

From Sentiment Analysis to Preference Aggregation

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[Joint work with Andrea Loreggia, Francesca Rossi and Vijay Saraswat]

What is the collective sentiment about ...?

www.sentiment140.com/search?query=shutdown&hl=en

Sentiment140

Tweet 676 Like 531 +1 153

shutdown English Search

Sentiment analysis for shutdown

Sentiment by Percent

Sentiment by Count

Positive (5)
Negative (5)

Tweets about: shutdown

Shoq: RT @hapkidogal: McCain rips Cruz over **shutdown**: ?Stop! You?re wrong, you?re crazy!?! The Raw Story <http://t.co/e51y5wVBuj> @Shoq @maddow @K?
Posted: 20 seconds ago

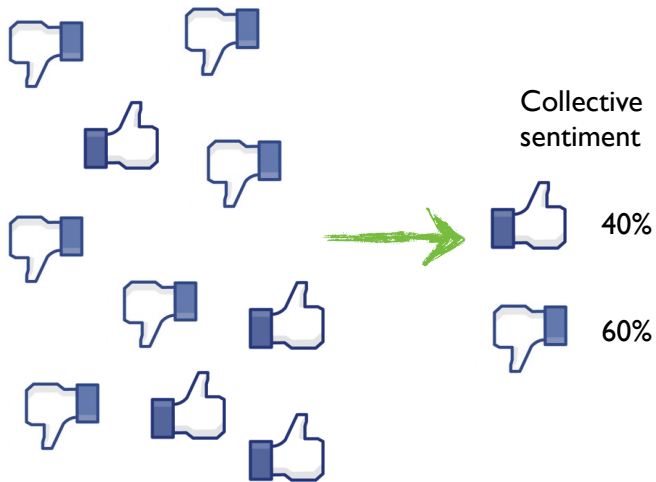
RickyRayinGA: Now today @WhiteHouse Will Justify @SenTedCruz **#shutdown** over #Obamacare #ACA @CNN @NBCNews @CBSNews @foxnews @whpresscorps @SpeakerBoehner
Posted: 1 minute ago

molevy777: RT @Tsek_Bastard: S/O to the people that are killing Krejcir's crew -You're scaring away the Eastern Europeans ! Strip-Clubs will **shutdown** ?
Posted: 1 minute ago

LindahSindy: **#GOPshutdown** If only bartenders in DC were gvt employees. Boehner would have ended the **#shutdown** days ago
Posted: 1 minute ago

The results for this query are: Accurate Inaccurate

Aggregation of individual polarities (like/dislike)



Outline

1. Basic definitions: sentiment analysis and preference aggregation
2. Multiple alternatives:
 - Basic **collective sentiment paradox**
 - Counting paradoxes
3. Data structures from individual text:
 - pure sentiments (polarity)
 - pure preference (preorder)
 - sentiment and preferences (**SP-structures**)
4. Aggregation of SP-structures: Borda* rule
5. Open problems: six challenges in **preference analysis**

Sentiment Analysis

Ingredients:

- An **entity** x (no assumption about its structure)
- A **corpus** of individual expressions \mathcal{T} by a set of individuals \mathcal{I}
- A notion of **polarity**: $\{+, -, N\}$, 5-star scale or graded sentiment

Several NLP techniques used to extract the collective sentiment:

- entity extraction to find expressions mentioning x in \mathcal{T}
- word-count, Naive Bayes, and other **machine learning** techniques to extract the polarity of a single expression in \mathcal{T}

Most common approach:

The **percentage of positive expressions** is the collective sentiment about x

Preference Aggregation

Ingredients:

- A set of candidates \mathcal{X}
- A set of individuals \mathcal{I} expressing preferences as linear/weak orders on \mathcal{X} or as sets of approved candidates in \mathcal{X}

Voting rules are used to identify a set of **most preferred candidates**.
Several rules are possible!

We focus on two definitions of voting rules:

Borda rule - linear orders: if a voter ranks candidate c at j -th position this gives j points to c . The alternatives with highest score are the winners.

Approval voting - sets of candidates: the winners of **approval voting** are the candidates which receive the highest number of approvals.

Part I: The Problem

Basic collective sentiment paradox

Two candidates a and b are competing in an election:

- Sentiment analysis extracts 100% positive comments for b
- Majority rule elects a with a majority of 90 vs 10

Alternatives at the left of | are **positive**, preferences from left to right:

90 voters	a	b		
10 voter		b		a
<hr/>				
Majority rule winner: a				
Collective sentiment predictor: b				

Sentiment analysis can give the wrong result when predicting the majority rule!

More generally: sentiment analysis is problematic
in comparing **more than two alternatives**

Counting paradoxes: characterisation

A simple result to characterise collective sentiment paradoxes:

Proposition

A collective sentiment paradox with 2 candidates occurs iff:

$$N(a|b) \geq N(b|a)$$

$$N(ba|) + N(b|a) + N(|ba) > N(ab|) + N(a|b) + N(|ab)$$

or symmetrically for b winning in SA.

How to **quantify** the fraction of paradoxical profiles?

Awkward formula:

$$\sum_{l=\frac{n+1}{2}}^n \binom{n}{l} \sum_{t=0}^{n-l} \binom{l}{t} 2^{l-t} \sum_{m=t}^{n-l} \binom{n-l}{m} 2^{n-l-m}$$

Counting paradoxes: simulation

We performed experiments with 2 entities:

- sampling 10.000 profiles with the impartial culture assumption
- enumerating all paradoxical profiles up to $|\mathcal{I}| = 93$ (see figure below)

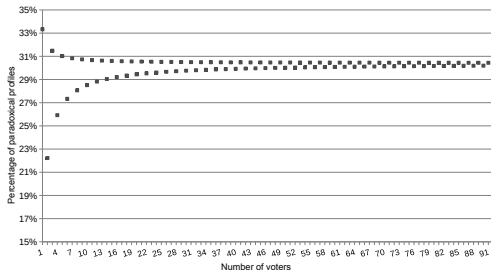


Figure: % of collective sentiment paradoxes

Sentiment analysis and preference aggregation differ in **30% of the profiles**

Part II: Data Structures

Preference Analysis

Mix the ingredients of sentiment analysis with those of preference aggregation:

- A **set** of entities/items/alternatives \mathcal{X}
- A corpus \mathcal{T}_i of individual expressions for each i in a set \mathcal{I} of individuals
- What is the **most preferred entity**?

Lesson learned from collective sentiment paradoxes:
Polarity extraction is not sufficient if we want to **compare entities**!

What data structure we can/want to extract from individual expressions?

- polarity/graded polarity/score
- only binary comparisons between alternatives
- a combination of sentiment and preference

Raw Data Extraction

Two forms of opinions can be extracted with existing NLP techniques:

- Objective opinions: "Nikon is a good camera" → **score** of a single entity
- Comparative opinions: "I prefer Canon to Nikon" → **binary comparisons**

Definition

The **raw data** extracted from individual expressions \mathcal{T}_i is a tuple (σ_i, P_i, N_i) :

- $\sigma_i : D_i \rightarrow \mathbb{R}$ to represent objective opinions on $D_i \subseteq \mathcal{X}$
- subsets P_i and N_i of \mathcal{X} preordered by \leq_i^P and \leq_i^N , representing positive and negative comparative opinions

Pang et. al., Thumbs up? Sentiment Classification Using Machine Learning Techniques, EMNLP-2002.

Ganapathibhotla and Liu, Mining Opinions in Comparative Sentences, COLING-2008.

Jindal and Liu, Mining Comparative Sentences and Relations, AAAI-2006.

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Example

Three entities a , b and c , and three individuals:

- $\sigma_1(a) = 5, \sigma_1(b) = \sigma_1(c) = 4$ and $P_1 = N_1 = \emptyset$
- $\sigma_2(b) = 1, P_2 = \emptyset$, and $N_2 = \{a, c\}$ with $a \geq_2^N c$
- $\sigma_3(c) = 0, P_3 = \{a, b\}$ with $a \geq_3^P b$, and $N_3 = \emptyset$

Pure Sentiment Data

Definition

The *pure sentiment data* associated with raw data (σ_i, P_i, N_i) is a function $S_i : \{D_i \cup P_i \cup N_i\} \rightarrow \{+, -, 0\}$ defined as:

$$S_i(c) = \begin{cases} \text{sgn}(\sigma_i(c)) & \text{if } c \in D_i \setminus (P_i \cup N_i) \\ 0 & \text{if } \sigma_i(c) = 0 \\ + & \text{if } c \in P_i \\ - & \text{if } c \in N_i \end{cases}$$

Example

Pure sentiment data only deals with *polarities*:

- $S_1(a) = S_1(b) = S_1(c) = +$
- $S_2(b) = +$ and $S_2(a) = S_2(c) = -$
- $S_3(a) = S_3(b) = +$ and $S_3(c) = 0$.

The *most popular candidate* using approval voting is b .

Pure Preference Data

Definition

The pure preference data associated with raw data (σ_i, P_i, N_i) is a **preordered** set $(\mathcal{D}_i, \leq_i^{\mathcal{D}})$ where $\mathcal{D}_i = D_i \cup P_i \cup N_i$ and

$$x \leq_i^{\mathcal{D}} y \Leftrightarrow \begin{cases} x \leq_i^P y \text{ and } x, y \in P_i & \text{or} \\ x \leq_i^N y \text{ and } x, y \in N_i & \text{or} \\ x \in N_i \text{ and } y \in P_i & \text{or} \\ \sigma_i(x) \leq \sigma_i(y) \text{ and } x, y \in D_i & \end{cases}$$

Example

Pure preference data only deals with pairwise comparisons:

- $a \geq_1 b \sim_1 c$
- $b \geq_2 a \geq_2 c$
- $a \geq_3 b \geq_3 c$

The **most preferred candidate** using the Borda rule is a .

Sentiment Preference Structures

Definition

An SP-structure over \mathcal{X} is a tuple $(\mathcal{P}, \mathcal{N}, \mathcal{Z})$ such that:

- \mathcal{P} , \mathcal{N} and \mathcal{Z} form a partition of \mathcal{X}
- \mathcal{P} and \mathcal{N} are ordered respectively by *preorders* $\leq^{\mathcal{P}}$ and $\leq^{\mathcal{N}}$

An SP-structure $(\mathcal{P}_i, \mathcal{N}_i, \mathcal{Z}_i)$ can be extracted from raw data (σ_i, P_i, N_i) :

- \mathcal{P}_i is the union of P_i and the set of entities with positive score
- Analogously for \mathcal{N}_i . \mathcal{Z}_i is the set of entities with zero or no score
- Preordered relations extracted from σ_i and copied from P_i and N_i

SP-structures combine (interpersonally non-comparable) scores with (incomplete) pairwise comparisons between entities

Example

Agent 1	Agent 2	Agent 3	
a		a	\mathcal{P}
$ $		$ $	
$b \sim c$	b	b	
<hr/>			
		c	\mathcal{Z}
<hr/>			
	a		\mathcal{N}
	$ $		
	c		

Table: SP-structures extracted from the previous example.

Part III: Aggregation of SP-structures

Aggregating SP-structures

Definition

The **Borda*** score of entity $c \in \mathcal{X}$ in SP-structure $(\mathcal{P}, \mathcal{N}, \mathcal{Z})$ is defined as:

$$s^*(c) = \begin{cases} 2 \times |\text{down}^{\mathcal{P}}(c)| + |\text{inc}^{\mathcal{P}}(c)| + |\mathcal{Z}| + 1 & \text{if } c \in \mathcal{P}_i \\ -2 \times |\text{up}^{\mathcal{N}}(c)| - |\text{inc}^{\mathcal{N}}(c)| - |\mathcal{Z}| - 1 & \text{if } c \in \mathcal{N}_i \\ 0 & \text{if } c \notin \mathcal{P}_i \cup \mathcal{N}_i \end{cases}$$

Given a profile \mathcal{S} of SP-structures, the **most popular candidates** are the ones maximising the sum of the individual Borda* score:

$$B^*(\mathcal{S}) = \operatorname{argmax}_{c \in \mathcal{X}} \sum_{i \in \mathcal{I}} s_i^*(c)$$

Example of using Borda*

Agent 1	Agent 2	Agent 3	
a		a	\mathcal{P}
 $b \sim c$		 b	
	b	c	\mathcal{Z}
	a		\mathcal{N}
	 c		

Table: SP-structures extracted from the previous example.

The **most preferred candidate** under the Borda* rule is a .

What we know about Borda*

A profile is **purely preferential** if all comparisons are positive (negative) for all individuals. A profile is **purely sentimental** if only positive/neutral sentiment is expressed and no pairwise comparison.

Theorem

If a profile S is purely preferential, then $B^(S) = \text{Borda}(S)$.*

If a profile S is purely sentimental, then $B^(S) = \text{Approval}(S)$.*

Axiomatic properties adapted from Social Choice Theory:

Theorem

The Borda rule satisfies consistency, faithfulness, neutrality and the cancellation property.*

Theorem

If S is a profile in which all individuals rank a above b then $b \notin B^(S)$.*

Part IV: Open Problems

From Sentiment Analysis to Preference Aggregation

Six challenges to study the use of preference/voting tools in sentiment analysis:

1. What preferences/opinions can be **extracted** from the individuals text?
Our proposal: sentiment score and pairwise comparison (raw data)
2. How to best **represent** (compactly) individual preferences and sentiments?
Our proposal: SP-structures based on preorders
3. How to **aggregate** the individual information into a collective opinion?
Our proposal: generalise Borda and Approval with the Borda rule*
4. Is it possible to identify influencers and prevent **strategic behaviour**?
Example: creation of fake accounts (cloning)...
5. How should preference aggregation methods be **validated**?
6. How to deal with **big data** in sentiment and preference analysis?

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Thank you for your attention!