Semi-Supervised Learning for Multi-Category Emotion Recognition in Text

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Emotion Recognition Problem

Goal

Identify emotions expressed in texts

Applications

- Fine-grained analysis of emotional reactions in social media about products, persons, companies, or events
- Visualization of emotional content [1]
- Discovering information of interest to people [2]

Challenges of ER

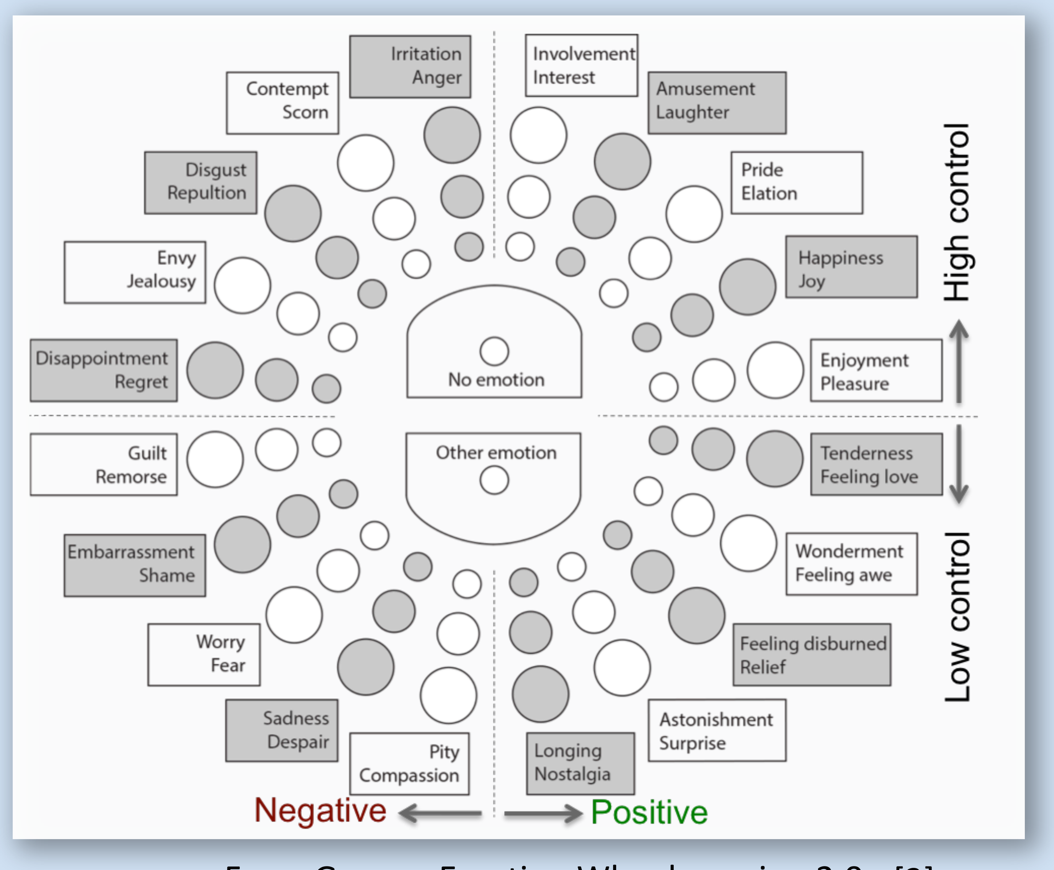
- Few ground-truth data
- Lack of domain-specific emotional terms in existing emotion lexicons

Semi-supervised Learning

Idea

Learn a refined emotion classifier over the data pseudo-labeled by the limited initial classifier

Categorical Emotion Model

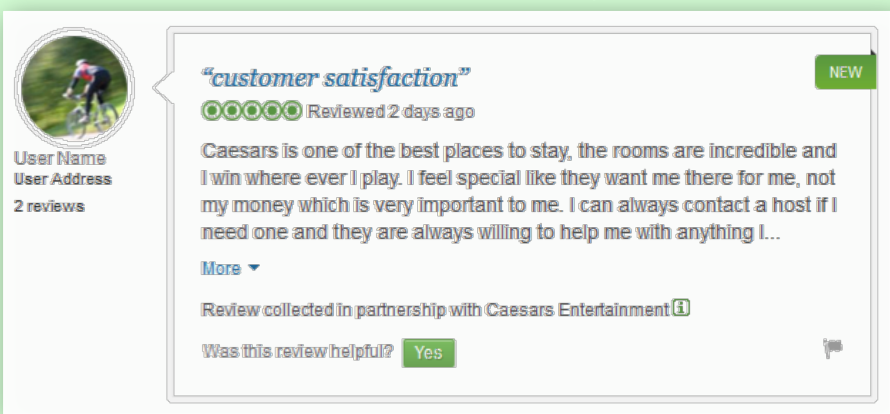


From Geneva Emotion Wheel, version 2.0 [3]

Working on Reviews

Dataset

- 68 048 reviews from TripAdvisor



An example of review

Challenges

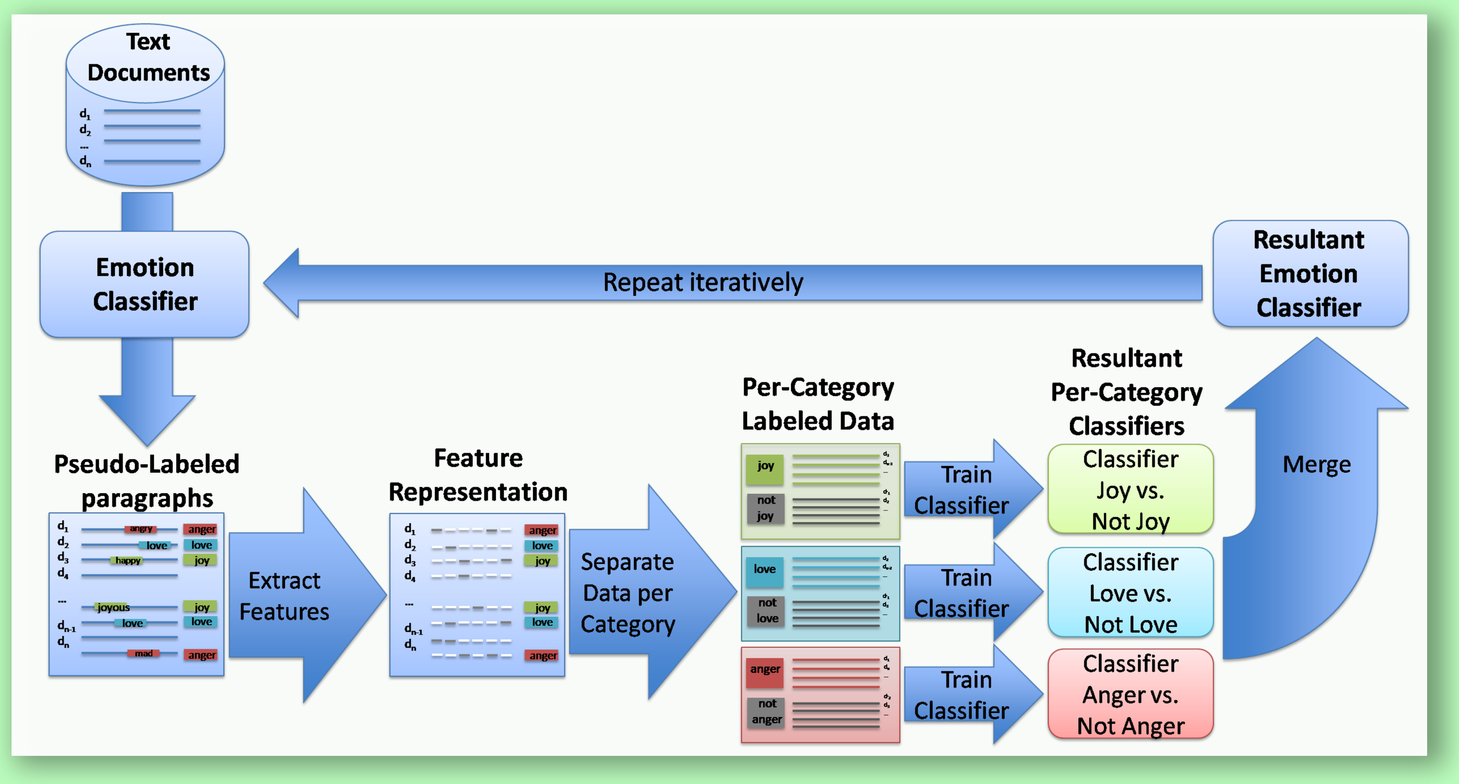
- Multiple emotions within a review
- Presence of negated emotions

Experiments

Refining emotion lexicons with domain-dependent terms by learning classifiers

Semi-Supervised Learning

Framework

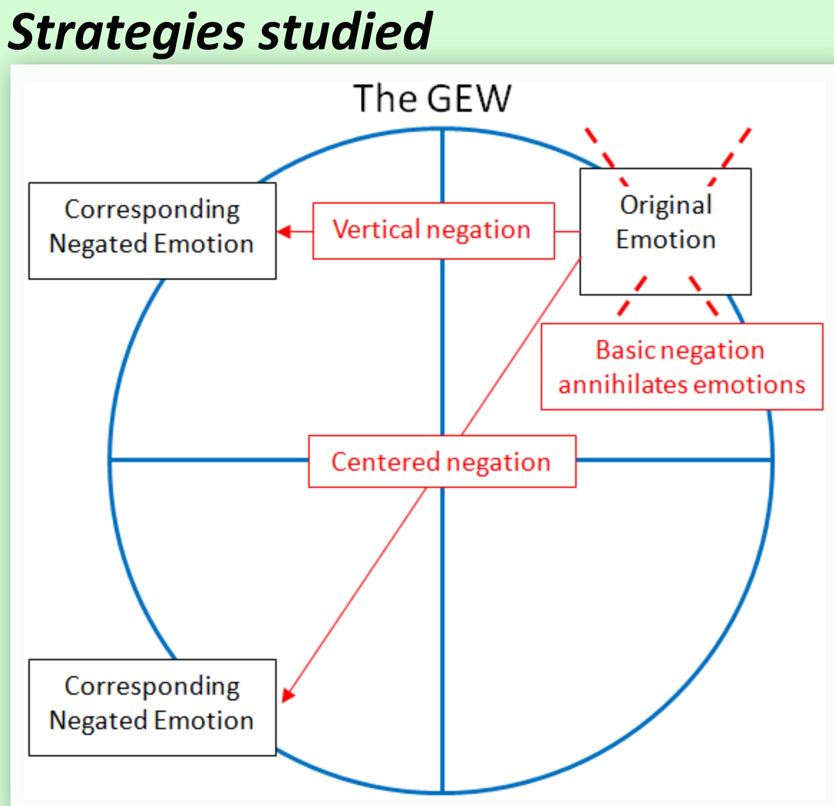


Experiments

Evaluating semi-supervised learning framework with Linear SVM as classifiers

Studying Negation

Strategies studied



Experiments

Finding to what emotion correspond a negated emotion as in:

"We did not enjoy the cheap room"

Resulting Lexicons

Top words for emotions Pleasure and Amusement

The weights indicate the importance of the feature for the emotion considered

Emotion Pleasure	
Features	Weights
comfort	0.307
enjoy	0.258
pleas	0.211
strip	0.058
best	0.052
bed	0.049
top	0.046
check	0.039

Emotion Amusement	
Features	Weights
fun	0.125
smil	0.026
laugh	0.015
go	0.010
catch	0.010
sinc	0.009
great	0.009
big	0.008
even	0.008
say	0.007
decid	0.007
call	0.006

"a lovely huge bed"

"catch a few shows"

"the gentleman who checked us in was cordial"

The Performance

Performance of the classifiers for emotions Pleasure and Amusement

Emotion Pleasure

	Unigram			Bigram		
Iter. #	P	R	F1	P	R	F1
Initial	0.828	0.324	0.466	0.828	0.324	0.466
1	0.821	0.311	0.451	***0.857***	***0.3243***	***0.471***
2	0.793	0.311	0.447	0.828	0.324	0.466
3	0.759	0.297	0.427	0.757	**0.378**	**0.505**
4	0.769	0.270	0.400	0.722	**0.351**	**0.473**
5	***0.833***	***0.338***	***0.481***	0.681	**0.432**	**0.529**
12	0.705	**0.419**	**0.525**	0.673	**0.500**	**0.574**

in **bold**: an increase in performance
in *italic*: both recall and precision increase

Emotion Amusement

	Unigram			Bigram		
Iter. #	P	R	F1	P	R	F1
Initial	0.600	0.273	0.375	0.600	0.273	0.375
1	**0.857**	0.273	**0.414**	**1.000**	0.227	0.370
2	0.600	0.273	0.375	**0.833**	0.227	0.357
3	**0.667**	0.273	**0.387**	**0.833**	0.227	0.357
4	**0.667**	0.273	**0.387**	**0.800**	0.182	0.296
5	**0.750**	0.273	**0.400**	**0.800**	0.182	0.296
8	***0.700***	***0.318***	***0.438***	**0.714**	0.227	0.345

in **bold**: an increase in performance
in *italic*: both recall and precision increase

Results

- Relative increase in F1-score reaches 23% for Pleasure and 13% for Amusement
- Both recall and precision increase

The Best Strategies

Performance with negation

Emotion	Reference	Basic	Vert.	Cent.
1-Interest	**0.949**	0.946	0.915	**0.949**
2-Amusement	**0.977**	0.976	/	/
4-Joy	0.995	**0.996**	/	0.993
5-Pleasure	**0.991**	**0.991**	0.989	0.982
6-Tenderness	0.978	0.978	0.964	**0.979**
7-Awe	0.957	**0.961**	0.955	/
9-Surprise	**0.991**	**0.991**	/	/
10-Nostalgia	**0.991**	**0.991**	**0.991**	0.973
12-Sadness	**0.933**	**0.933**	**0.933**	**0.933**
13-Worry	0.943	**0.945**	/	/
14-Shame	**0.769**	**0.769**	0.731	0.761
16-Regret	0.991	0.991	**0.992**	0.980
18-Disgust	**0.922**	**0.922**	/	/
20-Anger	0.927	**0.935**	0.902	0.883

- / : not enough data to train and test on
- Categories 3, 8, 11, 15, 17 and 19 lack data

Results

- Best strategy is emotion-dependent
- Negation is not symmetric

Future work

- Study of emotion intensifiers such as "very" or "barely"
- Study of polarity shifters such as "but" or "although"
- Study of a more fine-grained approach of negation
- Study of different languages

References

[1] Renato Kempter, Valentina Sintsova, Claudiu Musat, and Pearl Pu. "EmotionWatch: Visualizing Fine-Grained Emotions in Event-Related Tweets." In *the 8th International AAAI Conference on Weblogs and Social Media*, 2014

[2] Lionel Martin and Pearl Pu. "Prediction of helpful reviews using emotions extraction." In *Proceeding of the Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014

[3] Klaus R Scherer. "What Are Emotions? And How Can They Be Measured?" *Social Science Information* 44, no. 4 (2005): 695–729

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