



Using Social Media Data to Predict New Product Success

3 April 2019

Overview of Presentation



to Prediction	Machine Learning Using Motives	The Motive Model	Preparing Sales Data to Play Nicely With SM	Proof that SM Can Predict New Product Sales	Key Takeaways & New Directions

in4mation insights and Converseon partnership: We take Converseon "research grade" social data and build it into our predictive models

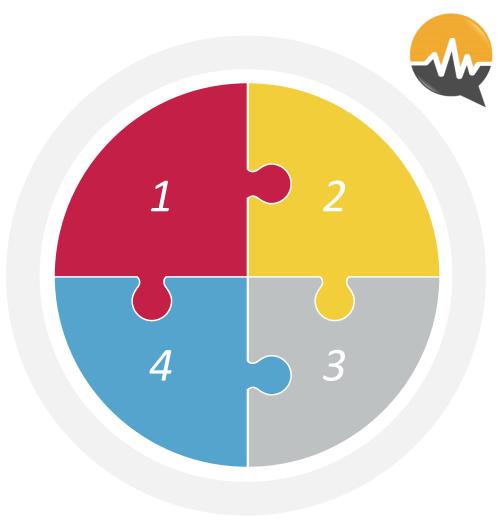


Category Expertise

New Product Forecasting Food & Beverages

Modeling Integrators

Bayesian Experts Innovative Approaches Link Attributes to Sales Segmenting Markets



Collaborative Methodology

Converseon Convey API allows all of us to participate in refining the rules, so results are relevant to our issues

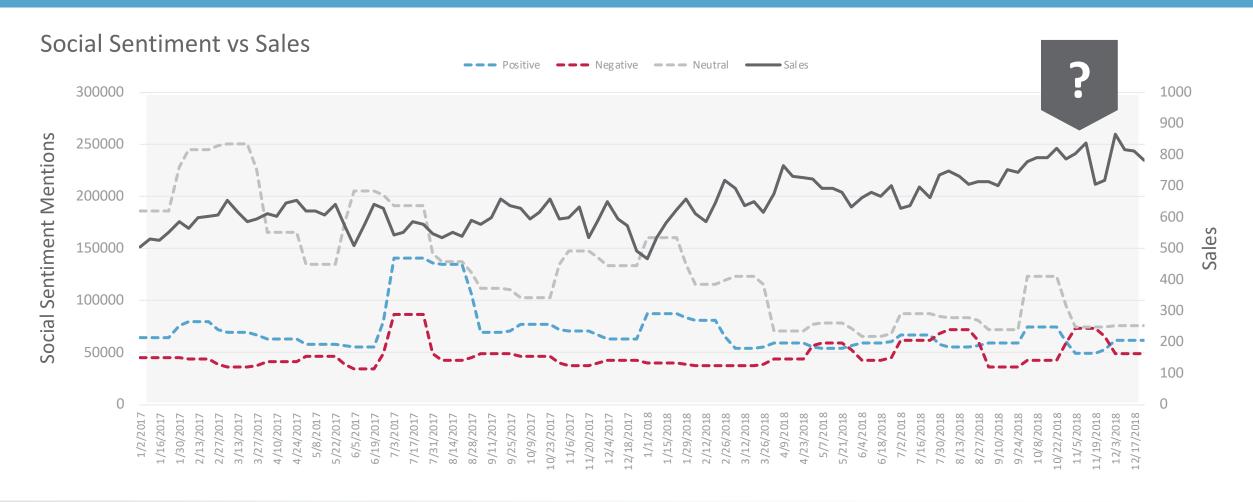
Multiple Metrics

Beyond sentiment—emotions and intensity using NLP for better predictors of sales and more precise social context

Using Natural Language Processing (NLP) for sales prediction



How do we develop social media time series that are prediction grade?



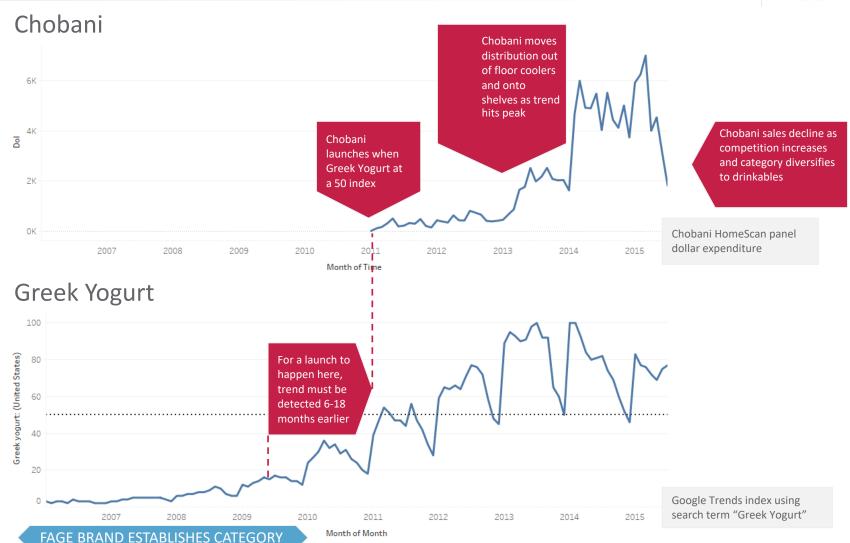
Can social media be used to predict new product success?



YOGURT EXAMPLE

Depending on how fast you can bring a product to market, a new trend must be detected 6-18 months before launch.

Even identifying potential acquisition targets requires significant lead time.



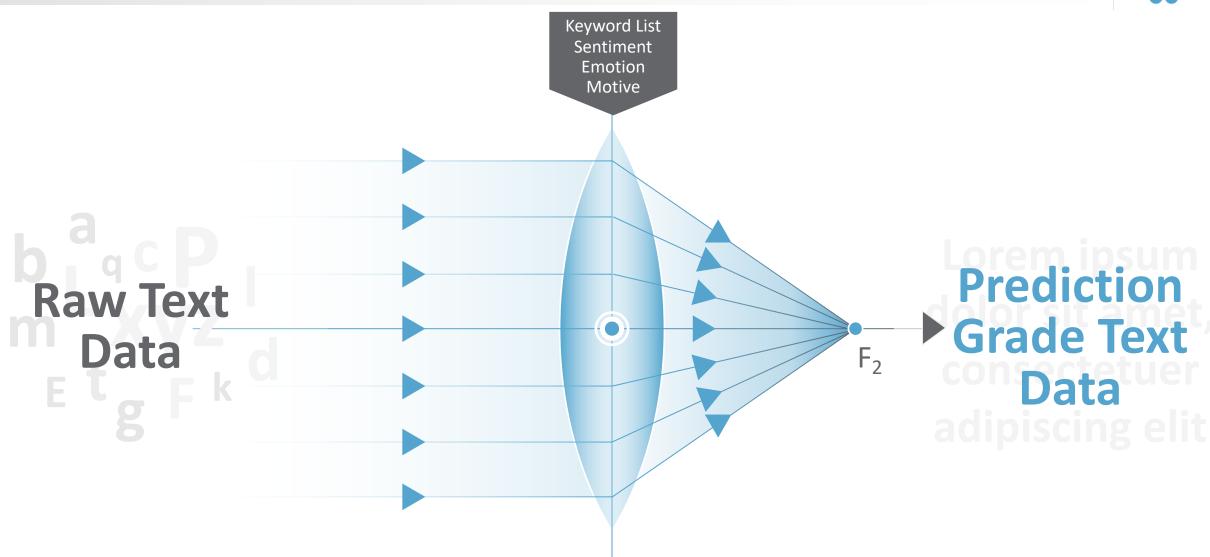
What does text data look like?



we were at parrot cay the first night and met our servers richard was the head server santana the server and tita the assistant server all were excellent the entire cruise really really attentive and friendly we learned an important lesson the first night don t order fish ever more later in this report dw ordered the grouper and it was so fish y she could the teat it we do enjoy good food and dining out at home and she s not a picky eater however she earned that reputation the first night after she couldn t eat the fish she just wanted a chicken breast she really didn t eat it either so the stafff insisted on bringing another dish it was a vegetarian mushroom disththettsthessaidwæssvenyggood agemenal motte om the flood for the terretien tirip tiri pvia sygazoglobodt buntre mræmkæb kæble allefalli molusochsæthieten img oværlobehoj æyn jewery eighty anight with the treatment to be the complete of the com

Motive as a lens





Why Converseon's Convey API is better than other SL platforms



Develop a variety of strategies to capture motives

"It's a family favorite recipe"

Motive Wording

" I wanted to satisfy a craving"

" I needed something that was quick and easy to prepare"

Short Handle
Favorite Recipe
Craving

Quick & Easy

Examples of Machine Learning Analysis

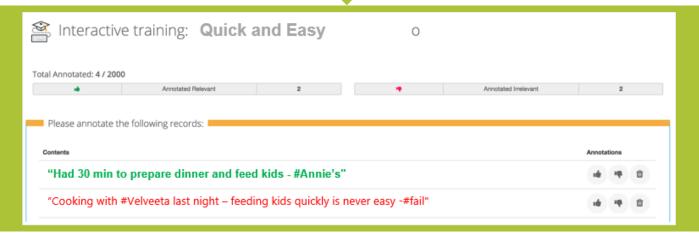
Keyword List + Positive Sentiment / Joy

Anticipation +

Positive Sentiment (to be validated)

Convey Custom Classifiers

Jointly tune the semi-supervised model



The model predicts market share by telling us which motives drive preference for which feature levels



















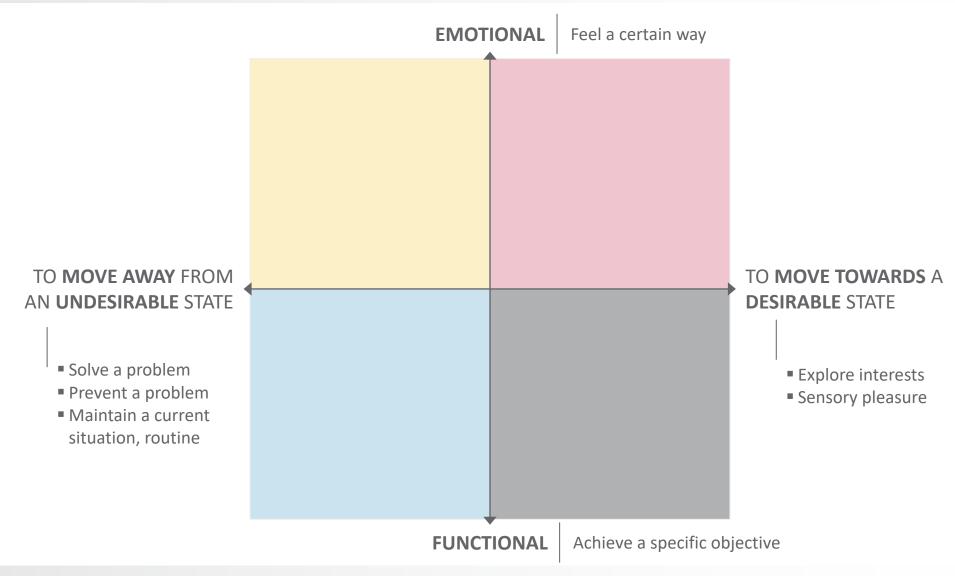
REALM OF CHOICE

REALM OF MARKET STRUCTURE

Mental model for developing motives



10



Motives break down into different types....



EMOTIONAL

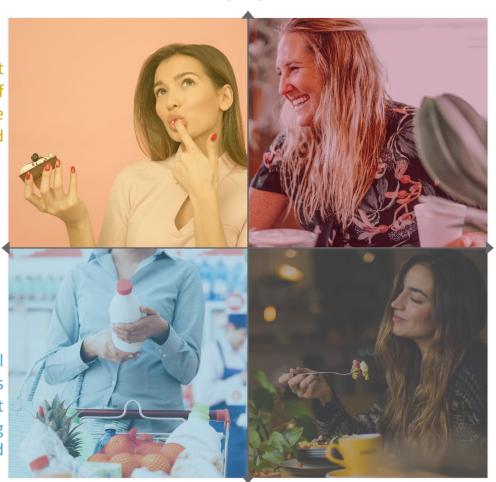
Emotional / Avoid Problems

I wanted a brand I can trust
I wanted to calm myself
I wanted to feel safe
I did not want to be surprised

TO **MOVE AWAY** FROM AN **UNDESIRABLE** STATE

Functional / Avoid Problems

I wanted something with no artificial ingredients
I wanted something convenient
I wanted to satisfy a craving
I wanted something less processed



Emotional / Desirable

I wanted to be in a good mood
I wanted to take a break
I wanted to take care of family
I wanted some variety

TO MOVE TOWARDS A
DESIRABLE STATE

Functional / Desirable

I wanted to eat organic food
I wanted something with recognizable
ingredients
I wanted something filling
I want something that can be eaten everyday

FUNCTIONAL

Defining the motive filters: *Recognize Ingredients*



Relevance—Topic Modeling

Assumed Relevant

	Relevant			
High-Confidence Results	Ingredients Driving Excitement/Enjoyment about Food Greens & Ingredients That Are Specifically Perceived as Healthy			
Interesting High- Confidence Sub-Themes	Breakfast Motivated to Shop at Farmer's Markets & Eat Locally/Sustainably Sourced Food			
Lower-Confidence Results	Motivated to Eat Organic Food (Very Common: "I Love Organic Food.") Health-Conscious Eating & Recipe Sharing without Detailed Ingredient Profiles	Veganism: Posts about Seeking Vegan Food Options & Eating Vegan Healthy/ Clean Eating and Fitness/ Weight Loss		
Results Assumed Irrelevant	Posts Generally about Veganism ("Ethical/Environmental" Veganism, No Mention of Specific Food / Not about Current Eating Activities) Lists of Ingredients in Recipes (Lacking Consumer Commentary, often Recipe Sharing on Facebook)			
	of Specific Food / Not about Current Eating Activities) Lists of Ingredients in Recipes (Lacking Consumer Commentary, often Recipe			

Irrelevant

Motive Model—High Correlation

Clean Eating

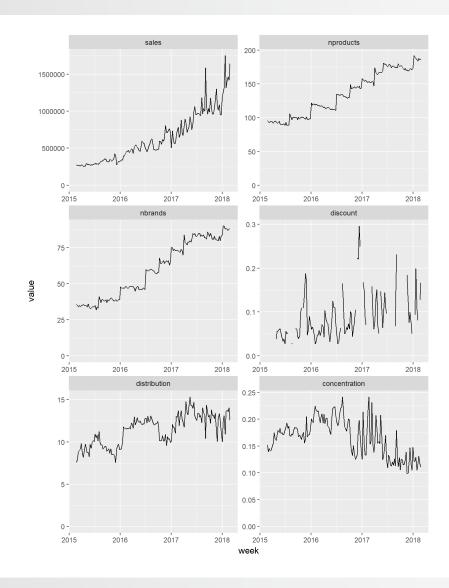
Recognize ingredients Not overly processed Fresh ingredients Feel smart about food choices

> Use of color green LUVO PLANTED EVOL ANNIE'S

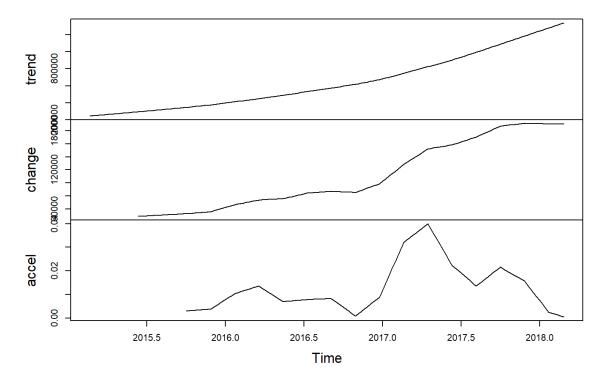


What does the sales data look like?



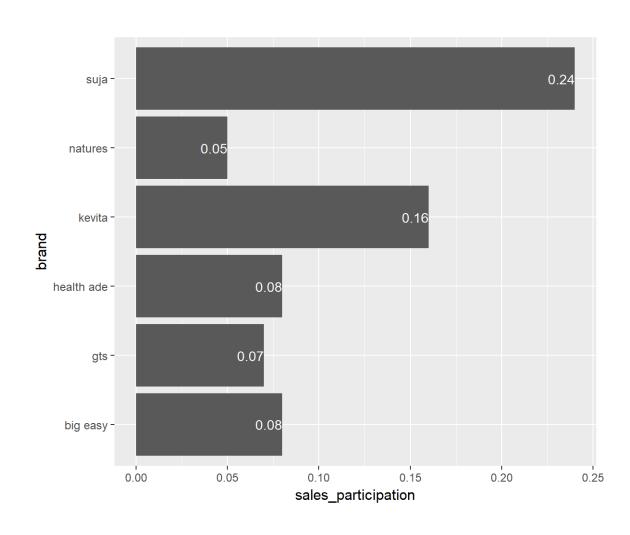


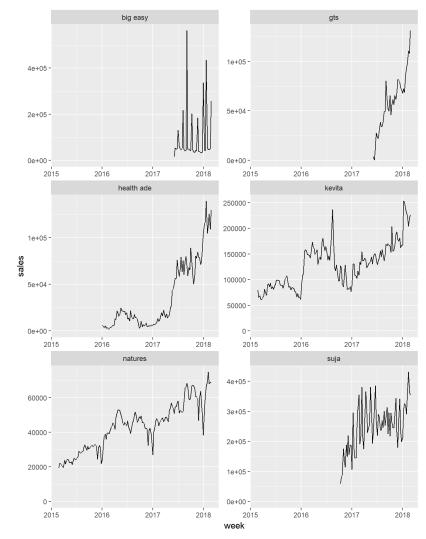
cbind(trend, change, accel)



Is this a one-off or an incipient trend?







Using NLP on sales data – descriptive labels





Identify

Attributes were identified by parsing the UPC text description of each product, e.g.

180 SNACKS ALMOND POP BLUEBERRS NUTRITIONAL SNACK BR RICE RP 1 OZ - 0180332000041



Identifiable Attributes

- brand is 180 Snacks
- product is a snack in the shape of bar
- contains rice, almondblueberries
- size is 1 oz

Aa

Text Normalization

In order to identify attributes, text was normalized to account for different spelling, stemming, etc. e.g.
BLUEBERRS, BLUEBERRY, BLUEBERRY, BLUEBERRIES.



Bigram Attributes

In order to identify bigram attributes/concepts, word correlations were computed, e.g., almond milk, non-dairy, meat substitute, gluten free.

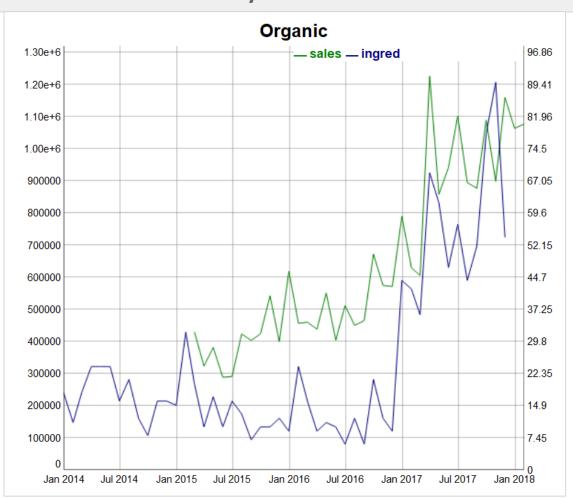


In order to identify cooccurring attributes word/ bi-gram correlations were computed, e.g., (chocolate cookies, ginger tea).

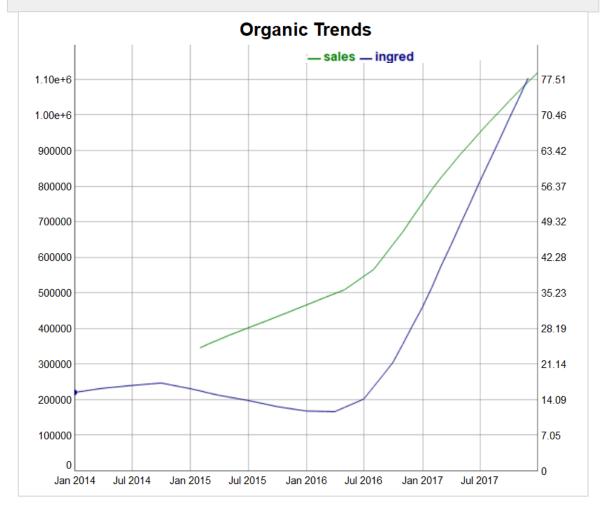
The motive (recognize **ingred**ients) predicts an acceleration in sales of organic foods with recognizable ingredients



Converseon SM trained by motive



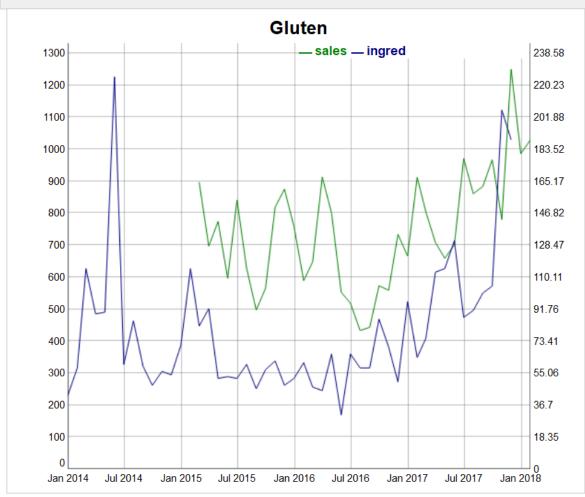
Smoothed time series



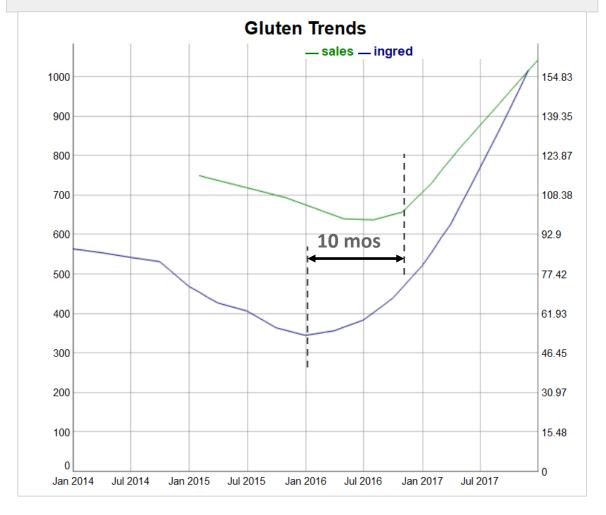
The motive (recognize **ingred**ients) predicts an acceleration in sales of gluten-free foods with recognizable ingredients



Converseon SM trained by motive



Smoothed time series



Designing a bigger experiment



What Did We Learn?



It takes a lot of unique posts to make this work. (>1MM)



The stronger the filter, the better the result.



Training the machine-learning classifier on motives DOES have strong predictive qualities.

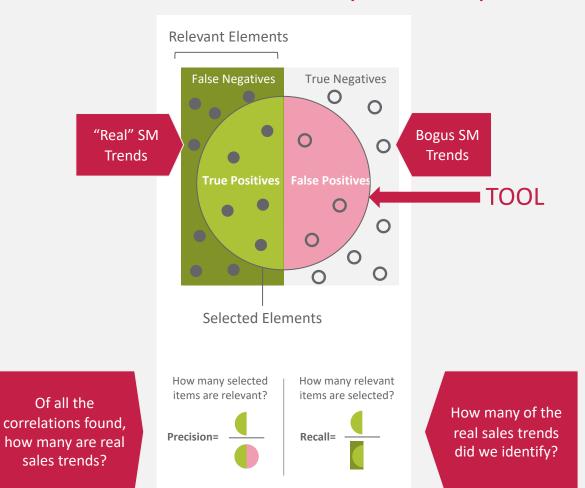


Can predict inflection in sales trends at least 90 days before they happen.



There is a feedback loop: in the beginning SM predicts sales but after a while the sales activity itself may also contribute to the SM trend.

A Better Test—currently Underway



© 2019 by in4mation insights, LLC Confidential

Key Takeaways



There is a **big role** for inclusion of SM time series as predictors in models:

- Marketing Mix/ Business Drivers
 - New Products

Modeling leads to a **forward-looking** rather than backward-looking use of SM data.

It takes a relatively high volume of posts, good cleaning procedures, and NLP expertise to make the time series useful.

A combination of survey data & behavioral data is better than either one alone.



Questions?

Mark Garratt
mgarratt@in4ins.com

Stuart Schwartz <u>sschwartz@in4ins.com</u>

www.in4ins.com

