Recommending Social-Interactive Games for Adults with Autism Spectrum Disorders (ASD)

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ABSTRACT

Games play a significant role in modern society, since they affect people of all ages and all walks of life, whether it be socially or mentally, and have direct impacts on adults with autism. Autism spectrum disorders (ASD) are a collection of neurodevelopmental disorders characterized by qualitative impairments in social relatedness and interaction, as well as difficulties in acquiring and using communication and language abilities. Adults with ASD often find it difficult to express and recognize emotions which makes it hard for them to interact with others socially. We have designed new interactive and collaborative games for autistic adults and developed a novel strategy to recommend games to them. Using modern computer vision and graphics techniques, we (i) track the player's speech rate, facial features, eye contact, audio communication, and emotional states, and (ii) foster their collaboration. These games are personalized and recommended to a user based on games interested to the user, besides the complexity of games at different levels according to the deficient level of the emotional understanding and social skills to which the user belongs. The objective of developing and recommending short-head (i.e., familiar) and long-tail (i.e., unfamiliar) games for adults with ASD is to enhance their necessary social interacting skills with peers so that they can live a better life.

CCS CONCEPTS

• **Information systems → Recommender systems**;

KEYWORDS

Game Recommendation; Adults with Autism; Social Interaction

1 INTRODUCTION

Autism Spectrum Disorders (ASD) are pervasive disorders of the growth and development of the brain diagnosed with significant impairments. ASD, which persist throughout life and lead to significant disability, are widespread. Over 3.5 million Americans have ASD [3]. Major complexities regarding people with ASD include (i) speech disorder, (ii) difficult to express/recognize emotions which makes it hard for them to interact socially, (iii) fixed interests and repetitive behaviors, (iv) impairments in social, communicative, cognitive and behavioral functioning, (v) sensory abnormalities, (vi) lack the sense of social reciprocity and fail to develop/maintain age appropriate peer relationships, and (vii) reduced ability to understand and make correct inferences about the mental states of others.

In addressing the disorders of children with ASD, a number of researchers [7, 10, 18, 22] have designed various tablet and tabletop games for children with the goals of enhancing their social-interacting and communication skills. Since existing games for autistic children are too primitive for adults with ASD, we first develop various computer games for these adults with different needs and skill set. Hereafter, we propose two different recommendation strategies, short-head and long-tail recommendation, to suggest personalized well-known and unknown games to the players, respectively. Our gaming system offers adults with ASD different individual and collaborative games to play to enhance their social-interactive skill.

2 GAME DESIGN

Our game design is based on affordable technology that is pleasing to touch and that connects to an Internet game which can be played with more than one person, either remotely or collocated.

Designing Speech Therapy Games. Adults on the autism spectrum often have difficulties producing intelligible speech with either high or low speech rate. Since speech is an important media of communication, socialization, and interaction with the world [9], these adults need assistance while delivering speech to communicate to people around them. We start our speech therapy game with mono-syllabic words, which is followed by the pronunciation of both mono-syllabic and di-syllabic words.

Learning Facial Expressions. People with ASD have difficulty interacting socially. Conventional methods, which use medicinal means, special education, and behavioral analysis [11, 23], are not always successful and are usually expensive. We have utilized an interactive game design, which uses modern computer vision and graphics techniques, for autistic adults to (i) recognize the facial expressions of the player, and (ii) animate an avatar, which mimics the player's facial expressions. These games recognize six basic facial expressions: anger, disgust, fear, joy, sadness, and surprise. Four modes are designed for the games: (a) *recognize the facial expression*, (b) *build a face*, (c) *become your avatar*, and (d) *live a story*.

Giving Instructions through Eye Contact. One potential reason why adults with ASD may have pronounced interests in video games is that such games offer visually stimulating virtual environments, which may provide them opportunities to utilize their visual processing skills and preferences [20]. Based on this observation, we have created a game like Spaceteam where people have to call out instructions from their own screen to others who can execute

RecSys '18, October 2–7, 2018, Vancouver, BC, Canada

ACM ISBN 978-1-4503-5901-6/18/10...$15.00
https://doi.org/10.1145/3240323.3240405

the instructions. In our case, without using voice but facial signals, the designed game teaches people to communicate with eye contact. The eye tracker registers the fixations that the user carries out on the computer screen during the life cycle of the game.

Audio Communication. People with ASD have marked difficulties using (non-)verbal communication for social interaction [1]. We have developed an audio game that helps autistic adults modulate the vocal intonation appropriately when expressing emotions and use appropriate gestures and body language. The game analyzes users' vocal expressions using microphone, animation, video and audio clips. Different features modeling pitch, energy, and duration are adopted which can be conveyed to autistic adults rather easily by prompting them to speak louder or more quietly, etc.

Recognition of Emotional States. Autistic people have major difficulties in recognizing and responding to emotional and mental states of others [6]. Our animated games are designed to enhance emotion comprehension in autistic adults who are expected to recognize emotion and improve understanding of emotions. These emotion-teaching games ensure that information, which may otherwise be easily processed by the neurotypical brain, is not overstimulating and thus aversive to the autistic brain.

Engineering/Pilot Team. We have created a Star Trek-style game that helps people engage conversations. It is a game with two-player teams that contain two pre-defined roles, an engineer and a pilot. A team has to pilot and engineer a spaceship to beat other similar teams in a race or battle. The engineer and pilot must communicate to achieve the goal. The game is an effective medium for shrinking the gap between the amount of behavioral therapy recommended for adults with ASD and the amount they receive.

3 A GAME RECOMMENDER SYSTEM

In this section, we present our short-head and long-tail recommendation approaches for adults with autism. The former utilizes distinct features of video games to suggest familiar games, whereas the latter is based on graphical representations of users, items,[1] and graph traversals in recommending unfamiliar games to users.

3.1 Short-Head Recommendation

We consider various features that highlight traits of games in generating recommendations to users. These game features, which includes *ratings*, *topic relevance*, *sentiment analysis*, *category*, and *complexity*, are influential, since it is common for users to follow patterns of favoring a specific type of games. Respective meta-data for these features are available on various video game websites.[2]

3.1.1 Matrix Factorization (MF).

In our short-head recommendation system, adults with ASD provide ratings on games played by them in the past in a user profile, which are considered along with ratings offered by other players for rating prediction.

Attempts have been made in the past by relating users to similar users and an item to similar items on which user- and item-based rating prediction systems are developed. One of the major design deficiencies of these approaches is that whenever the dataset is *sparse*, both are forced to recommend using neighbors that are not really that similar. Matrix Factorization (MF) [19], on the other hand, is a better approach, since it does not require similar users or items to give recommendation. Thus, it is more stable than the other recommendation models for predicting user ratings. We adopt the singular value decomposition (SVD) [5] technique in MF to suggest games.

3.1.2 Topic Relevance.

To determine the *topic* covered in a game G, we employ the Latent Dirichlet Allocation (LDA) model [2]. To train an LDA model, the inputs to the model include (i) a set of training instances S, each of which is a brief description of a game represented as a *sequence* of words, and (ii) the number of latent topics N, which is 20 in our case, to produce. During the training process, LDA estimates the *probability* of a non-stop, stemmed word w given a (latent) topic z, i.e., $P(w|z)$, and the *probability* of a topic z given a description D, i.e., $P(z|D)$. A number of algorithms have been proposed for estimating $P(w|z)$ and $P(z|D)$, and Gibbs sampling [8] is an ideal choice, since it is easier to implement, more efficient, and faster to obtain good approximations than others [17].

Using a trained LDA, the classification process of LDA on a game G can be done with the created latent topics on D based on the distribution of words w_is in D and their probabilities in a topic z_j, i.e., $P(w_i|z_j)$. The *topic* z_j with the *highest probability*, i.e., $P(z_j|D)$, is chosen for D and is considered favorably if it matches the topics of games played by a user for whom games are suggested.

3.1.3 Sentiment Analysis.

Users' comments on a game can be used for measuring the overall sentiment towards the game. We utilize both users' ratings and comments on a game G to rank G, since users who have ranked G might not offer comments on G and vice versa. The sentiment scores of all reviews on G are averaged.

We first determine the *polarity* of each word w in each review r of G such that w is positive (negative, respectively) if its positive (negative, respectively) SentiWordNet[3] score is higher than its negative (positive, respectively) counterpart. We calculate the overall sentiment score of the reviews made on G, denoted $StiS(G)$, as

$$StiS(G) = \sum_{i=1}^{n} \frac{\sum_{j=1}^{m} SentiWordNet(Word_{i,j})}{|Rev_i|} \quad (1)$$

where n is the number of reviews on G, m is the number of words in the k^{th} ($1 \leq k \leq n$) review on G, $Word_{i,j}$ is the j^{th} word in the i^{th} review, and $|Rev_i|$ is the number of words in the i^{th} review of G.

As the highest (lowest, respectively) SentiWordNet score of any word is 1 (-1, respectively), $LS < StiS(G) \leq HS$, where $-0.9 \leq HS \leq 1$, $-1 \leq LS \leq 0.9$, and $HS - LS = 0.1$. $StiS(G)$ is rescaled so that its value, denoted $StiS_{Scaled}(G)$ and defined below, is bounded between 0 and 1, since a *negative* $StiS(G)$ value can be returned if the overall sentiment of G leans towards the negative region.

$$StiS_{Scaled}(G) = CL(StiS(G)) + \frac{0.9 - FL(StiS(G))}{2},$$
$$CL(StiS(G)) = \frac{\lceil StiS(G) \times 10 \rceil}{10}, FL(StiS(G)) = \frac{\lfloor StiS(G) \times 10 \rfloor}{10} \quad (2)$$

3.1.4 Categories of Games.

A game can be assigned a number of categories: *abstract, children, customizable, family, party, strategy, thematic*, and *war*. These categories are predetermined and have been widely-used and accepted by the gaming industry

[1] From now on, whenever we use the terms "users" and "items", we refer to adults with autism and computer games, respectively.
[2] www.ebizmba.com/articles/video-game-websites
[3] sentiwordnet.isti.cnr.it

and community. We personalize game recommendations by utilizing the game category feature with games played by a user, which is archived in a user profile PF. We compute the *category similarity* among all the games in PF with each game being considered for recommendation using the co-occurrence frequency, denoted $CoFreq$, of game categories. $CoFreq$ is pre-calculated using games with assigned categories extracted from game websites, denoted $GSet$.

$$CoFreq_{v,w} = \frac{F_{v,w}}{F_{v,v} + F_{w,w} - F_{v,w}} \quad (3)$$

where $F_{v,w}$ is the frequency of categories v and w that co-occur in the games in $GSet$, $F_{v,v}$ ($F_{w,w}$, respectively) is the frequency of category v (w, respectively) that occurs in each game in $GSet$.

We determine the *category co-occurrence frequency similarities*, denoted $CTS(G)$, among the games in a user profile PF and each game G to be considered for recommendation using Equation 4.

$$CTS(G) = \sum_{j \in PF} \frac{\sum_{(v,w) \in Z_{j,G}} CoFreq_{v,w}}{|PF_j| \times |G|}, Z_{j,G} = \sum_{i \in PF_j} \sum_{k \in G} (i,k) \quad (4)$$

where $|X|$ denotes the number of categories in game X, PF_j is the j^{th} game in PF, and $Z_{j,G}$ is the set of two categories in PF_j and G.

3.1.5 Complexity. With gaming experience, users have their own opinions on which complexity levels create better playing experiences for themselves. The commonly-used complexity ratings of games are 0-5, with 5 being most complex. The complexity score of game G, denoted $CS(G)$, considered for recommendation with respect to the highest-rated game HG in a user's profile, is defined as

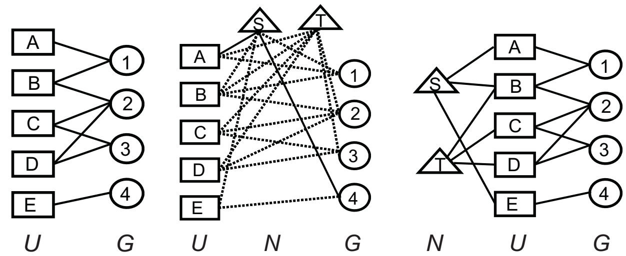
$$CS(G) = -|C_{avg_{HG}} - C_{avg_G}| \quad (5)$$

where $C_{avg_{HG}}$ (C_{avg_G}, respectively) is the *average complexity level* of HG (G, respectively). $CS(G)$ yields a *high* ranking score to G with respect to HG when the negated value is *small*, i.e., when the complexity level between G and HG is close.

3.1.6 Backpropagation (BP). Based on the respective scores of the features computed in Sections 3.1.1 through 3.1.5 for a game G to be considered for recommendation, we rank all the games for recommendation with respect to a user profile accordingly. To compute a single ranking score on G which determines the cumulative effect of the features for ranking propose, we rely on the Backpropagation (BP) model [15]. BP learns weights associated with various inputs, i.e., features in our case, and is often used for ranking.

3.2 Long Tail Recommendation

Besides recommending games in the "short-head" category, we also suggest games belonged to the "long-tail" class. Existing long-tail recommendation strategies [25] use bipartite graphs which represent a set of user nodes U connected with a set of game nodes G through a set of edges E, with their labels being the *ratings* assigned by users to games. We deviate from the traditional "long-tail" recommendation approach by introducing a third set of nodes N. The elements in N are *features* that describe U or G. Our long-tail approach differs significantly from that of Shang et al. [21], since the latter connect U to G and U to N separately and then additively combine the hitting times from each user u_i to another user u_j. Hence, their approach would represent the system as shown in Figure 1(c) in which S and T are *categories*. Based on this design, a random walker would never be directly connected nodes G and N as shown in Figure 1(b), which is our approach. The connections from U to N and U to G, as shown in Figure 1(c), essentially combine the results of two bipartite graphs as shown in Figure 1(a), but does not directly join N into the bipartite graph, whereas our method does.



(a) A simple user-item bipartite graph

(b) A tripartite graph with new path created from A to 4

(c) A tripartite graph in [21]

Figure 1: A bipartite graph and two different tripartite graphs

Our long-tail system, called *Extended tripartite approach*, uses "basic categories", a split-up version of the "full category" in [12]. A *full category* consists of a set of tags applied to a game, whereas a *basic category* breaks up the full category into its individual tags. We observe that creating *more* paths when connecting an item node to a category node allows the algorithm to make *better* recommendations. To improve the connectivity, we move from full categories to basic categories (see Figure 2 for an example).

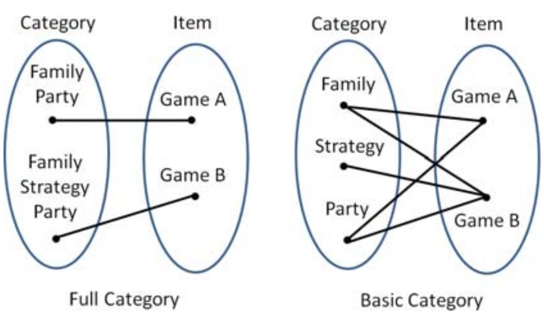


Figure 2: Full versus basic category graphs

Our tripartite algorithm connects the user, category, and item sets according to the following setups:

(1) *User-item*: the user's rating (specified in a user profile) for the item is 0 if the user has not rated the item; 1, otherwise.
(2) *User-category*: the Bayesian average for the category.
(3) *Category-item*: the *average* rating of the item divided by the number of basic categories for applicable basic categories.

A *Bayesian average* [24] weights the user-genre relationship as

$$W_{u,bg} = \frac{avg\_vote_u \times avg\_rating_u + votes_{u,bg} \times rating_{u,bg}}{avg\_vote_u + votes_{u,bg}} \quad (6)$$

where u is a user, bg is a basic category, avg_vote_u is the average number of items u has rated per basic category, which is computed by summing the number of items a user has rated that has a given basic category and taken an average of that value across all basic categories, avg_rating_u is u's average rating of basic categories in rated items, $votes_{u,bg}$ is the number of ratings u has made for bg, and $rating_{u,bg}$ is the average rating u has given bg.

With respect to (3) list above, a uniqueness of graph-based recommenders is the ability to make recommendations based on the *degree of connection* between a user and an item, which depends on the *weight* of a path as well as the number of paths, which is

$$W_{i,bg} = \begin{cases} \frac{i_{avg}}{|BG_i|}, & bg \in BG_i \\ 0, & bg \notin BG_i \end{cases} \quad (7)$$

where i is an item, i_{avg} is the average rating for i, bg is a basic category, and BG_i is the set of basic categories applied to i.

4 EXPERIMENTAL RESULTS

We have evaluated our recommendation strategies using *GSet* (as mentioned in Section 3.1.4) on ordinary game players to establish the foundation on the performance of our recommender prior to conducting a user study on adults with ASD for resource reason.

4.1 Short-Head Recommendation

Given a user profile and a set of new video games, we evaluate the performance of our short-head recommendation approach, called GAMRec, by computing the *ranking accuracy* of its recommendations and comparing its suggestions with two widely-used games recommenders, Amazon and Barnes & Noble. The usefulness of each game suggested by each recommender is determined by a number of independent appraisers, which serve as the *gold standard*.

We recruited 125 appraisers who are students at our university and were chosen to participate in our study because of their extensive collection and prior knowledge of video games. Each appraiser was asked to create a user profile and choose *five* designated games which the appraiser enjoy playing.[4] The performance evaluation of our short-head recommender, GAMRec, in comparison with recommendations made by Barnes & Nobles and Amazon, is shown in Figure 3, and the results are statistically significant ($p < 0.01$) [13].

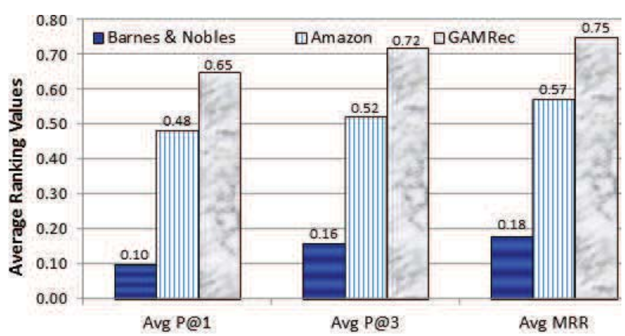


Figure 3: Evaluation on our short-head recommendation

4.2 Long-tail Recommendation

Recall and diversity are two metrics used to evaluate tripartite recommender systems. *Recall* [13] measures a recommender's ability to correctly learn a user's preferences, whereas *diversity* [4] qualifies how diverse a set of items a recommender suggests. A *Recall@N* measure is taken for different values of N (≥ 1). *Recall@5* (*Recall@10*, respectively) checks whether an item of interest is in the list of top-5 (top-10, respectively) recommendations. The results achieved by using our extended tripartite approach on long-tail recommendations are shown in Figure 4 and Table 1, where the T value dictates how long the random walker is allowed to traverse a graph.

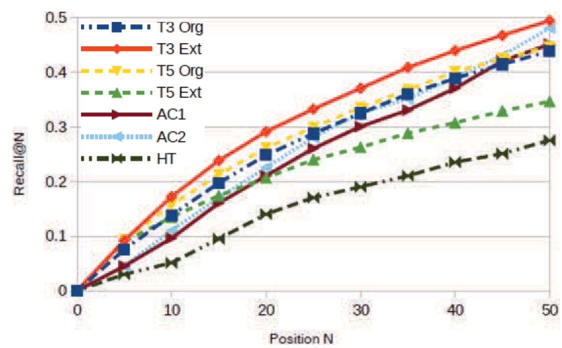


Figure 4: *Recall@N* values of various versions of bipartite and tripartite graph structure, where *T3 Org* and *T5 Org* are proposed by [12], whereas *AC1, AC2*, and *HT* are introduced by [25]

Table 1: *Diversity* of bipartite and tripartite graph algorithms

Algorithm	Diversity	Algorithm	Diversity
T3 Original [12]	0.404	T5 Original [12]	0.315
T3 Extended	**0.450**	T5 Extended	0.325
AC1 [25]	0.425	AC2 [25]	0.420
HT [25]	0.410		

Our $T3$ Extended algorithm outperforms the previous best tripartite graph-based algorithm, i.e., $T5$ Original [12], on *Recall@N* by 9.5%, which is statistically significant ($p < 0.01$). Figure 4 also shows the results of Yin's *Hitting Time* algorithm, HT, and *absorbing cost* algorithms, $AC1$ and $AC2$, which are outperformed by $T3$ Extended. Moreover, $T3$ Extended beats the previous best *diversity* score of AC1 by 2.5%, which is statistically significant ($p < 0.05$).

5 CONCLUSION

Autism spectrum disorders (ASD), which affect 1 in 68 children in the United States [16], can profoundly impact an affected individual's ability to lead a productive, independent life. To make the matter worse, children with ASD inherit the disorder from their childhood into adulthood, even though their maturity level and interests change with their age [14]. To alleviate these challenges encountered by autistic adults, we propose a recommender system, which includes the design of various computer games at different neurodevelopmental disorder levels, to suggest familiar (short-head) and unfamiliar (long-tail) games to adults with ASD. By providing computer games that are interested to autistic adults and allowing them to learn via a structured process, they can have a better future.

Performance evaluation on the usefulness and merits of our designed computer games and its recommendations for autistic adults will be conducted in a future year-long empirical study for its effect.

[4] Out of the 625 video games, a total of 453 distinct, designated games were included which created 453 lists of top-3 recommendations made by each recommender.

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