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Recommender Systems For Computer Tailored Health Communications

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Et al.

Recommender Systems For Computer Tailored Health Communications

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Computer Tailored Health Communication (CTHC)

- Personalizing health communications to individual patients using computer programs
- Collect baseline subject “profiles” consisting of demographic and domain specific information

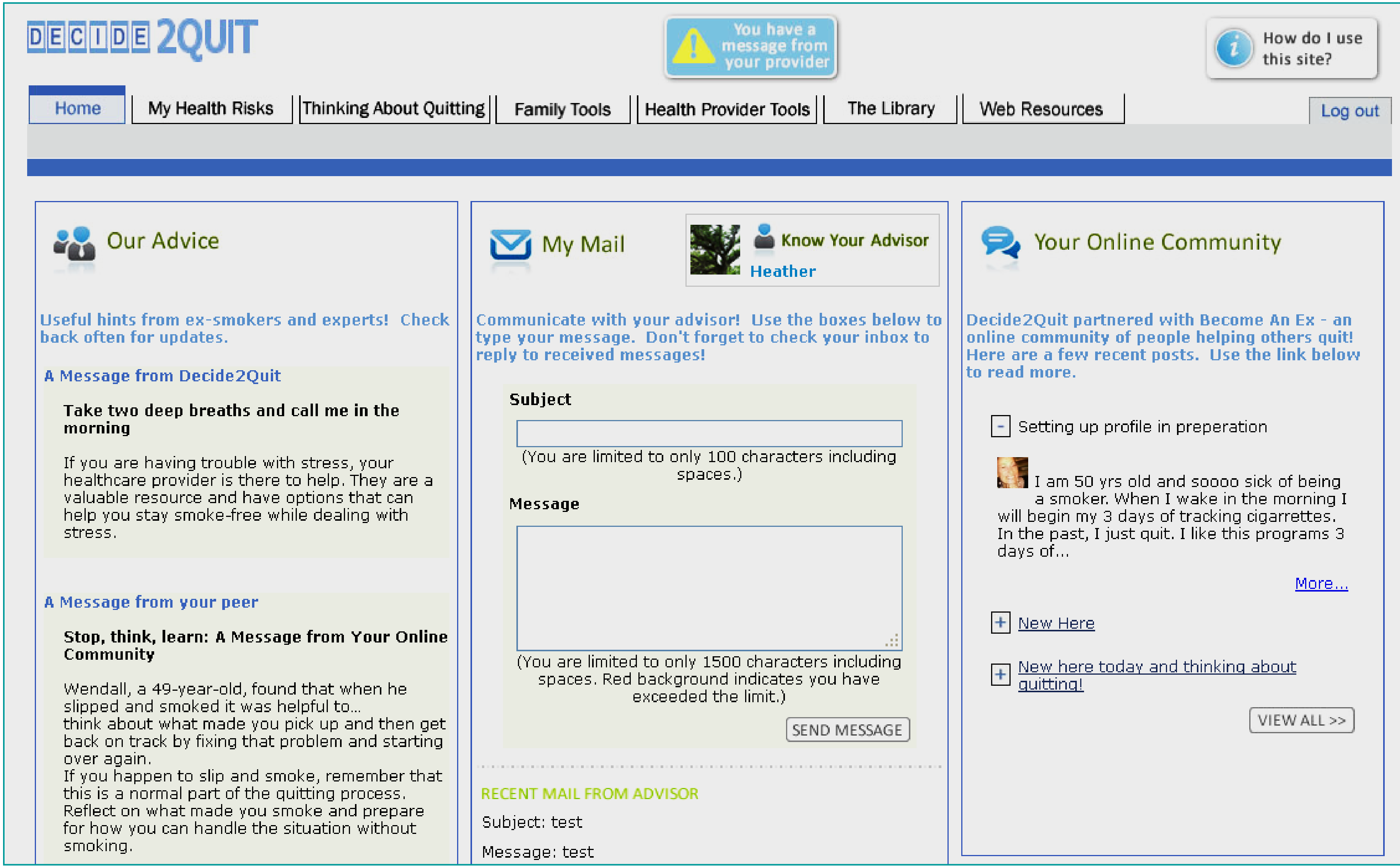
Subject Profile

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

Subject Profile

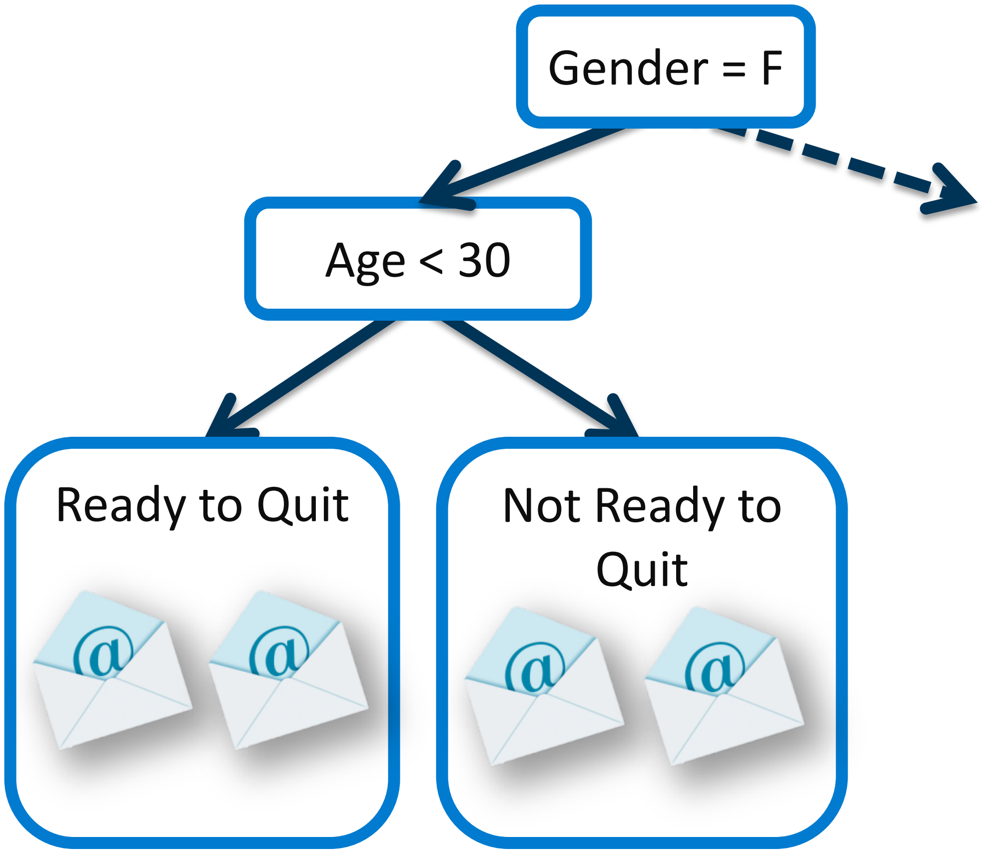
Gender:	Male
Age:	60-69
Readiness to Quit:	Medium
Cigarettes per day:	6

Example CTHC Intervention



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

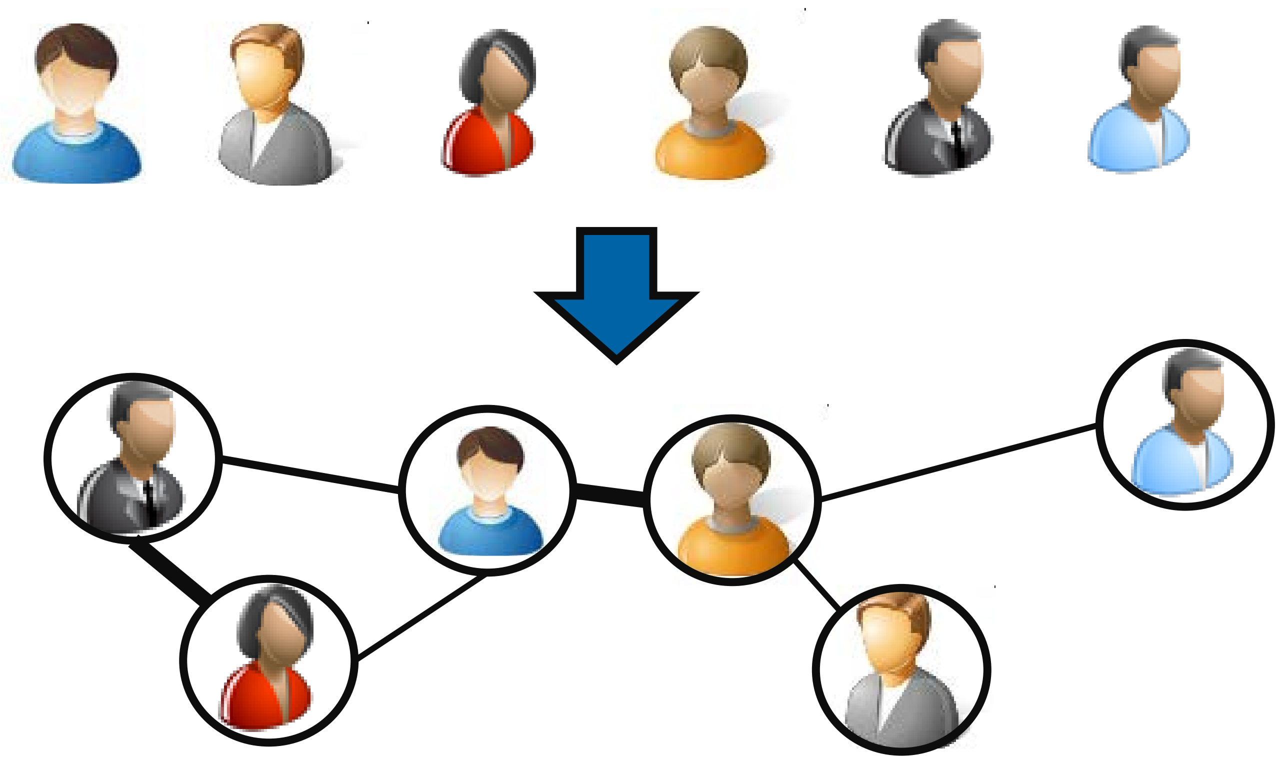
- The rules may fail to capture concepts that are important and relevant to individual subjects or patient sub-populations.
- There is no mechanism for adapting the rule to better serve the users over time.
- Cannot easily develop high-tailoring interventions

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 Recommenders Systems

- Collaborative filtering systems work by identifying user's with similar preferences. The assumption is that if a user like you liked an item, you'll like it to.



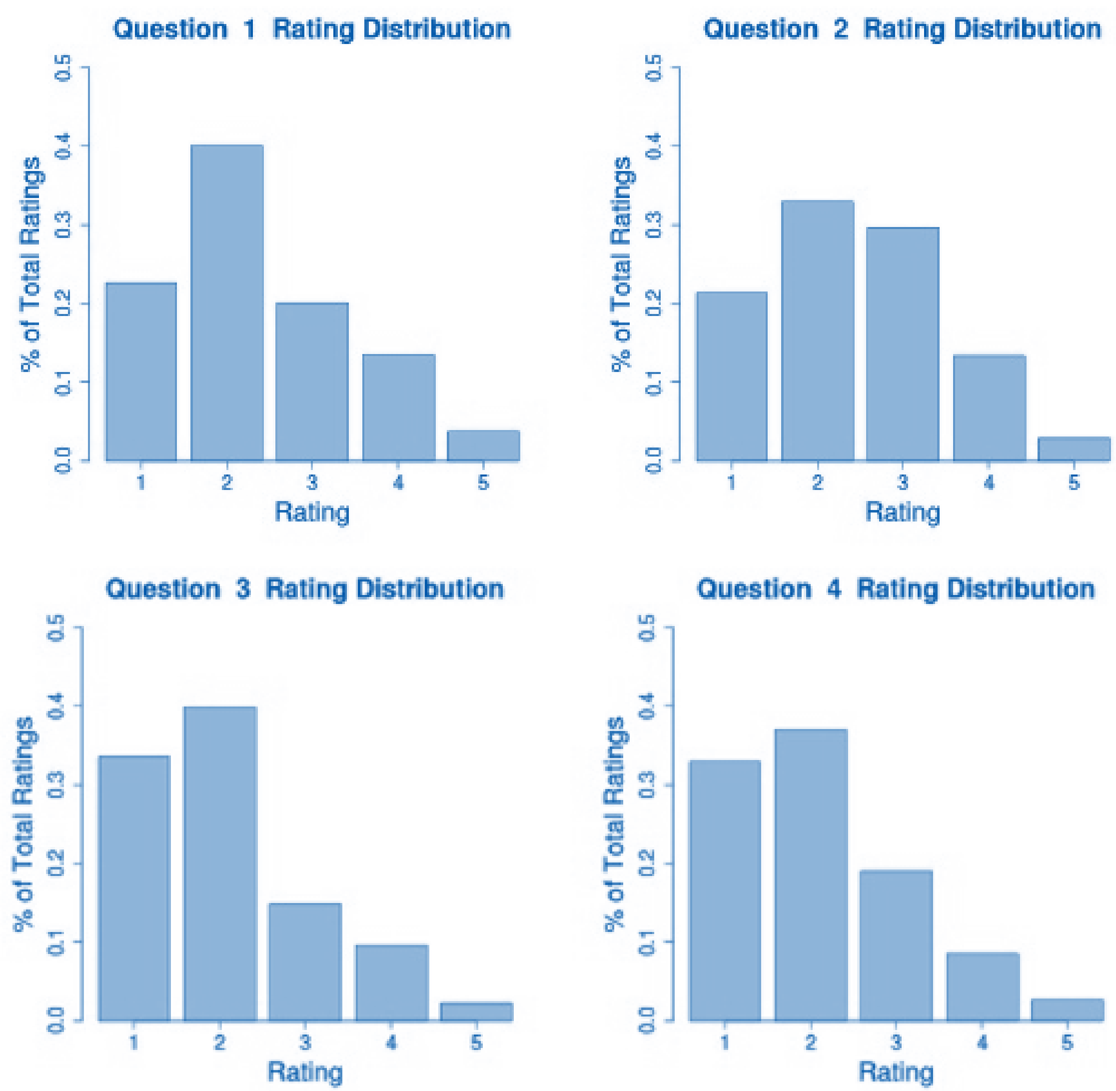
Collaborative Filtering CTHC

- **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.

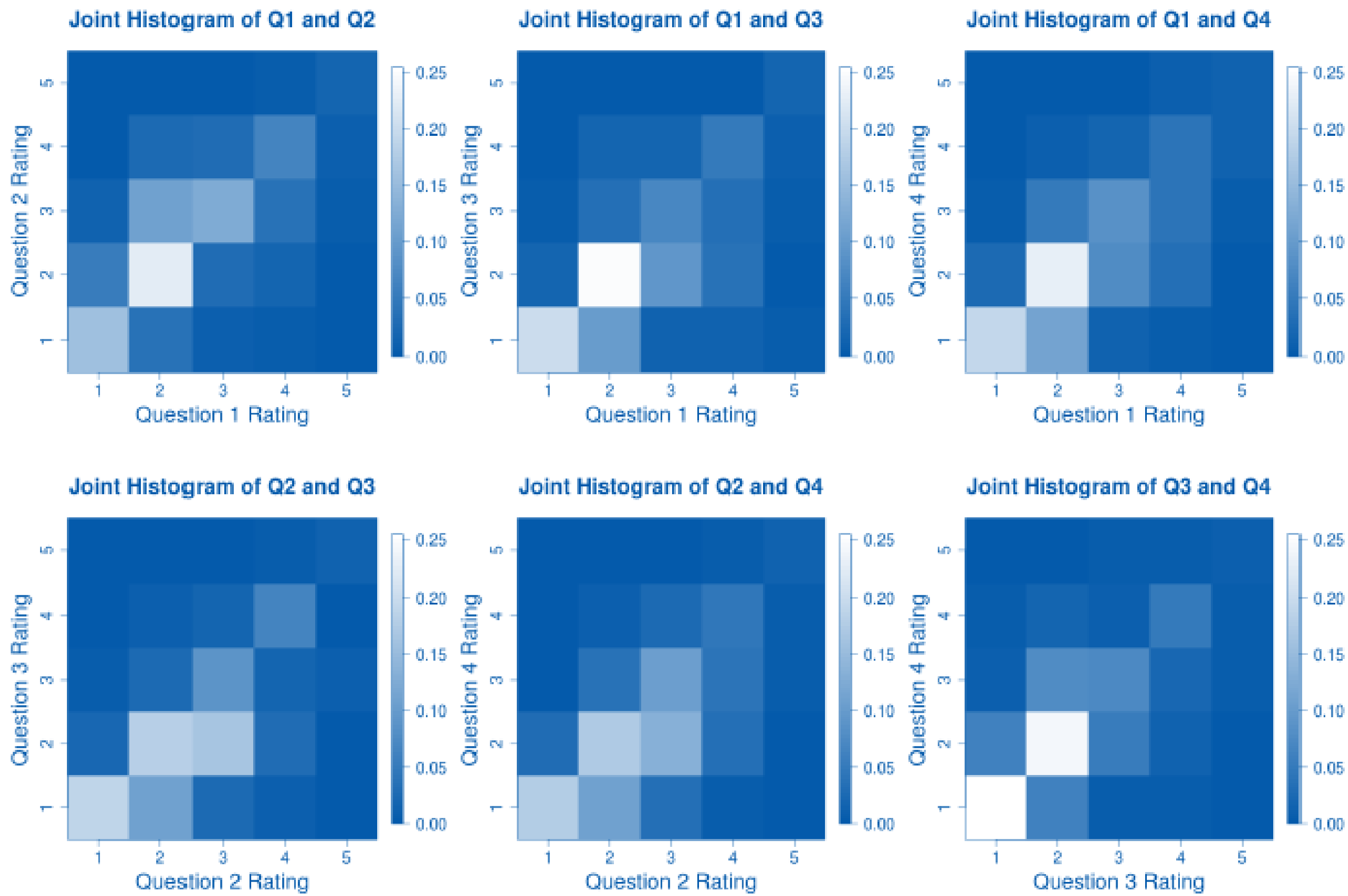
Pre-Pilot Data Collection

- 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.

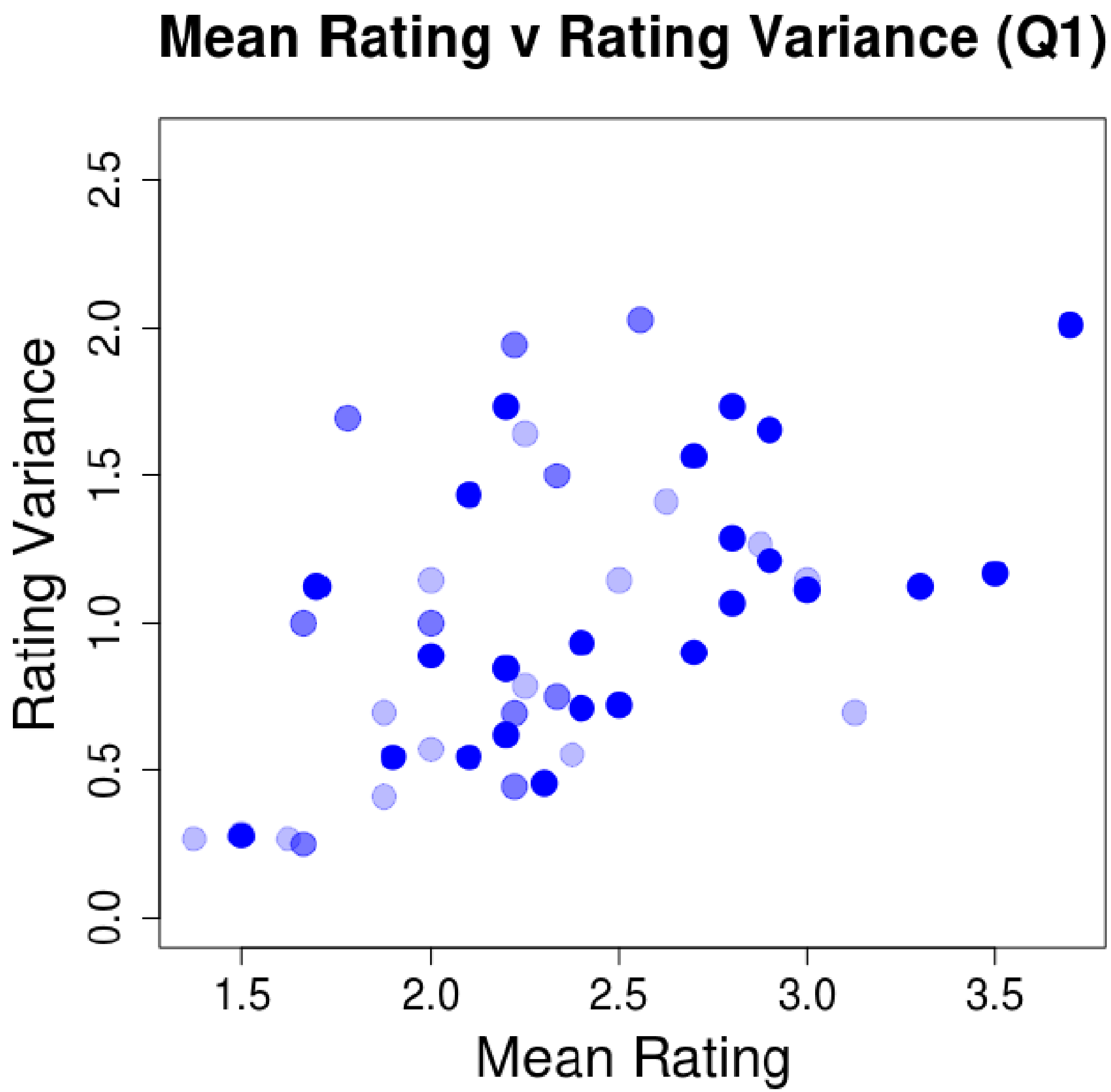
Initial Results: Marginal Rating Distributions



Initial Results: Joint Rating Distributions



Initial Results: Variance vs Mean by Message



Initial Results: Rating Prediction

- 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.

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

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

Conclusions

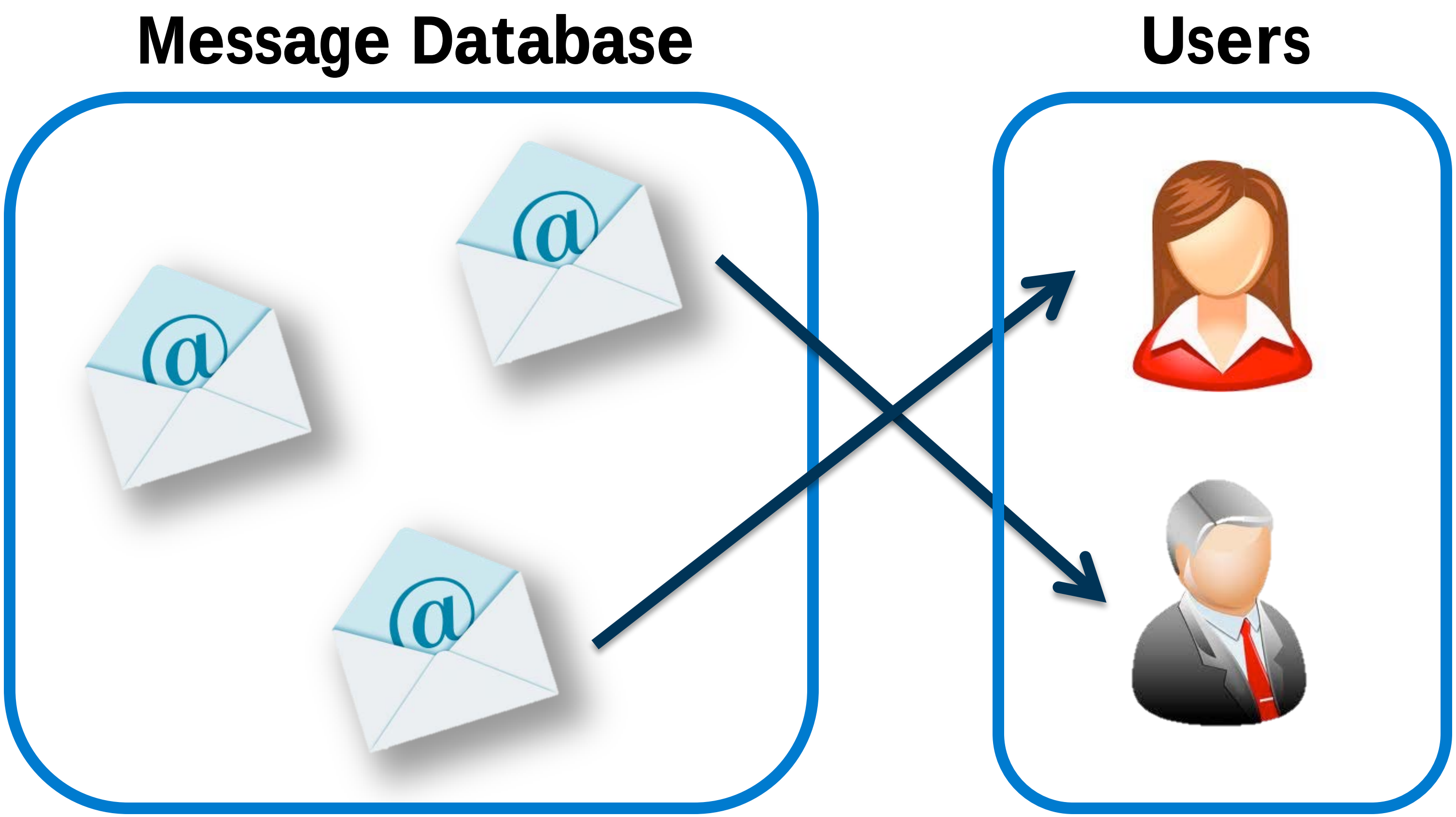
- Rating data from different questions are highly correlated
- The data indicate that there is a possibility for personalization
- Initial predictive results are positive

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.

Computer Tailored Health Communication (CTHC)

- Induce the adoption of healthy behaviors by sending personalized health communication messages to individual subjects.



Computer Tailored Health Communication (CTHC)

- **CTHC Applications:** There are many possible applications of CTHC systems.

Healthy Eating

Medication Compliance

Smoking Cessation

Computer Tailored Health Communication (CTHC)

- **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.*