Collective Emotions on the Internet
How to quantify and model 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
What are emotions?
- reflex reactions
- neural responses
- psychological states
- cognitive processes
- lifetime behavior

- physiological level
- core affect
- mood
- personality traits

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

- text-based emotion classification $\Rightarrow$ sentiment analysis
- measuring physiological responses of users

Citation:
- Fowler, Christakis, 2008
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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<table>
<thead>
<tr>
<th>input</th>
<th>text</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>neutral</td>
</tr>
<tr>
<td>C2</td>
<td>positive</td>
</tr>
<tr>
<td></td>
<td>negative</td>
</tr>
</tbody>
</table>
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**Survey based lexicon** (ANEW)

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

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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.

ANEW words

| k-1, love  | 8.72 |
| 2, mother  | 8.39 |
| 3, baby    | 8.22 |
| 4, beauty  | 7.62 |
| 5, truth   | 7.00 |
| 6, people  | 7.00 |
| 7, strong  | 7.00 |
| 8, young   | 6.90 |
| 9, girl    | 6.87 |
| 10, move   | 6.86 |
| 11, perfume| 6.76 |
| 12, queen  | 6.44 |
| 13, name   | 5.35 |
| 14, lie    | 2.79 |

\[ \sum v_k f_k \]
\[ \sum f_k \]

\[ v_{Billie \ Jean} = 7.1 \]
\[ v_{Michael \ Jackson} = 6.4 \]
\[ v_{Pollyanna} = 6.3 \]
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*P. S. Dodds, C. M. Danforth, 2010

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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)
  - lexic: 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})

Measuring physiological response

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

†IAPS - International affective picture system

The Zygomaticus peak

\[ z(t) = \begin{cases} z_0 e^{(\beta_1(x - \Theta))} & x \leq \Theta, \\ z_0 e^{(\beta_2(x - \Theta))} & x > \Theta. \end{cases} \]

- uniform distribution of peak time \( \Theta \)
- Yet to understand relation between valence and parameters of fit

- tools to estimate valence from physiological data
- training from valence values of IAPS emotional picture system.

Heart rate and skin conductance

- 1270 variables in SSPS data
- Baseline extraction, rescaling \( \Rightarrow \) time series analysis
Modeling framework: Brownian agents

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


Valence and Arousal

- \textbf{valence:} nonlinear influence of information
  \[
  \mathcal{F}_v[h_\pm(t), v_i(t)] = h_\pm(t) \sum_{k=0}^{n} b_k v^k(t)
  \]
- \textbf{arousal:} subthreshold dynamics: nonlinear response
  \[
  \mathcal{F}_a \propto (h_+(t) + h_-(t)) \sum_{k=0}^{n} d_k a^k(t)
  \]
- \textbf{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
  \[
  \dot{a}_i = \dot{a}_i(t) \Theta[T_i - a_i(t)] - a_i(t) \Theta[a_i(t) - T_i]
  \]

Modeling framework: Schema

- agents described by \textit{arousal} $a$, \textit{valence} $v$, \textit{expression} $s$
- arousal causes expression wrt on valence
- emotional information stored in field $h$
  \[
  h_\pm = -\gamma h_\pm h_\pm(t) + s n_\pm(t) + l_\pm(t)
  \]
- valence and arousal are affected by the field

Valence dynamics

- \textbf{Cubic dependence on the valence}
  \[
  \dot{v} = -\gamma_v v(t) + h_\pm(t) \{ b_0 + b_1 v(t) + b_2 v^2(t) + b_3 v^3(t) \}
  \]
  - allow for 'silent' mode: $v(t) \to 0$: $b_0 = 0$
  - positive and negative valences 'equal': $b_2 = 0$
  - \textit{collective emotions} emerge if $b_1 \cdot h_\pm > \gamma_v$
    \[
    \Rightarrow \text{regime with high emotional information (!)}
    \]
Valence distribution

\[ p_s(v) \text{ under low } h \]
\[ p_s(v) \text{ under high } h \]
- polarization of emotions emerges under high information exchange
- agreement of analytical results with simulations

Collective arousal \[ x_i \sim U(x_{min}, x_{max}) \]
- amount of agents expressing emotions fluctuates
- appearance and fading of collective emotions can be observed

Arousal dynamics
- quadratic dependence on the arousal
  \[ \dot{a} = -\gamma_a a(t) + h(t) \{ d_0 + d_1 a(t) + d_2 a^2(t) \} \]
- 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
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

U.S. daily mood changes inferred from Twitter

http://www.ccs.neu.edu/home/amislove/twittermood/

Let’s start an emotional discussion ...

Januar 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.

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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. Garas, D. Garcia, FS, M. Skowron, EPJ DataScience (2011 subm.)
**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**

- $N = 10^4$, $V_r = -0.15$, $V_c = 0.05$, $\gamma_r = 0.2$, $A_r = 0.2$, $h = 0.01$, $c = 0.05$, $\gamma_h = 0.9$
- Distribution of $H$ (B) and rescaled distribution of inter-message time (C) similar to real data.

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**How do consumers really feel?**

- How do customers really feel?
  - Often wrong predictions in market research
  - Social effects (herding, emotions) commonly neglected

**How do consumers really decide?**

- Often wrong predictions in market research
- Social effects (herding, emotions) commonly neglected

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

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

**Bloomberg Businessweek**

Available on the iPad

**SPECIAL REPORT** March 1, 2011, 12:

Kia, Best Buy, and Viacom are using new tools to mine comments on the Web to see what consumers really think of their brands.

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**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.
Hot selling vs slow moving products: Emotions

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

![Weekly statistics graph]

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

**Distribution of emotional scores**

![Distribution of emotional scores graph]

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

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**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

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

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
Collective Emotions

EPJ Data Science starts Jan 2012 ... stay tuned

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