DEEP LEARNING IN MARKETING

Doctoral student in Marketing
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Marketing

- What is Marketing?
  - The activity, set of institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large (American Marketing Association 2013)

Marketing

- What is Marketing?
  - Simply put, Marketing is meeting customer needs profitably.
  - A marketing researcher tries to
    1) Understand customer needs
    2) Propose and evaluate strategies to increase/maximize a firm's objective function

Marketing

- What is Marketing?

Need Recognition → Marketing Strategies → Strategy Evaluation

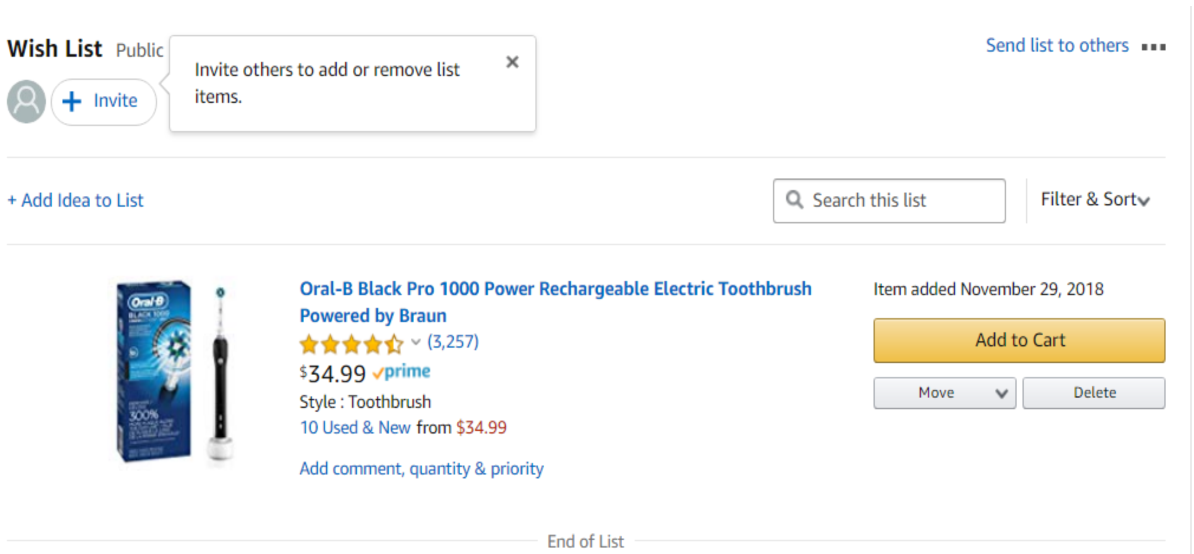
Marketing

- What is Marketing?

Need Recognition → Marketing Strategies → Strategy Evaluation

<u>Primary data</u>
Panel interviews
Surveys

<u>Secondary data</u>
Past purchases
Past browsing
Baskets, Wish list



Marketing

- What is Marketing?

Need Recognition → **Marketing Strategies** → **Strategy Evaluation**

Primary data
Panel interviews
Surveys

Secondary data
Past purchases
Past browsing
Baskets, Wish list

STP
Segmentation
Targeting
Promotion

4Ps
Price
Product
Place
Promotion

Marketing

- What is Marketing?

Need Recognition → **Marketing Strategies** → **Strategy Evaluation**

Need Recognition

Primary data
Panel interviews
Surveys

Secondary data
Past purchases
Past browsing
Baskets, Wish list

Marketing Strategies

STP
Segmentation
Targeting
Promotion

4Ps
Price
Product
Place
Promotion

Strategy Evaluation

Objective functions
Willingness to pay
Revenue
Profit
Customer retention
Returns

Deep Learning in Marketing

- Why Machine Learning (Deep Learning) in Marketing?
  - Unstructured data (e.g., text, image, video) become available in Marketing, and researchers want to apply the right methods to them.
    1) User-Generated Content (UGC) data (e.g., social media, online product reviews)
    2) Image data (e.g., product images, Instagram photos)
    3) Video data (e.g., advertising videos)
    4) Path data (e.g., customer's trajectory)

Deep Learning in Marketing

- Why Machine Learning (Deep Learning) in Marketing?

customerNumber	orderId	orderDate	Amount	sku	Qty	BillToZip
SYS71549	309057	2/1/2007 0:14	49.98	PSWDEP02	1	95148
SYS71549	309057	2/1/2007 0:14	49.98	PSWDJB02	1	95148
SYS64492	309059	2/1/2007 0:15	263.98	SIM2ADVPWD01	2	68504
SYS123873	309064	2/1/2007 0:34	57.94	AVN-422	1	90304
SYS123873	309064	2/1/2007 0:34	57.94	AVN-225	1	90304
SYS123873	309064	2/1/2007 0:34	57.94	HUNBJB	2	90304
SYS123873	309064	2/1/2007 0:34	57.94	AVN-611	1	90304
SYS123873	309064	2/1/2007 0:34	57.94	PSWRHP	1	90304
SYS45220	309066	2/1/2007 0:38	51.98	PCRSEP03	1	85338
SYS45220	309066	2/1/2007 0:38	51.98	LUVNT01	1	85338
SYS101405	309073	2/1/2007 1:02	48.98	PCRSJB03	1	10019

Deep Learning in Marketing

- Why Machine Learning (Deep Learning) in Marketing?

★★★★★ 24 Aug 2018

Color: 627 Rising Star

Favorite Lipstick

This is my favorite lipstick ever!!! I am not a lipstick person. Usually I wear gloss. I have been looking for a color that I can actually wear and not feel clownish. This reminds me of a lipstick from Benifit called Charge It. I have been looking to replace it since it was discontinued. This is darn close. It's such a nice natural color that can be worn every day. It is very glittery!!! I like that it is natural and glittery ...read more

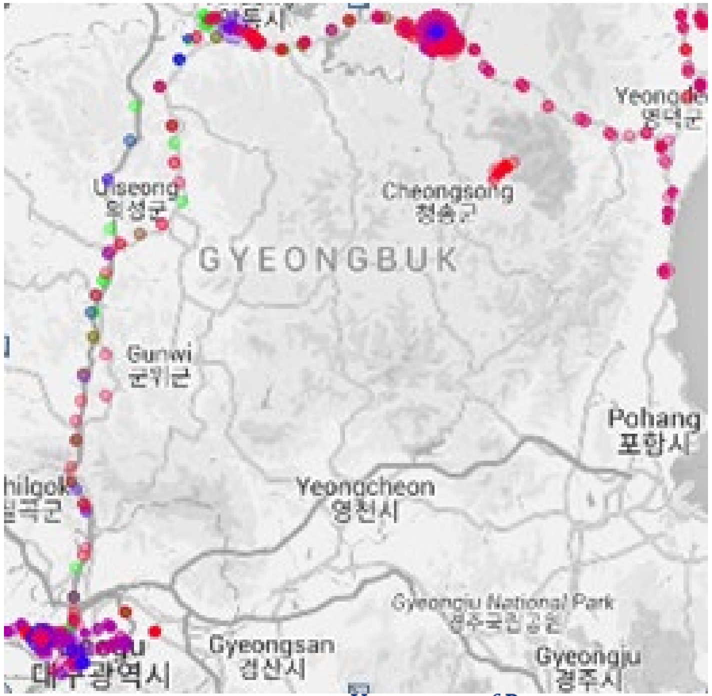
✓ Recommends this product

NOT HELPFUL (0) HELPFUL (1)

★★★☆☆ 1 Jun 2017

Really pretty

I love the colour (Dark Flower; although I'd call it a bright plum, not dark plum) and the way it feels. It glides on smoothly and feels as good as any balm. But, the longevity is fairly poor and it wears in such a way that it looks quite bad. I wasn't expecting a long-wear product, but I was hoping for better. Also, because it is so slick, it feathers into the lines around my mouth more than I am comfortable ...read more



Deep Learning in Marketing

- Recent research

Need Recognition → Marketing Strategies → Strategy Evaluation

Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

Liu, Dzyabura, and Mizik (2018) Visual Listening In: Extracting Brand Image Portrayed on Social Media

Deep Learning in Marketing

- Recent research

Zhang, Lee, Singh, and Srinivasan (2018) How Much is an Image Worth? Airbnb Property Demand Estimation Leveraging Large Scale Image Analytics

Deep Learning in Marketing

- Recent research

Need Recognition → Marketing Strategies → Strategy Evaluation

Dzyabura, Kihal, and Ibragimov (2018) Leveraging the Power of Images in Predicting Product Return Rates

Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- Identifying customer needs
  - Customer needs are abstract context-dependent statement describing the benefits, in customer's own words, that the customer seeks to obtain from a product or service

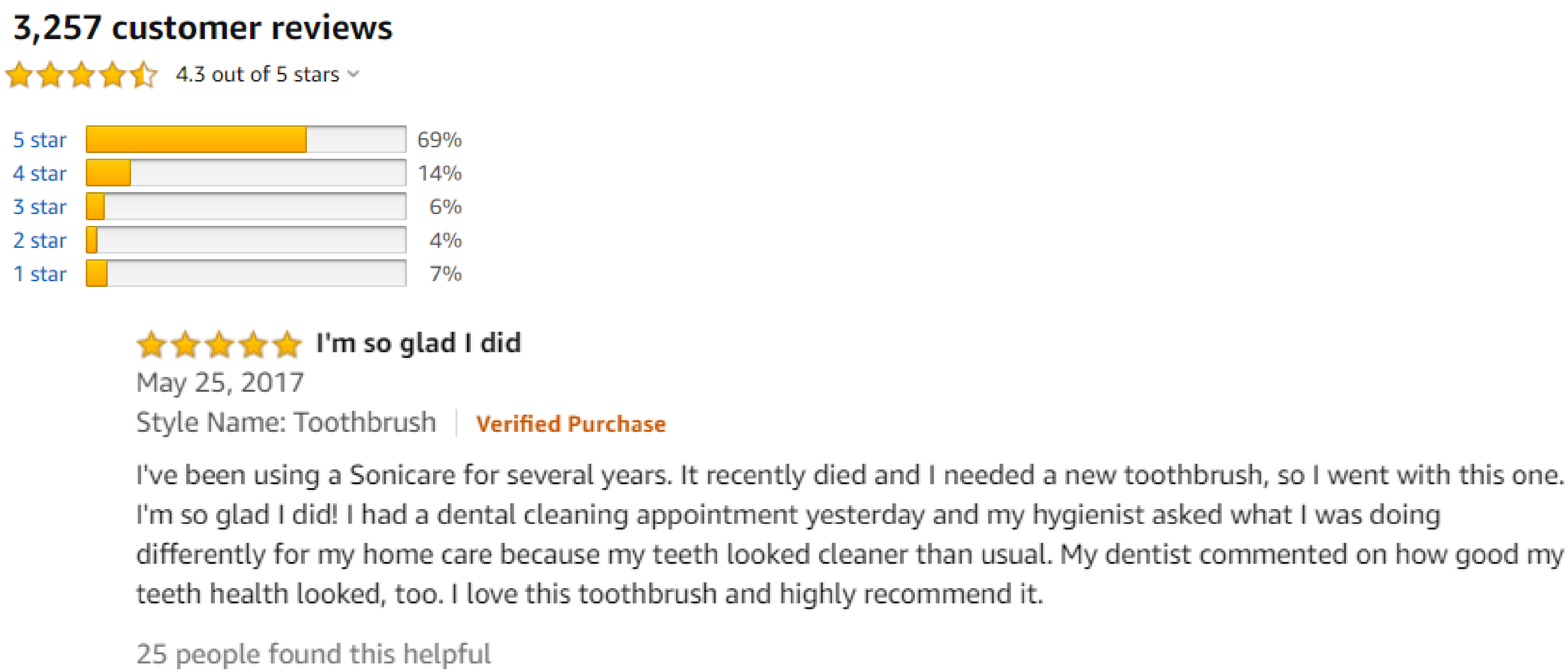
Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- Identifying customer needs from UGC
  - Traditional methods (e.g., experiential interviews and focus groups) are time-consuming and expensive.
  - UGC (e.g., online reviews, social media) provides rich textual data, and is available quickly and at a low cost.

Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- Multiple concerns on identifying customer needs from UGC
  - The very scale
  - Repetitive or not relevant
  - Unstructured and text-based

Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content



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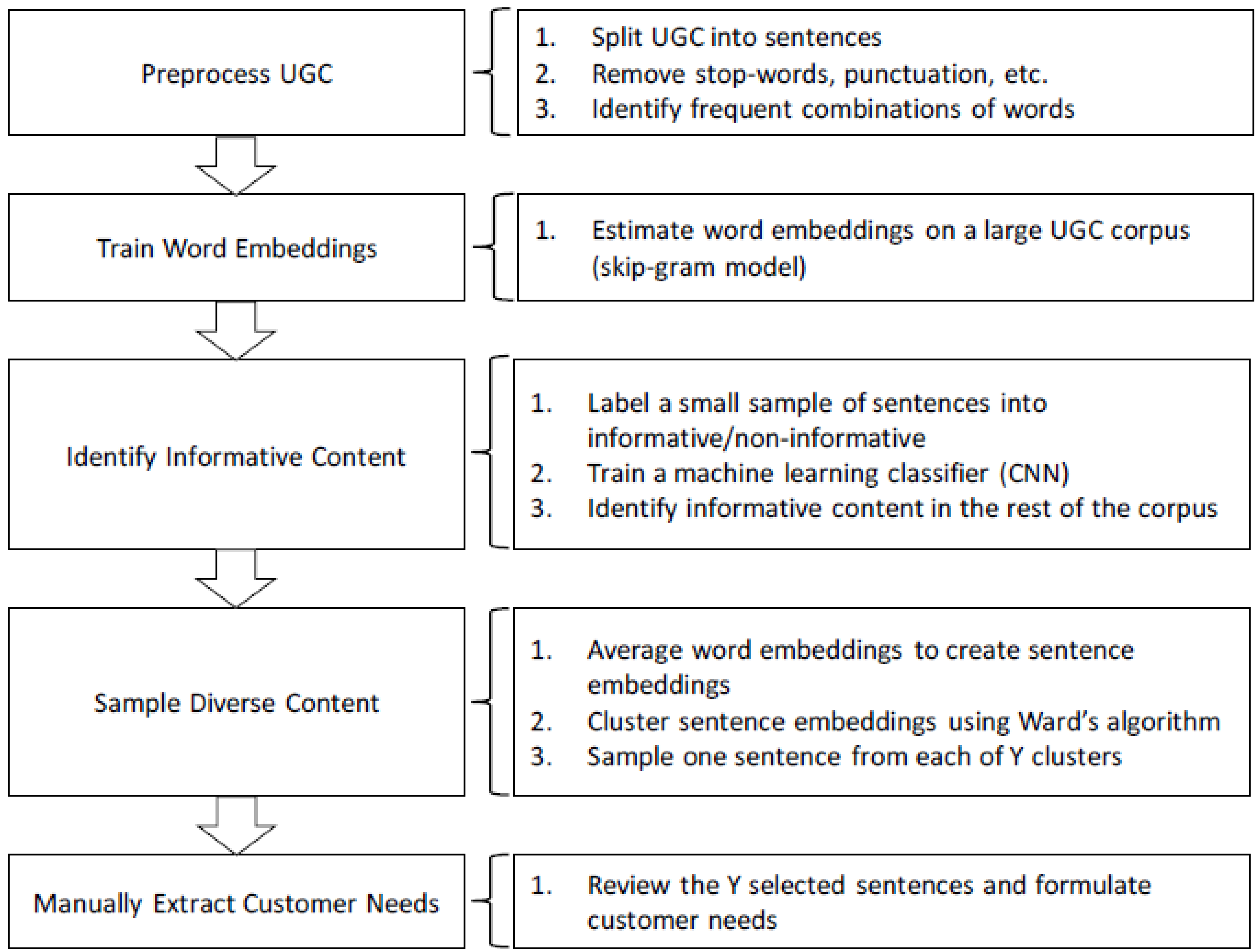
Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- Deep learning methods help identify customer needs from UGC.
  - Convolutional Neural Networks (CNN) filters out non-informative content.
  - Dense word and sentence embeddings sample a diverse set of non-redundant sentences for manual review.

Figure 1 System Architecture for Identifying Customer Needs from UGC



Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- Research questions
  - Does UGC contain sufficient raw material from which to identify a broad set of customer needs?
  - Do deep learning methods enhance efficiency?

R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

- Data sources
  - A detailed set of customer needs from an oral-care voice-of-the-customer (VOC) analysis by a professional market research consulting firm (see Table A1)
  - 115,099 oral-care reviews on Amazon from 1996 to 2014
    (1) 8,000 sentences, as costs to review interview transcripts are slightly more than costs to review 8,000 UGC sentences.
    (2) The sentences were reviewed by three experienced analysts from the same firm. The analysts were asked to determine each contained a customer need and, if so, whether the customer need could be mapped to Table A1.

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Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

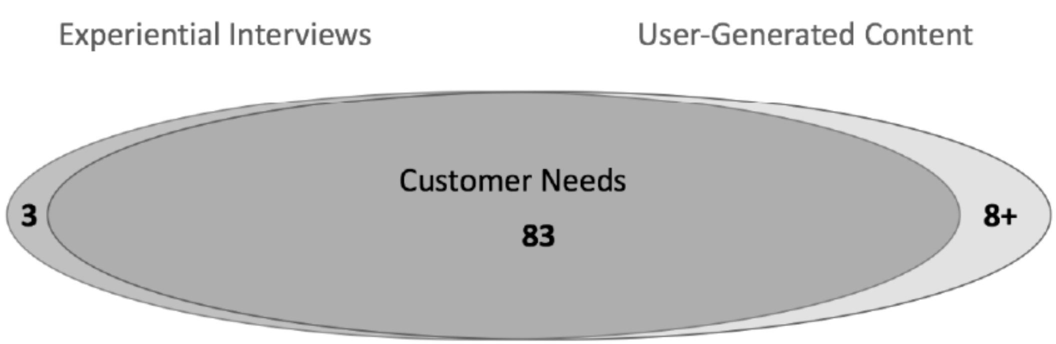
Table A1. **Voice of the Customer for Oral Care as Obtained from Experiential Interviews (22 examples of the 86 tertiary customer needs are shown—one for each secondary group. A full list of tertiary customer needs is available from the authors.)**

Primary Group	Secondary Group	#Needs	Examples of Tertiary Customer Needs (22 of 86 shown)
Feel Clean And Fresh (Sensory)	Clean Feeling in My Mouth	4	My mouth feels clean
	Fresh Breath All Day Long	4	I wake up without feeling like I have morning breath
	Pleasant Taste and Texture	3	Oral care liquids, gels, pastes, etc. are smooth (not gritty or chalky)
Strong Teeth And Gums	Prevent Gingivitis	5	Oral care products and procedures that minimize gum bleeding
	Able to Protect My Teeth	5	Oral care products and procedures that prevent cavities
	Whiter Teeth	4	Can avoid discoloration of my teeth
Product Efficacy	Effectively Clean Hard to Reach Areas	3	Able to easily get all particles, even the tiniest, out from between my teeth
	Gentle Oral Care Products	4	Oral care items are gentle and don't hurt my mouth
	Oral Care Products that Last	3	It's clear when I need to replace an oral care product (e.g. toothbrush, floss)
	Tools are Easy to Maneuver and Manipulate	6	Easy to grasp any oral care tool—it won't slip out of my hand
Knowledge And Confidence	Knowledge of Proper Techniques	5	I know the right amount of time to spend on each step of my oral care routine
	Long Term Oral Care Health	4	I am aware of the best oral care routine for me
	Motivation for Good Check-Ups	4	I want to be motivated to be more involved with my oral care
	Able to Differentiate Products	3	I know which products to use for any oral care issue I'm trying to address
Convenience	Efficient Oral Care Routine (Effective, Hassle-Free and Quick)	7	Oral care tasks do not require much physical effort
	Oral Care "Away From the Bathroom"	5	The oral care items I carry around are easy to keep clean
Shopping / Product Choice	Faith in the Products	5	Brands of oral care products that are well known and reliable
	Provides a Good Deal	2	I know I'm getting the lowest price for the products I'm buying
	Effective Storage	1	Easy to keep extra products on hand (e.g. packaged securely, doesn't spoil)
	Environmentally Friendly Products	1	Environmentally friendly products and packaging
	Easy to Shop for Oral Care Items	3	Oral care items I want are available at the store where I shop
	Product Aesthetics	5	Products that have a "cool" or interesting look

R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

- Results
  - The potential for self-selection in UGC does not seem to impair the breadth of customer needs.

Figure 4. Comparison of Customer Needs Obtained from Experiential Interviews with Customer Needs Obtained from an Exhaustive Review of a UGC Sample



R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

- Results
  - Prioritization survey to 197 customers from a panel; asking them to rate (1) importance of each need on a 0-to-100 scale and (2) whether they felt that their current oral care-products performed well on these needs on a 0-to-10 scale.

R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

- Results
  - Customer needs identified in both the interviews and UGC are the most important customer needs.
  - High-importance-low-performance customer needs are almost perfectly identified by both data sources.

Table 1. **Importance and Performance Scores for Customer Needs Identified from UGC and from Experiential Interviews (Imp = Importance, Per = Performance)**

Source of Customer Need	Count	Average Imp	Average Per	Quadrant (median splits)			
				High Imp High Per	High Imp Low Per	Low Imp High Per	Low Imp Low Per
Interviews ∩ 8,000 UGC [a]	74	65.5	7.85	29	11	11	23
Interviews ∩ 4,000 UGC [b]	9	63.9	7.97	6	0	0	3
UGC only	8	50.3	7.12	0	0	1	7
Interviews only	3	52.8	7.47	0	1	0	2

[a] Based on the first 8,000 UGC sentences that were fully-coded
[b] Based on the second 4,000 UGC sentences that were coded to test for interview-identified customer needs

R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

- Results
  - We cannot ignore low-importance-low-performance customer needs.
  - UGC-unique needs identify hidden opportunities (i.e., low-importance-low-performance customer needs).

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R1: Does UGC contain sufficient raw material from which to identify a broad set of customer needs?

Table A2. **Complete Set of Customer Needs that Were Unique to Either UGC or Experiential Interviews**

Customer Needs Unique to UGC	Customer Needs Unique to Experiential Interviews
Easy way to charge toothbrush.	Oral care tools that can be easily used by left-handed people.
An oral care product that is quiet.	I am able to tell if I have bad breath.
Responsive customer service (e.g., always answers my call or email, doesn't make me wait long for a response).	Advice that is regularly updated so that it is relevant to my current oral care needs—recognizes that needs change as I age.
An oral care product that does not affect my sense of taste (e.g. doesn't affect my taste buds).	
Oral care that helps me quit smoking.	
Easy to store products.	
Maintenance and repairs are simple and quick.	
Customer service can always resolve my issue.	

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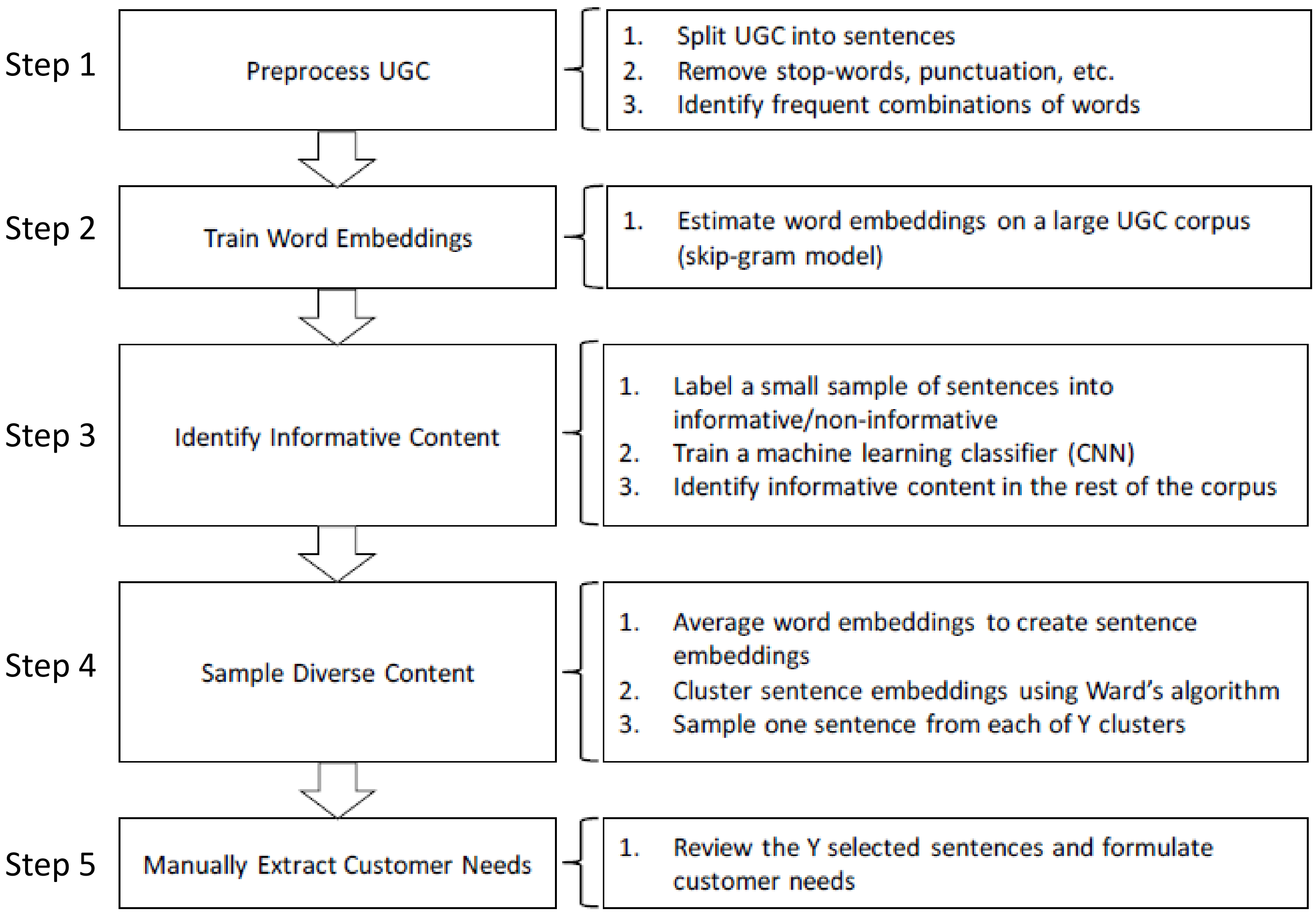
R2: Do deep learning methods enhance efficiency?

Figure 1 System Architecture for Identifying Customer Needs from UGC



R2: Do deep learning methods enhance efficiency?

Step 2

Train Word Embeddings

1. Estimate word embeddings on a large UGC corpus (skip-gram model)

embeddings on the preprocessed UGC corpus using a skip-gram model (Mikolov, et al. 2013a). The skip-gram model is a predictive model which maximizes the average log-likelihood of words appearing together in a sequence of c words. Specifically, if I is the number of words in the corpus, V is the set of all feasible words in the vocabulary, and $\boldsymbol{v}_i$ are d-dimensional real-vector word embeddings, we select the $\boldsymbol{v}_i$ to maximize:

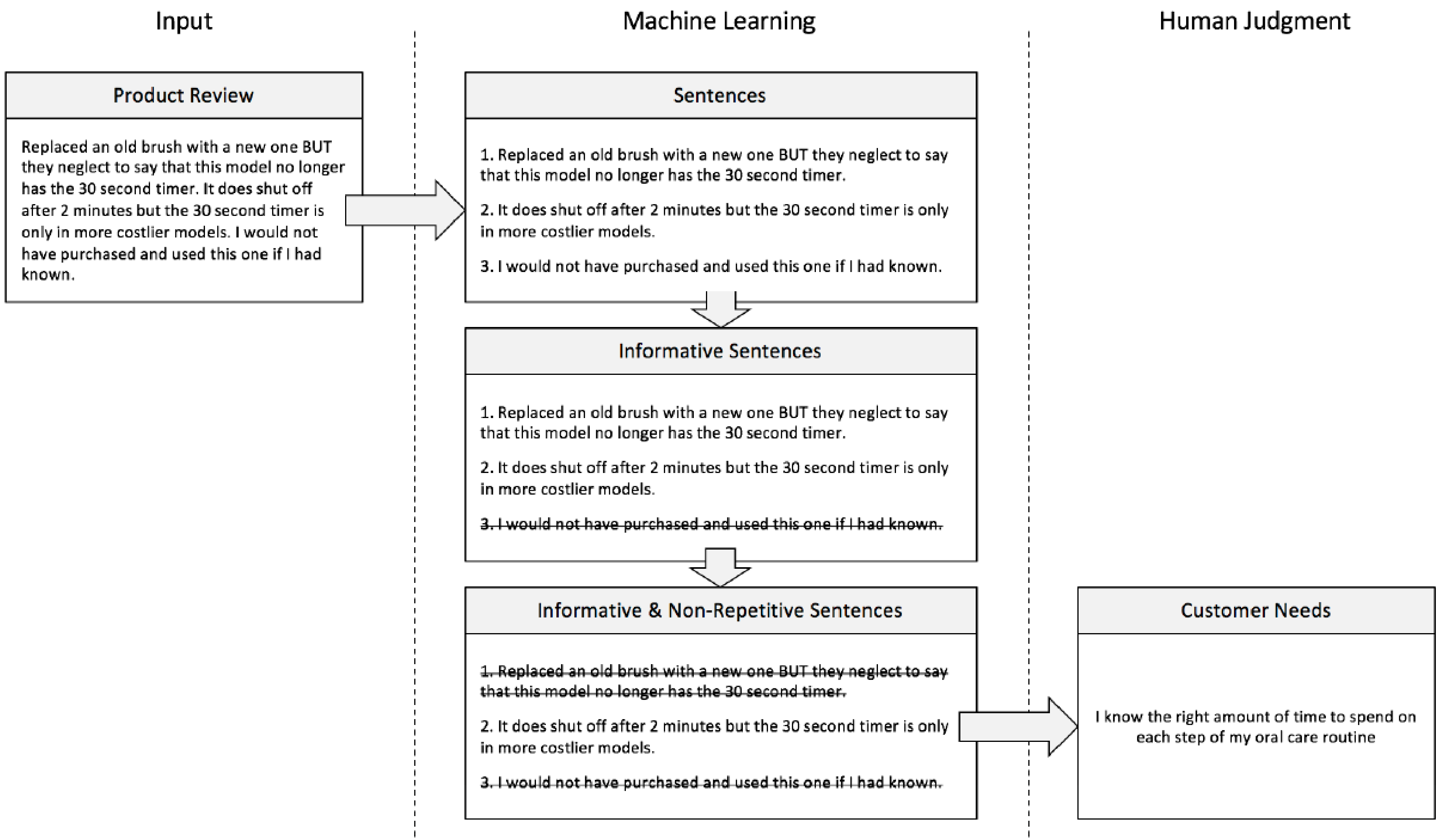
$$\frac{1}{I}\sum_{i=1}^{I}\sum_{\substack{-c\leq j\leq c\\ j\neq 0}} log\, p(word_{i+j}|word_i)$$

$$p(word_j|word_i) = \frac{exp(\boldsymbol{v}_j \boldsymbol{v}'_i)}{\sum_{k=1}^{|V|} exp(\boldsymbol{v}_k \boldsymbol{v}'_i)}$$

To make calculations feasible, we use ten-word negative sampling to approximate the denominator in the conditional probability function. (See Mikolov, et al. 2013b for details on negative sampling.) For our application, we use $d = 20$ and $c = 5$.

The trained word embeddings in our application capture semantic meaning in oral care. For example, the three words closest to 'toothbrush' are 'pulsonic', 'sonicare' and 'tb', with the last being a commonly-used abbreviation for toothbrush. Similarly, variations in spelling such as 'recommend',

Figure A1. Demonstration of the Application of the Proposed Machine Learning Hybrid Approach to an Amazon Review



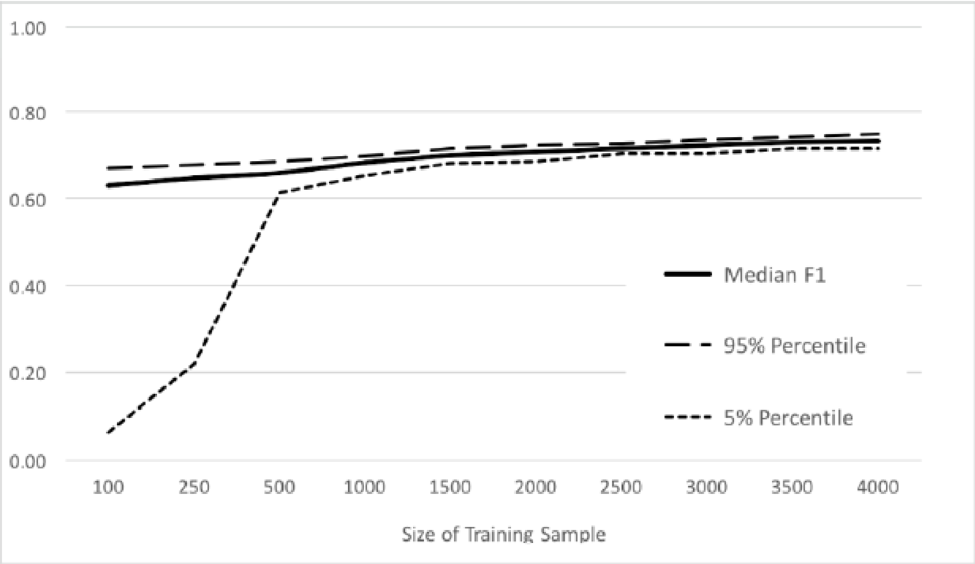
R2: Do deep learning methods enhance efficiency?

- First, CNN eliminates non-informative sentences
  - There is an opportunity cost to using analysts to classify informative sentences.
  - However, labeling sentences as informative or not is faster and easier than identifying needs from sentences; The ratio of time spent on identifying informative sentences vs. formulating customer needs is 20%

R2: Do deep learning methods enhance efficiency?

- First, CNN eliminates non-informative sentences
  - Performance of the CNN stabilizes after 500 training sentences.

Figure 5. F_1 **score as a Function of the Size of the Training Sample**



R2: Do deep learning methods enhance efficiency?

- First, CNN eliminates non-informative sentences
  - Focusing on F1, the CNN outperforms the other methods, although the other deep-learning methods do reasonably well.
  - We favor methods that miss fewer informative sentences (i.e., higher recall, at the expense of lower precision).

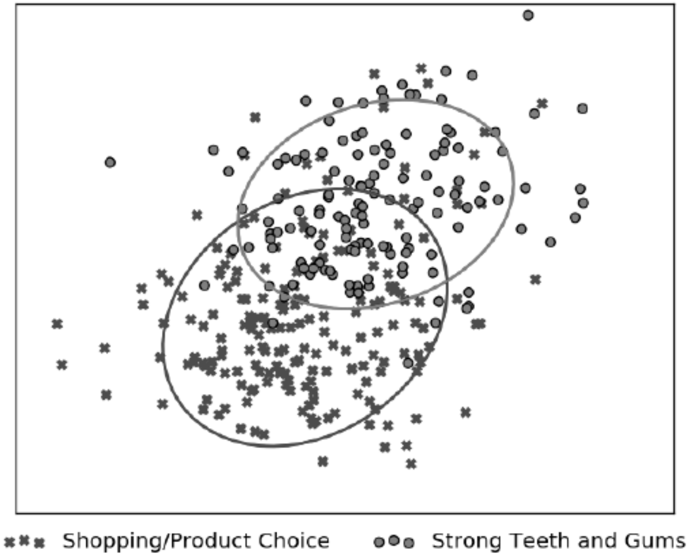
Table 2. Alternative Machine-Learning Methods to Identify Informative Sentences

Method	Precision	Recall	Accuracy	F_1
Convolutional Neural Network (CNN)	74.4%	73.6%	74.2%	74.0%
CNN with Asymmetric Costs ($\gamma = 3$)	65.2%	85.3%	70.0%	74.0%
Recurrent Neural Network-LSTM	72.8%	74.0%	73.2%	73.4%
Multichannel CNN	70.5%	74.9%	71.8%	72.6%
Support Vector Machine	63.7%	67.9%	64.6%	65.7%

R2: Do deep learning methods enhance efficiency?

- Second, Clustering sentence embeddings reduces redundancy

Figure 6. **Projections of 20-Dimensional Embeddings of Sentences onto Two Dimensions (PCA). Dots and Crosses Indicate Analyst-Coded Primary Customer Needs.**



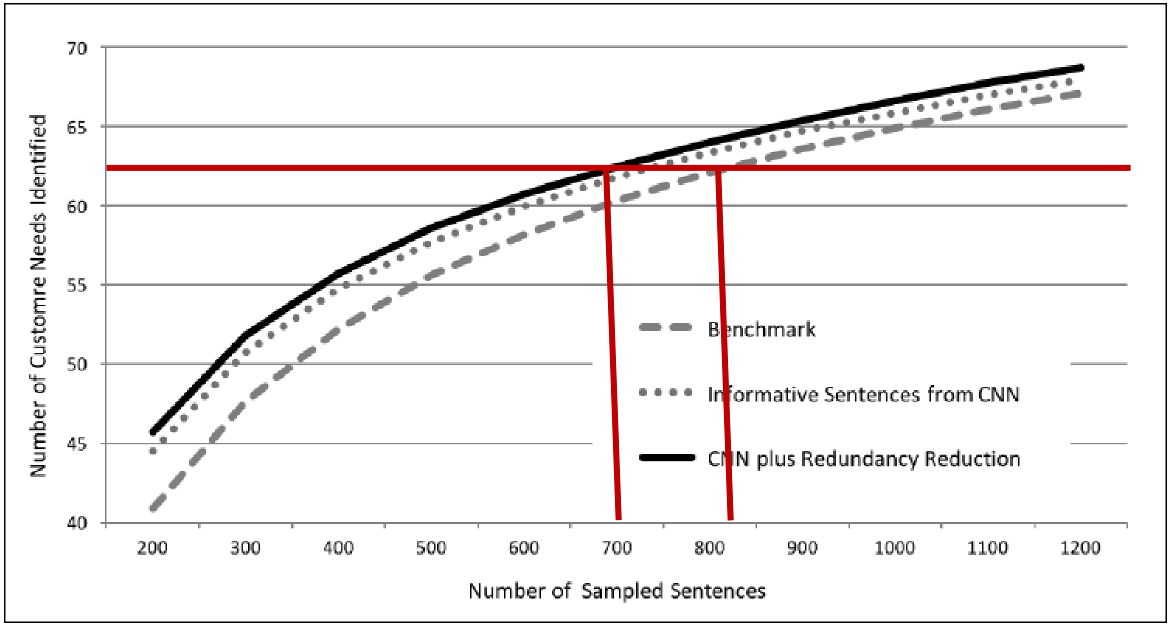
R2: Do deep learning methods enhance efficiency?

- Lastly, Deep learning methods improve efficiency of identifying customer needs (thus, enhance the probability of identifying low-frequency needs) from UGC.
- The authors compare the three methods:
  - Random draw from the corpus
  - CNN + Random sampling
  - **CNN + Sentence-embedding clusters**

R2: Do deep learning methods enhance efficiency?

- Lastly, deep learning methods improve efficiency.

Figure 7. Efficiencies among Various Methods to Select UGC Sentences for Review



R2: Do deep learning methods enhance efficiency?

- Lastly, deep learning methods improve efficiency.
  - Professional services costs dominate the expenses in a typical VOC study (e.g., 40% to interviewing customers, 50% to identifying customer needs, 10% to organizing customer needs into a hierarchy).
  - UGC eliminates the first 40%.
  - The proposed method allows a 15% reduction in the time allocated to identifying customer needs.
  - This method also enhances probability that the lowest-frequency customer needs are identified within a given cost constraint.

Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content

- In summary,
  - UGC does at least as well as traditional methods, even with a lower cost.
  - Deep learning methods help eliminate irrelevant and redundant content, making professional services more efficient.

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

- Motivation
  - The focus so far has been on UGC in the form of text.
  - However, images are on their way to surpassing text as the medium of choice for social conversations.
  - Consumers often tag brands, sharing with one another their mood and experience, associated with brands.

(a) #eddiebauer (b) #prada

Figure 1 **Sample images from Instagram hashtagged with brands**

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

- “Visual listening in” approach
  - Stage 1: Implement SVM and CNN to measure brand attributes from images.
  - Stage 2: Apply classifiers to brand-related images posted on social media to measure what consumers are visually communicating about brands.

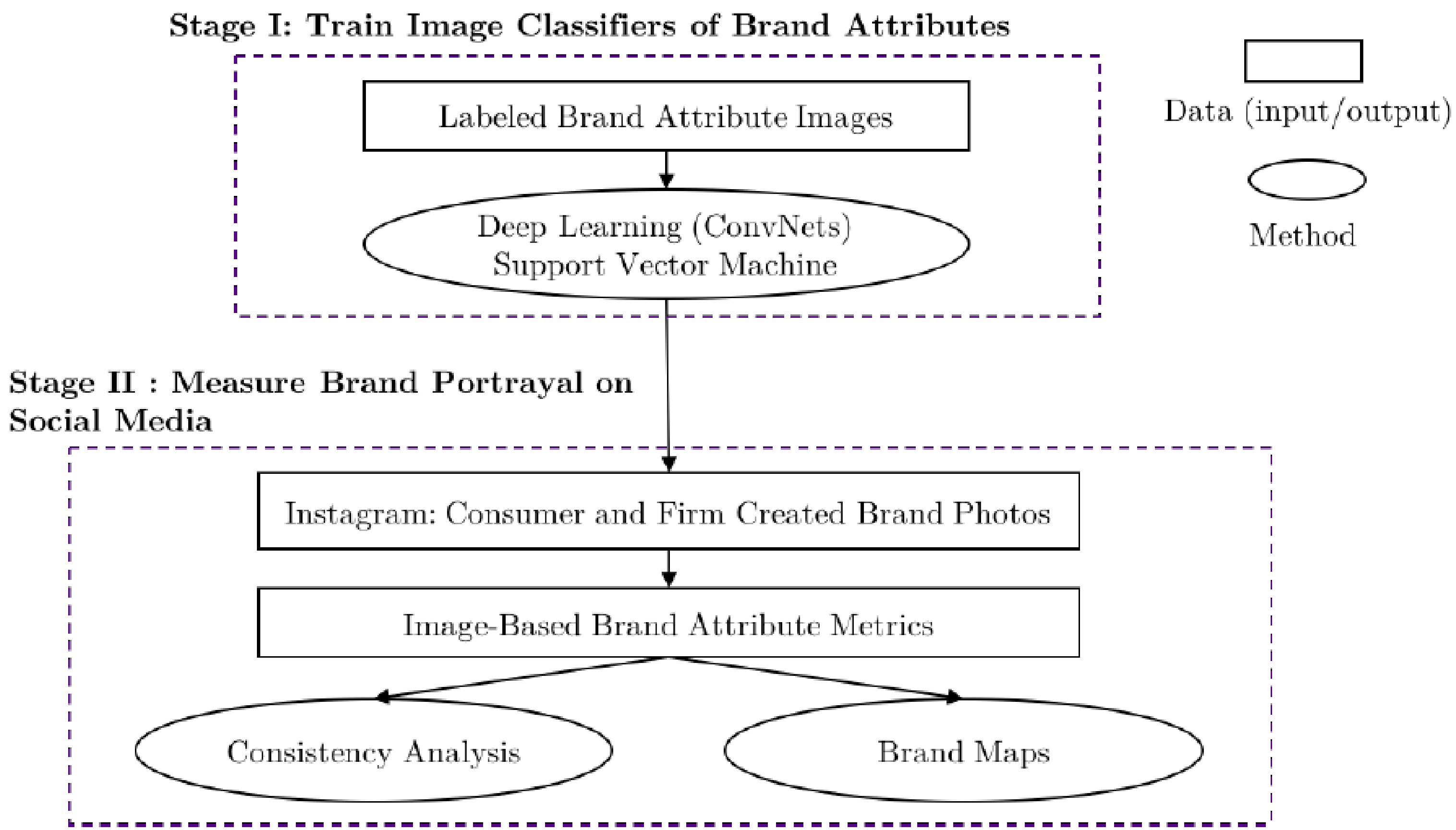


Figure 2 Framework for extracting brand image from consumer-created brand images on social media

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

- Stage 1: Identifying brand attributes in images
  - Brand categories: Apparel and beverage
  - Brand attributes: Glamorous, rugged, healthy, and fun
  - Steps

    (1) For each attribute, query it and collect about 2,000 images

    (2) Build and train image-classifier models

      - SVM using pre-defined features (color, shape, texture)
      - CNN which automatically identifies brand attributes

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

- Stage 2: Brand portrayal on social media
  - Data: Instagram data for 56 brands in apparel and beverages
  - Apply the trained image classifiers to predict the presence of the four perceptual attributes in an image.
  - For each brand, compute the proportion of images that are classified as reflecting that attribute.

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

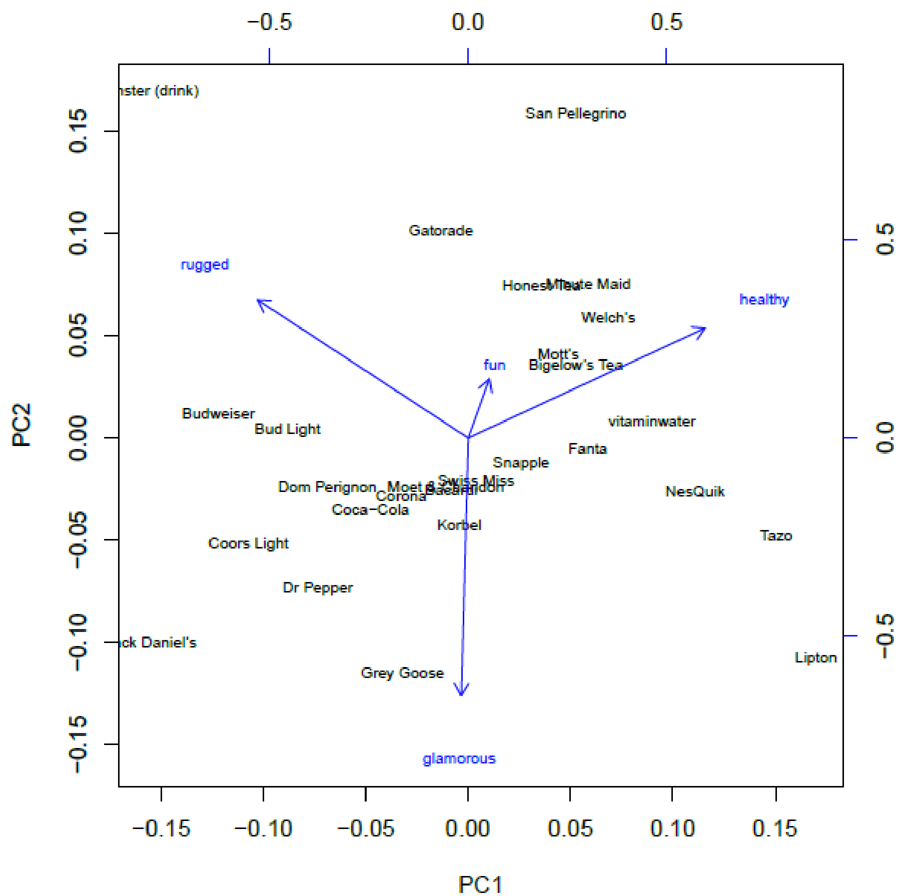
- Finding 1: Association with other brand measures
  - Compare (1) consumers' images with (2) images on the firm's official Instagram account, as well as with (3) consumer brand perceptions measured in a national brand survey

Table 4 **Pearson's correlation between different brand measures** ($^{*}p \leq 0.1$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$)

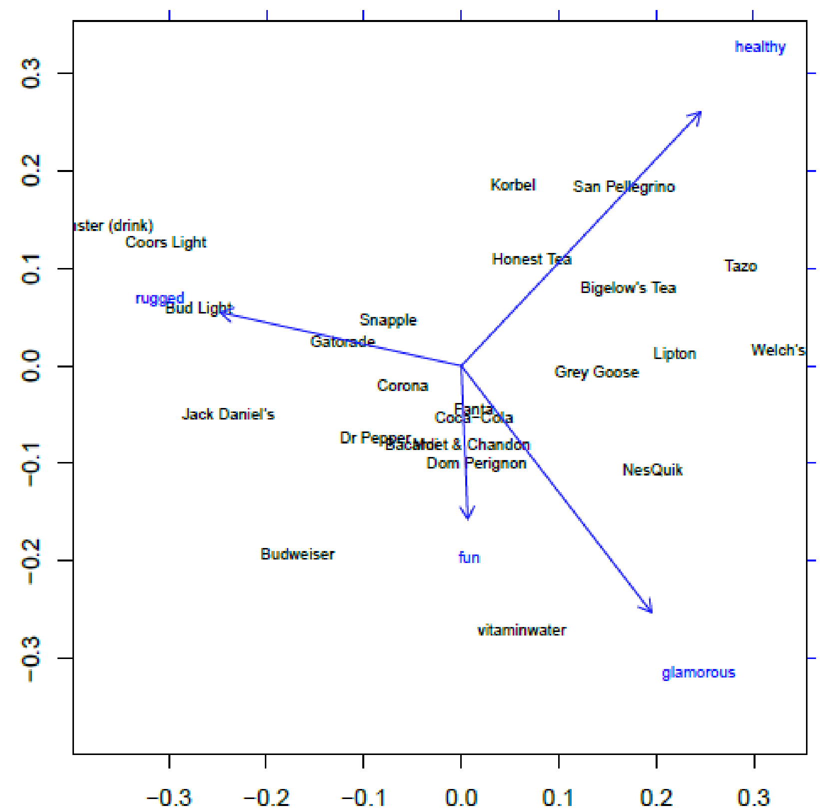
Category	Attribute	Consumer vs. Firm	Consumer vs. BAV	Firm vs. BAV
Apparel	glamorous	0.773***	0.287*	0.320**
	rugged	0.787***	0.569***	0.396**
	healthy	0.572***	0.222	0.242
	fun	0.633***	0.517***	0.329**
Beverages	glamorous	0.375**	0.004	0.167
	rugged	0.814***	0.322*	0.506***
	healthy	0.704***	0.803***	0.491***
	fun	0.516***	0.240	0.219

Liu, Dzyabura, and Mizik (2018) Extracting Brand Image Portrayed on Social Media

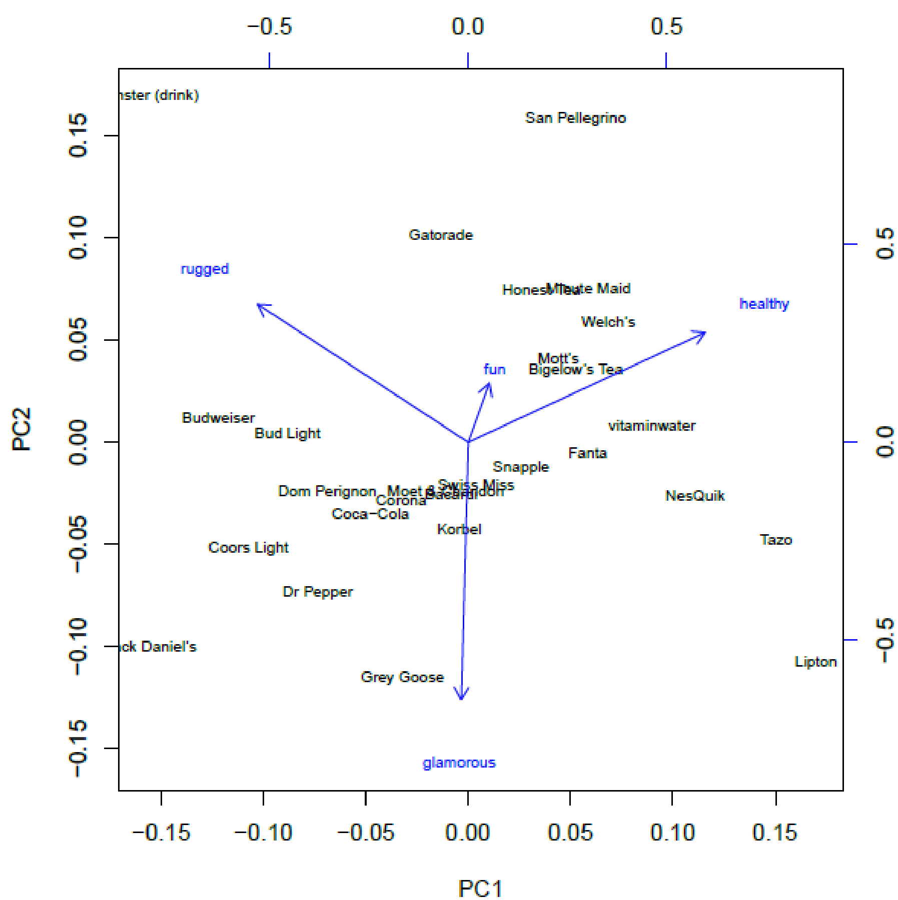
- Finding 2: Brand maps
  - Comparing three maps reveals (1) on which attributes the data vary most and (2) differences where certain brands fall on



(A) Map based on consumers' photos



(B) Map based on firms' photos



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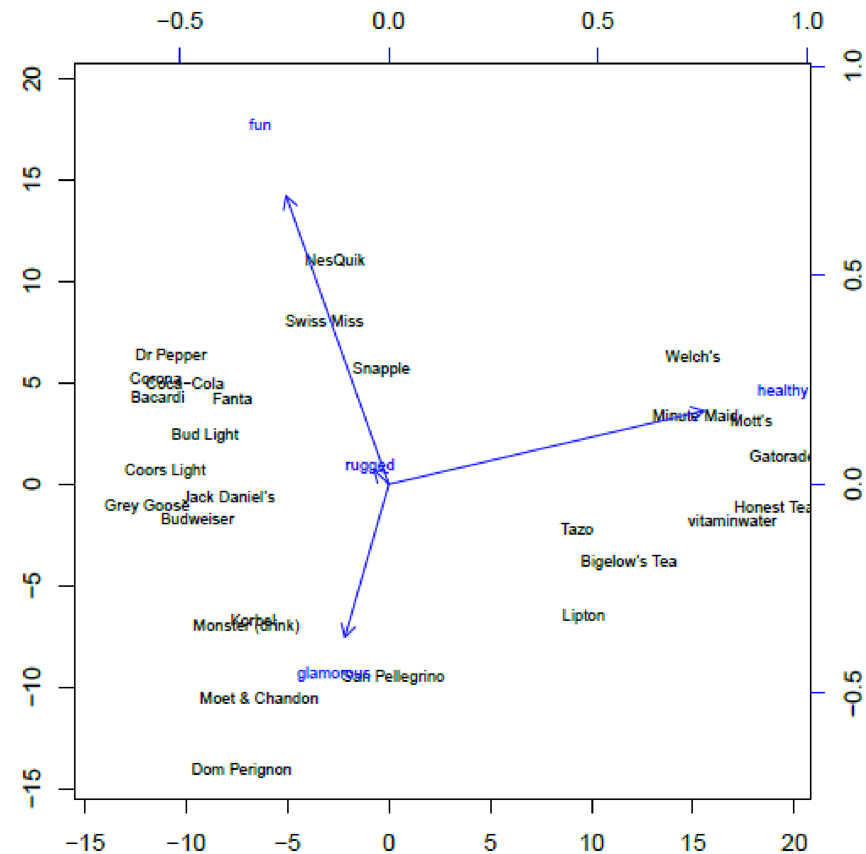
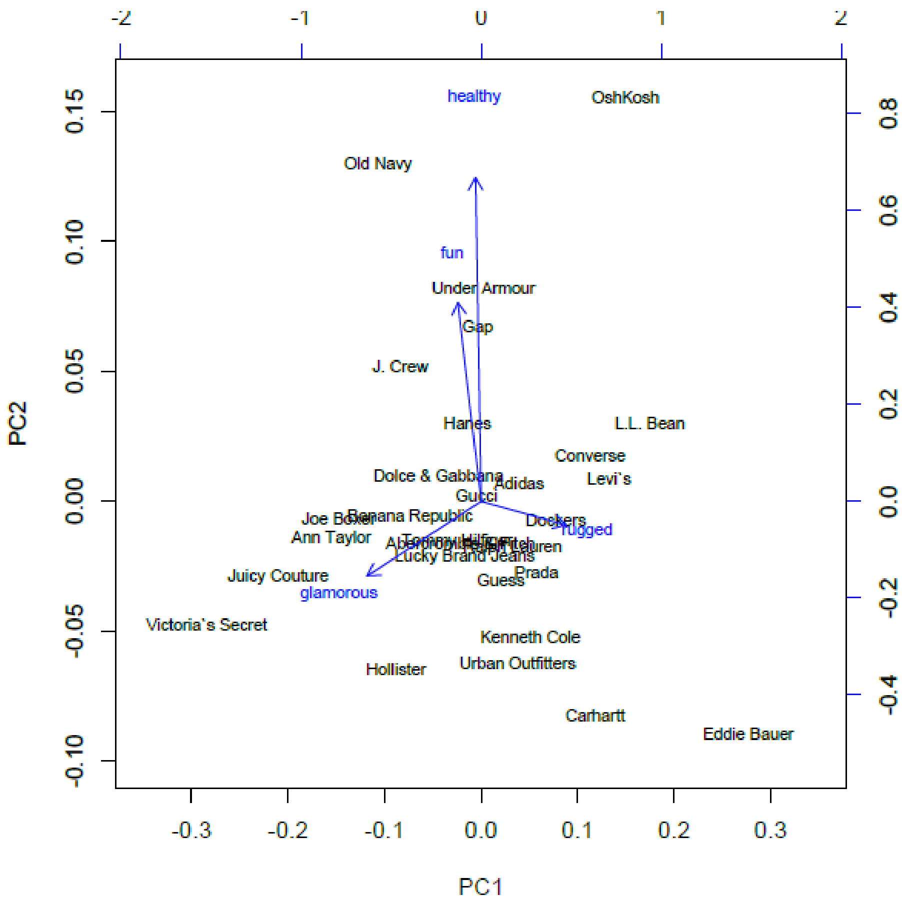


(C) Map based on consumer surveys



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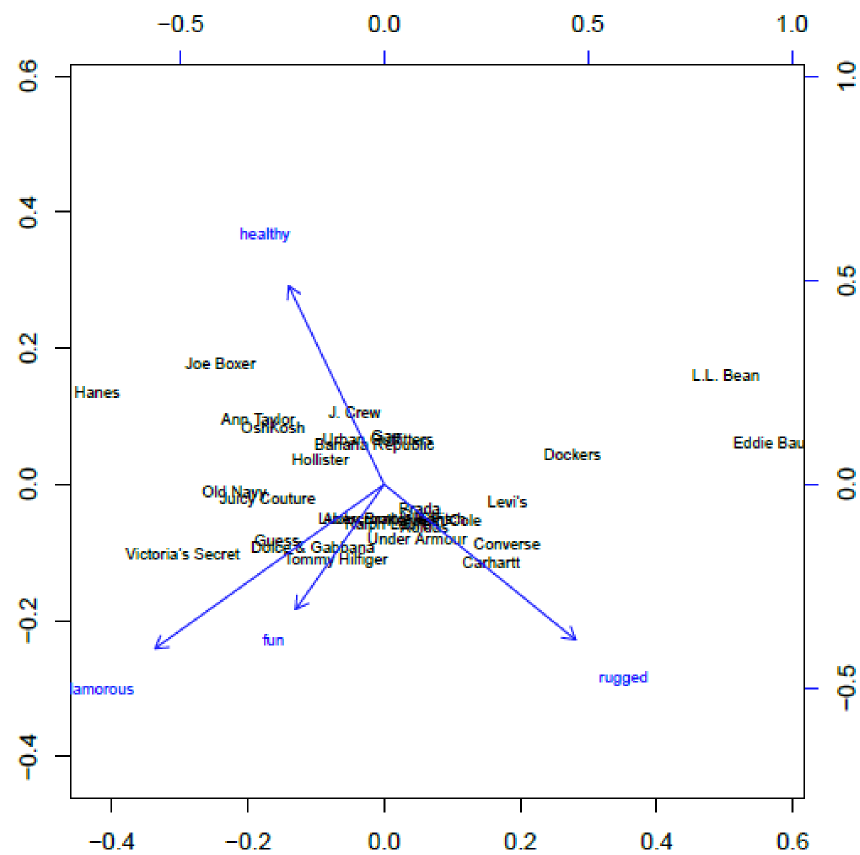

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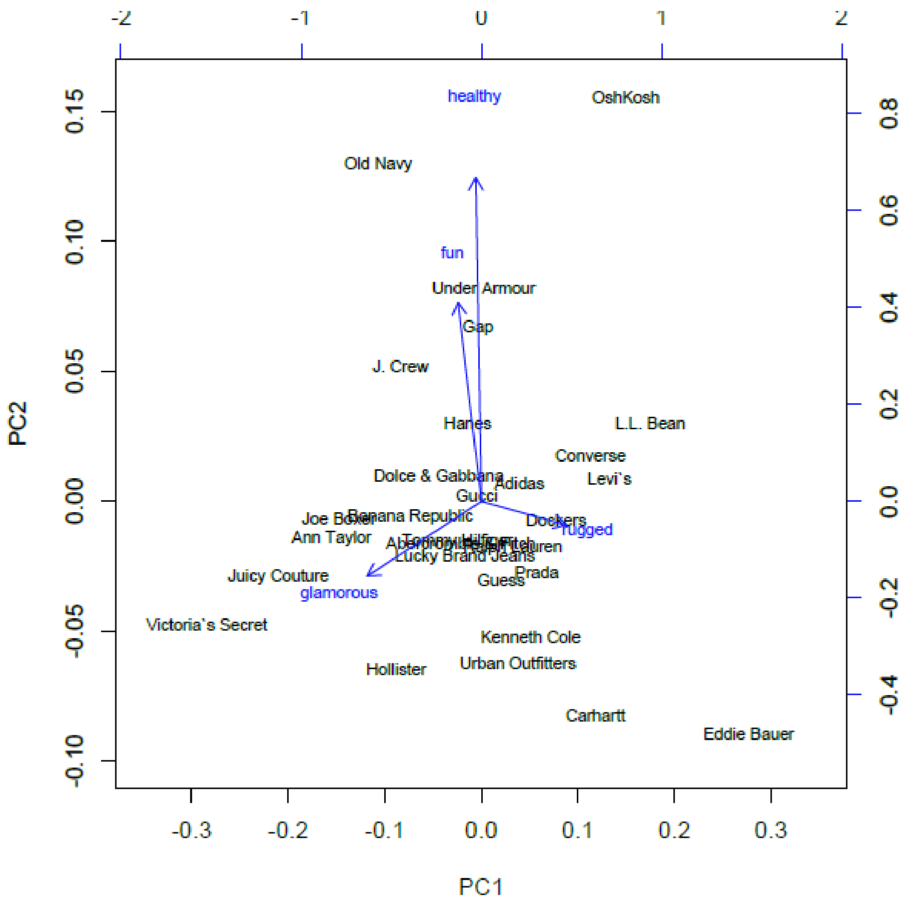

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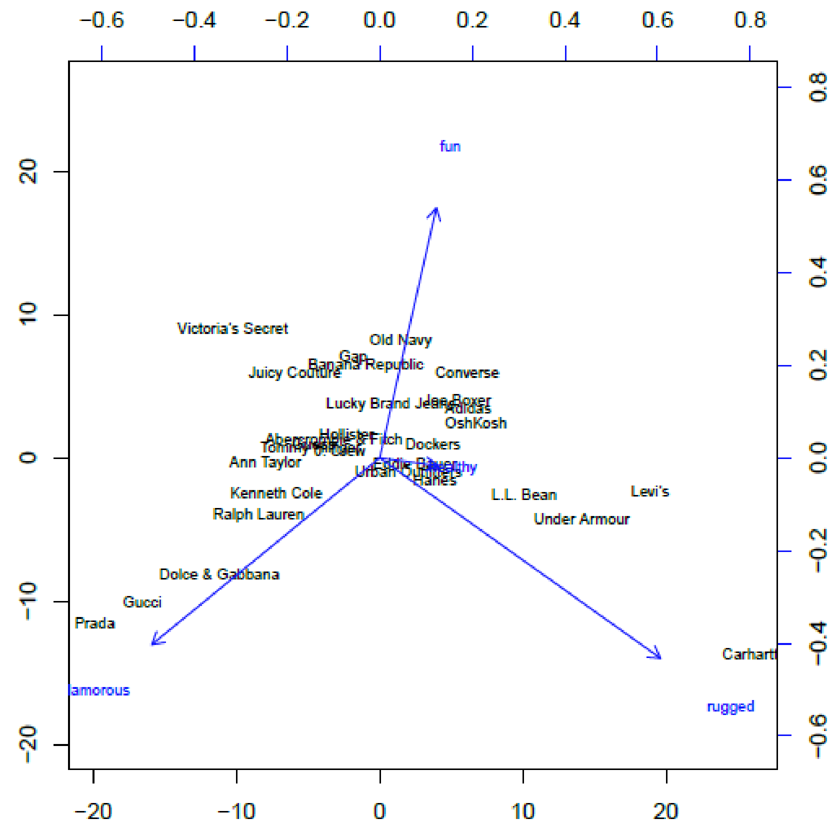

(C) Map based on consumer surveys

Deep Learning in Marketing Research

- Recent papers:
  - Timoshenko and Hauser (2018) Identifying Customer Needs from User-Generated Content
  - Liu, Dzyabura, and Mizik (2018) Visual Listening In: Extracting Brand Image Portrayed on Social Media
  - Dzyabura, Kihal, and Ibragimov (2018) Leveraging the Power of Images in Predicting Product Return Rates
  - Zhang, Lee, Singh, and Srinivasan (2018) How Much is an Image Worth? Airbnb Property Demand Estimation Leveraging Large Scale Image Analytics

Thank you!