Exploring Sentiment in Social Media: Bootstrapping Subjectivity Clues from Multilingual Twitter Streams

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Motivation

The language people use to express opinions and sentiment in social media is extremely diverse:

- informal, with abbreviations and misspellings;
- funny, creative, and entertaining;
- topics change rapidly;
- people to invent new words.

– Statistical models trained on social media data may degrade over time ("occupy" has not been indicative of sentiment before 2011).

– General, domain-independent sentiment lexicons exist for limited languages and have low coverage.

Bootstrapping has been used for learning sentiment lexicons in other domains (Turney and Littman, 2002; Banea et al., 2008) but previous works mainly relied on:

- existing NLP tools, e.g., syntactic parsers (Wiebe, 2000);
- information extraction (IE) tools (Riloff and Wiebe, 2003);
- rich lexical resources – WordNet (Esuli and Sebastiani, 2006).

Our approach:

I. handles creativity and dynamic nature of social media (SM);
II. does not rely on any language-dependent tools;
III. scales to many under-explored languages and dialects in SM;
IV. allows real-time sentiment analysis in a streaming mode.

Data and code available at:
http://www.cs.jhu.edu/~svitlana/

Approach

Goal: create Twitter-specific lexicons via bootstrapping sentiment-bearing terms from multilingual Twitter streams.

Assumptions:

- sentiment-bearing terms of similar orientation co-occur (opposite do not co-occur) at the tweet level;
- the co-occurrence of domain-specific and domain-independent terms is a signal of subjectivity.

English Initial Lexicon: strongly subjective terms from MPQA lexicon.

Russian, Spanish Initial Lexicons:

1) translated terms from MPQA lexicon,
2) expanded verbs, adverbs and adjectives using morphological rules,
3) propagated term polarity and verified it using annotator judgments.

Iterative bootstrapping procedure with parameters:

- Θ_{pr} probability of a new term appearing with strongly subjective terms, Θ_k terms added per iteration and Θ_{freq} term frequency.

Subjectivity:

$$p^{subj}(w) = \frac{c\left(w, L_B(\bar{\theta})\right)}{c(w)}$$

Polarity:

$$p^{pos}(w) = \frac{c\left(w, L_B^{pos}(\bar{\theta})\right)}{c(w)}$$

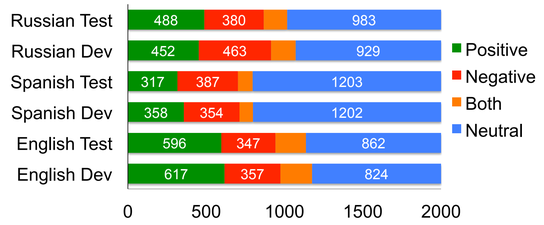
$$p^{pos}\left(w \middle| L_B(\bar{\theta})\right) + p^{neg}\left(w \middle| L_B(\bar{\theta})\right) = 1$$

- Optimize Θ parameters using grid search on DEV data by maximizing F-measure for subjectivity classification. English Θ = [0.7, 5, 50], Spanish and Russian Θ = [0.65, 3, 50].

Experiments

Data:

- 1M unlabeled tweets to bootstrap.
- 2K labeled tweets (DEV) used for parameter tuning.
- 2K labeled tweets (TEST) used to evaluate the quality of the lexicons.



Lexicon Evaluations: comparing with existing dictionary-expanded lexicons using rule-based subjectivity and polarity classifiers (Riloff, 2003).

I. English: 8K strongly subjective terms from SentiWordNet 3.0 (Esuli and Sebastiani, 2006).

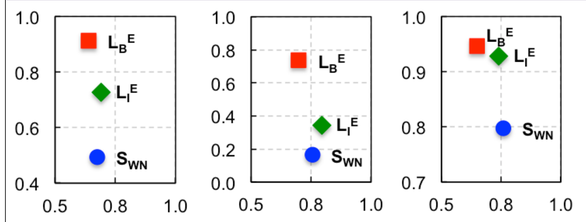
II. Spanish: 1.5K full and 2.5K medium strength terms from sentiment lexicons constructed by Perez-Rosas et al. (2012).

III. Russian: 5K terms from the lexicon constructed by Chetviorkin and Loukachevitchet (2012).

Error Analysis:

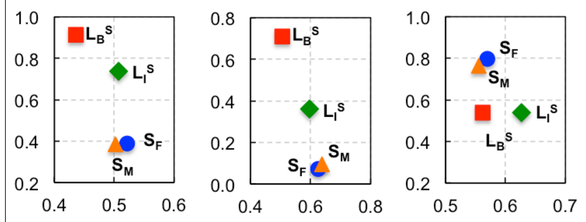
- POS tagging reduces FN errors for subjectivity classification (adjective, adverbs and verbs).
- FP errors for subjectivity classification: some terms are weakly subjective, can be used as subjective and neutral.
- Polarity classification errors: relying on positive or negative polarity but some term have mixed polarity.

Results



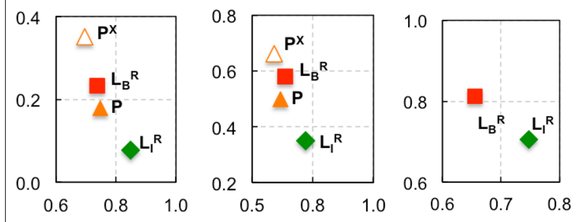
Precision (x-axis), recall (y-axis) for English: L_I^E = initial lexicon (5.1K), L_B^E = bootstrapped lexicon (21.5K), S_{WN} = SentiWordNet.

	$F_{subj} \geq 1$	$F_{subj} \geq 2$	F_{pol}
S_{WN}	0.57	0.27	0.78
L_I^E	0.71	0.48	0.82
L_B^E	0.75	0.72	0.78



Precision and recall for Spanish: L_I^S = initial (8.1K), L_B^S = bootstrapped lexicon (22.3K), S_F= full and S_M= medium strength lexicons.

	$F_{subj} \geq 1$	$F_{subj} \geq 2$	F_{pol}
S_F	0.44	0.17	0.64
S_M	0.47	0.13	0.66
L_I^S	0.59	0.45	0.58
L_B^S	0.59	0.59	0.55



Precision and recall for Russian: L_I^R = initial (3.7K), L_B^R = bootstrapped lexicon (10.8K), P = external and P_X = expanded lexicons.

	$F_{subj} \geq 1$	$F_{subj} \geq 2$	F_{pol}
P	0.55	0.29	-
P_X	0.62	0.47	-
L_I^R	0.46	0.13	0.73
L_B^R	0.61	0.35	0.73