**Using Affective Aware Pseudo Association Method to Connect Disjoint Users and Items for Making Cross-Domain Recommendations**

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**Abstract**

This paper introduces an ingenious text-based affective aware pseudo association method (AAPAM) to connect disjoint users and items across different information domains and leverage them to make cross-domain content-based and collaborative filtering recommendations. This paper demonstrates that the AAPAM method could seamlessly join different information domain datasets to act as one without additional cross-domain information retrieval protocols. Besides making cross-domain recommendations, the benefit of joining datasets from different information domains through AAPAM is that it eradicates cold start issues while making serendipitous recommendations.

**Keywords**

Behavioral Analysis, Emotion-aware Recommender System, Emotion prediction, Personality, Pseudo Users Association

**1. Introduction**

Researchers often encounter situations in working with multiple datasets in the same or different domains where disjoint object identifiers (ids) in a data file are present when making cross-references across different datasets. Thus, these objects with the same id assignment refer to disjoint objects. More succinctly speaking, object id 123 in data file A is not the same object id 123 in data file B. This paper intrigues by [1], which has examined a similar situation about disjoint users of a data file when making cross-references to different datasets within the domain. In that paper, a method known as an Affective Aware Pseudo Association Method (AAPAM) was used to pseudo associate connect (PAC) disjoint users across different datasets in the same domain. AAPAM method provides a way to PAC connect disjoint users pairwise by examining the affective index indicator (AII) values of disjoint users. AII value obtains from the computation of the Cosine Similarity of the pairwise disjoint users’ emotion vector (UVEC). When AII is one (1), it represents the pair of disjoint users with an identical emotion profile. In some aspects, AII with unity value represents a high certainty the pair of disjoint users are the...
same user virtually with different user id assignment reside in different datasets. Such PAC reconnection made for the pair disjoint users is known as a pseudo association. PAC disjoint users do not need to have a unity AII value. One can set a threshold value on AII; for example, 98%, any disjoint user’s AII meets the threshold becomes a member of the group. Group of disjoint users shares closely similar AII values as expressed in their emotion profiles. Other situations can make use of connecting disjoint users through the AAPAM. This paper will examine a few usages of such a method. This paper wants to expand the study from disjoint users to generalized disjoint objects to determine whether the same AAPAM method can connect disjoint objects across different datasets in different information domains. Disjoint objects have their emotion profile prepared similarly, as described in the paper [1].

The previous paper [1] works with four MovieLens datasets [2], namely, ml-latest-small (a.k.a. mlsm), ml-20m (a.k.a. ml20m), ml-25m (a.k.a. ml25m), and ml-latest (a.k.a. ml27m hereafter) datasets. Table 1 illustrates the statistics of each mentioned MovieLens dataset. The name of a MovieLens dataset reflects the number of ratings it contains.

Table 1 Statistics of MovieLens datasets.

| Attribute | Dataset | No. Users | No. Movies | No. Ratings | No. Overviews |
|-----------|---------|-----------|------------|-------------|---------------|
| mlsm      | 610     | 9742      | 100836     | 9625        |
| ml20m     | 138493  | 27278     | 20000263   | 26603       |
| ml25m     | 162541  | 62423     | 25000095   | 60494       |
| ml27m     | 283228  | 58098     | 27753444   | 56314       |

In each of the four MovieLens datasets, there are two data files named ratings, and tags contain user ids as a unique identifier. MovieLens stated that user ids found in ratings and tags data files are consistent within the same dataset but are not uniform across different datasets [3]. For example, in [1], user id 400 is only compatible within the same MovieLens mlsm dataset and is not across ml20m, ml25m, ml27m datasets. In other words, user id 400 in other MovieLens datasets are not the same user id 400 as in the mlsm dataset. However, [1] has demonstrated by using the AAPAM method, the disjoint user id 400 in mlsm can correctly connect to the proper user id in MovieLens datasets as depicted in Table 2.

The Affective Aware Pseudo Association Method (AAPAM) computes the Affective Index Indicator (AII) using the Cosine Similarity algorithm [4], as depicted in Equation 2, to express the closeness of the emotion profiles between two users or items. When using AAPAM to compare pairwise between User id 400 of mlsm against users in other MovieLens datasets, AII reveals, as depicted in Table 2, the closest other users’ emotion profiles that match the candidate user. User id 400 in mlsm can make a pseudo associate connection (PAC) to user id 66274 with AII 0.999916 in ml20m, or to user id 95449 with AII 0.999999 in ml25m or user id 89195 with AII 0.999999 in ml27m, respectively.

\[ \text{Inner}(x, y) = \sum_i x_i y_i = \langle x, y \rangle \]  
\[ \text{CosSim}(x, y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2} \sqrt{\sum_i y_i^2}} = \frac{\langle x, y \rangle}{||x|| ||y||} \]  

AAPAM also worked with The Movie Database (TMDB) [5], where the movie metadata was obtained by scraping from TMDB for movie overviews, poster images, and other metadata.
AAPAM applied the Tweets Affective Classifier (TAC), a method developed in [6] to classify a movie emotion profile. A movie emotion profile is also known as a movie vector, MVEC, which represents a multi-dimensional embedding of a probability distribution of seven primary human emotions: neutral, happiness, sadness, hate, anger, disgust, and surprise. Each user in [6] also has a user emotion profile, UVEC, where it contains the average value of all movies MVECs the user has watched.

Table 2 Pseudo Association Connection of ml-latest-small user id 400 to other users in different datasets through affective index indicator.

| Dataset | mlsm | ml20m | ml25m | ml27m |
|---------|------|-------|-------|-------|
| User1 ID PAC | 400 | 66274 | 95459 | 89195 |
| User1 Movie Count | 43 | 22 | 43 | 43 |
| User1 Watched List | 6 | 47 | 6 | 6 |
| movieID | 50 | 260 | 47 | 47 |
| | 60 | 300 | 260 | 260 |
| | 307 | 122886 | 122886 | 122886 |
| | 3418 | 3418 | 134130 | 134130 |
| | 168252 | 168252 | 168252 | 168252 |
| User1 UVEC | 0.16353 | 0.16250 | 0.16353 | 0.16353 |
| Neutral | 0.08874 | 0.08609 | 0.08874 | 0.08874 |
| Happiness | 0.12709 | 0.12654 | 0.12709 | 0.12709 |
| Sadness | 0.20332 | 0.20701 | 0.20332 | 0.20332 |
| Hate | 0.11934 | 0.11776 | 0.11934 | 0.11934 |
| Anger | 0.15881 | 0.16005 | 0.15881 | 0.15881 |
| Disgust | 0.13918 | 0.14005 | 0.13918 | 0.13918 |
| Surprise | 1.0 | 0.99992 | 0.99999 | 0.99999 |
| User1 Affective Index Indicator | | | | |

As illustrated in Table 2, user id 400 in the rating data file of the mlsm dataset has watched 43 movies; taking the average of all the 43 movies’ MVECs yields the UVEC for user id 400. As mentioned in [6], a movie’s MVEC is static and stays unchanged throughout the film’s life; whereas, a user’s UVEC changes its value each time the user watches a movie. The user’s UVEC reflects the up-to-date movie taste and preference of the user. A movie MVEC is unique, while a UVEC may not be unique when two users watched the same movie set.
Paper [6] advocates that every movie can obtain an emotion profile through TAC by classifying the movie’s moods over the corresponding movie overview. Figure 1 shows an example of the movie, "The Godfather (1972)"., which rated by the Internet Database (IMDb) portal as the top movie of all time [7], has its emotion profile, MVEC, classified by TAC using the movie’s overview as input. As shown in Figure 1, the movie’s overview feeds as input to TAC yields the movie emotion profile, MVEC. By ranking the probability distribution values of MVEC in the descending order, it yields "hate," a.k.a. "fear" in this paper, as the dominant mood for the example movie, followed by "anger," "disgust," "surprise," "sadness," "neutral," and "joy" a.k.a. happiness in this paper. One can perform the affective analysis for the film by describing the movie in the following way. The film "The Godfather (1972)" is a movie with plots full of hate. The film is an angry movie. It is a disgusting film due to its violent content.

Nevertheless, the movie's plots are full of surprises, but overall a sad film. No viewer would say, "The Godfather (1972)" is a joyful film. By merely reciting the ranking of moods in MVEC, one explains the movie. Similarly, one can look at a user’s UVEC who has watched the film feel how well the user liked it.

Besides, the AAPAM method can PAC connect disjoint users from different datasets within the same domain; this study believes the same technique can PAC connect disjoint users and items among different datasets across different domains. Unlike MovieLens datasets, some other movie datasets such as TMDb highlight the average voting score, the sentiment rating value on a scale of 1 (lowest) to 10 (highest), of a movie by a group of users who have watched and rated the movie through the voting count attribute in the data file instead of individual user’s sentiment. TMDb does not maintain user information, and neither contains a user-id field in the dataset. When applying the AAPAM to connect MovieLens and TMDb domains, the PAC connection applies to movie items between MovieLens and TMDb. Here, the PAC connection between movie A in MovieLens to movie B in TMDb indicates how similar the two movies' emotion profiles, MVECs, form a one-to-one relationship. However, when applying the PAC to connect a user in MovieLens and a movie item in TMDb, the movie item MVEC in TMDb must first be normalized with the respective voting count. The normalized MVEC represents the average UVEC of the group of users who have rated it. Thus, the PAC connection between user A in MovieLens to the normalized MVEC of movie B in TMDb indicates how similar user A to a group of users B is in the form of a one-to-many relationship.

In the recent release of the updated version Amazon Review Data (2018) repository [8], [9], and [10], the repository maintains product reviews and product metadata on 29 categories stored in two data groups: Complete-review-data and Small-subsets-for-experimentation. This study uses the following two data files in the Small-subsets-for-experiment group of 5-core: the reviews_Toys_and_Games_5.json, a.k.a Toys_and_Games hereafter, and the Digital_Music_5.json, a.k.a. Digital Music hereafter. The data size of Amazon Review Data (2018) contains 233.1 million reviews in the Complete-review-data group spanning across 29 product categories from May 1996 to October 2018. Some categories have fewer than 90,000 to 900,000 reviews, while many have over one million to more than 51 million reviews. Also
available for experimentation are subsets of smaller datasets with reviews ranging from a few thousand to a few million, as depicted in Table 3 in JSON format [11].

Amazon Review Dataset contains reviewerID and reviewerName, which can be combined to form a unique user id. The ASIN code stands for Amazon Standard Identification Number, represents a unique product code to use as an item id. The vote field contains a reviewer rating score on a 1 (lowest) scale to 5 (highest). The reviewText contains subjective writing of the reviewer's sentiment, a source for emotion classification for the item emotion profile, IVEC. In the Amazon Review Dataset case, a user's emotion profile, UVEC, represents the average value of all items’ IVECs the user has reviewed. Note that IVEC in Amazon Review Dataset is equivalent to MVEC in MovieLens.

Table 3. A sample review extracted from Amazon Review Dataset.

```
{
  "reviewerID": "A2SUAM1J3GNN3B",
  "asin": "0000013714",
  "reviewerName": "J. McDonald",
  "vote": 5,
  "style": {
    "Format": "Hardcover"
  },
  "reviewText": "I bought this for my husband who plays the piano. He is having a wonderful time playing these old hymns. The music is at times hard to read because we think the book was published for singing from more than playing from. Great purchase though!",
  "overall": 5.0,
  "summary": "Heavenly Highway Hymns",
  "unixReviewTime": 1252800000,
  "reviewTime": "09 13, 2009"
}
```

This study intends to show it is possible to make Collaborative Filtering [12] and [13] recommendation of items to an active user once the AAPAM method has proved to work for PAC connecting disjoint users and items in MovieLens's mslm dataset to Toys_and_Games, and Digital_Music data files in Amazon Review Dataset. In [1], [6], and [14], these papers had examined issues related to recommendations making by affective aware recommenders. The Recommenders involved in making recommendations were all within the same domain confined by the MovieLens datasets. This paper aims to demonstrate any Recommenders, besides making recommendations the usual way within the confined domain, also can make cross-domain recommendations by embracing the AAPAM technique. For example, a cross-domain recommendation may appear in the following situations: “People who enjoyed movie T in MovieLens may choose to play V in Toys_and_Games and listen to W in Digital Music.” Another example of cross-domain recommendation between a user in MovieLens and a group of users in TMDb may appear as follow: “People who enjoyed movie X in MovieLens may also enjoy movie Y of the similar taste of group users Z in TMDb.” Using the AAPAM method to make cross-domain recommendations for disjoint users and items in different datasets across different domains is the contribution this paper makes, and this investigator team may be the first to perform such a study.

2. EXPERIMENTAL AND COMPUTATIONAL DETAILS
2.1. EXPERIMENTAL AND COMPUTATIONAL DETAILS
This study applies affective features to three data sources that it uses: users’ emotion profiles, UVECs, and items’ emotion profiles, IVECs, or MVECs equivalent. No disjoint users and items can interconnect without adding affective features across data sources of MoieLensm TMDb, and Amazon Review Dataset. Affective aware features are added to the data sources through Tweets Affective Classifier (TAC) as developed in [6]. Table 2, Table 4, and Table 5 depict samples after added affective features UVEC and MVEC in this study’s data sources.

Table 4. TMDb movie emotion profile example.

| tmdbId   | 2   | 525662 |
|----------|-----|--------|
| movieId  | 4470| 189111 |
| Mood     | Disgust | Hate |
| Neutral  | 0.15705037 | 0.11876434 |
| Happiness| 0.08608995 | 0.05086204 |
| Sadness  | 0.15583897 | 0.12669845 |
| Hate     | 0.07506061 | 0.3391073 |
| Anger    | 0.08469571 | 0.13069303 |
| Disgust  | 0.26612538 | 0.13746719 |
| Surprise | 0.17513901 | 0.096407644 |

Table 5. Amazon Review Dataset of Digital Music from Small Subsets for Experimentation Group.

| userId | 8129   | 13878 |
|--------|--------|-------|
| Neutral| 0.1976067315 | 0.1826606686 |
| Happiness| 0.137053136 | 0.176639161 |
| Sadness| 0.1214098371 | 0.1509535014 |
| Hate   | 0.0877815959 | 0.0599035051 |
| Anger  | 0.0799363965 | 0.0571205363 |
| Disgust| 0.1656119045 | 0.1604166086 |
| Surprise| 0.2106004065 | 0.2123112464 |

2.2. Tweets Affective Classifier

Tweets Affective Classifier (TAC), an emotion classifier developed in [6], can classify six basic human emotions plus the neutral mood as affective features of a tweet text. When applying TAC to TMDb’s movie overview, it classifies the mood of the overview, which becomes the movie’s emotion profile, MVEC, as depicted in Table 4. After joining the movie emotion profile in the TMDb data file with the rating data file in MovieLens, users’ emotion profiles, UVECs can be computed by taking the average of MVECs from all the movies has watched by the user. Similarly, TAC can be applied to users’ reviews in any rating data file of Amazon Review Dataset to obtain users’ emotion profiles, UVECs, as depicted in Table 5.

TAC is built from an asymmetric butterfly wing double-decker bidirectional LSTM - CNN Conv1D architecture [6], [15], and [16] as depicted in Figure 2, Figure 3, and Figure 4 in block diagrams for the classifier to detect and recognize emotional features from tweets’ text messages. A preprocessed seven emotional word embeddings were applied to train TAC through pre-trained GloVe embeddings using the glove.twitter.27B.200d.txt dataset [17]. There are two types of input word embeddings: trainable emotion words embeddings and frozen emotion words embeddings, i.e., the weights in the embeddings are frozen and do not allow for modification during TAC’s training session.
The training process begins with training the first half of the butterfly wing by feeding preprocessed TAC input emotional word embeddings to the double-decker bidirectional LSTM neural nets. The frozen emotional word embeddings are fed to the top bidirectional LSTM, while the trainable emotional word embeddings feed to the bottom bidirectional LSTM. Next, it concatenates the top and bottom bidirectional LSTM of the double-decker neural net. The double-decker bidirectional LSTM is fed in parallel to seven sets of CNN Conv1D neural nets. The dropout regularization unit with a parameter set at 0.5 to prevent overfitting. It concatenates all the Conv1D outputs to form the first half of the butterfly wing neural nets’ overall production.

Tweets Affective Classifier (TAC)

The first half butterfly wing architecture

Asymmetric Double Decker Butterfly Wing Bidirectional LSTM - CNN Conv1D

The second half of the butterfly wing neural nets architecture is different from the first. The training process of the second half wing begins by setting up two groups of Conv1D neural nets. Each group contains seven CNN Conv1D neural nets. The preprocessed TAC’s frozen emotional word embeddings are fed as input in parallel to group one of the Conv1D neural net while feeding in parallel to the other group's trainable emotional word embeddings. The dropout regularization parameter is set at 0.5 for all seven pairs of conv1Ds to prevent overfitting. Concatenation of all seven pairs of Conv1D outputs becomes a single output and fed to a single bidirectional LSTM with the dropout regularization parameter set at 0.5 to prevent overfitting.

Next, the first half of the butterfly wing output is concatenated with the second half to form the overall production output. The output then feeds to a MaxPooling1D with the dropout regularization value set at 0.5. Then the flow goes through a Flatten neural net before flowing through a Dense neural net. Finally, the process flows through another Dense neural net using sigmoid as an activation function to classify the emotion probabilistic distribution values. TAC output the emotion classification in the form of the probabilistic distribution of seven values that sum to one (1). Each value indicates the amount in the percentage of the emotion class. Thus, the seven-emotion probabilistic distribution value forms an emotion profile of an object.
2.3. PAC Disjoint Users within Same and Across Different Domains

A word of caution is on user id that appears across different MovieLens datasets. MovieLens collects datasets anonymously. Thus, there is no guarantee that a user id that appears in one dataset is the same person who bears the same user id in a different dataset. Using user id to make cross-reference metadata across different MovieLens dataset may not produce a consistent result. In this study, the mlsm dataset designates as the training dataset. The other datasets: ml20m, ml25m, and ml27m, are concatenated into a large dataset uses for testing.

Figure 3. Second Half of Asymmetric Butterfly Wing Double-decker Bidirectional LSTM-CNN Conv1D Architecture Block Diagram of Tweets Affective Classifier.

Figure 4. Concatenate two half butterfly wing architecture block diagram of Tweets Affective Classifier.
To overcome the disjoint user's deficiency across different MovieLens datasets, an affective aware pseudo association method (AAPAM) deploys to associate disjoint user across different datasets. The pseudo associate connection (PAC) connects disjoint users across various datasets method works as follow:

- For each user id in a MovieLens dataset, compute the user's UVEC.
- Concatenate ml20m, ml25m, and ml27m datasets together as a massive dataset use for testing. Note that all user id in the testing dataset should have their UVEC computed.
- For each user id in the training dataset, compute the pairwise Cosine Similarity for the training user id against each user id in the testing dataset.
- The Cosine Similarity result obtained from the pairwise user id will go through a ranking and sorting in descending order. The top pairwise user id on the sorted list, indicated by the AII value, has the closest match of emotion profile between the training user id and the testing user id. PAC connects the most similar pair of training user id and testing user id.
- Table 2 depicts user id 400 of mlsm PAC connects to other user ids across Movielens datasets.

A careful examination of Table 2 regarding the PAC of user id 400 in the mlsm dataset to the other three larger MovieLens datasets, user id 400 in mlsm PAC to user id 66274 in ml20, user id 95459 in ml25m, and user id 89185 in ml27m, the Cosine Similarity between user id 400 in mlsm or its AII value and other PAC users is virtually identical. Except for PAC users in ml20m, the other PAC users' AII values in ml25m and ml27m are identical. Both PAC users in ml25m and ml27m have the same history of movie watched list as user id 400 in mlsm. Thus, their UVECs are correctly aligned. Therefore, one can deduce that all said three users are the same in the MovieLens dataset.

The AAPAM scheme works. The method provides a means to associate disjoined users across different datasets within the same domain. However, reconnecting the disjoined users for user id 400 in mlsm to other PAC users does not offer any additional values. Those PAC disjoined users do not contain any value-added information to user id 400. The method failed to enlarge the extra data point for user id 400 in mlsm.

Instead of selecting a low movie watched count user as a test user, such as user id 400 in mlsm who only has watched 43 films, a high film viewing count user is favorable for the test user. In the mlsm dataset, the following users have movie watched count in the range of 1,300 to 2,700. Depicted in Table 7 are selected test users with respective PAC information. Table 7 contains seven columns. The first column represents the identity of user 1 to user 3. The role they play for the specific row information. For example, after the label row, row 1 shows user 1 who user id is 414 in the mlsm dataset, can PAC to user id 125022 in the ml20m dataset. Alternatively, user id 414 can PAC from mlsm dataset in MovieLens to user id 10354 of Digital Music dataset or user id 93437 of Toys and Games dataset in Amazon.

Moreover, the same user can PAC from mlsm to user id 236165 in the ml27m dataset. The above PAC actions are all involving disjoint users in the same MovieLens domain. However, columns 6 and 7 of Table 7 show user id 414 has a choice to PAC from mlsm dataset in MovieLens to user id 10354 of Digital Music dataset or user id 93437 of Toys and Games dataset in Amazon. Indeed, besides capable of connecting disjoint users from different datasets within the same domain, PAC can also connect disjoint users from different datasets across different domains. There are rows in Table 7 that contain rated movies counts for each user in its respective dataset. Also, rows holding movies watched list, UVECs, and the AII values indicate individual users' Cosine Similarity.

2.4. Making Cross Domain Recommendations
The paper in [14] illustrated a strategy of making recommendations through a Comparative Platform implemented with various affective aware Recommenders within the MovieLens domain. Table 6 depicts the five top-20 recommendations list generated by the five respective Recommenders in the Comparative Platform. The five Recommender algorithms deployed in [14] are Item-based Collaborative Filtering Recommender, User-based Collaborative Filtering Recommender, Genres Aware Recommender, Emotion Aware Recommender, and Multi-channel Affective Recommender. Moreover, in the article [14], a follow-up paper of [1] illustrated the validation method's development for recommendations made by the Comparative Platform Recommenders. As an example, Table 6 depicts the top-20 recommendations for the user id 414 made by the five Recommenders in the Comparative Platform Recommenders.

Table 6. Top-20 Recommendations List Generated by Recommenders in Comparative Platform for Test User ID 414.

| U414 | IBCF | UBCF | GAR  | EAR  | MAR  |
|------|------|------|------|------|------|
| 1    | 1291 | 1258 | 73499| 858  | 131714|
| 2    | 1196 | 8368 | 3030 | 53519| 129229|
| 3    | 260  | 2424 | 4565 | 363  | 704  |
| 4    | 1270 | 1230 | 3389 | 3109 | 112911|
| 5    | 1210 | 1982 | 1049 | 3330 | 1606 |
| 6    | 2115 | 3176 | 2153 | 6981 | 3389 |
| 7    | 2571 | 1219 | 809  | 3211 | 2421 |
| 8    | 1240 | 48385| 7925 | 5569 | 3704 |
| 9    | 1197 | 34542| 131714| 5853 | 442  |
| 10   | 1036 | 1449 | 112897| 4224 | 4367 |
| 11   | 1136 | 6879 | 27837| 4608 | 87430|
| 12   | 1200 | 42418| 1867 | 135133| 2826 |
| 13   | 1214 | 520  | 1606 | 109673| 1049 |
| 14   | 2716 | 1183 | 704  | 2009 | 122922|
| 15   | 4993 | 2788 | 56775| 110655| 64695|
| 16   | 1265 | 1693 | 91485| 29  | 2683 |
| 17   | 2028 | 40732| 115727| 4433 | 3702 |
| 18   | 7153 | 2324 | 32511| 2256 | 131739|
| 19   | 3578 | 1333 | 6664 | 3028 | 76743|
| 20   | 858  | 2728 | 761  | 2450 | 57326|
| Hit %| 90%  | 65%  | 20%  | 35%  | 30%  |

AAPAM demonstrates its ability to PAC connect disjoint users across the same or to a different domain. By integrating Recommender with the PAC capability, the Recommender can make recommendations across a different domain; for example, PAC connects disjoint users from the MovieLens domain to users in the Amazon domain. The PAC connects disjoint users because they share similar affective features, and their respective UVEC closely match each other. Table 8 shows the result of a Recommender making a cross-domain recommendation between the MovieLens and Amazon domains.

3. RESULTS AND DISCUSSION

Table 7 depicts the PAC connections of disjoint users in MovieLens to Amazon Digital Music (MUS) and Toys and Games (T&G) datasets.
Table 7. PAC Connect Disjoint Users from MovieLens to Users in Amazon.

| Dataset | mlsm | ml20m | ml25m | ml27m | MUS | T&G |
|---------|------|-------|-------|-------|-----|-----|
| U1      | 414  | 125022| 131662| 236165| 10354| 97437|
| U2      | 448  | 63555 | 134534| 182133| 15262| 206109|
| U3      | 474  | 96370 | 107581| 54271 | 6559 | 180146|
| U1icnt  | 2698 | 694   | 694   | 2698  | 5    | 20  |
| U2icnt  | 1864 | 290   | 1842  | 1863  | 6    | 7   |
| U3icnt  | 2108 | 2108  | 434   | 2108  | 5    | 6   |
| U1uvec  | neutral | 0.16635 | 0.16651 | 0.16651 | 0.16635 | 0.13140 | 0.15147 |
|         | happy   | 0.09731 | 0.09717 | 0.09717 | 0.09731 | 0.07738 | 0.09371 |
|         | sad     | 0.11809 | 0.11856 | 0.11856 | 0.11809 | 0.14019 | 0.11820 |
|         | hate    | 0.16420 | 0.16368 | 0.16368 | 0.16420 | 0.17097 | 0.17993 |
|         | anger   | 0.11518 | 0.11425 | 0.11425 | 0.11518 | 0.12458 | 0.13003 |
|         | disgust | 0.17250 | 0.17262 | 0.17262 | 0.17250 | 0.19243 | 0.17438 |
|         | surprise| 0.16637 | 0.16720 | 0.16720 | 0.16637 | 0.16304 | 0.15228 |
| U2uvec  | neutral | 0.17283 | 0.17278 | 0.17312 | 0.17284 | 0.17307 | 0.14432 |
|         | happy   | 0.09686 | 0.09763 | 0.09671 | 0.09688 | 0.07707 | 0.08709 |
|         | sad     | 0.11605 | 0.11663 | 0.11601 | 0.11605 | 0.12110 | 0.12285 |
|         | hate    | 0.16121 | 0.16128 | 0.16130 | 0.16113 | 0.15901 | 0.18886 |
|         | anger   | 0.11228 | 0.11215 | 0.11237 | 0.11227 | 0.12302 | 0.12316 |
|         | disgust | 0.17099 | 0.17031 | 0.17084 | 0.17099 | 0.19971 | 0.18004 |
|         | surprise| 0.16979 | 0.16922 | 0.16996 | 0.16984 | 0.14702 | 0.15369 |
| U3uvec  | neutral | 0.16886 | 0.16886 | 0.16933 | 0.16886 | 0.13541 | 0.15547 |
|         | happy   | 0.09975 | 0.09975 | 0.09930 | 0.09975 | 0.09764 | 0.08779 |
|         | sad     | 0.11872 | 0.11872 | 0.11947 | 0.11872 | 0.15502 | 0.12221 |
|         | hate    | 0.16088 | 0.16088 | 0.16035 | 0.16088 | 0.18060 | 0.20552 |
|         | anger   | 0.11261 | 0.11261 | 0.11282 | 0.11261 | 0.09618 | 0.11536 |
|         | disgust | 0.17192 | 0.17192 | 0.17220 | 0.17192 | 0.17441 | 0.17048 |
|         | surprise| 0.16726 | 0.16726 | 0.16653 | 0.16726 | 0.16074 | 0.14316 |
| U1AII   | 1.0    | 0.99999 | 0.99999 | 1.0    | 0.99485 | 0.99961|
| U2AII   | 1.0    | 0.99999 | 0.99999 | 0.99999 | 0.99380 | 0.99935|
| U3AII   | 1.0    | 0.99999 | 0.99999 | 1.0    | 0.98890 | 0.99922|

The PAC connections show three disjoint users’ ids: 414, 448, and 474 in MovieLens’s mlsm dataset are pseudo associated to three larger MovieLens’ datasets as well as pseudo associated cross-domain to Amazon users in the Digital Music dataset and Toys and Games dataset. The table shows the Amazon user id in the numeric format resulting from the programming assignment for computational convenience. The actual Amazon user id is in alphanumeric. To map the user id in numeric back to the actual user id requires a mapping function. For example, in Table 7, the U1 user has id 414 in the mlsm dataset PAC connects to user id 10354 in the Amazon Digital Music dataset. The actual user id 10354 in the Amazon Digital Music dataset is “A3CBNRI1SZJJDE”.

3.1. Making Recommendations using Products in Amazon to PAC Users from MovieLens

As shown in Table 7, each user also shows the consumed items count in the respective dataset. For example, U1 user id 414 in MovieLens mlsm dataset has watched 2698 movies; whereas,
U1 PAC user id 10354 in the Amazon Digital Music dataset has reviewed five music, and U1 PAC user id 97437 in Amazon Toys and Games dataset has reviewed 20 items. The following table depicts a sample of Amazon user id 10354 and 97437 have reviewed. The attribute names in Table 8 are as follow:

- **Rid**: reviewer id
- **ASIN**: Amazon Standard Identification Number. Except for books, the ASIN is the same as the ISBN. Almost all products on Amazon has their ASIN. It is a unique code Amazon assigns to a product that carries in the inventory.
- **unixTime**: Timestamp in Unix Julian time.
- **Overall**: rating score with scale 1 (lowest) to 5 (highest).
- **Summary**: short sentiment statement of a product review.

Table 8. Sample of Product Reviews by Amazon Users.

| Rid    | ASIN          | unixTime     | Overall | Summary                      |
|--------|---------------|--------------|---------|------------------------------|
| 10354  | 9714721180    | 1023408000   | 5       | Has it really been 18 years  |
| 10354  | B001237HCI    | 1078358400   | 1       | Why, Oh Why                  |
| 10354  | B001237HCI    | 1078358400   | 1       | Why, Oh Why                  |
| 10354  | B001UEYM5E    | 1194134400   | 2       | Politically correct metal    |
| 10354  | B0057PSUZA    | 1061769600   | 2       | Flat                         |
| 97437  | 6301935063    | 1389312000   | 5       | a fairy tale                 |
| 97437  | 6303605672    | 1408752000   | 4       | a philosophical assassin     |
| 97437  | 6305538972    | 1401753600   | 5       | eat or be eaten              |
| 97437  | B00005ASOS    | 1408752000   | 5       | an eternal test for believers|
| 97437  | B00005JPA6    | 1401408000   | 1       | black humor                  |

Table 8 listed five review samples for rid 10354 in Digital Music and Rid 97437 in Toys and Games. One product with ASIN 971421180 rated with 5 in the Overall score by Rid 10354 while the other products rated very low. Digital Music product with ASIN 971421180 becomes the right candidate for making a recommendation to other users who have a similar taste of Rid 10354. In Toys and Games Rid 97437, there are three product reviews rated with five Overall scores. The first in the 5-score list with ASIN 6301935063 becomes the candidate for recommendation to other users. Hence, both Amazon products with ASIN 971421180 in Digital Music and ASIN 6301935063 in Toys and Games will recommend MovieLens U1 user id 414.

### 4. Conclusions

In this study, the concept of Affective Index Indicator (AII) of Affect Aware Pseudo Association Method (AAPAM) has further developed to make Pseudo Associate Connect (PAC) two or more disjoint users and items in different datasets across different information domains. Often, subjective writing such as product descriptions and sentiment reviews of products found in a product database are sources for emotion classification for product emotion profiles. Similarly, when users interact with products, it will leave a trail of interaction history embedded with users’ preferences and choices to become the source for user emotion profile formulation. This paper demonstrated cross-domain recommendations making is possible using the AAPAM to PAC disjoint users across different domains. This paper showed how to join two
disparate domain datasets for making recommendations seamlessly through detailed illustration. One can extend the PAC disjoint users from MovieLens to, for example, an advertisement database, then ads with similar emotion profiles can be recommended to MovieLens users.

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