**Dynamic Program Switching based on real time analysis of user interactions across various platforms**

**Current Problem**: Suppose a user viewing some program got bored and is conveying his displeasure on chat, social media posts or even by changing his facial expressions, we do not have any mechanism to automatically switch the content to something that suits the user’s current status/mood. Most of the existing solutions of program recommendations use the static profiling of user and ignore other potential recent factors influencing user’s watch behavior. Moreover, none of the existing solutions provides recommendations based on real time actions of the user. Recent development in this field have made several attempts to detect user current moods and switch the content accordingly. However, these systems are not as efficient as it is supposed to be. Analysis of all data from different sources and then recommended some content to user based on his historical interest profile and presently detected mood, still remains a challenge.

**Proposal:**

  The steps performed by the system are as follows

We propose a system and method for real-time data analytics based user attention determination and content auto content switching. The system considers historically build profile as well as the present mood of the user to auto switch or recommend new content suitable for present mood of the user. Key aspect of the present disclosure related for efficient way of present mood detection based on analysis of dynamically selected data source feeds, wherein the data source feeds include feeds from instant chat feeds, feeds from social media interactions in context of the content being played, feeds from IoT device (in-home sensors etc) representing user facial expression and presence in front of display screen.

The present system consider only those feeds which is closely related to content being played or the existing context in which recommendations are being made. Selection of data feeds is very important here.

1.To start with, the system can limit the amount of data or source of data that it will evaluate/analyze. For example, the system can limit to 5 social media platforms and analyze active feeds from these social media platforms only for presently active sessions (instead of the entire feed). User’s social media activities like chats, posts in real time (during the content play time) are taken into consideration for this. This helps in deriving both the personality and the current mood of the user, without much burden on system as the data feeds are selected intelligently to limit the data be analyzed.

2. Based on the data crowded by the system, the mood determination module estimates the mood of the user, which can be further confirmed by using expressions captured from IoT devices (For example embedded cameras, microphones etc) and these expressions include user’s facial expressions, body language, speech, etc.

3. (Existing steps) System then performs mapping of the user behavior to a suitable entertainment item based on predetermined graph of meta data. Based on the determined/evaluated mood/interest level of the user from real-time analysis, the system can generate list of recommended contents or a suitable genre. Further, the determined genre can be used to get the list of available programs from EPG data.

Once a suitable content is discovered, we take either of the following actions

•  Recommend the content to the user (prompt). For recommending appropriate content user profile build using historical data can be used.

•  Switch the content if that option is enabled

•  Switching from linear to VOD channel if content not available on linear channel with user’s permission

The algorithm to derive a user recommendation consist of **3 stages . (Explained in attached doc)**

**1. Dynamic construction of activities graph based on multiple factors.**

The present system consider change based on near past user behavior, surroundings, habits, culture, etc. These dynamically changing factors which influence the users to watch particular content need to be captured and analyzed thoroughly.

Our proposed system will analyze the factors like influence of his friends’ circle, social media activities, trending topics, his facial expressions, etc. and these are the potential factors to be considered for content switch. We assign weightage to each and every factor. However, this weightage can also change dynamically through the feedback loop.

Ex :

In the Dynamic graph shown below, the action genre has a weightage of 30% assigned to it. This 30% is contributed by events like the user following action movies, liking action movies related posts on social media. However, this does not mean that the user has actually watched all those action movies. Also, the weightage of that factor will be increased if he has actually watched action movies due to these factors.

**TF(Total Factor)** =30% indicates that the user has 30% preference for action genre. It is just the preference over other genres. Note that TF wont indicate anything about whether he has actually watched that content or not. This is determined by **relative factor (RF)** which is maintained separately. And this RF may be more or less than TF. RF is calculated dynamically when the user actually watched the particular content.

The diagram shown here is **N-ary tree** which grows dynamically as and when factors influencing user behavior change, i,e. the number of intermediate and leaf nodes of this tree changes dynamically and corresponding **TF and RF** are also assigned dynamically .

There are many factors to be considered and each factor will in turn contain many sub factors and so on. The weights assigned to these factors are relative in nature. Increase in any one of the sub factors will lead to an increase in the corresponding parent factor.

This graph will be dynamically updated in real time.

CB factor

TF 5% %, RF 5 %

watching factor

TF 60 % , RF 70 %

Action, weight=70

Social media factors

TF 30 %, RF 10%

Facial expression factor

TF 5 %, RF 5 %

Comedy 30 %

**2. Content Mapping.**

In addition to the user activities graph, we also maintain content graphs which assign weights to the various contributing factors (meta data) in the entertainment contents. The key point is this graph will also maintain non trackable data like good songs, good shooting location, hero/heroine contributions with their weightages. Note that these weightages are also relative.

**Note that for movies the relative weightages are fixed. However, for series, the relative weightages will change as more and more contents get added with time.**

The avengers

Robert 30

Chris 25

There will be many factors associated to a movie, and they will have their own relative weightages.

There will be a separate graph connecting these two graphs with weightages, these will change dynamically based on user actions.

User A

**3. Real time analysis of the user behavior taking existing user’s activities graph as a reference.**

We will collect past 30 mins data of the user’s activities in real time. We will consider all of his activities, interactions, facial expressions and convert them to keywords.

Once we capture behaviors and keywords we will generate a dynamic graph in real time with the help of the existing user’s activities graph. The preferences stated in activities graph help in resolving some contradictory actions performed by the user in last 30 mins.

The main point here is that the activities graph will be used as a reference to assign weightage to each and every factor in the newly constructed dynamic graph.

Then this newly constructed graph is used to extract a suitable content from the content graph and derive the recommendation accordingly .