Emotion Analysis in Natural Language

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UMAP2017 BRATISLAVA

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What and why Emotion?

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What is Emotion?

- emotion is a reaction to events
- emotion leads to changes in multiple organismic subsystems

Emotion is the conduit that connects our mind to our body

https://www.youtube.com/watch?v=9J1lXEXFHog

Why Emotion Matters?

My son in law booked us in here and we were very pleased with his choice.
Check in was smooth and easy.
The hotel is smart, trendy and very well situated for exploring the city. We went into town virtually every day and most of the town is walkable even to the castle on the far side of town..
Our rooms were very large with a spacious bathroom complete with hair dryer. Basic soap and shampoo are provided.
The wardrobe space is a bit limited but we managed.
The room was serviced daily and was kept very clean. There is a fridge stocked with the hotels items, all chargeable.
There is no facility in the room to make tea or coffee but we always pack a mini kettle and put some milk in the fridge.
We had breakfast only which was OK but at the peak time on the weekends, 8.30 ish it was a bit chaotic and they could do with a second coffee maker.
All in all I would recommend this hotel and would stay there again.

My son in law booked us in here and we were very **pleased** with his choice.

Check in was **smooth** and **easy**.

The hotel is **smart**, **trendy** and **very well situated** for exploring the city. We went into town virtually every day and most of the town is **walkable** even to the castle on the far side of town..

Our rooms were **very large** with a **spacious** bathroom **complete** with hair dryer. The bed is **comfortable** and so are the pillows.

The wardrobe space is a bit **limited** but we managed.

The room was serviced daily and was kept very **clean**. There is a fridge stocked with the hotels items, all **chargeable**.

There is **no facility** in the room to make tea or coffee but we always pack a mini kettle and put some milk in the fridge.

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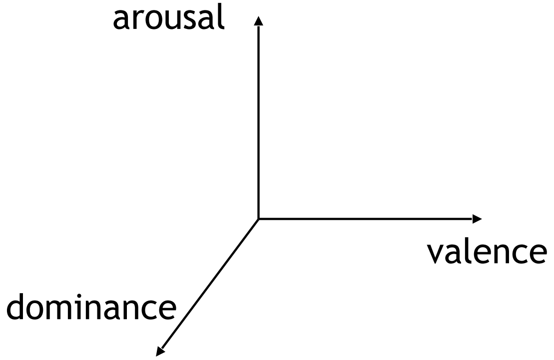
All in all I would **recommend** this hotel and would stay there again.

How to model emotions?

Dimensional



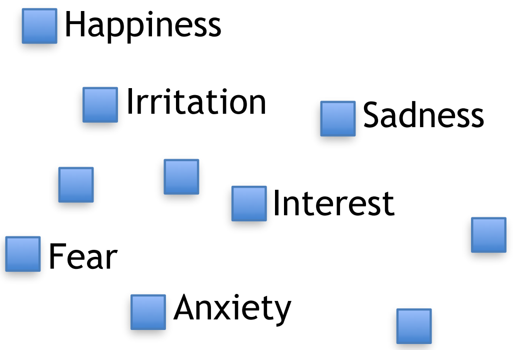
Pros

- More universal
- Can describe any experience

Cons

- Difficult to express states linguistically

Categorical



Pros

- Provides linguistic labels
- Allows variety of applications

Cons

- No agreement on the unique set

Categorical - Ekman

Happy

Fear

Surprise

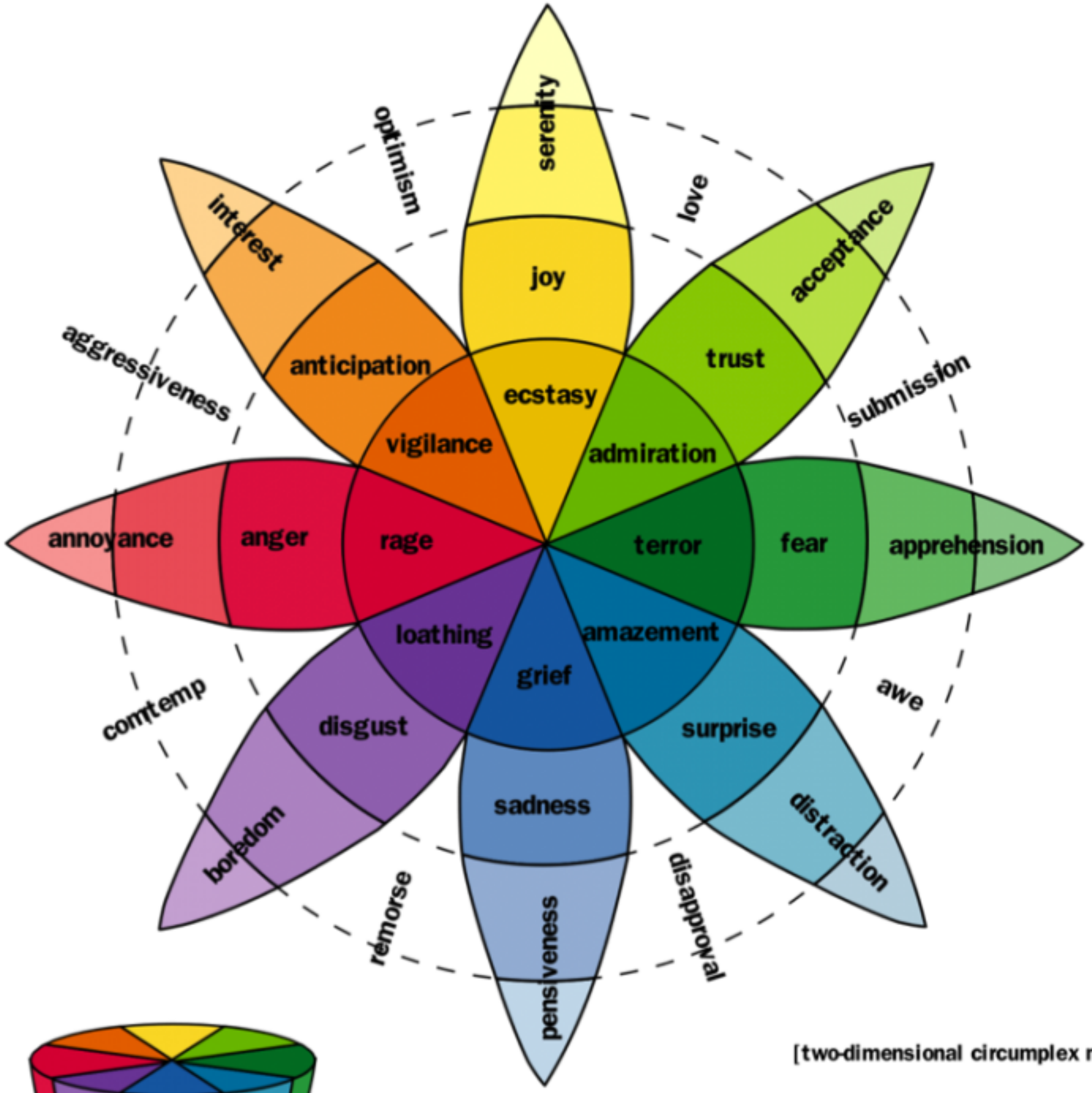
Sad

Anger

Disgust

Ekman, An argument for basic emotions, 1992

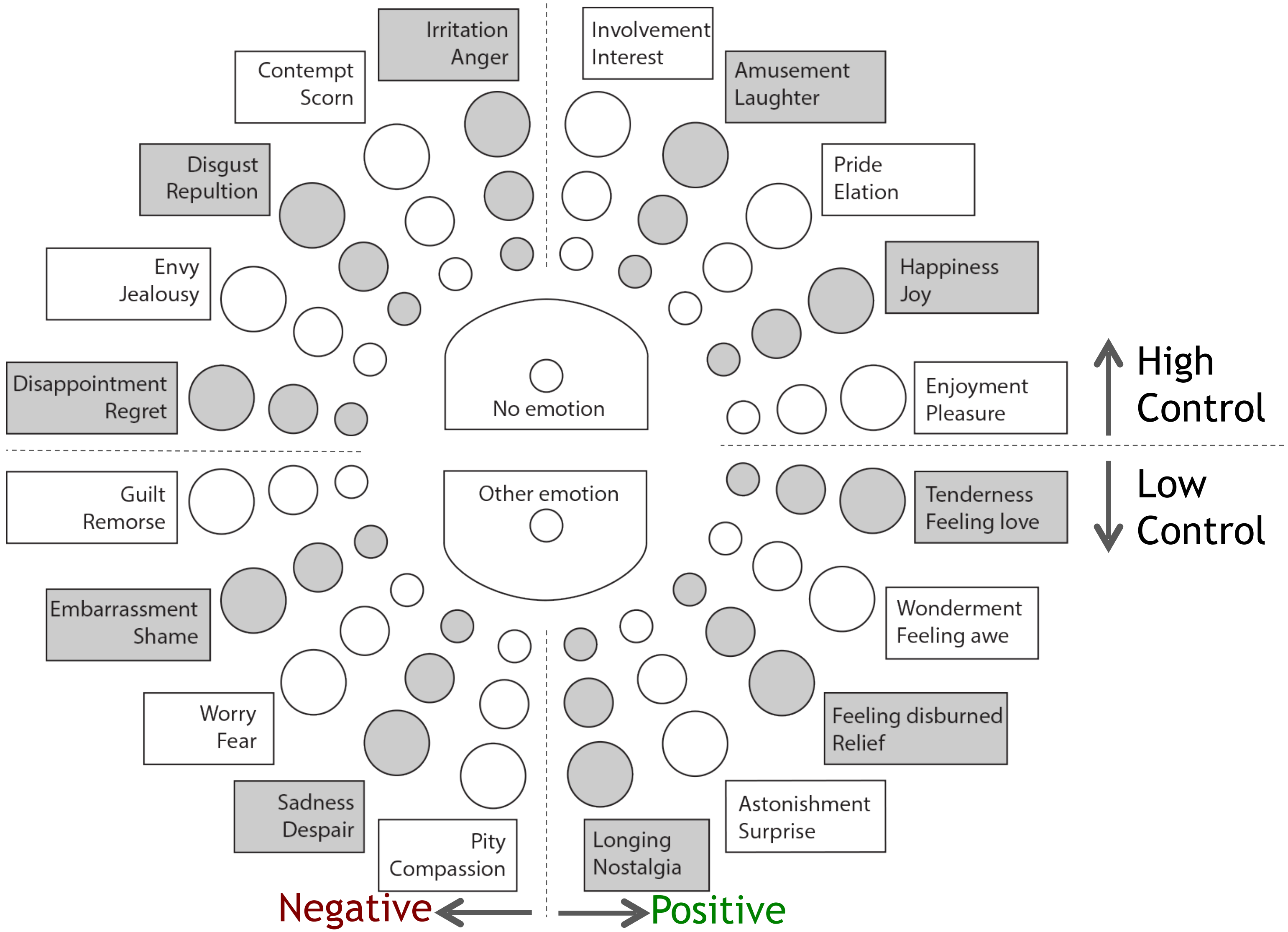
Plutchik's Wheel of Emotions



[two-dimensional circumplex model]

[three-dimensional circumplex model]

Geneva Emotion Wheel



Irritation
Anger

Involvement
Interest

Contempt
Scorn

Amusement
Laughter

Disgust
Repultion

Pride
Elation

Envy
Jealousy

Happiness
Joy

Disappointment
Regret

No emotion

Enjoyment
Pleasure

High
Control

Low
Control

Guilt
Remorse

Other emotion

Tenderness
Feeling love

Embarrassment
Shame

Wonderment
Feeling awe

Worry
Fear

Feeling disburned
Relief

Sadness
Despair

Astonishment
Surprise

Pity
Compassion

Longing
Nostalgia

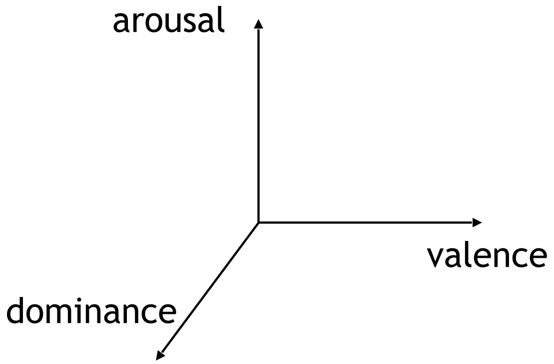
Negative

Positive

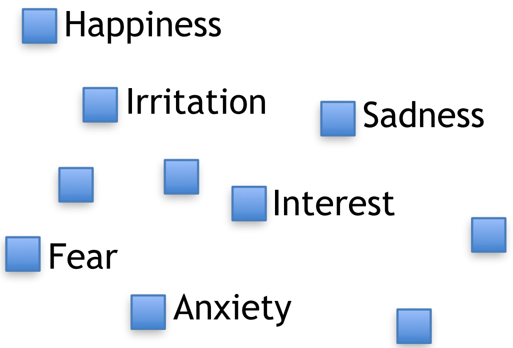
GEW, adapted version 2.0

How to model emotions?

Dimensional



Categorical



Pros

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How to Detect Emotions?

facial expression
voice
galvanic skin response (GSR)
skin temperature
electrocardiogram (ECG)
electroencephalogram (EEG)
gesture
text

Emotion Recognition in Natural Language

Which emotions are expressed?

As a mother I know the **pride** in one’s child, as an American I know the **pride** in one’s country. I feel a little both for you.

Pride

Reference

Ekman, An argument for basic emotions, 1992. Cognition & Emotion. 6 (3): 169–200.

Klaus R Scherer. What are emotions? and how can they be measured? *Social science information*, 44(4):695–729, 2005.

Plutchik, The Nature of Emotions, 2002. American Scientist. 89 (4): 349.

Brave & Nass, Agents that care: Investigating the effects of orientation of emotion exhibited by an embodied computer agent, 2003.

The emotional life of your brain: how its unique patterns affect the way you think, feel, and live - and how you can change them. By Richard Davidson and Sharon Begley, 2002.

Thinking, fast and slow. By Daniel Kahneman, 2011.

2

Emotion Lexicons

Gabby should only feel immense pride in her accomplishments at Rio. Ignore the jealous haters. (Pride/Elation, strong)

Have you seen Chinese swimmer #Fu Yuanhui? Her reactions are infectious, hysterical and really authentic. #Rio2016. (Happiness/Joy, strong)

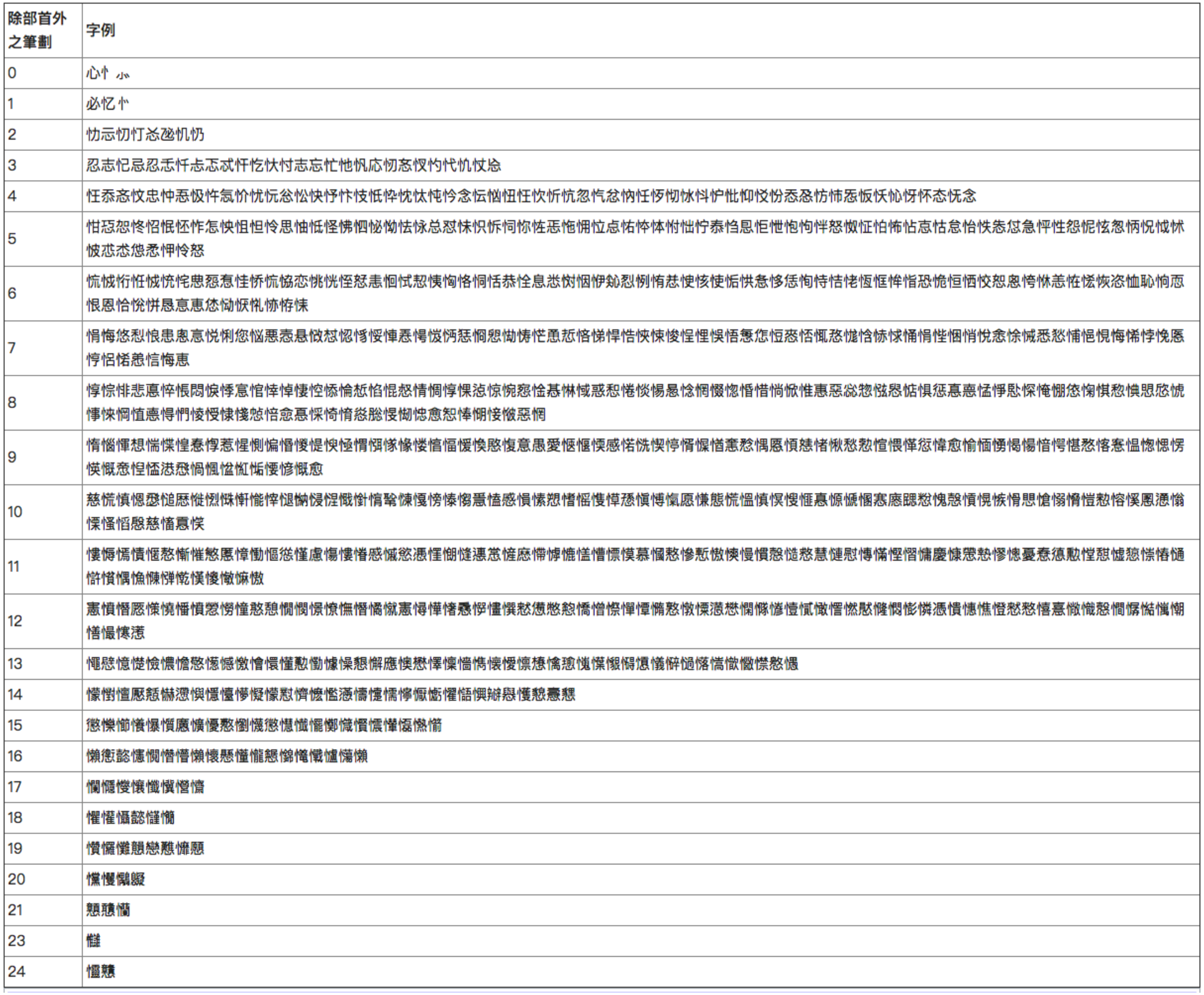
#realDonaldTrump first president in a long time that has the American people and their interests at heart. Thank you Mr. President. (Love/tenderness, worry/fear, sadness/despair, embarrassment/shame)

Speaker and audience emotions are not the same

Emotion Lexicons

- General Inquirer
- ANEW
- Bing Liu’s Lexicon
- OpinionFinder
- WordNet Affect
- NRC
- GALC (geneva affect label coder)
- LIWC (linguistic inquiry and word count)

爱恨怕悲念恋



除部首外之筆劃	字例
0	心忄⺗
1	必忆⺖
2	忇忈忉忊怂忍忛忋
3	忍志忋忌忍忎忏忐忑忒忓忔忕忖志忘忙忚忛応忉忞忟忇忛忟忩
4	忹忝忞忟忠忡忢忣忤忥忦忧忨忩忪快忬忭忮忯忰忱忲忳忴念忶忷忸忹忺忻忼忽忾忿怓忹忽怺忟料怕怭怬怮份态忍怰怖忑怲忺怵怶怀态怃念
5	怙怘怨怤怊怋怌怍怎怏怚怛怜思怞怟怪怫怬怭怮怯怰总怼怵怾怷怸怹怺恶怉怐恊位点怘怙怍怵怶怷怸怹泰怡恩恒怉怐怑怒怓怔怕怖怗怘怙怠怡怢怣怤急怦性怨怩怪怫怬怭怮怯 怶怸怹怺总怦怜怒
6	恍恘恗恀恄恔恌患恖恴恅恑恒恓恋恌恍恎恏恐恑恒恓恔恕恖恗恘恙恚恛恜恝恞恟恠恡恢恣恤恥恦恧恨恩恪恫恬恭恮息恰恱恲恳恴恵恶恷恸恹恺恻恼恽恾恿悀悁悂悃 恨恩恰悦悀悬悥惠悆悧悘悙悚悛悜
7	悁悔悠悡悢患悤悥悦悧您悩悪悫悬悭悮悯悰悱悲悳悴悵悶悷悸悹悺悻悼悽悾悿惀惁惂惃惄情惆惇惈惉惊惋惌惍惎惏惐惑惒惓惔惕惖惗惘惙惚惛惜惝惞惟惠 悙悋悻悫悎悔惠
8	惇悰悱悲惪悴悵悶悷悸悹悺悻悼悽悾悿惀惁惂惃惄情惆惇惈惉惊惋惌惍惎惏惐惑惒惓惔惕惖惗惘惙惚惛惜惝惞惟惠惡惢惣惤惥惦惧惨惩惪惫惬惭惮惯惰惱惲想惴惵惶惷惸惹惺 惻惼惽惾惿愀愁愂愃愄愅愆愇愈愉愊愋愌愍愎意愐愑愒愓愔愕愖愗愘愙
9	惰惱惲想惴惵惶惷惸惹惺惻惼惽惾惿愀愁愂愃愄愅愆愇愈愉愊愋愌愍愎意愐愑愒愓愔愕愖愗愘愙愚愛愜愝愞感愠愡愢愣愤愥愦愧愨愩愪愫愬愭愮愯愰愱愲愳愴愵愶愷愸愹 愺愻愼愽愾愿慀慁慂慃慄慅慆慇慈
10	慈慌慎慏慐慑慒慓慔慕慖慗慘慙慚慛慜慝慞慟慠慡慢慣慤慥慦慧慨慩慪慫慬慭慮慯慰慱慲慳慴慵慶慷慸慹慺慻慼慽慾慿憀憁憂憃憄憅憆憇憈憉憊憋憌憍憎憏 憐憑憒憓憔憕憖憗
11	慺慻慼慽慾慿憀憁憂憃憄憅憆憇憈憉憊憋憌憍憎憏憐憑憒憓憔憕憖憗憘憙憚憛憜憝憞憟憠憡憢憣憤憥憦憧憨憩憪憫憬憭憮憯憰憱憲憳憴憵憶憷憸憹憺憻憼憽 憾憿懀懁懂懃懄懅懆懇懈應
12	憲憤憯愿憷憢憣憦憥憦憧憨憩憪憫憬憭憮憯憰憱憲憳憴憵憶憷憸憹憺憻憼憽憾憿懀懁懂懃懄懅懆懇懈應懊懋懌懍懎懏懐懑懒懓懔懕懖懗懘懙懚懛懜懝懞懟 懠懡懢懣
13	懤懥懦懧懨懩懪懫懬懭懮懯懰懱懲懳懴懵懶懷懸懹懺懻懼懽懾懿戀戁戂戃戄戅戆懤懥懦懧懨懩懪
14	懫懬懭懮懯懰懱懲懳懴懵懶懷懸懹懺懻懼懽懾懿戀戁戂戃戄戅戆懪懫
15	懲懳懴懵懶懷懸懹懺懻懼懽懾懿戀戁戂戃戄戅戆
16	懶懤懥懦懧懨懩懪懫懬懭懮懯懰懱懸
17	懶懷懸懹懺懻懼懽
18	懼懽懾懿戀戁
19	戃戄戅戆戀戀戁戂
20	戃戄戅戆
21	戇戆戄
23	戄
24	戅戆

412 characters with heart in it, the most complex one has 28 strokes

OlympLex 2013 (EPFL)

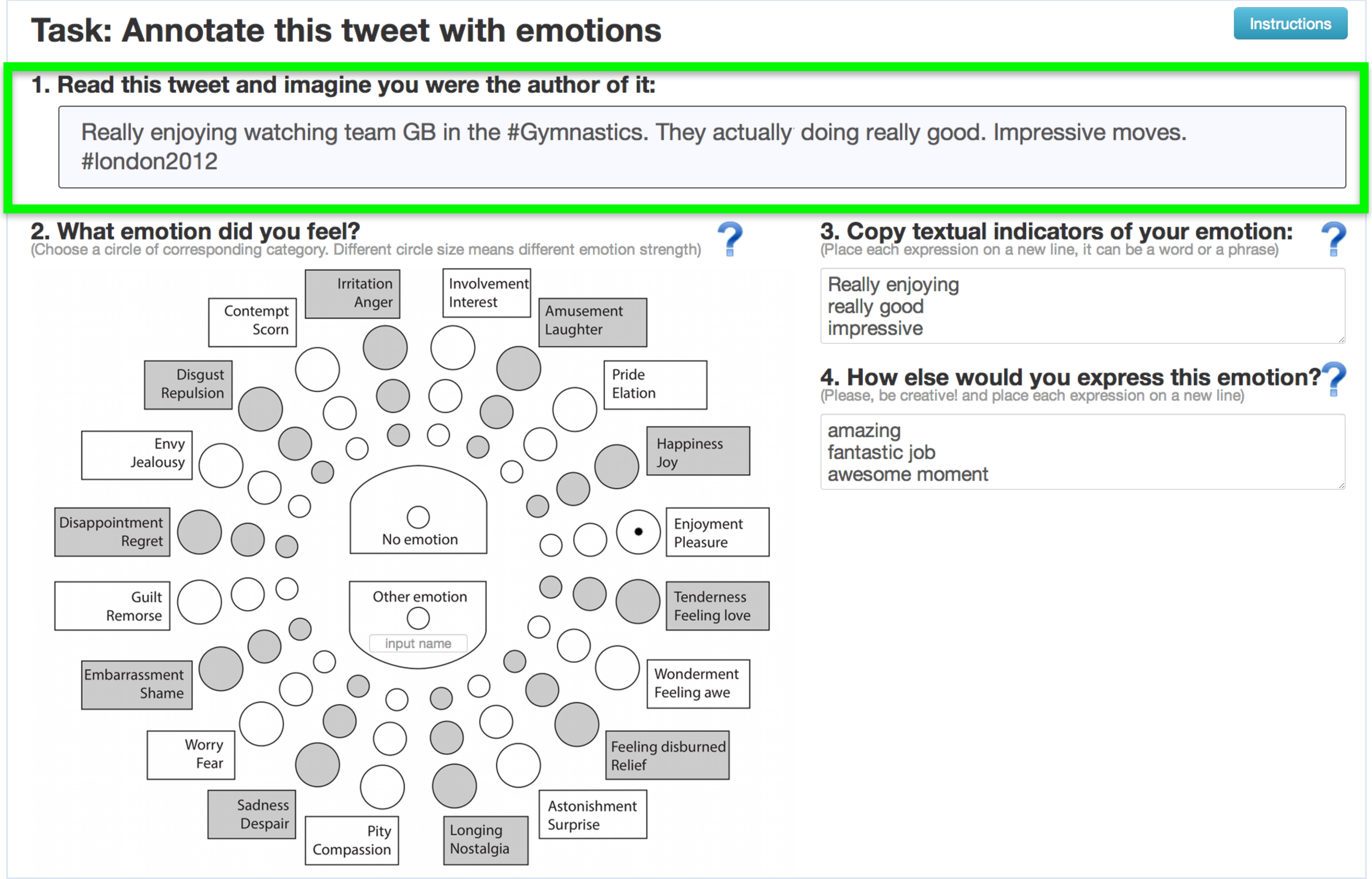
- Create an emotion lexicon dedicated to sport events
- Distinguish up to 20 categories of emotions
- Develop a novel method for crowd worker

Crowdsourcing by Darwin

Watch Video

Darwin’s Letters - a Visualisation

Our Human Computation Task



Task: Annotate this tweet with emotions

1. Read this tweet and imagine you were the author of it:

Really enjoying watching team GB in the #Gymnastics. They actually doing really good. Impressive moves. #london2012

2. What emotion did you feel?

(Choose a circle of corresponding category. Different circle size means different emotion strength)

3. Copy textual indicators of your emotion:

(Place each expression on a new line, it can be a word or a phrase)

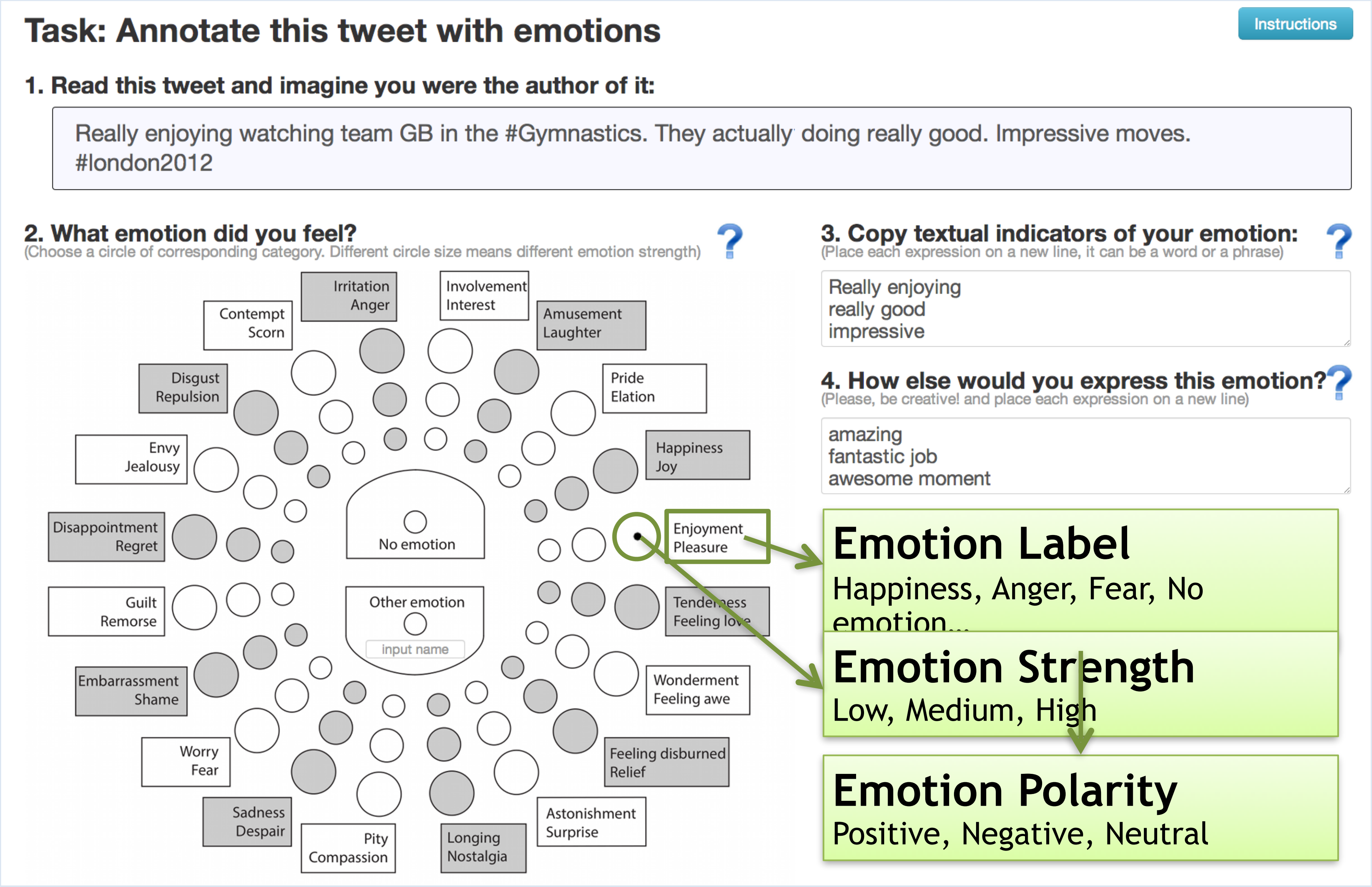
Really enjoying
really good
impressive

4. How else would you express this emotion?

(Please, be creative! and place each expression on a new line)

amazing
fantastic job
awesome moment

Human Computation Task



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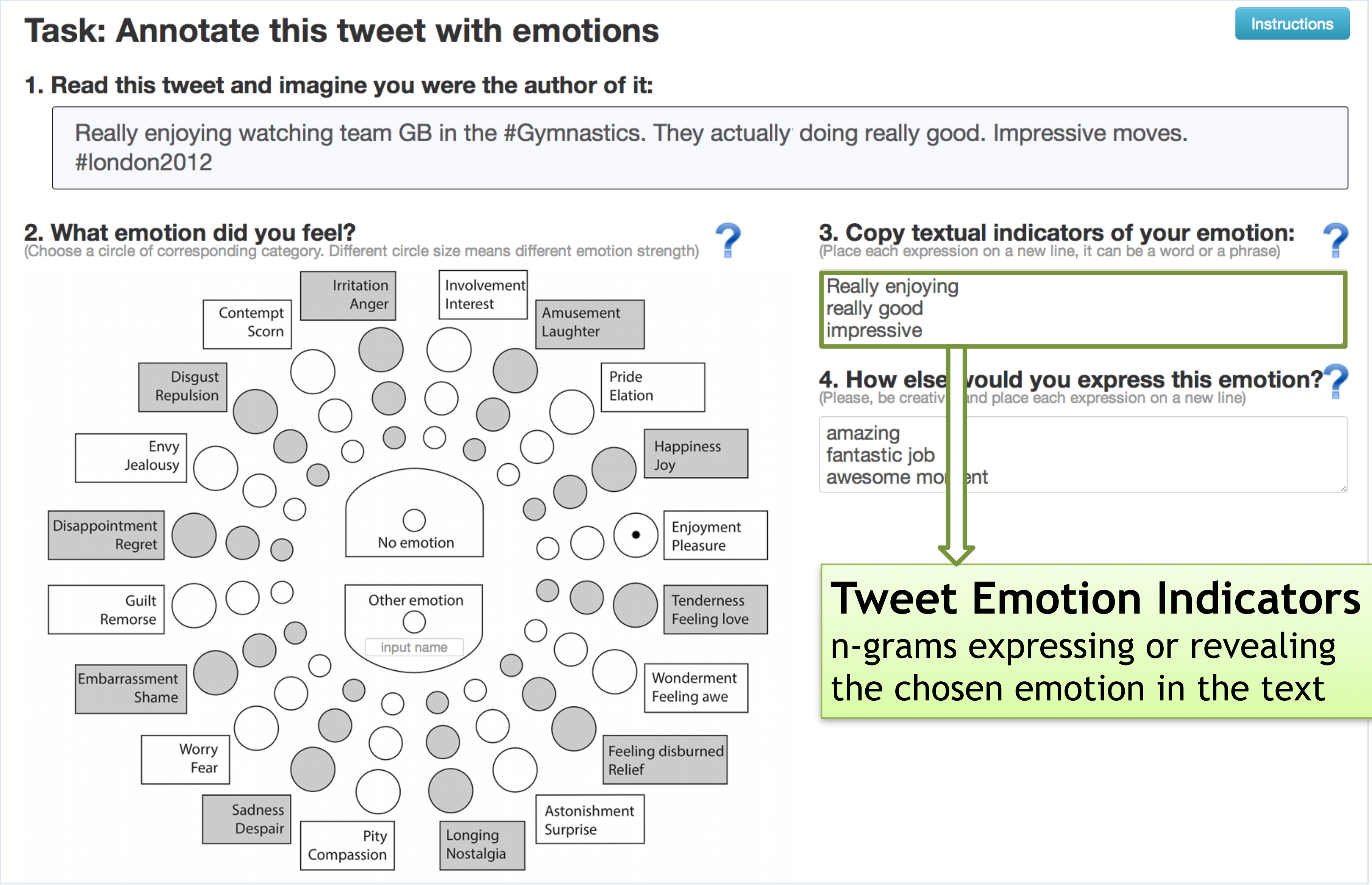
Emotion Label
Happiness, Anger, Fear, No emotion...

Emotion Strength
Low, Medium, High

Emotion Polarity
Positive, Negative, Neutral

Human Computation Task



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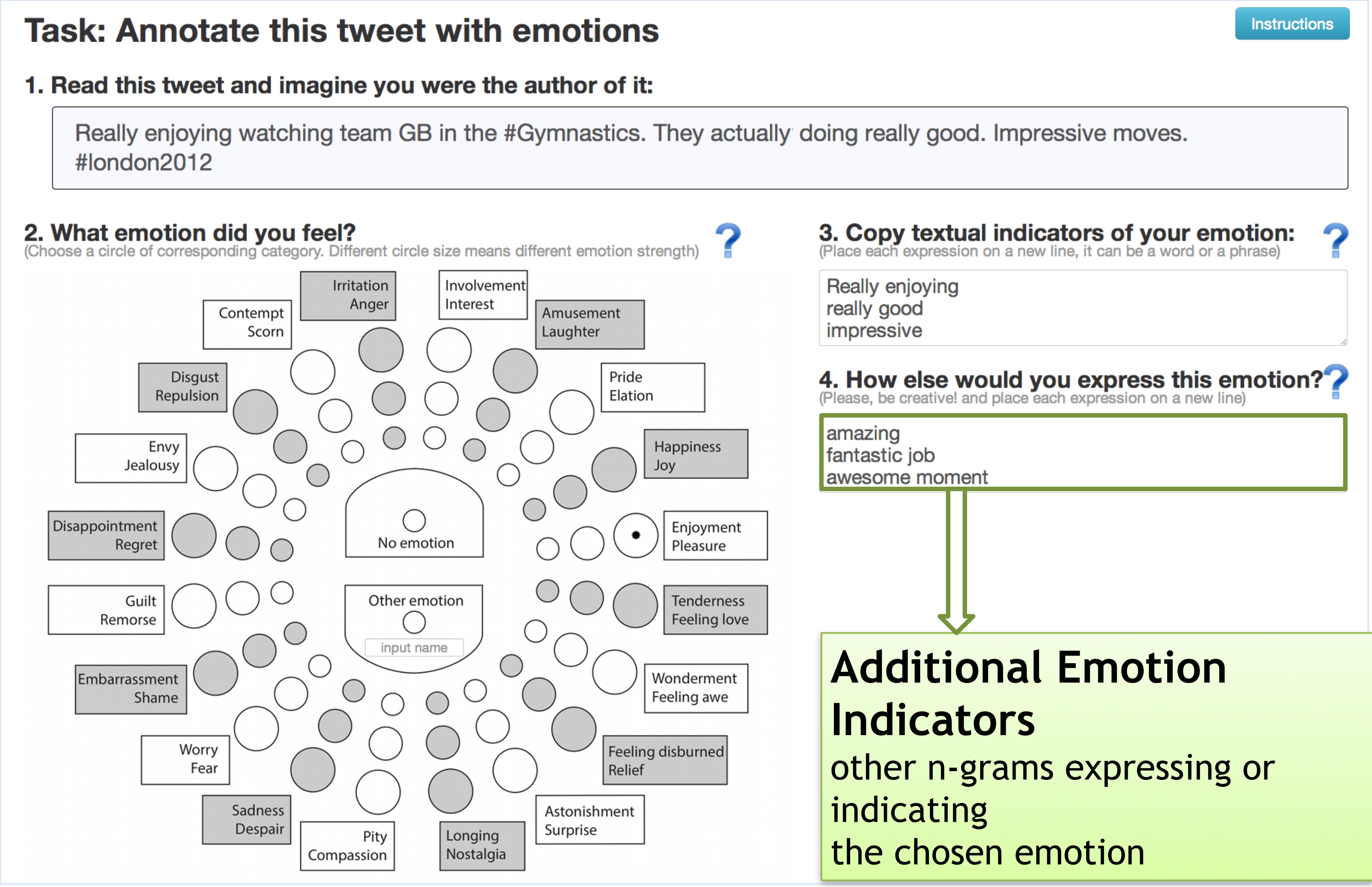
Tweet Emotion Indicators

n-grams expressing or revealing the chosen emotion in the text

Human Computation Task



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fantastic job
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Additional Emotion Indicators

other n-grams expressing or indicating
the chosen emotion

SREC (Sport-related Emotion Corpus)

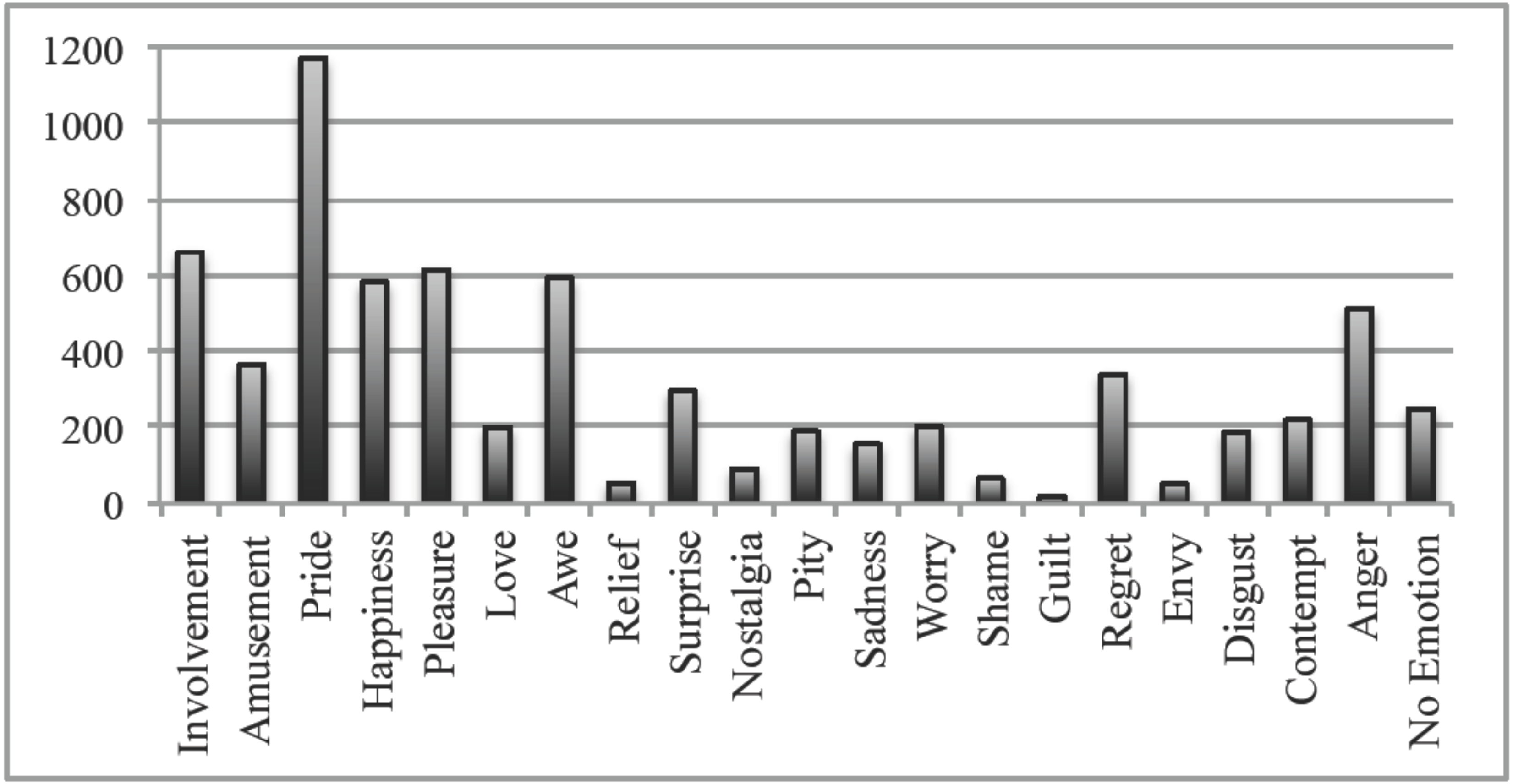
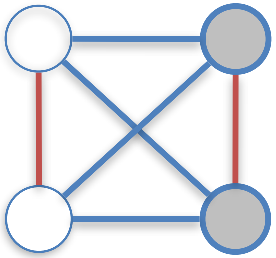


Figure 4.3: Distribution of emotion labels in crowdsourced workers' answers comprising the SREC data (i.e. after the application of posterior quality control).

Quality of Labels

Observed agreement: A



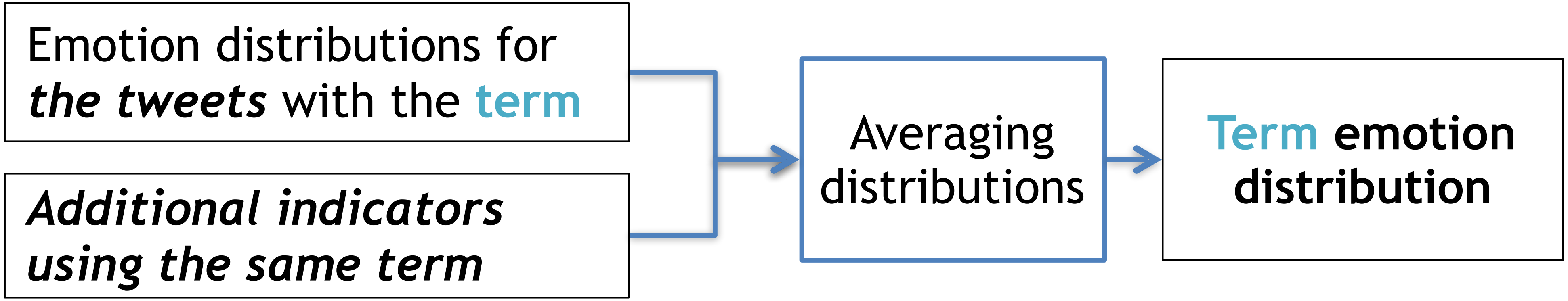
$A = 2/6 = 0.33$

Kappa: $\kappa = \frac{A - A_c}{1 - A_c}$,

where A_c - chance agreement

	Agreement	Kappa
Emotion category	29.3%	0.24
Polarity	75.7%	0.52
Strength	43.8%	0.13

How did we aggregate results?



Emotion distributions for ***the tweets*** with the **term**

Additional indicators using the same term

Averaging distributions

Term emotion distribution

Example term: **hopefully**

Tweets

Hopefully she can smash it and bring home medal

They are now watching the #TeamGB boys hopefully get medal

Hopefully #TeamGB will get an #Olympic Gold Soon!

Additi-onal

hopefully

OlympLex 2013 (EPFL)

- Number of annotation ~2000 tweets
- Contains 3,193 terms
- Examples (per quadrant)

Anger, Disgust, Scorn, … unfair, mad, ugh, annoyed, ticked off, idiots, slap, offended, epicfail, …	***Pride, Happiness, Interest, …*** bravo, champions, my girl, hero, woohoo, sohappy, good job, yessss, …
ouch, noooo, eek, tough to watch, heartbroken, feel so bad, fearful, … ***Sadness, Fear, Pity, …***	astounded, luv u, incredible talent, omg, marry me, desiring, amaze, … ***Love, Surprise, Awe, …***

Lessons Learned

- Crowdsourcing is a viable approach to collect annotated data
- Distinguish speaker’s emotions from the audience’ emotion
- Online inexpert workers require training
- Provide context for emotion labelling
- Consider diversity as an advantage rather than noise

Reference

The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. Volume: 29 issue: 1, page(s): 24-54. Article first published online: December 8, 2009;Issue published: March 1, 2010

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OlympLex" Valentina Sintsova, Claudiu Musat, and Pearl Pu. Fine-Grained Emotion Recognition in Olympic Tweets Based on Human Computation. In Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis (WASSA), 12–20. Association for Computational Linguistics, 2013.

3

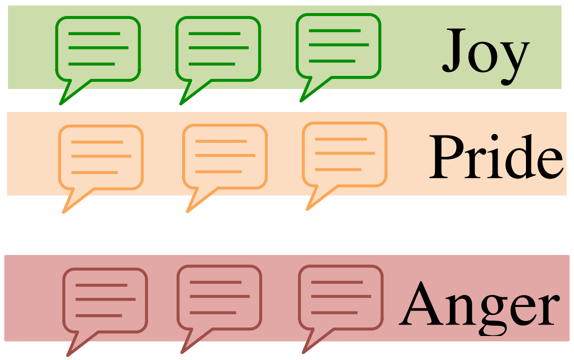
Lexicons -> Classifiers

Why classifiers?

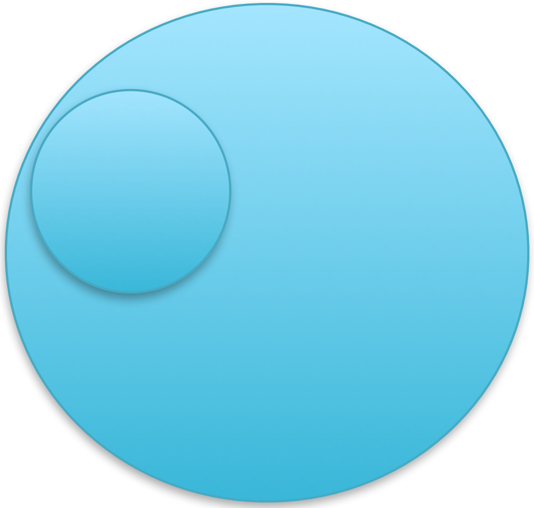
- Scalability
- Domain dependent words
- Fine-grained detection

Classifiers are more suitable for machines, more adapted to big data, capable of integrating the nuances of how humans collectively express emotions.

Supervised learning



Semi-supervised learning



Distant Learning

How does our method work?

GALC Scherer, 2005

Happiness

- cheer*
- bliss*
- delect*
- delight*
- enchant*
- enjoy*
- felicit*
- happ*
- merr*

Joy

- ecstat*
- elat*
- euphor*
- exalt*
- exhilar*
- exult*
- flush*
- glee*
- joy*
- jubil*
- overjoyed
- ravish*
- rejoic*

Interest/ Involvement

- absor*
- alert
- animat*
- ardor*
- attenti*
- curi*
- eager*
- enrapt*
- engross*
- enthusias*
- ferv*
- interes*
- zeal*

Surprise

- amaze*
- astonish*
- dumbfound*
- startl*
- stunn*
- surpris*
- aback
- thunderstruck
- wonder*

Anger

- anger
- angr*
- cross*
- enrag*
- furious
- fury
- incens*
- infuriat*
- irate
- ire*
- mad*
- rag*
- resent*
- temper
- wrath*
- wrought*

Sadness

- chagrin*
- deject*
- dole*
- gloom*
- glum*
- grie*
- hopeles*
- melancho*
- mourn*
- sad*
- sorrow*
- tear*
- weep*

Disgust

- abhor*
- avers*
- detest*
- disgust*
- dislik*
- disrelish
- distast*
- loath*
- nause*
- queas*
- repugn*
- repuls*
- revolt*
- sicken*

Fear

- afraid*
- aghast*
- alarm*
- dread*
- fear*
- fright*
- horr*
- panic*
- scare*
- terror*

Disappointment

- comedown
- disappoint*
- discontent*
- disenchant*
- disgruntl*
- disillusion*
- frustrat*
- jilt*
- letdown
- resign*
- sour*
- thwart*

GALC as the initial classifier

How does our method work?

13:6 V. Sintsova and P. Pu

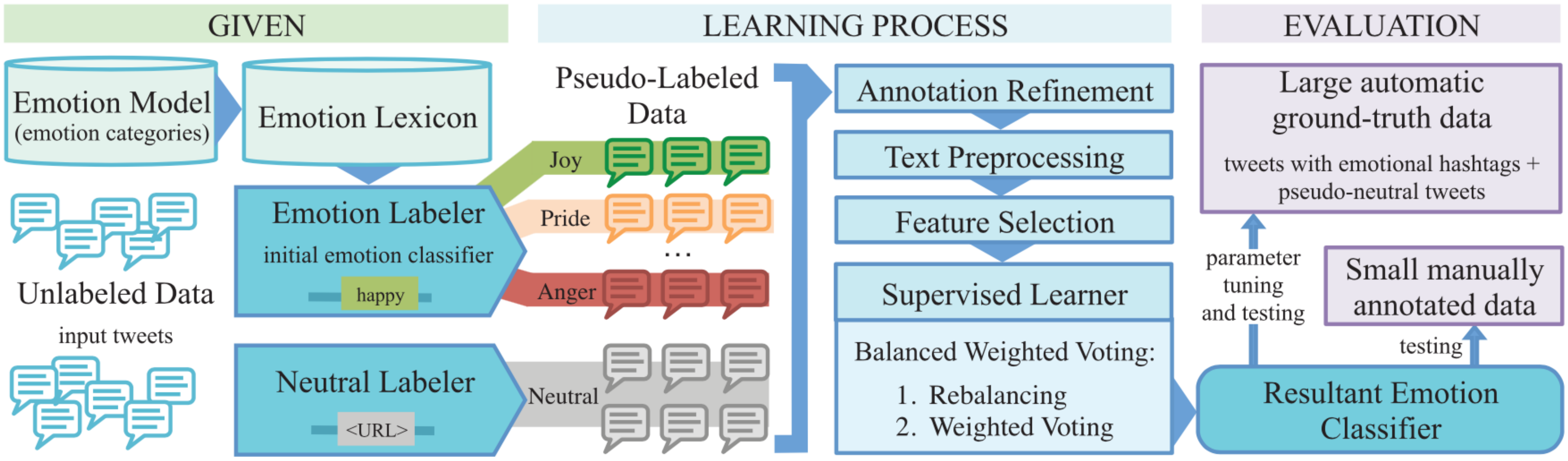
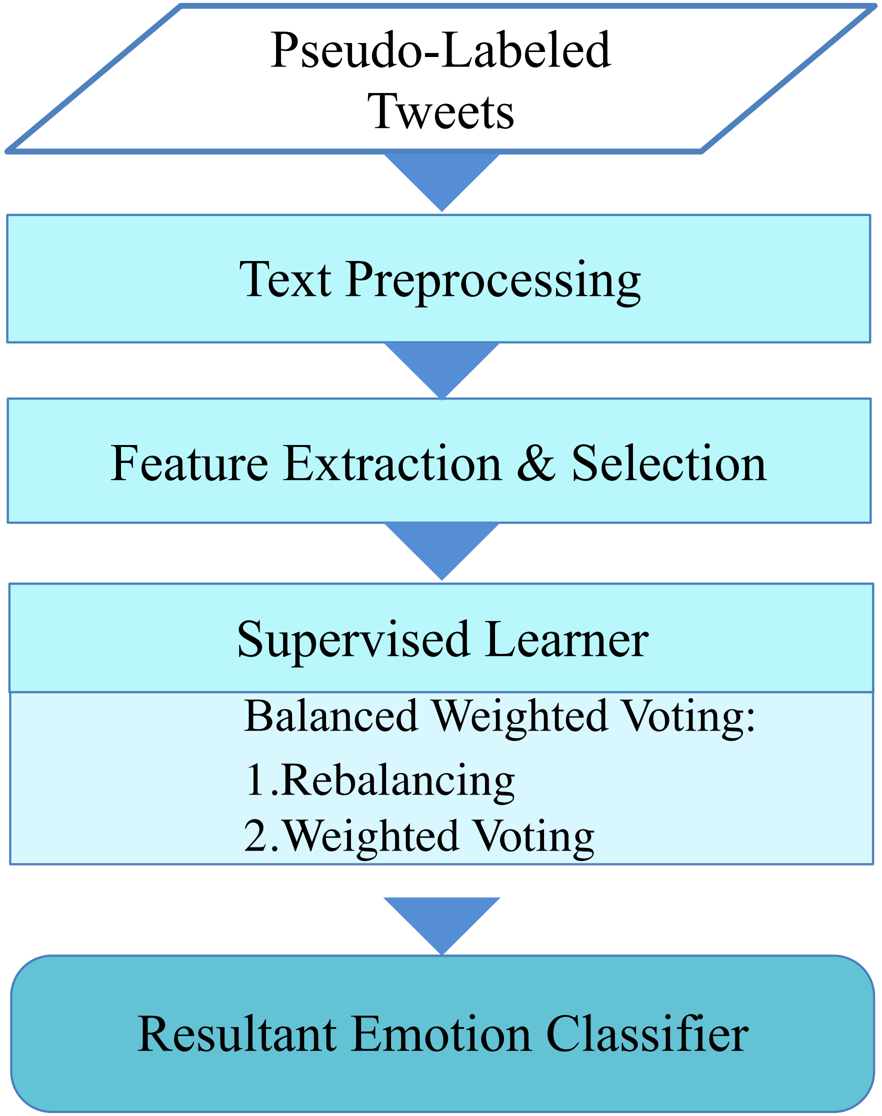


Fig. 1. The framework for our distant supervision method.

Valentina Sintsova and Pearl Pu. Dystemo: Distant Supervision Method for Multi-Category Emotion Recognition in Tweets. ACM Transactions on Intelligent Systems and Technology (TIST). (forthcoming) 2016

Balanced Weighted Voting



Pseudo-Labeled Tweets

Text Preprocessing

Feature Extraction & Selection

Supervised Learner

Balanced Weighted Voting:

1. Rebalancing
2. Weighted Voting

Resultant Emotion Classifier

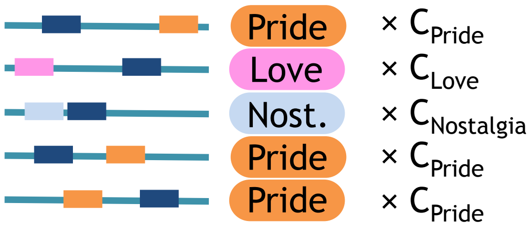
So proud 2 be British massive well done 2 all of Team GB! :D

Pride

so proud <int> be british massive
well done <int> all of team gb ! <emot59>

proud, so proud, proud <int>, massive, well, massive well, done, well done, done <int>, <emot59>

Learn from all tweets with “well done”



well done

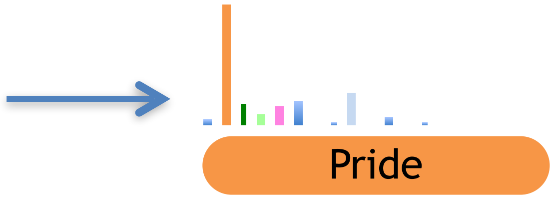


Table I. Evaluating Distant Supervision Algorithms on Automatic Test Data S_T

Emotion Labeler	Algorithm	macro P	macro R	macro F1	A	micro P	micro R	micro F1	rank
-	Random	2.5	1.3	1.7	41.6	8.7	4.4	5.8	
GALC	Initial	20.6	3.6	4.8	52.2	23.6	5.1	8.4	
	mcl-MNB	**21.4**	12.2**	**10.3**** ↑	**62.0**** ↑	**30.6****	28.1**	**29.3**** ↑	1
	mcl-LogReg	7.5**	**23.9****	8.9** ↑	43.1** ↓	9.6**	30.4**	14.6** ↑	6
	1vR-MNB	11.8**	17.1**	9.7** ↑	57.0** ↑	16.9**	**34.6****	22.7** ↑	4
	1vR-LogReg	12.1**	8.8**	8.1** ↑	54.4** ↑	22.0**	20.9**	21.5** ↑	5
	PMI-based	12.7**	10.2**	9.3** ↑	53.1** ↑	28.0**	26.4**	27.2** ↑	3
	BWV	16.8**	11.5**	9.8** ↑	57.8** ↑	27.2*	29.1**	28.2** ↑	2
Olymp-Lex	Initial	11.4	9.7	7.1	47.4	19.3	19.3	19.3	
	mcl-MNB	**19.7****	11.2**	6.8 ↓	58.5** ↑	26.3**	27.0**	26.7** ↑	3
	mcl-LogReg	9.1**	12.4**	7.6** ↑	42.9** ↓	16.1**	21.6**	18.4** ↓	6
	1vR-MNB	19.4**	12.3**	7.3 ↑	58.9** ↑	23.3**	28.3**	25.6** ↑	4
	1vR-LogReg	11.1*	**16.5****	**9.8**** ↑	51.3** ↑	17.1**	27.9**	21.2** ↑	5
	PMI-based	15.8**	9.6	7.3 ↑	58.8** ↑	28.3**	26.0**	27.1** ↑	2
	BWV	17.8**	9.4	6.7 ↓	**59.4**** ↑	**29.9****	**29.2****	**29.5**** ↑	1
PMI-Hash	Initial	12.1	17.0	11.5	23.7	21.8	42.0	28.7	
	mcl-MNB	22.8**	15.9**	13.1** ↑	64.4** ↑	37.6**	43.0**	40.1** ↑	3
	mcl-LogReg	14.4**	18.7**	14.8** ↑	52.7** ↑	30.9**	41.8	35.5** ↑	6
	1vR-MNB	19.9**	16.7	14.2** ↑	**64.6**** ↑	37.5**	43.3**	40.2** ↑	2
	1vR-LogReg	17.6**	**18.9****	**16.2**** ↑	60.6** ↑	35.4**	42.2	38.5** ↑	5
	PMI-based	22.3**	15.6**	14.4** ↑	63.8** ↑	**38.5****	41.3**	39.9** ↑	4
	BWV	**29.3****	15.5**	13.1** ↑	64.1** ↑	37.3**	**44.4****	**40.6**** ↑	1

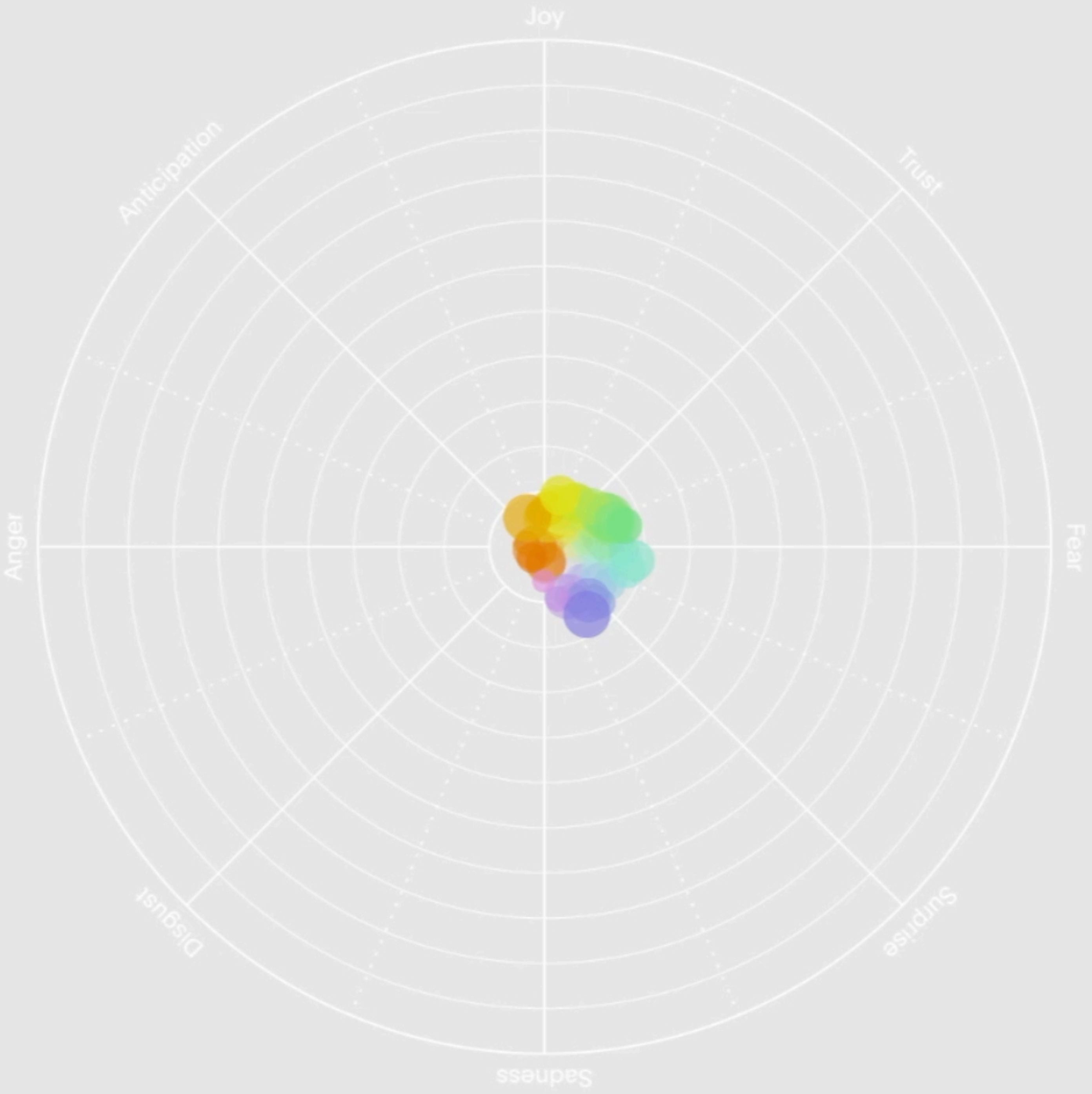
All performance scores are percentages. The results of learned classifiers are compared with those of corresponding initial classifiers. One asterisk * indicates a p-value ≤ 0.05; two asterisks ** indicate a p-value ≤ 0.01.

Lessons Learned for Emotion Recognition in Tweets

- Distant learning is a viable approach to build emotion classifiers across domains
- Including pseudo-neutral documents avoids over-classifying emotional content
- Can be applied to dialogs, food & mood data, etc.

Food & Mood

Top Words



3:35

13 October 2016

Reference

Supervised:

Saima Aman and Stan Szpakowicz. Identifying expressions of emotion in text. In Text, Speech and Dialogue, pages 196–205. Springer, 2007.

Semi-supervised using emoticons and hashtages:

Changhua Yang, Kevin Hsin-Yih Lin, and Hsin-Hsi Chen. Building emotion lexicon from weblog corpora. In Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions, pages 133–136. ACL, 2007.

Munmun De Choudhury,Michael Gamon, and Scott Counts. Happy, nervous or surprised? Classification of human affective states in social media. In *Proceedings of Sixth International AAAI* Conference onWeblogs and SocialMedia (ICWSM), 2012.

Saif M Mohammad. #Emotional tweets. In *Proc. 1st Joint Conf. on Lexical and Comput. Semantics (*SEM)*, pages 246–255. ACL, 2012.

Distant learning without labels and structural data:

Valentina Sintsova and Pearl Pu. Dystemo: Distant Supervision Method for Multi-Category Emotion Recognition in Tweets. ACM Transactions on Intelligent Systems and Technology (TIST), 8(1):Article No 13, 2016

4

Modifiers: emotion shifts

Examples

I am not ashamed: the emotion has shifted from shame to pride

I feel so relieved now: intensifier to increase the degree of relief

I feel a little sad: it diminishes the degree of sad

I know i should be happy: shift from happy to sad/regret

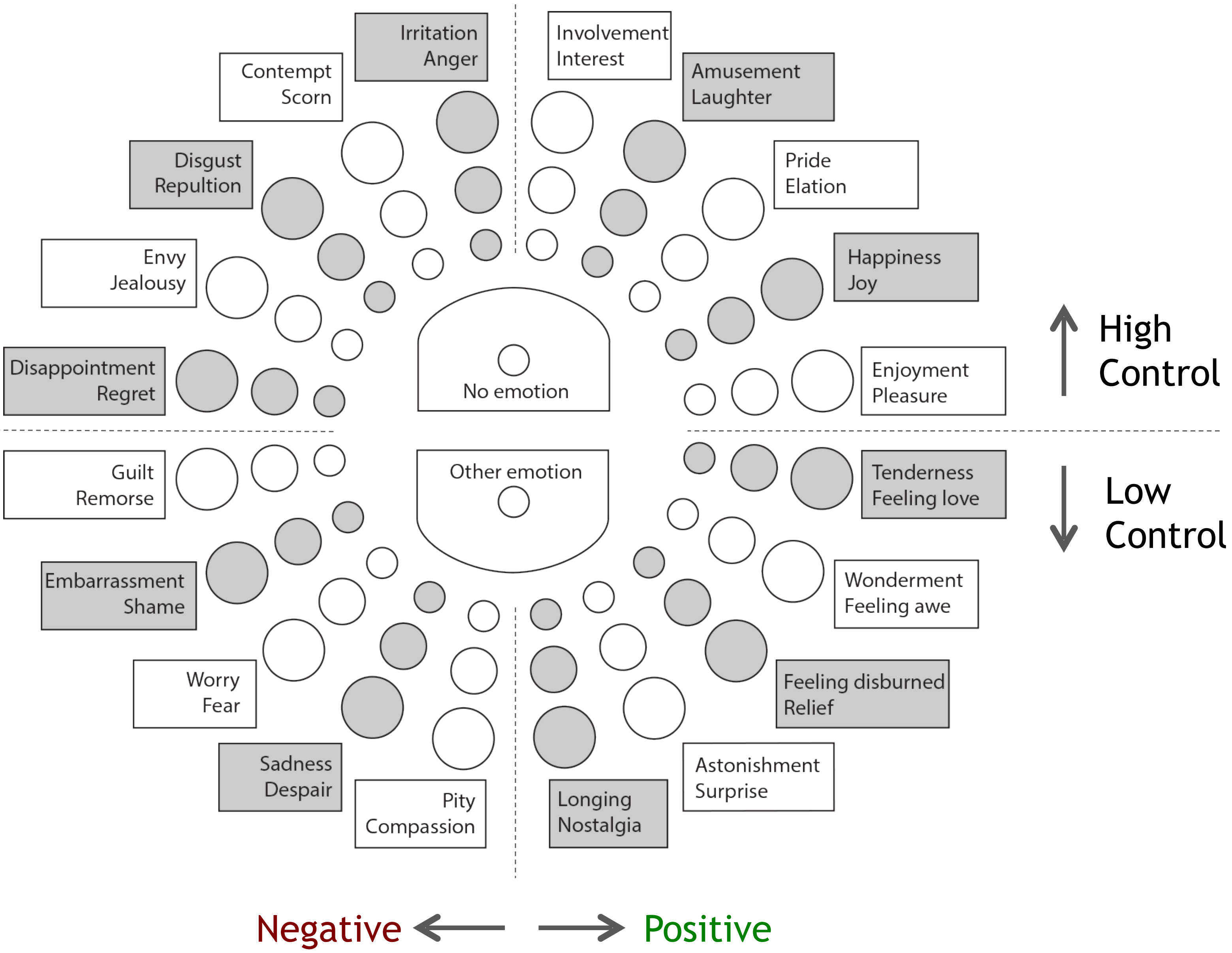
I'll be sad if you leave: fear for event that may happen

Do you love her? interest/involvement, anger

I was happy then: disappointment/regret

Novelty

- treat 6 modifiers simultaneously
- data-driven method
- re-mapping



Irritation
Anger

Involvement
Interest

Contempt
Scorn

Amusement
Laughter

Disgust
Repultion

Pride
Elation

Envy
Jealousy

Happiness
Joy

Disappointment
Regret

No emotion

Enjoyment
Pleasure

High Control

Guilt
Remorse

Other emotion

Tenderness
Feeling love

Low Control

Embarrassment
Shame

Wonderment
Feeling awe

Worry
Fear

Feeling disburned
Relief

Sadness
Despair

Astonishment
Surprise

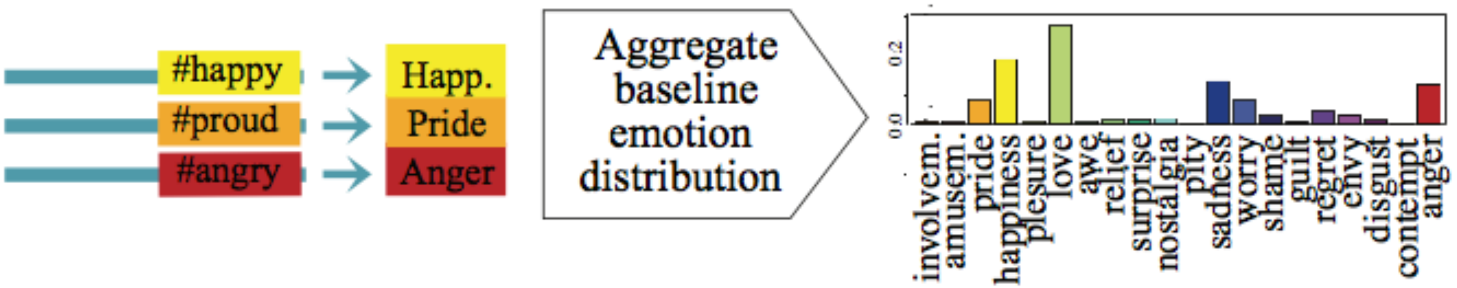
Pity
Compassion

Longing
Nostalgia

Negative ← → Positive

GEW, adapted version 2.0

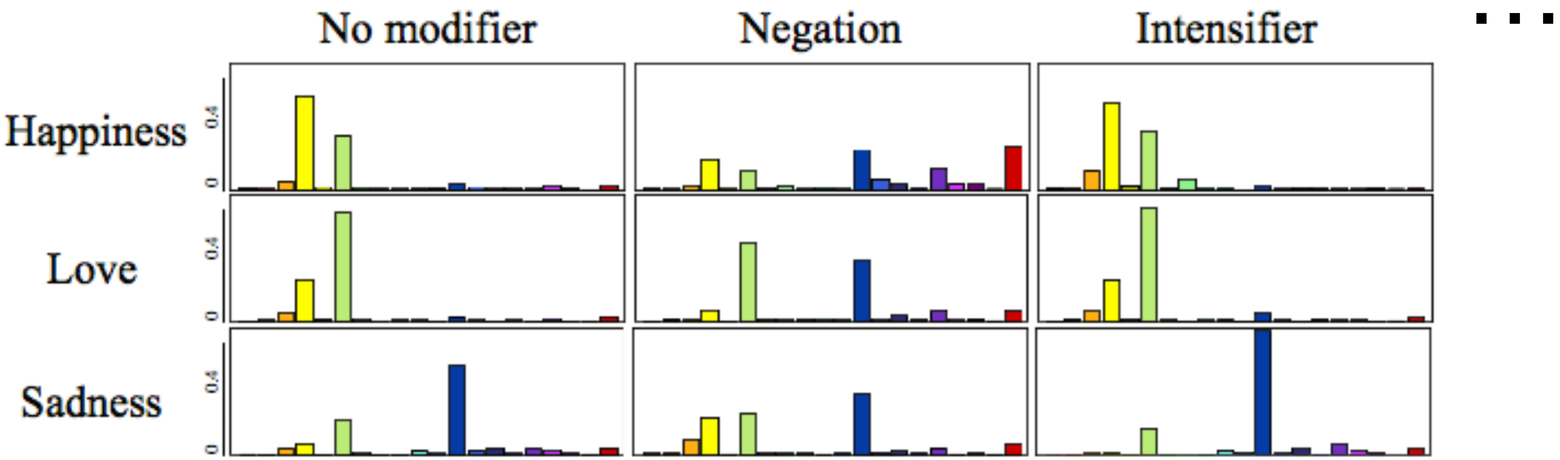
1. Collect tweets with emotional hashtags



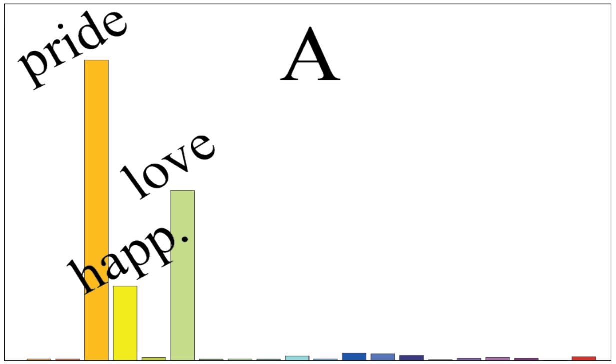
2. Detect lexicon emotional terms and their modifiers

	TERM EMOTION	DETECTED MODIFIER	HASHTAG EMOTION
(a) I am happy you are here #joy	Happiness	No modifier	Happiness
(b) *Not* ashamed to admit it #proud	Shame	Negation	Pride
(c) I love you *so much* #love	Love	Intensifier	Love

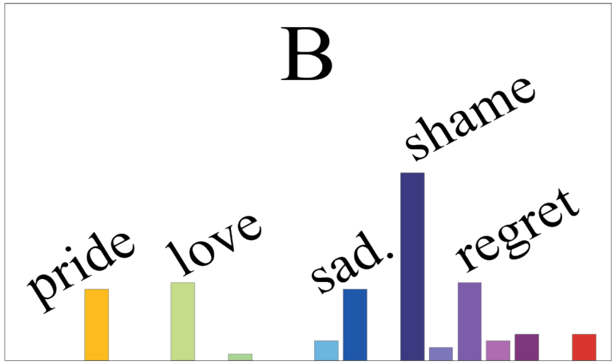
3. Aggregate distributions of hashtag emotions for each term emotion and modifier class



Pride, non-modified

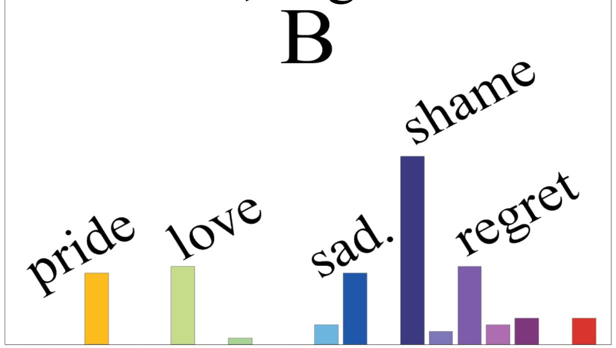


Pride, negated



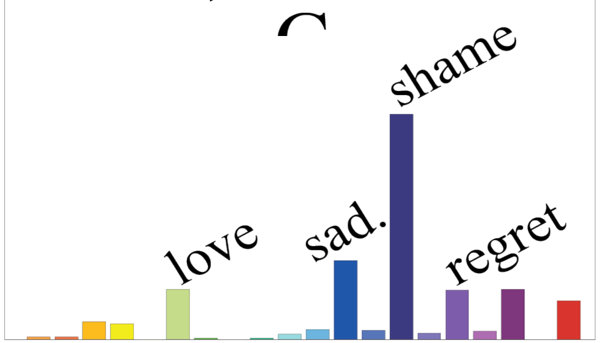
Kullback-Leibler divergence = 1.96

Pride, negated

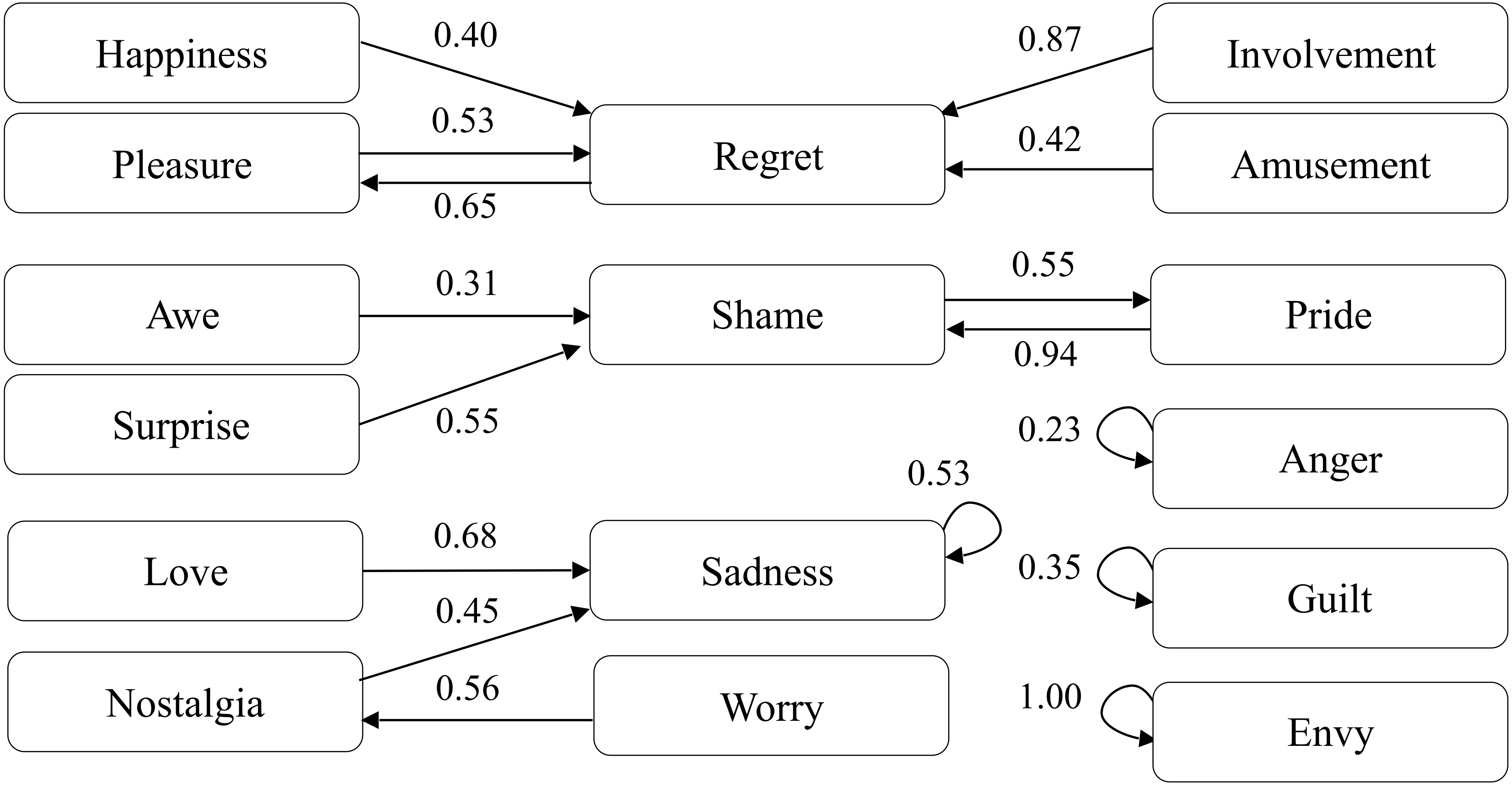


Smallest KL divergence to (0.24)

Shame, non-modified



Shifts of Emotions under Negation



All 6 Modifiers

Modifier	Modified to non-modified average distance	Average Certainty Coefficient	% of Emotion Shift
Intensifiers	0.14	1.32	17%
Past Tense	0.17	0.75	6%
Modality	0.19	0.74	19%
Conditionality	0.27	0.82	36%
Diminishers	0.30	1.17	38%
Interrogation	0.41	1.51	53%
Negation	0.80	0.56	75%

References of our work

- OlympLex

  Sintsova, Valentina, Claudiu-Cristian Musat, and Pearl Pu. "Fine-Grained Emotion Recognition in Olympic Tweets based on Human Computation." In 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis (WASSA), 2013.

- Dystemo

  Sintsova, Valentina, and Pearl Pu. “Dystemo: Distant Supervision Method for Multi-Category Emotion Recognition in Tweets.” ACM Transactions on Intelligent Systems and Technology (TIST), 2016.

- Modifiers Analysis

  Sintsova, Valentina, Margarita Bolivar Jimenez, and Pearl Pu. “The Impact of Modifiers on Emotional Statements,” in Proceedings of the International Conference on Computational Linguistics (COLING), 2008.

- Incentive Schemes for Inexpert Workers

  Sephora Madjiheurem, Sintsova, Valentina, and Pearl Pu. “Qualitative Framing of Financial Incentives – A Case of Emotion Annotation ,” arxiv.org/abs/1609.00439.

5

Conclusion

EmotionWatch Video

http://ijcai13.org/video/05

Thank You!