CSE 515 (Fall2016) Phase 3 Report: Group 17

Anshuman bora, Arizona State University

vraj delhivala, Arizona State University

satyam jaiswal, Arizona State University

saumya parikh, Arizona State University

Tanmay patil, Arizona State University

**Abstract**

Finding similarity of frames between multiple videos is not enough. They also have to be listed according to some kind of importance or relevance. In phase2, we listed them by sorting with respect to the similarity index. The frame with highest similarity came first and the top *k* frames were selected as most similar sub-sequence. In phase3, we have improved the listing logic by implementing intelligent algorithms which list similar frames by significance, relevance and also by nearest neighbor importance in high dimensional spaces. SIFT vectors in a reduced space have been used as input considering they describe important visual features. Algorithms like PageRank and ASCOS++ have been used for ranking according to significance. Relevance feedback based algorithms like personalized PageRank and personalized ASCOS ++ have been used and nearest neighbor based technique of Locality Sensitive Hashing has also been used. This report talks about all these implementations in detail.

**Keywords**

**Feature Extraction, Similarity Graph, Significant Frame, Relevant Frame, Page Rank, ASCOSS, Personalized PageRank, Locality Sensitive Hashing, Multi-dimensional Indexing**

# Introduction

Terminology

1. Clustering: Clustering is defined as grouping data or points into groups such that more similar data are in the same group. Clustering comes under unsupervised learning.
2. Indexing: Is a mechanism with which access to large data managed in files. [1]
3. Classification: This is a method in which data is split into predefined classes. It comes under supervised learning.
4. Relevance feedback: Is a mechanism used in algorithms where the user gives feedback on the relevance of documents in an initial set of results. [2]
5. PageRank: PageRank is an algorithm which is used by Google to rank the webpages on the internet. [3]
6. ASCOS++: Asymmetric Network Structure Context Similarity, takes into account all the nodes and the weight of edges between the nodes for calculation of similarity measure. [4]
7. LSH: Locality sensitive hashing, algorithm for solving the approximate or exact Near Neighbor Search in high dimensional spaces. [5]

Goal Description

Phase 3 involves around experimenting with clustering, indexing, classification and relevance feedback. The detailed goal description are as follows:

1. Task1: In task1 we had to implement Video Feature Extraction algorithm where Principal Component Analysis (PCA) had to be applied to the original space to get a reduced vector space.
   1. Input: The input to this algorithm is ‘*d*’ (the target reduced dimensionality) and *‘filename.sift’* (file containing SIFT features)
   2. Output: the output would be a file named ‘filename\_d.spc’ which would contain entries in the form of *{<i, j, l, x, y>, [dim-1 , . . , dim-d]}*, such that i = video, j = frame and l = cell indices. x and y and provide the position of the SIFT key point and [dim-1, . . , dim-d] are the reduced dimensions. The program is also expected to output the d dimensions in the form of *<original\_index, score>* in non-increasing order of scores.
2. Task2: In task2 we have to create a similarity graph using the reduced SIFT vector space.
   1. Input: Integer *K* and SIFT key points in file *‘filename\_d.spc’.*
   2. Output: Graph(V, E) where V are the nodes corresponding to each frame and E are the edge pairs corresponding to <va, vb> where vb is one of the most similar frames to vb, from a different video that vb. This graph will be stored in *‘filename\_d\_k.gspc’* in the format of *<va, vb, sim(a,b)>*
3. Task3: The goal of task3 is to list most similar frames according to significance. This is to be done using 2 methods namely, PageRank and ASCOS++.
4. Task4: This task is similar to the previous task. The only difference is that the similar frames are to be listed according to relevance. The algorithms to be used are Personalized PageRank and Personalized ASCOS++.
   1. Input: Filename *‘filename\_d\_k.gspc’* and integer *‘m’* where m is number of the most significant frames to be listed.
   2. Output: Visualize the *m* frames for PageRank and ASCOS++ both.
5. Task5: This task involves implementing multi-dimensional index structures and nearest neighbor search using Locality Sensitive Hashing (LSH) tool.
   1. Input: Filename *‘filename\_d.spc’* , number of layers *L*,the number of buckets *2^k.*
   2. Output: File *‘filename\_d.lsh’* containing entries in the form {layer\_num, bucket\_num, <i;j;x;y>}.
6. Task6: A similarity-based video object search tool is to be implemented.
   1. Input: LSH index file, integer n, object in the form *{i ,j, <x1, y1>, <x2, y2>}* such that <x1, y1> & <x2, y2> is a rectangle containing the object.
   2. Output: Visualize the top n frames. Also output should contain:
      1. Number of unique SIFT vectors considered.
      2. Number of overall SIFT vectors considered.
      3. Number of bytes of data from the index accessed to process the query.

Assumptions

For this phase, we have made the following general and specific assumptions:

Overall:

1. The frames of the video are divided in cells, where cell 1 is the top left cell of the frame.
2. While comparing two frames, we have performed the comparison on cellular level.
3. All the decimal values for SIFT, vectors have a precision of 6.
4. For every task in this phase, the file video\_mappings.csv is always available.
5. Each node in the following tasks represents a unique frame of the input video files.

Task1:

1. The input values k and d will always be less than equal to the total number of dimensions.

Task3:

1. The convergence criterion for PageRank is checked at every iteration.
2. The convergence criterion for ASCOS++ has been fixed at 25 iterations for faster calculations.
3. A guessing Matrix is needed as input in PageRank as well as in ASCOS++. The matrix is constructed with the following formulae: If represents a node and represents another node and gives the edge between the two nodes, then if there is an edge between the two nodes, will have a value of 1, else will be 0.
4. The Jacobi iterative method package is available for calculations of ASCOS++.
5. The value of Damping factor, c is 0.85 in PageRank calculations.
6. The value of discounted parameter, d is 0.9 in ASCOS++ calculations.
7. There is an error rate of 0.001 for the convergence condition for the PageRank algorithm.
8. The PageRank for every node is initialized with a value = 1/n, where n is the total of nodes in our graphs.
9. Tolerance factor for Jacobi calculation is XXX.

Task4:

1. It is assumed that the personalized PageRank algorithm will converge after 100 iterations.
2. For personalized ASCOS++ the convergence criterion is assumed to be after 25 iterations.
3. The guessing matrix for personalized PageRank is same as same as task 3.
4. The guessing matrix for personalized ASCOS++ we start with something similar to task 3 with the added job of increasing the weights (multiply by 2) of all the outgoing nodes of the given seed frames(nodes).

Task5: Nice

Task6:

1. Hash function family which was used in task 5, should be provided as ‘.mat’ file for this task.
2. Output from Task 1 should be provided.

# implementation

Task 1: Video Feature Extraction

Nice. For vectors, such as SIFT vectors the number of dimensions can go as high 132. Computing similarity between video frames using such long vectors becomes a tedious task. And the extra work is wasted, as a lot of these dimensions are not important, or significant to the overall identification of the feature at that point. Thus, their contribution to the similarity measurement is negligible and can be removed. This process is done using various dimensionality reduction techniques. The most relevant features of the video were extracted after this task. Principle Component Analysis was applied on the dimensions of the video that we got from output of phase II.

This algorithm gives principal components from a set of dimensions. Each principal component returned will be a linear combination of the original columns or dimensions[pca]. The pca() function of MATLAB returns various values. For dimensionality reduction, we consider the score, coefficients and latent. To express the same data in the new coordinates formed by the principal components, the new first dimension should be a linear combination of the original ones. This is given by the score, or by calculating M\*coeff (where M is the input matrix). The importance of each principal component can be determined by how much variance of the data it explains. This is given by latent. These are in fact the eigenvalues. For calculating the PCA, we took the feature vectors of each frame of the videos. These were concatenated to form a matrix. So, if n = number of frames, and c = number of dimensions (c = bins for histogram, c = 132 for SIFT, etc.).

1. We would get an matrix which would contain the entire feature vectors. This matrix would be then passed to the pca function, which would return the score, coefficients and latent, using the eigenvalue decomposition method.

2. The latent vector is then sorted, and the order of the indices is recorded. The score matrix is then rearranged, based on the order of the indices. This matrix represents the sorted principal components matrix. The dimensions can be reduced by removing the last columns, which have the least variances, and are consequently the least significant dimensions. Thus an matrix is reduced to .

**Output Format**

Task 2: Video Frame Similarity Graph Generation

Nice.

**Output Format**

Task 3: Most Significant Frame Selection

**2.3.1 PageRank:**

PageRank(PR) algorithm calculates how important a page, or a node in our case, is by considering how many pages point to it. It is an iterative approach, with each step bringing us closer to the desired result or convergence. We start by giving each node an equal PR value given by 1/n, where n is the total number of nodes in the graph. We introduce a damping factor, d, which is used to bring in the factor of randomly travelling to a different page. We take its value as 0.85, as this value give the best possible solution. The equation looks something like this:

*PR(A) = (1-d) + d (PR(T1)/C(T1) + ... + PR(Tn)/C(Tn))*

Where, PR(Tn) = PageRank of each page.

C(Tn) = Each page evenly spreading its PageRank among its outgoing links.

**2.3.2 Ascos++:**

ASCOS, Asymmetric Network Structure Context Similarity, states that the similarity score from a node to a node is dependent on the similarity score from node ’s in-neighbors to node . ASCOS++ is a similarity measure which enriches ASCOS by including the weighted paths between all the nodes of a network. Its general formula is as follows:

Where is the weight of edge e (), and , c is the discounted parameter which is used to control the relative importance of direct and the indirect neighbors. We take its value as 0.9 for our calculations. gives the similarity measure between two nodes and .

Initially we used the naïve approach for implementation. But the program was taking too much time to execute, more than an hour to be precise, to run a single iteration. Hence, we decided to move on to the distributed approach. The distributed approach uses the following formula:

Where **A=** [] is the adjacency matrix of a graph G, **P** is the column normalized matrix of **A** and **Q** = []=[]**.** This turns ASCOS++ into a classic systems of linear algebra equations, in which is a coefficient matrix with dimension n by n; is an unknown column vector with n variables to be solved; and is a constant column vector of size n. We choose the initial value of adjacency matrix such that if two nodes, has an edge between them then the value of similarity, otherwise it is 0.

We then apply the Jacobi iterative method to solve this system of linear equation. We use the Jacobi because this approach possesses high degree of natural parallelism for distributed computation.

**Output Format**

Videoname=xx, videonumber=yy, framenumber=zz, similiarityvalue=ss

Task 4: Most Relevant Frame Selection

This task is a special case of Task 3. Here we assigned special status to some of the frames (seed frames) so that we get a biased output in favor of the seed frames.

For personalized ASCOS++, we take the seed frames as the seed nodes. We then reassign the out-weights of all the edges of the seed nodes. Here we have simply doubled the value of each outgoing node from the seed node, while keeping the other edges untouched.

Then the same approach as task 3 is applied to the modified network.

**Output Format**

Videoname=xx, videonumber=yy, framenumber=zz, similiarityvalue=ss

Task 5: Multi-dimensional Index Structures and Nearest Neighbor Search

Nice.

**Output Format**

Task 6: Similar Video Object Search

Nice.

**Output Format**

# interface specification

1. All codes regarding this phase must run from MATLAB.
2. All the videos should also be placed in the same directory.
3. The output files will be created in the same folder.

# system requirements The output files will be created in the same folder.

1. The MATLAB software.

2. Plenty of storage in the system to store the input and output files.

# related works

PageRank

PageRank algorithm is heavily used in a wide range of fields. It is used in recommendation systems like Amazon to recommend shoppers about their next purchase and Netflix users about which movie to watch next. This algorithm has really helped improve the user experience in these sites. Another major use of this algorithm is in ranking of tweets in the social networking site Twitter. It is not possible for Twitter, which generate millions of tweets on any given day, to show all tweets for a search query. It uses this algorithm to improve the search results.[51]

ASCOS++

ASCOS++ is a measure which have had very limited application so far. As this measure captures the similarity scores among any pairs of nodes in a network, it has been used in discovering similar objects in a social network. [521]

Locality Sensitive Hashing

LSH is used in Near Duplicate Detection, an approach in which is used in web crawling to determine similar kinds of websites. [531] It is also used for hierarchical clustering of data, an approach which seeks to build a hierarchy of clusters, either bottom up or top down. [532] LSH is also heavily used in Acoustic fingerprinting, a process in which audio signals are converted into a condensed state which helps in finding similar audio samples from a database. [533]

# conclusion

Nice.

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