

# Dynamic Gain Estimation in Ambient Media Services

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## ABSTRACT

This paper presents a mechanism for dynamically estimating the gain in ambient media services. Gain estimation is an attempt to measure the extent to which a certain media service is useful for a user in a particular context. Such a measure may provide invaluable support for personalizing a user's ambient environment through the selection of timely, context-aware and interesting media services. The proposed method considers multiple factors including the user's profile, context, media reputation, and the interaction history to dynamically estimate the gain of a service. The gain estimation method has been incorporated in a prototype smart mirror system in a smart environment setting. Experimental results demonstrate the suitability of the proposed method.

## Categories and Subject Descriptors

H.1.2 [User/Machine Systems]: Human factors; H.3.4 [Systems and Software]: User profiles and alert services

## General Terms

Human Factors, Design, Management

## Keywords

Gain estimation, ambient intelligence, ambient media, personalization

## 1. INTRODUCTION

The emerging concept of ambient media is rapidly gaining popularity like never before. Providing users with the media services based on their context is generally known as the premise of ambient media. Furthermore, the vision of media spread into the natural environment of humans [10] and displayed through various objects in the physical space [7, 9] promotes a unique requirements for delivering ambient media to the user's environment.

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The physical space on the other hand, as a result of technological advances, gets augmented with myriad sensors and a plethora of networked devices that are sometimes embedded in everyday objects around us. This lays the foundation of the ambient intelligence (AmI) paradigm [6, 1] and holds the promise of providing ambient media services to the user in a context-sensitive and often proactive manner. However, predicting the media services that are of interest to a user in the ambient environment is a very challenging task. This is due to the fact that 1) the number of available media services increases over time, making it difficult for people to manage them properly and 2) the user's expectations from the ambient systems to learn their behaviour, predict their needs and deliver media services that would provide an increased level of satisfaction in the current context. Clearly these facts are related to two important issues, which are information overload and context-aware media selection. Therefore, we need a mechanism to estimate the extent to which a certain service is useful and satisfying to a user, which is to determine the gain of the ambient media services. The gain estimation will reduce both the user's cognitive load of selecting media from a huge list and enable the ambient system to provide the user's with personalized media services for a better quality of experience.

The various media services that can be provided in the user's surrounding context are heterogeneous in nature such as visual services, audio services, audio/visual services, and so forth. The user's need for these services also varies in different context based on their activities and changing priorities [7]. A user may require a particular type of service (e.g. traffic news) in one context (e.g. driving), whereas he/she might be happy to access other types of services (e.g. movie) at a different context (e.g. home). Moreover, a single media service may not be as satisfying to a user as oppose to providing him with multiple media services at the same time. For example, reading the updated news feed while listening to music might provide him with an increased level of satisfaction than just reading the news feed. Therefore, we not only need to estimate the gain in a service but also to estimate it dynamically so that the changing preferences and requirements of the user can be considered.

There are many existing works that provide mechanisms to personalize media and information for a particular user. Research on user modeling [5, 21], context-aware information systems [11, 17, 13] and recommendation systems [2, 19, 12] can be considered as related to gain estimation from a higher-level that address the problem of personalization, contextualization and recommendation. For example, the

user modeling research usually analyzes a user’s knowledge, goals and interaction to model a user’s preferences for personalization and adaptation of information and services. Likewise, research on context-awareness and recommendation systems provides mechanisms to deliver information and suggest items and/services to the user based on the current context and ratings provided by other users, respectively. Although related, these works are limited in scope and do not specifically address the dynamic requirements of ambient media as a whole. In this paper, we focus on deriving a mechanism to dynamically determine the gain in ambient media services, which would facilitate the selection of right and relevant services towards providing a higher quality of experience in the user’s ambient environment.

Our proposed method of dynamic gain estimation considers the user’s profile, context, interaction history, and media reputation and shows how the changing preference of the users can be maintained in the ambient environment. The changing preference of a user is represented using scores and is maintained as part of the user’s profile. The context is accessory information, which we capture through various sensing technologies and which helps to conceptualize contextual gain. The gain in a particular media service, due to its subjective flavour, incorporates interaction history that serves the purpose of obtaining the feedback of the user in an implicit manner and makes the gain estimation more reflective of the user’s needs. The media reputation resembles the ratings usually obtained by collaborative filtering to determine the popularity and relevance of a particular media, which we use in the gain estimation method when applicable.

In the remainder of this paper, we briefly comment on some related work (Section 2), followed by problem formulation (Section 3) and the proposed method (Section 4). We then present our preliminary experimental results (Section 5) and then conclude the paper with some future works directions (Section 6).

## 2. RELATED WORK

Our work in this paper is semantically related to the works in the domain of user modeling, context-aware information systems, and recommendation systems with respect to deriving models and techniques for personalized and context-aware media service provisions. Therefore, we briefly comment on some works in these domains.

Research on user modeling (UM) focuses on analyzing a user’s knowledge, goals and interactions to model the user’s preferences for personalizing information and services for the target user. A user modeling process uses the observable information about a user, such as his interaction history, and generates unobservable information about him, such as preference scores [21]. UM is generally used in many personalization applications, which are mostly web information centric. Although, the proposed work utilizes some UM principles, such as the inclusion of interaction history information, it aims to estimate contextual gain in ambient media services that is not only tied to information services.

The gain estimation is also motivated by the works in context-aware information access and presentation such as [20, 18, 17, 13, 3]. The work in [20] provides a mechanism to show information of various types in the large display based on the user’s preferences and display templates. However, it is not clear if and how the user’s preference attributes

change over time and impact the subsequent information delivery. Authors in [18] present a relevant-feedback based preference learning mechanism, where the high-capability master device learns the user’s preference based on the feedback from the low-capability slave devices by observing the user’s behaviour. The learned preference is used for multimedia personalization in a pervasive environment. The authors in this paper have not provided any indication how the learned preference will evolve based on the user’s context. In [17], the authors proposed a content filtering and presentation approach based on co-occurrence analysis from historical interaction data. Based on the co-occurrence, they used a content utility score for different content types and utilized this score as a basis for selecting subsequent content for the user. This work however, does not provide any detail as to how the user’s preference for an individual media item would change over time. The authors in [13] proposes a framework for combining the user’s profile and situational context in order to provide services based on the capability of a mobile device. Our work, in contrast to [13], focuses on determining gain in a media service, which can be used for adopting various service selection mechanisms. In another work [3], the authors present a semantic-based ambient media selection framework for intelligent home media entertainment. Like ours, this work uses the different dimensions such as the user’s profile, interaction history, and context to personalize media, however, it does not provide the details of how the preference scores are evolved. Furthermore, unlike the above works, we also utilize the reputation of a media in the gain estimation process.

Finally, we relate the gain estimation problem with the rating estimation problem in typical recommendation systems. For example, in [19] the authors presented the CoMeR platform that supports media recommendations for smart phones using a hybrid mechanism, which consists of a content-based scheme for determining similarity of a media item to the user’s preference context, a Naive Bayes classifier for determining the relevance of an item to the situation context, and a rule-based scheme for checking the presentation suitability of a media against device-capability context. The work in [2] considers multiple dimensions to recommend items to users based on the time, the user and the media item. Unlike the recommendation system referenced here, which usually recommends a particular item, our focus of the gain estimation is different in that we aim to estimate gain in media services where more than one service may be selected depending upon the availability of ambient devices in the environment, each having their own specifications.

It can be summarized that the above works are related to ours from a higher level, although not quite within the same scope. In this paper, we focus our attention to gain estimation and emphasize that it can be utilized to adopt several principles of selecting a set of services based on the dynamically computed gain.

## 3. PROBLEM DESCRIPTION

The dynamic gain estimation problem can be considered as a multi-dimensional problem, which aims to determine the gain in a media service for a user in a particular context he or she is in. Along this line we consider the following notations:

- There is a set  $\mathbf{S}$  of  $n$  media services of  $k$  different

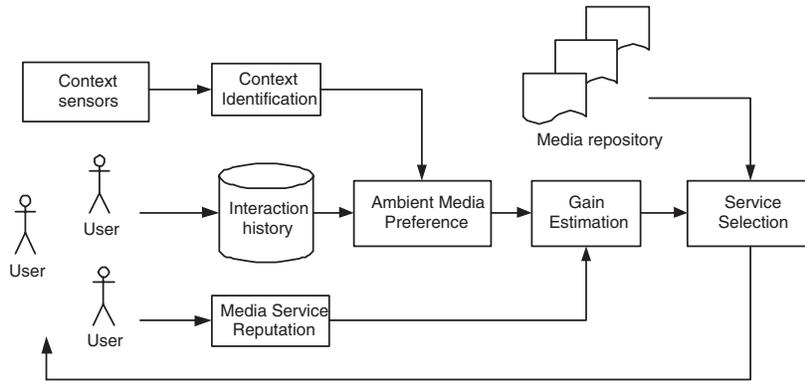


Figure 1: Schematic view of the dynamic gain computation process.

types in an ambient environment. Let these services be of heterogeneous types such as movies, music, news feed, sports feed, camera feed, weather forecast, background lighting and so on. Each of these services are described using some representative meta attributes such as *Movie(media type, director, genre, actor, actress, release date, ...)*, *RSS Feeds(media type, feed location, ...)* and so on.

- A user has a certain gain,  $g_i(c_x) \in [0, 1]$  from a service  $S_i$ ,  $1 \leq i \leq n$  in a particular context,  $c_x$ .
- The reputation of a media service  $S_i$  is  $R_i$ ,  $0 \leq R_i \leq 1$ ,  $1 \leq i \leq n$ , which is usually collected from the external source or is computed based on association among the services.
- The user interact with the different services in a smart environment setting and his/her interaction data is recorded.

Our objective is to derive a mechanism to dynamically estimate the gain  $g_i(c_x)$  of the available media services in an ambient environment based on the user’s preference, context, media reputation and the interaction history.

## 4. PROPOSED METHOD

### 4.1 Overview

Before delving into details, here we first provide an overview of the key factors that influence the estimation of gain in ambient media services. These are the user’s context, profile, interaction history and media service reputation. Figure 1 shows how these factors are used in the overall gain estimation and service provisioning scenario.

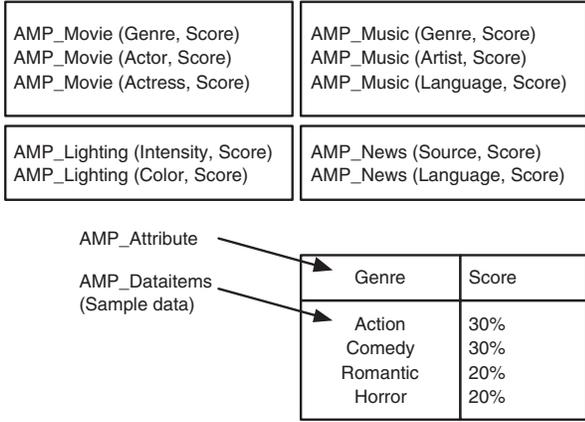
As shown in Figure 1, context sensors are used to capture the user’s current context. The context may be characterized by different attributes such as where (user’s location), when (time of presence), what (the activities), with whom (the companion of the user), and what mood (of the user). This characterization is based on the existing works in context-awareness, for example [15, 16]. The combination of the different context attributes will result in several unique context identifiers. For example, with respect to user A, if we consider different attributes such as where (home, office), when (weekday morning, weekday noon) and

with whom (family, friends), the several context identifiers would be  $C1 = \text{User A}(\text{home, weekday morning, family})$ ,  $C2 = \text{User A}(\text{home, weekday morning, friends})$ ,  $C3 = \text{User A}(\text{home, weekend noon, family})$ , and so on. The context identification module analyses the input streams from the sensory system and determines the current context of the user. The detail of context capture and reasoning is not included in this paper.

The user profile we define has two distinct parts, one contains static user-related parameters (e.g. name, age, sex), while the other preserves the user’s contextual preference information that is dynamically updated based on the user’s interaction history. We call the dynamic part an ambient media preference or AMP. The AMP is maintained for different context identifiers. The AMP contains the scores of metadata-related attributes of different types of media services reflecting the liking score of a user. Figure 2 shows an example set of ambient preference attributes for a user in a particular context. For each media type, the AMP contains the scores for individual attributes of the media. The sum of the scores of all the dataitems in a particular attribute should be normalized to 100%. Note that the attributes in the AMP do not refer to a particular media service; rather they give an indication to the user’s preference at the media attribute level. The scores in the AMP for a user change over time, which reflect their changing need for media services in different contexts. However, how to maintain the changing preferences of a user in a dynamic fashion is a non-trivial issue. We will provide these details in Section 4.2.

As mentioned previously, the interaction history is used to update the preference scores in AMP. Users in the ambient environment either select different media services through explicit interaction or a system automatically predicts a set of services and provides them to the user, which the user interacts with. On a regular basis, the gain estimation process utilizes this interaction data to continuously update AMP to reflect the changes in the user’s interest.

The other factor that influences the gain in a service is the reputation. Reputation usually refers to how good or trustworthy a service or vendor is in terms of content, delivery and other aspects. A reputation system collects feedback about the participants and products and helps to determine trustworthiness among the participants [14]. With respect to the ambient media services, reputation can play a role when determining a particular service gain based on the ratings



**Figure 2: A set of sample ambient preference attributes of a user in a particular context.**

provided by different users in a collaborative manner. For example, a particular movie may have been rated positively higher and such a rating score may be considered along with the AMP scores, when determining the gain of a service to a user. We should, however, note that in cases when reputation is not available, the proposed gain estimation method will ignore this value and estimate gain only based on the AMP scores. We will elaborate further on this issue in Section 4.3.2.

It is apparent from Figure 1 that the gain estimation is done on-the-fly. This is due to fact that the user’s interaction history in a particular context is used to recalculate gain for subsequent instances of service provisioning. In the following, we first present how the changing user preference is maintained in the AMP and then show how the gain is computed for the media services.

## 4.2 Ambient Media Preference

The AMP attributes can be either explicitly provided by the user or implicitly collected by the system. During the system initialization phase, the user may choose to provide few entries of the preference attributes, while the system can later use the interaction history data to automatically update the initial scores provided by the user. Two particular issues are involved in the maintenance of AMP attributes for a user. First, how to incorporate the user’s interaction data to add and update dataitems in AMP attributes? Second, how to delete an existing dataitem based on the observation of usage data? We discuss these issues in turn.

### 4.2.1 Addition and updating of a dataitem

Let us consider Figure 2, which shows a sample AMP for a user, and Figure 3, which shows a sample service usage history. Note that a user may select more than one media type at a particular instance, such as a movie and a news feed. However, in Figure 3 we only show the case of movie service to demonstrate the update of AMP. The computation of other type of services follows the same procedure.

In order to add a new dataitem score or update an existing dataitem score, we first define a relative weight factor ( $\delta$ ) for that dataitem based on service usage history. This is computed as the ratio of the number of times a

- t1 - Home, Weekend Evening, Movie  
(Gladiator, Action, Russell Crowe, Connie Nielsen);
- t2 - Home, Weekend Evening, Movie  
(Kill Bill, Action, Uma Thurman, Lucy Liu);
- t3 - Home, Weekend Evening, Movie  
(Rambo, Action, Sylvester Stallone, Julie Benz);
- t4 - Home, Weekend Evening, Movie  
(Bean, Comedy, Rowan Atkinson, Pamela Reed);

**Figure 3: Example scenario of movie service usage over time in a particular context.**

particular dataitem of an attribute appears in the service usage history to the total number of occurrences of that particular media service type. For example, after time instance  $t_4$ ,  $\delta_{action} = 3/4$ ,  $\delta_{comedy} = 1/4$ ,  $\delta_{romantic} = 0/4$ , and  $\delta_{horror} = 0/4$ . The normalized scores of each of the dataitems within each attribute are computed using Eq. (1).

$$w'_{k,C_x}(t) = \frac{w_{k,C_x}(t-1) + \delta_k}{\sum_{k=1}^p (w_{k,C_x}(t-1) + \delta_k)} \quad (1)$$

where,  $p$  = all the dataitems in each attribute.  $w'_k$  and  $w_k$  are the updated and existing scores of each of the dataitems, respectively. The term  $C_x$  refers to a particular context identifier. Note, if the AMP attributes are not explicitly provided by the user, Eq. (1) will generate a score equal to 1 (i.e. 100%) for the first dataitem of an attribute (e.g. *action* in *genre*), however, the scores of the dataitems will gradually be distributed once more dataitems are added.

The denominator of Eq. (1) is used for normalization purposes and essentially its value is equal to 2. This is due to the fact that the sum of  $w_{k,C_x}(t-1)$  and the sum of  $\delta_k$  individually equals to 1. Therefore, we can rewrite Eq. (1) as,

$$w'_{k,C_x}(t) = \frac{w_{k,C_x}(t-1) + \delta_k}{2} \quad (2)$$

We use this equation to gradually update the scores of the dataitems of all the attributes in the AMP. For example, after instance  $t_4$ , the updated scores of the *genre* dataitems, by considering the initial scores as of Figure 2, would be the following:

$$\begin{aligned} w'_{Action,C_x}(t) &= (0.30 + 3/4)/2 = 0.53 \\ w'_{Comedy,C_x}(t) &= (0.30 + 1/4)/2 = 0.27 \\ w'_{Romantic,C_x}(t) &= (0.20 + 0/4)/2 = 0.10 \\ w'_{Horror,C_x}(t) &= (0.20 + 0/4)/2 = 0.10 \end{aligned}$$

Please note, it may not be computationally efficient to update the scores after every occurrence of service usage. Therefore, we define a *window of interval*, which is used to indicate how frequently we should update the scores using the interaction history data. The size of the window can be adjusted depending on the specific application scenario. In this particular example, we considered 4 as the *window of interval* and hence updated the scores after instance  $t_4$ .

### 4.2.2 Deletion of a dataitem

It is also necessary to delete an existing dataitem of an attribute from the AMP. This is based on the observation when a particular attribute or a dataitem is no longer of

	<table border="1"> <thead> <tr> <th>Genre</th> <th>Score</th> </tr> </thead> <tbody> <tr> <td>Action</td> <td>53%</td> </tr> <tr> <td>Comedy</td> <td>27%</td> </tr> <tr> <td>Romantic</td> <td>10%</td> </tr> <tr> <td>Horror</td> <td>10%</td> </tr> </tbody> </table>	Genre	Score	Action	53%	Comedy	27%	Romantic	10%	Horror	10%	<table border="1"> <thead> <tr> <th>Actor</th> <th>Score</th> </tr> </thead> <tbody> <tr> <td>Russell Crowe</td> <td>15%</td> </tr> <tr> <td>Sylvester Stallone</td> <td>20%</td> </tr> <tr> <td>...</td> <td>...</td> </tr> <tr> <td>...</td> <td>...</td> </tr> <tr> <td>Johnny Depp</td> <td>15%</td> </tr> </tbody> </table>	Actor	Score	Russell Crowe	15%	Sylvester Stallone	20%	...	...	...	...	Johnny Depp	15%	<table border="1"> <thead> <tr> <th>Actress</th> <th>Score</th> </tr> </thead> <tbody> <tr> <td>Connie Nielsen</td> <td>10%</td> </tr> <tr> <td>Uma Thurman</td> <td>20%</td> </tr> <tr> <td>...</td> <td>...</td> </tr> <tr> <td>...</td> <td>...</td> </tr> <tr> <td>Meg Ryan</td> <td>25%</td> </tr> </tbody> </table>	Actress	Score	Connie Nielsen	10%	Uma Thurman	20%	...	...	...	...	Meg Ryan	25%
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Figure 4: Gain estimation based on AMP, given a set of sample AMP scores and media repository.

interest to the user. Here we simply demonstrate this case by considering the frequency of usage of a dataitem or attribute for a specified period of time and according to a predefined threshold we delete that dataitem, given that the appearance of that dataitem falls below a threshold. However, different data mining techniques can be adopted for determining the deletion, the detail of which are not explained in this paper. The deletion process is followed by an update of the existing scores, which is done using Eq. (3).

$$w'_{k,C_x}(t) = w_{k,C_x}(t-1) + \frac{w_{k,C_x}(t-1) \times w_{d \neq k}}{\sum_{k=1}^p (w_{k,C_x}(t-1)) - w_{d \neq k}} \quad (3)$$

Where,  $w_{d \neq k}$  is the item to be deleted and  $p =$  all the dataitems of an attribute.  $w_{k,C_x}(t-1)$  is the existing score of a dataitem in an attribute.

Similar to the addition/update of AMP scores, the deletion of a particular dataitem also requires a decision on when to delete a dataitem. This again may be determined empirically based on the particular application scenario.

### 4.3 Dynamic Gain Estimation

Once we obtain the AMP scores at a particular instance, we can compute the gain of the media services by following a three-step process. These are a) gain based on AMP b) gain based on AMP and reputation, and c) gain refinement. We describe these steps in the following.

#### 4.3.1 Gain based on AMP

The gain of the media services that are in the media repository is computed based on the AMP scores. An illustrative example is given in Figure 4. In this figure we consider a set of sample AMP scores as updated after time instance  $t_4$  (see Figure 3) and based on these scores we estimate the gain of the media services in the media repository. The process of gain estimation can be precisely expressed as,

$$g'_{i,amp} = \sum_{k=1}^j w'_{k,i} * \beta_{k,a} \quad (4)$$

Where,  $g'_{i,amp}$  is the gain of the media service  $S_i$  based on AMP, which is considered as a temporary gain at this step.  $w'_{k,i}$  refers to the score in AMP of an attribute's dataitem of a media service  $S_i$ , as computed using Eq. (2). The variable

$j$  refers to all the attributes related to a media service type (e.g. movie) that appear in AMP.  $g'_{i,amp}$  is computed as the weighted average of the AMP score of an attribute and the weight assigned to the attribute itself. The weight  $\beta_{k,a}$  in Eq. (4) refers to the relative importance of the attribute to a user. For example, a user might be more interested in the *genre* attribute than the other attributes and hence the *genre* attribute should have a higher weight when computing the gain. In the particular example shown in Figure 4, we consider the weights 0.5, 0.3 and 0.2 corresponding to *genre*, *actor* and *actress*, respectively. In a similar fashion, the gain of all the available media services can be computed dynamically.

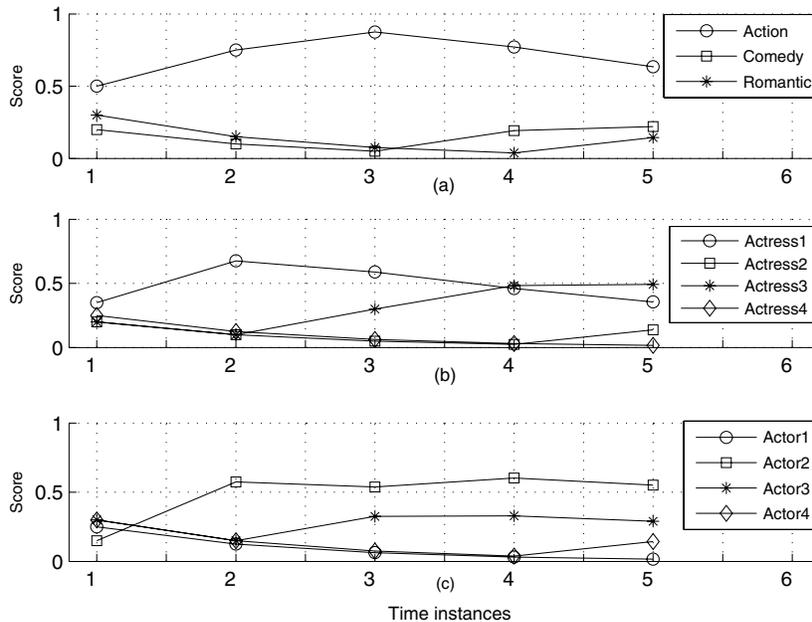
#### 4.3.2 Gain based on AMP and reputation

As mentioned earlier in Section 4.1, we use the reputation of a media service along with the AMP scores to compute gain. For this, we aggregate the temporary gain as computed using Eq. (4) with the reputation of the media services. This is done using Eq. (5) in the following.

$$g'_{i,amp,R_i} = \alpha * g'_{i,amp} + (1 - \alpha) * R_i \quad (5)$$

Where,  $g'_{i,amp,R_i}$  is the gain of the media service  $S_i$  based on AMP and the reputation  $R_i$  of that service.  $\alpha$  and  $(1 - \alpha)$  are the weights assigned to the AMP-based gain and the reputation, respectively. Therefore, in Figure 4, if we assume the reputation of Movie1 as 0.74 and the value of  $\alpha$  as 0.70, the updated gain of Movie1 becomes 0.47 according to Eq. (5). The value of  $\alpha$  should be set as per the importance of AMP scores and reputation to a user.

It should be noted that the proposed method uses reputation along with other factors to compute gain in media services, where the reputation is subject to the availability. However, the proposed method would work without the reputation as well. This is clear from Eq. (5), where we can set  $\alpha = 1$  to ignore the reputation and give full importance to the AMP-based gain estimation. We also like to mention that even if the reputation of a service from an external source is not available, we can compute it by using a technique proposed in [4]. In [4], we proposed a mechanism to compute reputation of a multimedia service based on its association with another service. We will apply this technique in future to compute reputation of ambient media services.



**Figure 5: Changes in AMP scores after movie service usage by a user in a particular context. Here, (a) refers to the changes in genre (b) changes in actress and (c) changes in actor attributes.**

### 4.3.3 Gain refinement

The gain computed using Eq. (4) or (5) need to be refined based on the perspective that a particular media service (e.g. a movie) will have less gain to a user if it has been selected for his/her in the past. In particular, we need a mechanism that would restrict the selection of some media services multiple times in a row. Nevertheless, in the ambient context, this is not true for all services. There are cases when the media services would have no decay in gain (e.g. RSS feed, music). We define some rules in order to handle these cases that reflects the user’s requirements.

## 5. IMPLEMENTATION AND RESULTS

We demonstrate the proposed method by incorporating it in an earlier work [8], where we have developed web services based infrastructure and a smart mirror interface for accessing various information and appliance services in a simulated smart home environment. In [8], the selection of services was based on a static user profile, which has been augmented with the proposed gain estimation mechanism. Most of the development is carried out using C# programming language. The particular user context is captured by using cameras, motion sensors and RFIDs as well as by analyzing usage log data.

The experiments with the prototype were carried out based on the participation of twenty graduate level student volunteers. For demonstration, we have initially selected thirty media services (e.g. different movie clips, music, RSS feeds for news and weather forecast) to be accessible by the system. At first, the volunteers were asked to provide their media service preferences. However, only a few of them actually provided such data, which we stored as AMP scores as a startup. In the following, we provide a description of the results that are obtained via experiments.

## 5.1 Ambient Media Preference Updates

Using the proposed method, the prototype system dynamically updates the AMP scores based on the interaction history of the user. For clarity, we mention one particular case of a user whose initial preference scores for movie service were the following:

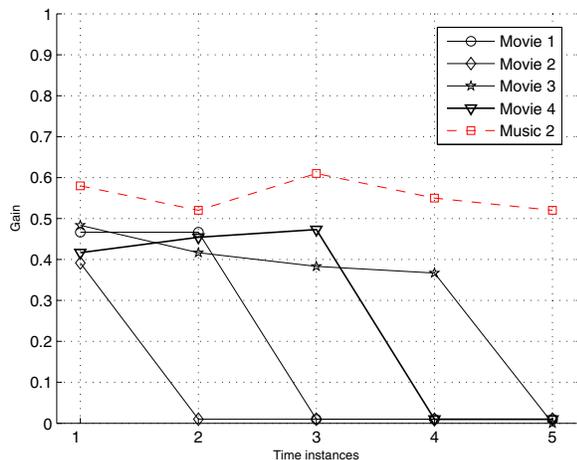
genre (action=0.50, comedy=0.20, romantic=0.30);  
 actress (actress1=0.35, actress2=0.20, actress3=0.20, actress4=0.25);  
 actor (actor1=0.25, actor2=0.15, actor3=0.30, actor4=0.30).

In different time instances and in similar contextual situations, this particular user selected different movie services over a period of time that is recorded in the interaction history. Based on this information, the scores are updated using Eq. (2) and the results are presented in Figure 5. We only show few instances of AMP updates in this figure.

It is clear from Figure 5 that the scores in AMP are updated at every sample instance. These scores reflect the changing preference of a user in the different metadata attributes of the media services. Although, in this figure we only show the changes of movie attributes, we applied our proposed mechanism to update AMP scores that correspond to the attributes of other media services, such as music.

## 5.2 Gain Estimation

The preference update process is followed by the dynamic gain estimation process. Recall, the gain estimation is based on AMP scores and/or the reputation of the media services. In our model, we manage and update the preference scores based on the interaction data, while the reputation score is obtained from external sources. Eq. (5) is used to obtain



**Figure 6: Example estimated gain of different types of media services in a particular context.**

the dynamic gain of a service, where the value of  $\alpha$  is assumed to be 0.7 to give more importance to AMP scores over reputation score.

In Figure 6, we show how the gain value changes in the case of different types of services (e.g. movie and music). In this case, we assumed the initial reputation of four movie services and one music service as 0.60, 0.45, 0.70, 0.65 and 0.80, respectively, which we use along with the AMP scores to compute gain. The figure shows that the gain of movie2 has decayed after instance  $t_1$  as it was viewed by the particular user at that instance. Similarly, the gain of movie3 has decayed after instance  $t_4$  as it was viewed by this user at instance  $t_4$ . On the other hand, for some different type of media service, the gain is not enforced to be decayed sharply. The decision of whether the gain value will decay or not for different types of services is described earlier in Section 4.3.3.

### 5.3 Media Service Selection

The dynamic estimation of gain in services shows new possibilities in selecting ambient media services for personalizing the user’s environment. To demonstrate this, we have first used a simple strategy to select Top  $k$  services with the most gain for the user in the smart mirror interface. We faced two obvious problems with this approach. The first one is the selection of multiple similar services at the same time. For example, the selection of 2 movie services at the same time having most gain, which makes little sense. The second one is the selection of multiple different types of services. For example, the selection of a movie service (audio and video) and a music service (audio), which are hard to perceive at the same time. We defined some rules to resolve these issues. We will elaborate on this in the future.

Overall, in our experiment, about 70% of the users (14 users) provided positive feedback in terms of the ease of use and the appropriateness of service selection, which reflected their interaction history and changing preference. These users were also interested in adopting the proposed approach in their home environment, which is encouraging. About 20% of users (4 users) did not like the idea of automatically

selecting services for them and capturing their interaction history. The other 10% of users (2 users) did not provide any feedback as to whether they liked the service provisioning approach or not.

## 6. CONCLUSION

In this paper, we present a novel mechanism to dynamically estimate the gain in ambient media services. The proposed work incorporates the user’s context, profile, service reputation and interaction history to derive the gain estimation model. The estimated gain reflects the changing preference of a user over a period of time in different contexts. Preliminary experiments show that the gain estimation based selection of media services in the surrounding environment provides better quality of experience to the user. However, large scale evaluation needs to be conducted to justify the overall suitability of the proposed method, which we aim to do as a future work. Nevertheless, the proposed method shows new possibilities.

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