Personality-based recommender systems: an overview

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- partly from Sergipe-FAP:

FAPITEC/SE
Fundação de Apoio à Pesquisa e à Inovação Tecnológica do Estado de Sergipe

- and Universidade Federal de Sergipe, head of Capacite project:

Capacite

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  - Post-doctoral at Swiss Federal Institute of Technology, Lausanne(EPFL)- from 2012
  - This presentation is being supported by École Polytechnique Fédérale de Lausanne (EPFL)

Outline

- First part - basic theories and Knowledge towards to PBRS:
  - Contextualization of Affective computing at RecSys;
  - Human decision-making & computer decision making;
  - Personality theory;
  - Personality extraction;
  - Personality profile representation and standardization.
- Second part - Personality-based Recommender Systems:

RecSys slogan:

We are leaving the age of information and entering the age of recommendation.

Chris Anderson in The Long Tail

So what???

- Are you sure about this?
- ....

Do you remember ....

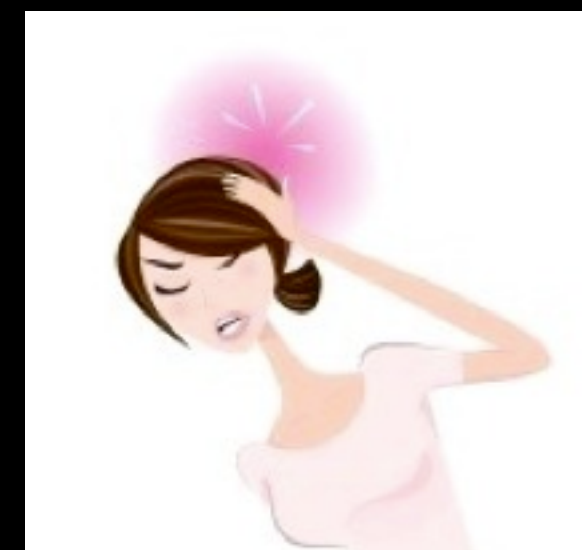
How about the old times??

Dublin – September 11th, 1930

Good morning, Mrs. Johnson!

- Imagine:
  - (even if the pharmacist doesn’t know you, could he offer you something adequate?)

- just by looking at your physiological situation...



Could this information help?

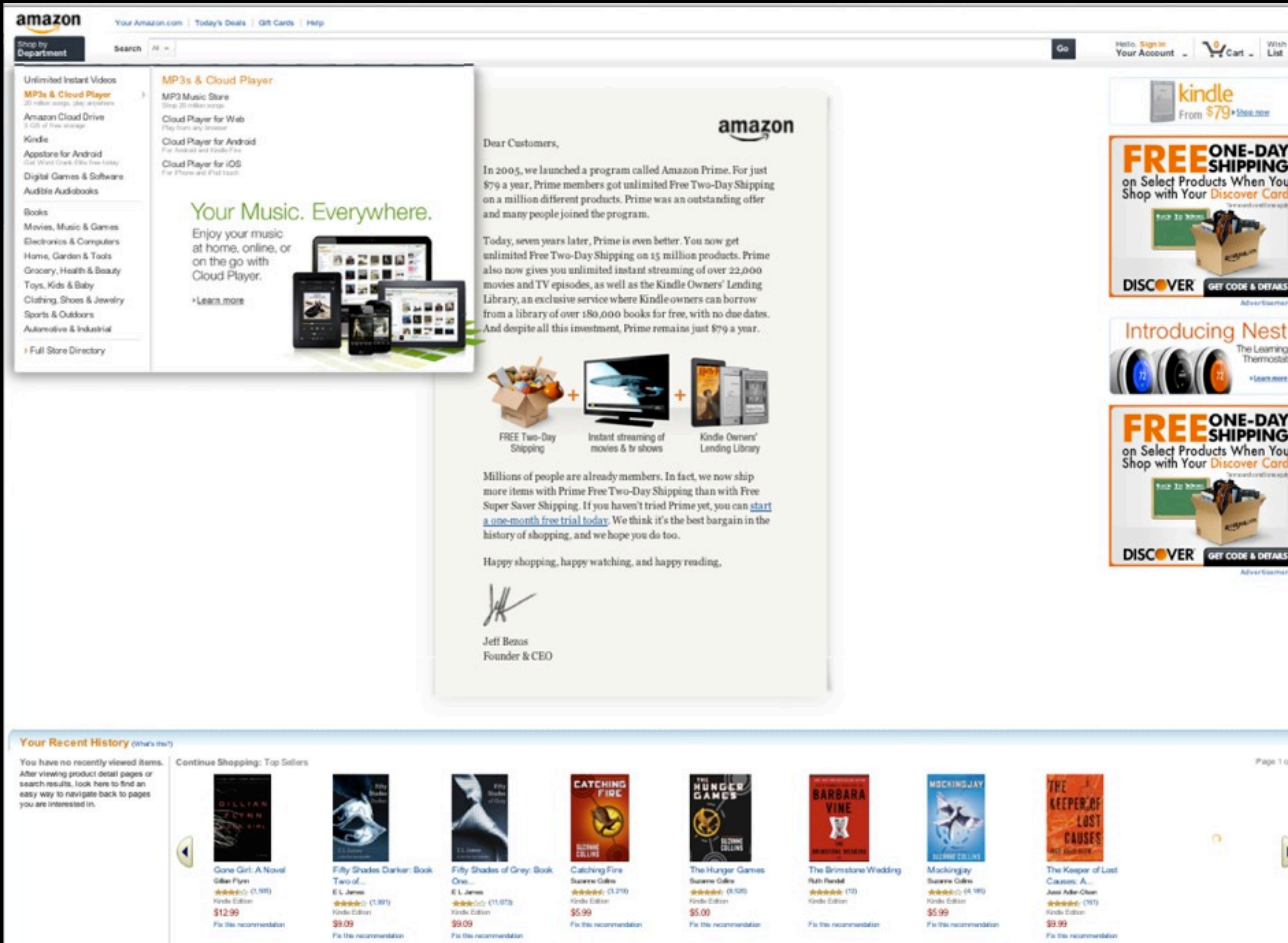
psycho-affective

physiological

- So...going back to the slogan…
- Is recommendation something new?

How about computers?

- Could computers effectively understand your psycho-affective, physiological data (subtle information)?
- Then, could computers offer you something new?
- Look at AMAZON, for instance...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In 2005, we launched a program called Amazon Prime. For just $79 a year, Prime members got unlimited Free Two-Day Shipping on a million different products. Prime was an outstanding offer and many people joined the program.
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- Do computers effectively know you?


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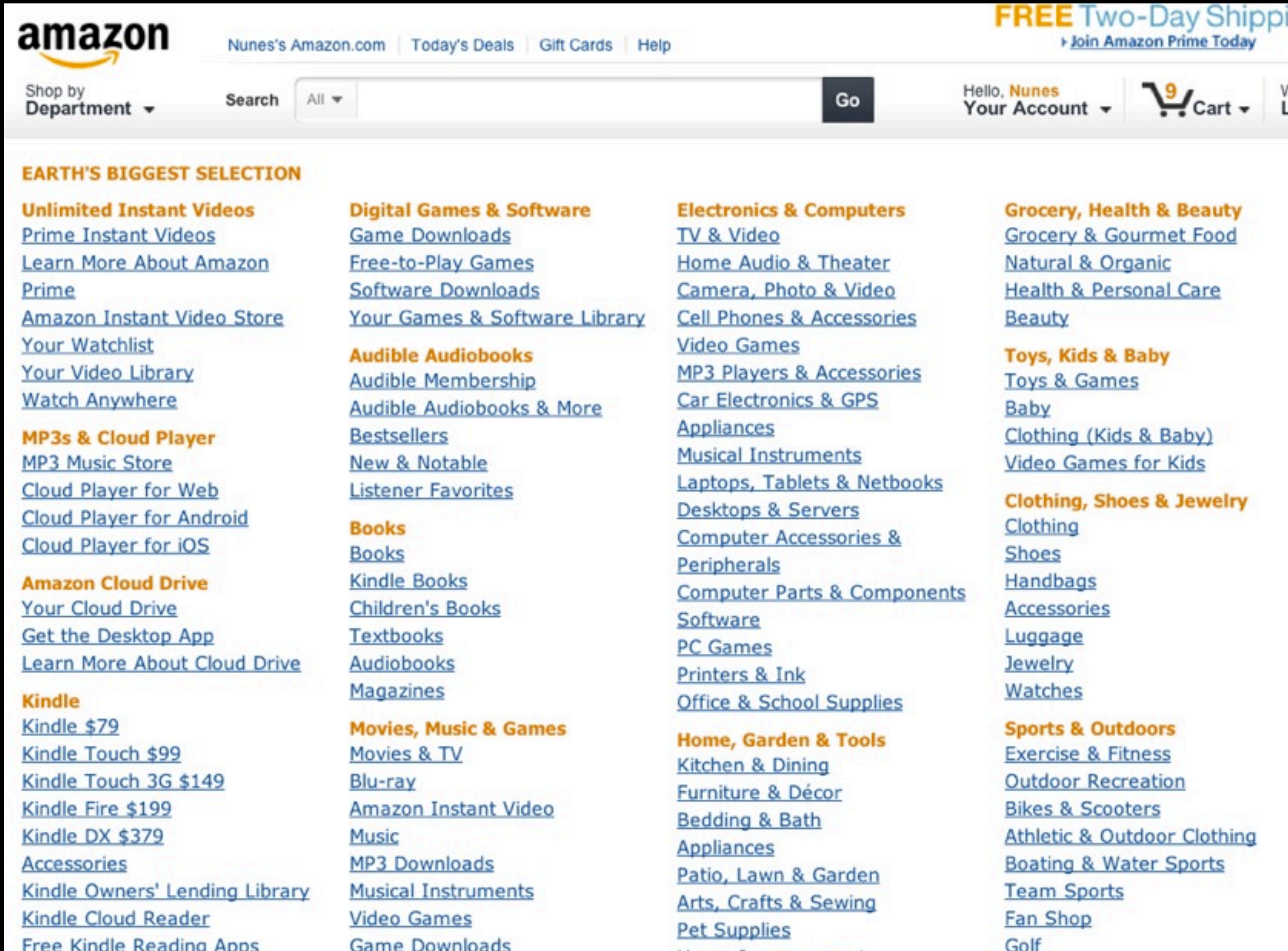
Kindle Help
Kindle Help Home
Get to know your Kindle
Kindle Software Updates
Kindle Troubleshooting

- How much information do computers know about **you**?
    - Do they perceive some subtle information?

How about products?

- How much subtle information does AMAZON know about its **products?**
- How many products does it have in order to match your expectations?
- Are there too much data to analyze and make a good recommendation ???



YES....

OVERLOAD....

Now, Affective Computing comes!!

- in order to improve recommendations, it might treat 2 aspects:
  - tailoring user needs;
  - addressing the cold-start problem;

Affective Computing & Human Decision-Making

AC: what is it about?

[*Picard, 1997*]

- How to recognize/extract emotions;
- how to model emotions;
- how to express emotions;
- how to simulate/feel emotions (robots);
- how induce emotions in humans.

Why use it?

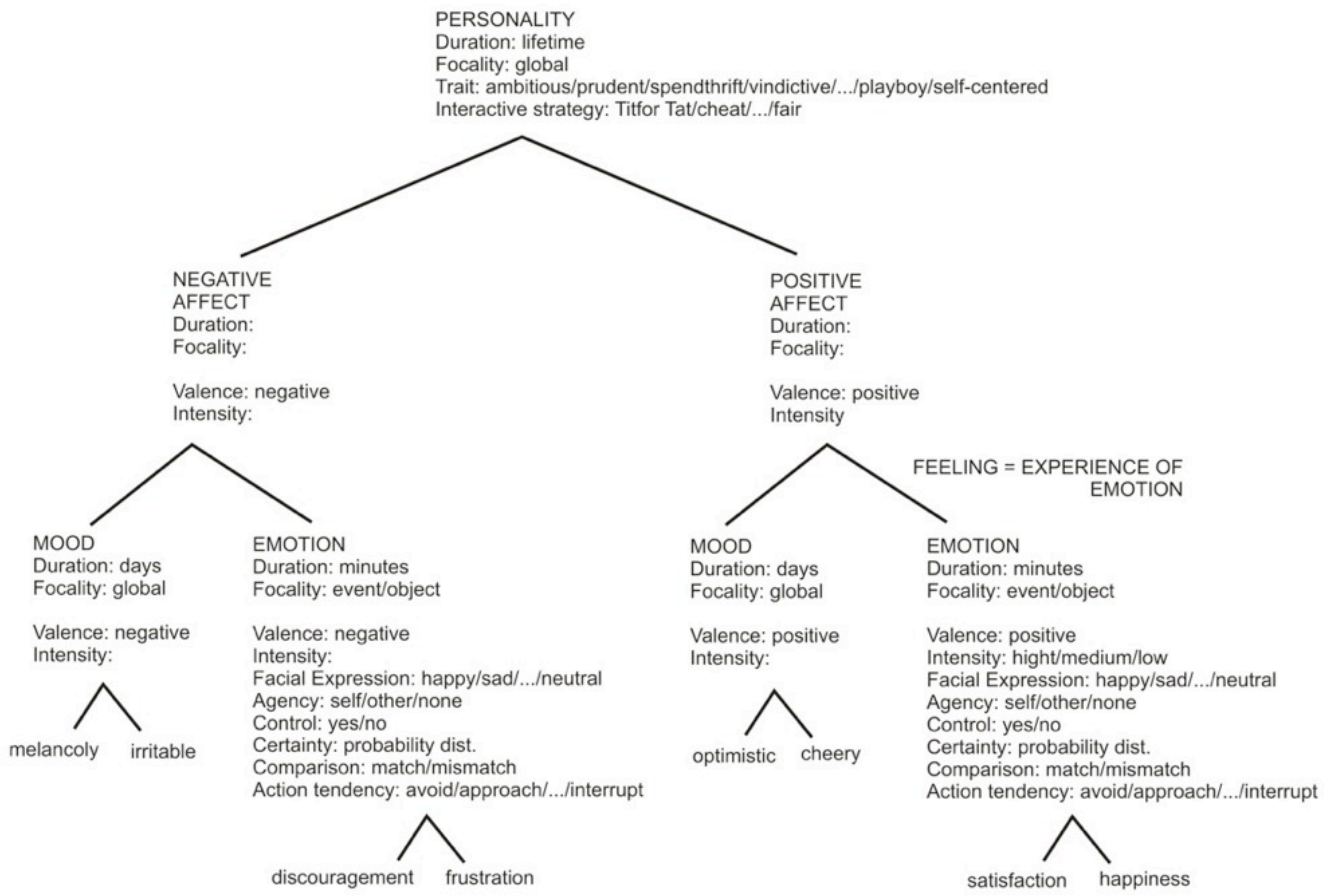
- improve the human-machine interface;
- optimize/personalize human-computer interaction;
- improve the computer decision-making (based on human metaphor);

However...

- metaphorically, think ...
- When you feel some <u>emotion</u> in your life, is it related to some other psychological aspect?
- <u>what aspect?</u>

- Why have psychologists been studying so many psychological aspects including emotion and Affective Computing scientists so few?

- ...such as Personality;
- Unfortunately, Affective Computing scientists started to study personality much later than emotions;
- for instance, *Lisetti [2002]*, describes how important personality is ...



[Lisetti, 2002]

Imagine a shopping scenario

- at a real (physical-offline) shopping center in town:
  - human decision-making;
- at a virtual shop (online)- such as Amazon:
  - computer decision-making;
- How would a vendor personalize and recommend products for you?

- Do computers use this type of information?

Coming back to the Recsys slogan...

- Studies have demonstrated how important psychological aspects of people, such as Personality Traits and Emotions, are during the human decision-making process *[Damasio, 1994; Simon, 1983; Picard, 1997; Trapp at al, 2003 and Thagard, 2006].*

- Is recommender systems, implemented in computers, something new?
  - and, if it uses psychological aspects, such as personality, then, is it new?
- why couldn't we implement in computers a metaphor of the human decision-making process in order to improve personalization, investing in returning clients?

Emotion & Personality

Emotion

- instantaneous;
- short life-time;
- changes constantly;
- dependent on events in the environment;

Personality

- more stable;
- in adulthood, remains stable over a 45-year period;

Emotions

- easy measurable in humans;
- physiological information;
- intrusive methods;
- modeled in computers to improve the user-computer interaction;

Personality

- hard to extract in a short interaction;
- hard to extract from the user intentionally;
- personality implies Emotions;

- Emotion can indicate the user's psychological state (mood) at a given moment ...
- However, it does not give an indication of what kind of product the user might be interested in.

Personality Theory

- does not have a common definition:
  - *Funder [2001]:*
    - human thinking patterns +
    - emotions +
    - behaviors +
    - others psychological mechanisms .

- Many approaches *[Funder, 2001]:*
    - trait approach;
    - biological approach;
    - psychoanalytic approach;
    - phenomenological-humanistic approach;
    - behavioral approach;
    - and cognitive approach.

Trait approach

- differentiates people psychologically by using conceptualized and measurable traits ;
- Traits is a formal way to implement personality in computers;
- more used by computer scientists;

- Allport 1921 = 17,953 traits *[Allport, 1921]*;
  - Cattel proposes 4,500 traits;
  - Later, reduced 99% by orthogonal methods, concluding that only 5 factors were replicable *[Goldberg, 1990]*:
    - the formal beginning of the Big Five [John and Strivastava, 1999].

The Big Five factors/dimensions

- Extraversion;
- Agreeableness;
- Conscientiousness;
- Open to experience;
- Neuroticism.

Big Five Factors	Facet
Extraversion	Warmth Gregariousness Assertiveness Activity Excitement-Seeking Positive Emotions
Agreeableness	Trust Straightforwardness Altruism Compliance Modesty Tender-Mindedness
Conscientiousness	Competence Order Dutifulness Achievement Striving Self-Discipline Deliberation
Neuroticism	Anxiety Angry Hostility Depression Self-Consciousness Impulsiveness Vulnerability
Openness to Experience	Fantasy Aesthetics Feelings Actions Ideas Values

- personality might predict emotion:
  - look at:
    - Extraverts:

Your score on Extraversion is high, indicating you are sociable, outgoing, energetic, and lively. You prefer to be around people much of the time.

Extraversion Facets

* *Friendliness.* Friendly people genuinely like other people and openly demonstrate positive feelings toward others. They make friends quickly and it is easy for them to form close, intimate relationships. Low scorers on Friendliness are not necessarily cold and hostile, but they do not reach out to others and are perceived as distant and reserved. Your level of friendliness is average.

* *Gregariousness.* Gregarious people find the company of others pleasantly stimulating and rewarding. They enjoy the excitement of crowds. Low scorers tend to feel overwhelmed by, and therefore actively avoid, large crowds. They do not necessarily dislike being with people sometimes, but their need for privacy and time to themselves is much greater than for individuals who score high on this scale. Your level of gregariousness is high.

    - *but «context-aware» [Ricci, 2012];*

Computational Personality Acquisition methods

- Explicit methods:
  - test-based (questionnaire-based);
  - story-based;
- Implicit methods:
  - text-based;
  - keyboard-based;
  - kinect-based;

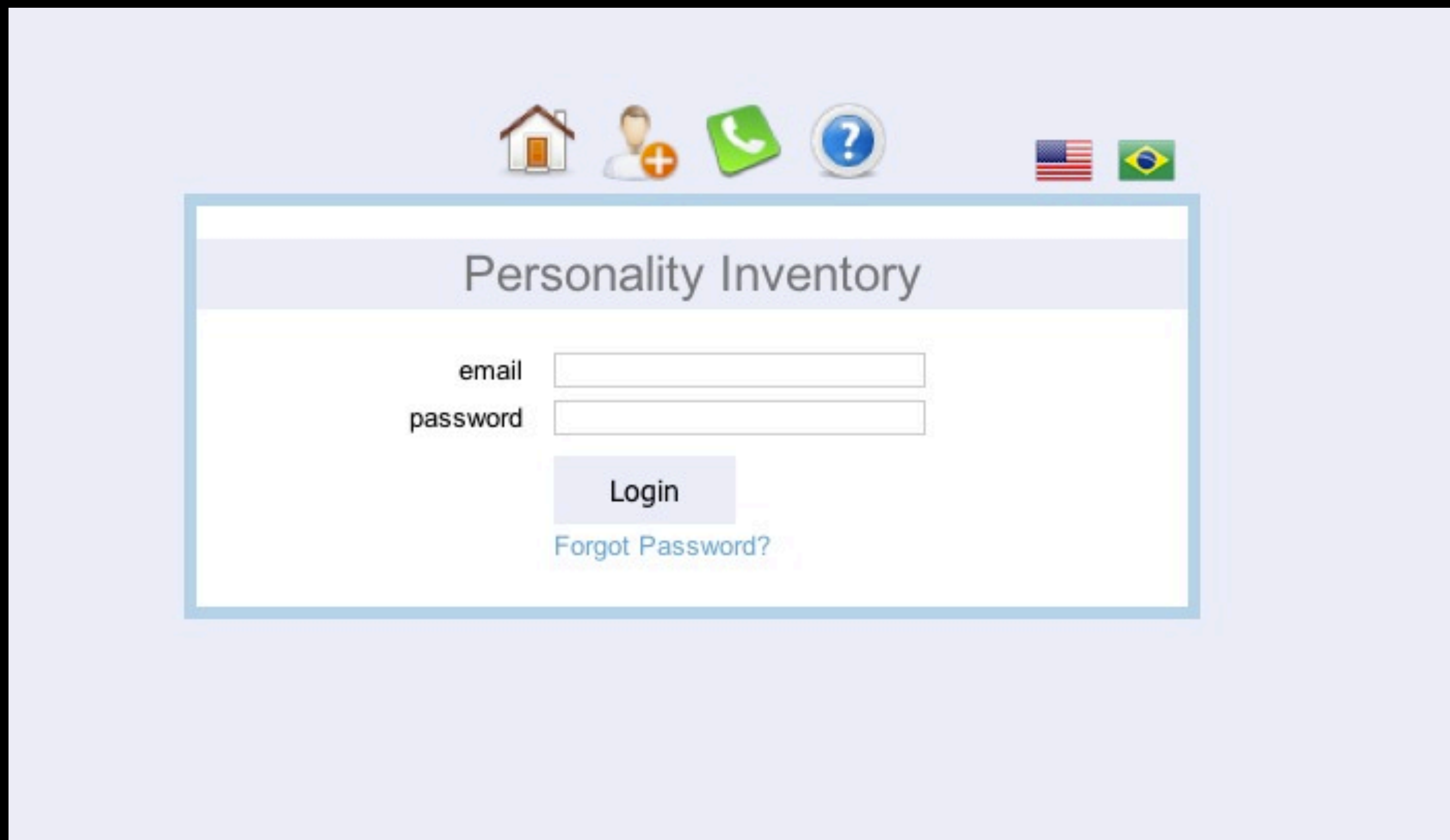
Personality: test-based

- computer narrative:
  - set of traits;
  - differentiates someone from another;
- many inventories are based on the Big Five:

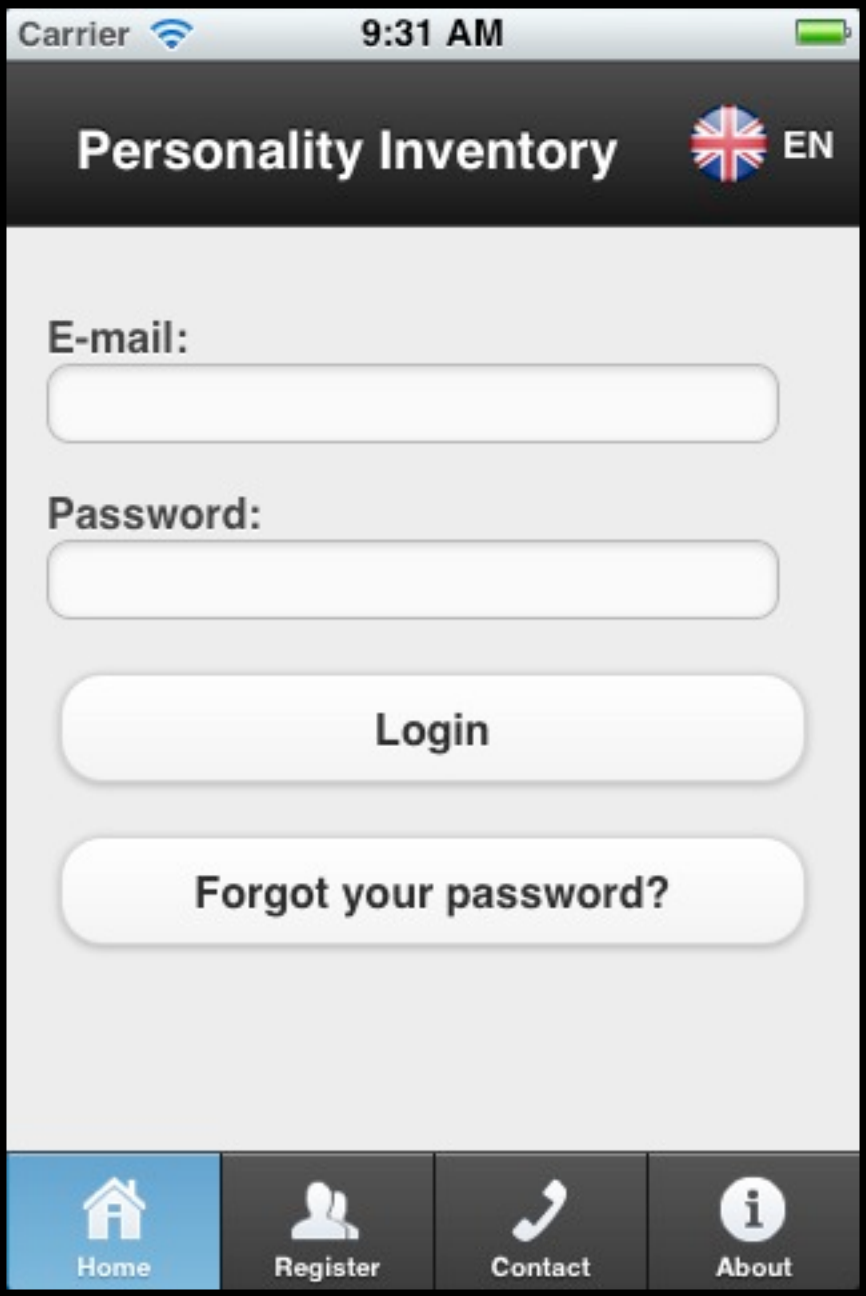
- 240-items NEO-PI-R (Revised NEO Personality Inventory) *[Costa and MCrae,1992];*
- 300-items NEO-IPIP (International Personality Item Pool, Neuroticism-Extroversion-Openness Personality Inventory) *[Johnson, 2000; Johnson, 2005]*. IPIP Consortium *[Goldberg, 1999];*
  - 5 Big Five factors + 30 facets;
- ......
- 10-items TIPI (Ten-Item Personality Inventory) *[Gosling et al, 2003];*
  - 5 Big Five factors;
    - *psychometric quality different from the bigger one;*

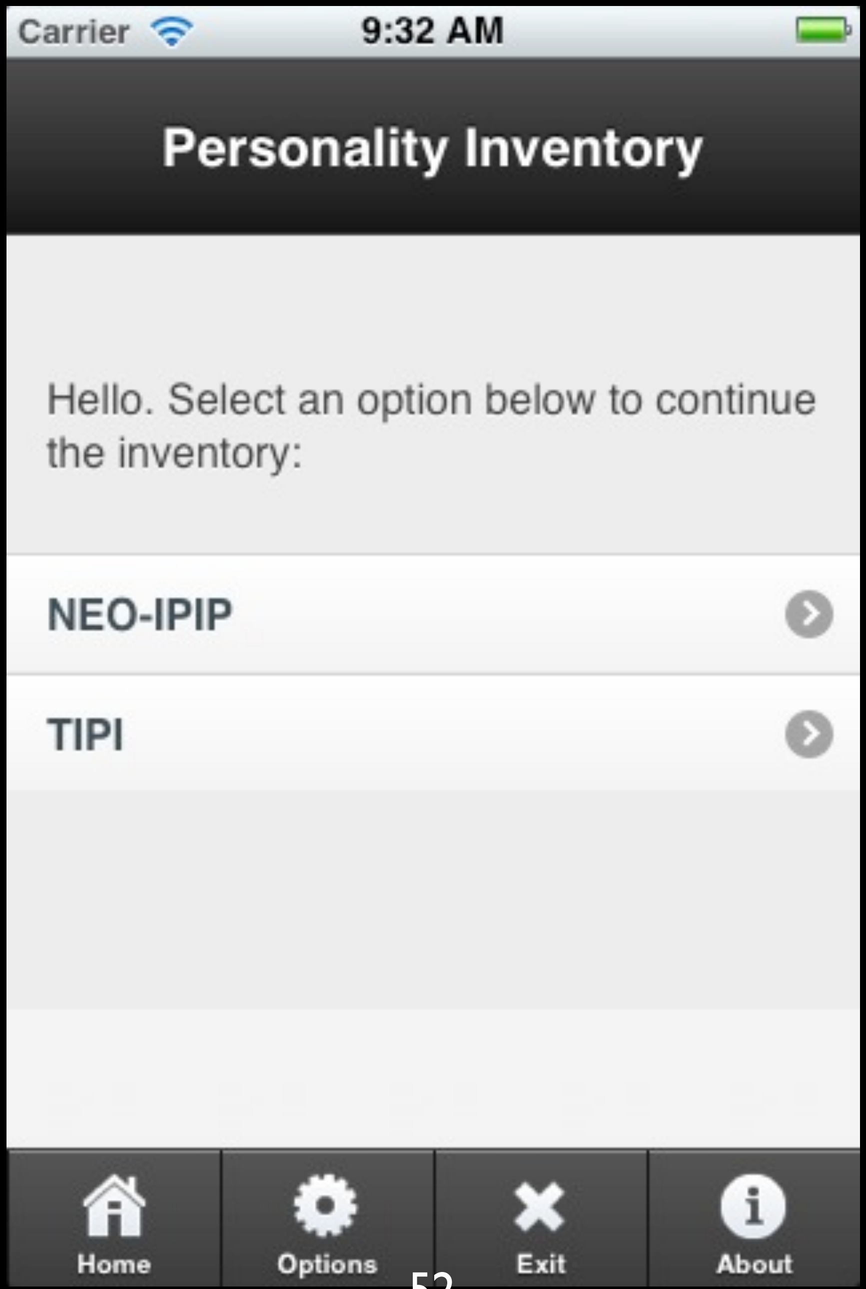
NEO-IPIP and TIPI - Universidade Federal de Sergipe's Version

Old web version:



- new Mobile based version





PersonalityML

Personality: story-based

- stories that represent the Big Five traits (polarized model : high & low);
  - based on 20 item from IPIP;
  - *[Dennis et al, 2012]* parlty satisfied with the results;

Openness to Experiences (V)

High

Oliver believes in the importance of art and has a vivid imagination. He tends to vote for liberal political candidates. He enjoys hearing new ideas and thinking about things. He enjoys wild flights of fantasy, getting excited by new ideas.

- http://homepages.abdn.ac.uk/m.dennis/pages/w/?page_id=231

- We are working on transforming the NEO-IPIP and TIPI into a « story » (such as we did in the «comic book»)

Personality: text-based

- Psychologists said that language can be used as a psychological marker [*Pennebaker et al, 2002*];
- then, *Mairesse et al [2007]* developed the Personality Recognizer that extracts information from the way people use words (personality cues);

- How did Mairesse develop his experiment?
  - collects individual corpora;
  - extracts relevant features from texts based on LIWC (a Dictionary-based identification, created for the Linguistic Inquiry and Word Count- LIWC- program and Medical Research Council (MRC) Psycholinguistic database dictionary);
  - collects associated personality ratings (based on NEO-PI-R- Big Five factors);

- builds statistical models of personality ratings;
- uses regression algorithms to estimate the scores of Big Five Personality Traits

- http://people.csail.mit.edu/francois/research/personality/demo.html

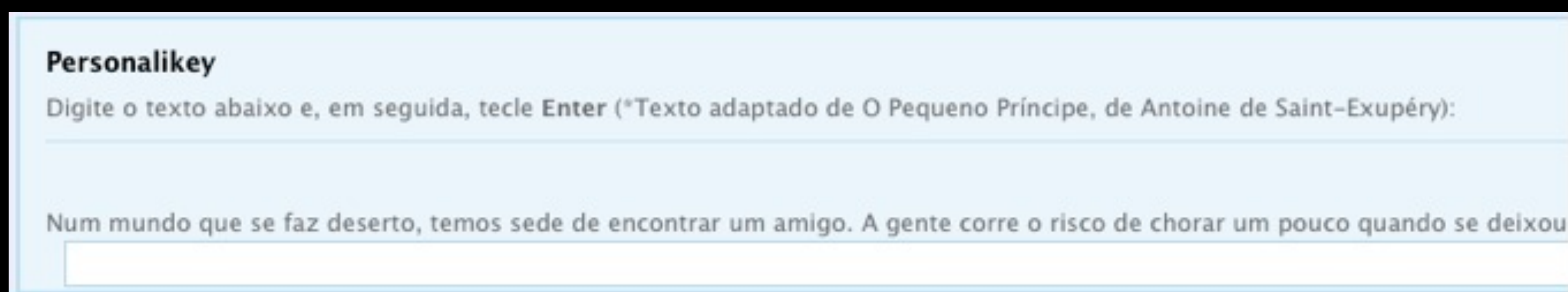
- *Minamikawa and Yokoyama [2011]:*
  - create a tool to extract personality from Japanese blogs in order to recommend groups:
    - use Multinomial Naïve Bayes;
    - use an Egogram (integrative approach from psychology and psychotherapy (psychoanalytic, humanist and cognitive approaches));

- *Nunes et al at UFS:*
  - we are doing a portuguese version of Personality Recognizer:
    - LIWC, WordNet (not good in portuguese);
    - Onto.PT (http://ontopt.dei.uc.pt/)

Personality: keyboard-based

- *Gosling [2008]* said that individuals consciously and unconsciously leave traces of their individuality in the spaces around them;
- Why not by keyboard typing?
- *Montalvão and Freire [2006*] said that each person has his own typing pattern;

- *Porto and Costa [2011]* developed an experiment to recognize human personality by using typing patterns:
  - extract the user's typing rhythm (KeyPress, «hold time», keyDown, keyUp)



  - collect associated personality ratings from NEO-IPIP;
  - apply a clustering technique to match the typing rhythm and personality;

- We did 5 experiments:
  - from 282 to 85 participants;
  - we find some correlation in 10 facets;
  - more results to be published;

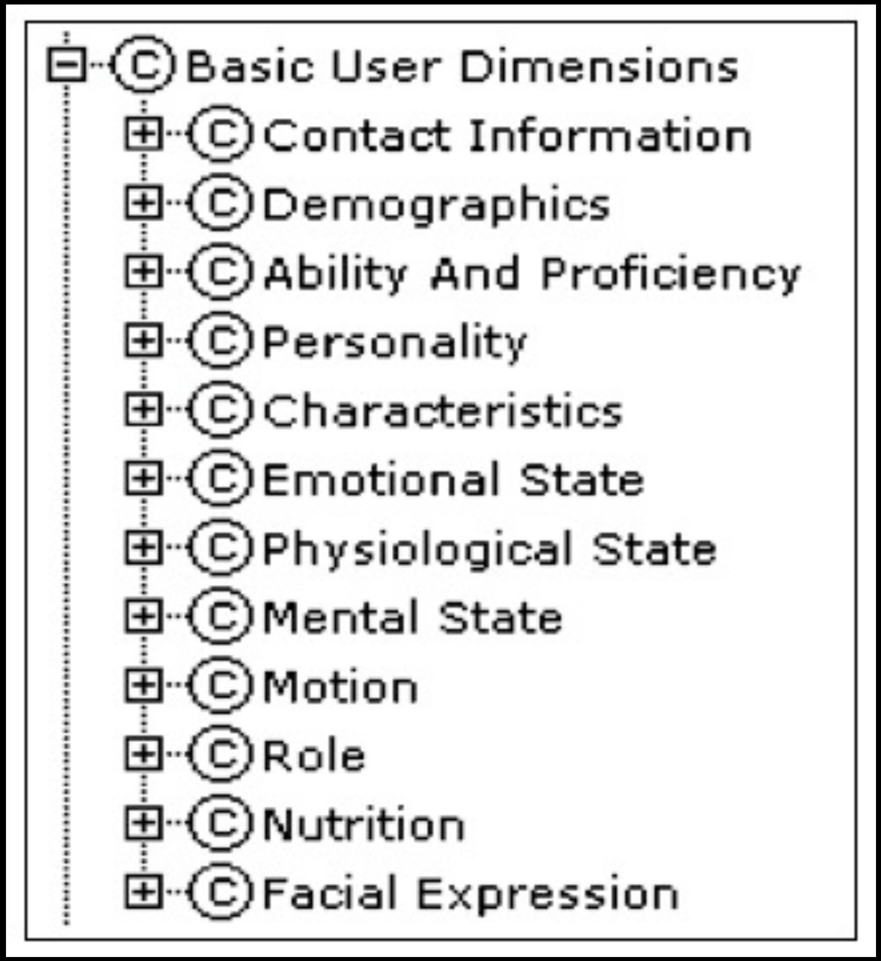
Personality Profile representation and standardization

How do we represent and store the Personality extracted before?

- Identitiy from the real world is stored in virtual world as an User profile;
- However, can the traditional “Profile” store the psychological aspects, such as personality?

yes !!!

- GUMO Ontology- [*Heckmann, 2005*];



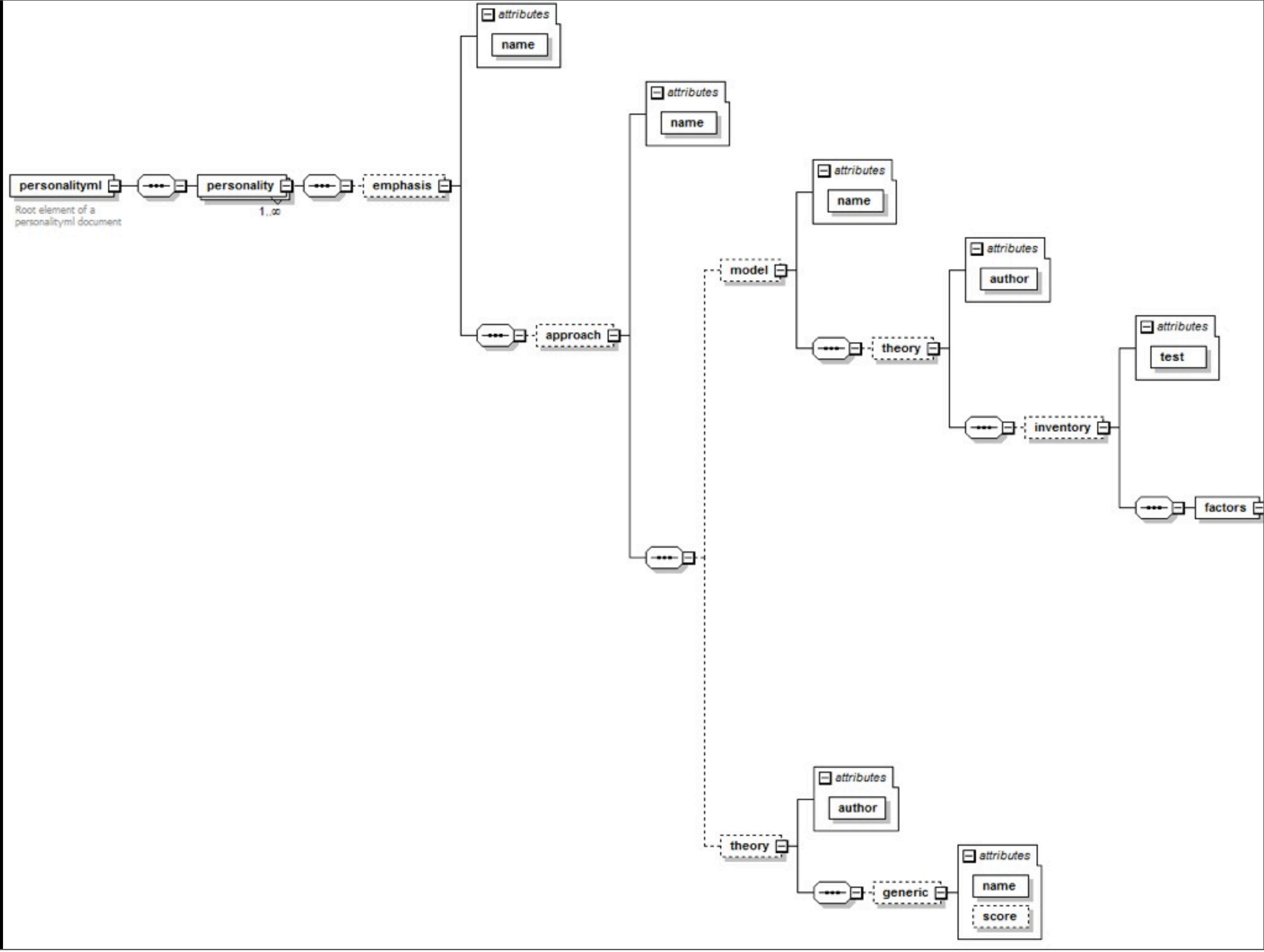
- Personality
  - MyersBriggs Type Inventory
    - Introvert versus Extravert
    - Sensor versus Intuiter
    - Thinker versus Feeler
    - Judger versus Perceiver
  - Eysencks Three Factor PEN Model
    - Normality - Psychoticism
    - Introversion - Extraversion
    - Stability - Neuroticism
  - Five Factor Model
    - Extraversion-Energy-Enthusiasm
    - Agreeableness-Altruism-Affection
    - Conscientiousness-Control-Costraint
    - Neuroticism-NegativeAffectivity-Nervousness
    - Openness-Originality-OpenMindedness
  - extravert
  - introvert
  - thinking
  - feeling
  - sensing
  - intuiting
  - judging
  - perceiving
  - controled
  - optimistic
  - pessimistic
  - tempered
  - neurotic
  - agreeable
  - open-minded
  - intelligent
  - excessiv
  - indulgent

- Characteristics
  - talkative
  - assertive
  - dominant
  - quiet
  - reserved
  - shy
  - retiring
  - sympathetic
  - kind
  - warm
  - helpful
  - fault-finding
  - cold
  - unfriendly
  - organized
  - thorough
  - efficient
  - careless
  - disorderly
  - frivolous
  - tense
  - anxious
  - moody
  - worrying
  - stable
  - calm
  - contented
  - imaginative
  - artistic
  - inventive
  - commonplace
  - cooperative

- GUMO (Generic User Model)-2005. Unfortunately, people do not effectively use it;
- UPP - User Psychological Profile-2007:
  - used in Recommender Systems *[Nunes, 2008]*;
- how about the standardization?

PersonalityML

- ? comes to standardize the representation of Personality;
- ? XML based;
- ? recommender inputs;
- ? ...



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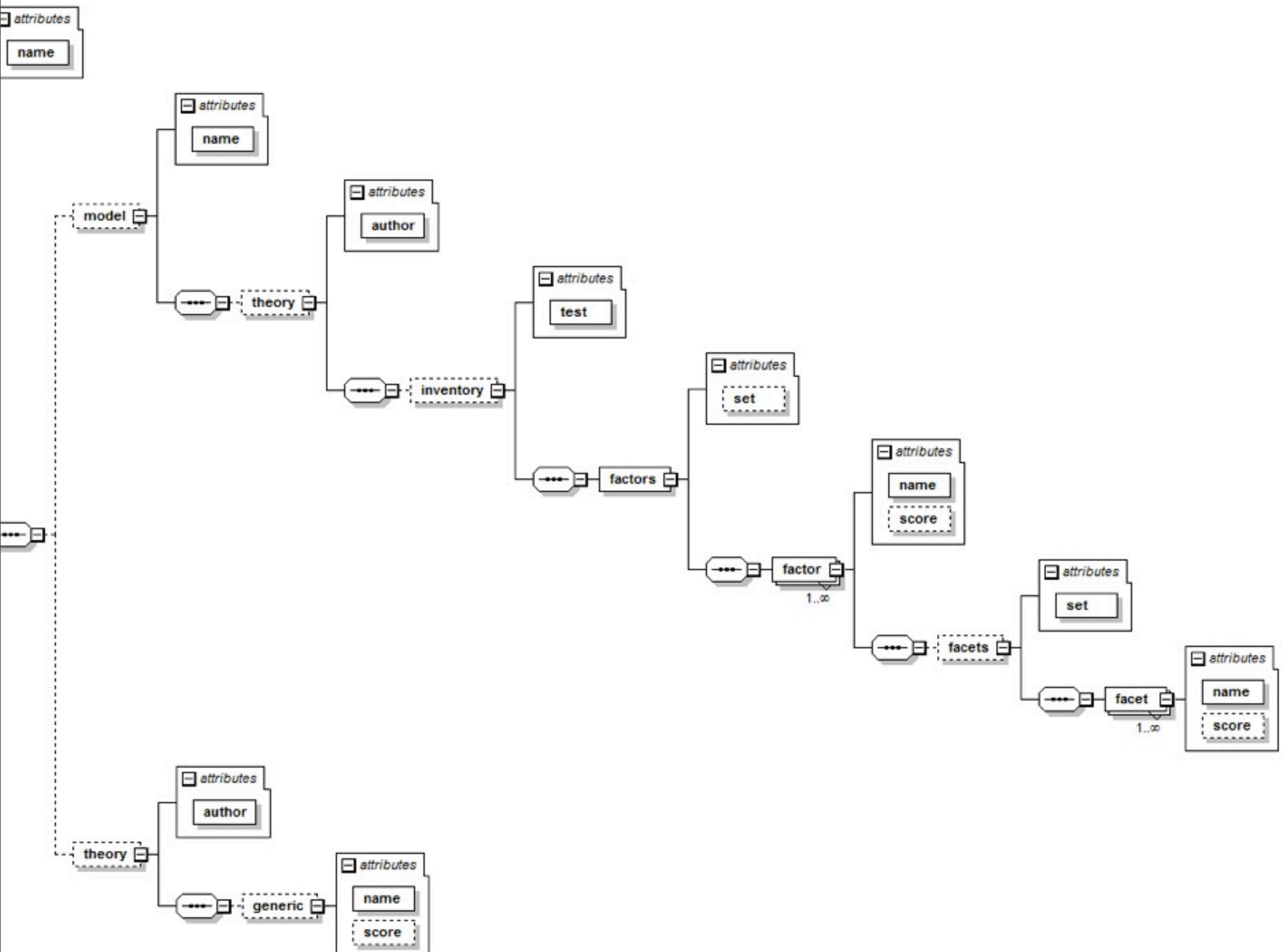
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- availabe at www.personalityresearch.com.br
    - Personality ML Structure;
    - xsd;
    - “comic book”.

Personality-based Recommender Systems

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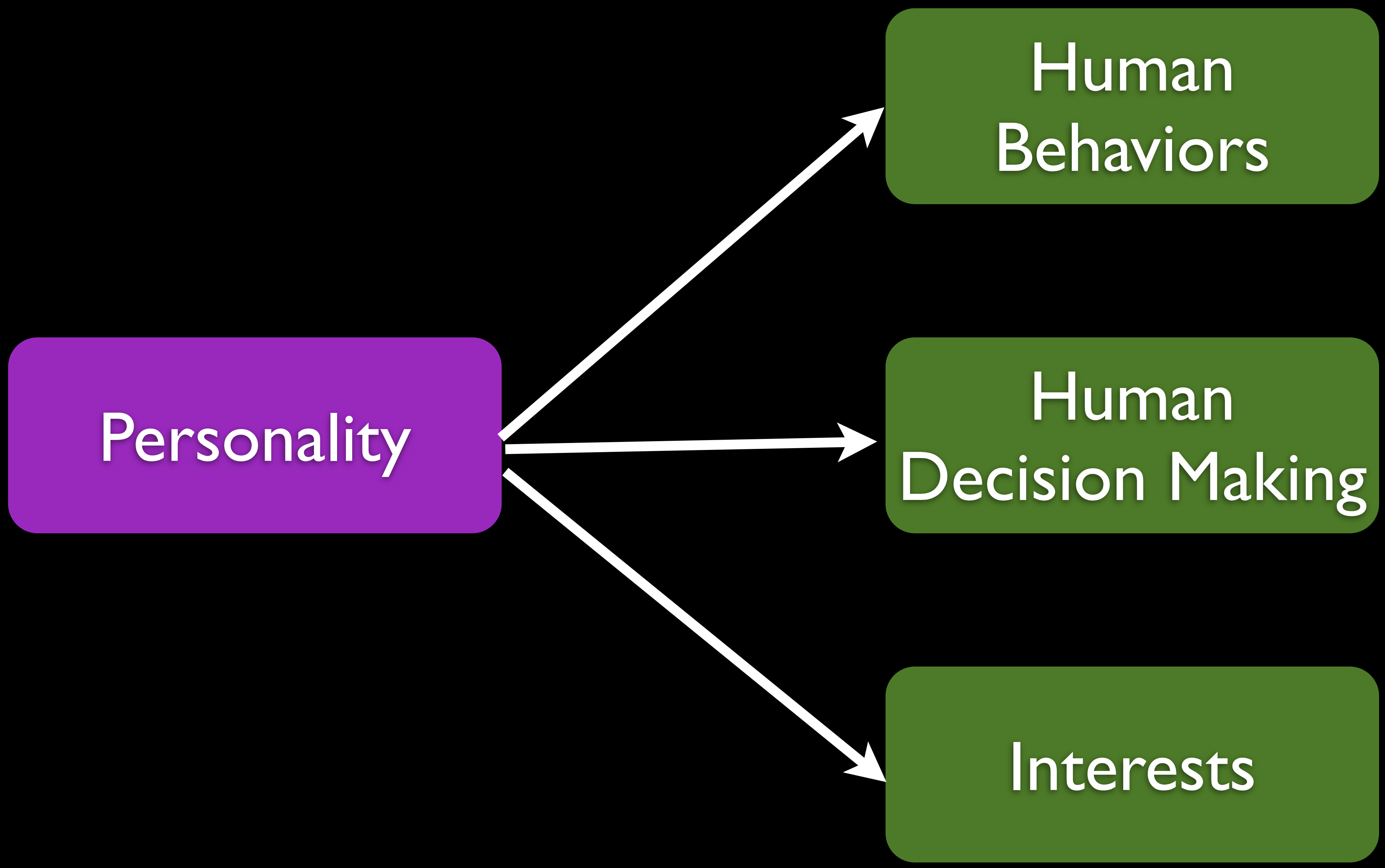
Outline

- Personality-based recommender technologies and systems
- User perception issues
- Conclusions
- Future research and application directions

Motivation


Personality
Human Behaviors
Human Decision Making
Interests

- How to use personality in **recommender Systems**?

- How about **user experience**?

PBRS Technologies

Personality Acquisition	User Modeling
Recommendation Generation	User Perception

PBRS Technologies

Personality Acquisition

User Modeling

Recommendation Generation

User Perception

PBRS Technologies

Personality Acquisition	User Modeling
Recommendation Generation	User Perception

Personality in social matching system

PB Social Matching System

PB Social Matching System

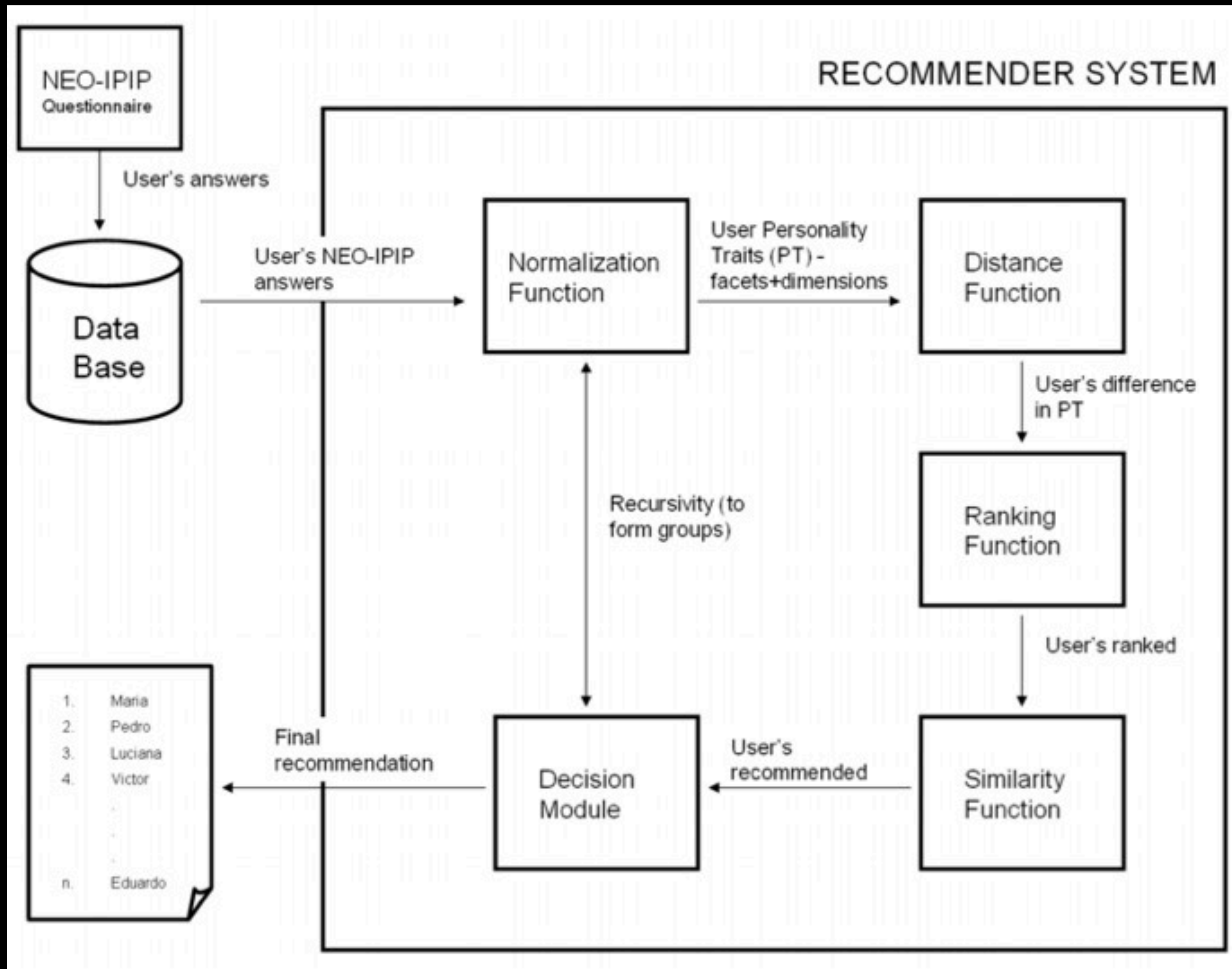
PB Social Matching System

The psychological literature indicates there is a strong relationship between personality similarity and attraction.

People prefer to interact with others who have similar Personality.

[Nass and Lee, 2000; Reeves and Nass, 1996]

PB Social Matching System



[Nunes, 2008]

Recommending President

- Recommending a "French Presidential candidate" based on psychological reputation of presidential candidates (December 2006 - July 2007, covering the Elections for President in France)

Ségolène Royal

Nicolas Sarkozy

Recommending President

Table 4.1: Results of experiment 1

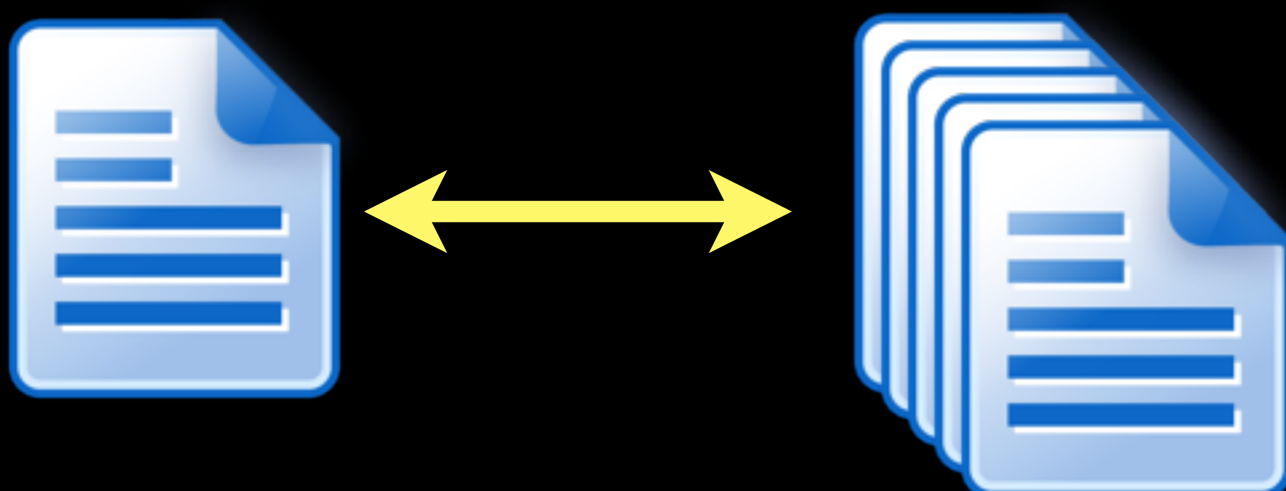
	Participants	Real Vote	First Recommendation: based on 30 facets	Second Recommendation: based on Big Five
1	User 46	Ségolène Royal	Ségolène Royal	Ségolène Royal
2	User 173	Ségolène Royal	Ségolène Royal	Ségolène Royal
3	User 174	Ségolène Royal	Ségolène Royal	Ségolène Royal
4	User 172	Ségolène Royal	Ségolène Royal	Ségolène Royal
5	User 166	Ségolène Royal	Ségolène Royal	Ségolène Royal
6	User 154	Ségolène Royal	Ségolène Royal	Ségolène Royal
7	User 180	Nicolas Sarkozy	Nicolas Sarkozy	Nicolas Sarkozy
8	User 168	Nicolas Sarkozy	Nicolas Sarkozy	Nicolas Sarkozy
9	User 171	Ségolène Royal	Ségolène Royal	Nicolas Sarkozy
10	User 49	Nicolas Sarkozy	Nicolas Sarkozy	Ségolène Royal

Personality in content-based information filtering systems

Temperament-based Filtering

[Lin and McLeod, 2002]

Temperament-based Filtering

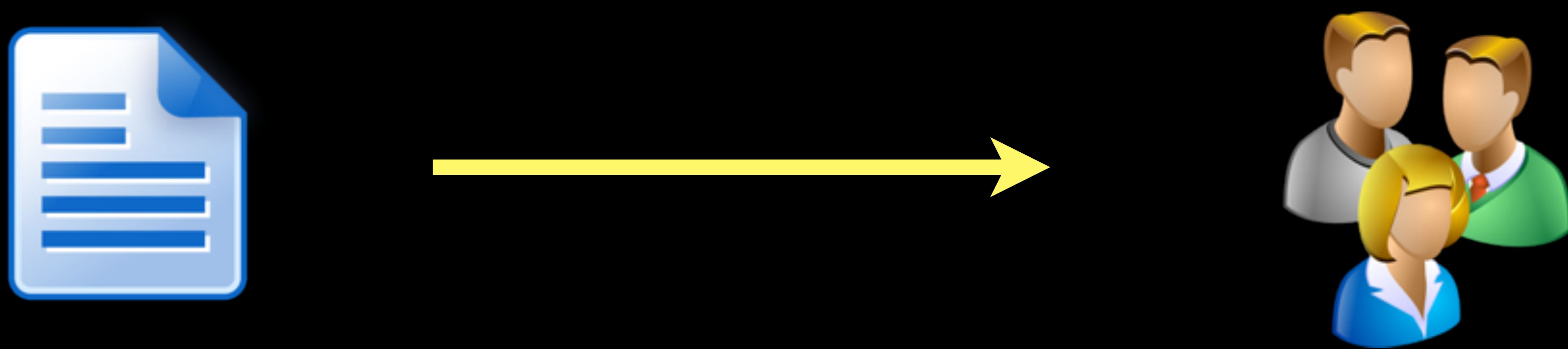


[Lin and McLeod, 2002]

Temperament-based Filtering

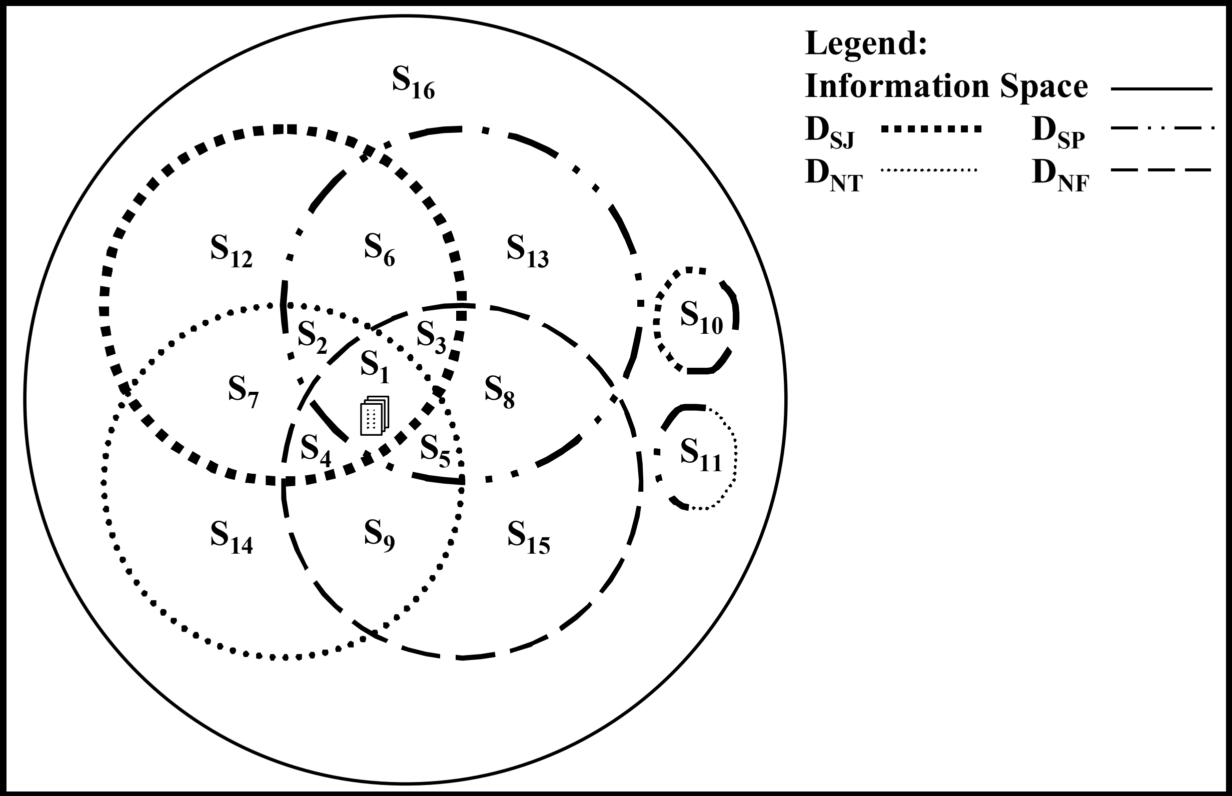
[Lin and McLeod, 2002]

Temperament-based Filtering



[Lin and McLeod, 2002]

Temperament-based Filtering



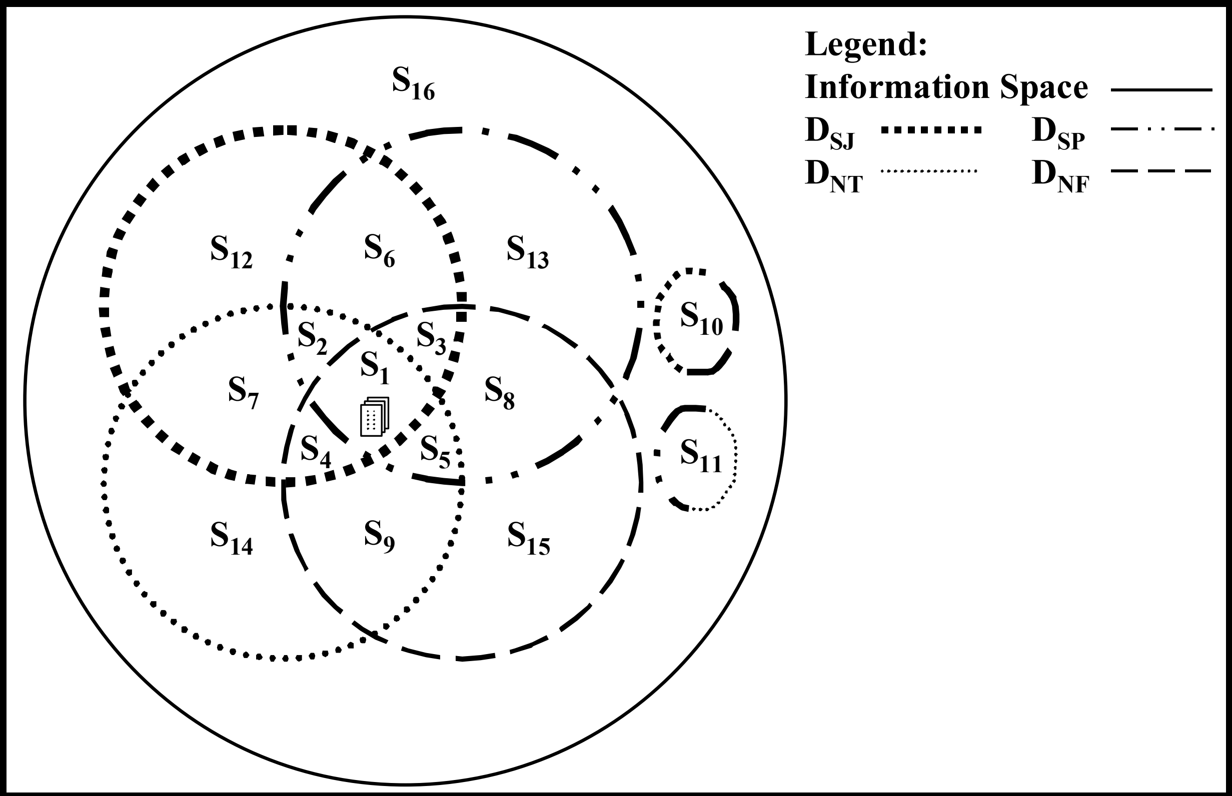
Segments of a sample information space

1. Segment information into subspaces based on temperaments
2. To reduce the size of comparisons when searching within a segment, segments are clustered by content-based approach.
3. Infer the target segment and cluster

$$(S_{target}, C_{target}) = \arg\max_{s \in S, c \in C_s} Pop(V_c, V_k)$$

$$Pop(V_c, V_k) = e_c\, Sim(V_c, V_k)$$

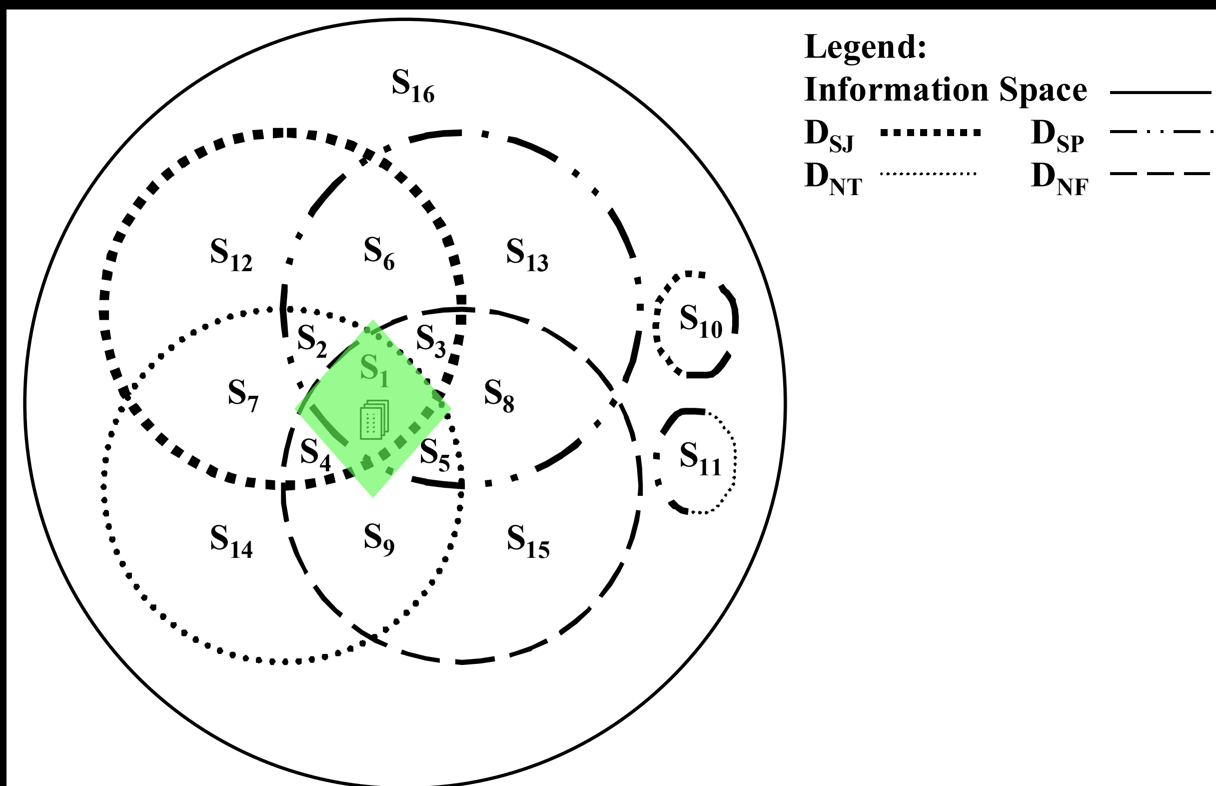
Temperament-based Filtering



Segments of a sample information space

- More than 85% of the user population would be better satisfied.

Temperament-based Filtering



Segments of a sample information space

- More than 85% of the user population would be better satisfied.
- Address the new user problem

Personality in collaborative filtering systems

Personality-based CF

- Rating-based Similarity
  - Neighborhood Formation (e.g., Pearson Correlation)

$$simr(u,v) = \frac{\sum_{i \in I_u \cap I_v} (r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (r_{u,i} - \bar{r}_u)^2 (r_{v,i} - \bar{r}_v)^2}}$$

  - Rating Prediction

$$\tilde{r}_{u,i} = \bar{r}_u + \kappa \sum_{v \in \Omega_u} simr(u,v)(r_{v,i} - \bar{r}_v)$$

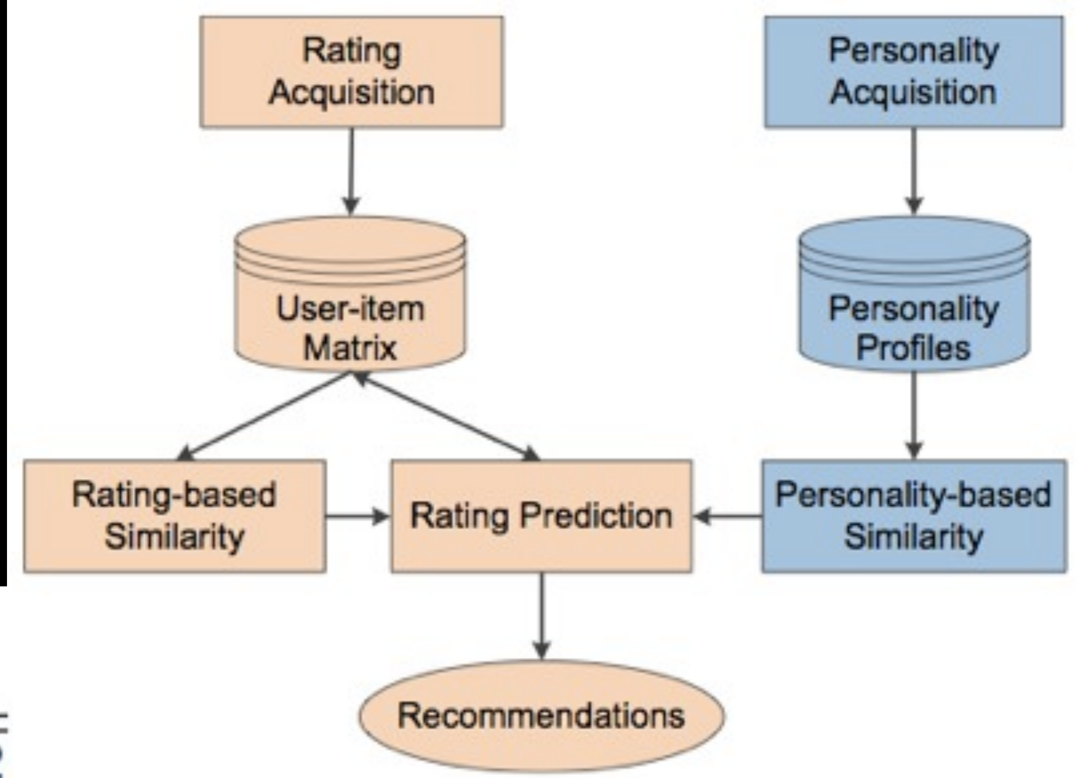
Personality-based CF

Is it possible to use human personality characteristics to alleviate the cold-start problem in CF?

Personality-based CF

- Personality-based CF
  - Personality characteristics are used to calculate the similarity of users

$$simp(u,v) = \frac{\sum_k \left(p_u^k - \bar{p_u}\right)\left(p_v^k - \bar{p_v}\right)}{\sqrt{\sum_k \left(p_u^k - \bar{p_u}\right)^2 \sum_k \left(p_v^k - \bar{p_v}\right)^2}}$$



The overall proposed CF model.

- Linear Hybrid CF

$$sim(u,v) = \alpha * simr(u,v) + (1-\alpha) * simp(u,v)$$

[Rong and Pu, 2011]

Personality-based CF

- Cascade Hybrid CF

$$r'_{u,i} = \begin{cases} r_{u,i} & \text{if rating for item } i \text{ has been provided by user } u \\ \tilde{r}_{u,i} & \text{otherwise} \end{cases}$$

$$\tilde{r}_{u,i} = \bar{r}_u + \kappa \sum_{v \in \Omega_u} simp(u, v)(r_{v,i} - \bar{r}_v)$$

	user 1	user 2	user 3	user 4
item 1	1		0	
item 2		0		1
item 3	0			1
item 4		1		0

Personality-based CF

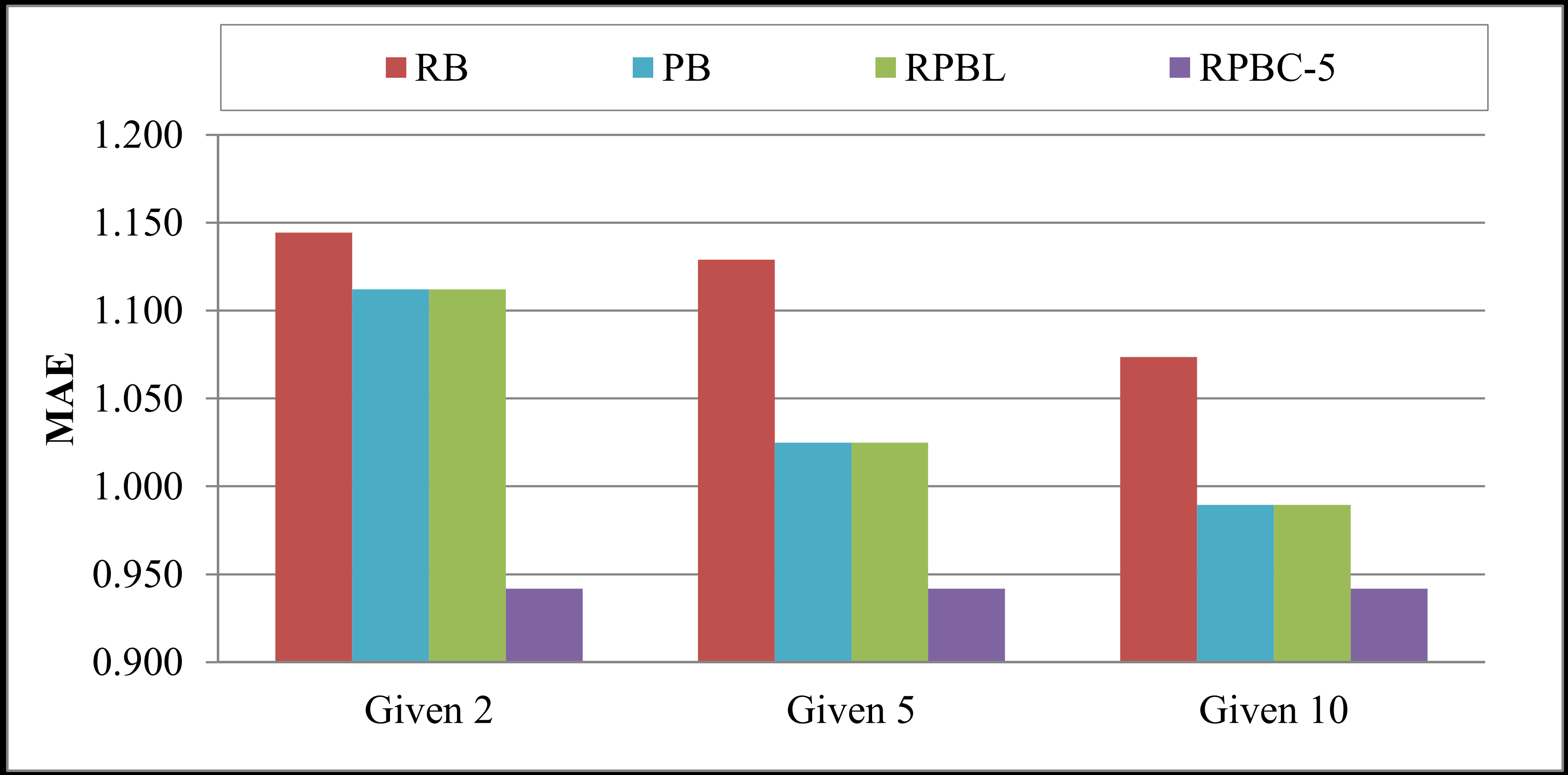
- Cascade Hybrid CF

$$r'_{u,i} = \begin{cases} r_{u,i} & \text{if rating for item } i \text{ has been provided by user } u \\ \tilde{r}_{u,i} & \text{otherwise} \end{cases}$$

$$\tilde{r}_{u,i} = \bar{r}_u + \kappa \sum_{v \in \Omega_u} simp(u, v)(r_{v,i} - \bar{r}_v)$$

	user 1	user 2	user 3	user 4
item 1	1	1	0	0
item 2	0	0	1	1
item 3	0	0	1	1
item 4	1	1	0	0

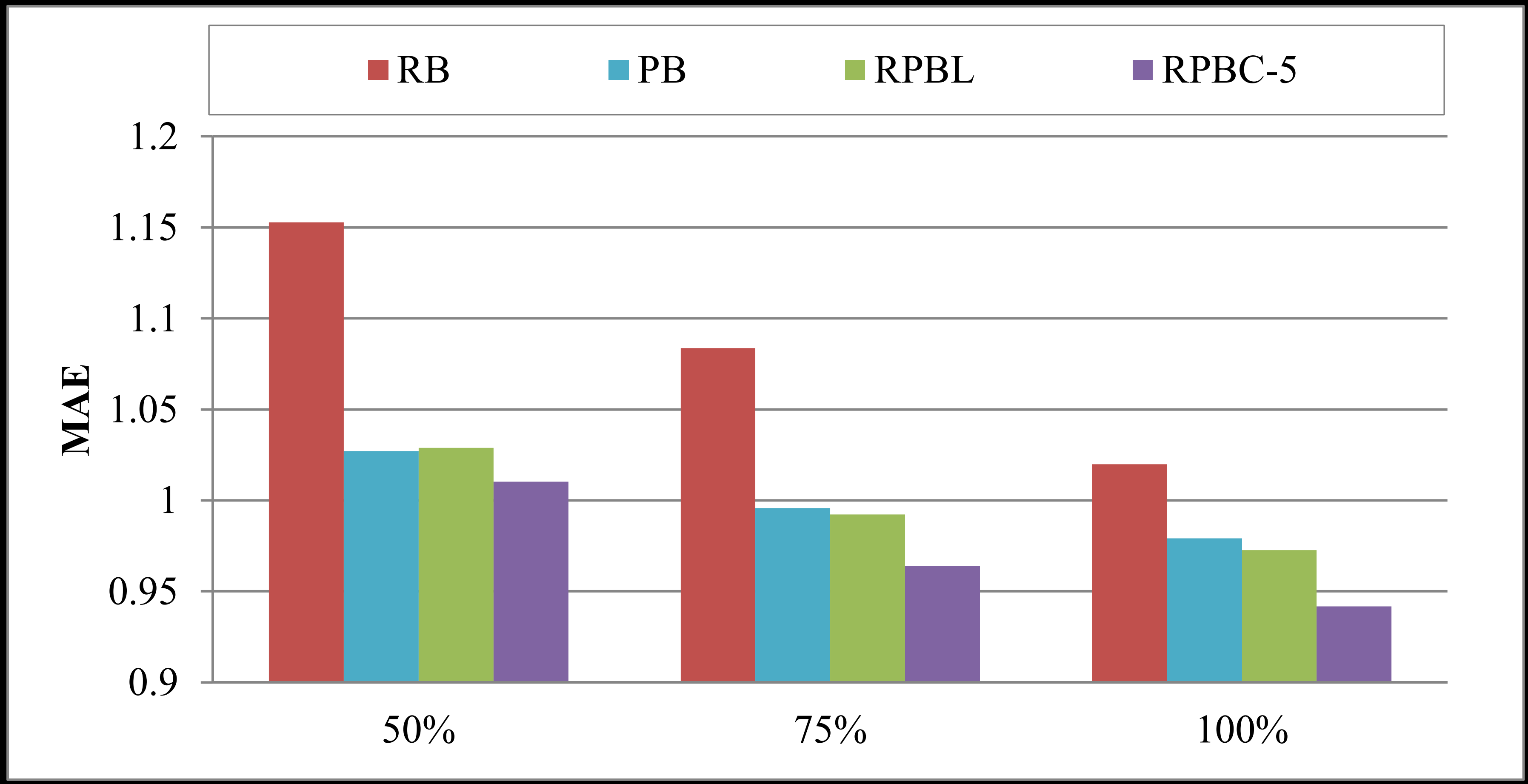
Results



Prediction performances in the scenario of ***new user***

(RB: rating based CF, PB: personality based CF, RPBL: rating-personality based linear hybrid approach, RPBC-5: rating-personality based cascade hybrid approach with β = 5)

Results

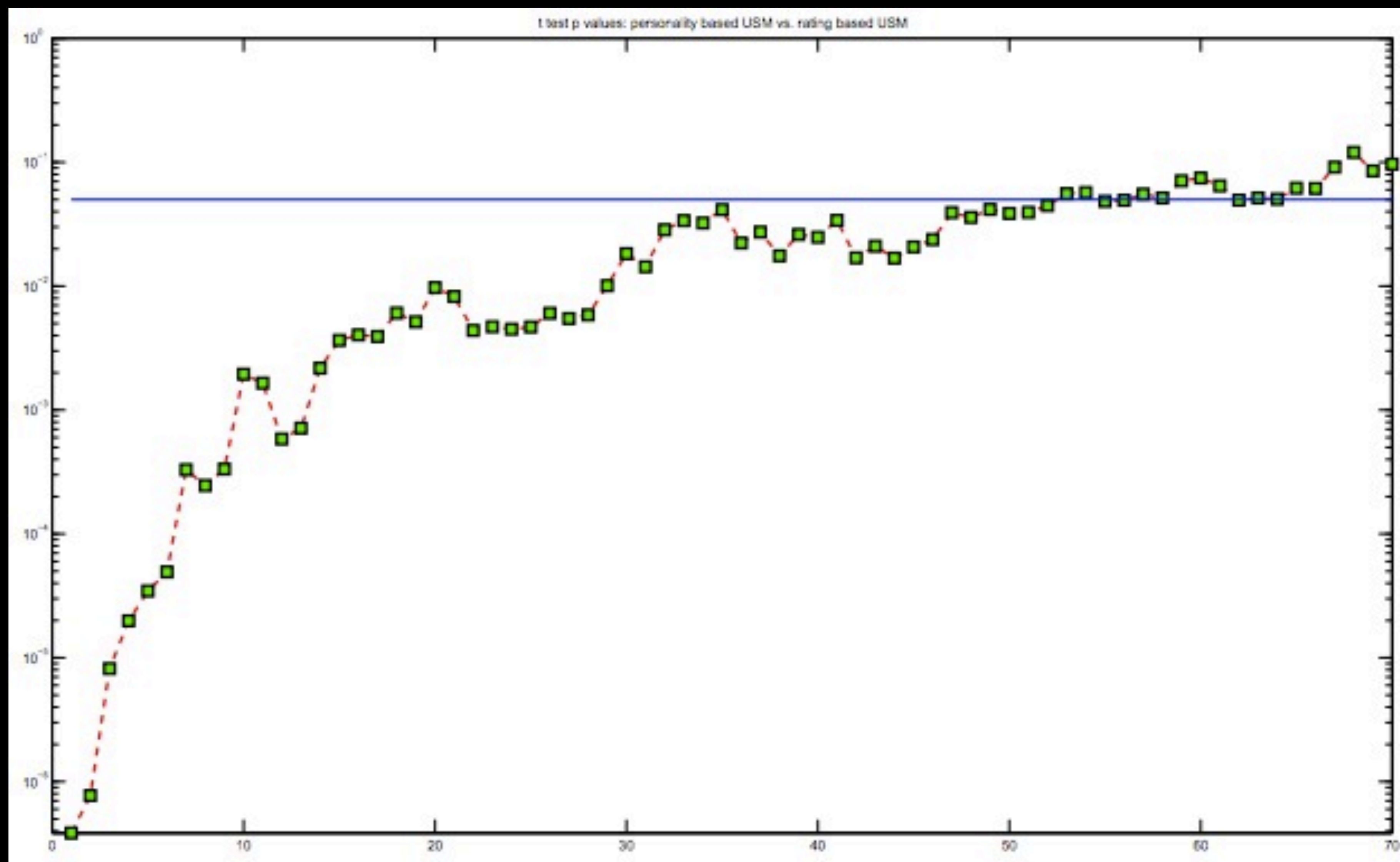


Prediction performances in the scenario of ***sparse dataset***

(RB: rating based CF, PB: personality based CF, RPBL: rating-personality based linear hybrid approach, RPBC-5: rating-personality based cascade hybrid approach with β = 5)

New User Problem Period (CSP)

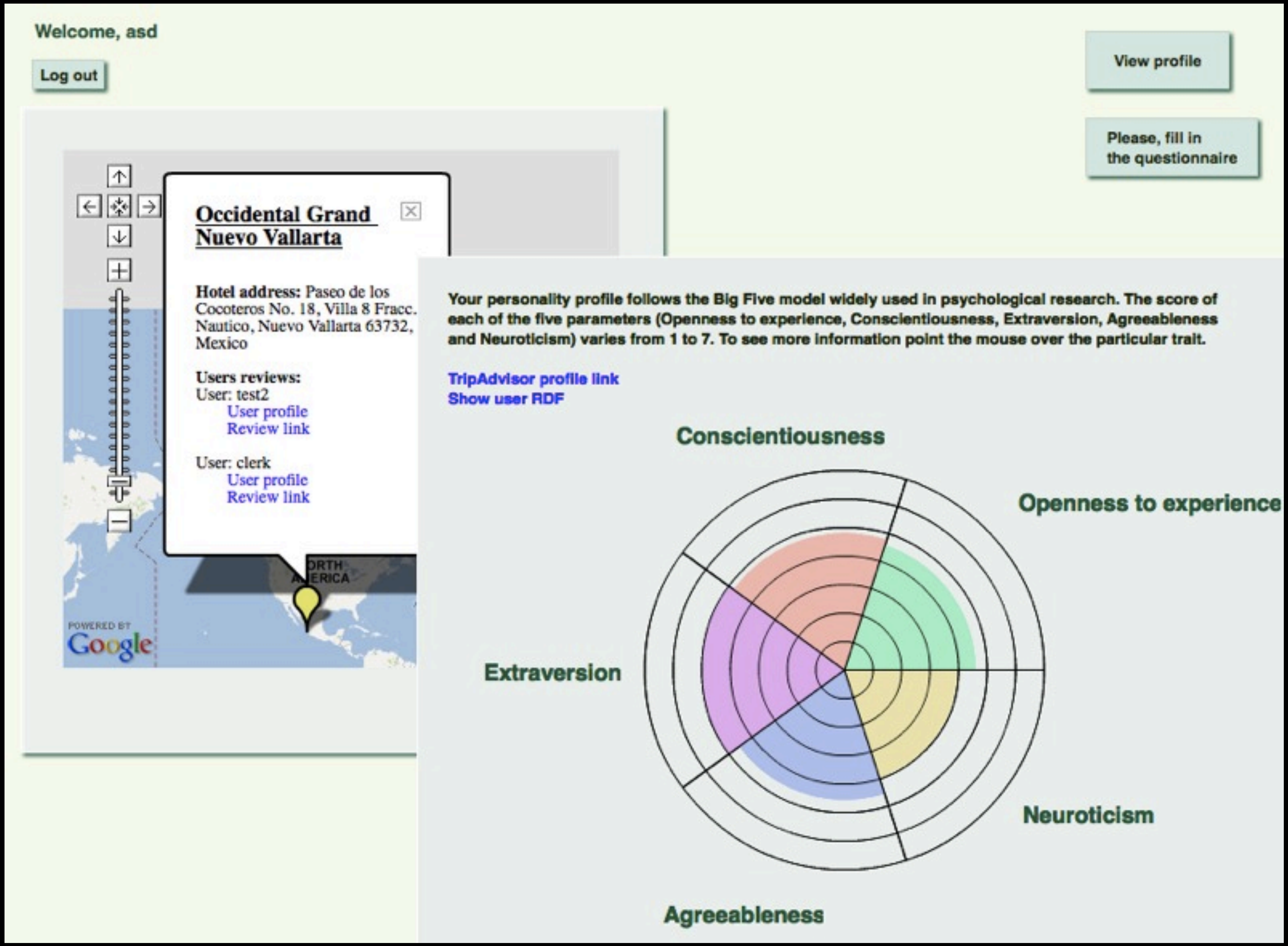
50



p values of the t-test of the comparison of the personality based USM and rating based USM.

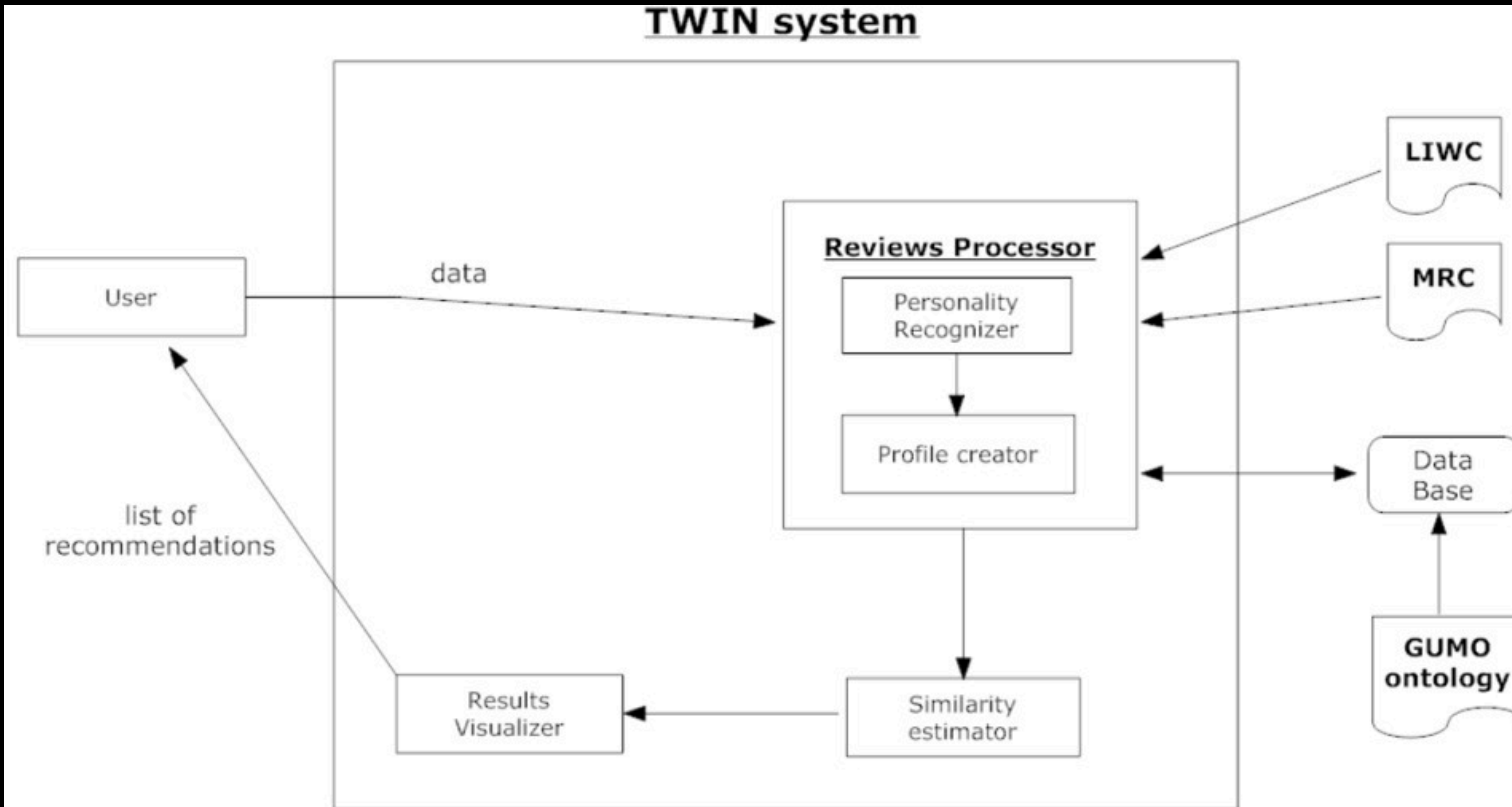
[Tkalčič et al., 2011]

TWIN Recommender

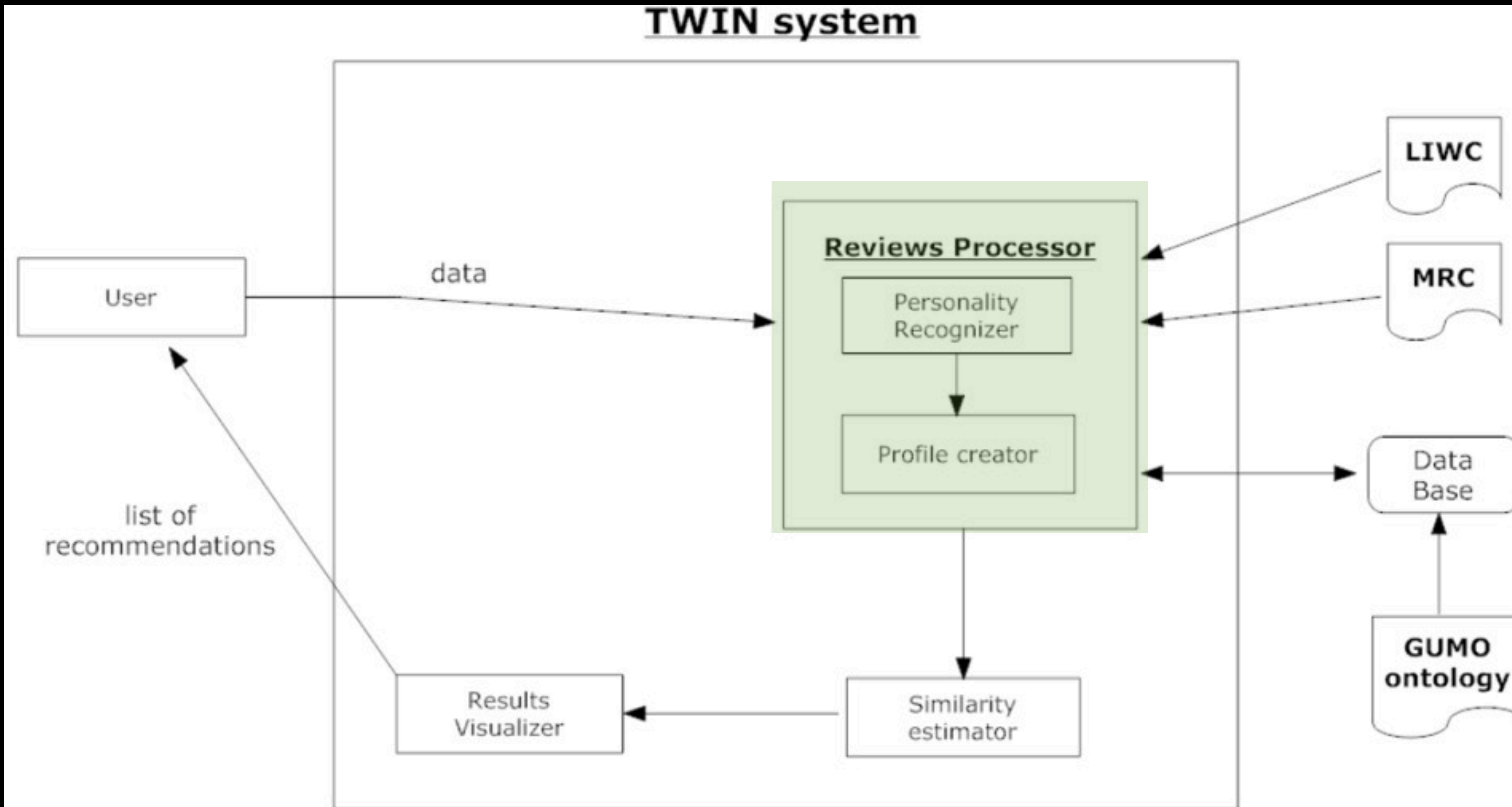


[Roshchina et al., 2011]

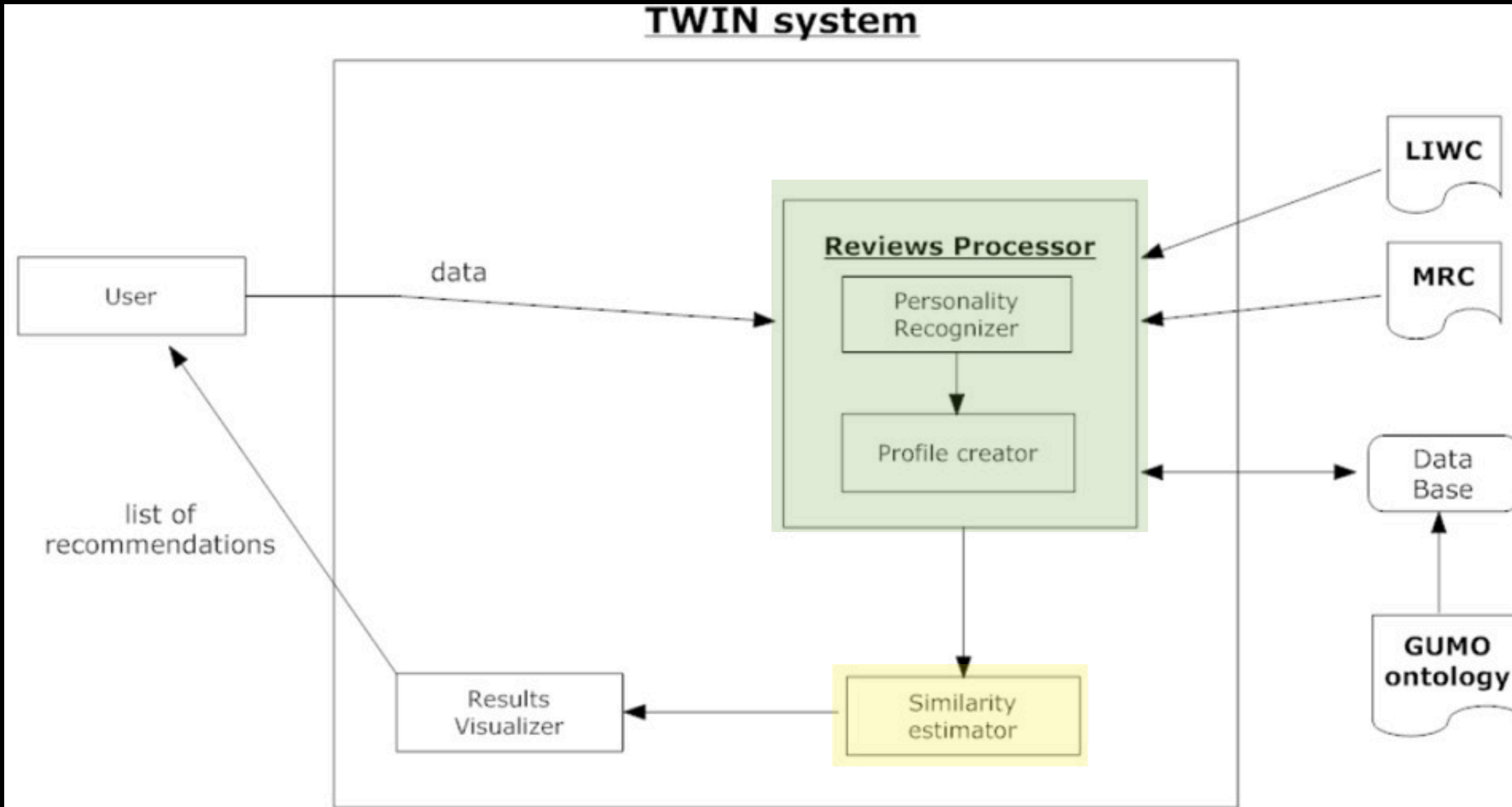
TWIN Recommender



TWIN Recommender



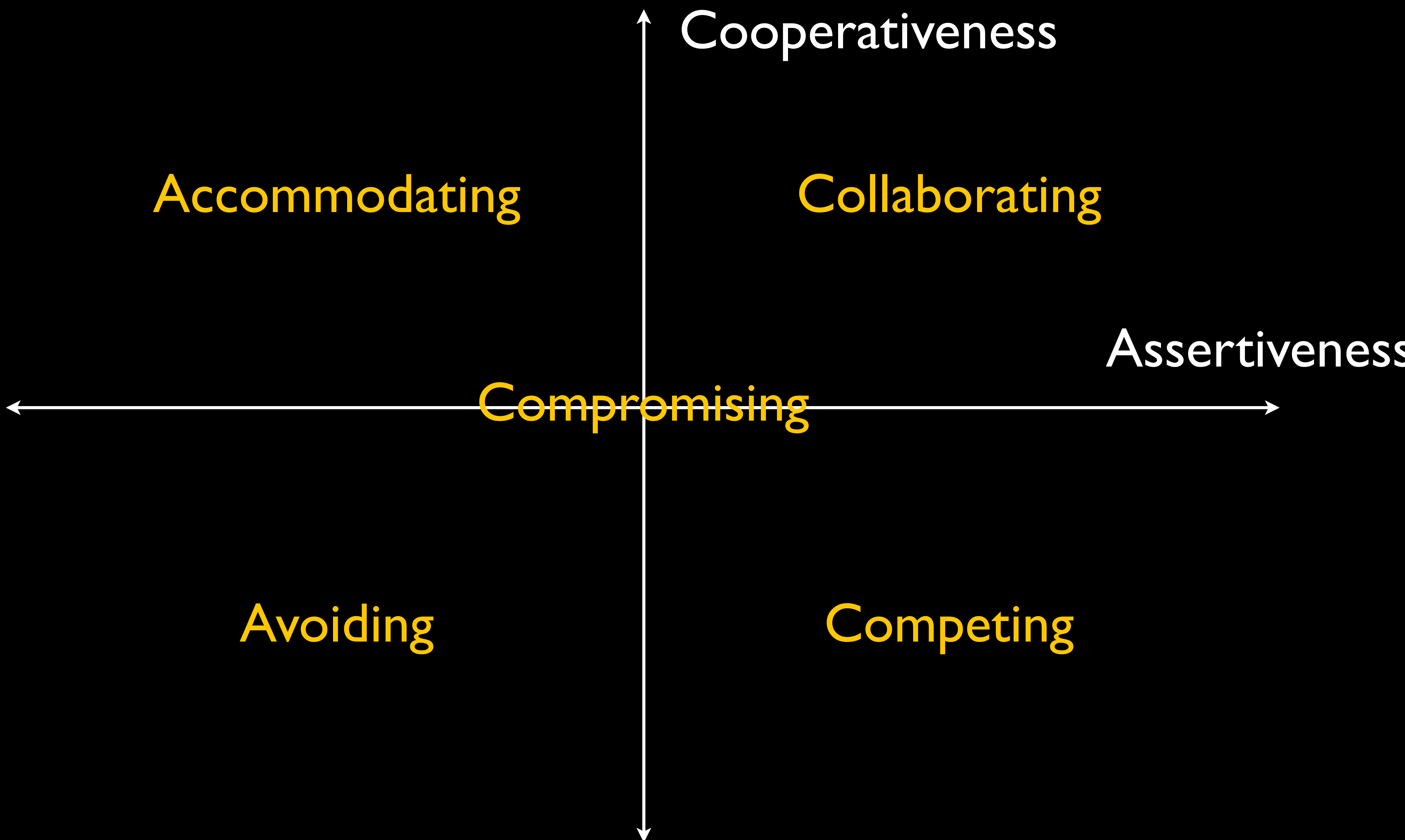
TWIN Recommender



Personality in Group Recommenders

Personality Aware Group Recommendations

Personality Aware Group Recommendations



Personality Aware Group Recommendations

- Assertive behaviours penalize the differences with the best choice of another members
- Cooperative behaviours reward the differences with the best choice of another members.

- Conflict Mode Weight (CMW) = 1 + Assertiveness - Cooperativeness

[Recio-Garcia et al., 2010]

Personality Aware Group Recommendations

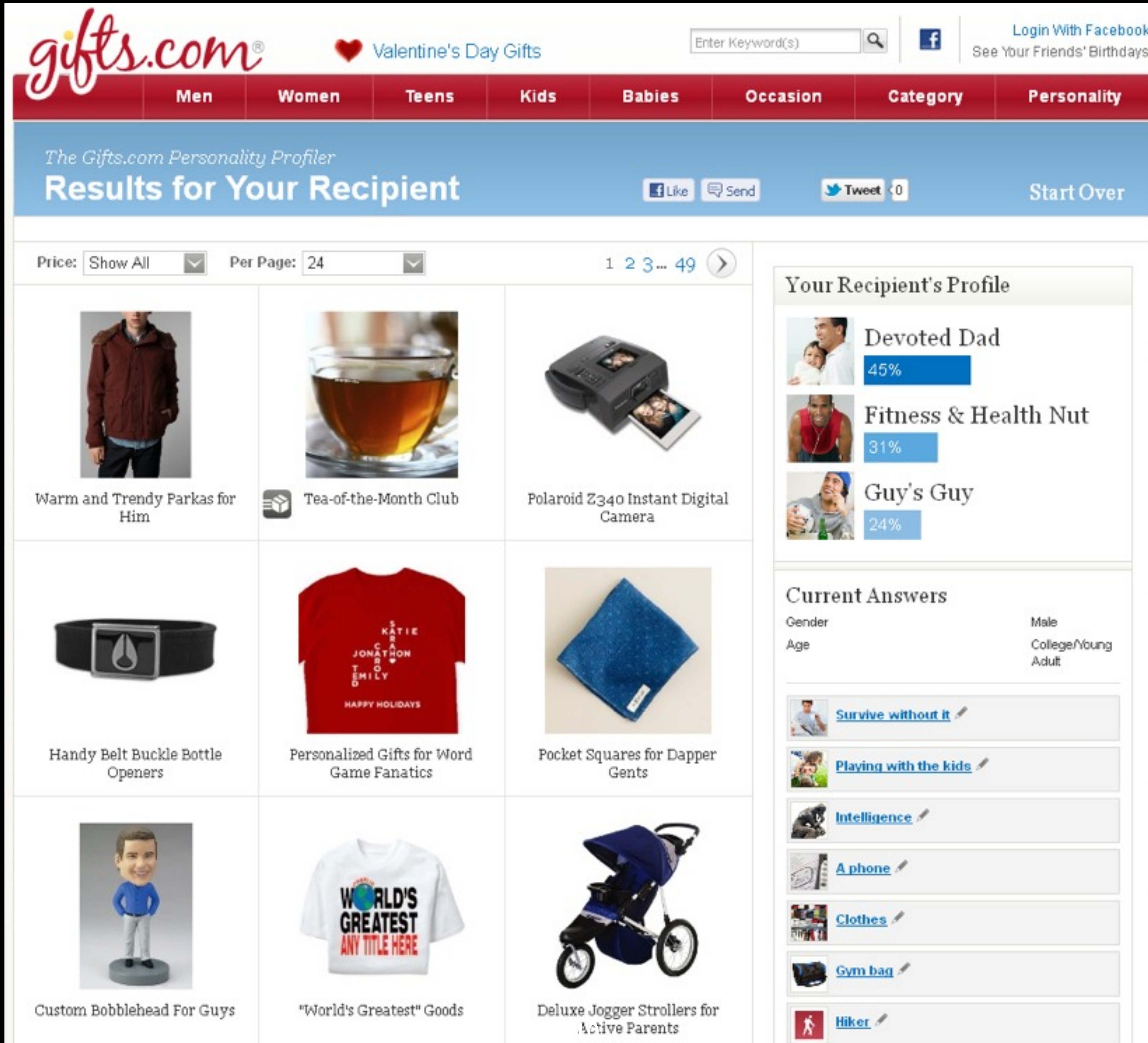
- 90% of groups with more accurate recommendations have at least a member with a high assertive value. (leader)

- Recommender works better for groups with a high dispersion in the CMW value

[Recio-Garcia et al., 2010]

Personality-based Recommender Applications


gifts.com
Enter Keyword(s)
SUMMER PIN-OFF
Pinterest Giveaways
Men
Women
Teens
Kids
Babies
Occasion
Category
Personality
The Gifts.com Personality Profiler
If the garbage disposal broke, he would...
Fix it himself
Call a plumber
Survive without it
NONE OF THE ABOVE
«Back | Start Over


gifts.com
Valentine's Day Gifts
Enter Keyword(s)
Login With Facebook
See Your Friends' Birthdays
Men
Women
Teens
Kids
Babies
Occasion
Category
Personality
The Gifts.com Personality Profiler
Results for Your Recipient
Like
Send
Tweet
0
Start Over
Price: Show All
Per Page: 24
1 2 3... 49
Warm and Trendy Parkas for Him
Tea-of-the-Month Club
Polaroid Z340 Instant Digital Camera
Handy Belt Buckle Bottle Openers
Personalized Gifts for Word Game Fanatics
Pocket Squares for Dapper Gents
Custom Bobblehead For Guys
"World's Greatest" Goods
Deluxe Jogger Strollers for Active Parents
Your Recipient's Profile
Devoted Dad
45%
Fitness & Health Nut
31%
Guy's Guy
24%
Current Answers
Gender
Male
Age
College/Young Adult
Survive without it
Playing with the kids
Intelligence
A phone
Clothes
Gym bag
Hiker

PARSHIP.ch
Die Online-Partneragentur

My Personality Test

A B C

Each partner proposal you receive from PARSHIP is, by comparing the personality dimensions of 30 selected especially for you. The basis for this selection is our scientific personality test.

Therefore please take quiet time 10 to 15 minutes to answer the following questions honestly and spontaneously. Immediately after the personality test you will first partner proposals and a detailed personality report with your test result.

Have fun with these questions!

Regardless of your current place of residence, where you want to live?

- In a big city with big-city feel
- In the environment of a large city
- In a more tranquil town
- Or quite a bit quieter in the country
- Anytime, I can feel in many places ...

→ More

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- In a big city with big-city feel
- In the environment of a large city
- In a more tranquil town
- Or quite a bit quieter in the country
- Anytime, I can feel in many places ...

More

logout

first we have to get to know you

Hello **tester_movie**!

The following questions will ask about your feelings on certain issues, how you would react in certain situations, and how your body and mind relate to the outside world. Your answers to these questions will provide our server with the information required to adequately model your personality and thus get a good idea of who you are.

The questions use slider-bar technology to provide you with a continuous range over which to answer. Simply grab and slide the bar to the answer that you feel most comfortable with. If you feel somewhere between two answers, slide the bar wherever is most accurate.

Question 1:

Imagine you are selecting dinner at a restaurant you have visited a few times. The restaurant has a broad menu of foods you are not totally familiar with. What is the percentage chance you will try something new even though you may not like it?

100%   75%   50%   25%   0%

Question 2:

Which answer best describes how serious your favorite movies are:

Just Fun!   Real-Life   Harsh Real-Life   Super Harsh

- More ...

PBRS Technologies

Personality Acquisition

User Modeling

Recommendation Generation

User Perception

User Perception

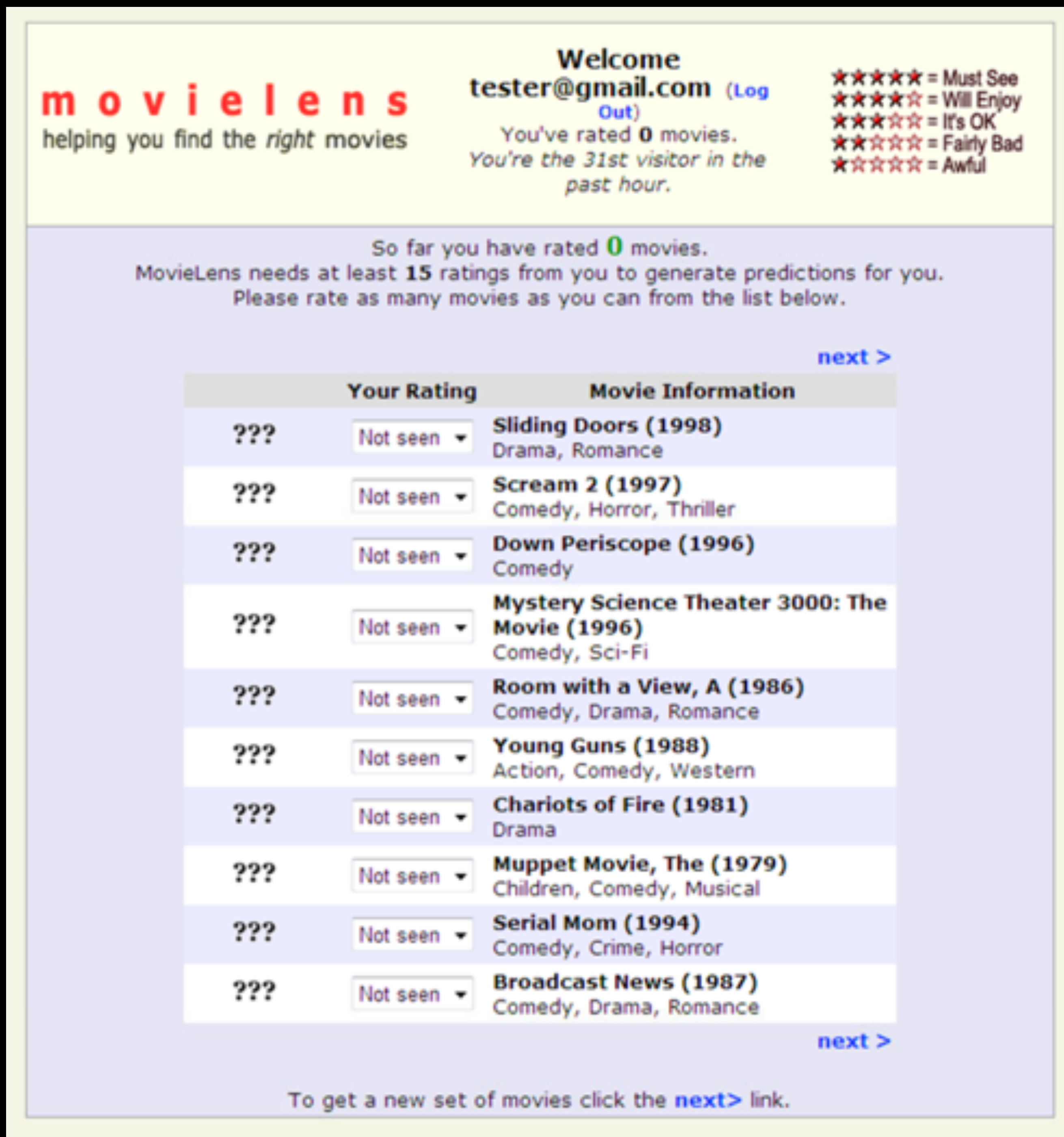
User Satisfaction of Personality-based Recommender Systems

Study 1

1. Can personality quiz-based recommendation method be accepted by users?
2. Which aspects of the system would influence user acceptance of personality-based approaches?

[Rong and Pu, 2009]

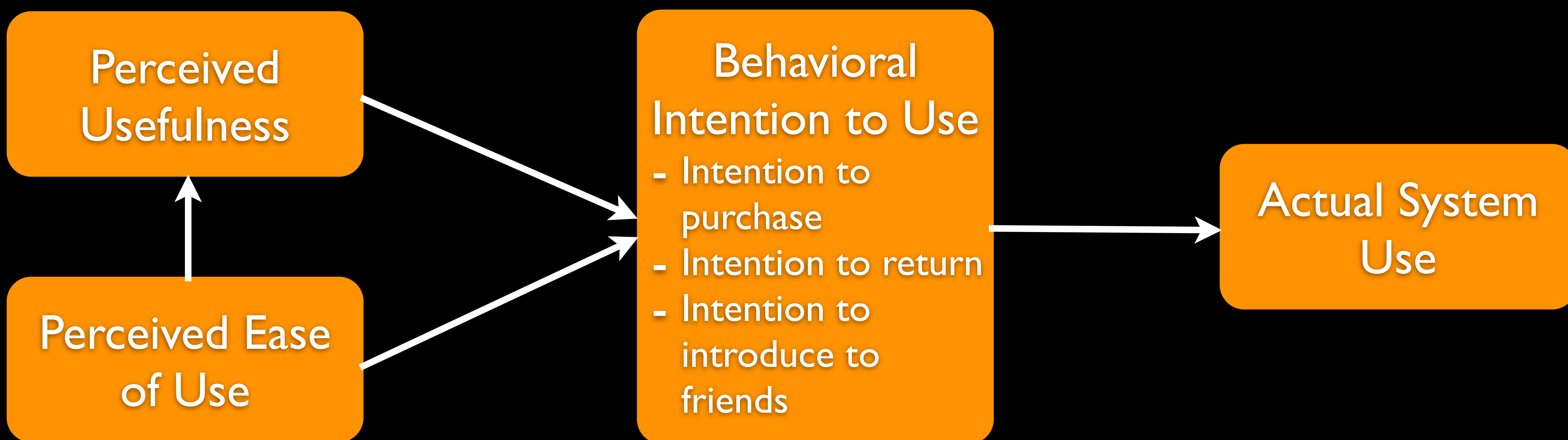
Study Setup


m o v i e l e n s
helping you find the right movies
Welcome
tester@gmail.com (Log Out)
You've rated 0 movies.
You're the 31st visitor in the past hour.
★★★★★ = Must See
★★★★☆ = Will Enjoy
★★★☆☆ = It's OK
★★☆☆☆ = Fairly Bad
★☆☆☆☆ = Awful
So far you have rated 0 movies.
MovieLens needs at least 15 ratings from you to generate predictions for you.
Please rate as many movies as you can from the list below.
next >
Your Rating
Movie Information
??? Not seen Sliding Doors (1998) Drama, Romance
??? Not seen Scream 2 (1997) Comedy, Horror, Thriller
??? Not seen Down Periscope (1996) Comedy
??? Not seen Mystery Science Theater 3000: The Movie (1996) Comedy, Sci-Fi
??? Not seen Room with a View, A (1986) Comedy, Drama, Romance
??? Not seen Young Guns (1988) Action, Comedy, Western
??? Not seen Chariots of Fire (1981) Drama
??? Not seen Muppet Movie, The (1979) Children, Comedy, Musical
??? Not seen Serial Mom (1994) Comedy, Crime, Horror
??? Not seen Broadcast News (1987) Comedy, Drama, Romance
next >
To get a new set of movies click the next> link.


WHAT TO RENT?
logout
first we have to get to know you
Hello hcitester!
The following questions will ask about your feelings on certain issues, how you would react in certain situations, and how your body and mind relate to the outside world. Your answers to these questions will provide our server with the information required to adequately model your personality and thus get a good idea of who you are.
The questions use slider-bar technology to provide you with a continuous range over which to answer. Simply grab and slide the bar to the answer that you feel most comfortable with. If you feel somewhere between two answers, slide the bar wherever is most accurate.
Question 1:
Imagine you are selecting dinner at a restaurant you have visited a few times. The restaurant has a broad menu of foods you are not totally familiar with. What is the percentage chance you will try something new even though you may not like it?
100% 75% 50% 25% 0%
Question 2:
Which answer best describes how serious your favorite movies are:
Just Fun! Real-Life Harsh Real-Life Super Harsh

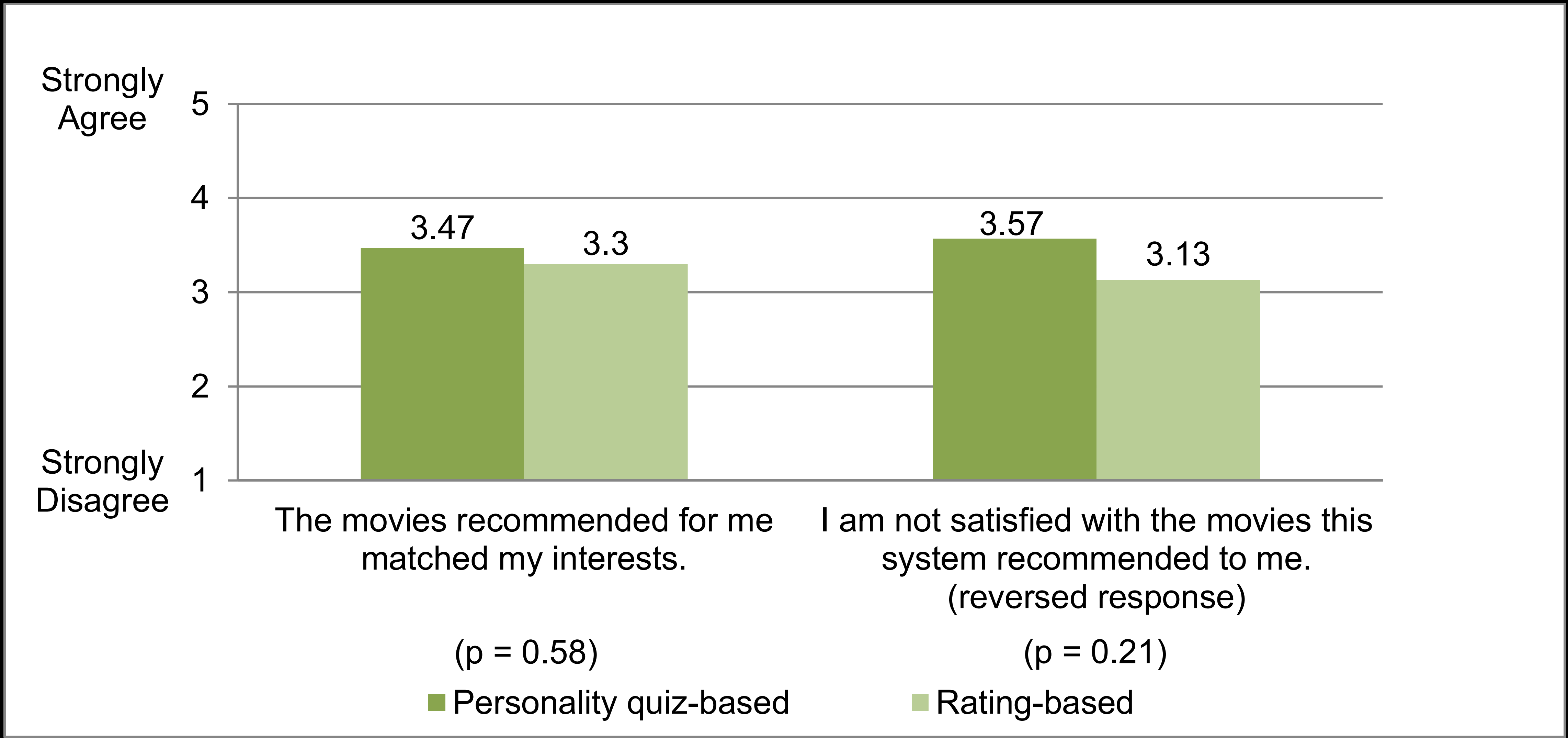
Study Setup

- Evaluation Criteria: Technology Acceptance Model (TAM) [Davis 1889]



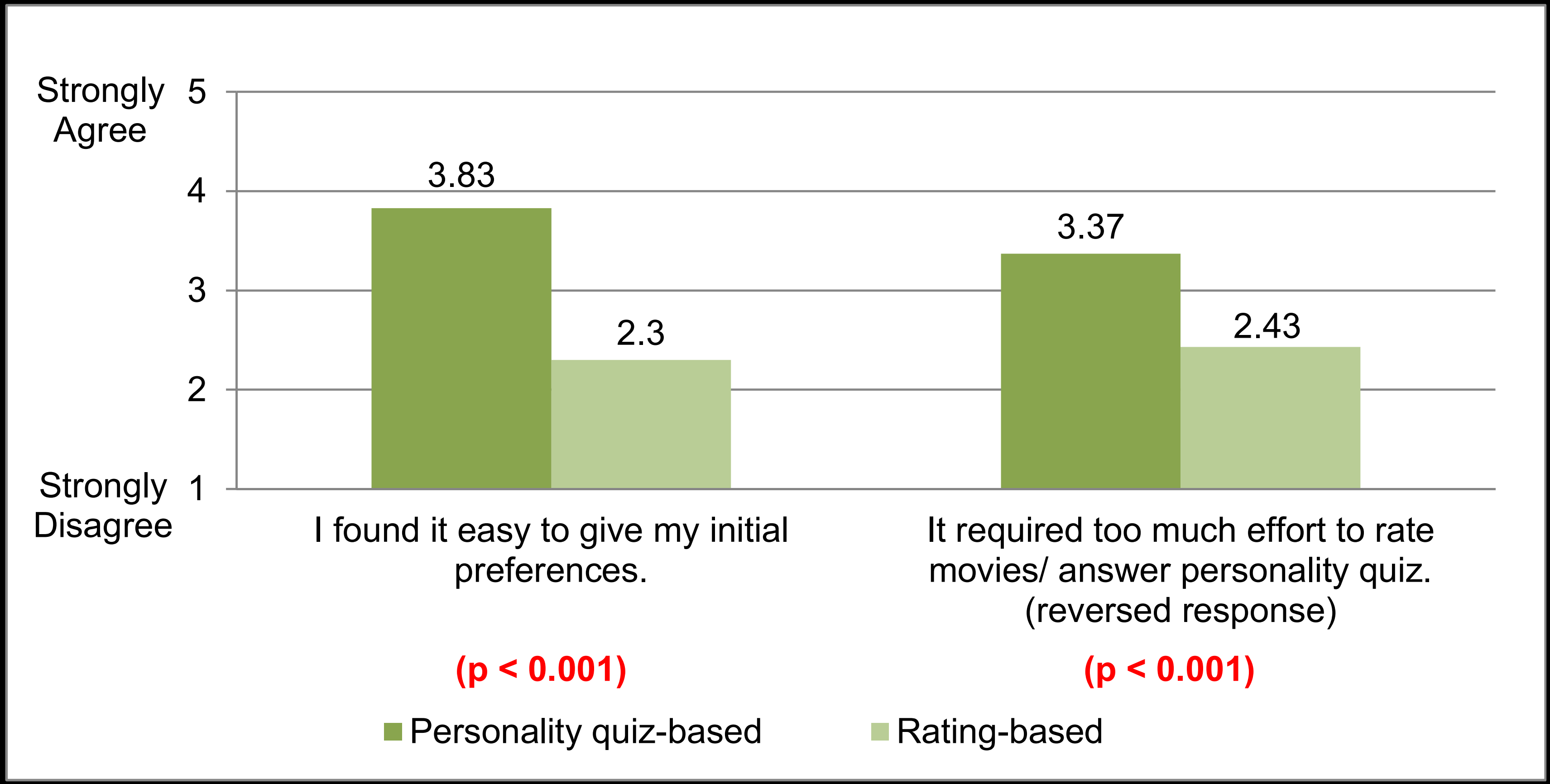
Results

- Recommendation Accuracy: not significantly different



Results

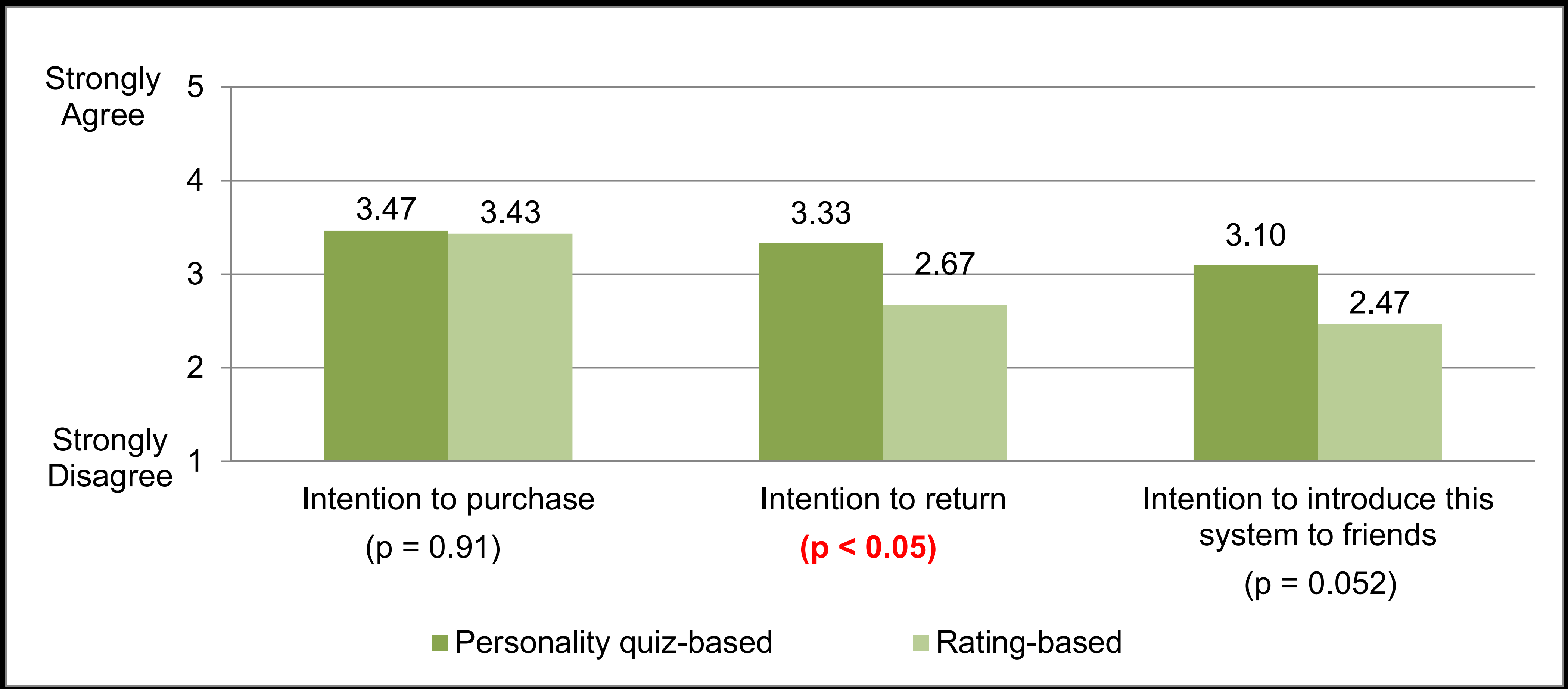
- Perceived Ease of Use



- Actual Task Completion Time
  - Whattorent: 6.8m vs. MovieLens: 18.7m ($p < 0.001$)

Results

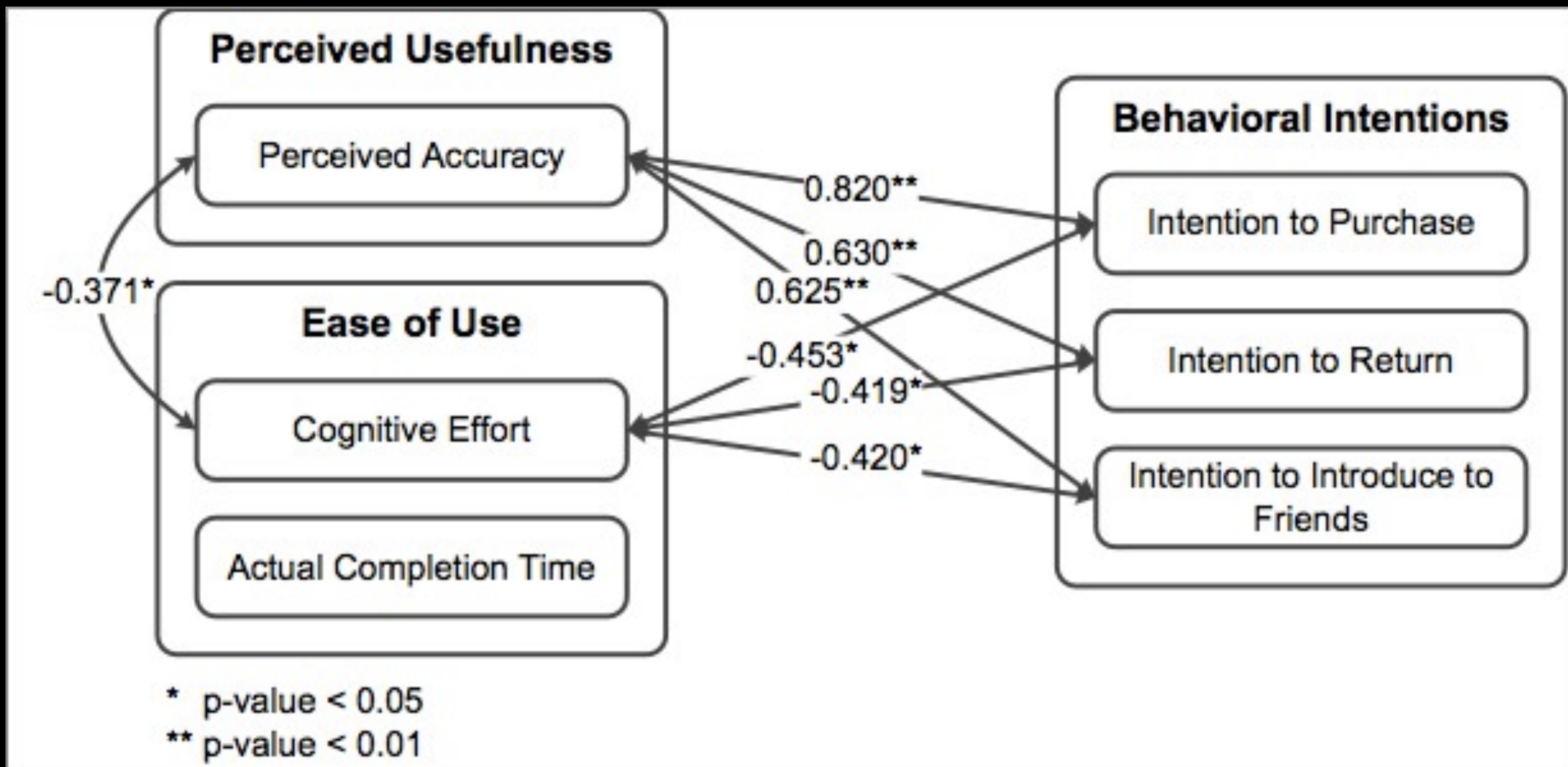
- Intention to Use



- Preference: 53% Whattorent vs. 13% MovieLens

Results

- Correlation Analysis



Study Conclusion

- Ease of use is one dominant merit of the personality-based approach
- Perceived accuracy and ease of use determine users' acceptance of the personality-based system
- More subjects preferred the personality-based system.
- Problem: Transparency

Study 2

- Investigate the feasibility of using personality quizzes to build user profiles not only for an active user but also his or her friends (i.e., for self vs. for friends)

- Investigate the influence of domain knowledge on user perception of personality-based recommender systems (i.e., domain experts vs. domain novices)

[Rong and Pu, 2010]

Study Setup

- Personality Evaluation
  - TIPI (Ten Item Personality Inventory) [Gosling et al., 2003]
- Participants
  - 80 subjects (32 females) from 17 countries
  - expert users (17), medium users (32), novice users (23)
- User Tasks
  - User personality quiz to find songs for self and one friend

Study Setup

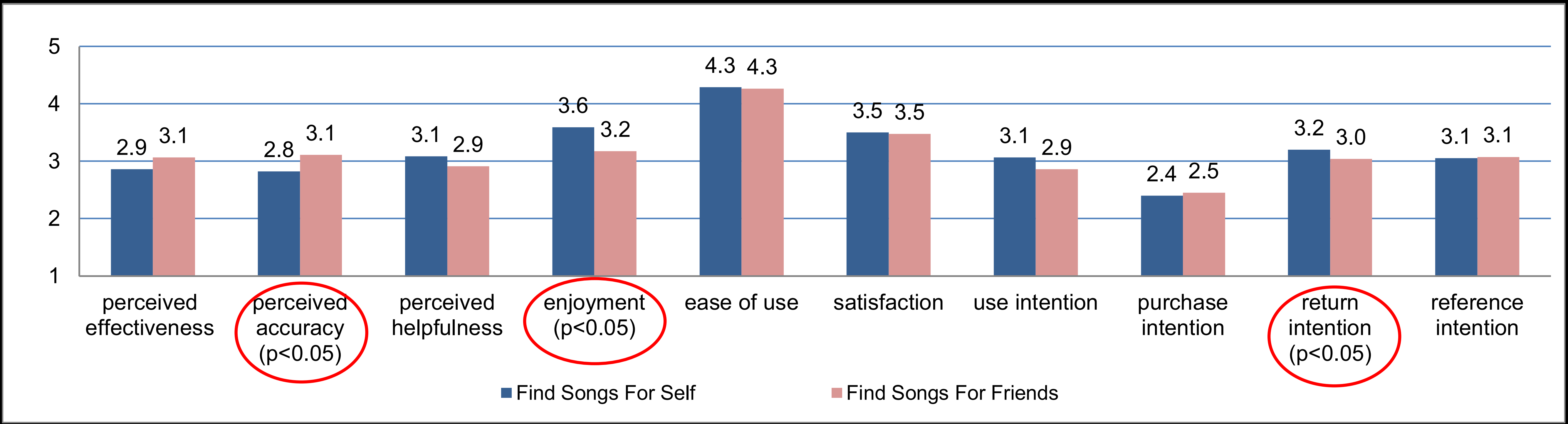
- Evaluation Criteria: ResQue Model [Pu, Chen and Hu, 2011]

System Quality → Beliefs → Attitudes → Behavioral Intentions

System Quality	Beliefs	Attitudes	Behavioral Intentions
Qualities of Recommended Items	Perceived Ease of Use	Satisfaction	Use the System
Interaction Adequacy	Perceived Usefulness	Trust	Purchase
Interface Adequacy	Control/Transparency	Confidence	Continuance
			Social Influence

Results

- Self- vs. Friend-Recommendations



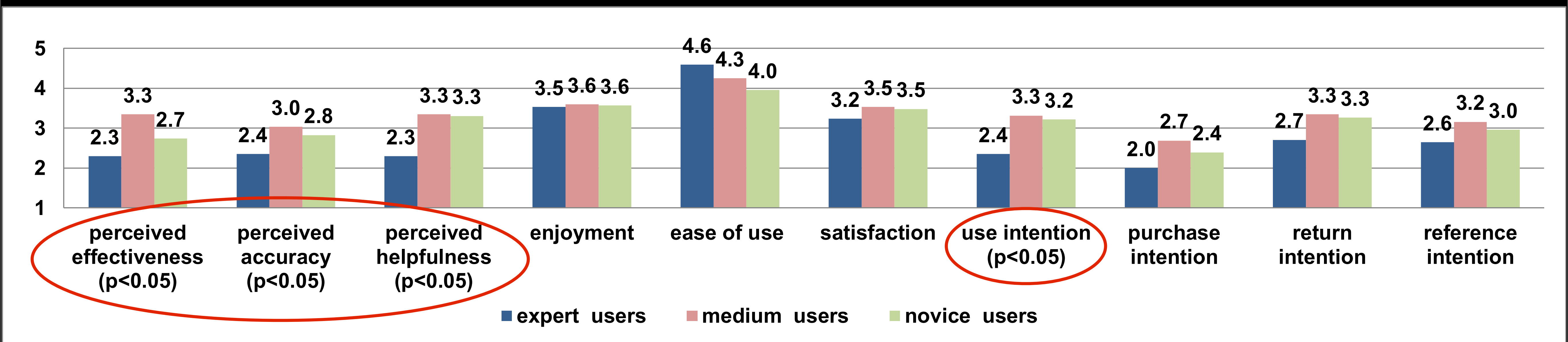
Average users' responses to the subjective measurements
(1: strongly disagree, 5:strongly agree)

Results

- Medium Users vs. Expert Users
- Novice Users vs. Expert Users

Results

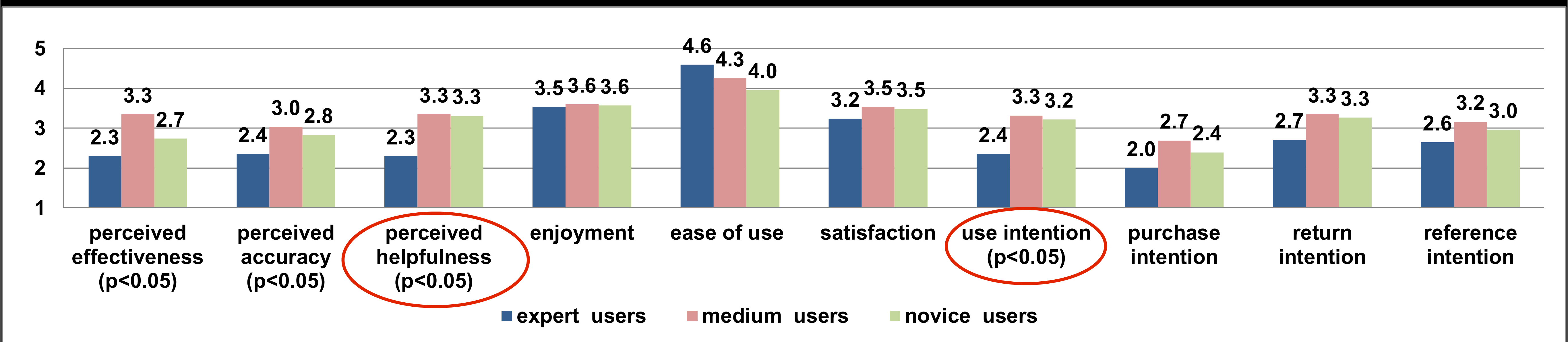
- Medium Users vs. Expert Users
- Novice Users vs. Expert Users



Subjective responses in the scenario of finding songs for self
(Expert uses: 17, Medium users: 32, Novice users: 23)

Results

- Medium Users vs. Expert Users
- Novice Users vs. Expert Users



Subjective responses in the scenario of finding songs for self
(Expert uses: 17, Medium users: 32, Novice users: 23)

Study Conclusion

- Users with low level of music domain knowledge gave higher subjective evaluation scores than domain experts
- There is a system-adaptivity requirement
- Problem: Privacy and Control

Conclusions

- Advantages
  - Provide personalized services
  - Enhance the interaction experience between systems and users
  - Address the cold-start problem
  - ...

Conclusions

- Disadvantages
  - Transparency, privacy and control Issues
  - Difficult to acquire users' personality
  - It is not intuitive to have the relations between personality characteristics and recommended items
  - ...

Future Directions

- Design efficient and pleasant ways to acquire users' personality information
- Develop methods which automatically mapping personality characteristics and items or item features
- Design friendly user interfaces for PBRS
- Need a lot of work...

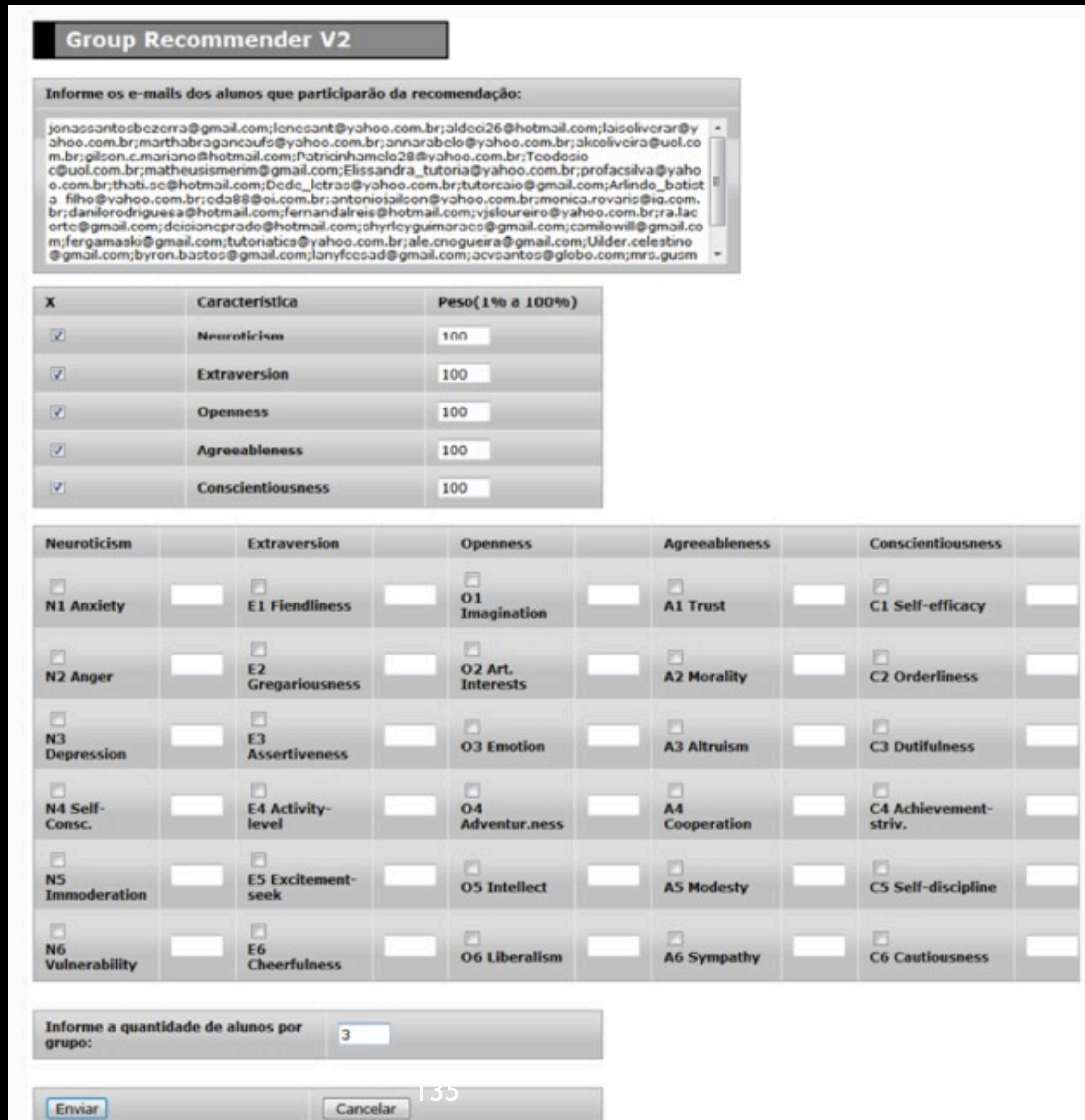
Conclusions

- Why scientists stopped publishing in the personality field (I mean, this year)?
  - is personality hard to extract ?
  - is personality hard to formalize and store ?
  - Is it already standardized ? (to be used anywhere as recommender inputs, cookies)?

New research directions

- at Universidade Federal de Sergipe:
  - Geolocated personality-based recommender systems for Brazilian mega events 2014-2016 (Personal-Movie);

Group recommender 3.0 - for mobile;



PersonalityML 2.0

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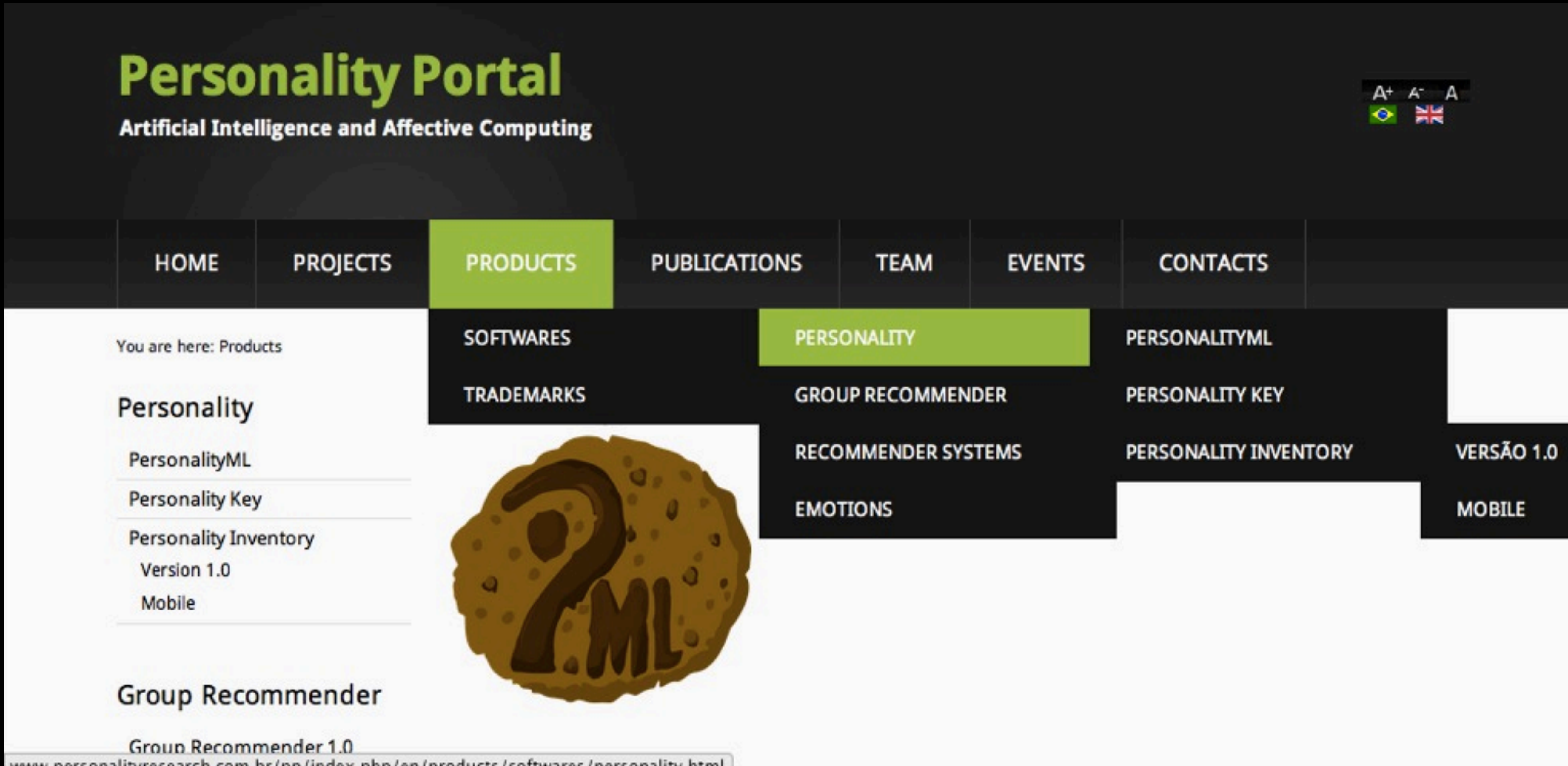
      <facets set="Facets NEO-IPIP checks">
       <facet name="warmth" score="62"/>
       <facet name="gregariousness" score="44"/>
       <facet name="assertiveness" score="13"/>
       <facet name="activity value" score="46"/>
       <facet name="excitement-seeking" score="60"/>
       <facet name="positive-emotions" score="42"/>
      </facets>
     </factor>
    </factors>
   </inventory>
  </model>
 </approach>
</personality>
```

- ? Personality Recognizer:
  - ? by « comic book » stories;
  - ? by text in Portuguese (text-mining);
  - ? by Typing;
  - ? by Kinect;

- Project with Univ. Montpellier II -Lirmm-France:
  - treating Post-Stroke patients by using Affective computing in order to recommend the better rehabilitation, considering patient motivation;



- www.personalityresearch.com.br
- http://200.17.141.213/~gutanunes/
- gutanunes@gmail.com

- Thank you very much!

- questions?

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