The Next Generation of Social Intelligence
Implicit, explicit and predictive
Dirty Secret of Most Social Data

Current State:

- Imprecise – average sentiment accuracy is 60%
- Analyst bias
- “Rules-Based”
- Low recall (record level)

- No sample frame
- “One size fits all”
- “Same old metrics”
- High irrelevancy (often 70-75%)
- Don’t know who is speaking
- “Garbage in, garbage out”

“Data quality remains an issue. When asked about their satisfaction with general data quality, 74% of respondents reported positive results. But when we dug deeper and asked about the specifics of the data, many changed their tunes. In fact, the five responses showing the most dissatisfaction all centered on data: the ability to weed out spam; the accuracy of the tool’s automated sentiment analysis; influencer identification tools; multilingual and international capabilities; and the tool’s integration capabilities. These data challenges make a direct call to CI teams to get involved and bring their past data management experience to the table.

– Forrester Research
The Next Generation: Precise, Meaningful and Predictive

Explicit and Implicit
ConveyAPI: Leverages Deep/Machine Learning to Unlock Deeper and More Meaningful Explicit and Implicit Data from Social Conversation

Data approach as represented by Converseon’s ConveyAPI technology

Semi Supervision: Keeps “humans in the loop” for continuous training

Customizable: Trains to domain and brands (“small” may be good for selling smartphones, bad for hotel rooms)

Accurate: Close approximation of human performance at scale (humans that agree with each other) – generally 90-95%

Scalable: Now allows the accuracy of human coding at large scale and speed

Vertical and Brand/Domain Specific

Custom Classifiers: Enables unlimited number of custom classifiers (intent, purchase phase, etc.)

Vertical and brand specific

High Relevancy and Recall: Isolates key data sets rapidly and at most detailed level.
Three Levels of Intelligence

**Standard Classifiers**
- Sentiment (target level)
- Emotion
- Intensity
- Relevancy
- Confidence

Highly precise “out of box” Standard classifiers
Record, sentence and entity

**Domain/Brand Specific**
- Industry specific
- Brand Specific
- Function specific

Ability to rapidly choose and create classifiers based on specific industries, brands, needs.
Auto, pharma, CPG, Unileve etc.

**Custom Classifiers**
- Customer journey
- Intent
- Purchase stage, etc.

Ability to create nearly unlimited additional Classifiers to isolate and analyze and Address specific insight requirements.

Recent test of performance versus 10,000 human coded records found
A variance of less than 5%

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Relevancy Example

- Relevance feedback allows you to be in control
- The best boolean query achieved only 15% relevancy
- Machine learning trained custom classifier raised relevancy to 85% in less than an hour

Training: "spam"

Verify items to keep    Verify items to toss    Teach system

Teach system
These documents were difficult, please review them

- spam is like my personal heaven
- @sarahabalala @ShirlynHuang @peanutbutterxz hehei竖竖竖竖 can see! Someone spam photos like siao!!!
- Are you ready for the Canada’s Anti-Spam legislation? We are! Thanks for the Lunch & Learn @juliasmail! http://t.co/jgzb7NzXKb
- I will have eaten #spam for all three meals today. Wouldn’t have it any other way.
- just found a confirmation email in the spam folder. You should eat your own dog food. http://t.co/7mSlyl7Hfm
“New” metrics via custom classifiers unlock deeper insight, implicit meaning and “tune” to your category/brand
Emotion!
Converseon’s Social Intelligence Solutions Map
Emotions….and More

- Mines conversations from more than 200 million sources
- Cleans, filters and analyzes data across multiple dimensions, including sentiment, intensity, emotion, intent, purchase stage, and more.
- Provides near human level precision. Recent test of 10,000 records found only a 5% variance from human coded gold standard
- Technology can be used on top of most other social monitoring platforms
CarMax customers often write online that they trust the company’s used car appraisals and prices.

“I think people were afraid of a truck that new being sold; most people probably thought there was something wrong with it. I went back to the dealer I bought it from to see about a buy back. They made me a ridiculous offer [...] I then went to Carmax who made an offer about half way between NADA clean trade and full retail value. I accepted their offer and walked away with a check in my hand.”

Bimmerfest.com, 03-01-2012

- In limited instances, authors also express anger and distrust toward CarMax’s buy and sell rates.

**Bold typeface** added for emphasis.

Source: Converseon analysis of public online records, March 2012.
In addition to expressing how much they enjoy eating DiGiorno pizza, many associate it with after-work relaxation and express their eagerness to eat it.

Emotions Expressed in Messages about DiGiorno

• When customers express their **anticipation** for eating DiGiorno pizza, they sometimes associate it with watching TV or movies:

  “Off work...#RedBox and Digiorno pizza the rest of the night #ChillMode #BeGreat”
  Twitter.com, 03-03-2012

  “So I guess law & order svu and these digiorno pizza strips are gonna be the highlight of my night”
  Twitter.com, 03-03-2012

  “Looks like its gonna be a digiorno, 4 loko, and the wire night”
  Twitter.com, 03-04-2012

**Bold typeface** added for emphasis.
Source: Converseon analysis of public online records, April 2012.
Specific Emotions in the Purchase Process

Multiple Categories

- 11% Fear
- 42% Distraction
- 22% Apprehension
- 19% Painsiveness
- 14% Acceptance
- 14% Trust
- 54% Pensiveness
- 41% Serenity
- 42% Surprise
- 42% Interest
- 27% Sadness
- 22% Annoyance
- 19% Disgust
- 17% Anger
- 12% Anticipation
- 6% Joy

Smartphone Category

- 14% Fear
- 25% Distraction
- 41% Apprehension
- 35% Painsiveness
- 17% Acceptance
- 11% Trust
- 35% Pensiveness
- 17% Serenity
- 17% Surprise
- 11% Interest
- 11% Sadness
- 5% Annoyance
- 5% Disgust
- 5% Anger
- 5% Anticipation
- 5% Joy
Conversus Application Allows Users to Access ConveyAPI and Build Custom Classifiers

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**Dataset List**

<table>
<thead>
<tr>
<th>NAME</th>
<th>DESCRIPTION</th>
<th>Actions</th>
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<tbody>
<tr>
<td>Roku Returns</td>
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<td>![View Dataset] ![Train Model] ![Analyze] ![View Results] ![Delete]</td>
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<tr>
<td>Discovery: Shows related to Alaskan Bush People</td>
<td>For Sentiment Analysis Comparison of Alaskan Bush People</td>
<td>![View Dataset] ![Train Model] ![Analyze] ![View Results] ![Delete]</td>
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<td>Verizon Deal V2</td>
<td>updated data set</td>
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<tr>
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<td>Mentions of Verizon in relation to a business deal</td>
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**Active Training Models**

<table>
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<th>Actions</th>
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<tr>
<td>Roku Returns</td>
<td>![Continue Training] ![Delete]</td>
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<tr>
<td>Marriott Final Classifier</td>
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<tr>
<td>Alaskan Bush People</td>
<td>![Continue Training] ![Delete]</td>
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<td>![Continue Training] ![Delete]</td>
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<tr>
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<td>![Continue Training] ![Delete]</td>
</tr>
<tr>
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<td>That's AweSOME!Anybody that</td>
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<tr>
<td>there is a danger that Sanofi will</td>
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</tr>
<tr>
<td>They just talked twice this week</td>
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<tr>
<td>RT @staceyisimms @AmyDBMine I started on #A</td>
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<tr>
<td>But there's no print ads, no web</td>
<td>6</td>
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<tr>
<td>RT @Peakabull #IWishPeopleKn</td>
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<td>Really badly done and a totally u</td>
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<tr>
<td>@Drchik23 @BioKaiser Toujeo la</td>
<td>9</td>
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<td>Good find, where do you find th</td>
<td>10</td>
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<tr>
<td>RT @AmyDBMine I started on #A</td>
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<tr>
<td>Website Categories Why Afrezza</td>
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</table>
Multiple Peer Reviewed Studies Have Shown Predictive Capabilities to Convey Powered Data

Professor Wendy Moe and David Schweidel, conducted analysis of social conversation versus offline brand tracking using Converseon data.

New WOMM Media Mixed Modeling Study (utilizing Converseon data)

Conclusive proof that social media data predict sales...now what?

In: big data, branding, content marketing, facebook, listening, market research, social media

Tuesday, the results of a landmark study were made public proving that the quantity of social media conversations about a brand has a statistically significant relationship to changes in its sales.

“Researchers today announced the results of a landmark study that measured the impact of "consumer word of mouth" in six diverse categories, finding that online and offline consumer conversations and recommendations account for 13% of consumer sales, on average...About one-third of the sales impact is attributable to word of mouth acting as an "amplifier" to paid media, such as television, with consumers spreading advertised messages. The study was based on sophisticated econometric modeling of sales and marketing data.”
How can you access?

• If you have an application in need of social data, it is available through a REST API

• Converseon provides a full range of research and consulting products to clients looking for turnkey solutions

• If you have a basic listening tool and want to do additional processing on the data, a simple-to-use “Conversus” app is available (see booth for demo)

• Available via select partners (Brandwatch)

• If you want to integrate more deeply into other applications, such as brand tracking, our consulting and research group is available to assist