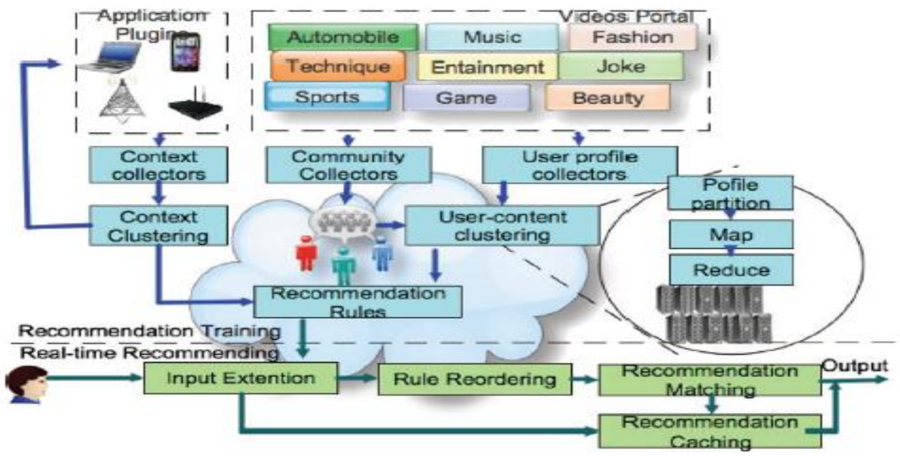
interaction with in multimedia application and social network internet.



Recommendation systems focus on a specific domain. For example, Google News provides modified news recommendation services for a substantial amount of online readers. Amazon uses the recommender system to help users find their desired products. YouTube uses user watching history to forecast and advocate videos for users. The systems make recommendation based on the similarity of content titles, tags, or imagery. Some systems find user-interested objects based on user's character reading history in term of content. CB recommender systems are easy to implement. However, in some scenario, simply representing the user's profile information by a bag of words is not adequate to capture the accurate benefit of the user. The existing System is several disadvantages in our Project. I.e.

- Online Trading is being hosted on Stand Alone Server.
- So many memory of consume.
- Spammer detection
- Slow process
- Causes bottleneck in the process of system implementation.
- Difficult to reuse video-tag module.
- Payment for combination of Physical Hosting and Hardware is demanded by the Web Hosting.
- Lack of scalability in Dedicated Servers.
- Difficult to identify the Spammers in online.
- Noise and inconsistencies inherent to the data, and illustrates the difficulty of the task.
- Provider on monthly basis, increasing total cost.

4. Research-Methodology

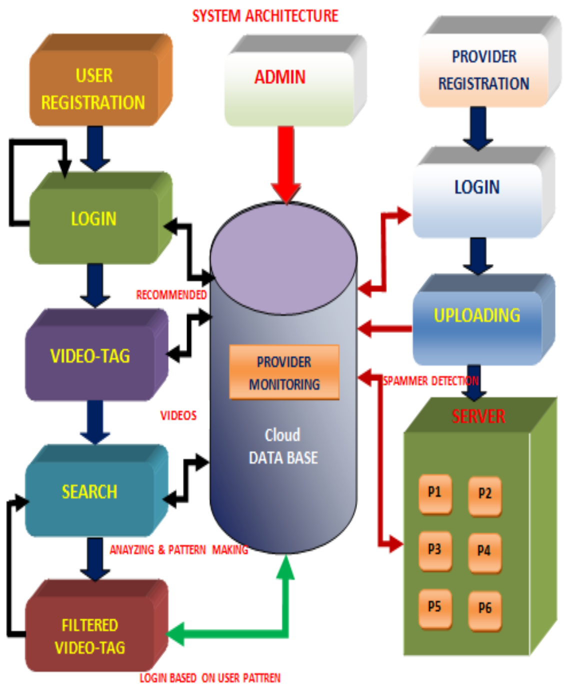
Cloud-based mobile multimedia recommendation system which can reduce network overhead and speed up the recommendation process The users are classified into several groups according to their context types and values. With the accurate classification rules, the context details are not necessary to compute, and the huge network overhead is reduced. Moreover, user contexts, user relationships, and user profiles are collected from video-sharing websites to generate multimedia recommendation. That the proposed approach can recommend desired services with high precision, high recall, and low response delay**.** User clusters are collected instead of detailed user profiles. To avoid the explosion of network overhead, user-behavior-based clustering is performed first, and the collectors calculate user clusters according to the clustering rules and then report the user cluster to the recommender only.

4.1 Advantages of Proposed System

- Proposed tag-cloud recommendation approaches.
- A computing platform distributed in large-scale data center.
- Computing and storage resources.
- A search system ranked lists of top videos.
- Reusability and extensibility of this framework component.
- Private Storage space for each and every Provider.
- Detection video spammers and promoters Process is easy.
- A search system ranked lists of top videos.
- Reusability and extensibility of this framework component.
- Detecting users who disseminate video pollution, instead of classifying the content itself.

4.2 System Architecture

System Architecture is simply defined for the how work the system. First users register the information and store the media in cloud it is use the recommendation system because it is filtered the videos and store the data in server for particular user id. It is providing the so many platforms for upload the videos and every time admin proving the services for agent and monitoring the user behaviors. Provider registration and login the web page for through the internet and upload the videos and spammer detection. The using cloud for online videos upload and multimedia using the particular user for show the video and decrease the overhead of the network. It is explain the system work for this flow and store the media easy ways and recommendation system.



4.3 Problem as a Solution

K-means (is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an *objective function*, in this case a squared error function. The objective function

4.4 Algorithm as a Solution

Step 1: Start the Process

Step 2: Given some training data $\mathcal{D}$, a set of *n* points of the form

$$\mathcal{D} = \left\{ (\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p,\, y_i \in \{-1, 1\} \right\}_{i=1}^{n}$$

Step 3: where the y_i is either 1 or −1, indicating the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a *p*-dimensional vector.

Step 4: $\mathbf{w}\cdot\mathbf{x}-b=0$, The parameter $\frac{b}{\|\mathbf{w}\|}$ determines the offset of the hyper plane from the origin along the normal vector $\mathbf{w}$.

Step 5: The region bounded by them is called "the margin". These hyper planes can be described by the equations $\mathbf{w}\cdot\mathbf{x}-b=1$ and $\mathbf{w}\cdot\mathbf{x}-b=-1$.

Step 6: We add the following constraint: for each i either

$\mathbf{w}\cdot\mathbf{x}_i - b \ge 1$ for $\mathbf{x}_i$ of the first class

Or

$\mathbf{w}\cdot\mathbf{x}_i - b \le -1$ for $\mathbf{x}_i$ of the second.

Step 7: Primal form: The optimization problem presented in the preceding section is difficult to solve because it depends on ||w||, the norm of w, which involves a square root.

Step 8: Fortunately it is possible to alter the equation by substituting $\|\mathbf{w}\|$ with $\frac{1}{2}\|\mathbf{w}\|^2$ (the factor of 1/2 being used for mathematical convenience) without changing the solution (the minimum of the original and the modified equation have the same w and b).

Step 9: End the Process

5. Conclusion

To storing the data into the drive or local server, it becomes lengthy process to fetch the data. Here cloud recommendation system used for storing and categorized of data and provide all fulfillment of user.it provide simple facility to access the actual data from the cloud server. Generally at the time of uploading files on any multimedia server we need to provide full information, so any one provide false information and tag this video on server. At the time of fetching the data user may confused to see high volume of same data.so to eliminate this problem using cloud computing, this mechanism is used.

6. Future Enhancement

As we know that very well today cloud is the leading technology and each and every mechanism support to the cloud. Future of this mechanism is as bright as plumbum because of recommendation system stores and fetch the data from little memory space called cache. This mechanism will be very helpful to access the media files from cloud server.

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