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Recommender Systems For Computer Tailored Health Communications

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Recommender Systems For Computer Tailored Health Communications

Rajani Sadasivam¹, Benjamin M. Marlin², James Allan¹ and Thomas Houston²

1: UMass Medical School, Dept. of Quantitative Health Science
2: UMass Amherst, School of Computer Science
Personalizing health communications to individual patients using computer programs

Collect baseline subject “profiles” consisting of demographic and domain specific information

**Subject Profile**
- Gender: Female
- Age: 20-29
- Readiness to Quit: High
- Cigarettes per day: 2

**Subject Profile**
- Gender: Male
- Age: 60-69
- Readiness to Quit: Medium
- Cigarettes per day: 6
Current State of the Art

Behavioral experts write rule-based systems to select messages by matching subject profiles to message content.

Current CTHC are Effective, but can they be more effective?
Limitations of CTHC Systems

- The rules may fail to capture concepts that are important and relevant to individual subjects or patient sub-populations.

- There is no mechanism for adapting the rule to better serve the users over time.

- Cannot easily develop high-tailoring interventions
Collaborative Filtering Recommenders Systems

Explicit or implicit user feedback from a large community of users has been used successfully to personalize product recommendations in internet-based systems.
Collaborative filtering systems work by identifying users with similar preferences. The assumption is that if a user like you liked an item, you’ll like it too.
Deploying collaborative filtering recommender systems in the CTHC case involves several challenges:

- Unclear what aspect of messages users should be rating (preference, relevance, influence, emotional impact,...)
- Small data set sizes when system first start’s operating
- Limited interaction with user (one message rating per day)

We are exploring several solutions to these issues:

- Pre-pilot study to assess four possible questions
- Development of a hybrid system that uses explicit ratings, implicit data from website visits, user profile information and message content information.
100 subjects each supplied ratings for four aspects of five randomly selected messages from a pool of 50 messages.

We had subjects rate the following four message aspects:

- Question 1: This message influences me to quit smoking
- Question 2: This message affected me emotionally
- Question 3: This message was relevant to my everyday life
- Question 4: I would like more messages like this one

Analyzed the resulting data for quantitative difference between questions as well as ability to predict ratings.
Initial Results: Marginal Rating Distributions

- **Question 1 Rating Distribution**
  - Rating: 1, 2, 3, 4, 5
  - % of Total Ratings: 0.0, 0.3, 0.4, 0.1, 0.0

- **Question 2 Rating Distribution**
  - Rating: 1, 2, 3, 4, 5
  - % of Total Ratings: 0.0, 0.2, 0.4, 0.2, 0.0

- **Question 3 Rating Distribution**
  - Rating: 1, 2, 3, 4, 5
  - % of Total Ratings: 0.2, 0.4, 0.3, 0.1, 0.0

- **Question 4 Rating Distribution**
  - Rating: 1, 2, 3, 4, 5
  - % of Total Ratings: 0.2, 0.3, 0.4, 0.1, 0.0
Initial Results: Joint Rating Distributions
Initial Results: Variance vs Mean by Message

Mean Rating v Rating Variance (Q1)
We assess rating prediction accuracy by holding out some rating values, using a model to predict their values and then computing the average prediction error. The model can base predictions on different information sources.

<table>
<thead>
<tr>
<th>Question</th>
<th>B</th>
<th>BU</th>
<th>BM</th>
<th>BF</th>
<th>BUM</th>
<th>BUF</th>
<th>BMF</th>
<th>BUMF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1: Influence</td>
<td>0.8783</td>
<td>0.8663</td>
<td>0.8783</td>
<td>0.7672</td>
<td>0.8667</td>
<td>0.7612</td>
<td>0.7734</td>
<td>0.7612</td>
</tr>
<tr>
<td>Q2: Emotion</td>
<td>0.8929</td>
<td>0.8746</td>
<td>0.8929</td>
<td>0.7893</td>
<td>0.8747</td>
<td>0.7547</td>
<td>0.7766</td>
<td>0.7538</td>
</tr>
<tr>
<td>Q3: Relevance</td>
<td>0.7648</td>
<td>0.7649</td>
<td>0.7648</td>
<td>0.7655</td>
<td>0.7637</td>
<td>0.7556</td>
<td>0.7656</td>
<td>0.7510</td>
</tr>
<tr>
<td>Q4: Preference</td>
<td>0.8844</td>
<td>0.8915</td>
<td>0.8860</td>
<td>0.8327</td>
<td>0.8913</td>
<td>0.8551</td>
<td>0.8350</td>
<td>0.8506</td>
</tr>
</tbody>
</table>

B: Bias term, U: User profile information, M: Message content information, F: Latent factors
Conclusions

- Rating data from different questions are highly correlated

- The data indicate that there is a possibility for personalization

- Initial predictive results are positive
Next Steps

- Launched an expanded rating data collection effort - 20 ratings per user from 700 users

- Estimate a more detailed model which will be deployed and tested as part of a recommendation system within Decide2Quit.org.

- Evaluate the system in terms of the ratings users supply for the messages the system selects for them.
Induce the adoption of healthy behaviors by sending personalized health communication messages to individual subjects.
**CTHC Applications:** There are many possible applications of CTHC systems.

- Healthy Eating
- Medication Compliance
- Smoking Cessation
Example Messages:

Breathing gets easier: Everyone knows that smoking is bad for you. However, after you quit you may notice that you can breathe better and that you have more energy. Quitting also lowers your risk of getting cancer from smoking.

Why quitting makes you look younger: Smoking ages. It ages women's skin more than men's. After you quit smoking, your skin will begin to look younger. Your complexion will be a healthier color within weeks.

Dying from Smoking: Did you know? Each year 440,000 U.S. adults die from smoking. This means that smoking plays a part in 1 out of every 5 deaths.