', Advances in Information Retrieval Theory, ICTIR, pp. 350-353, 2009.
[21] Youzheng Wu, Chiori Hori, Hideki Kashioka &Hisashi Kawai, "Leveraging social QA collections for improving complex question answering", Computer Speech & Language, Volume 29 Issue 1, pp.1-19,2015.
[22] Hiroyuki Sakai & Shigeru Masuyama, ,"A Multiple-Document Summarization System with User Interaction", In Proceedings of the 20th International Conference on Computational Linguistics, COLING '04, C04-1144, ACL Anthology, pp.1001-1007,2004.

Authors' Profiles

Dr. K. Karpagam is working as Asst. Professor in Department of Computer Applications, Dr.Mahalingam College of Engineering and Technology, Pollachi. She has 15 years of academic experience and currently pursuing research in Anna University, Chennai. The area of research interests includes Machine learning ,text mining, Question Answering system and information retrieval..

Dr. A. Saradha is working as Professor and HOD, Department of Computer Science and Engineering, IRTT, Erode. She has 25+ years of academic experience. Her research interests are Semantic Web, Human Computer Interaction, Image processing.

Dr. K. Manikandan is working as Associate Professor in the School of Computer Science & Engineering ,VIT Vellore. He received Best Faculty Award-2014 from ICTACT,Govt of Tamilnadu. Research Area includes Mobile Network ,Cloud Computing, Big Data Analytics and Machine learning

K. Madusudanan is working as Asst. Professor in Department of Computer Applications, Dr.Mahalingam College of Engineering and Technology, Pollachi. He has 17 years of academic experience. The area of research interests includes semantic web, text mining and information retrieval.

How to cite this paper: K.Karpagam, A. Saradha, K.Manikandan, K.Madusudanan, "Enhancement of Single Document Text Summarization using Reinforcement Learning with Non-Deterministic Rewards", International Journal of Information Technology and Computer Science(IJITCS), Vol.12, No.4, pp.19-27, 2020. DOI: 10.5815/ijitcs.2020.04.03