

University of Stuttgart Institute for Natural Language Processing



SEMALYTIX

Emotion Analysis

between Academia, Industry, Linguistics, Humanities, and Computer Science

Al2Future, Zagreb, Croatia

October 11/12, 2018

Roman Klinger

)@roman_klinger **in** romanklinger http://www.romanklinger.de/



Motivation

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So happy that America is making it possible for ALL of its people to be married to the ones they love! #MarriageEquaility





Which emotions are expressed?

Anger Anticipation Disgust Fear Joy Sadness Surprise Trust

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Motivation



2 Tiny 4 you @art_eric



I'm not angry... just aggressively disappointed.

Which emotions are expressed?

Anger Anticipation Disgust Fear Joy Sadness Surprise Trust

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Motivation





Why criticise religions? If a path is not your own. Don't be pretentious. And get down from your throne. **#religion #peace #worldpeace**

Original (Englisch) übersetzen

22:11 - 25. Juni 2015

9 ti 0 🛛

Which emotions are expressed?

Anger Anticipation Disgust Fear Joy Sadness Surprise Trust

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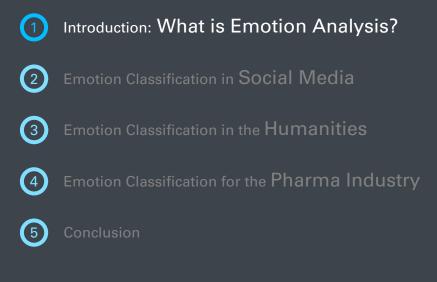
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Goal of this Presentation

- Emotion analysis is not just a more fine-grained version of sentiment analysis.
- Challenging task.
- Many open research and application questions.

Outline



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What is Emotion Analysis?

Sentiment analysis	Subjectivity analysis				
positive vs. negative	subjective vs. objective				
(neutral, mixed)					
Emotion analysis discrete (Ekman/Plutchik)	Emotion analysis cont. (Posner/Russell/Peterson)				
discrete emotion classes	valence and arousal				

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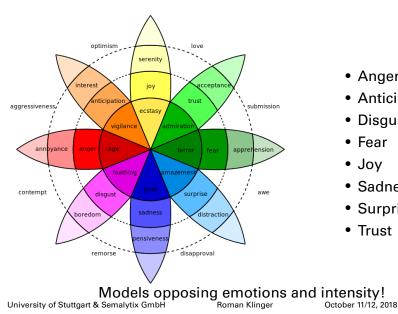
Emotion Models: Ekman



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Emotion Models: Plutchik's Wheel

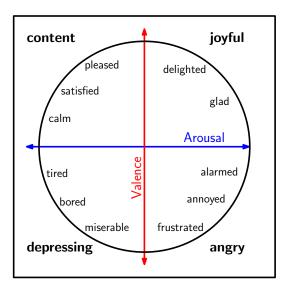


- Anger
- Anticipation
- Disgust
- Fear
- Joy
- Sadness
- Surprise
- Trust

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Emotion Models: Continuous



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What are emotions? Physiological reactions?

James-Lange Theory (1884, 1885)



Heart pounding, trembling, sweating, running away



Cannon-Bard Theory (~ 1925)

Emotions are independent of physiological signals

- backed by experiments: no reliable correlation between physiological changes and emotions
- ⇒ physiological reaction and emotion reaction are independent

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What are emotions? Physiological interactions?

Valins Effect

(Stuart Valins, 1966)





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Appraisal Theories: Why are there emotions?

Scherer, 2005

Emotions are "an episode of interrelated, synchronized changes ... in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism"

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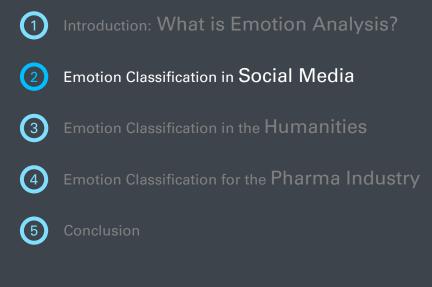
Summary

Emotions have different components...

- Cognitive appraisal
- Bodily symptoms
- Reactions
- Expression
- Subjective perceptions
- ...

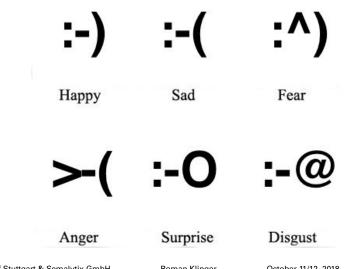
...what we do with text?

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Ekman in Social Media



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Corpora

Dataset	Туре	Annotation	Size	Source	Avail.	
AffectiveText	Ê	+ {valence}	1,250	Strapparava (2007)	D-U	
Blogs	C	🚟 + {mixed, noemo}	5,025	Aman (2007)	R	
CrowdFlower	y	🚟 + {fun, love, …}	40,000	Crowdflower (2016)	D-U	
DailyDialogs	Q		13,118	Li et al. (2017)	D-RO	
Electoral-Tweets	y	*	4,058	Mohammad (2015)	D-RO	
EmoBank	8 🖻 C		10,548	Buechel (2017)	CC-by4	
EmoInt	y	🚟 - {disgust, surprise}	7,097	Mohammad (2017)	D-RO	
Emotion-Stimulus		🗰 + {shame}	2,414	Ghazi et al. (2015)	D-U	
fb-valence-arousal	f	100	2,895	Preoțiuc (2016)	D-U	
Grounded-Emotions	7	88	2,585	Liu et al. (2017)	D-U	
ISEAR	&	🚟 + {shame, guilt}	7,665	Scherer (1997)	GPLv3	
Tales			15,302	Alm et al. (2005)	GPLv3	
SSEC	y	*	4,868	Schuff et al. (2017)	D-RO	
TEC	y	🗰 + {±surprise}	21,051	Mohammad (2012)	D-RO	

Bostan/Klinger, COLING 2018

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Task Description and Research Question

Corpus Generation Task

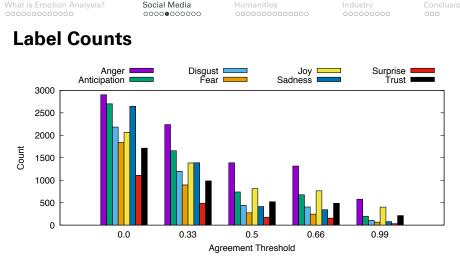
• 4870 Tweets with preexisting annotation of sentiment and stance (SemEval 2016)

Research Questions

- What's the inter-annotator agreement?
- Which annotation layers interact?
- How well is it possible to computationally estimate such annotations?

Schuff et al, WASSA 2017

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- \Rightarrow Seldom that all annotators agree
- ⇒ Low number of majority vote annotations
- \Rightarrow Low quality of annotation combination?

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Difficult Examples (1)





That moment when Canadians realised global warming doesn't equal a tropical vacation **#BCwildfire #Canadaburns #globalwarming**

S Original (Englisch) übersetzen

17:59 - 7. Juli 2015

AngerAnticipationDisgustFearJoySadnessSurpriseTrust> 0.33> 0.33> 0.33> 0.33

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Difficult Examples (2)

"2 pretty sisters are dancing with cancered kid"



AngerAnticipationDisgustFearJoySadnessSurpriseTrust> 0.0> 0.0> 0.0> 0.0> 0.0

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Cooccurrences of Labels

		Emotions							Sentiment			Stance		
	Anger	Anticipation	Disgust	Fear	yol	Sadness	Surprise	Trust	Positive	Negative	Neutral	In Favor	Against	None
Anger	2902	1437	1983	1339	774	2065	711	640	275	2534	93	630	1628	644
Anticipation		2700	1016	1029	1330	1369	482	1234	1094	1445	161	772	1291	637
Disgust			2183	1024	512	1628	526	404	126	2008	49	429	1291	463
Fear				1840	466	1445	407	497	306	1445	89	448	982	410
Joy					2067	682	438	1101	1206	750	111	596	952	519
Sadness						2644	664	613	345	2171	128	604	1429	611
Surprise							1108	222	219	801	88	257	521	330
Trust								1713	1082	558	73	500	860	353
Positive							—		1524	0	0	485	673	366
Negative									1524	3032	0	622	1665	745
Neutral										3032	312	97	71	144
Noutial														
In Favor												1204	0	0
Against None													2409	0 1255

 Many cooccurrences as expected (pos w/ pos, neg w/ neg)Positive Anger Negative Joy Positive Disgust

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Examples

Positive Anger

"Lets take back our country! Whos with me? No more Democrats!2016" "Why criticise religions? If a path is not your own. Don't be pretentious. And get down from your throne."

Negative Joy

"Global Warming! Global Warming! Global Warming! Oh wait, it's summer."

"I love the smell of Hillary in the morning. It smells like Republican Victory."

Positive Disgust

"#WeNeedFeminism because #NoMeansNo it doesnt mean yes, it doesnt mean try harder!"

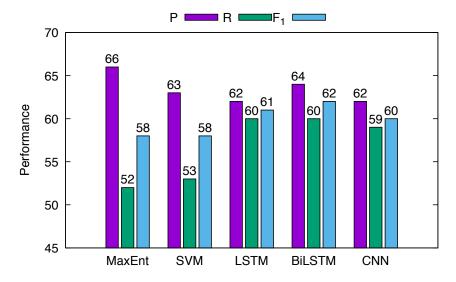
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Models



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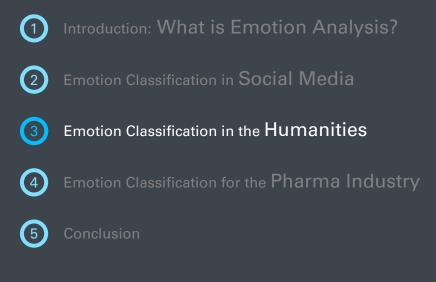
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Conclusion: Emotion Classification in Social Media

- Deep learning better than traditional models (but super-slow)
- Still difficult problem with challenging instances
- Enables a lot of analysis tasks: Query for tweets including specific entities to evaluate the associated emotion (we will come back to that later)

Outline





Literary Studies

Our Research Question

Can we characterize literature with the help of emotion analysis?

Gaspar Melchor de Jovellanos painted by Francisco José de Goya y Lucientes

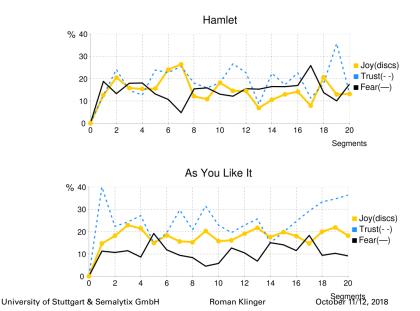
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Previous Work: Mohammad, 2011

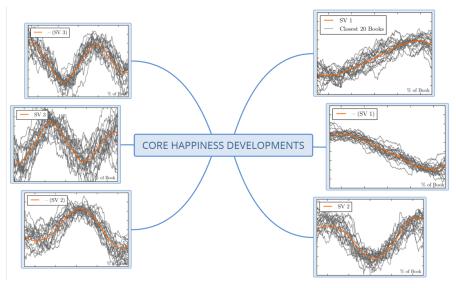


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Previous Work: Reagan, 2016



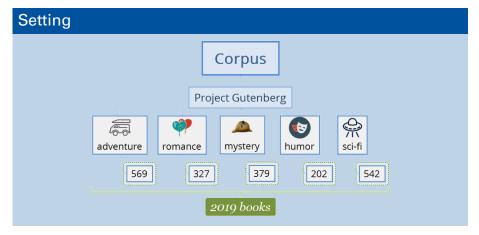
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Can we use this information to predict genres?



Kim et al, LaTeCH-CLfL 2017

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Setting

Features

- Emotion scores
- Bag-of-words
- Emotion words

Models

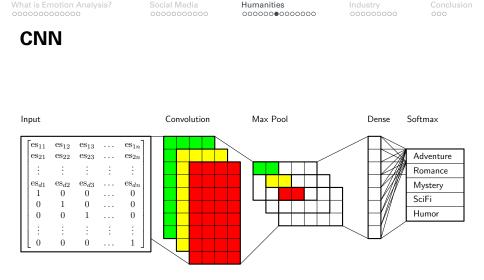
• Random Forrest, Multi-layer Perceptron, CNN

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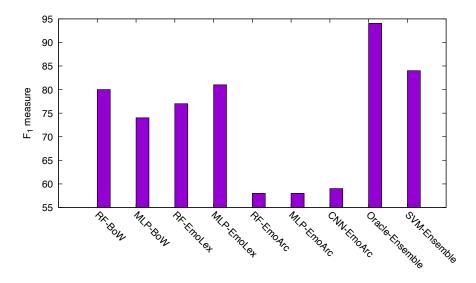


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Results for Genre Classification

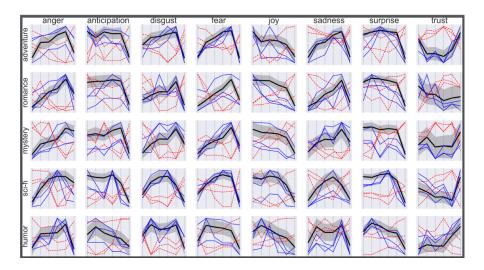


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Genres and Emotion



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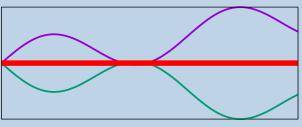
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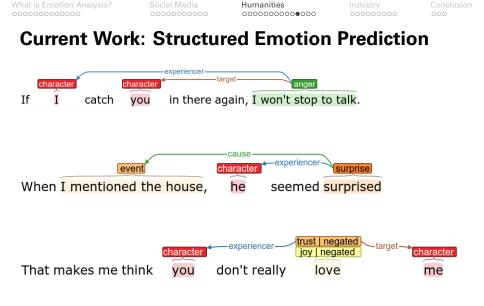
Summary and Future

• Emotion curves and words predict genres clearly better than random

Challenge

Approach ignores differences in characters and interactions





REMAN Corpus (Kim, COLING 2018)

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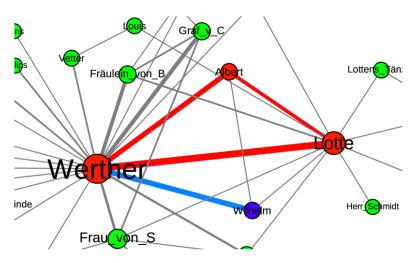
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Emotion Character Networks



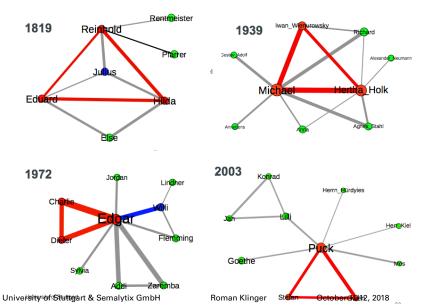
(Barth, Kim, Murr, Klinger. DHd 2018)

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Emotion Character Networks



IEST Implicit Emotions Shared Task

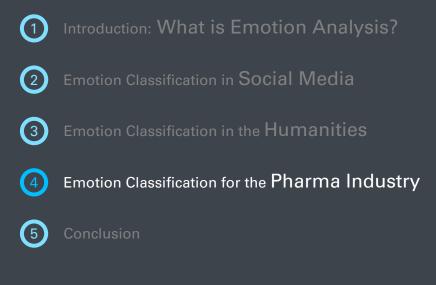
Example Instances

- It's EMOTION when you feel like you are invisible to others.
- My step mom got so EMOTION when she came home from work and saw that the boys didn't come to Austin with me.

Material online

http://implicitemotions.wassa2018.com Klinger, De Clercq, Mohammad, Balahur, WASSA 2018

Outline



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⁷ Dark Data Understanding



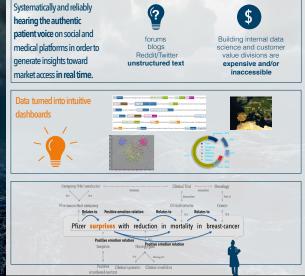
BEACON™ scales Dark Data Understanding by combining:

- cutting-edge analytics
- data visualisation
- full service integration

It takes unstructured text and structures it. It understands the text's context the way a human expert would. It pro-vides highly intuitive and actionable insights, in real-time.

Problem

Commercialisation



"I imagine mum would have also have been suffering something similar as well as her other symptoms. She was put on antipsychotics. Sadly though, she is still suffering delusions to some degree."

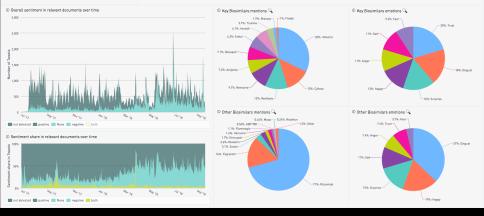
"... have found the treatment easy to deal with [...] Ive suffered minor things such as higher than normal temperatures, joint aches, itching, appetite loss and joint aching [...] none of these side effects have stopped me operating as normal tho." ③ Number of relevant documents

271k

Documents crawled between 2017-07-01 and 2018-09-12

Number of relevant documents

🔳 All Documents 📒 Retweets 🔳 Original Tweets



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Examples

Anger

If you suffer from psoriasis, postnatally prepare to turn into a hideous scaly beast! #ShitTheyDontTellYou #LongSleevesAgain #ltchyAF

Joy

So grateful power has been restored & I was able to get my remicade infusion today. ? #HurricaneIrmaAftermath #autoimmune

Sadness

So far today: my insurance decided to stop covering my humira, my hip aching from the rain moving in, my foot is swollen, and I wanna cry.

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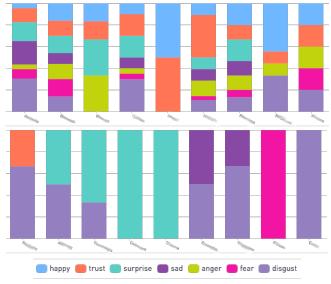
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Comparison of Biosimilars



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Challenges

- Training on SSEC, testing on biosimilar data lead to $\approx 3\,\% \textit{F}_1$
- Reannotation (of test, then of training data) is expensive and takes time (though that's what we do)
- Method selection for transfer learning from existing corpora is not solved

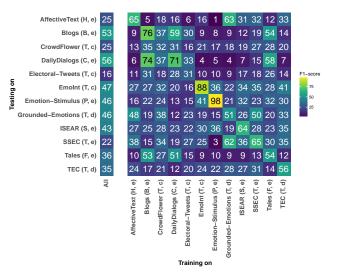
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Transfer learning between corpora



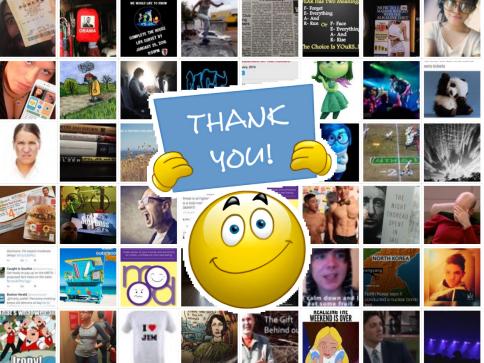
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Conclusion

- Emotion analysis backed well by psychology
- Transfer to natural language processing incomplete
- Models typically overfit to text source or domain
- Huge potential in applications across different domains



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