

Do we need to believe Data/Tangible or Emotional/Intuition?

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Introduction

- The reign of the datum : the new "black gold" of companies
- The modalities of decision-making are changing
- The decision-making results from a complex mechanism: Rational decision-making / Intuitive decision-making
- The power of emotion in decision-making process





Rational decision-making versus intuitive decision-making

RATIONAL DECISION-MAKING

- Based on a conscious and extensive cognitive process
- Based on abstract and explicit knowledge
- Sequential process based on causal relationships
- Does not take into account the emotion

INTUITIVE DECISION-MAKING

- Mainly based on nonconscious processes
- Based on past experience
- Holistic process that is based on free associations
- Essentially based on emotion



(Simon, 1987; Ericsson & Charness, 1994; Epstein, 1994; Nonaka, 1995; Shapiro & Spence, 1997; Janis, 1997; Burke & Miller, 1999; Lieberman, 2000; Hogart, 2001; Kahneman, 2003; Noordink & Ashkanasy, 2004; Sadler-Smith & Shefy, 2004; Sinclaire & Ashkanasy, 2005; Dane & Pratt, 2007)



What is emotion?

- An emotion is an affective state characterized by:
 - A physiological reaction (James, 1884; Janet, 1926)
 - A behavioral expression (Scherrer, 1986; Ekman, 1994; Rimé, Corsini & Herbette, 2002)
 - A subjective manifestation (Frijda, 1986; Lazarus, 1999; Scherer, Schorr & Johnstone, 2001)
- Our emotions reflect an appraisal of things that surround us
- They are positive or negative and produce attraction or rejection





Decision making and emotions

- The emotion: First factor of decision (Bechara & Damasio, 2000)
- A positive or negative emotional state influences the way people judge the outside world (Schwarz & Clore, 1983; Lerner & Keltner, 2000)



 People in a positive emotional state are more risk averse than those with a negative or neutral mood (Isen & Patrick, 1983)



Decision making and emotions

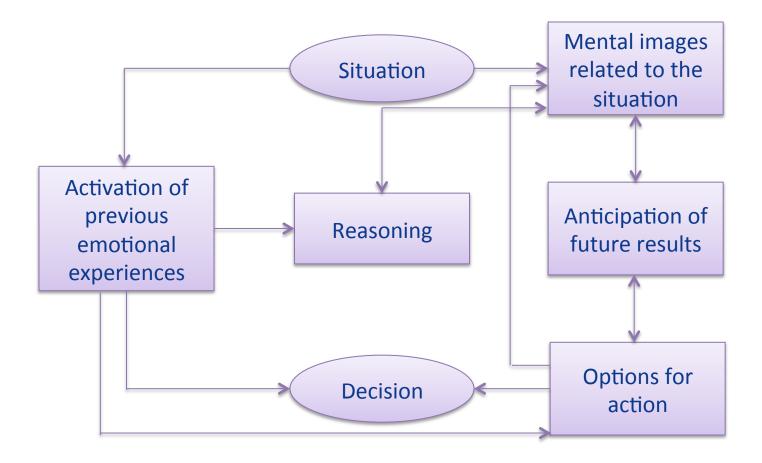
 A positive emotional state facilitates complex decision-making by reducing confusion and increasing the ability to assimilate information (Isen & Means, 1983; Estrada, Isen & Young, 1997)

 Mood affects the content of the decisionmaking (Forgas & George, 2001)





Impact of emotion over reason







Emotion and e-commerce

- Emotion-oriented e-commerce: A new and fascinating research to understanding the purchasing behaviour of online consumers (Leon & Nikov, 2010)
- For the online consumer, it's very important to feel emotions related to the act of buying and owning a product / service (Murray, 2013)
- The anticipation of emotions or feelings associated with the consumption of the product /service coming (Giraud & Bonnefont, 2000)
- The Future of E-Commerce: the Brands and Emotion (Crémer, 2011)





E-commerce and recommender system

For consumer	For e-commerce website							
Deduce time and complexity for ecouch	Serve as an automated shopping guide.							
Reduce time and complexity for search	Optimize the web server capacity							
Clarify ambiguous and ineffable needs	Increase the quantity of items sold							
Ideact and a second	Increase the diversity and variety of items sold.							
Identify unconscious needs	Maintain a high level of consumer fidelity.							
	Optimize profitability							
	Identify consumer preference							





A brief description of recommendation methodologies

Statistics

- List the most popular item based on different pre-defined criteria
- Various technics and criteria (ranking/rating) are applied

Demographic

- If consumer has demographic features d1, d2..., she belongs to group X
- Popular items of group X will be proposed to her

Item-based CF

 If consumer buys item X, and X have the attributes a1, a2 a3..., find an item Y whose attributes is most similar to X

Communitybased

- Identify the consumer's friends
- Identify their preference and choices to find the popular items
- · Propose these items to consumer

Knowledgebased

- Predefine the constraints or cases
- Consumer indicate her preference based on these conditions
- · System provide optimal solution

Contentbased

- Consumer prefers items who have value v1, v2, v3...
- Item A possess value v1, v2, v3...
- Propose item A to her



User-based CF

 If both consumer X and Y bought / appreciate item A, B..., consumer X also bought / appreciate item C, propose C to consumer Y



Current recommendation methodologies

New Taxonomy Clarifies the Functionality of Methodologies

Generalization

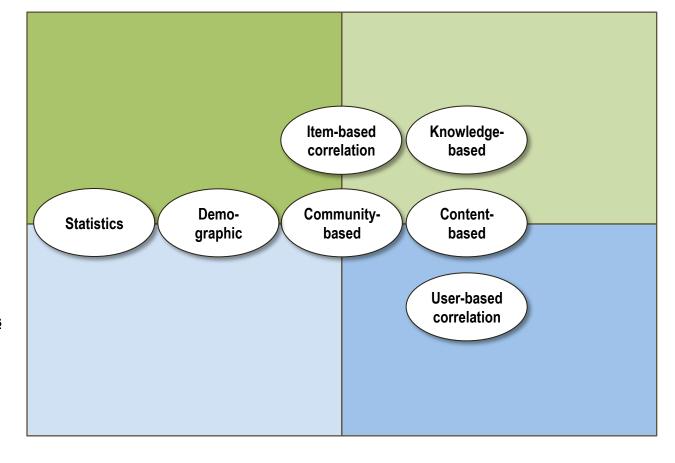
(appeal to a specific person)

Personalization

(popular for a group of people)

Conscious (planned)

Unconscious (unplanned)







Recommender system in e-commerce websites

Hybrid strategy is widely adopted by e-commerce websites

Methodology	Amazon	Taobao	Ebay	Fnac	Decitre
Item based correlation	Y	Υ	Y	Υ	Y
User based correlation	Y	Υ	Y	N	N
Content-based correlation	Y	Y	Y	N	N
Statistics (ranking/rating)	Y	Υ	Y	Υ	Y
Demographic	Unknown	Υ	N	N	N
Knowledge-based	Y	Υ	Unknown	Υ	N
Community-based	N	N	N	N	N



Notes: Y – Deployed; N – Not Deployed; Unknown – Information not available



Are marketing chefs satisfied with their recommenders?

Effectiveness criteria are not yet well defined or applied

Lack of measurement metrics system "We measure the click-through and order conversion rate (of the recommended item) ... but it seems not enough to find out where are the problems."

Good relevance but low click-through

"It's good that quite a lot of consumers buy the items we recommended, but many of them didn't click the recommendation link as we expected..."

Good click-through but poor conversion

"Our click-through rate is amazing, but the order conversion rate is far from satisfaction...many people quite the page just a few

Lack of New criteria other than relevance

"We improve algorithm and architecture... we think that user

experience and trust is also important ... but we don't know how to



A performing recommender with pure chance

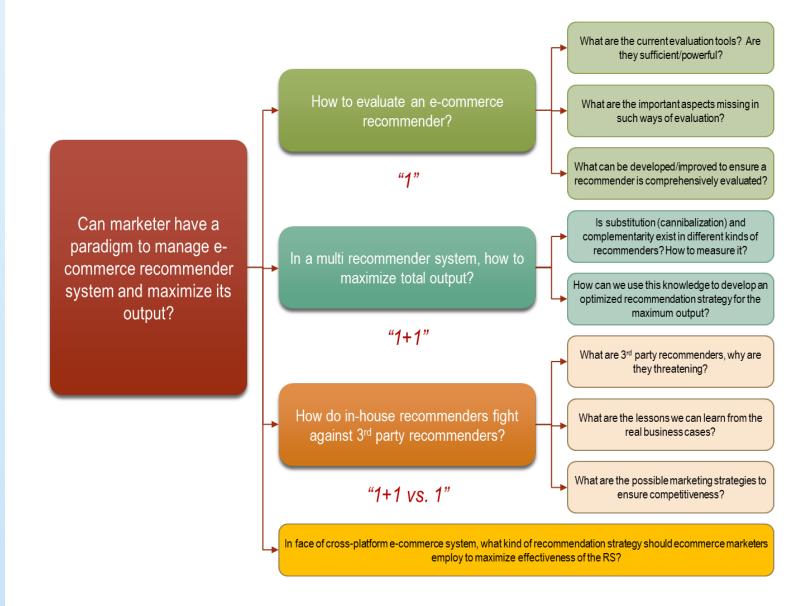
"We thought our recommender was great, but when we ran an A/B test, the control group (recommender based on pure chance) had the similar performance!"

Effectiveness of multi-recommender system

"We put different kinds of recommenders across the shopping process, but it seems that our customers are very focused on what they plan to buy..."



What are the challenges for marketers and researchers?

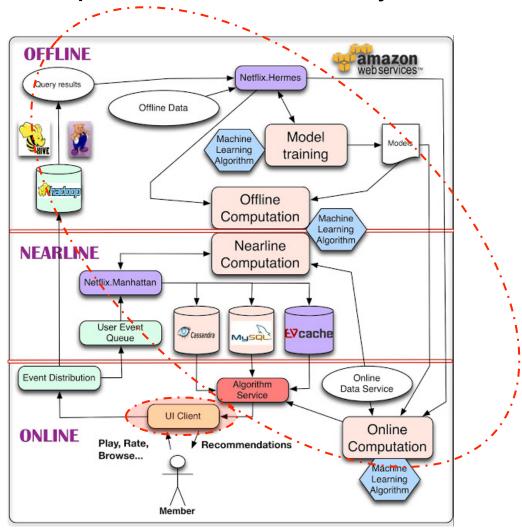






Research focus of recommender effectiveness

Example of Netflix recommender system





Source: Netflix Tech Blog (http://techblog.netflix.com/2013/03/system-architectures-for.html)



Recommender system and emotion

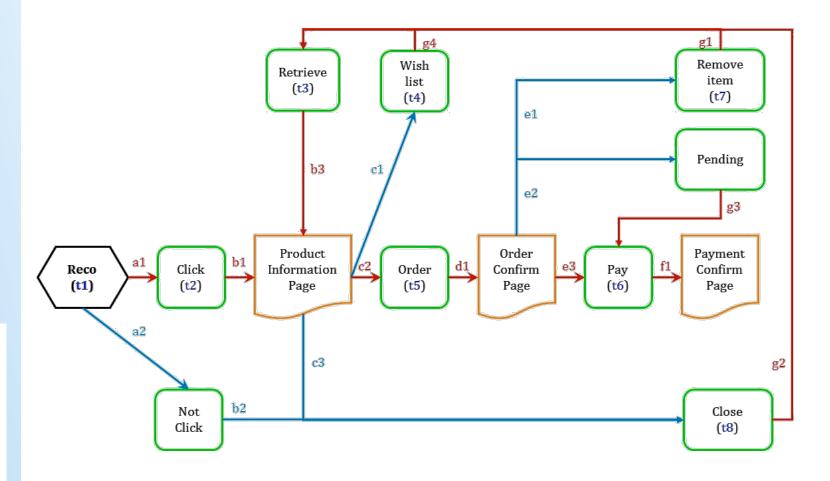
Decision	Description	Critical Factors Related to Recommender
Click	Click on the recommended item	 Attractiveness of the item (conscious, unconscious needs) The type of information presented The place where recommendation is presented The layout/design of the recommendation interface The consumer's state of mind Consumer's trust in the recommender system
Browse	Browse the item page in detail	 Waiting time for the page to be fully loaded to the browser Attractiveness of the item (conscious, unconscious needs) The consumer's state of mind
Wish list	Keep the item into wish list	 Attractiveness of the item (conscious, unconscious needs) The consumer's state of mind
Order / Remove	Put the item into the shopping cart	 Attractiveness of the item (conscious, unconscious needs) Other consumer's reviews Cost of the item Comparison with other recommendations (same category)
Purchase / Cancel	Pay for the item	 Attractiveness of the item (conscious, unconscious needs) Cost of the item / delivery Ease of payment Comparison with other recommendations (same category)
Retrieve	Retrieve the item recommended	 Attractiveness of the item (conscious, unconscious needs) Recommender system function





Fundamental of the problem: consumer behaviour

Consumer behavior model with e-commerce recommender







Possibility to capture behavioural data from e-commerce...

Consumer behavioral data from server (example)

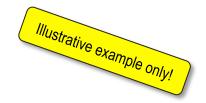
User ID	Reco Posted (t1)	Reco Clicked (t2)	Reco Page Retrieved (t3)	Reco Liked (t4)	Reco Ordered (t5)	Reco Purchased (t6)	Reco Item Removed (t7)	Reco Page Closed (t8)	Reco Value (€)	Basket Value (€)	Basket Item (units)	First registration date	Total Item purchased (units)	Total Purchase experience (times)	Total Payments (€)	Total Visits (times)	X1 CLK	X2 RTV	X3 LK	X3 ORD	X4 PUR	X5 ABD	X6 CLS
																	t2-1	t3-t1	t4-t*	t5-t *	t6-t5	t7t5	t8-t*
Example 1	16:30:55				16:36:00	16:45:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75	0:00:05			0:05:00	0:09:00		\longrightarrow
Example 2	16:30:55				16:36:00		16:45:00		15.00			2010/10/10	31	9	1170.00	75	0:00:05			0:05:00		0:09:00	
Example 3	16:30:55				16:36:00			16:45:00	15.00			2010/10/10		9	1170.00	75	0:00:05			0:05:00			0:09:00
Example 4	16:30:55				16:36:00	20:18:00		16:45:00	15.00	68.00	5	2010/10/10		10	1238.00	76	0:00:05			0:05:00	3:42:00		0:09:00
Example 5	16:30:55	16:31:00						16:45:00	15.00			2010/10/10		9	1170.00	75	0:00:05						0:14:00
Example 6	16:30:55		17:00:00		17:06:00	17:10:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75		0:29:05		0:06:00	0:04:00		
Example 7	16:30:55		17:00:00		17:06:00		17:10:00		15.00			2010/10/10	31	9	1170.00	75		0:29:05		0:06:00		0:04:00	
Example 8	16:30:55		17:00:00		17:06:00			17:10:00	15.00			2010/10/10	31	9	1170.00	75		0:29:05		0:06:00			0:04:00
Example 9	16:30:55		17:00:00		17:06:00	20:18:00		17:10:00	15.00	68.00	5	2010/10/10	36	10	1238.00	76		0:29:05		0:06:00	3:12:00		0:04:00
Example 10	16:30:55		17:00:00					17:10:00	15.00			2010/10/10	31	9	1170.00	75		0:29:05					0:10:00
Example 11	16:30:55	16:31:00	17:00:00		17:06:00	17:10:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75	0:00:05	0:29:05		0:06:00	0:04:00		
Example 12	16:30:55	16:31:00	17:00:00		17:06:00		17:10:00		15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05		0:06:00		0:04:00	
Example 13	16:30:55	16:31:00	17:00:00		17:06:00			17:10:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05		0:06:00			0:04:00
Example 14	16:30:55	16:31:00	17:00:00		17:06:00	20:18:00		17:10:00	15.00	68.00	5	2010/10/10	36	10	1238.00	76	0:00:05	0:29:05		0:06:00	3:12:00		0:04:00
Example 15	16:30:55	16:31:00	17:00:00					17:10:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05					0:10:00
Example 16	16:30:55							17:10:00	15.00			2010/10/10	31	9	1170.00	75							0:39:05
Example 17	16:30:55	16:31:00		16:32:00	16:36:00	16:45:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75	0:00:05		0:01:00	0:05:00	0:09:00		
Example 18	16:30:55	16:31:00		16:32:00	16:36:00		16:45:00		15.00			2010/10/10	31	9	1170.00	75	0:00:05		0:01:00	0:05:00		0:09:00	
Example 19	16:30:55	16:31:00		16:32:00	16:36:00			16:45:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05		0:01:00	0:05:00			0:09:00
Example 20	16:30:55	16:31:00		16:32:00	16:36:00	20:18:00		16:45:00	15.00	68.00	5	2010/10/10	36	10	1238.00	76	0:00:05		0:01:00	0:05:00	3:42:00		0:09:00
Example 21	16:30:55	16:31:00		16:32:00				16:45:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05		0:01:00				0:14:00
Example 22	16:30:55		17:00:00	17:02:00	17:06:00	17:10:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75		0:29:05	0:02:00	0:06:00	0:04:00		
Example 23	16:30:55		17:00:00	17:02:00	17:06:00		17:10:00		15.00			2010/10/10	31	9	1170.00	75		0:29:05	0:02:00	0:06:00		0:04:00	
Example 24	16:30:55		17:00:00	17:02:00	17:06:00			17:10:00	15.00			2010/10/10	31	9	1170.00	75		0:29:05	0:02:00	0:06:00			0:04:00
Example 25	16:30:55		17:00:00	17:02:00	17:06:00	20:18:00		17:10:00	15.00	68.00	5	2010/10/10	36	10	1238.00	76		0:29:05	0:02:00	0:06:00	3:12:00		0:04:00
Example 26	16:30:55		17:00:00	17:02:00				17:10:00	15.00			2010/10/10	31	9	1170.00	75		0:29:05	0:02:00				0:10:00
Example 27	16:30:55	16:31:00	17:00:00	16:32:00	17:06:00	17:10:00			15.00	68.00	5	2010/10/10	36	10	1238.00	75	0:00:05	0:29:05	0:01:00	0:06:00	0:04:00		\Box
Example 28	16:30:55	16:31:00	17:00:00	16:32:00	17:06:00		17:10:00		15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05	0:01:00	0:06:00		0:04:00	\Box
Example 29	16:30:55	16:31:00	17:00:00	16:32:00	17:06:00			17:10:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05	0:01:00	0:06:00			0:04:00
Example 30	16:30:55	16:31:00	17:00:00	16:32:00	17:06:00	20:18:00		17:10:00	15.00	68.00	5	2010/10/10	36	10	1238.00	76	0:00:05	0:29:05	0:01:00	0:06:00	3:12:00		0:04:00
Example 31			17:00:00	16:32:00				17:10:00	15.00			2010/10/10	31	9	1170.00	75	0:00:05	0:29:05	0:01:00				0:10:00



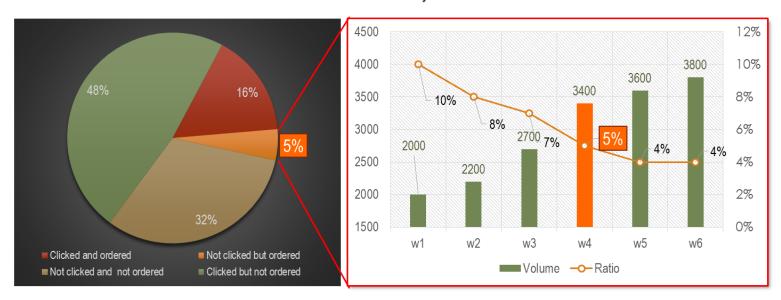


... and analyse the effectiveness of recommenders

Improvement areas are identified



Metrics to determine the consumer trust in the recommender system



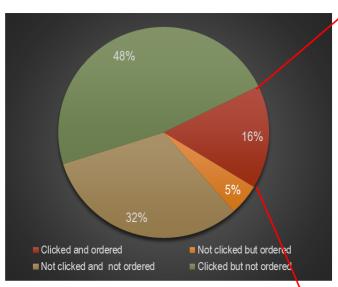


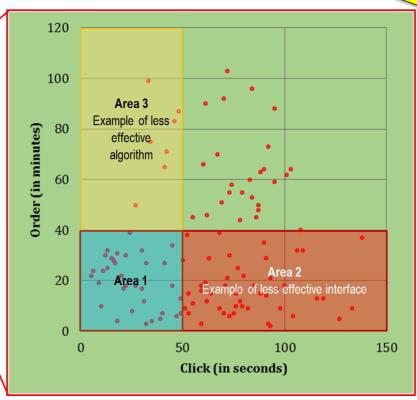


... and analyse the effectiveness of recommenders

Improvement areas are identified

Tools to determine the effectiveness of different factors contributing to the recommender





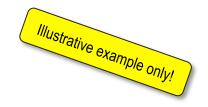
WIP, Illustrative only!



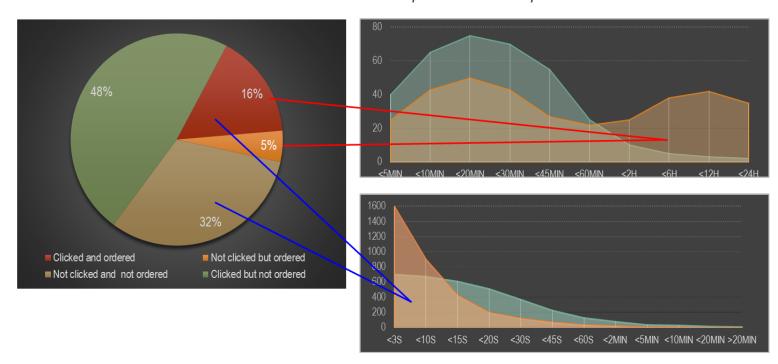


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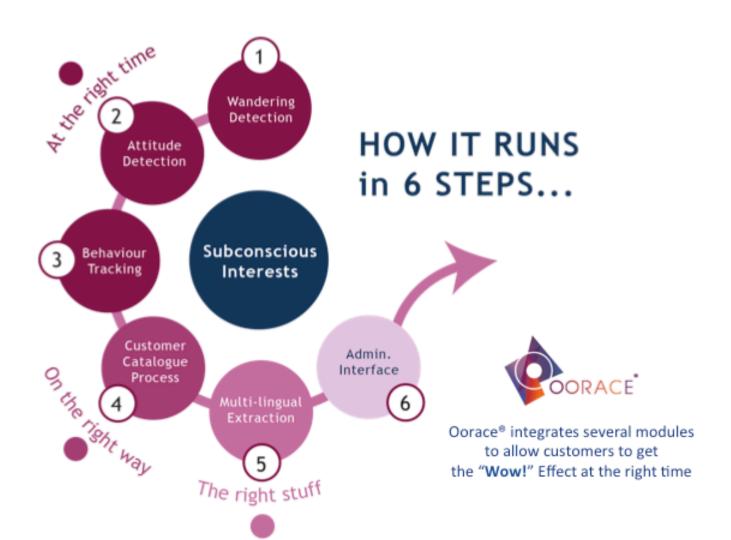
Performance of the same e-commerce recommender when placed in different places of the website







The contribution of Search'XPR™







Conclusion

- Emotions make up a substantial part of our decision-making process
- Everyone has the choice to be guided by his intuition and his emotions
- Emotional intelligence is essential to validate the relevance of emotional signals



So, trust your emotions while leaving the control to your cortex



QUESTIONS & ANSWERS



