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A Pattern Tree User Queries based Key Frame Extraction and Sentimental Divergence Classification in Semantic Data Analysis

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Abstract : Semantic data mining is mining model where domain ontologies are used as essential knowledge and support the huge number of data vial real life onotologies symbolized in semantic web languages. The several semantic data research works concentrates only on the key frame extraction. However, the classification issue I sentimental data analysis.

Methods/statistical analysis : Several semantic data research works concentrates only on the key frame extraction. However the classification is a demanding issue in sentimental data analysis. In order to improve the semantic data analysis, key frame Extraction and Sentimental Divergence Classification (KFE SDC) framework is introduced using Reuters 21578 Text categorization Collection Data Set. Initially Semantic Pattern Tree is constructed, based on the use query. Next, Key Frame Extraction model is used for the effectively describing the document contents and extracting the similar data based on the user query.

Findings : The extraction model helps to reduce the complexity of finding the semantic data. Finally, Sentimental Divergence classification is performed by Naïve Bayes classifier is used to classify the sentiment data from the opinions appraisals that are collected after the extraction process. The sentimental divergence classification aimed to improve the semantic data analysis with higher classification accuracy

Applications : Experimental results demonstrate that the proposed KFE-SDC framework not only leads to reduction over the parameters execution time for key frame extraction and computational complexity, but also outperforms the higher sentimental data classification accuracy

Keywords: Semantic data mining, user query, key frame extraction, semantic pattern tree and semantic data analysis.

1. INTRODUCTION

The query optimization is the method of converting one query into an additional one by the semantic knowledge to present similar answer in semantic information processing. Many of the researchers have contributed towards semantic web query[8,22] optimization by extensive approaches. An object-based method is presented in [1] for on-the-fly extraction of key frames describing the salient visual content of videos. The method is depending on the spatial segmentation for the identification of essential events. Though, it is suitable only for the low-level attributes of relevant objects for presenting the vector that explains each frame based on object types. A new approach is planned in [2] for key frames extraction on human action recognition from 3D video sequences. For classifying the human actions, an Energy Feature (EF) combining kinetic energy and potential energy is extracted as of 3D video sequences. A Self-adaptive Weighted Affinity Propagation (SWAP) algorithm is designed to extract the key frames. However, the actions do not able to recognize human activities.

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Clustering or segmentation techniques are used for the extraction of the key-frames. An approach is planned in [3] for the weighted fusion of many descriptors which calculates the weight of all descriptor. The weights reveal the importance of all descriptor for the particular video shot. Though, clustering technique failed to calculate the number of clusters (key-frames) automatically.

MostoBM is planned in [4] is a benchmark for analyzing the data replacement systems in ontologies. It also presents three real-world and seven synthetic data exchange patterns that instantiated into many situations. But, the benchmark provides comparatively lesser performances. Transferring the polarity of features (TPF) is designed in [5] for the cross-domain sentiment classification. The polarity of features is instructive for sentiment classification. The algorithm transmits the polarity of features from source domain to the target domain with self-determining features as the bridge. But, it is not suitable for the distance methods in sentiment classification.The work designs an detailed understanding of the KFE-SDC framework, with the following contributions: (1) Semantic Pattern Tree is constructed based on the user query; (2) Key Frame Extraction model is to describe the document contents and extracting the similar data based on the user query; (3) Sentimental Divergence Classification is performed by Naive Bayes Classifer to classify the sentiment data from the opinions appraisals that are collected after the extraction process; (4) experiments were conducted to evaluate the efficiency of semantic data analysis of KFE-SDC framework and to reduce the complexity..

The rest of the paper is organized as follows. In Section 2, a summary of related works for key frame extraction and sentiment classification in semantic data are explained. In Section 3, the proposed framework of Key Frame Extraction and Sentimental Divergence Classification (KFE-SDC) framework with the help of diagram is described. In Section 4, experimental settings are presented with detailed analysis of results with graph and table explained in Section 5. In Section 6, the concluding remarks are included.

2. SENTIMENT ANALYSIS MODEL

In [10,11] base and restricted hybrid composition was established by relation routing system for answering the difficult semantic queries. CROWDOP called cost-based query optimization approach is planned in [12] for declarative crowd sourcing systems. CROWDOP consider equal cost and latency in the query optimization ideas and creates query plans between the cost and latency.

Reverse keyword search in [13,14] for spatio-textual top-k queries (RST Q) has keywords with target object provides the spatio-textual top-k result. Hybrid index KcR-tree is planned to summarize the spatial and textual information for processing the user query. But, the search failed to rank the target object with least query modification. Sentiment classification technique termed as ASLDA is designed in [7,19]. The words in subjective documents comprise two types, namely sentiment element words and auxiliary words. They are sampled from sentiment issues and auxiliary topics. Though, the above mentioned methods take large amount of time for processing. There classification models are employed in [14,20] for text classification by Waikato Environment for Knowledge Analysis (WEKA).

In[16] a new system was designed to help the users for well-organized design of semantic queries for particular domain in lesser time interval and more effective efficient in terms of accuracy. In [17,19] an enhanced unsupervised classification framework IRT is designed where the self-expandable topic is denoted as hash and it failed in including the polarity updation. In [18] Sentiment analysis[15] model derived from the common-sense knowledge taken out from ConceptNet based ontology and context information. ConceptNet based ontology is employed to find out the domain concepts that created the essential features.

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3. ARCHITECTURAL FRAMEWORK OF KEY FRAME EXTRACTION AND SENTIMENTAL DIVERGENCE CLASSIFICATION

The key aim of Key Frame Extraction and Sentimental Divergence Classification by constructing the semantic pattern tree (SPT). The SPT detects the frame based on the ordering functions used in KFE-SDC framework. The pattern of query language is described by semantic pattern tree on framework ‘T_0’ is nothing but to expand the user queries.

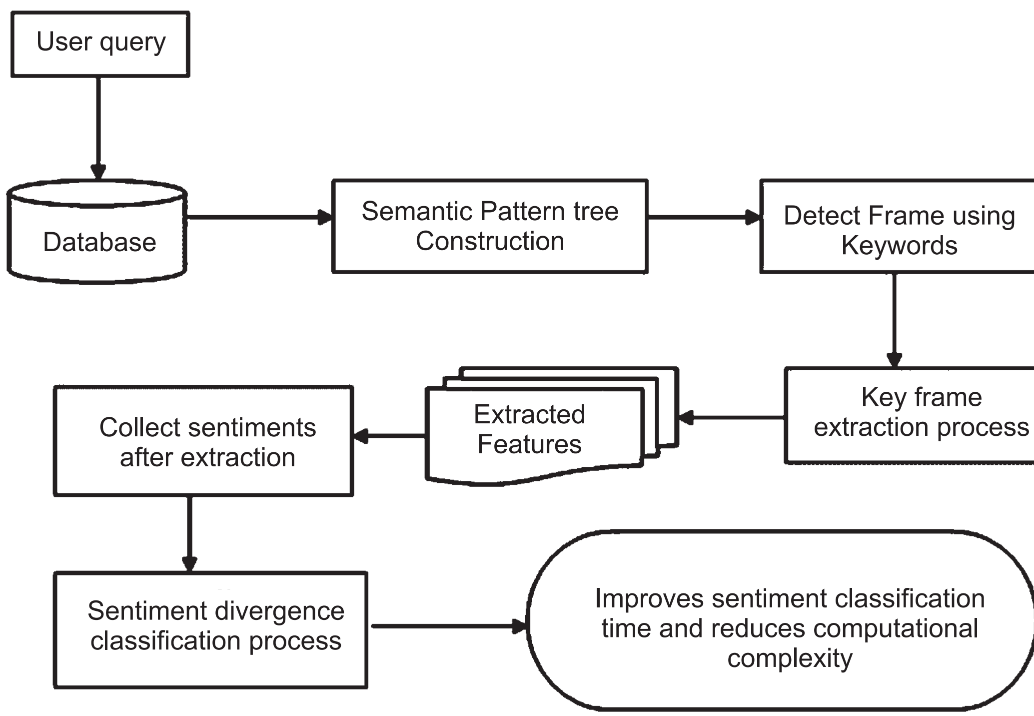

Figure 1: Architecture Framework of KFE-SDC

3.1. Semantic Pattern tree Construction

Semantic Pattern Tree construction in KFE-SDC is carried out by the random transformation that denoted as ‘T_0’. The semantic pattern tree with root node carries the topic of the user fetched query. The vertex and edges of semantic pattern tree in KFE-SDC is described as,

Semantic Pattern Tree $(T_0) = \{v, e, q\}$ (1)

User result Tree $(T'_0) = \{v', e', q'\}$

As’ T_0^{1}’ is the system for fetching the document from (2), the user result is stored in T_0' on the vertices v' and edges e' respectively. When $T_0 = T_0'$, the property takes place in KFE-SDC framework as per (1) and (2).Figure 1 shows the construction of SPT.

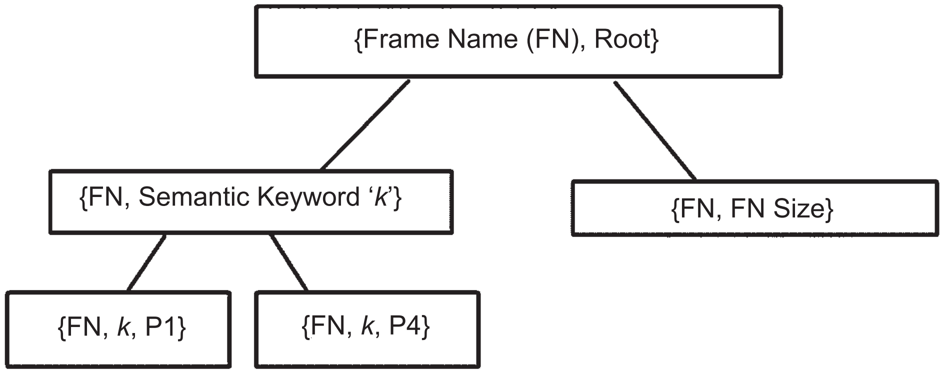

Figure 2: Construction of Semantic Pattern Tree

In the figure the edges are on left side and right side of vertices. This clearly describes the construction of semantic pattern tree using KFE-SDC framework. The tree contains the document name on root vertices ‘*v*’. It represents the semantic keywords on left and the document size on the right. In Figure 2, ‘*k*’ is located on different web page where count denoted as ‘P1’ and ‘P4’.

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3.1.1. Calculate the Number of Key-Frames

Initially, the number of key-frames (*i.e.*,) rank of matrix are taken. The number of singular values is similar to the rank of matrix X. Text-based document is a non-structured data and there is not easy linear relationship between the text frames where the rank of matrix X is high. In order to avoid the complication process, rank of matrix X is taken as comparatively lower one

$$\begin{array}{lrcl}
\text{For} & X & \in & R^{mxn}, \\
 & p & = & \min(m, n) \\
\text{if} & (((n < r) & = & \text{rank}(X)) \ \&\& \ (X_n = \sum_{j=1}^{n} (\sigma_i \, \beta_i \, \gamma_i)^{T})) \\
\text{then,} & \min_{\text{rank}(Y) = n} \|X - Y\|_F & = & \|X - X_p\|F \\
 & & = & \sqrt{\sum_{j=k+1}^{p} \delta_i^2}
\end{array} \tag{3}$$

Eqn (4) is used to determine the approximate rank of matrix where the number of key-frames is extracted from the document. From (5), this equation is the main information by the removal of smaller singular values. The largest integer p that satisfied $s(k) \geq \alpha$ is chosen as the suitable rank r, where threshold α, the selected key-frames and the available text based information are comparatively higher. For static text data, as frames are very nearer in text data content, approximate linear relation in which the rank of matrix X is very small. With increasing complexity of text content in particular frame of entire document, the nonlinear connection between frames is improved. The singular values are separated and the rank of matrix X is larger and the chosen key-frames are developed into additional one. It is suitably observed with common sense where many key-frames are extracted for the text document with higher complexity:

$$v(k) = \frac{\sqrt{\delta_1^2 + \delta_2^2 + \delta_3^2 + \ldots, + \delta_n^2}}{\delta_1^2 + \delta_2^2 + \delta_3^2 + \ldots + \delta_l^2} \tag{5}$$

$$l = \min(m, n)$$

3.1.2. Locate Specific Key-Frames

Locate key-frames prefers the linearly independent sub-set of matrix. The lesser correlation defines the largest visual variations and the text data content variation between frames is represented by inter-frame distance. The inter-frame distance is used to choose the frames with largest visual variations in the entire document. The histogram distance between each frame and previous frame, is calculated

$$D(j, j+1) = \sqrt{\sum_{j=2}^{s} [K_j(a) - K_{j-1}(a)]^2} \quad (6)$$

From Eqn (6), $K_j(a)$ denotes the gray value of the a^{th} pixel in frame and s denotes the total number of the frames inside a text document and the frames are extracted with the higher distance as key-frames in an entire document. The extracted key frames are given for the sentimental classification using keywords which is described briefly in section 3.2.

3.2. Sentimental Divergence Classification

Sentiment Classification Algorithm is used to analyze and classify the particular sentences or words combination to create a number of key-frames by identified users. Sentiment classification objective is to calculate the polarity of users' perspective hidden in reviews. Polarity divergence features in sentimental classification are positive/negative in one domain but negative/positive in another.

3.2.1. Naive Bayes Classifier

The frequency of sentimental word is calculated through differentiating sentimental data using Naïve Bayes. So the scores are as below

$$P\left(\frac{c}{d}\right) = \frac{P\left(\frac{f}{c}\right) * P(c)}{P(d)} \quad (7)$$

$$c^* = \arg\max c\, P\left(\frac{c}{d}\right)$$

From Eqn (7) and (8), c and d represents the class and document. maxc denotes the maximum of the class and the f represents a feature. P(c) and P (f/c) are attained by maximum probability calculations for unseen features. The probability of classification can be obtained in four different forms, namely very negative, negative, positive and very positive in the rating of (–5 or –4), (–3, –2, or –1), (1, 2, or3) and (4 or 5) respectively. The algorithm depending on the dictionary of sentimental keywords is carried out with the sentiment classification algorithm are described as given below.

// Sentiment Classification Algorithm

Input : Identify semantic keyword '*k*' on FN

Step 1: Calculate the sentimental keywords in dictionary with the negative or positive words

Step 2: Compute the frequency of the sentimental words in the document

Step 3: The variable weights are changed through adding Sentiment words

Step 4: Naive Bayes classifier generate sentiment data using (7) and (8)

Step 5: Repeating the steps (1) to (4) for classifying the new contents.

Output : Enhanced sentimental Data Analysis

The above sentimental classification algorithm is to identify the data through computing the frequency of sentiment words in content matching the dictionary of keywords. The Sentiment Classification Algorithm aimed to improve the semantic data analysis with higher accuracy.

4. EXPERIMENTAL EVALUATION

Key Frame Extraction and Sentimental Divergence Classification (KFE-SDC) framework uses JAVA language to execute the experimental work.

These attributes are used to extract the key frames and classify the features in the text document. KFE-SDC framework experiment is compared with the existing object-based method and transferring the Polarity of Features (TPF) approach for cross-domain sentiment classification. The experiment is conducted on the factors such as efficient in terms of computational complexity, execution time for keyframe extraction and sentimental data classification efficiency.

Sentimental data classification accuracy is one of the performance metrics to measure the accuracy of correct classification made regarding the sentiment keywords provided by the user. The Sentimental data classification accuracy is defined as the number of keywords correctly classified (including both positive and negative words) and is evaluated by the following formula.

$$SDCA = \frac{\text{No. of keyword}_{cc}}{\text{Total number of keywords}} \tag{9}$$

From (9) Sentimental Data Classification Accuracy 'SDCA' is the ratio of the number of keywords correctly classified No.of keywords$_{cc}$ to the total number of key words. Computational complexity involved during key frame extraction is the resources required to measure number of key frame and is as given below. It is the product of number of queries considered and the time taken for key frame extraction

$$CC = n * \text{Time (key frame extraction)} \tag{10}$$

Where 'CC' is the computational complexity and 'n' refers to the number of queries considered during each iterations. The execution time for key frame extraction is the time taken to extract the positive and negative words with respect to the number of queries. The execution time for key frame extraction is mathematically formulated as given below

$$ET = \sum_{i=1}^{n} \text{Queries}_i * \text{Time (PNW)} \tag{11}$$

From (11), the execution time 'ET' is obtained using the Queries 'R$_i$' and time for generating classes with the aid of positive and negative words 'PNW'. It is measured in terms of milliseconds (ms).

5. RESULTS ANALYSIS OF KFE-SDC

Table 1
Performances of Sentiment Data Classification Accuracy using Various Methods

No. of keywords (Number)	*Sentiment data classification accuracy (%)*		
	KFE-SDC	*Object based method*	*TPF approach*
5	85.34	80.21	72.08
10	87.64	82.98	74.69
15	90.32	84.39	75.36
20	91.75	85.68	77.96
25	92.45	86.32	80.63
30	93.87	87.21	82.64
35	94.67	90.23	85.33

In order to analyze the features of the KFE-SDC framework, the performance was carried out in an effective way on basis of five attributes, like TOPICS, LEWISSPLIT, CGISPLIT, OLDID and NEWID. The results are compared with the object based method. The experimental results using JAVA are evaluated and examined with table values and graphical demonstration. To provide with detailed results in Table 1, we use Naive Bayes Classifier to attain the sentimental data classification accuracy and comparison is made with two other existing techniques, object-based method and TPF approach respectively.

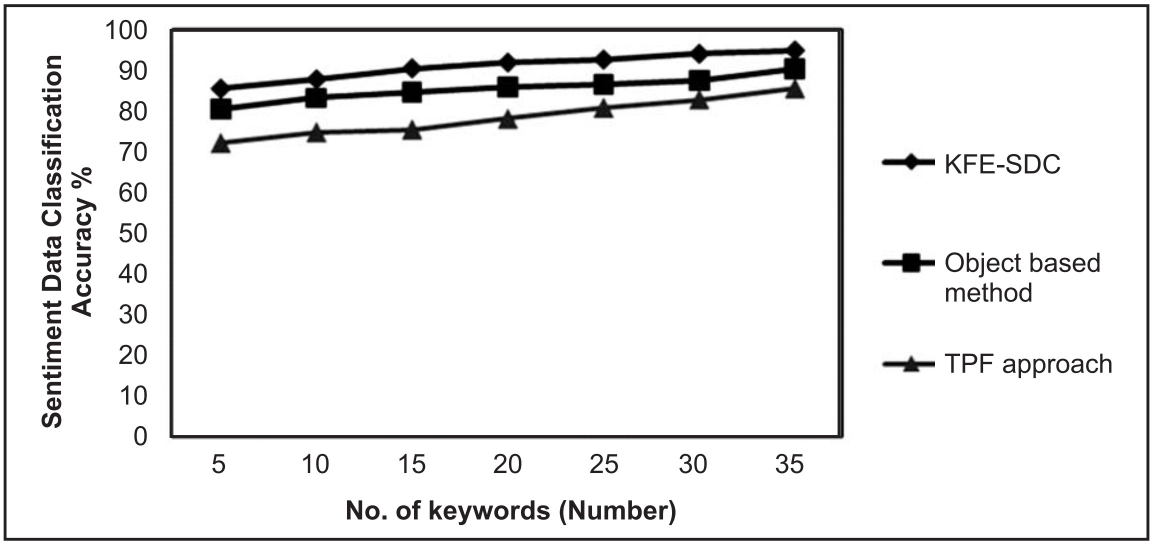

Figure 3 : Show that the proposed KFE-SDC framework provides higher sentiment data

Classification accuracy when compared to existing object-based method[1,26]and transferring the Polarity of Features (TPF) approach for cross-domain sentiment classification [2,25]This is because of the application of Naïve Bayes Classifier which classifies the sentiment data from the opinions appraisals that are collected after the extraction process that results in the improvement of sentiment data classification accuracy by 4 – 7 % compared to object-based method. Additionally, with the classification of semantic data the semantic keywords on each edge point from different levels is recognized that results in the improvement of sentiment data classification accuracy by 9 – 16 % compared to TPF approach.

Table 2

Performances of Computational complexity using Various Methods

No. of User Query (Number)	*Computational complexity (ms)*		
	KFE-SDC	*Object based method*	*TPF approach*
5	1.27	1.32	1.51
10	1.34	1.45	1.60
15	1.42	1.53	1.68
20	1.58	1.66	1.82
25	1.69	1.73	1.93
30	1.75	1.83	1.96
35	1.89	1.92	1.99

The Table 2 shows the comparison of computational complexity against number of user query.
In Figure 4, the computational complexity is plotted with respect to number of queries range from 5 – 35. Furthermore, we can also observe that by increasing the number of queries, the computational complexity is reduced but comparatively development is examined by the proposed KFE-SDC framework. An there is a reduction in computational complexity by 6 – 42 % and 22 – 65 % compared to RB and LP approach respectively.

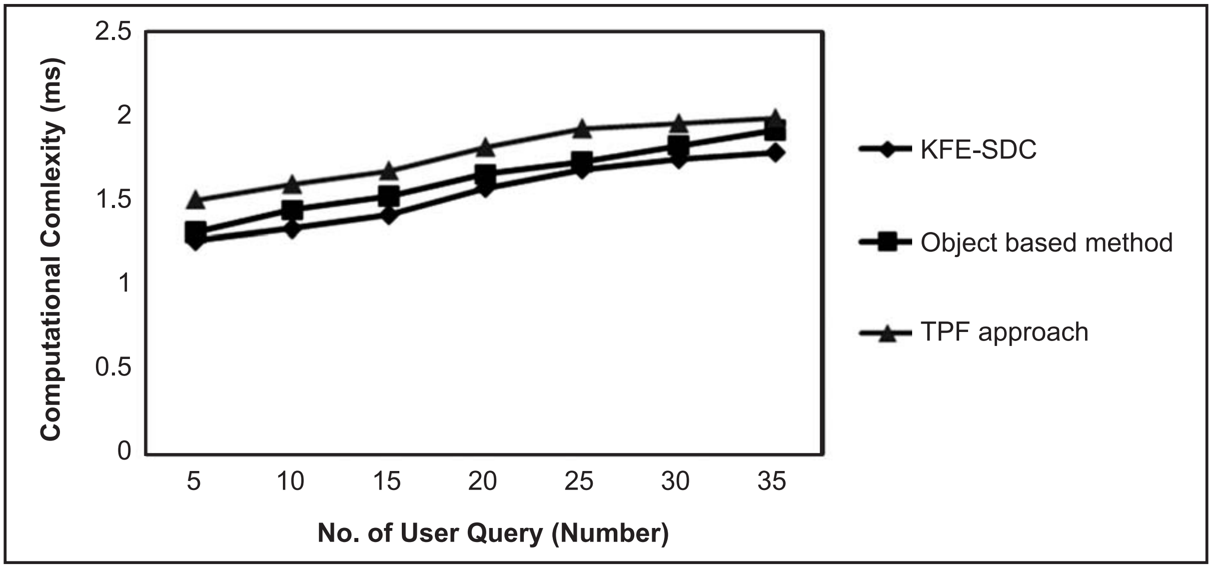

Figure 4: Measure of Computational Complexity

Table 3
Performances of Execution Time for Key Frame Extraction using Various Methods

No. of User Queries (Number)	*Execution Time for Key Frame Extraction (ms)*		
	KFE-SDC	*Object based method*	*TPF approach*
5	38.21	46.59	52.36
10	41.32	48.69	55.89
15	44.15	51.33	59.65
20	46.35	53.26	65.35
25	48.61	55.12	67.85
30	53.36	59.21	71.32
35	55.96	63.85	74.85

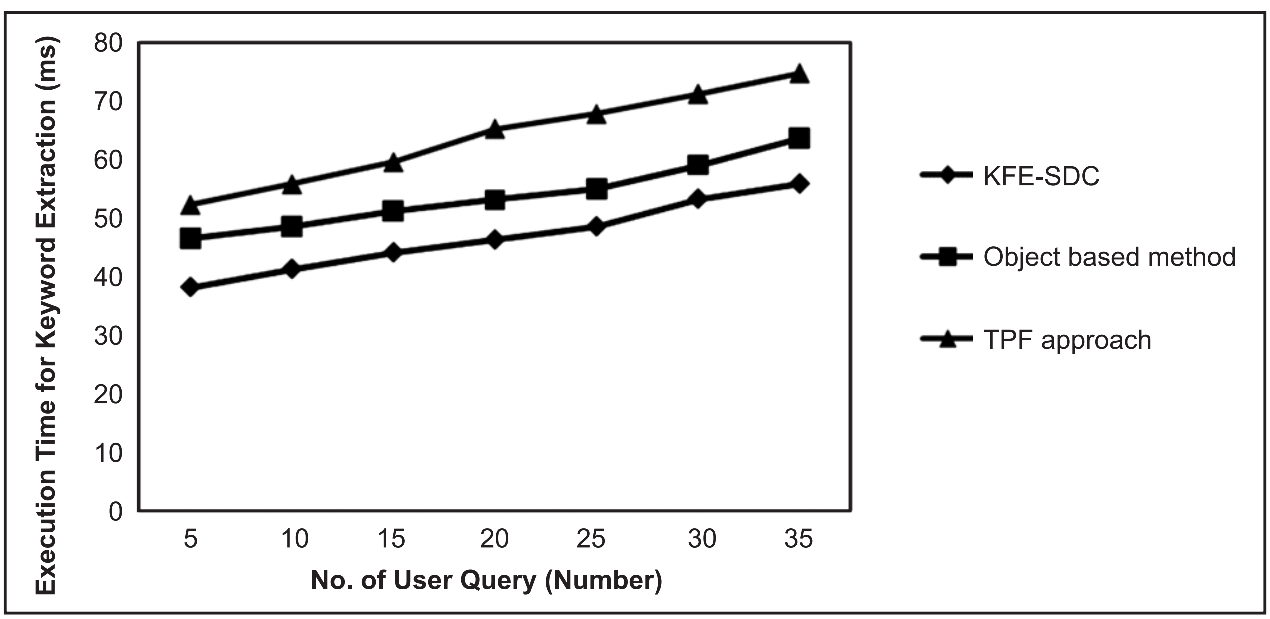

Figure 5: Measure of Execution Time for Key Frame Extraction

The execution time for key frame extraction using KFE-SDC framework is presented in a detailed manner in Table 3. We consider the approach with different number of queries acquired from the UCI repository using five attributes for experimental purpose using JAVA

Execution time for key frame extraction using KFE-SDC framework with two mentioned methods[1,2] is shown in the in Figure 5. approach differs from the object-based method [1,19]and transferring the Polarity of Features (TPF) approach for cross-domain sentiment classification[23,24]in that key frame extraction model is used for describing the document contents and extracting the similar data based on the user query that reduced the execution time for key frame extraction by 10 – 23 % and 32 – 40 % compared to RB and LP approach respectively.

6. CONCLUSION

The Key Frame Extraction and Sentimental Divergence Classification (KFE-SDC) framework improved the sentiment data analysis on mentioned standard data set. The KFE-SDC framework uses Semantic Pattern Tree based on the Key Frame extraction model to effectively describing the document contents and extracting the similar data based on the user query. The extraction model helps to reduce the complexity of finding the semantic data. Finally, Sentiment Divergence Classification is performed using Naïve Bayes Classifier to classify the sentiment data from the opinions appraisals that are collected after the extraction process. Experimental results demonstrate that the proposed KFE-SDC framework not only leads to reduction over the parameters execution time for key frame extraction and computational complexity, but also outperforms the higher sentimental data classification accuracy compared to start-of-the art-methods.

7. REFERENCES

1. Barhoumi W, Zagrouba E. On-the-fly extraction of key frames for efficient video summarization, Elsevier, AASRI Procedia, 2013, 4, pp. 78–84.
2. Zhang Y, Hua X, Lia P, Lia L, Wua X. Cross-Domain sentiment classification–feature divergence, polarity divergence or both, Elsevier, Pattern Recognition Letters, 2015 Nov 1, 65, pp. 44–50.
3. Ioannidis A, Chasanis V, Likas A. Weighted multi-view key-frame extraction, Elsevier, Pattern Recognition Letters, 2016 Mar 1, 72, pp. 52–61.
4. Yongxiong W, Shuxin S, Xueming D. A Self-adaptive Weighted Affinity Propagation Clustering for Key Frames Extraction on Human Action Recognition, Elsevier, Journal of Visual Communication and Image Representation, 2015 Nov , 33, pp. 193–202.
5. Hwang M, Choi C, Kim P. Automatic Enrichment of Semantic Relation Network and Its Application to Word Sense Disambiguation, IEEE Transactions on Knowledge and Data Engineering, 2011Jun, 23(6), pp. 845-858.
6. Ning X, Jin H , Jia W, Yuan P. Practical and effective IR-style keyword search over semantic web, Elsevier, Information Processing & Management, 2009 Mar, 45(2), pp. 263–271.
7. Wong T L, Lam W. Learning to Adapt Web Information Extraction Knowledge and Discovering New Attributes via a Bayesian Approach, IEEE Transactions on Knowledge and Data Engineering, 2010Apr, 22(4), pp. 523-536.
8. Bollegala D, Matsuo Y, Ishizuka M. Automatic Discovery of Personal Name Aliases from the Web, IEEE Transactions on Knowledge and Data Engineering, 2011Jun, 23(6), pp. 831-844.
9. Rivero C R, Herna´ndez I, Ruiz D, Corchuelo R. Benchmarking Data Exchange among Semantic-Web Ontologies, IEEE Transactions on Knowledge and Data Engineering, 2013Sept, 25(9), pp. 1997-2009.
10. Cheng J, Wang W, Gao R. Massive RDF Data Complicated Query Optimization Based on MapReduce, Elsevier, Physics Procedia, 2012, 25, pp.1414–1419.
11. Liao Z, Zhang G, Yi A, Zhang G, Liang W. A Relation Routing Scheme for Distributed Semantic Media Query, Hindawi Publishing Corporation, The Scientific World Journal, 2013 Sept, 2013, pp .1-15.
12. Fan J, Zhang M, Kok S, Lu M, Ooi B C. CrowdOp: Query Optimization for Declarative Crowd sourcing Systems, IEEE Transactions on Knowledge and Data Engineering, 2015Aug, 27(8), pp . 2078-2092.
13. Lin X, Xu J, Hu H. Reverse Keyword Search for Spatio-Textual Top-k Queries in Location-Based Services, IEEE Transactions on Knowledge and Data Engineering, 2015Nov, 27(11), pp . 3056-3069.

14. Bornea M A, Vassalos V, Kotidis Y, Deligiannakis A. Adaptive Join Operators for Result Rate Optimization on Streaming Inputs, IEEE Transactions on Knowledge and Data Engineering, 2015Oct, 22(8), pp .1110-1125.

15. Lee J , Min J K, Oha A, Chung C W. Effective ranking and search techniques for Web resources considering semantic relationships, Elsevier, Information Processing & Management, 2014 Jan, 50(1), pp. 132–155.

16. Zenz G, Zhou X, Minack E, Siberski W, Nejd W. From Keywords to Semantic Queries Incremental Query Construction on the Semantic Web, Elsevier, 2009 Sept, 7(3), pp. 166–176.

17. J. Manikandan, M. Manikandan,“VLSI based Pipelined Architecture for Radix-8 Combined SDF-SDC FFT”,Indian Journal of Science and Technology,2016 July, 9(28), Doi no:10.17485/ijst/2016/v9i28/94599

18. K. Malathy, B. Justus Rabi,“A Novel VLSI Based Radix-2 Single Path Delay Commutator (R2SDC) FFT Architecture Design”,Indian Journal of Science and Technology,2016 Mar, 9(11), Doi no:10.17485/ijst/2016/v9i11/82298

19. J. Manikandan, M. Manikandan,“VLSI based Pipelined Architecture for Radix-8 Combined SDF-SDC FFT”,Indian Journal of Science and Technology,2016 July, 9(28), Doi no:10.17485/ijst/2016/v9i28/94599

20. Shah Khusro, Fouzia Jabeen, Syed Rahman Mashwani, Iftikhar Alam, “Linked Open Data: Towards the Realization of Semantic Web - A review”,Indian Journal of Science and Technology,2014 Jan, 7(6), Doi no:10.17485/ijst/2014/v7i6/38378.

21. Samira Ghayekhloo, Zeki Bayram,“A Novel Rubric and Feature-based Appraisaland Comparison Framework for the Evaluationof Semantic Web Services Composition Approaches”,Indian Journal of Science and Technology,2015 Dec, 8(33), Doi no:10.17485/ijst/2015/v8i33/72733.

22. B. Gladys Gnana Kiruba,“A Survey on Ontology System in Semantic Web using Intelligent Techniques”,Indian Journal of Science and Technology,2016 Aug, 9(35), Doi no:10.17485/ijst/2016/v9i35/98021

23. Ravichandran M, Kulanthaivel G, Chellatamilan T. Intelligent Topical Sentiment Analysis for the Classification of E-Learners and Their Topics of Interest, Hindawi Publishing Corporation, The Scientific World Journal, 2015 Feb, 2015, pp.1-9.

24. Agarwal B, Mittal M, Bansal P, Garg S. Sentiment Analysis Using Common-Sense and Context Information, Hindawi Publishing Corporation, Computational Intelligence and Neuroscience, 2015 Feb, 2015, pp.1-10.

25. Liang J, Liu P, Tan J, Bai S. Sentiment Classification Based on AS-LDA Model, Elsevier, Procedia Computer Science, 2014, 31, pp. 511–516.

26. Bilal M, Israr H, Shahid M, Khan A. Sentiment classification of Roman-Urdu opinions using Naive Bayesian, Decision Tree and KNN classification techniques, Elsevier Journal of King Saud University - Computer and Information Sciences, 2015 Dec, pp.1-15.