University of Stuttgart
Institute for
Natural Language Processing

Amplifiers, Downtoners, and Negations in Emotion Analysis

An Empirical Analysis in Microblogs

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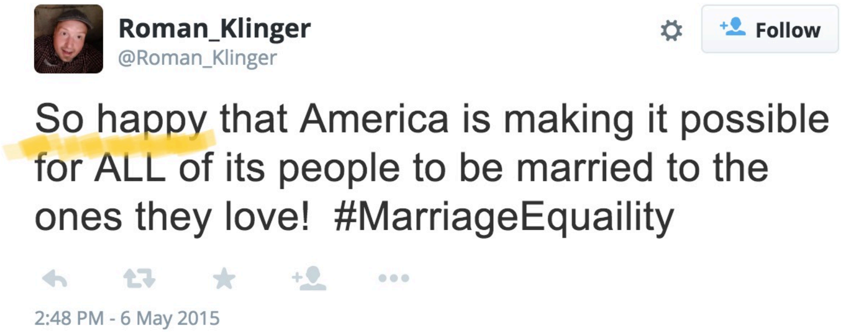
Florian Strohm and Roman Klinger

@roman_klinger

Motivation



Which emotions are expressed?

Anger, Disgust, Fear, Joy, Sadness, Surprise

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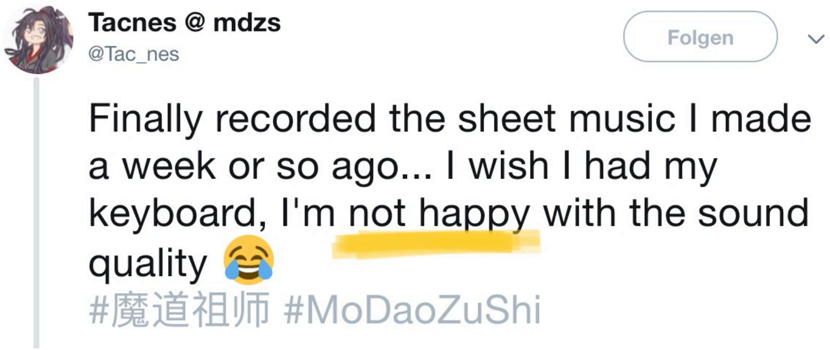

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Motivation

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Anger, Disgust, Fear, Joy, Sadness, Surprise

Goal of this work

- Get a better understanding of the use and impact of modifiers on emotion expressions
- Extend previous work for sentiment and modifiers to emotion classes

Not the goal

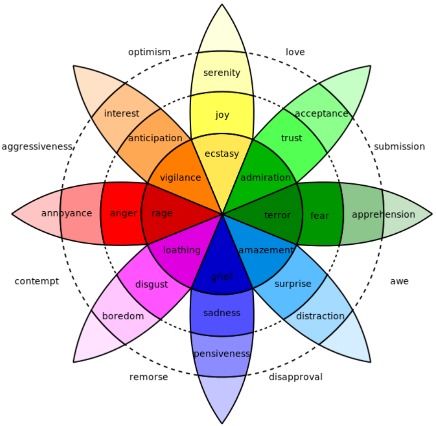
- Build the best classifier

Outline

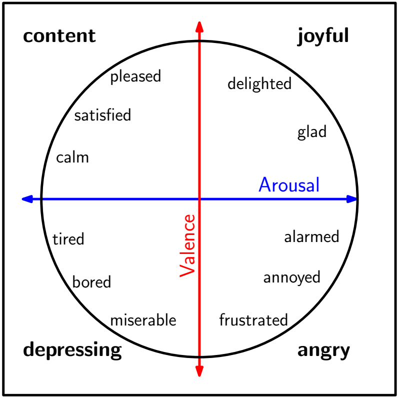
Emotion Models: Ekman (the classes we use)

Other Emotion Models

Plutchik's Wheel

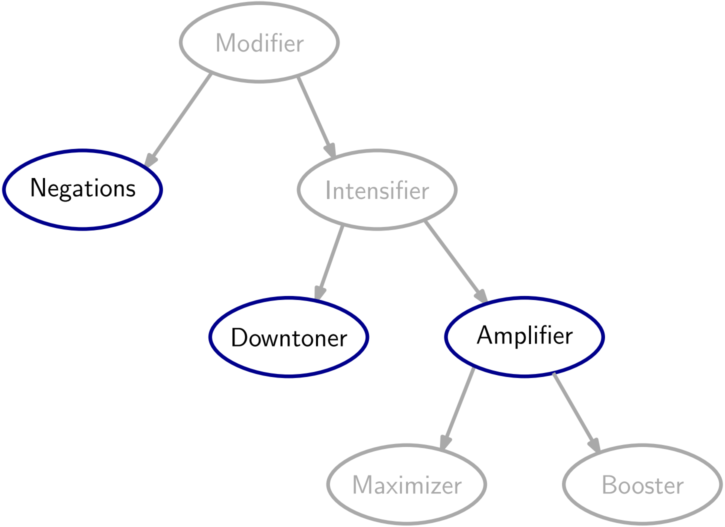


Valence-Arousal



Outline

Modifiers


Modifier
Negations
Intensifier
Downtoner
Amplifier
Maximizer
Booster

Outline

1. Motivation
2. Fundamentals
   - Emotions
   - Modifiers
3. Previous Work on Sentiment or/and Modifiers
4. Methods and Results
   - Cue and Scope Detection
   - Emotion Classification
   - Dictionary-based Classification for Model Introspection
5. Ongoing and Future Work

Previous Work

- Modifier scope detection:
  - Rule based, *e.g.*, Chapman et al., 2001
  - Machine learning, *e.g.*, Councill et al., 2010; Reitan et al., 2015
  - Dependency-parsing, *e.g.*, Jia et al., 2009
- Valence Shifting
  - Rule-based, Polanyi/Zaenen 2006
    (next slide, the work we extend)
  - Machine learning-based, using sequence classifiers implicitly, *e.g.*, Felbo et al., 2017
- Several surveys: Wiegand, 2010; Zhu, 2014; Morante, 2012

Previous Approach in Sentiment Analysis (Polanyi/Zaenen 2006)

Dictionaries:

- Dictionaries with positive ($+2$) and negative (-2) words
- Intensifiers (± 3), diminishers (± 1), negators ($\times(-1)$)
- Detect scope of modifier and change weight of words

Example

That is not good .

Score: -2

Question to Answer

What are appropriate factors
when we have more than two classes?

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Question

- How do we find the cue?
- How do we decide if an emotion word is in the scope?

Cue Detection

- Dictionary compiled from different sources
- Filter for precision

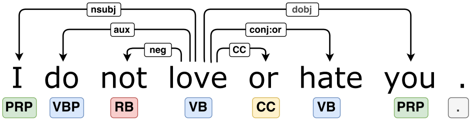
- Negations: no never don't lacks ...
- Amplifiers: deeply highly lots more ...
- Downtoners: almost quite partially some ...

Scope Detection

- Next-*n* heuristic:
  n tokens after cue, up to punctuation/adversive conjunction

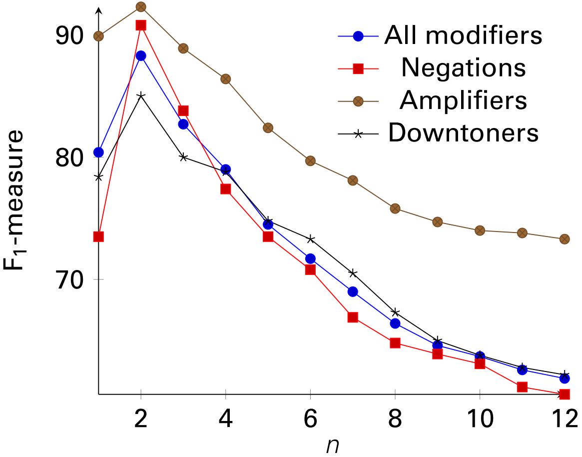
$$t_1 \quad \overset{\text{cue}}{t_2} \quad \overset{\text{scope}}{\underbrace{t_3 \quad t_4}_{n \text{ tokens}}} \quad t_5$$

- Dependency tree heuristic:
  Rules on dependency tree, extended to more modifiers
  (similar to Jia 2009:)



- Machine learning:
  Word and dependency tree based features
  (similar to Councill 2010)

Scope Detection: Results



Scope Detection: Results

Evaluation on manually annotated corpus for emotion words

	Next-2	DepTree	SVM
Modifier	F_1	F_1	F_1
Negator	**90.7**	86.2	83.7
Amplifier	**92.7**	86.7	90.4
Downtoner	**80.0**	60.0	60.7
Macro-avg.	**87.8**	77.7	78.3

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Question

- Does this cue/scope detection improve classification performance?

Classification: Setting

- SVM with bag of words, no n-grams with $n > 1$
- Prefix each word in scope with modifier-specific string

she does not like or trust but fear you

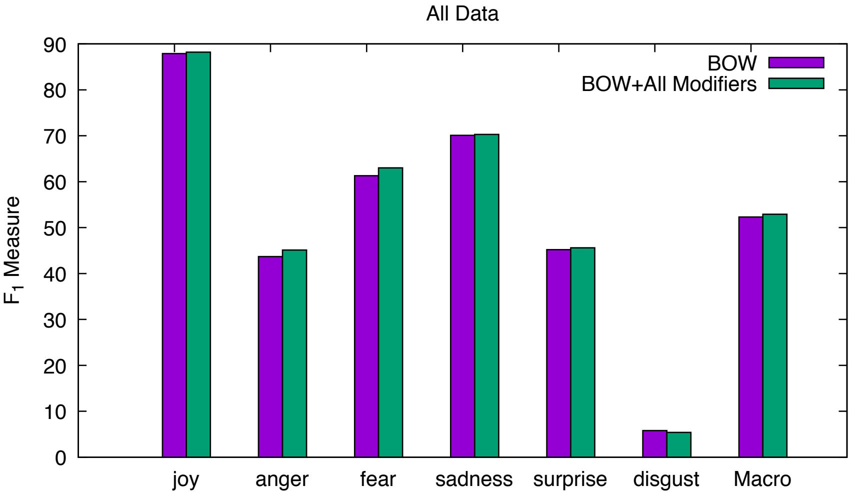
$\Longrightarrow$

she does neg_like neg_trust but fear you

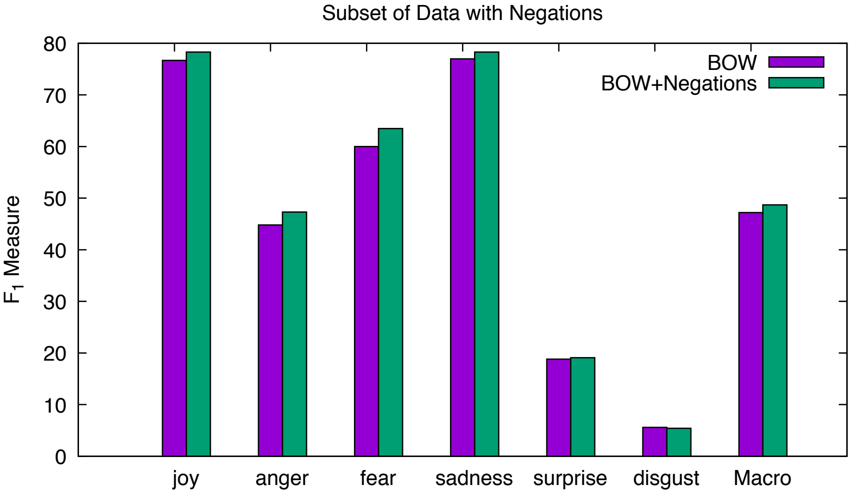
- Data, author-annotated via hashtags:

Emotion	Train	Test
joy	597.992	299.028
anger	59.591	29.501
fear	68.886	34.504
sadness	207.026	103.607
surprise	24.582	12.483
disgust	1.923	877
total	960.000	480.000

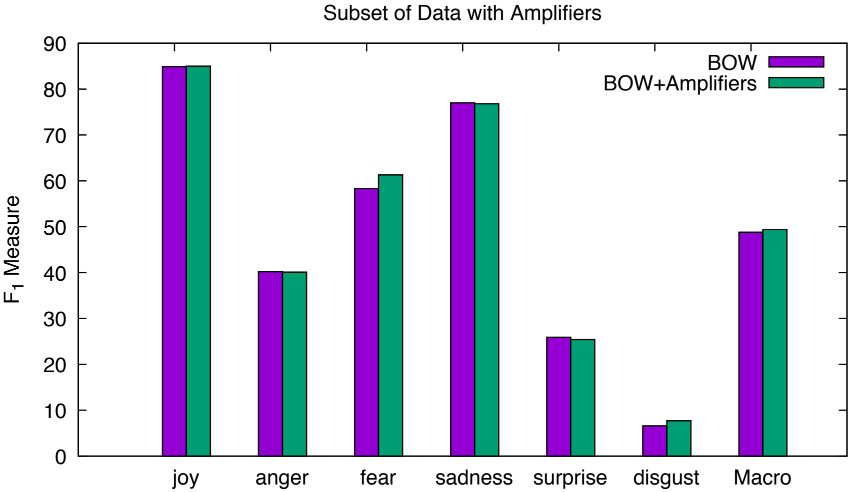
Classification Results, All Data



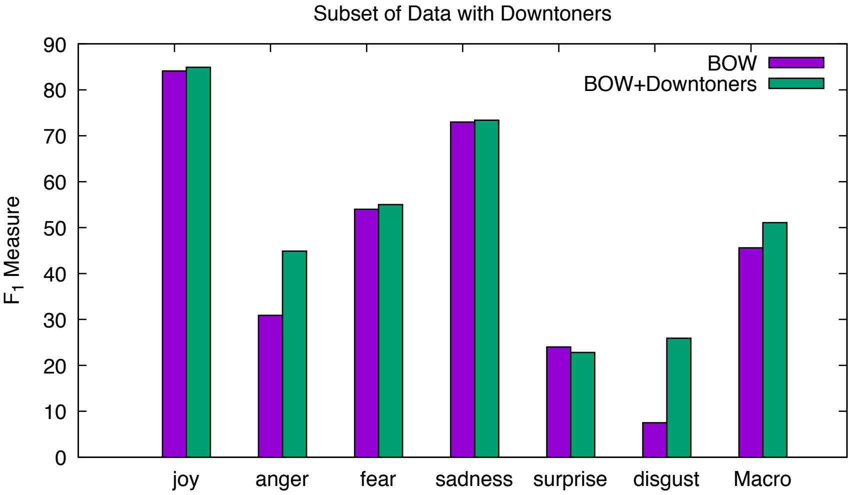
Classification Results, Negation Data



Classification Results, Amplifier Data



Classification Results, Downtoner Data



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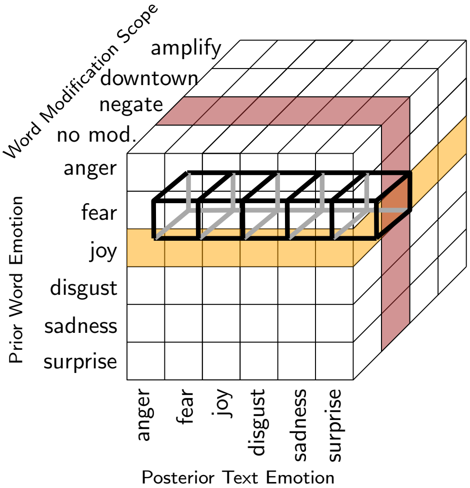
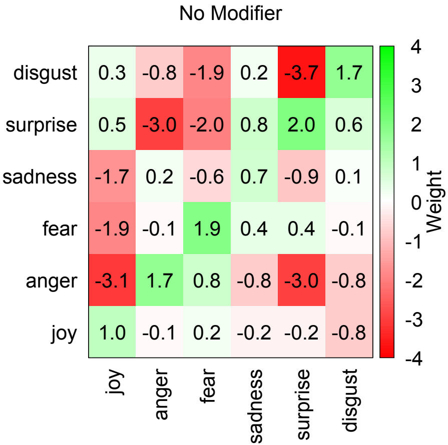
Dictionary-based Classification: Setting



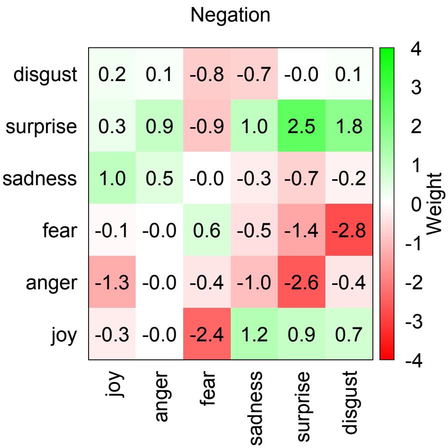
- Training:
  Hill climbing for F_1 on balanced training set
- Inference:
  Maximum a postiori
- Example: "not happy"

Results: No Modifier



- Diagonal has highest values (green)
- Some emotion words do not change other emotions (white)
- Being angry doesn't go well with joy or surprise, surprise not with anger (red)

Results: Negations



- Diagonal has low absolute values (except for surprise)
- Neg. joy → sadness
- Neg. surprise → surprise
- Neg. sadness → joy
- Mostly lower positive weights, some strong negative weights
- Some negations mean “nothing”: anger, disgust

Negation Examples

Joy ⇒ Sadness

"Not sure how this happened but in two days I've somehow gained 5 lbs...so not happy about this. #ugly #fatty #depressed #sad"

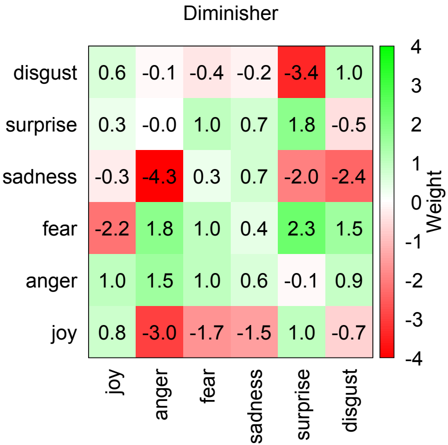
Sadness ⇒ Joy

"Yes! I'm about to eat this piece of cheesecake and I don't feel guilty about it. #indulgingalittle #cheesecake #happy"

Fear ⇒ Fear

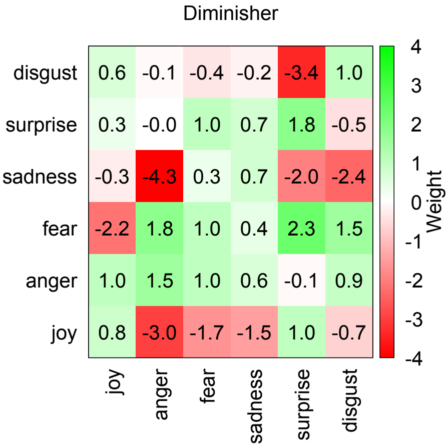
"Don't worry, let God take control. #worry"
""No fear is stronger than you are." - Mark David Gerson #fear #quote #spirituality"

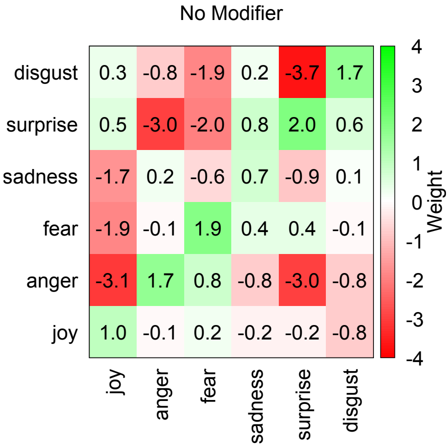
Results: Downtoner



- Nothing surprising, similar to no modifier, mostly lower weights
- Some exceptions, e.g. “a bit sad” → no anger at all

Results: Downtoner





Downtoner Example

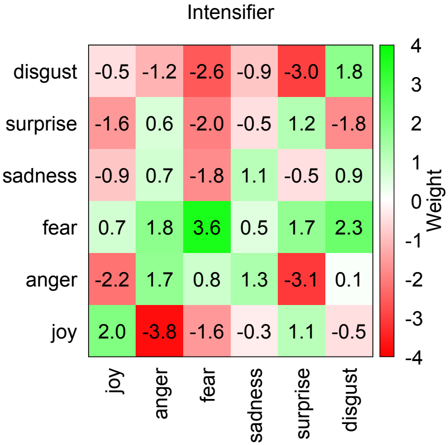
Sadness ⇒ Sadness, Joy

"pray more and worry less #pray #faith #love #peace #happiness..."

Joy...

"Just a bit happy to be back in Ibiza..."

Results: Amplifier



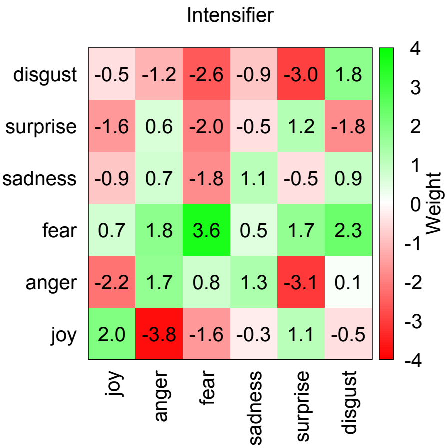
- "Stronger" weights
- Especially clearer separation from (some) other emotions

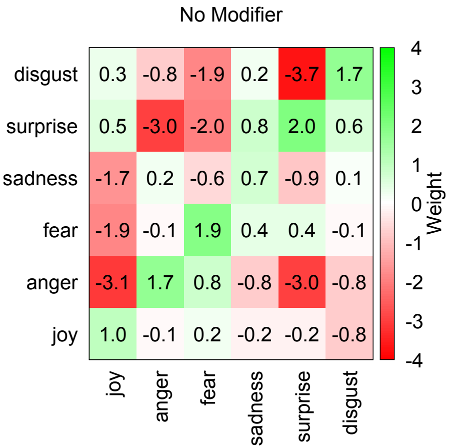
Amplifier Example

Joy ⇒ 2· Joy

"Wishing you a very happy day! #happiness #positivity'

Results: Amplifier





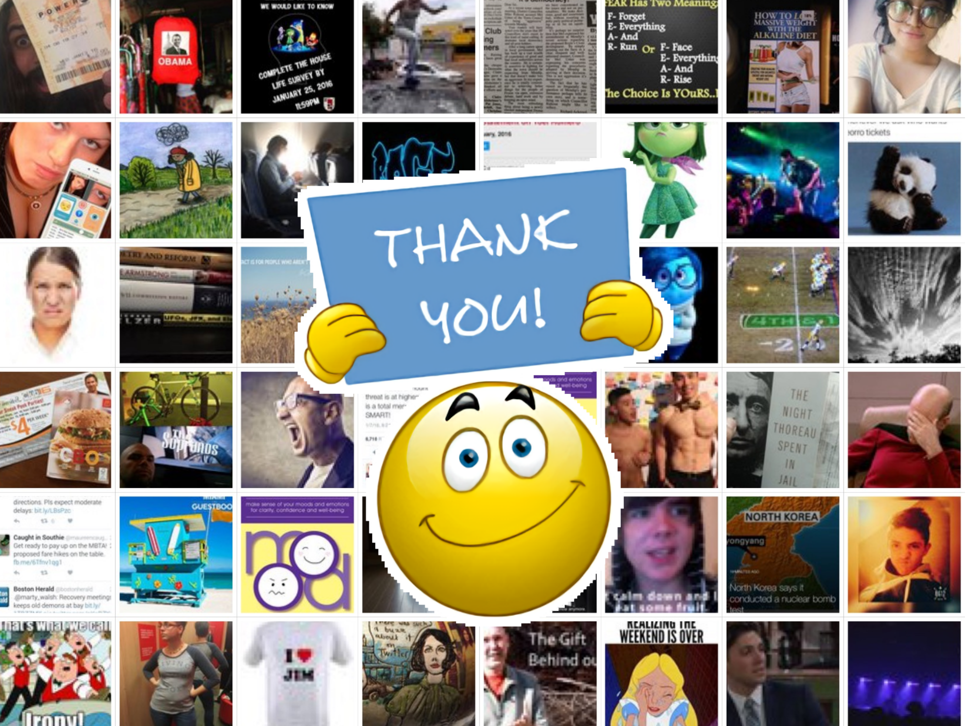
Take Home

- Model enables interesting insights, mostly in line with Plutchik's emotion model, but, first time, empirically shown.
- SVM with specific features performs better in prediction tasks, specific handling is not (here) necessary practically
- Analysis reveals different uses of modifications (e.g. comparisons need distinction)

Outline

Ongoing and Future Work

- Represent modifiers in distributional spaces.
  Optimize space to work well.
- Use attention mechanisms/other ways of model introspection in deep learning approaches
- Compare to emotion intensity prediction tasks
- Analyze the use of modifiers and how specific they are for each emotion.


THANK YOU!