Concept-Level Sentiment Analysis

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Talk Outline

- Introduction
- Eras of the Web
- Evolution of NLP Research
- Background on Opinion Mining
- Concept-Level Sentiment Analysis
- Sentic Computing
- Challenges
- Conclusion
Web: Connecting People

The potential for knowledge sharing today is unmatched in history: never before have so many knowledgeable people been connected.

Leonardo’s discoveries and inventions in science, art, engineering, and aesthetics, were based only on his perception of the world.

The Web as a Lab

The Web today not only represents an unlimited data store but also a multi-disciplinary laboratory environment for world-scale experiments.

Information Overload

Between the dawn of the Internet and year 2003, there were five exabytes of information on the Web. Now, we create five exabytes every two days.

The Web is evolving towards a shared social experience, in which consumers will rely on their peers as they make online decisions and will shape future products.

Information today is extremely portable and processable. However, this collected intelligence is far from being addressed as collective intelligence.

Not So Structured

According to different evaluation schemes and reviewers, a very positive and a very negative review might both have the same star rating.

Sentiment analysis research evolved from heuristics to discourse structure, from coarse- to fine-grained analysis, from keyword- to concept-level mining.

A Possible Path to NLU

Natural language processing  Sentiment analysis  Natural language understanding
Evolution of NLP

NLP technologies evolved from the era of punch cards (7 minutes per sentence) to the era of Google and its like (less than a second per sentence)

In a Web where UGC has hit critical mass, NLP is becoming key for aggregating information although systems are still limited by what they can ‘see’

More Than We See

Language is somewhere in between perception and understanding – a translucent material, so that the world bears the tint and focus of what we express through it.

We can understand almost anything, but we can’t understand how we understand.

Albert Einstein

We understand human mental processes only slightly better than a fish understands swimming.

John McCarthy

How the mind works is still a mystery. We understand the hardware, but we don't have a clue about the operating system.

James Watson
AI Winters

The key failure of AI is the persistency in seeking the best way to solve a problem, which leads to the creation of expert (rather than intelligent) systems

“This past Saturday, I bought a Nokia phone and my girlfriend bought a Motorola phone. We called each other when we got home. The voice on my phone was not so clear, worse than my previous phone. The camera was good. My girlfriend was quite happy with her phone. I wanted a phone with good voice quality. So my purchase was a real disappointment. I returned the phone yesterday.”
Keyword Spotting

Although the most naïve approach, the accessibility and economy of keyword spotting make it one of the most popular. However, it only relies on surface features.

Lexical affinity assigns arbitrary words probable “affinity” to particular emotions – “accident” has a 75% probability of indicating a negative affect.

By feeding a ML algorithm a large training corpus, statistical methods not only learn the valence of affect words, but also that of other arbitrary keywords.

By relying on ontologies or semantic networks, concept-level approaches step away from blindly using affect keywords and word co-occurrence frequencies.

For auto-categorization:

cloud computing \neq cloud, computing

For opinion mining:

take pain killer \neq take, pain, killer
Conceptualization

Concepts are immaterial entities that only exist in the mind of the speaker. To be communicated, they must be represented in terms of some concrete artifact.

You can know the name of all the different kinds of ‘pipe’, but you know nothing about a pipe until you comprehend its purpose and method of usage.

In standard human-to-human communication, people usually rely on the presumption that facts or definitions are known and proceed to build upon it.

Common-Sense

People usually provide only useful information and take the rest for granted. The rest is common-sense: obvious things people know and usually leave unstated.

Why Common-Sense?

great phone: +
faulty device: -

long battery life: ?
long queue: ?
small battery: ?
small seat: ?
cold train: ?
cold beer: ?
Available KBs

Attempts to build common and common-sense knowledge bases are countless and include both hand-crafted resources and automatically-built KBs.

Acquiring Knowledge

The serious game engine for common-sense knowledge acquisition (SGECKA) aims to collect knowledge from game designers through the development of games.

POG-Based Acquisition

Game designers drag and drop objects from libraries into scenes. They specify a POG triple that describes how each object can be used.

Data Collection

POG data is encoded and collected in XML format. Interaction semantics between objects and characters are specified for each scene, together with affect information.

Affective Information

POG specifications not only allow game designers to define interaction semantics between objects, but also affective reactions of different characters.

Feeling and Thinking

The question is not whether intelligent machines can have emotions, but whether machines can be intelligent without any emotions.

To Feel or Not to Feel?

<table>
<thead>
<tr>
<th>Adaptive behavior</th>
<th>Emotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>protection</td>
<td>fear / terror</td>
</tr>
<tr>
<td>incorporation</td>
<td>acceptance / trust</td>
</tr>
<tr>
<td>destruction</td>
<td>anger / rage</td>
</tr>
<tr>
<td>reproduction</td>
<td>joy / ecstasy</td>
</tr>
<tr>
<td>reintegration</td>
<td>sadness / grief</td>
</tr>
<tr>
<td>orientation</td>
<td>surprise / astonishment</td>
</tr>
<tr>
<td>rejection</td>
<td>disgust / loathing</td>
</tr>
<tr>
<td>exploration</td>
<td>expectancy / anticipation</td>
</tr>
</tbody>
</table>

Aspect-Based Analysis

“I love the new iPhone5 screen! the battery life is so short though”

document/paragraph-level approach: neutral polarity
clause/concept-level approach: screen+, battery-
Deconstructing Aspects

![Bar chart showing positive and negative aspects of a cellular phone](chart.png)
Aspect Comparison

positive

PHONE

Picture

Battery

Camera

Size

Weight

negative

Cellular Phone 1

Cellular Phone 2
Sentic Computing

AffectNet Graph

# AffectNet Matrix

<table>
<thead>
<tr>
<th>Objects</th>
<th>Properties (with simplified form)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>contains knowledge</td>
</tr>
<tr>
<td></td>
<td>contain knowledge</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>book</td>
<td>...</td>
</tr>
<tr>
<td>ice</td>
<td>...</td>
</tr>
<tr>
<td>newspaper</td>
<td>...</td>
</tr>
<tr>
<td>magazine</td>
<td>...</td>
</tr>
</tbody>
</table>
Hourglass Model

The mind is made up of different independent resources. Turning some sets of resources on while turning others off result in different emotional states.

Hourglass Model

<table>
<thead>
<tr>
<th>Interval</th>
<th>Pleasantness</th>
<th>Attention</th>
<th>Sensitivity</th>
<th>Aptitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>[G(1), G(2/3)]</td>
<td>ecstasy</td>
<td>vigilance</td>
<td>rage</td>
<td>admiration</td>
</tr>
<tr>
<td>[G(2/3), G(1/3)]</td>
<td>joy</td>
<td>anticipation</td>
<td>anger</td>
<td>trust</td>
</tr>
<tr>
<td>[G(1/3), G(0)]</td>
<td>serenity</td>
<td>interest</td>
<td>annoyance</td>
<td>acceptance</td>
</tr>
<tr>
<td>(G(0), −G(1/3)]</td>
<td>pensiveness</td>
<td>distraction</td>
<td>apprehension</td>
<td>boredom</td>
</tr>
<tr>
<td>(−G(1/3), −G(2/3)]</td>
<td>sadness</td>
<td>surprise</td>
<td>fear</td>
<td>disgust</td>
</tr>
<tr>
<td>(−G(2/3), −G(1)]</td>
<td>grief</td>
<td>amazement</td>
<td>terror</td>
<td>loathing</td>
</tr>
</tbody>
</table>

Hourglass Model

Sentic Medoids

In order to cluster AffectiveSpace, a k-medoids approach can be adopted in place of k-means, in which it is more robust to noise and outliers.

The integration of a bio-inspired paradigm with principal component analysis allows for better comprehension of non-linearities in AffectiveSpace

ELM-Based Reasoning

The high generalization performance, low computational complexity, and fast learning speed of ELM can be exploited to parallelize the process.

Hierarchical Scheme

An SVM-based classifier first filters out unemotional concepts and an ELM-based predictor then classifies emotional concepts in terms of four dimensions.

Parallel Framework

Available Tools

- AffectNet
- AffectiveSpace
- IsaCore beta
- Sentic Parser
- SenticNet-1.0
- SenticNet-2.0
- SenticNet-3.0
- Sentic API
SenticNet 3

http://sentic.net/api

<table>
<thead>
<tr>
<th></th>
<th>SenticNet</th>
<th>Stanford</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I love the movie which you hate</td>
<td>+</td>
<td>−</td>
</tr>
<tr>
<td>2. The phone is very big to hold</td>
<td>−</td>
<td>+</td>
</tr>
<tr>
<td>3. You are making fun of me</td>
<td>−</td>
<td>+</td>
</tr>
<tr>
<td>4. You are not so beautiful</td>
<td>−</td>
<td>+</td>
</tr>
<tr>
<td>5. The tooth hit the pavement and broke</td>
<td>−</td>
<td>+</td>
</tr>
<tr>
<td>6. I am one of the least happy person in the world</td>
<td>−</td>
<td>0</td>
</tr>
<tr>
<td>7. I love Starbucks but they just lost a customer</td>
<td>−</td>
<td>0</td>
</tr>
<tr>
<td>8. I doubt that he is good</td>
<td>−</td>
<td>+</td>
</tr>
<tr>
<td>9. Receiving payments has never been this simple &amp; fast</td>
<td>+</td>
<td>−</td>
</tr>
<tr>
<td>10. I am eagerly looking forward to Dr. Wu's future work</td>
<td>+</td>
<td>−</td>
</tr>
</tbody>
</table>

http://sentic.net/demo
Sentic Patterns

The car is nice but expensive
The car is expensive but nice

<table>
<thead>
<tr>
<th>Left conjunct</th>
<th>Right conjunct</th>
<th>Total sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neg.</td>
<td>Pos.</td>
<td>Pos.</td>
</tr>
<tr>
<td>Pos.</td>
<td>undefined</td>
<td>Neg.</td>
</tr>
<tr>
<td>Neg.</td>
<td>undefined</td>
<td>Pos.</td>
</tr>
<tr>
<td>undefined</td>
<td>Pos.</td>
<td>Pos.</td>
</tr>
<tr>
<td>undefined</td>
<td>Neg.</td>
<td>Neg.</td>
</tr>
<tr>
<td>Pos.</td>
<td>Pos.</td>
<td>Pos.</td>
</tr>
</tbody>
</table>

Sentic Patterns

<table>
<thead>
<tr>
<th>Matrix predicate (h)</th>
<th>Dependent predicate (d)</th>
<th>Dep. comp. (x)</th>
<th>Overall polarity</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pos</td>
<td>Pos</td>
<td>Pos</td>
<td>Pos</td>
<td>a</td>
</tr>
<tr>
<td>Pos</td>
<td>Pos</td>
<td>Neg</td>
<td>Neg</td>
<td>b</td>
</tr>
<tr>
<td>Pos</td>
<td>Neg</td>
<td>Pos</td>
<td>Neg</td>
<td>c</td>
</tr>
<tr>
<td>Pos</td>
<td>Neg</td>
<td>Neg</td>
<td>Pos</td>
<td>d</td>
</tr>
<tr>
<td>Neg</td>
<td>Pos</td>
<td>Pos</td>
<td>Neg</td>
<td>e</td>
</tr>
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<td>Neg</td>
<td>Pos</td>
<td>Neg</td>
<td>Neg</td>
<td>f</td>
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<td>g</td>
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<td>Neg</td>
<td>Neg</td>
<td>Neg</td>
<td>Neg</td>
<td>h</td>
</tr>
<tr>
<td>Pos</td>
<td>Neutral</td>
<td>Pos</td>
<td>Pos</td>
<td>i</td>
</tr>
<tr>
<td>Pos</td>
<td>Neutral</td>
<td>Neg</td>
<td>Neg</td>
<td>j</td>
</tr>
<tr>
<td>Neg</td>
<td>Neutral</td>
<td>Pos</td>
<td>Neg</td>
<td>k</td>
</tr>
<tr>
<td>Neg</td>
<td>Neutral</td>
<td>Neg</td>
<td>Neg</td>
<td>l</td>
</tr>
</tbody>
</table>

Sentic Patterns

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentic Patterns</td>
<td>84.15%</td>
</tr>
<tr>
<td>Machine Learning</td>
<td>67.35%</td>
</tr>
<tr>
<td>Ensemble Classification</td>
<td>86.21%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Socher et al. 2012 [59]</td>
<td>80.00%</td>
</tr>
<tr>
<td>Socher et al. 2013 [57]</td>
<td>85.40%</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>86.21%</td>
</tr>
</tbody>
</table>

the camera has [long focus time]
the camera takes a [long time] to [focus]
the [focusing] of the camera takes [long time]
the [focus time] of the camera is very [long]

long_focus_time
Semantic Parsing

The semantic parser deconstructs text into concepts through a graph-based concept extraction algorithm and a MDS-based similarity detection technique.

I am going to the market to buy vegetables and some fruits
Candidate Spotting

After chunking and stemming, each potential noun chunk is paired with stemmed verbs in order to detect verb + object multi-word expressions.
Candidate Selection

Matches between the object concepts and the normalized verb chunks are searched in a parse graph that maps all the multi-word expressions of the knowledge base.
Concept Extraction

Candidate spotting
- buy
- buy vegetable
- buy fruit
- vegetable and fruit
- buy vegetable and fruit

Candidate selection
1. buy vegetable and fruit
2. buy vegetable; buy fruit
3. buy; vegetable and fruit
4. buy; vegetable; fruit
Similarity Detection

Because of the richness of natural language, a technique for spotting similar meanings in multi-word expressions is used to detect concepts in their various forms.
Semantic Similarity
Evaluation

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Syntactic similarity</td>
<td>65.6%</td>
<td>67.3%</td>
<td>66.4%</td>
</tr>
<tr>
<td>Semantic similarity</td>
<td>77.2%</td>
<td>70.8%</td>
<td>73.9%</td>
</tr>
<tr>
<td>Ensemble similarity</td>
<td>85.4%</td>
<td>74.0%</td>
<td>79.3%</td>
</tr>
</tbody>
</table>

Table 1: Performance of different similarity detection algorithms over 200 concept pairs

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Concept extraction accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naïve parser</td>
<td>65.8%</td>
</tr>
<tr>
<td>POS-based bigram</td>
<td>79.1%</td>
</tr>
<tr>
<td>POS-based + similarity</td>
<td>87.6%</td>
</tr>
</tbody>
</table>

Table 2: Performance of different parsing algorithms over 50 natural language sentences
Sentic Panalogy

Several analogous representations of the same problem should be kept in parallel so that the system can switch tracks when problem-solving stalls

Sentic Activation

AI and Semantic Web

Sentic Album

Cyber Issue Detection

Tweets about the price of rice (per month)

Food Price Inflation
In spite of demonstrated benefits, routine HRQoL assessments remain rare as few patients are willing to spend the time needed to fill-in long questionnaires daily.

Sentic PROMs allow patients to evaluate their health and healthcare experience to accordingly aggregate text and visual data in a semi-structured way.

Sentic Blending

Sentic Blending

Expression Analysis

<table>
<thead>
<tr>
<th>classified as</th>
<th>disgust</th>
<th>joy</th>
<th>anger</th>
<th>fear</th>
<th>sadness</th>
<th>neutral</th>
<th>surprise</th>
</tr>
</thead>
<tbody>
<tr>
<td>disgust</td>
<td>84.24%</td>
<td>0%</td>
<td>2.34%</td>
<td>13.42%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>joy</td>
<td>4.77%</td>
<td>95.23%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>anger</td>
<td>15.49%</td>
<td>0%</td>
<td>77.78%</td>
<td>0%</td>
<td>3.75%</td>
<td>2.98%</td>
<td>0%</td>
</tr>
<tr>
<td>fear</td>
<td>1.12%</td>
<td>0%</td>
<td>0%</td>
<td>92.59%</td>
<td>2.06%</td>
<td>0%</td>
<td>4.23%</td>
</tr>
<tr>
<td>sadness</td>
<td>0.32%</td>
<td>0.20%</td>
<td>1.68%</td>
<td>0%</td>
<td>66.67%</td>
<td>31.13%</td>
<td>0%</td>
</tr>
<tr>
<td>neutral</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0.88%</td>
<td>1.12%</td>
<td>98.00%</td>
<td>0%</td>
</tr>
<tr>
<td>surprise</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>6.86%</td>
<td>0%</td>
<td>2.03%</td>
<td>91.11%</td>
</tr>
</tbody>
</table>
Open Challenges

1. Deconstructing text into concepts
2. Building AffectiveSpace & IsaCore
3. Clustering AffectiveSpace & IsaCore
4. Aggregating SenticNet data
Real Challenges

**Ironic Detection**

*I love iphone5 because the battery lasts so little that after half a day I am free from calls and emails*

**Theory of Mind**

*It is good that you killed the professor*

**Intent Mining**

*big/small room, warm/cold water*

**User Profiling**

*hard/soft bed, small/big phone, cheap/expensive bag*
Sentiment analysis is distinguishing itself as a separate field and is moving toward content-, concept-, and context-based natural language analysis.

3Q Sentiment Analysis

To achieve real machine intelligence, a computer needs to be able to not only perform reasoning (IQ), but also interpret emotions (EQ) and cultural nuances (CQ).

Machines That Think

The world has changed less since Jesus Christ than it has in the last century. In another century’s time, machines might be able to think as humans do.

Reverse Turing Test

Sentic computing does not aim to replace humans but, rather, to exploit differences in human-computer abilities and costs so as to achieve symbiotic HMI.
Announcements

UAI 2014 Workshop on Multidisciplinary Approaches to Big Social Data Analysis
http://sentic.net/mabsda

IEEE CIM Special Issue on New Trends of Learning in Computational Intelligence
http://sentic.net/learning

ICDM 2014 Workshop on Sentiment Elicitation from Natural Text for Information Retrieval and Extraction
http://sentic.net/sentire