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Problem: We have chosen the first challenge: Increase the revenue growth with top ecommerce players

The aim is to design and deliver best in class shopper experience across this channel and make more data-driven decisions.

Our Approach: HUL IT division at present has 5 core capabilities across the market value chain: **Live Wire**-Granular Data Analysis, **JARVIS**-Advanced Analytics, **People Data Centre (PDC)**-Social Conversation, **Smart Pick** - Consumer Journey, and **Maxima**-Precision Targeting & Deployment.

Having understood the 5 core capabilities of HUL IT division across the market value chain, we tried to arrive at a solution to create a new capability to enrich the shopper experience and boost the ecommerce revenue growth.

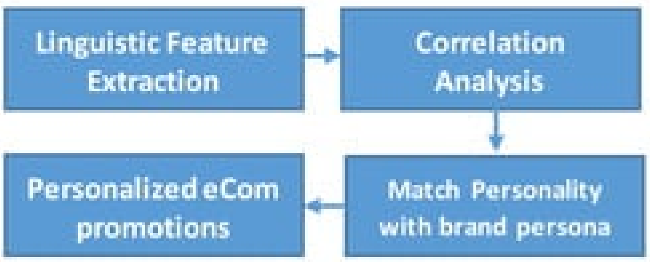
Over the years, traditional recommender algorithms were used to analyse the search patterns and digital foot prints across different channels to perform 'remarketing' and recommender ads.

Our Idea: Taking further, our big idea is "to analyse the Personality of the customers using 'Personality Prediction Algorithms' and match that with the existing HUL Brands' persona".

Any user on social media would leave their foot print and content in the form of likes, comments and status updates etc.,. We want to use this 'Content and Linkage data' to predict the personality of a user and correlate it with the Big 5 personality traits (Openness, Extraversion, Neuroticism, Agreeableness, Conscientiousness (Refer- Appendix for more information on Big 5 personality traits).

A Machine Learning Algorithm is developed to understand the personality traits of a customer and match him with the existing HUL Brands.

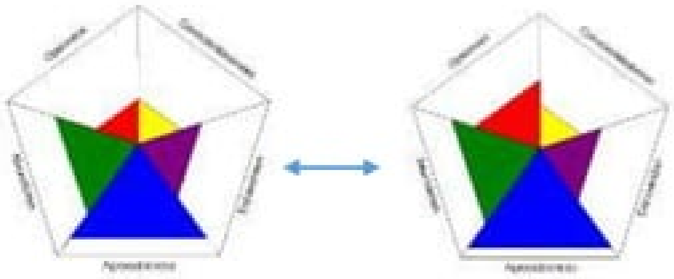
This ML Algorithm would include 4 processes:



Linguistic Feature Extraction: Extract words or sequences of words. For example – Key words on statuses or comments like – *'Can't Wait'*, *'Weekend Party'*, *'lit'* etc., will be extracted.

Correlation Analysis: Develop relation between language used and Personality Variables. The words that were extracted by the algorithm are grouped into different linguistic features like Swear words, Anxiety Words, Work related words etc. Once grouped, a correlation analysis is done by linking these groups with 5 personality traits. (Refer- Appendix Table 3 for sample correlation analysis)

Matching personality with HUL brands' persona: The difficult job is to understand HUL brands' persona and match that with the personality traits. Different brands have different TGs, different brand architypes and positioning. This data needs to be properly normalized across 5 personality traits and matched with the customer's personality traits using 'Precision Targeting'



Customer Traits | Lipton green Tea Traits

For example, a customer who is popularly tagged, who agrees with much of the content (liking, commenting positively on posts more than an average) and has less openness like – not updating status, not sharing his moments etc., can have the above personality traits. The other side, from the communications of Lipton green tea, it is evident that customers trust the recommendations given to them regarding the usage of the brand. This reflects that they are highly agreeable. Hence, there is a strong match between the customer traits and Lipton green tea traits.

Personalized ecommerce promotions: For this person (exampled above), a personalized Lipton Green Tea ecommerce banner/native ad is promoted over different social channels to him (using Maxima).

> CTRs and conversion rates were 1.3 and 1.2 times higher when the persuasive advertising message was tailored to the psychological profile of the preexisting behavioral audience

(Source: http://www.pnas.org/content/114/48/12714)

Here we explained the idea with just 5 personality traits. But considering the bandwidth of HUL IT, these traits can be extended further to improve Precision Targeting

Appendix

Sources:

H.V. Zhao, W.S. Lin and K.J.R Liu, "Behavior modeling and forensics for multimedia social networks" Proc. Signal Processing Magazine, IEEE (Volume:26 , Issue: 1), pp.118-139, 2009.

Y. Bachrach, M. Kosinski, T. Graepel, P. Kohli and D. Stilwell, "Personality and Patterns of Facebook Usage", Proc. the 3rd Annual ACM Web Science Conference, pp. 24-32, 2012.

T. DuBois, J. Golbeck, J. Kleint, and A. Srinivasan. Improving Recommendation Accuracy by Clustering Social Networks with Trust. In Recommender Systems & the Social Web, 2009.

Big 5 Personality Traits:

1. Personality traits and their social Media Behavior

Personality Trait	Personality Behavior	Facebook Behavior
Openness	High openness means appreciation for art, adventure, more creative and has new ideas.	Positively correlated with number of likes, group association and number of status update
Conscientiousness	Spontaneous approach in life, well organized, reliable and consistent.	Negatively correlated to number of likes and group associations but positively related to photos uploaded
Extraversion	Prone to live in external world, positive emotions, expressive, friendly and socially active	Positively associated with status update, tendency to use "Like" and Number of Facebook friend and Facebook group
Agreeableness	Friendly and compassionate, cooperative	Negatively correlated with the number of likes but positively co related with tagged.
Neuroticism	Related to emotions and mood swing. Negative emotions such as anger, anxiety, depression	Positively correlated with number of likes and number of groups.

2. Personality traits and their social Media Behavior

Personality Traits	Behavior on Facebook
Extraversion	Frequent user of Facebook
	More use Facebook Component
	More number of Facebook Friends
	More Facebook groups
Neuroticism	Spend more time on Facebook, more use of Facebook wall
	Less use of private message
	Share more information
Agreeableness	More number of friends
Openness	More use of Facebook for communication
	More number of components
	More knowledge of features
Conscientiousness	Limited Facebook activity

3. Table 3

Correlation between social media foot prints and Personality traits					
	Opennes s	Consc .	Extraver t	Agreeabl e	Neurocitis m
Linguistic Features					
Swear Words	0.006	0.	0.032	0.	--0.120
Social Processes (e.g. Mate, talk, they, child)	0.010	0.264	0.091	0.	0.
Human Words (e.g. baby, man)	0.078	0.203	0.070	--0.050	0.
Affective Processes (e.g. Happy, cried, abandon)	0.105	0.	0.136	0.203	0.038
Positive Emotions (e.g. Love, nice, sweet)	0.052	0.045	0.117	0.167	0.
Anxiety Words (e.g. Worried, fearful. nervous)	0.044	-- 0.150	0.008	0.101	0.192
Perceptual Processes (e.g. Observing. heard, feeling)	--0.040	0.	0.	0.	0.096
Seeing Words (e.g. View, saw, seen)	0.060	0.	0.	0.013	0.067
Biological Processes (e.g. Eat, blood, pain)	0.	0.042	0.038	0.154	0.067
Ingestion Words (e.g. Dish, eat, pizza)	0.	-- 0.050	0.029	0.031	0.207
Work Words (e.g. Job, majors, xerox)	0.134	0.096	0.154	0.048	0.
Money Words(e.g. Audit, cash, owe)	-0.161	0.024	0.012	0.	0.029
Structural Features					
Number of Friends	0.	0.	0.186	0.013	0.
Egocentric Network Density	0.	0.050	0.	0.059	0.032
Activities and Preferences					
Activities (char length)	0.115	0.095	0.188	0.066	0.
Favorite Books (char length)	0.158	0.	0.019	0.082	0.028
Personal Information					
Relationship Status (none listed,single, not single)	0.093	0.071	0.194	0.040	0.
Last Name length in characters	0.012	0.	0.000	0.	0.184

4. **Linkage Data based analysis:** Social Network can be analyzed with mapping and measuring of relationships between various entities

5. **Content based analysis:** Social networking sites have large amount of content in the form of text, image, audio and video. This huge database can be used for various researches.