Group Recommender Systems Tutorial

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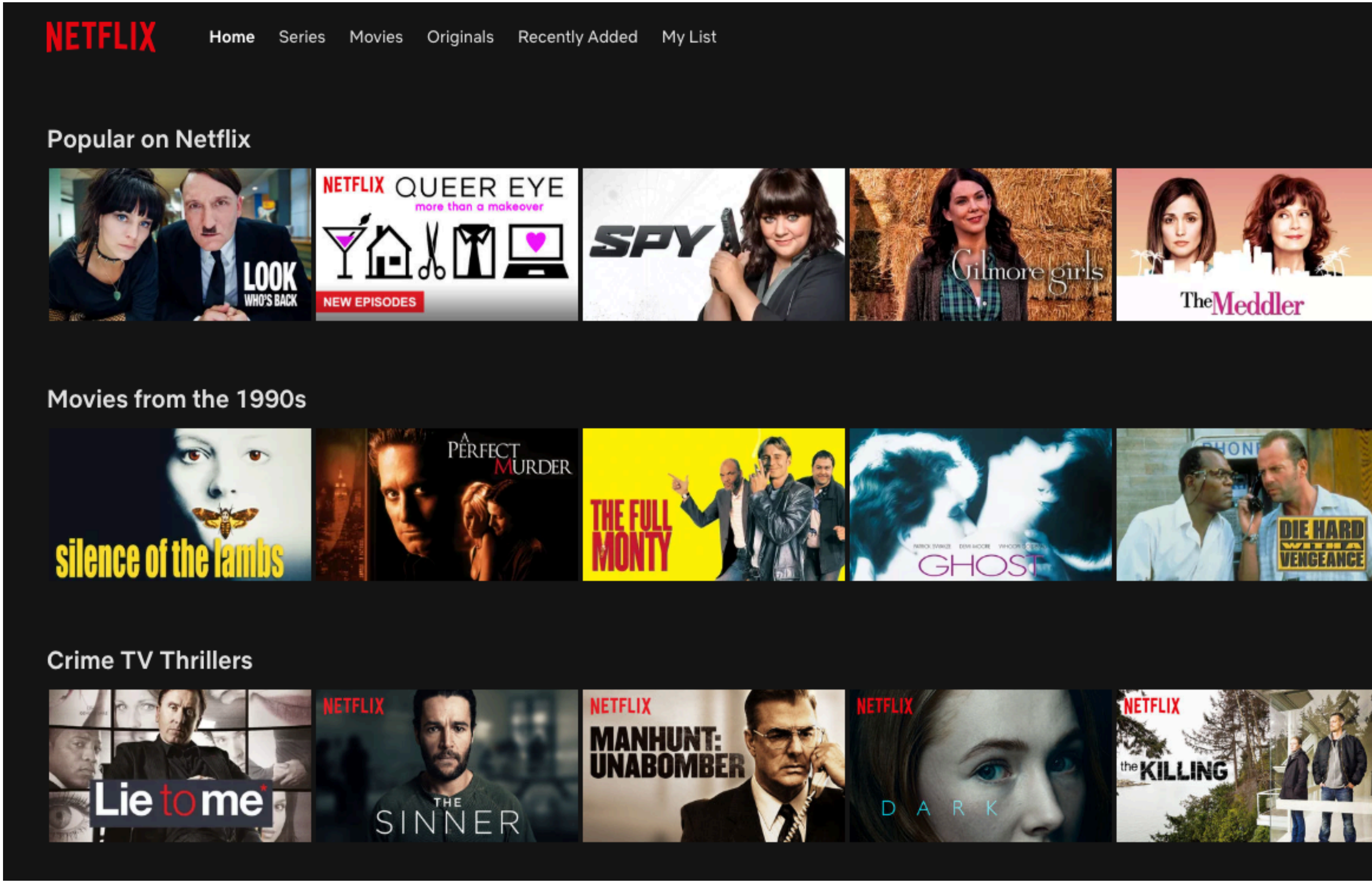
Judith Masthoff

Before we start…

RECOMMENDER SYSTEMS

Which movie should I watch?

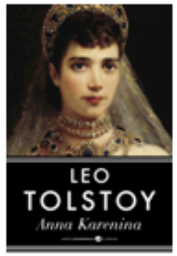


Which book should I buy?

Your recently viewed items and featured recommendations

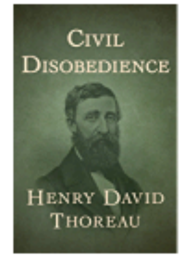
Inspired by your purchases

Six Not-So-Easy Pieces: Einstein's Relativity,…
› Richard P. Feynman
★★★★☆ 71
Kindle Edition
$8.17



Anna Karenina
› Leo Tolstoy
★★★★☆ 2,862
Kindle Edition
$0.77

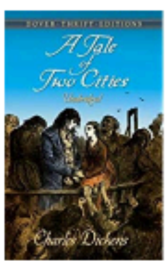
Six Easy Pieces: Essentials of Physics…
› Richard P. Feynman
★★★★½ 190
Kindle Edition
$8.17



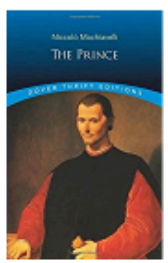
Civil Disobedience (Dover Thrift Editions)
› Henry David Thoreau
★★★★½ 27
Kindle Edition
$1.39

Frankenstein (The Original 1818…
Mary Shelley
★★★★☆ 3,528
Kindle Edition
$0.57

Books You May Like

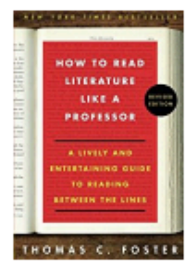


A Tale of Two Cities (Dover Thrift…
› Charles Dickens
★★★★½ 9,405
Paperback
$5.58 ✓prime

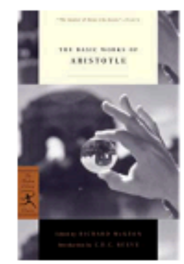


The Prince (Dover Thrift Editions)
› Niccolò Machiavelli
★★★★½ 1,632
Paperback
$3.00 ✓prime

The Iliad of Homer
Richmond Lattimore
★★★★½ 3,701
Paperback
$5.23 ✓prime



How to Read Literature Like a Professor: A…
› Thomas C Foster
★★★★½ 774
Paperback
$10.87 ✓prime



The Basic Works of Aristotle (Modern…
› Aristotle
★★★★½ 57
Paperback
$18.40 ✓prime

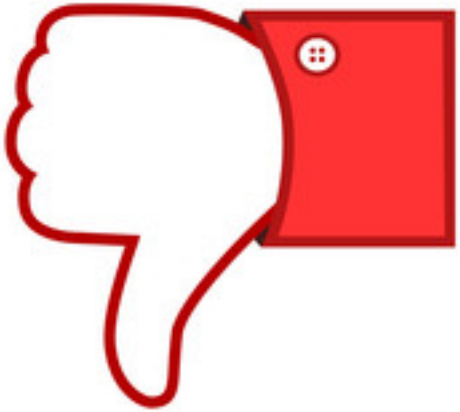
Explosion of Choice

- A trip to a **local supermarket**:
  - 285 varieties of cookies
  - 165 varieties of “juice drinks”
  - 75 iced teas
  - 275 varieties of cereal
  - 120 different pasta sauces
  - 80 different pain relievers
  - 40 options for toothpaste
  - 95 varieties of snacks (chips, pretzels, etc.)
  - 61 varieties of sun tan oil and sunblock
  - 360 types of shampoo, conditioner, gel, and mousse
  - …

Choice and Well-Being

- We have more choice, more freedom, autonomy, and self determination
- Increased choice should improve well-being:
  - added options can only make us better off?
- Increased affluence have accompanied by decreased well-being, actually

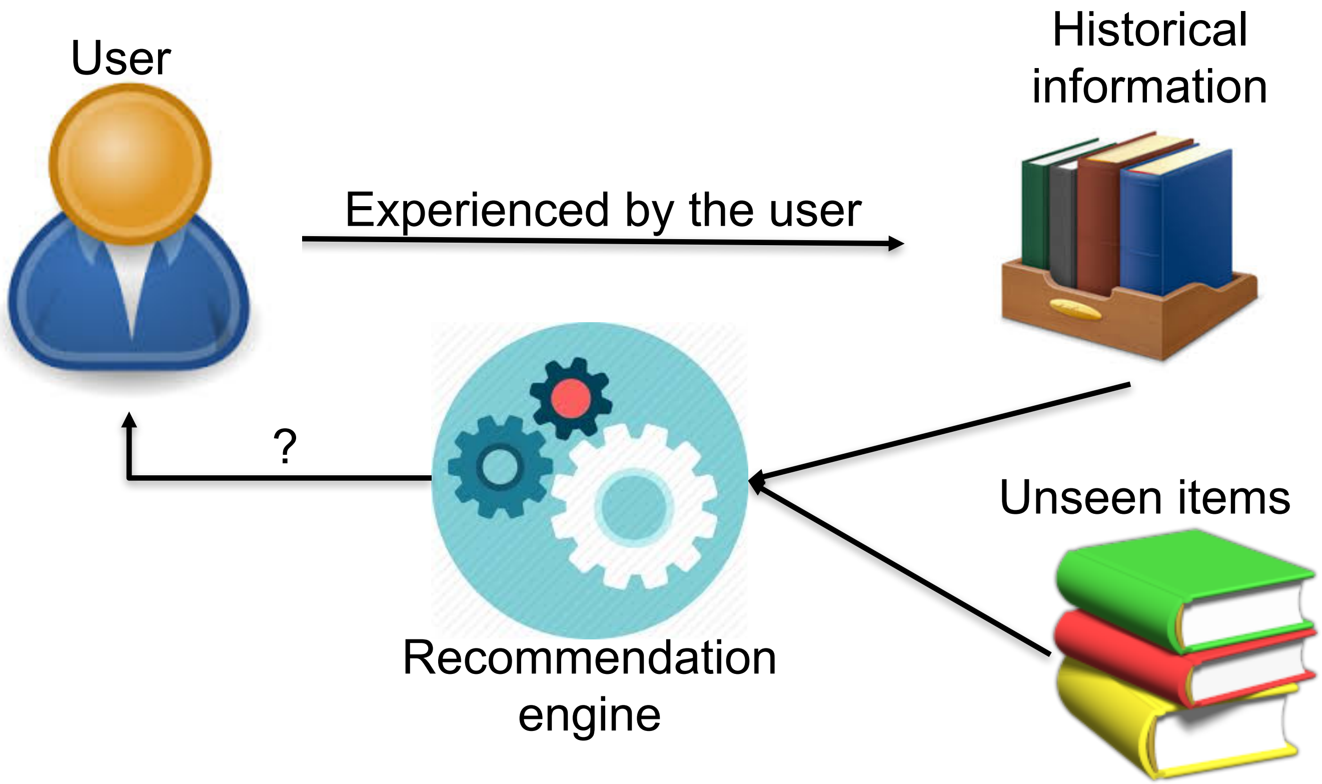
?



Recommender Systems (RSs)

- RSs help their users to find content of interest without fully knowing available alternatives
  - The system suggests content / items to their users
  - The system also provides explanations of suggestions
  - The goal is to provide information to help the users decide
- RSs use various technologies to deliver recommendations:
  - user modeling, adaptation and personalization
  - Persuasive technologies
  - Machine learning
  - Information filtering

Recommender Systems (RSs)



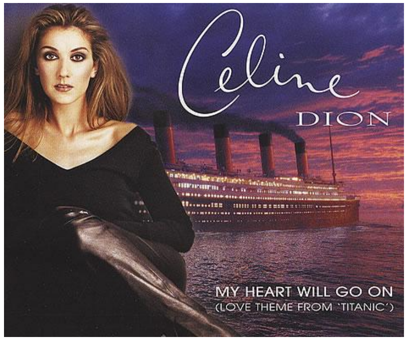
*"The recommendation problem: **estimating the response of a user for new items**, based on **historical information (preferences) stored in the system**, and **suggesting to this user novel and original items** for which the predicted response is high."* (Ricci, Rokach and Shapira, 2015)

Introduction to Group Recommender Systems

- Many items addressed by RSs are experienced in groups

MOVIES

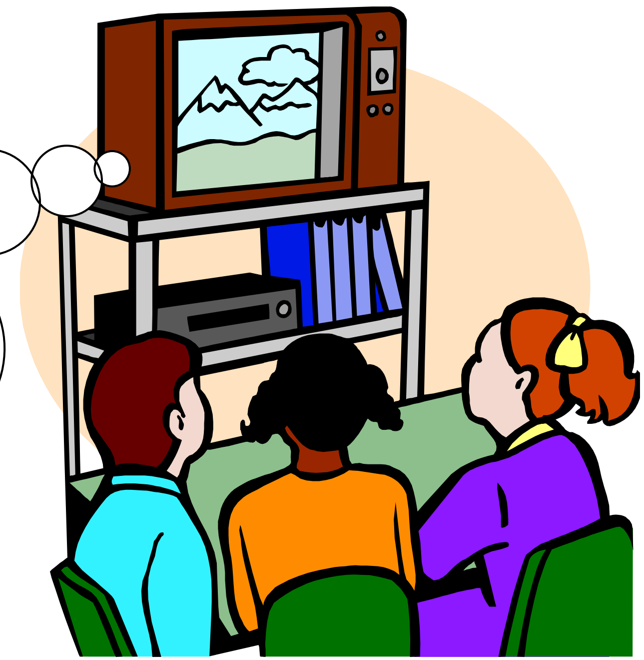
MUSIC



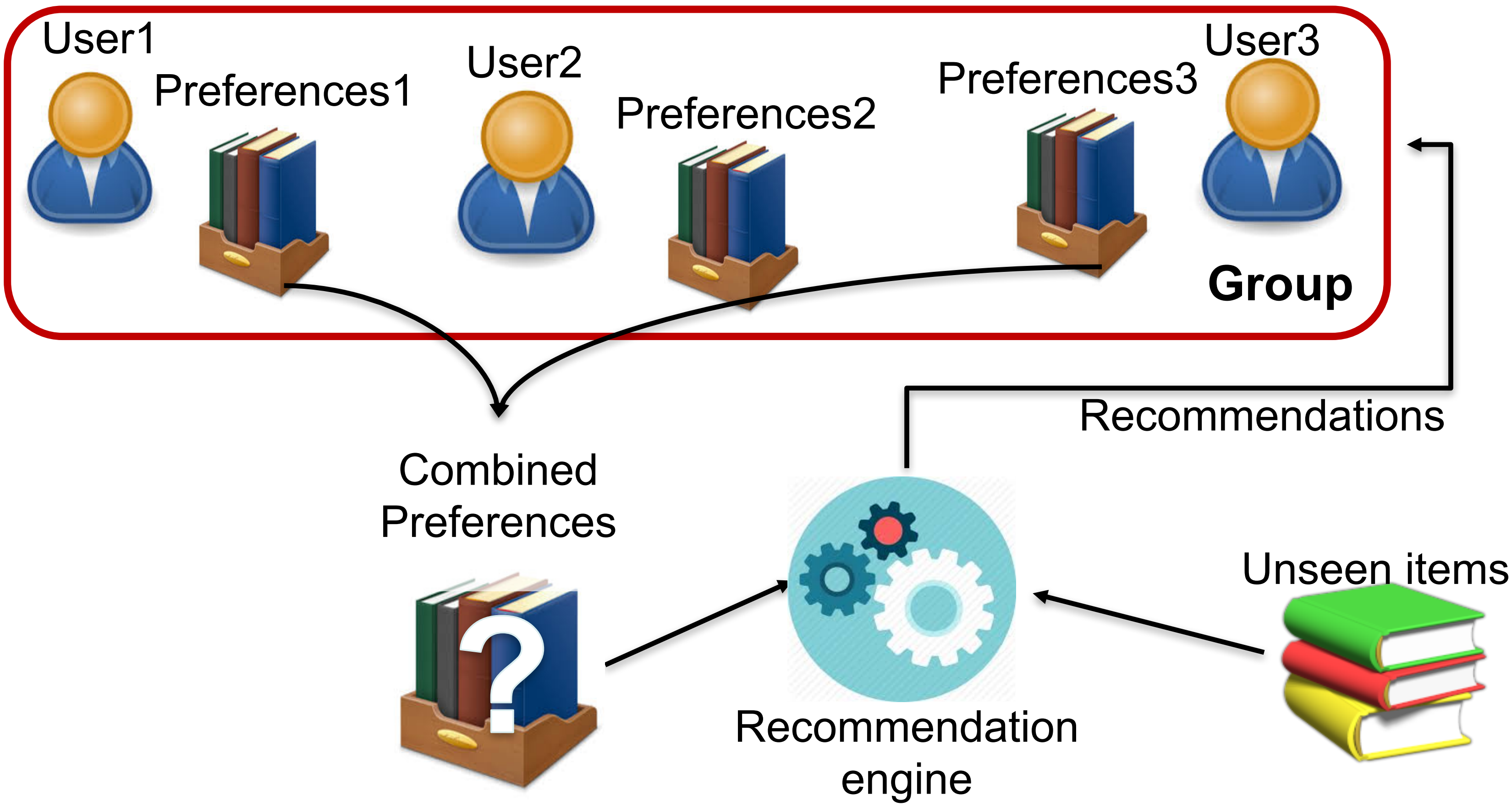
RESTAURANTS / TRAVELLING

Group Recommender Systems (GRSs): How to combine individuals' preferences into a group profile?

I know individual ratings of Peter, Jane, and Mary. What to recommend to the group?



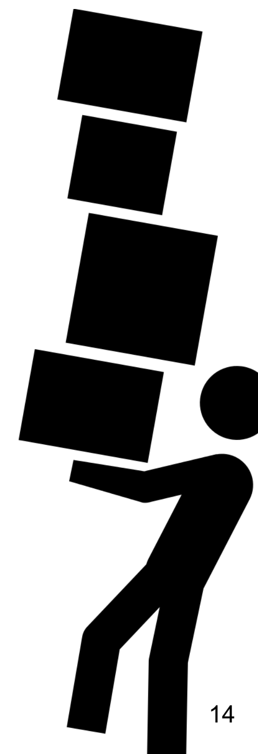
Problem statement & definition



GRSs Challenges

- Four main challenges identified by Jameson (2004)
  1. How to elicit individual preferences of group members
  2. How to aggregate individual preferences into a group model
  3. How to present and explain recommendations
  4. how to help users to make final decisions



Application Domains & Challenges

- Recommending a sequence of television items
  - Who is watching?
  - How to know when users are coming and leaving?
  - How to acquire preferences of individual users?
  - How to keep track of users' affective state over the sequence?
  - How to make sure that nobody gets too dissatisfied?
  - …

Application Domains & Challenges

- Recommending a tourism destination
  – Tourism object is a combination of products and services
  – Tourism object is less tangible than other types of products
  – An emotional experience
  – Explicit preference characterization is a problem
  – Tourism recommender systems lack user-item ratings

Classification of GRSs (1)

Several dimensions to classify GRSs (Masthoff, 2015)

1. **Group type** (Boratto, 2016)
   - Established groups (share long term interests)
     - e.g., movie recommendations to a group that always watches them together
   - Occasional groups (has a common specific aim)
     - e.g., recommending music in a fitness center
   - Random groups (do not have anything in common)
     - e.g., recommending news items in a public space

Classification of GRSs (2)

Several dimensions to classify GRSs (Masthoff, 2015)

2. **Individual group members' preferences**
   - Preferences are known prior to group recommendations
     - e.g., movie recommender systems usually have individual preferences that serve as an input for generating group model
   - Preferences are unknown prior to group recommendations
     - e.g., a recommender system that acquires individual preferences only during the group decision-making process

Classification of GRSs (2)

Several dimensions to classify GRSs (Masthoff, 2015)

3. **Recommendations consumption**
   - Recommendations are experienced by groups
     - e.g., music recommendations played in the background
   - Recommendations are presented to groups
     - e.g., list of movies recommended to a group

Classification of GRSs (3)

Several dimensions to classify GRSs (Masthoff, 2015)

4. **Behavior of the group**
   - Passive groups
     - group is passive with respect to how the group model is obtained – how individual preferences are aggregated
   - Active groups
     - group negotiates the group model – group preferences are agreed by group members before group recommendations are delivered

Classification of GRSs (3)

Several dimensions to classify GRSs (Masthoff, 2015)

5. **Recommendation type**
   - Recommending a single item
     - e.g., a movie recommender
   - Recommending sequence of items
     - e.g., a music recommender

Aggregation Strategies

- Aggregation strategy is a method that combines individual preferences into a group preference model

- State-of-the-art strategies are mainly motivated by the *Social Choice theory*

  "A theoretical framework for analysis of combining individual opinions, preferences, interests, or welfares to reach a collective decision or social welfare in some sense" (Sen, 2008)

- No winning aggregation strategy (Arrow, 1963)
  – "…no strategy useful in every context" (Pizzutilo et al., 2005)
  – Group type influences the performance of strategies (Gartrell et al. 2010)

What would you recommend?

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6

- Additive strategy – Individual ratings are summed

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6
GROUP	21	18	13	22	26	26	17	23	20	22

- Multiplicative strategy – Individual ratings are multiplied

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6
GROUP	100	180	43	378	630	648	180	432	210	384

Aggregation strategies

- Borda Count Strategy (Borda, 1781)

	A	B	C	D	E	F	G	H	I	J
John	8	1	0	2 ½	8	6	2 ½	4 ½	8	4 ½
Adam	0	7 ½	4 ½	7 ½	3	7 ½	2	7 ½	1	4 ½
Mary	9	1½	0	5½	8	7	1½	3½	5½	3½
GROUP	17	10	4½	15	19	20	6	15½	14½	12

- Points assigned to each alternative according to its position in individuals' ranked lists
  - The bottom of the list gets zero points, the next one up one point
- The points are summed to obtain group score

- Copeland Rule (Copeland, 1951)

	A	B	C	D	E	F	G	H	I	J
A	0	-	-	-	0	-	-	-	0	-
B	+	0	-	+	+	+	0	+	+	+
C	+	+	0	+	+	+	+	+	+	+
D	+	-	-	0	+	+	-	0	0	-
E	0	-	-	-	0	-	-	-	-	-
F	+	-	-	-	+	0	-	-	-	-
G	+	0	-	+	+	+	0	+	+	+
H	+	-	-	0	+	+	-	0	+	-
I	0	-	-	0	+	+	-	-	0	-
J	+	-	-	+	+	+	-	+	+	0
GROUP	+7	-6	-9	+1	+8	+5	-6	0	+3	-3

- Approval voting – Alternatives that are not strongly disliked

Threshold 5

	A	B	C	D	E	F	G	H	I	J
John	1			1	1	1	1	1	1	1
Adam		1	1	1	1	1	1	1		1
Mary	1			1	1	1		1	1	1
GROUP	2	1	1	3	3	3	2	3	2	3

Threshold 6

	A	B	C	D	E	F	G	H	I	J
John	1				1	1		1	1	1
Adam		1	1	1	1	1		1		1
Mary	1			1	1	1			1	
GROUP	2	1	1	2	3	3	0	2	2	2

- Least Misery strategy – Minimum of individual ratings

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6
GROUP	1	4	2	6	7	8	5	6	3	6

- Most Pleasure strategy – Maximum of individual ratings

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6
GROUP	10	9	8	9	10	9	6	9	10	8

- Average Without Misery strategy – Average of individual ratings, but without those scoring below some threshold

Threshold 4

	A	B	C	D	E	F	G	H	I	J
John	10	4	3	6	10	9	6	8	10	8
Adam	1	9	8	9	7	9	6	9	3	8
Mary	10	5	2	7	9	8	5	6	7	6
GROUP	-	18	-	22	26	26	17	23	-	22

Aggregation strategies

(Masthoff, 2004)

- Average
- Least misery
- Average without misery
- Multiplicative
- Plurality Voting
- Borda count
- Copeland rule
- Approval voting
- Most pleasure
- Fairness
- Most respected person

- Graph-based ranking (Kim et al, 2013)
- Spearman footrule rank (Baltrunas et al, 2010)
- Nash equilibrium (Carvalho & Macedo, 2013)
- Purity (Salamó et al, 2012)
- Completeness (Salamó et al, 2012)
- ……….

Exp1: What do people do?

I know individual ratings of Peter, Mary, and Jane. What to recommend to the group? If time to watch 1-2-3-4-5-6-7 clips…

Why?

Compare what people do with what strategies do

Exp1: Results

- Participants do ‘use’ some of the strategies
- Care about Misery, Fairness, Preventing starvation

Exp2: What do people like?

You know the individual ratings of you and your two friends. I have decided to show you the following sequence. How satisfied would you be? And your friends?

Why?

Which strategy does best?
Which prediction function does best?

Exp2: Results

- Multiplicative strategy performs best
  - FEHJDI is the only sequence that has ratings ≥ 4 for all participants for all individuals
- Prediction functions: Some evidence of normalization, Misery taken into account, Quadratic is better than linear

Examples of GRSs

- **MUSICFX** - chooses a radio station for background music in a fitness center for a group of people working out in that time
- **POLYLENS** - recommends movies based on individuals' ratings; allows users to make groups and ask for group recommendations
- **INTRIGUE** - recommends places to visit for tourist groups taking into account characteristics of subgroups
- **TRAVEL DECISION FORUM** - helps a group to agree on the desired attributes of a planned joint holiday
- **CATS** - helps users to choose a joint holiday, by enabling them to critique features of package holidays

Examples of GRSs

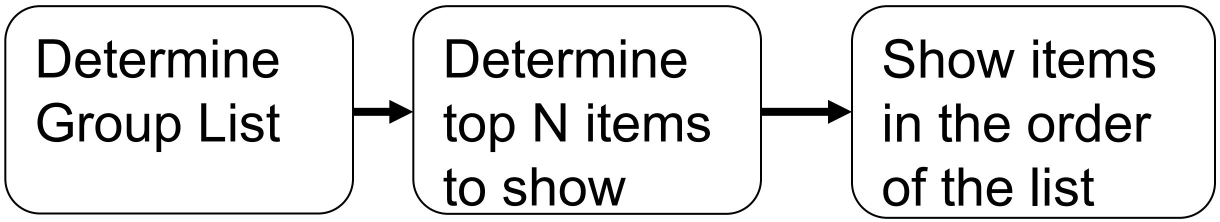
- **YU’S TV RECOMMENDER** - Recommends television programs for groups, based on individuals’ content preferences
- **GROUP ADAPTIVE INFORMATION AND NEWS** - adapts the display of news and advertisements to the group of people near it
- **HAPPYMOVIE** - movie recommender that builds group profile based on members’ personality and social relationships strength
- **INTELLIREQ** - supports groups in deciding on software requirements based on already defined user preferences

Recommending Sequences

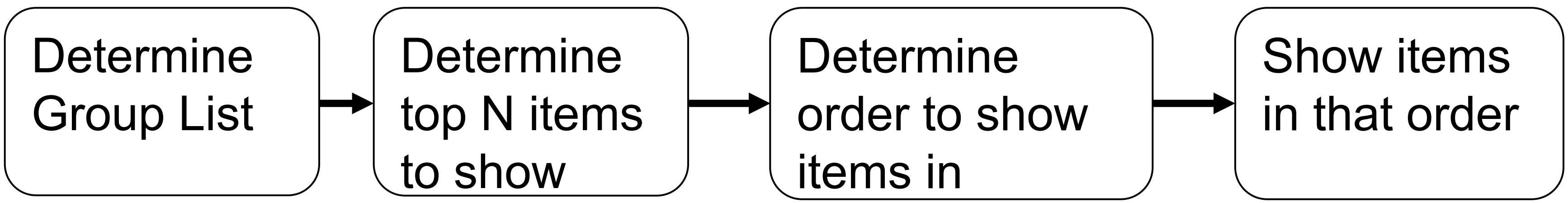
Why sequences?

- Sequences for groups are a lot more interesting than individual items
- With a sequence, it is harder to please everybody
- Fairness has a larger role
- Example domains:
  tourist attractions, music in shop, TV news

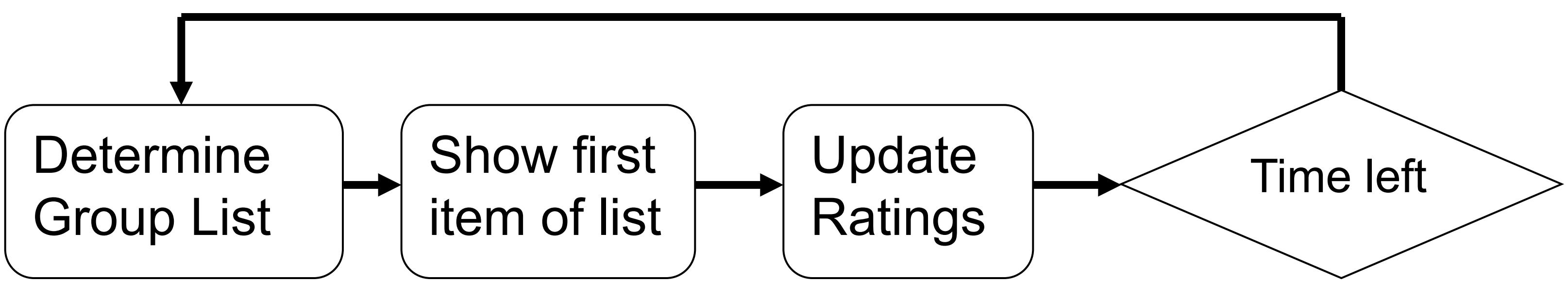
How to deal with order?



But: mood consistency, strong ending, narrative flow,..



But: given all this, perhaps other items are more suitable..



electronic commerce UNIVERSITY OF ABERDEEN Utrecht University

Exp3: Effect of mood, topic

[Insert name of your favorite sport's club] wins important game,
Fleet of limos for Jennifer Lopez 100-metre trip,
Heart disease could be halved, Is there room for God in Europe?,
Earthquake hits Bulgaria, UK fire strike continues,
Main three Bulgarian players injured after Bulgaria-Spain football match

How much would you want to watch these 7 news items?
How would they make you feel?

The first item on the news is "England football team has to play Bulgaria". Rate interest, resulting mood.

Rate interest in 7 news items again

Exp3: Results

- Mood can influence ratings
- Topical relatedness can influence ratings
- Effect of topical relatedness can depend on rating for first item
  - if interested then more likely to increase
- Importance dimension

Domain specific aspects of sequences

For example, in tourist guide domain:

- Mutually exclusive / hard to combine items
- Physical proximity
- Diversity concerns

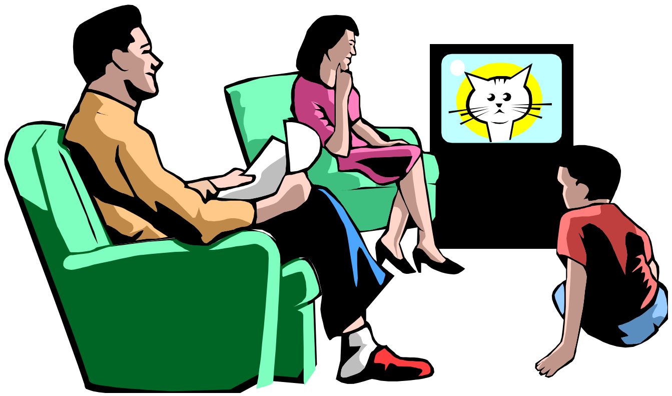
In news domain:

- Novelty concerns
- Topical relatedness

How about music?

Modelling Satisfaction

Why model satisfaction?



- When adapting to a *group* of people, you cannot give everyone what they like all the time

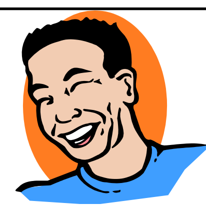
- But you don't want somebody to get too dissatisfied…

- When adapting a *sequence* to an individual, the order may impact satisfaction

Strategies that use satisfaction

Know how satisfied each user is with the items so far

And their profile

	B	C	H	I	J
	9	8	9	3	8
	5	2	6	7	6
	4	3	8	10	8

Decide which item to present next, trying to please the least satisfied user

Strongly support grumpiest strategy

- Pick item most liked by the least satisfied person
- If multiple items most liked, use existing strategy (e.g. Multiplicative) to choose between them

	A	B	D	E
Peter	10	4	6	10
Jane	1	9	9	7
Mary	10	5	7	9

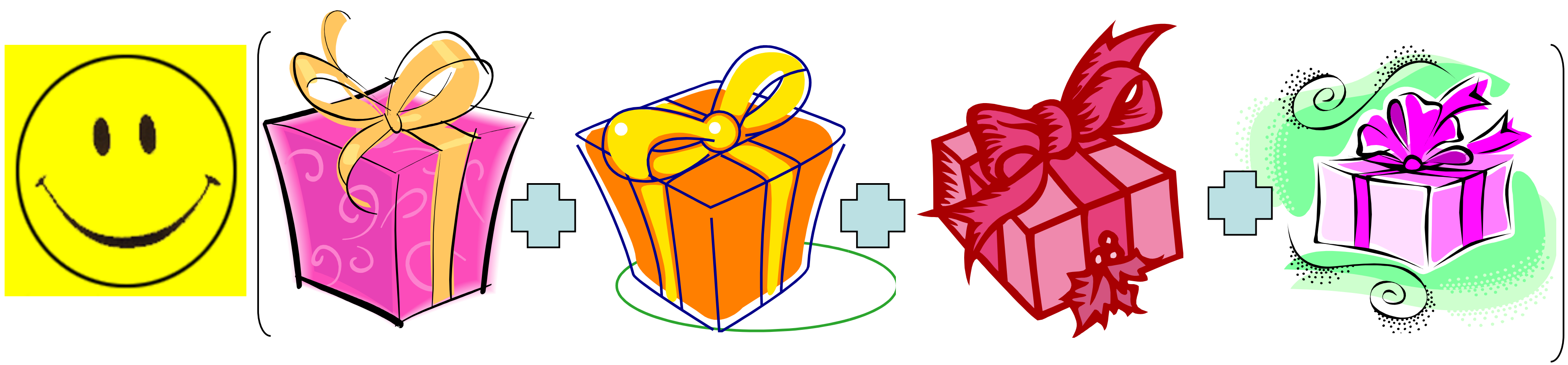
least satisfied so far

- Strategy would pick A
- Very bad for Jane
- Better to show E?

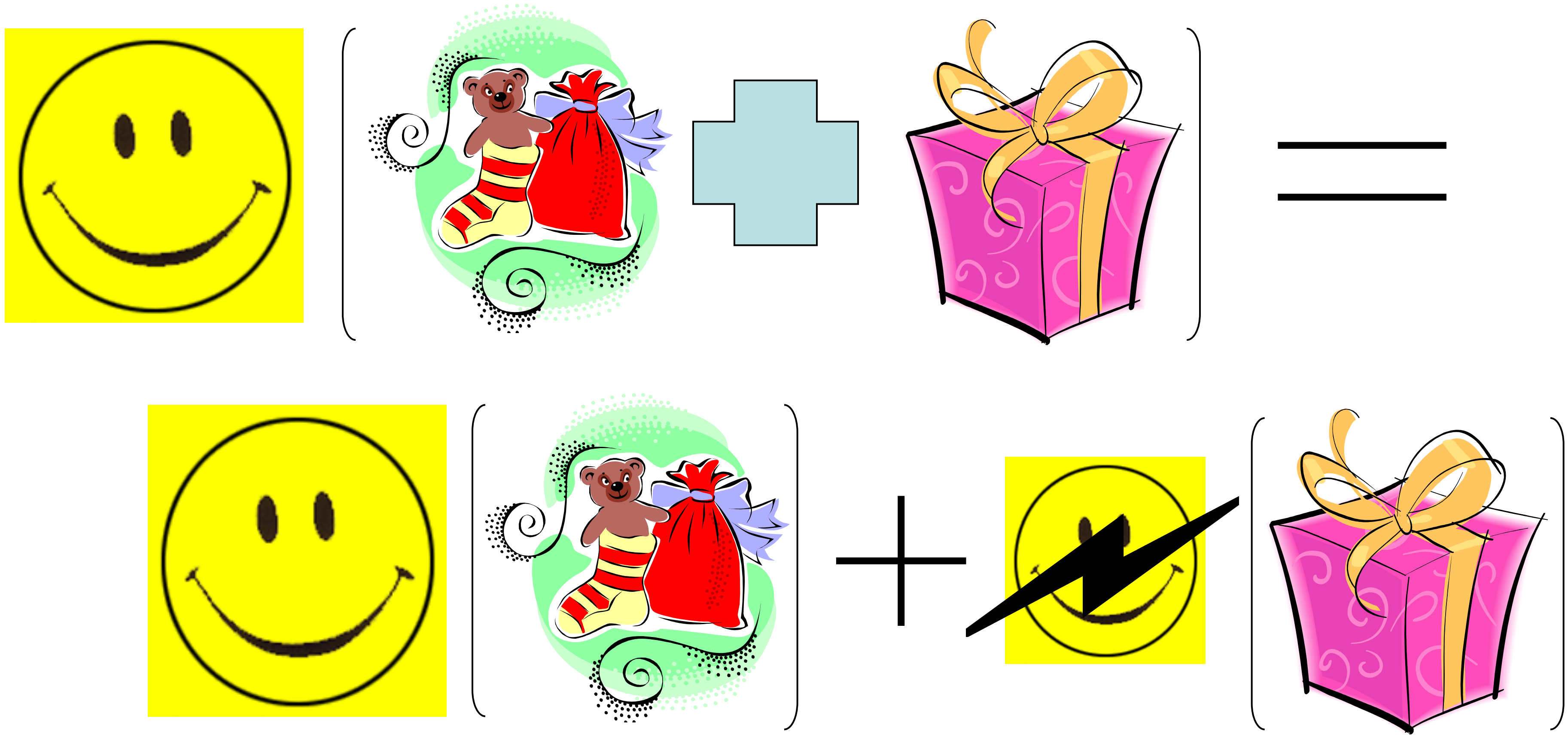
- Weakly support grumpiest strategy
  - Consider all items quite liked (say rating>7) by the least satisfied person
  - Use existing strategy to choose between them
- Strategies using weights
  - Assign weights to users depending on satisfaction
  - Use weighted form of existing strategy, e.g. weighted Average
  - Cannot be done with some strategies, such as Least Misery

Challenge is to model satisfaction

- Would like a model that *predicts* satisfaction of an individual user after a sequence of items



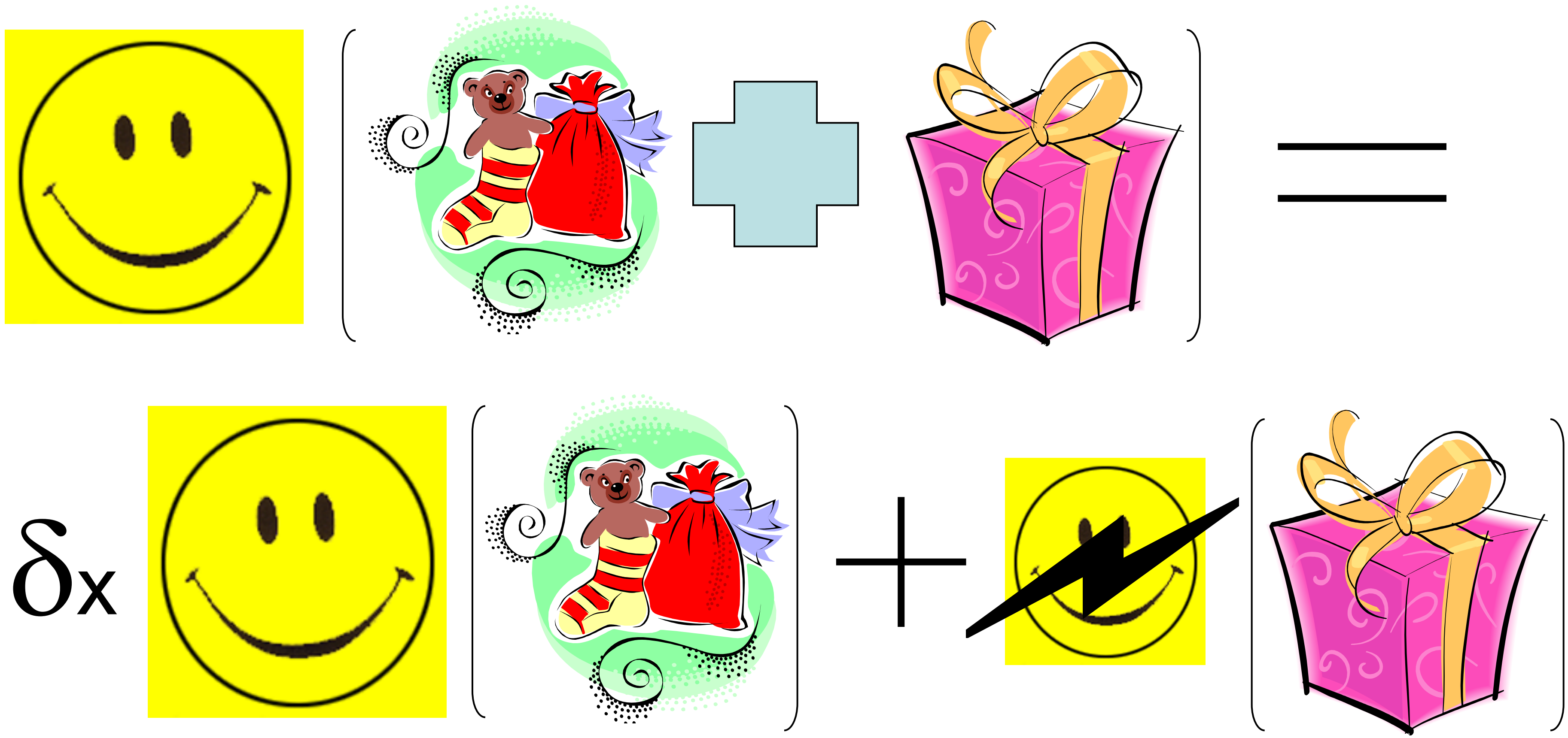
Basic model



 () =

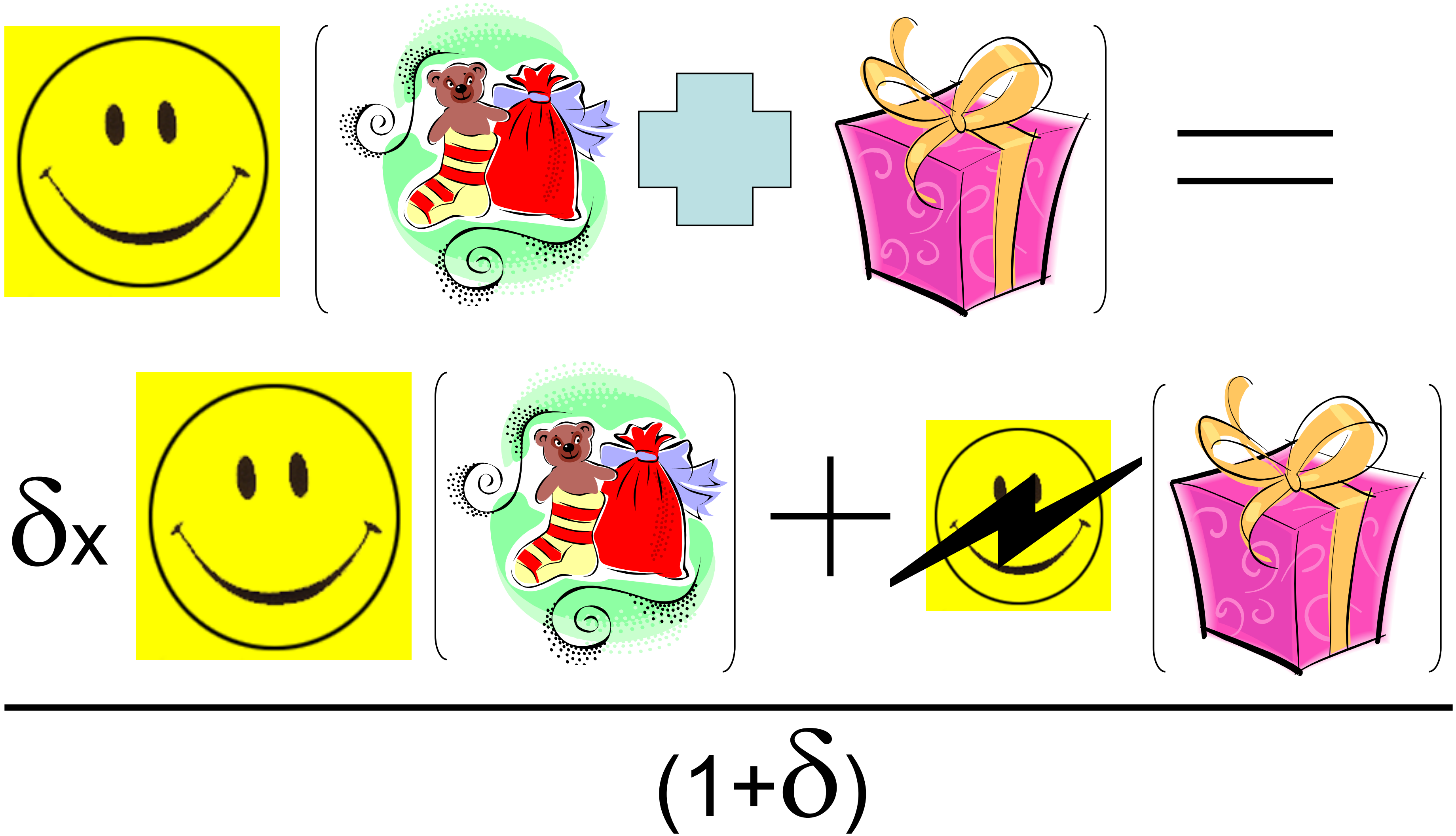
Quadratic(
Rebalanced(
Normalized(
Rating()))

Variant 1: Satisfaction decreases over time



$0 \leq \delta \leq 1$ δ=0: No memory δ =1: Perfect memory

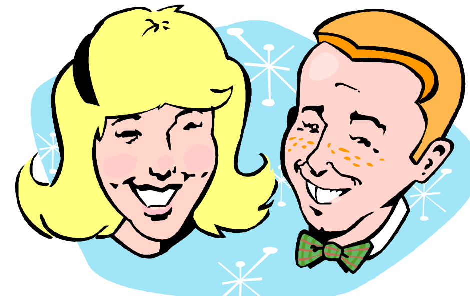
Variant 2: Satisfaction is bounded



Mood impacts evaluative judgement

Hardly ever.

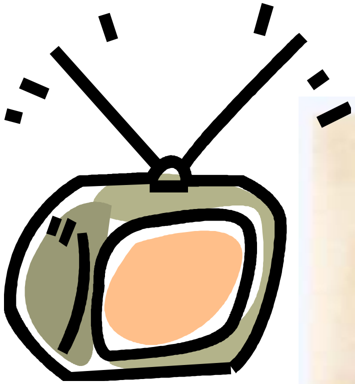
How often has your television broken down in the last years?

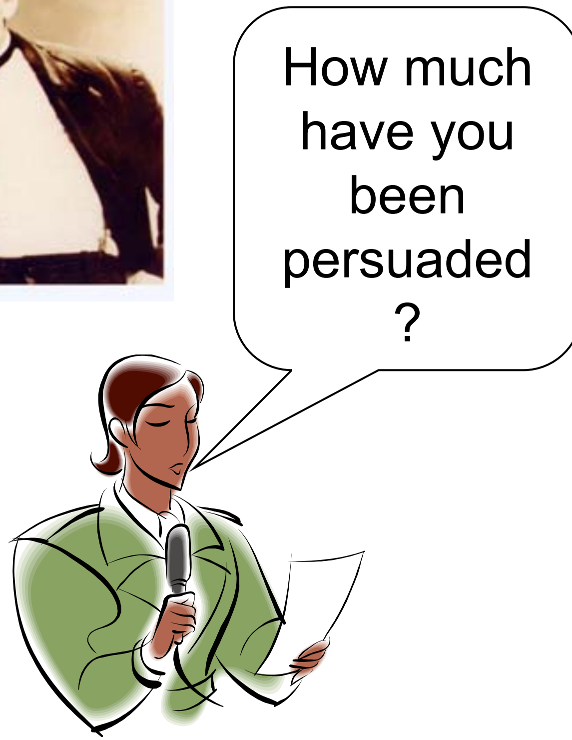


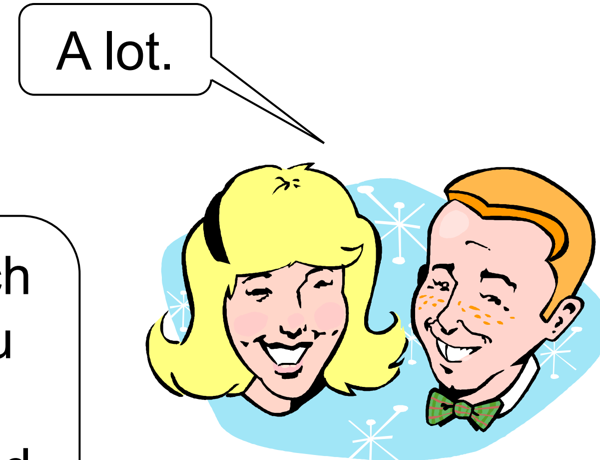
A lot!

Isen et al, 1978

Mood impacts evaluative judgement





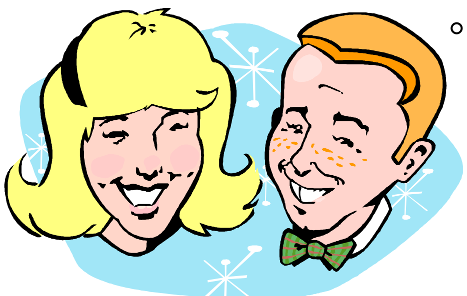


Mackie & Worth, 1989

Affective forecasting can change actual emotional experience

I am expecting to like this…

It is ok.



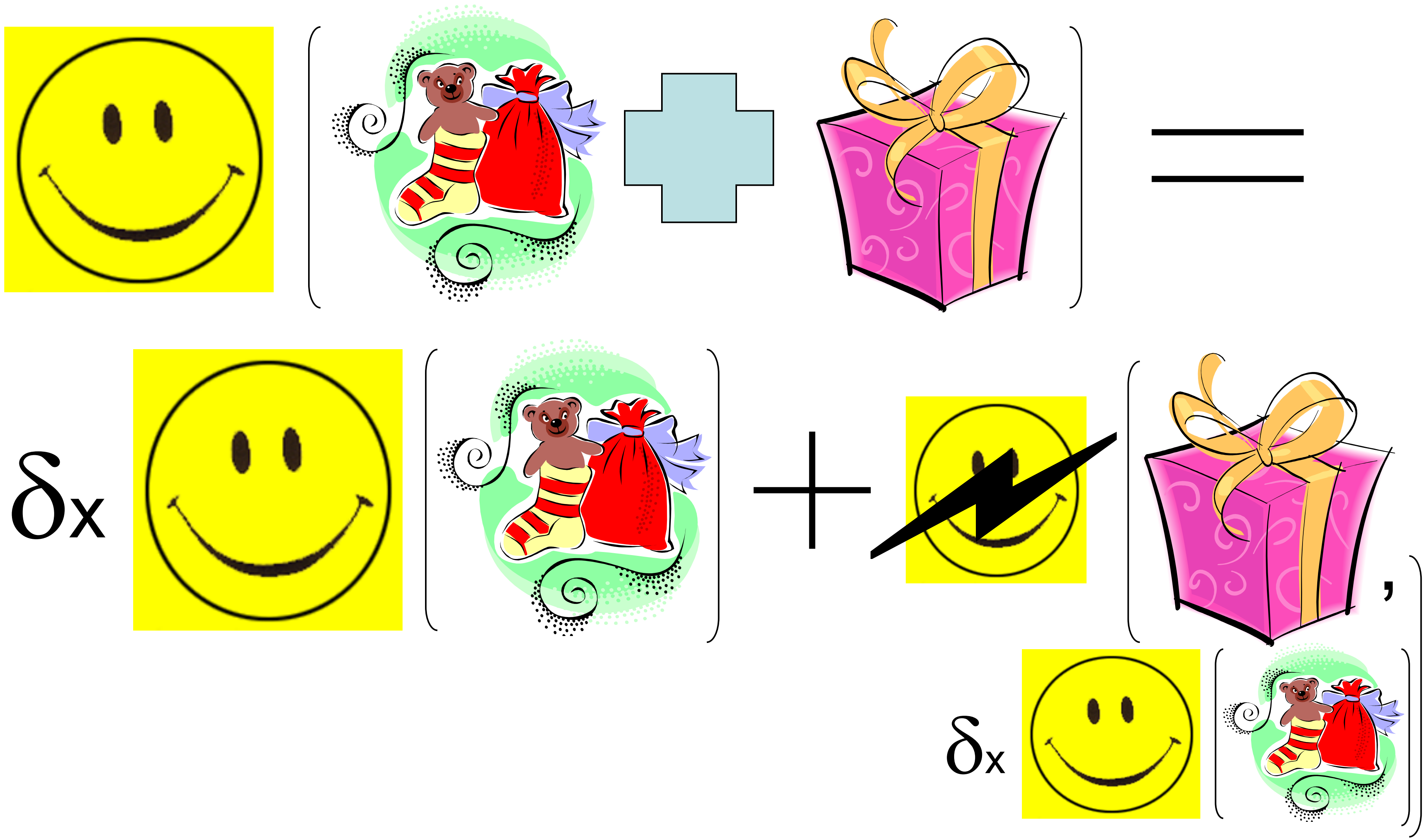
Assimilation

I am expecting to hate this…

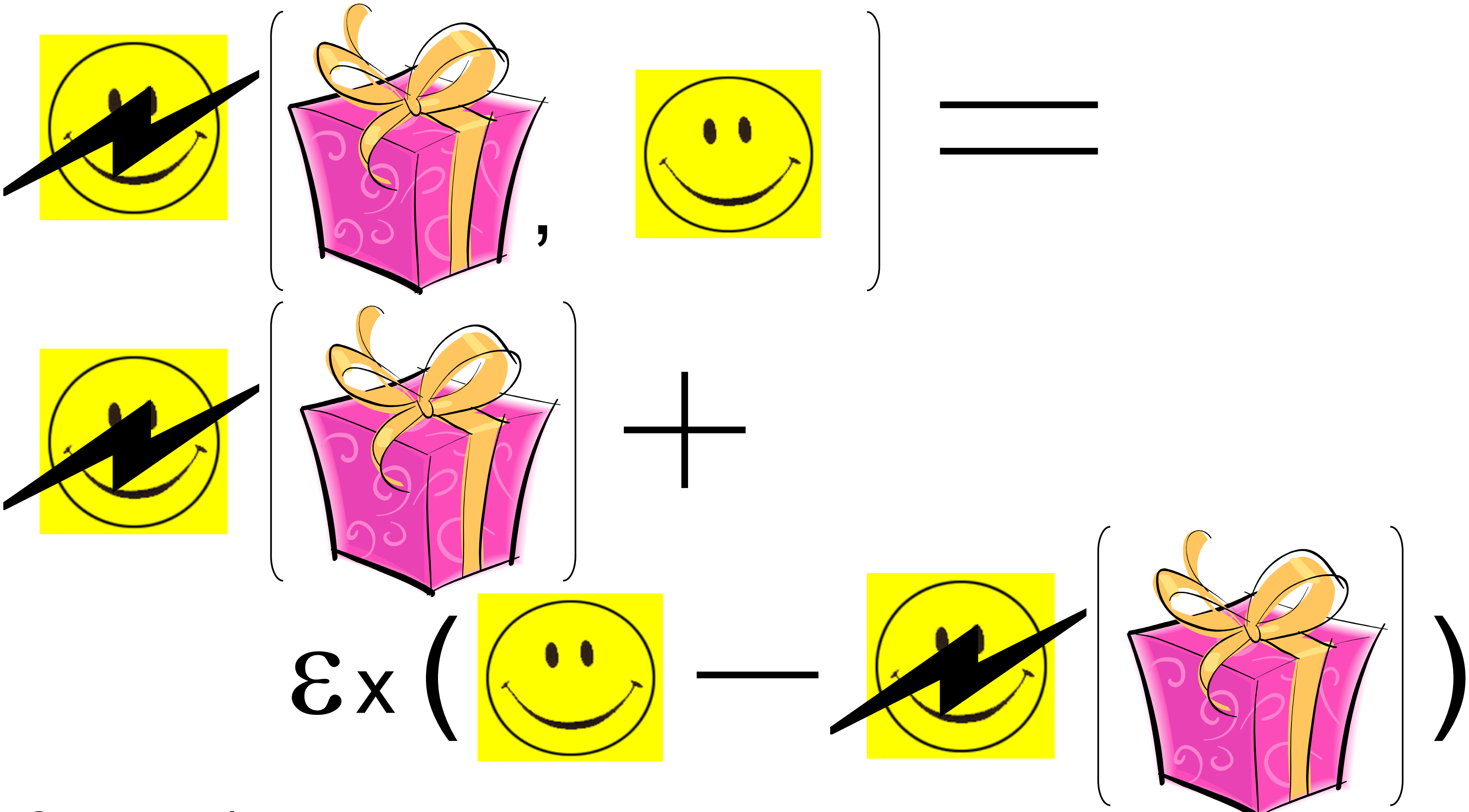
I really hate it..

Wilson & Klaaren, 1992

Variant 3: Impact depends on mood



Impact depends on mood

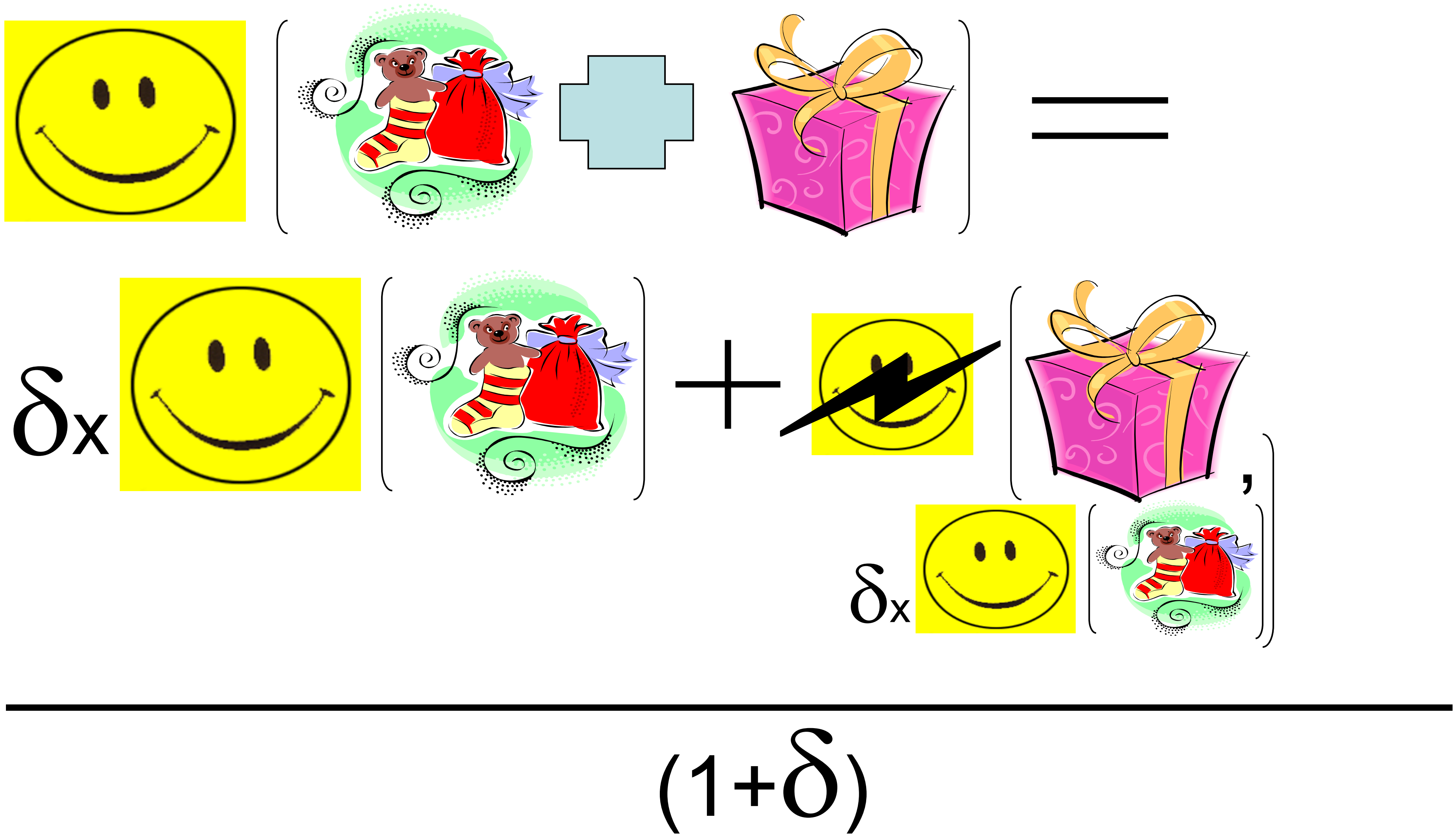


$0 \leq \varepsilon \leq 1$ all

$\varepsilon = 0$: No impact mood

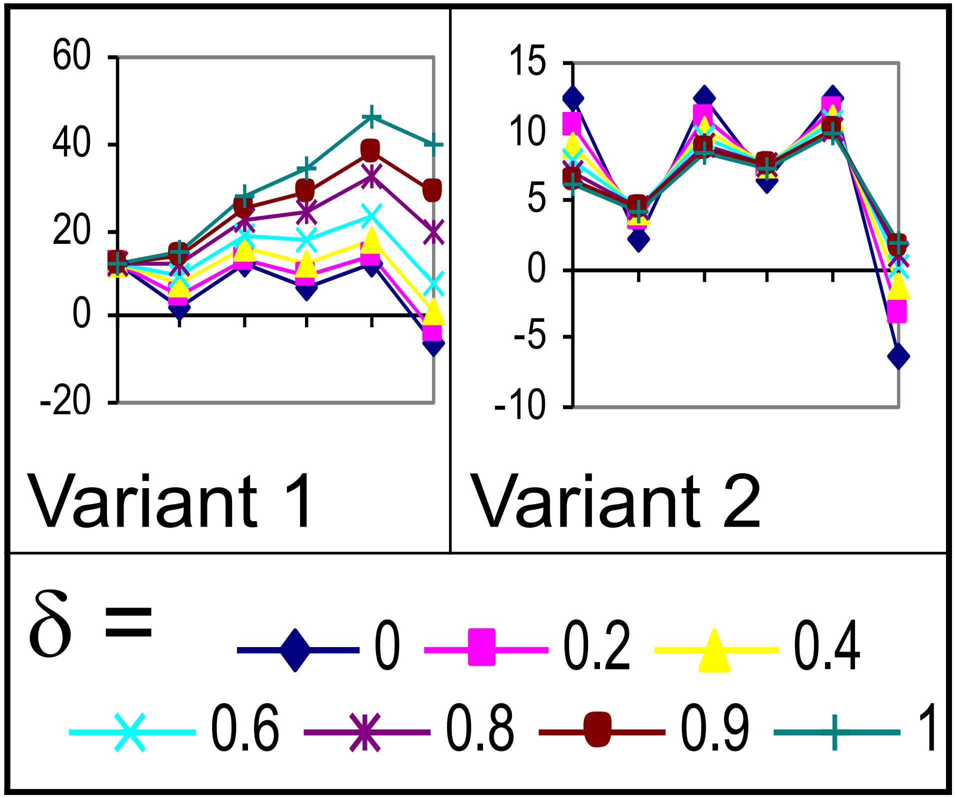
$\varepsilon = 1$: Mood determines

Variant 4: Combination of Variants 2 and 3



Evaluation by simulation

- Models predict satisfaction of Peter, Jane, Mary with a sequence, given δ, ε
- Compare to human predictions (from Exp2)
- Some strategies bad for any δ
- δ should be high (>0.5), ε low
- Multiplicative best for high δ



Jane, sequence from Multiplicative strategy

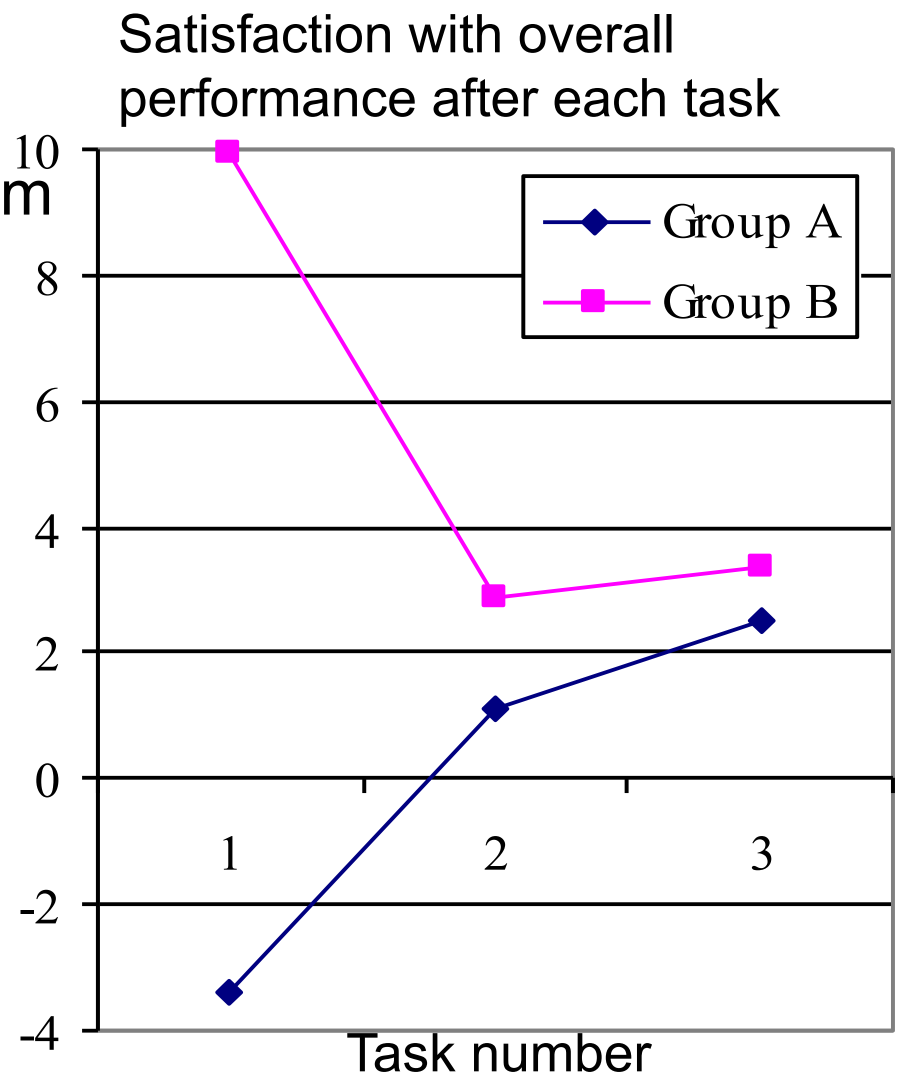
Evaluation by study (Exp4)

Group A: Hard – Easy –Medium
Group B: Easy – Hard – Medium

Variants 1 and 2 predict lower satisfaction for group B (easy first) after 2 tasks, due to emotions wearing off.

Assimilation could result in higher satisfaction for B.

Variant 4 seems best



Emotional contagion

Totterdell et al, 1998; Barsade 2002; Bartel & Saavedra, 2000

Emotional contagion

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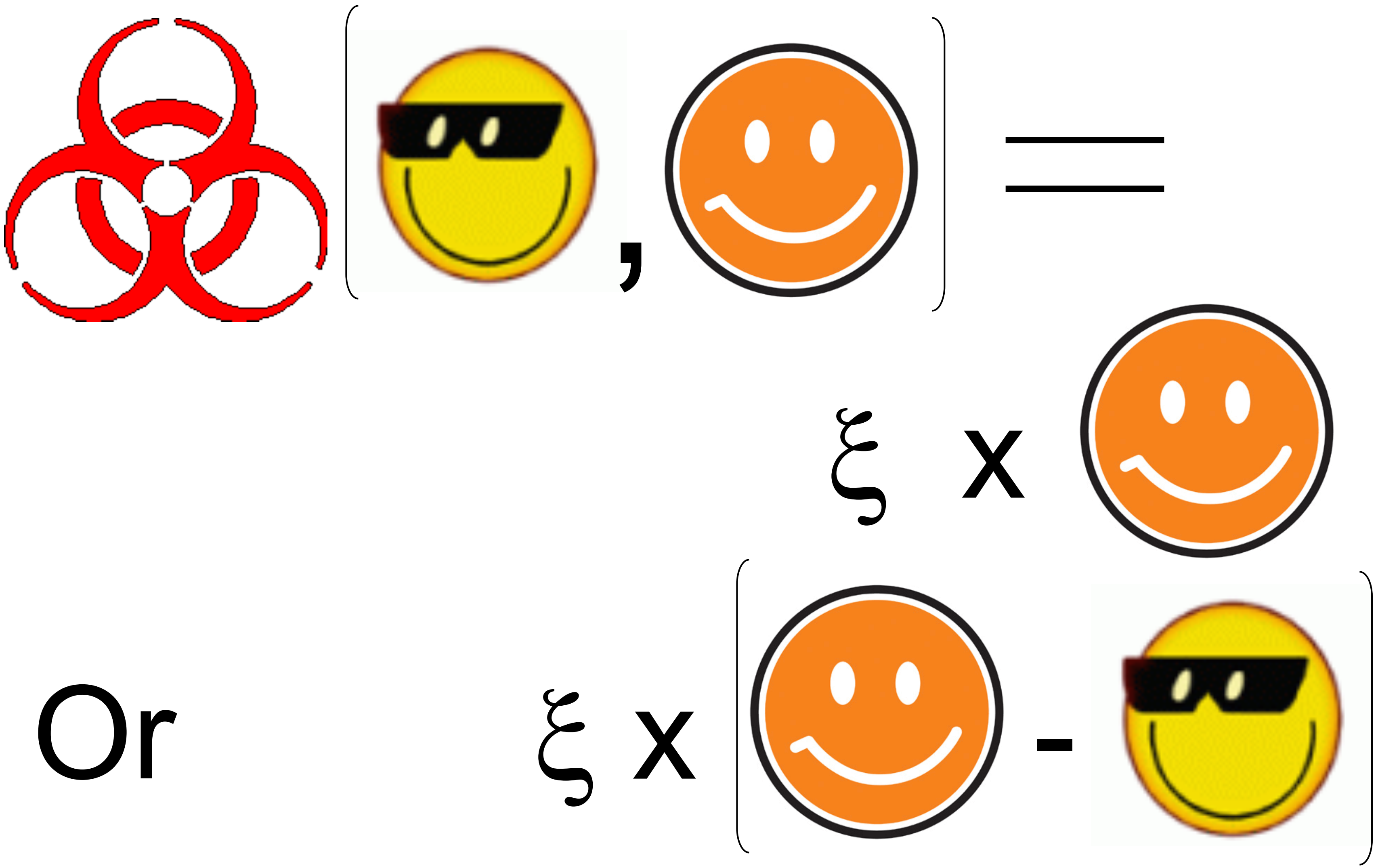
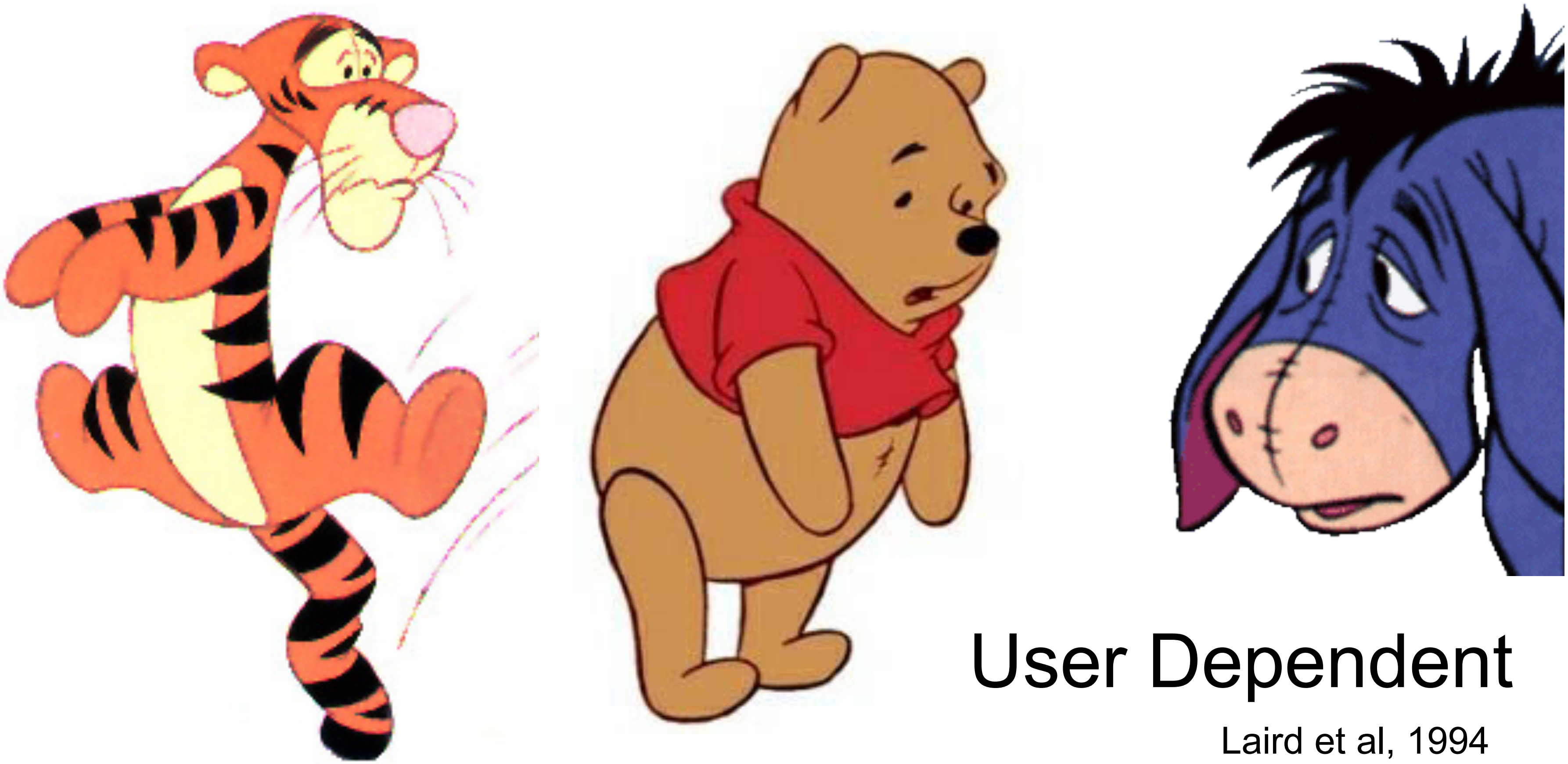
Emotional contagion



Susceptibility of emotional contagion



User Dependent

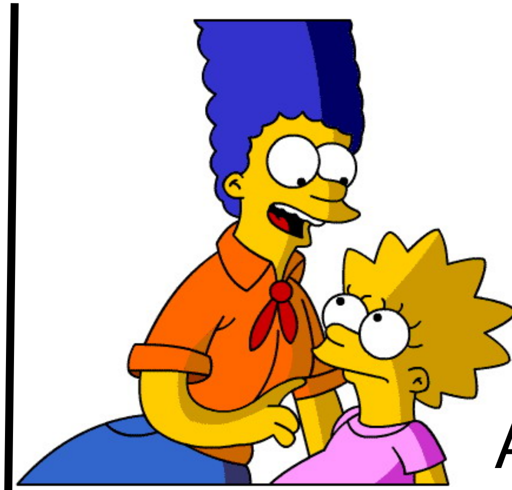
Laird et al, 1994

So, ξ should be user dependent

Types of relationship

“Somebody you share everything with, e.g. a best friend”

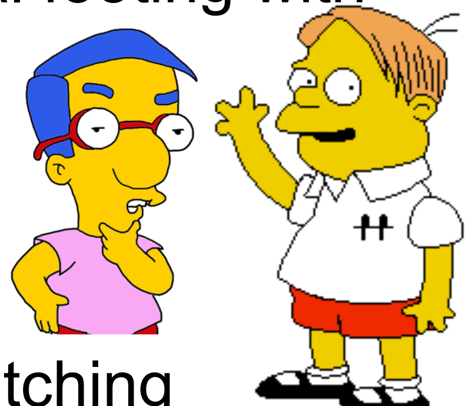
Communal Sharing



“Somebody you respect highly”

Authority Ranking

“Somebody you are on equal footing with”

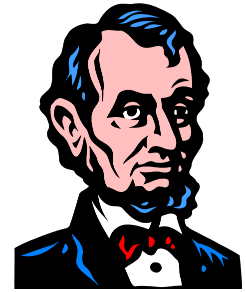


Equality Matching

“Somebody you do deals with / compete with”

Market Pricing

Susceptibility and types of relationship

When calculating  of  by 

Need to take account of  ’s susceptibility

And the relationship between  and 

ξ   $=$ ς  $\times$ ρ  

Exp5: Emotional contagion

- Susceptibility to emotional contagion measured using existing scale (Doherty, 1997)

- “Think of somebody [relationship type].
  Assume you and this person are watching TV together. You are enjoying the program a little. How would it make you feel to know that the other person is [enjoying it greatly / really hating it]? My enjoyment would…”

- We expect Authority Ranking and Communal Sharing to have more contagion.

- Will Market Pricing have negative ξ?

Exp5: Results

- Contagion happens
- More contagion for Authority Ranking and Communal Sharing relationships
- No difference between negative and positive contagion
- Susceptibility only seemed to make a difference for Communal Sharing relationships

Incorporating Group Attributes

What attributes matter?

- Remember the task I gave you at the start

- What attributes of the people in your group influenced the decision making (excluding their opinions on the music items)?

- Or could have influenced the decision making if they had been present in your group

Attributes of group members

- Demographics and roles (Ardissono et al, 2002; Senot et al, 2010)
- Personality
  - Propensity to emotional contagion
  - Agreeableness?
  - Assertiveness and cooperativeness (Quijano-Sanchez et al, 2013)

- Expertise (Berkovsky & Freyne; Gatrell et al, 2010, Herr et al, 2012)
- Personal impact/cognitive centrality (Liu et al, 2012; Herr et al, 2012)

Typically used to vary the weights of group members

Attributes of the group as a whole

- Relationship strength
  Gatrell et al (2010) propose:
    Most Pleasure for strong relations,
    Least Misery for weak, Average for intermediate

- Relationship type:
  Wang et al (2010) distinguish:
  - Positionally homogeneous vs heterogeneous groups
  - Tightly coupled versus loosely coupled groups

Typically used to select a different strategy

Attributes of pairs in the group

- Relationship strength / social trust
  (Quijano-Sanchez et al, 2013)
- Personal impact
  (Liu et al, 2012; Ye et al, 2012, Ioannidis et al, 2013)

Typically used to adjust the ratings of an individual in light of the ratings of the other person in the pair

Personality in Group Recommeder Systems

Personality

Personality reflects *“individual differences in emotional, interpersonal, experiential, attitudinal, and motivational styles”*

(McCrae and John, 1992)

Five-factor model (also known as the **Big Five)**

- Widely used model of personality
- Models human behavior in five orthogonal dimensions

Openness - the extent to which one is inclined towards new and unusual experiences

Conscientiousness - the extent to which one is precise, careful and reliable

Extraversion - the extent to which one is outgoing, cheerful, and warm

Agreeableness - the extent to which one is altruistic, caring, and emotionally supportive

Neuroticism - the extent to which one is distressed

- **Thomas-Kilmann Conflict Resolution Style**
  - In group decision-making setting conflicts might arise
  - Thomas & Kilmann defined behavior categories in a conflict
  - Four conflict resolution styles were identified

Competing (low cooperation & high assertion)

Collaborating (high cooperation & high assertion)

Avoiding (low cooperation & low assertion)

Accommodating & compromising (high cooperation & low assertion)

Personality in Recommender Systems

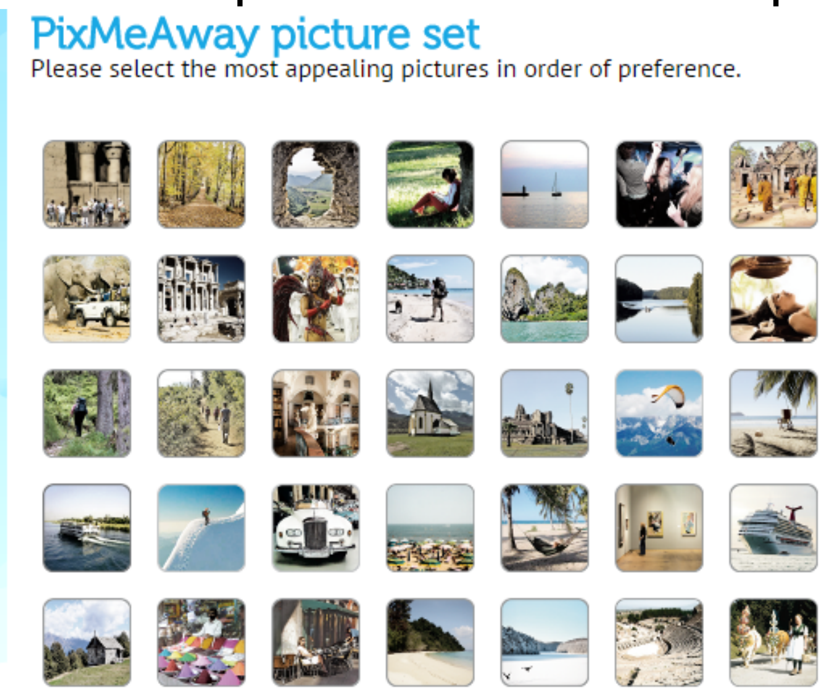
- Obtaining personality for RSs is challenging (Tkalcic, et al., 2018)
  - Usually, acquisition of personality is done with questionnaires
  - The questionnaires are used in user studies
  - In RSs this should not be the first option
  - The personality should be estimated in an unobtrusive fashion

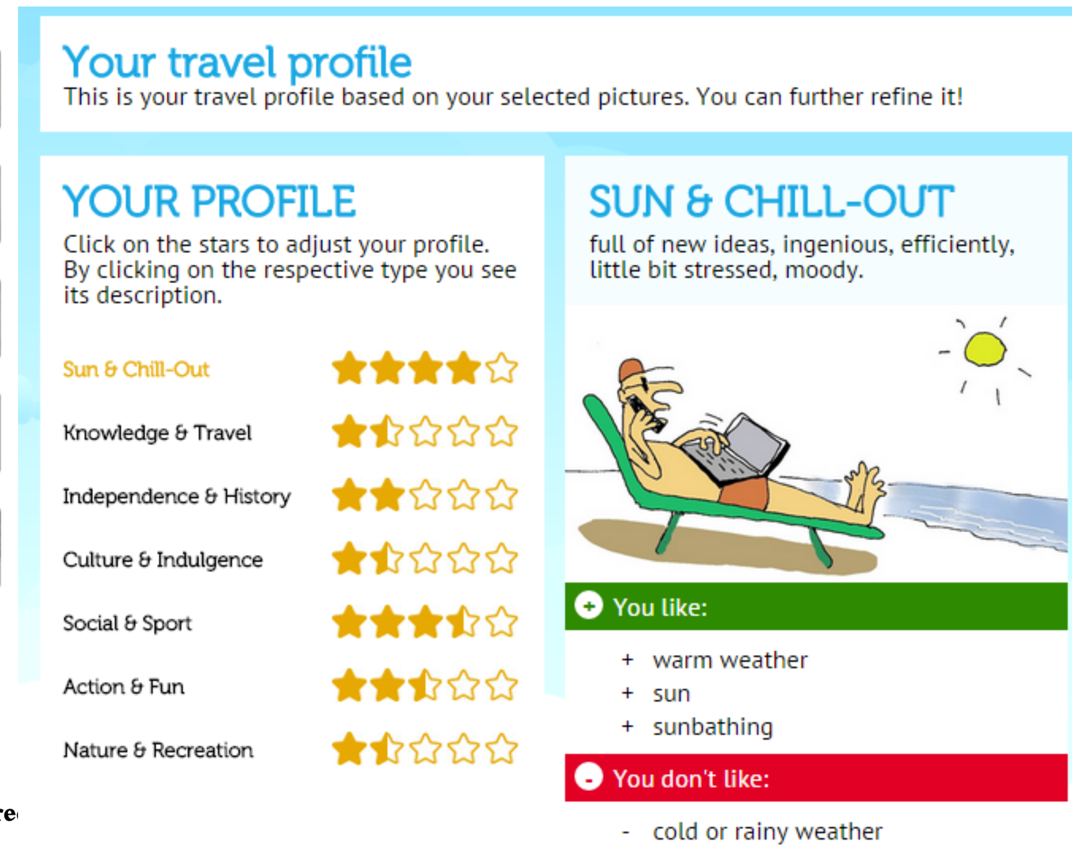
Obtaining personality information (examples) (Tkalcic et al., 2018)

- From *Twitter*: Above average number of followers and followees is correlated with *extraversion* (Quercia et al., 2011)
- From *Facebook*: user likes of movies, music, video games, etc. can be used to predict personality traits (Kosinski et al., 2013)
- From *Instagram*: color-based, low-level features of pictures can be used to predict personality traits (Skowron et al., 2016)

Picture-based approach to RSs (Neidhardt et al., 2014)

- Elicitation of user preferences through picture selection
- Representation of user profile through seven travel factors





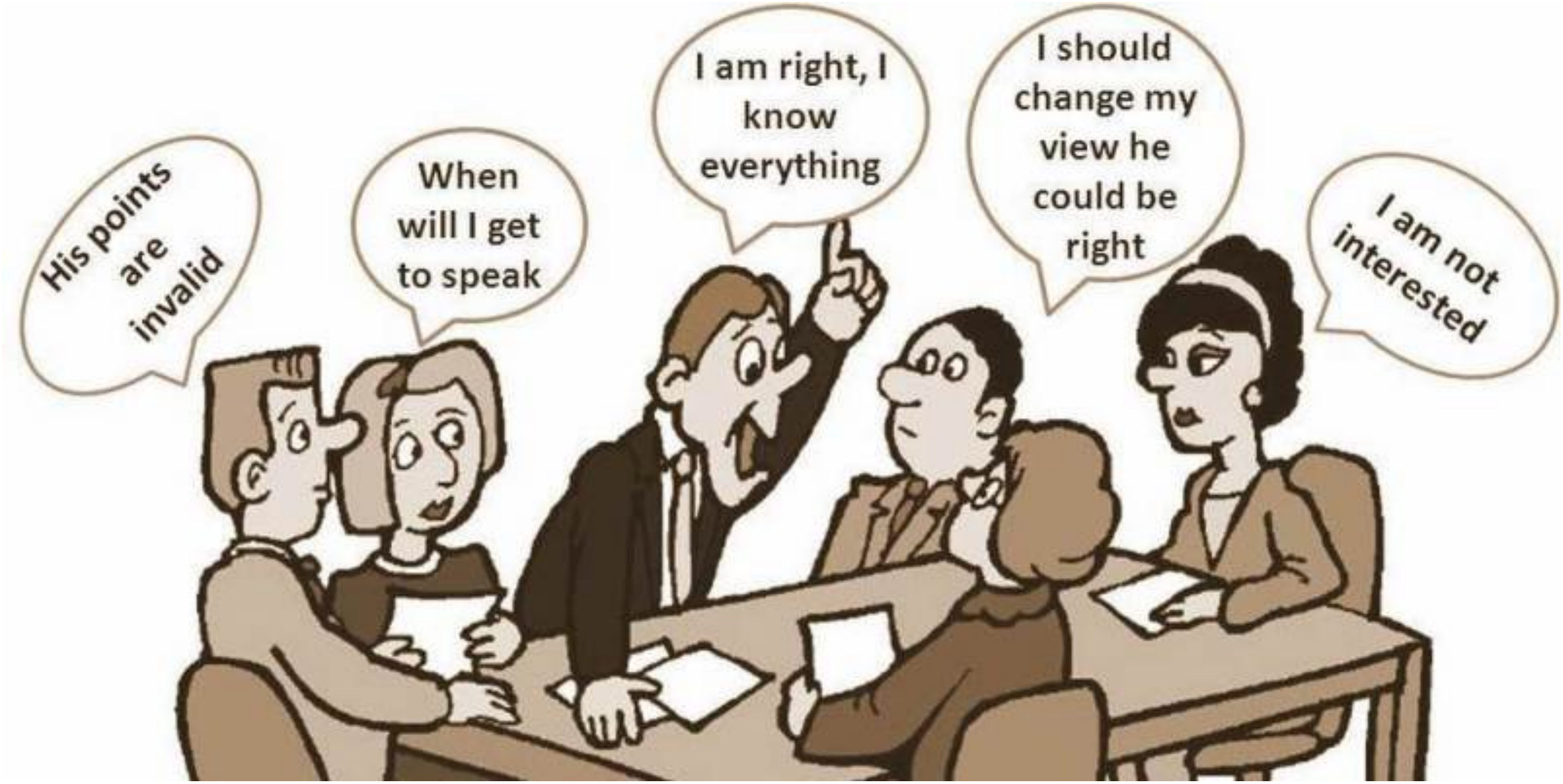
Picture-based approach to RSs (Neidhardt et al., 2014)

- Seven travel factors as a combination of:
  - Short term behavioral patterns, 17 Tourist Roles (Gibson & Yiannakis, 2002)
  - Long term personality descriptors, five-factor personality model
  - *Sun & Chill-Out, Knowledge & Travel, Independence & History, Culture & Indulgence, Social & Sport, Action & Fun, Nature & Recreation*

- Travel factors obtained with the factor analysis
  - Input of 22 dimensions (17 Tourist Roles + 5 personality traits)
  - Data sample of ~1000 participants
  - Data was collected with a 50-item questionnaire

Picture-based approach to RSs (Neidhardt et al., 2014)

- Recommendation process
  - Seven travel factors assigned to each picture
    - User profile is computed based on the travel factors scores of the selected pictures
  - Each destination / POI is also annotated with the seven travel factors
  - Recommendations are computed as Euclidean distance between user profile and destination / POI profile



PERSONALITY AND GROUPS

Personality and Group Behavior

- Study in the travel and tourism domain focusing on group decision-making process identified how personality traits are related with choice satisfaction (Delic et al., 2017)
  – Choice satisfaction measures individual group members' satisfaction with the final group decision

  – The task for participants, organized in two to five group members, was to decide on a destination that they as a group would like to visit

Personality and Group Behavior

- The results of the study showed:
  1. Differences between high and low satisfied participants
     – **High satisfied** participants were **more reliable, agreeable and less neurotic** (Big Five Factors)
     – **High satisfied** participants were **more collaborative** (Thomas-Kilmann Conflict Mode Instrument)
  2. Differences between high and low satisfied *"losers"*
     – **High satisfied losers** were **more open, social, outgoing and agreeable and less neurotic** (Big Five Factors)

Personality and Group Behavior

- The results of the study showed:

3. Conflict resolution style relation to the group decision-making outcomes
   - **Cooperative participants** often became **High satisfied Winners** and often were **satisfied even when they lost**
   - **Avoiders (passive participants)** were **highly satisfied when they won** but they fell into **low satisfaction when they lost**

INCORPORATING PERSONALITY IN GROUP PREFERENCE MODELS

Personality in GRSs – Example I

- Conformity as a personality trait
  - *“Conformity is a type of social influence involving a change in belief or behavior in order to fit in with a group”*
  - People of different personality types are differently prone to conformity

Personality in GRSs – Example I

Nguyen and Ricci (2017) evaluated the relationship between conformity and the type of preferences to be used in a group model

- Three types of conformity defined
  - Independence: Group members do not change their preferences
  - Conversion: Preferences of group members tend to become similar
  - Anti-conformity: Preferences become more divergent
- Two types of preferences were used
  - Long-term preferences: Independent individual preferences
  - Session-based preferences: Preferences developed during the group discussion

Personality in GRSs – Example I

- Simulation of the group decision-making process showed:
  - Long-term preferences should prevail in the group models for groups with the independence conformity type
  - Long-term and the session-based preferences should be equally used in the group models for groups with conversion conformity type
  - Session-based preferences should prevail in the group models for groups with the anti-conformity type

Personality in GRSs – Example II

- Quijano-Sanchez et al. (2006) used Thomas-Kilmann Instrument (TKI) to determine influence and conformity in groups
- The assumptions for the group decision-making process are:
  – The more assertive a person is the greater influence she will exhibit
  – The more collaborative a person is the greater conformity will be
- To determine assertiveness and cooperativeness a questionnaire evaluating TKI mode is needed

	Assertiveness		**Cooperativeness**	
TKI Mode	High	Low	High	Low
Competing	0.375	-0.075	-0.15	0
Collaborating	0.375	-0.075	0.375	-0.075
Avoiding	-0.375	0.075	-0.375	0.075
Accommodating	-0.15	0	0.375	-0.075

Personality in GRSs – Example II

- The TKI mode questionnaire results in *High* or *Low* for the four conflict resolution styles

- The assertiveness / cooperativeness is calculated by combining the scores of the four conflict resolution styles

- To encapsulate the personality into the group model, first, the ***conflict mode weight (cmw)*** is calculated

$$cmv(u) = \frac{1 + \text{assertiveness} - \text{cooperativeness}}{2}$$

Personality in GRSs – Example II

- In the second step, we calculate the ***personality-enhanced item-ratings*** for each user in the group
  - *Personality-enhanced rating* $p_{pers}(u_a, i)$, represents the new rating of the user u_a for the item i, that is influenced by the personalities of her fellow group members
  - Given the initial rating $p(u_a, i)$ of the user u_a for the item i, the *conflict mode weights* $cmw(u_a)$ of the u_a, and its fellow group members $cmw(u)$, the new rating is:

$$p_{pers}(u_a, i) = \frac{\sum_{u \in G(u_a \neq u)} (p(u_a, i) + (cmw(u_a) - cmw(u))}{|G| - 1}$$

Personality in GRSs – Example II

- Group rating $g_{pers}(G, i)$ of the group G for the item i is calculated as the average of the *personality-enhanced ratings*

$$g_{pers}(G, i) = \frac{\sum_{u \in G} p_{pers}(u, i)}{|G|}$$

Personality in GRSs – Example II

Coefficients for determining assertiveness and cooperativeness

	Assertiveness		Cooperativeness	
TKI Mode	High	Low	High	Low
Competing	0.375	-0.075	-0.15	0
Collaborating	0.375	-0.075	0.375	-0.075
Avoiding	-0.375	0.075	-0.375	0.075
Accommodating	-0.15	0	0.375	-0.075

User	Competing	Collaborating	Avoiding	Accommodating	***cmw(u)***
u_1	High	High	Low	Low	0.8
u_2	High	Low	Low	Low	0.8
u_3	Low	High	Low	High	0.2

$$cmv(u) = \frac{1 + \text{assertiveness} - \text{cooperativeness}}{2}$$

Personality in GRSs – Example II

User-item initial ratings

User	t_1	t_2	t_3	t_4	t_5
u_1	2	4	5	1	3
u_2	3	2	3	4	5
u_3	1	3	5	2	1
AVG	2	3	4.3	2.3	3

cmw(u)
0.8
0.8
0.2

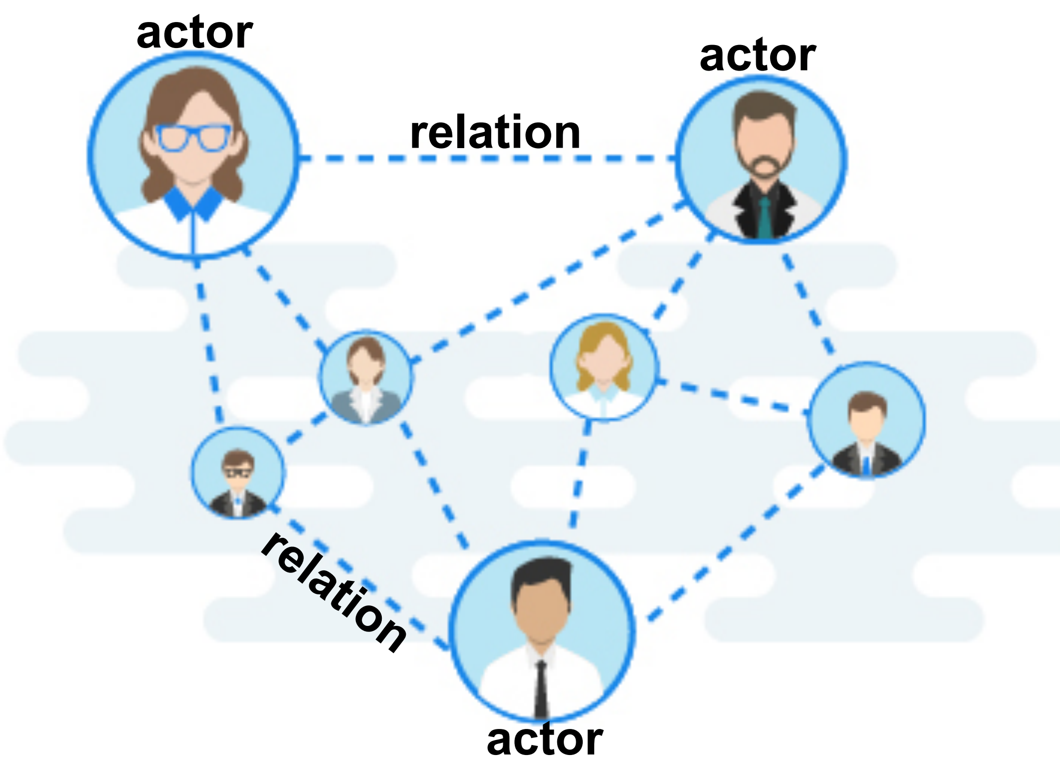
$$p_{pers}(u_a, i) = \frac{\sum_{u \in G(u_a \neq u)} (p(u_a, i) + (cmw(u_a) - cmw(u))}{|G| - 1}$$

Personality-enhanced user-item ratings

User	t_1	t_2	t_3	t_4	t_5
u_1	2.3	4.3	5.0	1.3	3.3
u_2	3.3	2.3	3.3	4.3	5.0
u_3	0.4	2.4	4.4	1.4	0.4
AVG	2	3	4.2	2.3	2.9

Social Relationships in Group Recommeder Systems

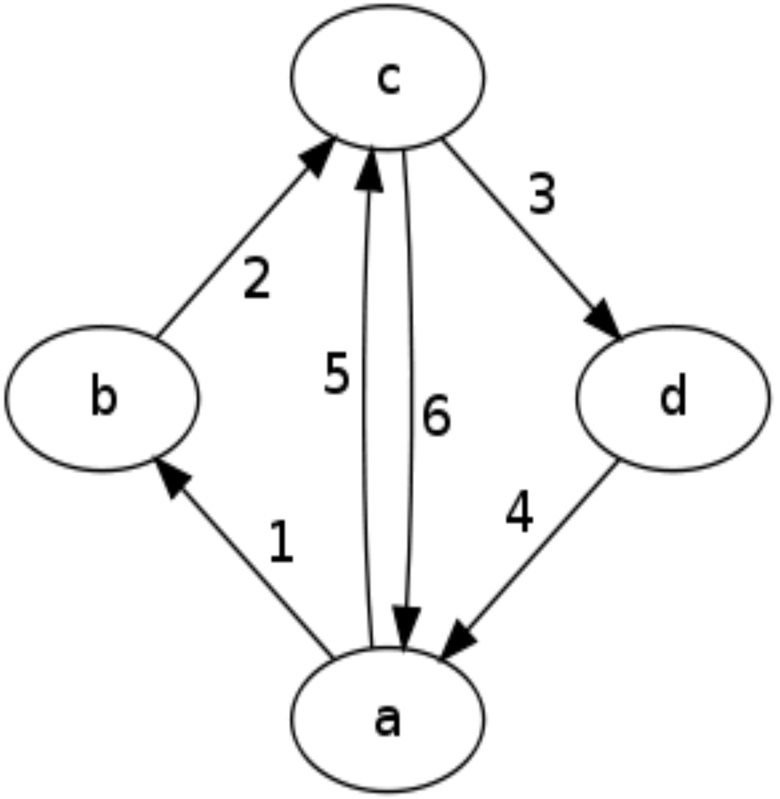
"Social network consists of finite set or sets of actors and the relation or relations defined on them"



(Wasserman and Faust, 1994)

Social Networks Metrics

- *In-Degree centrality* is the sum of weights of all in-links ($inDeg_c = 7$)
- *Out-Degree centrality* is the sum of weights of all out-links ($outDeg_c = 9$)
- *Degree centrality* combines in-degree and out-degree ($deg_c = 16$)
- *Closeness* is the sum of all the links in a graph ($closeness = 21$)



(Wasserman and Faust, 1994)

- *In-Degree centrality* – how do people perceive me? / how close they feel to me?
- *Out-Degree centrality* – how do I perceive other people? / how close do I feel to others?
- *Closeness* – how close we as a group / community are?

EXP: Social relationships in groups

- Social network theory defines **prominent actors** as:

“Those extensively involved in relationships with other actors”

- Prominence (centrality) is related to the social influence
  - Used in weighted group preference models (Christensen and Schiaffino, 2014)

- Do prominent actors get their way more often in the group decision-making process?

EXP: Social relationships in groups

- People of similar opinions / behaviors / attitudes often form (and are seen in) close / strong relationships
  - *”Homophily”* and Social influence (McPherson et al. 2001; Turner, 1991)

- Can this phenomena be used in GRSs?
- Are closely related groups more similar with respect to their preferences in comparison with the weakly related groups?

EXP: Social relationships in groups

- Social / group identity is correlated with the choice satisfaction in the group decision-making process (Delić and Neidhardt, 2017)
  - *"Individuals' self-concept derived from a membership to a social group and the emotional significance attached to that membership"* (Tajfel, 2010)

- Does the strength of the social relationships influence choice satisfaction in the group decision-making process regardless of the choice?

EXP: Results

- Prominent group members are **perceived** as more influential
- But, prominent group members **do not** have their way more often in the group decision-making process
- Closely related groups **perceive** their preferences as more similar
- Prominent group members **are** more satisfied with the group choice than non-prominent members
- Choice satisfaction is significantly related with the group closeness

EXP: Implications for GRS

- Members' prominence and group closeness are strong indicators of choice satisfaction

- Members' prominence, not found as indicators of social influence in group decision-making process
  - Centrality might not be used in the form of weights in group preference models

- Centrality and group closeness can be used as a **measure of group members' resilience to dissatisfaction** in a group preference model

EXP: Opinion shifting

- Start made in Francesco Barile's work (2017 paper in UMAP workshop)
- Considered:
  - Tie strength (Weak, Intermediate, Strong)
  - Relationship type (Like, Indifferent, Dislike)
  - Closeness of initial ratings (Small, Large)
- Some evidence of:
  - positive opinion shifts when initial ratings far apart
  - negative shifts when initial ratings close but disliking relationship

Social relationships in group models

- Quijano-Sanchez et al. (2013):
  → personality and social trust improve recommendation accuracy
  → social trust without the personality performs worse than the baseline

- Christensen and Schiaffino (2014):
  → Social influence as a combination of social trust, social similarity and social centrality
  → Social influence improve recommendation accuracy

- Gartrell et al. (2010):
  → aggregation method should be adapted according to the type of relationship within the group
  → Most Pleasure for strong relations; Least Misery for weak; Average for intermediate

Social Relationships in GRSs – Example I

- Quijano-Sanchez et al. (2013) used trust relations derived from social network (*Facebook*) to account for influence

- Trust relationship is calculated based on several factors:
  - *Intensity of the relationship* (e.g., how often a user name appears on the wall of the other user)
  - *Duration of the relationship* (how long have two users known each other)
  - *Distance in a social network* (e.g., two users are friends in a social network or have friends in common)
  - …

Social Relationships in GRSs – Example I

- Trust relationship between group members u_1 and u_2, given n social factors $f_i(u_1, u_2)$, and their corresponding importance weights w_i, is then:

$$t(u_1, u_2) = \sum_{i=1}^{n} w_i * f_i(u_1, u_2)$$

Social Relationships in GRSs – Example I

- Social trust was incorporated within the previously explained personality model
  - *Socially-enhanced rating* $p_{soc}(u_a, i)$, represents the new rating of the user u_a for the item i, that is influenced by the social trust between u_a and the other group members
  - Given the initial rating $p(u_a, i)$ of the u_a for the item i, the *conflict mode weights* $cmw(u_a)$ of the user u_a, and the trust between u_a and the other group members $t(u, u_a)$:

$$p_{soc}(u_a, i) =$$
$$p(u_a, i) + \left(1 - cmw(u_a)\right) * \frac{\sum_{u \in G(u_a \neq u)} t(u, u_a) * (p(u, i) - p(u_a, i)}{|G| - 1}$$

Social Relationships in GRSs – Example I

User-item initial ratings

User	t_1	t_2	t_3	t_4	t_5
u_1	2	4	5	1	3
u_2	3	2	3	4	5
u_3	1	3	5	2	1
AVG	2	3	4.3	2.3	3

cmw(u)
0.8
0.8
0.2

Symmetrical trust relationships

User	u_1	u_2	u_3
u_1	1.0	0.5	0.6
u_2	0.5	1.0	0.2
u_3	0.6	0.2	1

$$p_{soc}(u_a, i) =$$

$$p(u_a, i) + \left(1 - cmw(u_a)\right) * \frac{\sum_{u \in G(u_a \neq u)} t(u, u_a) * (p(u, i) - p(u_a, i))}{|G| - 1}$$

Socially-enhanced rating

User	t_1	t_2	t_3	t_4	t_5
u_1	1.99	3.84	4.9	1.21	2.98
u_2	2.91	2.12	3.14	3.81	4.82
u_3	1.40	3.16	4.84	1.92	1.80
AVG	2.1	3.04	4.29	2.31	3.2

Group Decision-Making Process

Group Decision Support

- Decision support is crucial in RS and even more for GRSs
- Helping groups reach decisions is listed as one of four GRSs challenges *(Jameson, 2004)*
- Stettinger et al. (2014) introduced a configurable group decision-support system where configuration is based on the decision task
- Nguyen and Ricci (2018) work on a chat-based GRS with a support for group decision-making

EXP: Group decision-making process

- Research in GRS (Masthoff, 2016) and Arrow's theorem (Arrow, 1963): there is no single best method to combine individual preferences
- Go beyond methods for combining individual preferences
- Focus on the decision-making process of 200 individuals organized in 55 groups
- Relate individual and group characteristics with different aspects of group decision-making process
- Predict how the groups reached their decisions based on their group characteristics

EXP: Group decision-making process

- Showing the importance of personalizing decision-making process as one of the main tasks of GRSs
- Different groups adopt different approaches to reach a decision even when faced with the same decision task
- Goal: Identifying relevant group and individual characteristics as indicators of personalization

EXP: Results

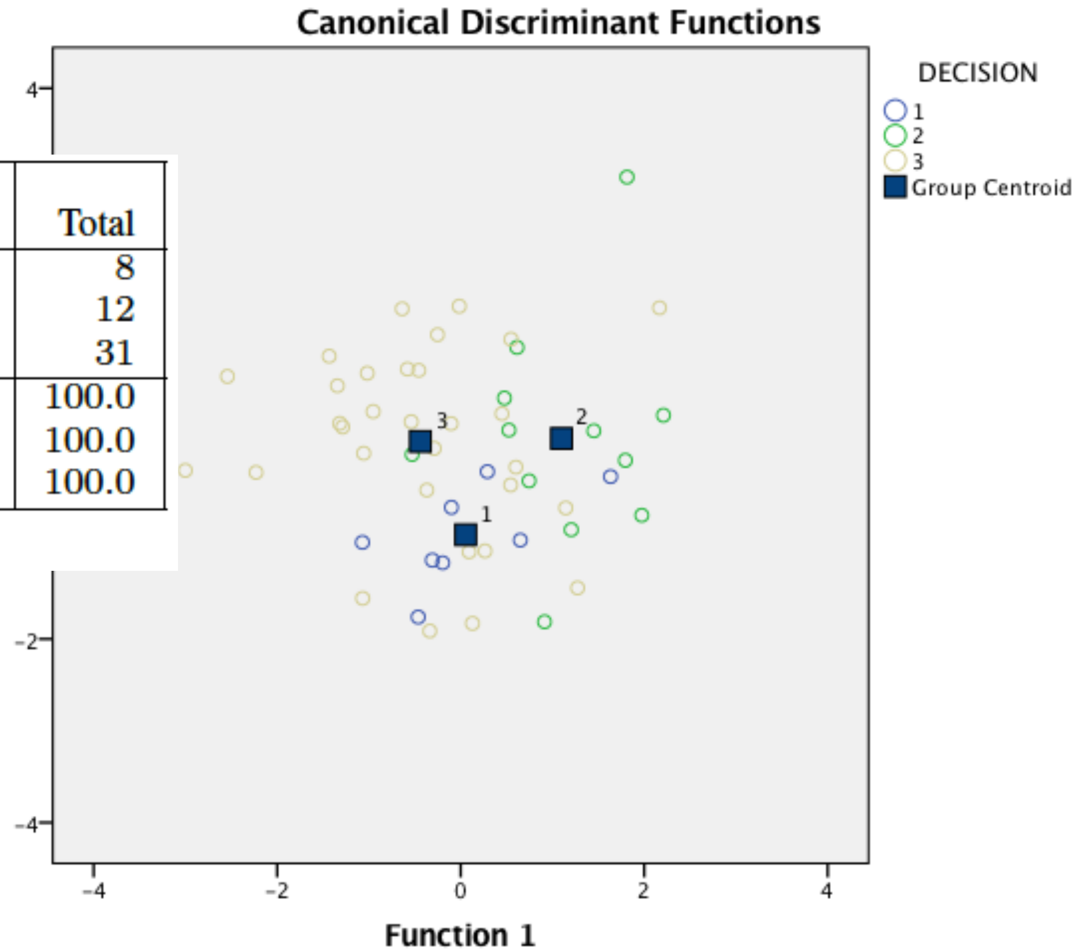
- Higher group agreeableness, conscientiousness and emotional stability, and lower diversity of preferences, correlates with a stronger tendency towards ”natural” decision reaching technique
- Higher diversity of group correlates with more unstructured decision-making process
- Higher group identity correlated with more collaborative group behavior and more “natural” preference disclosure technique

EXP: Results

- Decision-reaching technique can be predicted by with group characteristics:
  - Group diversity of implicit preferences
  - Group conscientiousness

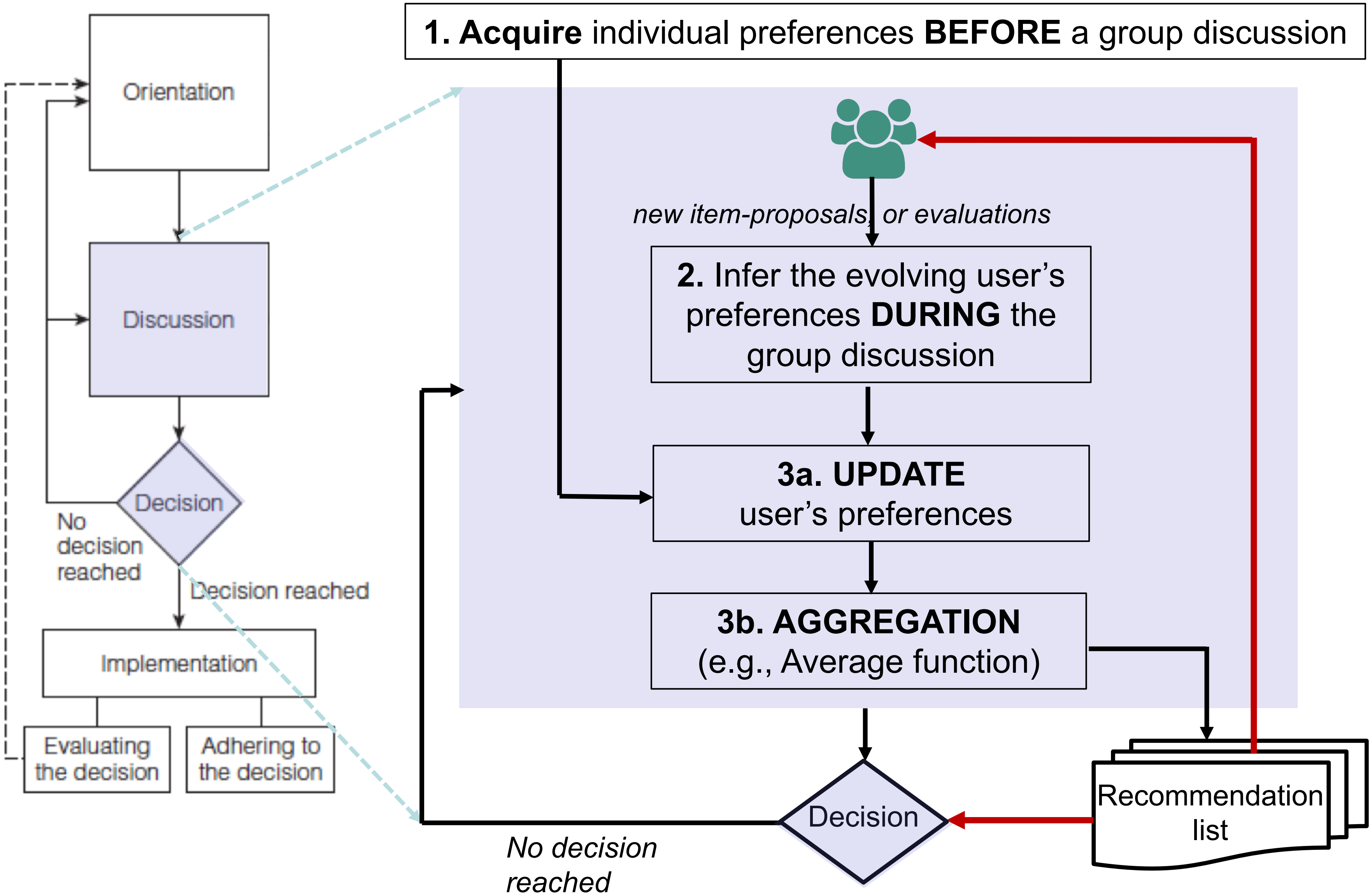
	DCSN	Predicted Group membership 1	2	3	Total
Count	1	7	1	0	8
	2	1	10	1	12
	3	8	4	19	31
%	1	87.5	12.5	0	100.0
	2	8.3	83.3	8.3	100.0
	3	25.8	12.9	61.3	100.0

70.6% of original cases correctly classified.



Delic et al. (2018)

Group decision-making in a GRS



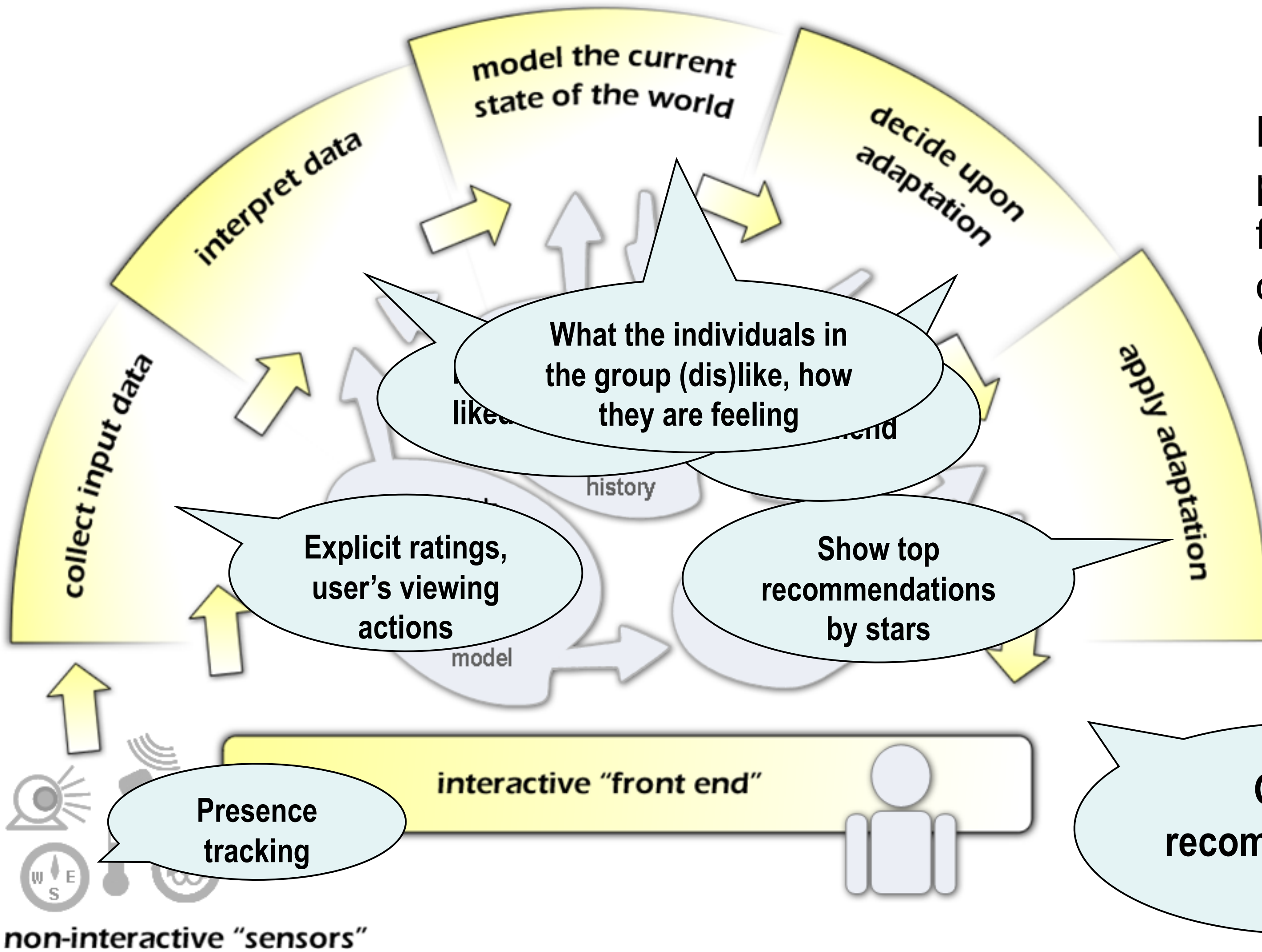
Nguyen and Ricci (2018)

Evaluation of Group Recommeder Systems

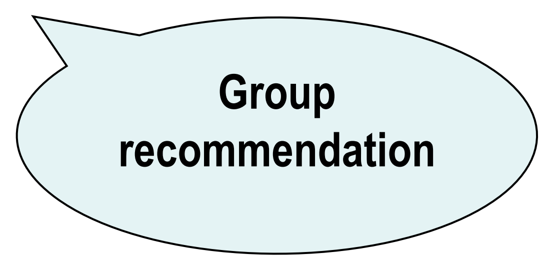
Slicing and Dicing

- Want to know *why* a group recommender system works / does not work
- Slicing: Layered evaluation (Paramythis et al, 2010)
  - Break adaptation process down into its constituents (“layers”)
  - Evaluate layers separately
- Dicing
  - Break system down into separate functionalities (e.g. provide recommendations, explain recommendations)
  - Evaluate functionalities separately

Layered evaluation



Most of this presentation focussed on one layer (DA or UM)



How to evaluate how good a strategy is?

- What does it mean for a group recommender strategy to be good?
- For the *group* to be satisfied?
- But how do you measure the satisfaction of a group?

- Utility for the group

This is what most researchers do, they take the average of the individuals' ratings (or average of a comparison of rankings of items).

What is the problem with this?

- Whether all individuals exceeded a minimum level of satisfaction

When? After a sequence of items? At each point in the sequence?

What is the problem with this?

Metrics (3)

Extent to which group members

- Think it is fair?
- Think it is best for the group?
- Accept the recommendation for the group?
- Do not exhibit negative emotions?

With or without having seen the options and individual preferences?

What is the problem with this?

Metrics (4)

Extent to which independent observers

- Think it is fair?
- Think it is good / best for the group?

Having seen the options and individual preferences

Having seen the reactions of the group members?

What is the problem with this?

Extent to which the recommendations correspond to

- What groups would decide themselves?
- What human facilitators would decide for the group?

What is the problem with this?

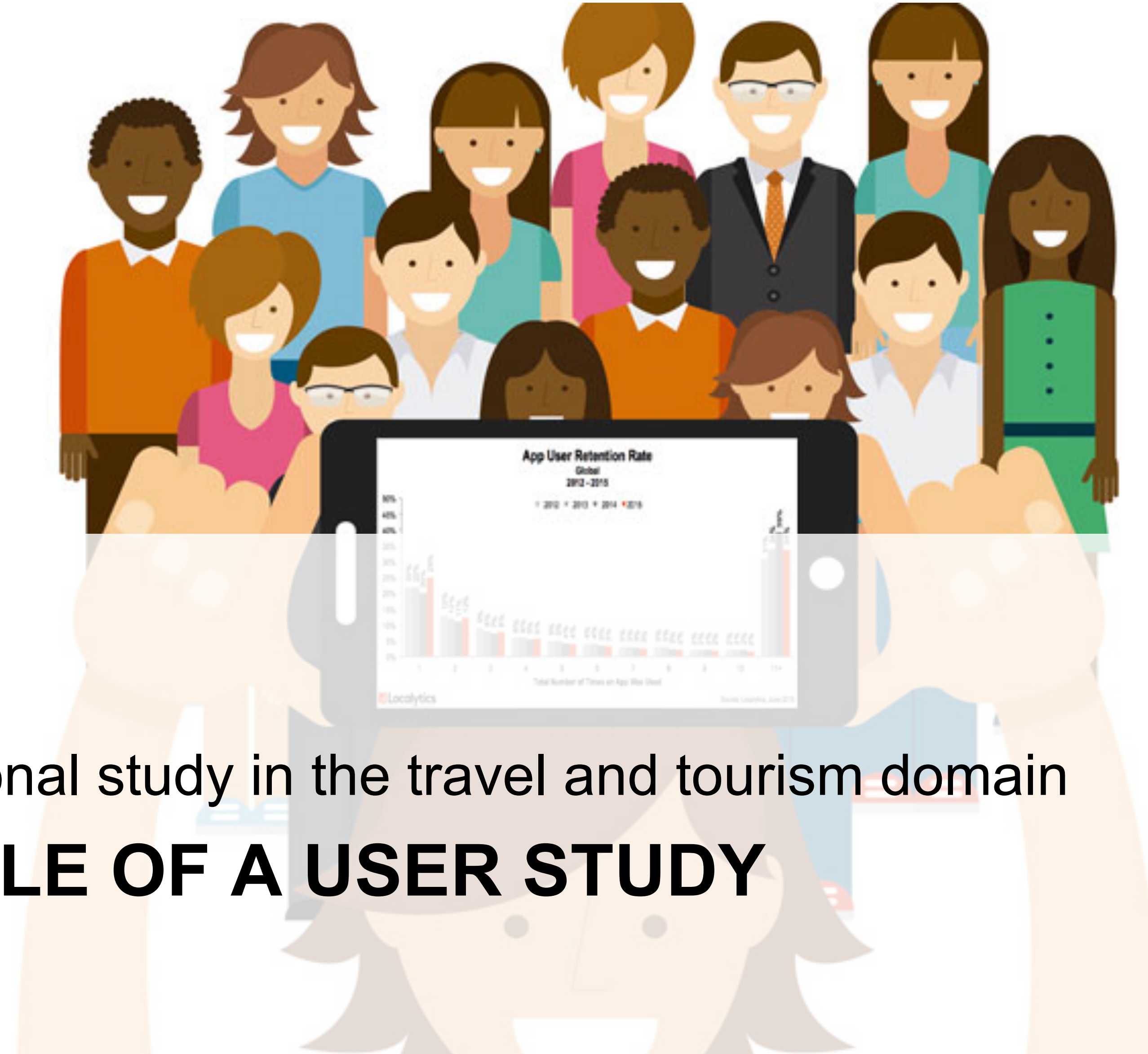
How to obtain groups for evaluation?

- Artificially construct groups
  - From existing data about individuals
  - Or: of invented individuals

- Use real groups:
  - But without group data
  - Or: to generate group data
    (e.g. What the group decides to watch when together)
  - Or: to provide recommendations and measure effect

Artificial groups

- From the datasets such as MovieLens containing ratings of single users (Ali and Kim, 2015)
- Groups are made synthetically according to some parameter
  - Homogeneous: groups of similar preferences
  - Heterogeneous: groups of diverse preferences
  - Random: group members selected randomly
- The task of a GRS is to find items that all group members rated with the highest rating



Observational study in the travel and tourism domain

EXAMPLE OF A USER STUDY

Study procedure

- In a cooperation with the International Federation for Information Technologies in Travel and Tourism (IFITT)
- First implementations at: TU Delft, UNI Klagenfurt, UNI Leiden, TU Wien
  – Part of regular lectures
- Three-phases structure

First study phase

- Pre-survey questionnaire
  - Data: Individuals‘ implicit and explicit preferences
- Differences:
  - Vienna implementation: Destinations ratings
  - Other implementations: Destinations rankings

Second study phase

- Group meetings/ discussions
- Differences:
  - Vienna implementation: observation carried out
  - Other implementations: no observation

Third study phase

- Post-survey questionnaire
  - Data: Study experience and feedback
- Differences:
  - No differences in implementations

Study procedure – First study phase

**Groups formations:
4 decision makers & 2 observers**

For decision makers: fill in online pre-questionnaire

- Captures individual profiles, preferences and dislikes

For observers: observation training

- How to perform observation in the specific e-tourism context

Measurements – First study phase

Demographic data

- age, gender, country of origin, university and student identification number

17 tourist roles and Big Five Factors

- 17 Tourist Roles
- Big Five Factors

Experience and ratings of ten destinations

- *“How many times have you visited each of these destinations?”*

Ranking of decision criteria

- budget, weather, distance, social activities, sightseeing

Study procedure – Second study phase

“Imagine that you are working on a research paper together with the other group members. Interestingly, your university offers you the opportunity to submit this paper to a conference in Europe. If the paper gets accepted, the university will pay to each group member the trip to the conference.

In addition, you will be able to spend the weekend after at the conference destination. Ten conferences will take place in European cities around the same summer period”

Decision makers

1. Ten destinations and Wiki pages

2. Decision task scenario

3. Group decision task

Audio & behavior (IPA) recording

Observers

“Discuss and choose first and second destination option that you as a group would visit together”

Interaction process Analysis – IPA

- A method to study small groups and interactions among group members
- Observing “units” of interaction
  - facial expressions, gestures, body attitudes, verbal acts…
- Twelve categories of behavior

  1. Show solidarity - ”Friendly”, 2. Show tension release, 3. Agree, 4. Give suggestion, 5. Give opinion, 6. Give information, 7. Ask for suggestion, 8. Ask for opinion, 9. Ask for information, 10. Disagree, 11. Show tension, 12. Show Antagonism – “Unfriendly”

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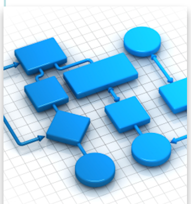
Measurements – Second study phase



Plan for group decision process and duration of different phases

Group members' roles

- e.g., leader, follower, initiator, information giver, opinion seeker..

Group members' behavior (Bales's IPA framework)

Social decision scheme

Strength of group members' preferences

Study procedure – Third study phase

1. For decision makers: fill in the post-survey questionnaire

- Study and task experience

2. For observers: interviews

- Observation task and reports
- Differences between reports
- Behavior of decision makers

Measurements – Third study phase

- The first and the second group choice
- Usage of the provided Wiki pages
- Description of the decision process
- Overall attractiveness of the ten predefined destinations
- Satisfaction with the group choice
- Difficulty of the decision process
- Identification and similarity with the other group members
- Assessment of the task

Measurements – Data structure

Big Five Factors Scores
Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism

Group Member's Behavior
12 behavior categories: Friendliness, Tension, Sharing/ Asking for opinion, information or suggestion, etc.

Group Member's Roles
Roles students played during discussion: Leader, follower, initiator, etc.

Tourist Roles Scores
Sun Lover, Archeologist, Anthropologist, Drifter, Seeker, Action Seeker, etc.

Group Members
General data: Student ID, University, Age, Gender, Group ID & Type (observer or decision maker)

Group Discussion
Discussion & decision plan
Time duration
Decision scheme

Destinations Ratings/ Rankings & Criteria Ranking
Individual destinations ratings/ranking
Individual criteria ranking
Group first and second choice
Satisfaction with group choice

Group Member's Experience
Organization, Feedback, Repeat

Group Dynamics
Group identification: „I see myself as a member of this group"
Group similarity: „I consider myself similar to the other group members…"

Group Decision Process Difficulty
„Eventually I was in doubt between some destinations."

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Open Challenges and Issues

Aim of explanations in any rec sys

Improve:

- Trust
- Effectiveness
- Persuasiveness
- Efficiency
- Transparency
- Scrutability
- Satisfaction

(Tintarev & Masthoff)

And these aims can conflict

Explanations may be even more important in group recommender systems

Which aims?

Sequence issue

- More work is needed on explaining sequences, particularly sequences that contain items the user will not like

Privacy issues

- Many aims may require explanations that reflect on other group members….
- How to do this without disclosing sensitive information?
- Even general statements such as “this item was not chosen as it was hated by somebody in your group” may cause problems

QUESTIONS?

KEEP
CALM
AND
RESEARCH
ON

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