The next level of modeling social interaction
How to detect, quantify and utilize emotional influence

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Outline

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

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

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: Why 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.

*(Credit: Calder et al. 2001)*

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

*(Fowler, Christakis, 2008)*

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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
Text-based emotion classification

- **Annotated lexicon**
  - positive and negative score for predefined words
- **Supervised learning**
  - training set: annotated text, output: subjectivity, polarity

![Diagram](image)

Survey based lexicon (ANEW)

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

![Graph](image)

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???)

How emotional is used language?

- positive words are more frequently used (Pollyanna hypothesis)
  - lexica: 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 \cdot 10^{-6}) “sunrise” (6.8 \cdot 10^{-6})

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

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

\[ E_i(t) = \{ v_i(t), a_i(t) \} \]

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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:
  \[ \begin{align*}
  \dot{v}_i &= -\gamma_{vi} v_i(t) + F_v + A_{vi} \xi_v(t) \\
  \dot{a}_i &= -\gamma_{ai} a_i(t) + F_a + A_{ai} \xi_a(t)
  \end{align*} \]
- \( \gamma_{vi}, \gamma_{ai} \): 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 $h$
- valence and arousal are affected by the field

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

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: $v(t) \to 0$: $b_0 = 0$
- positive and negative valences ‘equal’: $b_2 = 0$
- collective emotions emerge if $b_1 \cdot h_{\pm} > \gamma v$
  \[\Rightarrow \text{regime with high emotional information (!)}\]

Valence and Arousal

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

Valence distribution

\[
\begin{align*}
p_s(v) \text{ under low } h \\
p_s(v) \text{ under high } h
\end{align*}
\]
Arousal dynamics

- quadratic dependence on the arousal
  \[ \dot{a} = -\gamma_1a(t) + h(t)\{d_0 + d_1a(t) + d_2a^2(t)\} \]
- 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
  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 \( \xi_i \sim U(\xi_{\text{min}}, \xi_{\text{max}}) \)

- 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

\[ \text{http://www.ccs.neu.edu/home/amislove/twittermood/} \]
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Let's start an emotional discussion ...

Zürich als Hauptstadt?

ZURICH. "Was zum Teufel ist Bern? Ich bin mir sicher, dass man das Bundeshaus auch in Zürich aufstellen könnte. Yes, we can!" Mit solchen Parolen fordern bereits über 5000 Facebook-Mitglieder die Verlegung der Schweizer Hauptstadt nach Zürich. Mehrere Gruppen haben zum Ziel, über 100000 Einträge für eine Petition zu sammeln. Schließlich sei Zürich als Verkehrsknotenpunkt und internationaler Finanzplatz die einzige "Global City" der Schweiz. Zudem sei die Limmatstadt zum siebten Mal in Folge als Stadt mit der weltweit höchsten Lebensqualität ausgezeichnet worden. Die Berner wehren sich mit Händen und Füßen gegen die Bewegung: 1500 Mitglieder zählt die Gruppe "Anti-Petition, Bern bleibt Bundeshauptstadt". Berner Stagi Alexander Tschaüppin bleibt gelassen: "Schön, dass uns die Zürcher derart beneiden."

† 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


Emotional persistence of user behavior

- A) Most individual users are persistent wrt 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

\[ N = 10^4, V_c = -0.15, V_v = 0.05, \gamma_c = 0.2, A_v = 0.2, b = 0.01, c = 0.05, \gamma_h = 0.9 \]

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


How do customers really feel?

Most Loved – And Hated – Tech Companies

<table>
<thead>
<tr>
<th>Love</th>
<th>Like</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Google</strong></td>
<td>Apple</td>
</tr>
<tr>
<td>Intel</td>
<td>Microsoft</td>
</tr>
<tr>
<td>IBM</td>
<td>Facebook</td>
</tr>
<tr>
<td>Dell</td>
<td>Oracle</td>
</tr>
</tbody>
</table>

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.

How do consumers really decide?

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

Harry Potter

Rejected by 12 publishers. More than 400 million sales.

Carly Hennessy

2.2 Million dollars invested. Sold 378 copies in the first three months.

Manos: the hands of fate (1966)

Worst movie ever (IMDB.com). DVD sales boost, sequel in production.
### Emotional Influence Applications

#### Hot selling vs slow moving products: Emotions

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

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

**Distribution of emotional scores**

- (left) “Harry Potter and the Deathly Hallows”, (right) “Marley and Me”


#### An agent-based model for emotions in reviews

**Distribution of emotional scores** “Harry Potter” (blue), simulations (red)


### Project: Productivity in OSS

**SNF project:** Impact of social interactions on software evolution

- **Impact on emergence of collaboration**
  - Why do people contribute to OSS at all?
  - Emotions solve cooperation paradox ⇒ explain responsibility

- **Impact on project success/failure**
  - Role of emotional feedback of users and empathy of developers
  - Emotions as building blocks of self-organized, non-profit community

Example: OSS Forum fights
Open Source Software fora show bursts of negative conversations between users and developers:

- **OSS project hampered by CE**
- **Effect:** fork of Pidgin into FunPidgin

EU Project on Cyber Emotions (CE) [http://www.cyberemotions.eu/]
To understand the role of collective emotions in creating, forming and breaking-up ICT mediated communities as a spontaneous emergent behaviour occurring in complex techno-social networks

- Funded by 7th Framework Programme (start 02/2009)
- Collaboration of 8 European universities for 4 years

**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

**Conclusions**

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

- **empirics 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 ⇒ 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
New Journal: EPJ Data Science

Aims & scope

EPJ Data Science offers a platform to address the challenges of bringing together academic disciplines concerned with the same challenges:

- How to extract meaningful data from complex systems
- How to analyze data in a way that allows new insights
- How to integrate data from different sources

EPJ Data Science is currently addressing the establishment of data-driven sciences as a complementary approach to the traditional hypothesis-driven method. The (new) data-driven and predictive way of science makes complex systems sciences an emerging field. The aim is to transform the natural sciences and to bring the same changes to the economic and social sciences, as in the biological sciences, - without breakdown.

Aalto Complexity Networks Factory
Sannäs, FI
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