Modeling emotional agents

Data, Interaction, Simulation

Frank Schweitzer

In collaboration with: D. García, A. Garas

Chair of Systems Design at ETH Zurich

- Main Research Areas
  - Economic Networks & Social Organizations
    - e.g. ownership networks, R&D networks, financial networks, ...
    - e.g. online communities, OSS projects, animal societies, ...

- Methodological Approach: Data Driven Modeling
  - economic databases: ORBIS, Bloomberg, patent databases
  - online data: user interaction, communication records, blogs

Motivation: What drives our behavior?

- rational agent: calculates utility
  - perfect knowledge?, how to quantify utility?
- social “ingredients”: for the good and the bad
  - individual: (dis)trust, empathy, aggression, emotions
  - collective: herding, group feeling, collective emotions
What are emotions?

- reflex reactions
- neural responses
- psychological states
- cognitive processes
- lifetime behavior

- physiological level
- core affect
- mood
- personality traits

- short-lived psychological states that consume individual’s energy and strongly bias behavior (for example expression)

Russell’s dimensional model

- Valence
  - Pleasure associated with the emotion.
- Arousal
  - Degree of activity induced by the emotion.

A big difference: Happiness network

- time aggregated clusters of happy individuals based on two snapshots within 20 years
- correlations don’t show collective emotional states, but global lifetime happiness
- hypothesis of happiness contagion is not verified

Emotional Posts in Fora

- Example of a negative (left) and a positive (right) post

- Threads analysed in two different ways
  - text-based emotion classification ⇒ sentiment analysis
  - measuring physiological responses of users

Credit: Calder et al. 2001

Russell’s dimensional model

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Fowler, Christakis, 2008

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Text-based emotion classification

- **Annotated lexicon**
  - positive and negative score for predefined words

- **Supervised learning**
  - training set: annotated text, output: subjectivity, polarity

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Survey based lexicon (ANEW)

- dataset of word emotionality ⇒ valence, arousal, dominance
- improvement: stemming of words ⇒ better accuracy, recall

** Lyrics for Michael Jackson’s Billie Jean **

*She was more like a beauty queen from a movie scene, And mother always told me, be careful who you love, And be careful of what you do, ’Cause the lie becomes the truth. Billie Jean is not my lover, She’s just a girl who claims that I am the one. *

<table>
<thead>
<tr>
<th>ANEW words</th>
<th>$v_k$</th>
<th>$f_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. love</td>
<td>8.72</td>
<td>1</td>
</tr>
<tr>
<td>2. mother</td>
<td>8.39</td>
<td>1</td>
</tr>
<tr>
<td>3. baby</td>
<td>8.22</td>
<td>3</td>
</tr>
<tr>
<td>4. beauty</td>
<td>7.62</td>
<td>1</td>
</tr>
<tr>
<td>5. truth</td>
<td>7.80</td>
<td>1</td>
</tr>
<tr>
<td>6. people</td>
<td>7.33</td>
<td>2</td>
</tr>
<tr>
<td>7. strong</td>
<td>7.11</td>
<td>1</td>
</tr>
<tr>
<td>8. young</td>
<td>6.89</td>
<td>2</td>
</tr>
<tr>
<td>9. girl</td>
<td>6.67</td>
<td>4</td>
</tr>
<tr>
<td>10. movie</td>
<td>6.66</td>
<td>4</td>
</tr>
<tr>
<td>11. perfume</td>
<td>6.76</td>
<td>1</td>
</tr>
<tr>
<td>12. queen</td>
<td>6.44</td>
<td>1</td>
</tr>
<tr>
<td>13. name</td>
<td>5.55</td>
<td>1</td>
</tr>
<tr>
<td>14. lie</td>
<td>2.70</td>
<td>1</td>
</tr>
</tbody>
</table>

** britney = 7.1, thriller = 6.3, Michael Jackson = 6.4**

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What is problematic here?

1. **Performance of algorithm**
   - context sensitivity: emotions only in words?
   - subtle meaning: “That’s not bad ... – how good is it?”

2. **Quality of lexicon**
   - human ratings: English (1034 w), German (2902 w), Spanish (1034 w)
   - validation against independent measurements (physiology)?

3. **Inherent properties of used language**
   - how emotional is “neutral” communication?
   - what is the reference point for “normal” valence? (zero???)

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How emotional is used language?

- positive words are more frequently used (Pollyanna hypothesis)
  - lexta: no bias, full range of valence ⇒ neutral (mean, median)
  - frequency of word usage from Google N-gram dataset (10^{12} token)
  - example: $v = 0.715$, “party” (144.7 × 10^{-6}) “sunrise” (6.8 × 10^{-6})

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*P. S. Dodds, C. M. Danforth, 2010*

*D. Garcia, A. Garas, F.S., EPJ Data Science 1:3 (2012)*
Measuring physiological response

- physiological response to classified pictures and fora
- monitoring heart rate, skin conductance, frowning and smiling
- already known to correlate with valence and arousal

Outline

1 Motivation: Why Collective Emotions
2 Quantifying Emotions
3 Modeling Cyber Emotions
4 Applications
5 Outlook

Modeling framework: Brownian agents

- emotional state of agent $i$: $E_i(t) = \{v_i(t), a_i(t)\}$
- without external/internal excitation: $v_i(t) \rightarrow 0, a_i(t) \rightarrow 0$
  - relaxation into a ‘silent’ mode
- dynamics of the Brownian agent:
  \[
  \dot{v}_i = -\gamma_i v_i(t) + F_v + A_{vi} \xi_v(t) \\
  \dot{a}_i = -\gamma_i a_i(t) + F_a + A_{ai} \xi_a(t)
  \]
  - $\gamma_i, \gamma_i$: decay on valence and arousal
  - $F_v, F_a$: reflect specific influences

Modeling framework: Schema

- agents described by arousal $a$, valence $v$, expression $s$
- arousal causes expression wrt on valence
- emotional information stored in field $h$

\[ \dot{h}_\pm = -\gamma h_\pm(t) + sn_\pm(t) + l_\pm(t) \]

- valence and arousal are affected by the field

Valence and Arousal

- valence: nonlinear influence of information
  \[ F_v[h_\pm(t), v_i(t)] = h_\pm(t) \sum_{k=0}^{n} b_k v^k(t) \]
- arousal: subthreshold dynamics: nonlinear response
  \[ F_a \propto (h_+(t) + h_-(t)) \sum_{k=0}^{n} d_k a^k(t) \]
  - $a_i(t) > T_i$: agent takes action
  - expresses emotions in blogs, fora, reviews, ... \[ s_i(t + \Delta t) = f[v_i(t)] \Theta[a_i(t) - \Xi_i] \]
  - after expressing emotion, arousal is set back to zero
  \[ \dot{a}_i = \dot{a_i}(t) \Theta[\Xi_i - a_i(t)] - a_i(t) \Theta[a_i(t) - \Xi_i] \]

Valence dynamics

- Cubic dependence on the valence
  \[ \dot{v} = -\gamma v(t) + h_\pm(t) \left\{ b_0 + b_1 v(t) + b_2 v^2(t) + b_3 v^3(t) \right\} \]
  - allow for ‘silent’ mode: $v(t) \rightarrow 0$: $b_0 = 0$
  - positive and negative valences ‘equal’: $b_2 = 0$
  - collective emotions emerge if $b_1 \cdot h_\pm > \gamma v$

Valence distribution

- $p_s(v)$ under low $h$
- $p_s(v)$ under high $h$

- polarization of emotions emerges under high information exchange
- agreement of analytical results with simulations
Arousal dynamics

- quadratic dependence on the arousal
  \[ \dot{a} = -\gamma a(t) + h(t) \{ d_0 + d_1 a(t) + d_2 a^2(t) \} \]
- response to total information \( h(t) = h_+(t) + h_-(t) \)
- initial bias to positive arousal \( d_0 > 0 \)
- if \( d_2 \neq 0 \), two possible solutions
- two cases:
  1. \( d_2 < 0 \) lower solution unstable, higher stable \( \Rightarrow \) one CE
  2. \( d_2 > 0 \) lower solution stable, higher unstable \( \Rightarrow \) fluctuating CEs

Collective emotions oscillate

- valence polarizes with activity fluctuations
- agent trajectories show change in emotions

Collective arousal
\[ \Xi_i \sim U(\Xi_{\min}, \Xi_{\max}) \]

- amount of agents expressing emotions fluctuates
- appearance and fading of collective emotions can be observed

A big difference: Expression patterns

- U.S. daily mood changes inferred from Twitter
- no self-organized collective emotion, but daily/weekly effects
- possible origin: tweeds ‘good morning’, ‘good night’ dominate pattern

*http://www.ccs.neu.edu/home/amilove/twittermood/*
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Let’s start an emotional discussion ...

January 2009: Emotional discussion of more than 5,000 Facebook users to make Zurich the Swiss capital, instead of the much smaller Berne (‘What the hell is Berne?’). This raised an anti-campaign of another 1,500 Facebook users to keep Berne as the capital.

User temporal activity in IRC channels

- B) Power-law distribution of user delay: individual time dynamics are independent of conversation
- C) Distribution of inter-event time in each channel: channels have a natural time delay

Dialog systems can sample believable individual behavior from B and keep conversations natural if delays follow C

A) Most individual users are persistent with respect to emotions
- Hurst exponent $H$ measures deviation from random behavior ($H = 0.5$)

B) Conversations are persistent (social norms)
An agent-based model for chatroom users

\[ N = 10^4, \ V_\tau = -0.15, \ V_s = 0.05, \ \gamma_h = 0.2, \ A_v = 0.2, \ b = 0.01, \ c = 0.05, \ \gamma_v = 0.9 \]

Distribution of \( H \) (B) and rescaled distribution of inter-message time \( C \) similar to real data.

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**Emotional influence on the internet: Reviews**

- **rating vs. expressed emotion:** any difference?
  - high ratings do not correlate with positive emotions
  - emotional charge as additional information

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**How do customers really feel?**

**How do consumers really decide?**

- **often wrong predictions** in market research
- **social effects (herding, emotions)** commonly neglected

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**Sentiment Analysis Gives Companies Insight Into Consumer Opinion**

Kia, Best Buy, and Viacom are using new tools to mine comments on the Web to see what consumers really think of their brands.
Hot selling vs slow moving products: Emotions

Weekly statistics (ratings: blue, positive: green, negative: blue)

Distribution of emotional scores

(left) “Harry Potter and the Deathly Hallows”, (right) “Twilight: New Moon”

An agent-based model for emotions in reviews

CE Project: Monitoring, Mitigating

virtual humans
- emotional interaction beyond textual expression
- users realize “impact” of their text

visualization of collective emotions
- monitoring/prediction of emotional status of communities
- when (and where) are issues heating up?

emotional chatbots
- mitigate emotional problems, online conflicts, encourage cooperation, interaction ⇒ Artificial emotional intelligence
- The ultimate Touring Test

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Computational Social SCIENCE

**Engineering: “How?”**
- data analysis $\Rightarrow$ detect **statistical regularities**
- identify control parameters $\Rightarrow$ regulate
- prediction, control, efficient algorithms, optimization, ...

**Science: “Why?”**
- What does it mean to be human in an online world?
- theories of social influence, interaction, hypotheses
- building formal models of social behavior

**Questions to answer:**
- Do we understand the **generative** mechanisms?
- How does individual behavior result in collective behavior?
- **Mechanism design** on the individual level vs control theory

**Conclusions**
- emotions
  - differ from opinions(!), quantified by valence, arousal
  - collective emotions important in decision processes; overcome dilemma

- **emperics on emotions/cyber emotions**
  - sentiment mining in text, plus physiological responses
  - vast datasets to analyse: Myspace, IRC, Amazon reviews, Twitter ...

- **agent based model of collective emotions**
  - considers psychological variables (arousal, valence)
  - provides testable hypotheses on agent’s response
  - predicts distribution of valence $\Rightarrow$ data comparison
  - framework applicable to IRC chats, product reviews, ...

- **applications**
  - understand viral marketing based on emotions
  - impact on productivity: OSS
  - developing bots to enhance user interaction