University of Stuttgart
Institute for
Natural Language Processing

Sentiment and Emotion Analysis from Text

KULWI Workshop

November 19, 2018

Roman Klinger

@roman_klinger romanklinger
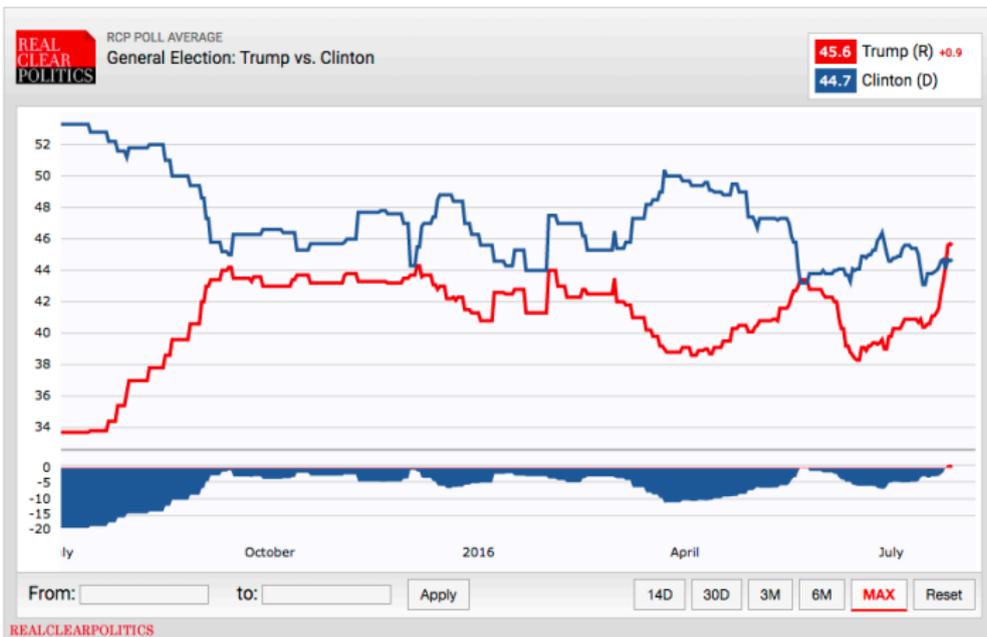http://www.romanklinger.de/

Outline

Outline

Motivation

Idea of Sentiment Analysis
(often synonymously used with "Opinion Mining")

- To extract the opinion of some holder towards a target

Examples

- Decide if product is positive or negative based on reviews
- Predict outcome of an election based on all Tweets mentioning a party or politician
- …

Motivation: Track Opinion over time

http://www.realclearpolitics.com/epolls/2016/president/us/
general_election_trump_vs_clinton-5491.html

Sentiment Analysis
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Emotion Analysis
○○○○○○○○○○○○○○○○○○

Emotion Classification in Literature
○○○○○○○○○○

Conclusion
○○○

Motivation: Use Cases and Applications
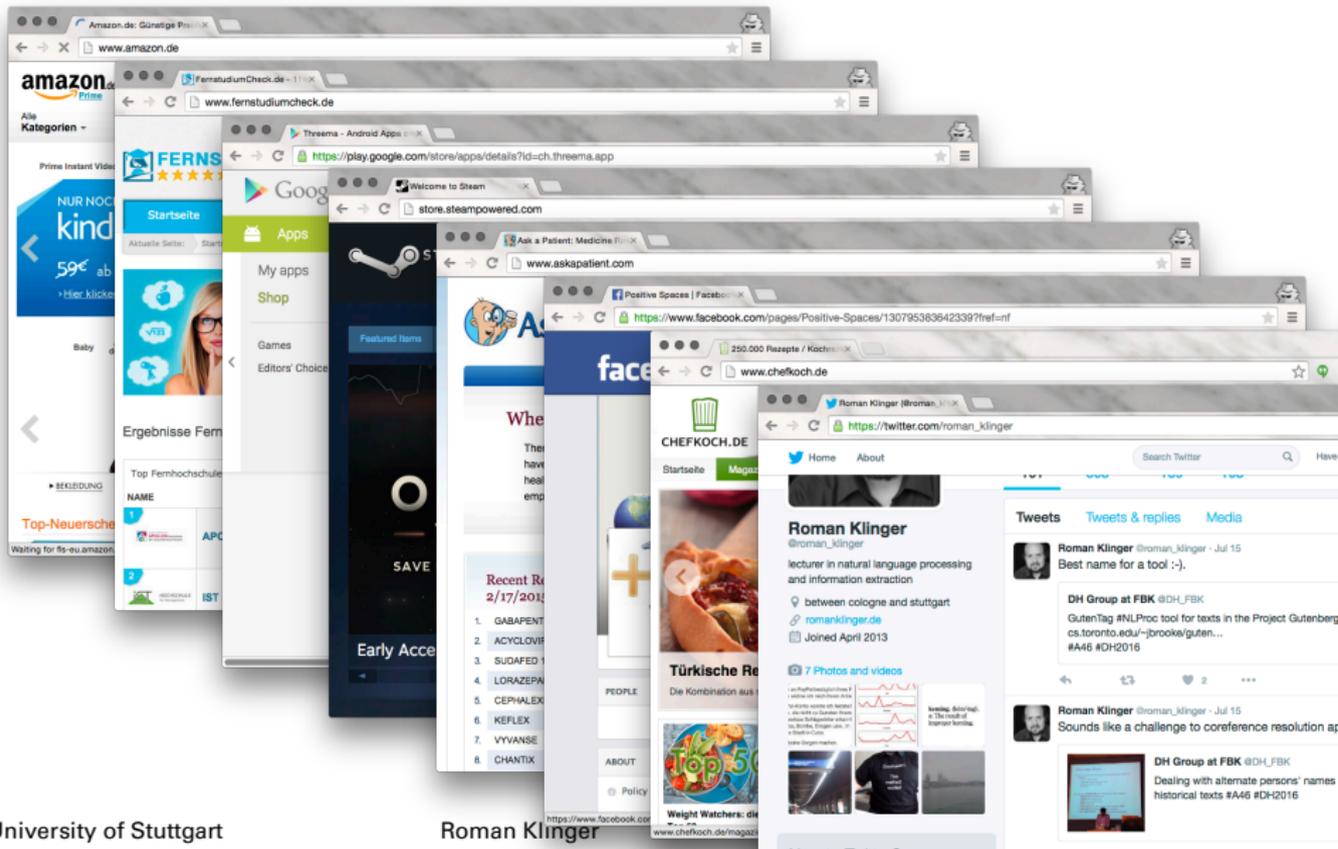
Task Definitions

Idea of Sentiment Analysis
(often synonymously used with "Opinion Mining")

- To extract the opinion of some holder towards a target

Simplification: Text Classification

- Input: Text
- Output: Class (positive, negative, neutral)

Sentiment Analysis
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Emotion Analysis
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Emotion Classification in Literature
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Conclusion
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Sentiment Analysis as Text Classification

Sentiment Analysis as Text Classification

Review for trash can

Great Deal!!!! …Shopped around for stainless steel trash can and the price and look and performance is awesome. Now I know people have complained about the motion sensor stopped working, but had for a few months and on a couple of occasions it did stop working, but due to the trash was up to the lid and hit the turn off button on the underside of the lid. The trash can seems be very good quality and looks great. The only complaint or recommendation would be to place the on and off switch inside the lid elsewhere or in a compartment where as it can be accidentally turned off.

`http://www.amazon.com/dp/B0031M9H3A`

More examples…

- "Elvis Mitchell, May 12, 2000: It may be a bit early to make such judgments, but Battlefield Earth may well turn out to be the worst movie of this century."

- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up."

- "Read the book"

State of the art in Sentiment Classification

Prerequisite 1

- Words are represented in vector space
  - Cooccurrence count, word2vec,...
- High-dimensional space, based on context
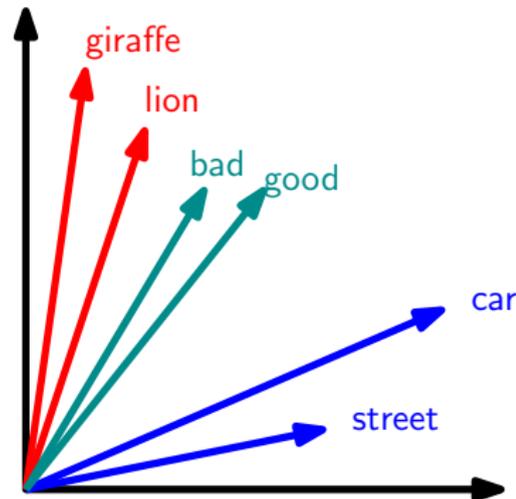
Prerequisite 2

- Vector space captures sentiment
- Typically not the case

Make Vector Spaces Sentiment Aware

Retrofitting to Dictionary

- Given vector space and
  dictionary of positive/negative words
- Move words of same polarity close to each other
- Faruqui et al. (2015)

Joint Learning

- Adapt vector space such that
  classification of document works better
- Tang et al. (2014)

Barnes/Klinger/Schulte im Walde: Assessing state-of-the-art sentiment models
on state-of-the-art sentiment datasets. WASSA 2017

Our Recent Work: Cross-Domain, Cross-Lingual

- Annotation is tedious and expensive
- Given an ...
  - Annotated corpus in source language/domain
  - Translation dictionary between source and target
  - Vector spaces in both domains/languages
- ...how can we build a model for the target domain?

Model Architecture
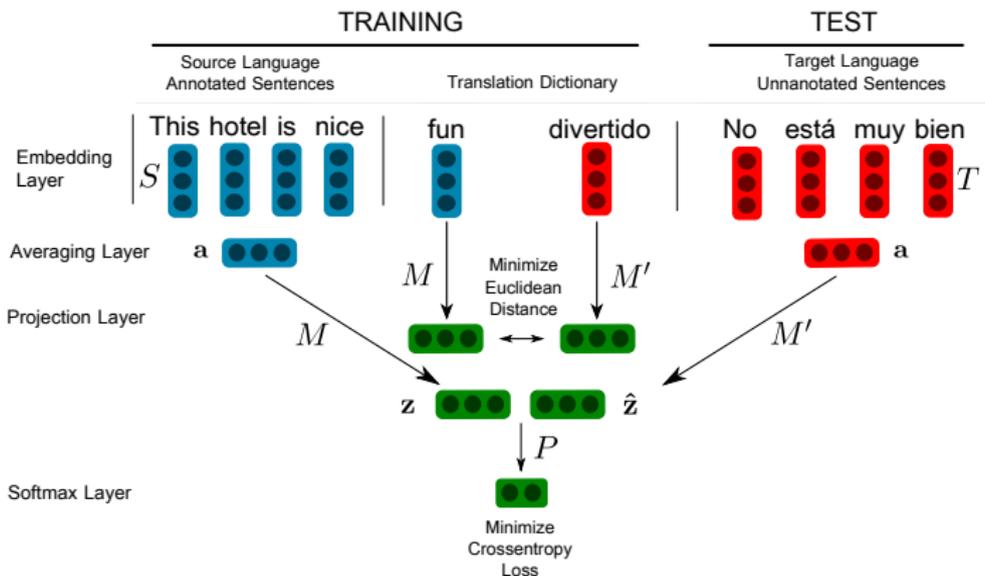
Barnes et al.: Bilingual Sentiment Embeddings: Joint Projection of Sentiment Across Languages. ACL 2018

Barnes et al.: Projecting Embeddings for Domain Adaptation: Joint Modeling of Sentiment Analysis in Diverse Domains. COLING 2018

Aspects and Subjective Phrases

Review for trash can

Great Deal!!!! stainless steel trash can
price look performance awesome
motion sensor stopped
working

trash lid
turn off button underside lid trash can
seems be very good quality looks great only complaint
recommendation place the on and off switch
lid compartment

`http://www.amazon.com/dp/B0031M9H3A`

Approaches for Targeted Sentiment Analysis

Closed Domain

- Given predefined set of relevant aspects
- Build classifiers for each aspect

Open Domain

- First detect aspect mention, then classify context
  - e.g. Hazarika et al. 2017: Modeling Inter-Aspect Dependencies for Aspect-Based Sentiment Analysis. NAACL 2018
  - Barnes/Klinger: crosslingual/crossdomain, JAIR, in review
- Joint models to extract subjective phrases and aspect mention
  - Klinger: ACL 2013, CoNLL 2015

Outline

Motivation

Roman_Klinger
@Roman_Klinger

⚙ **+ Follow**

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

↩ ⟲ ★ + •••

2:48 PM - 6 May 2015

Which emotions are expressed?

Anger   Anticipation   Disgust   Fear   Joy   Sadness   Surprise   Trust

Motivation

2 Tiny 4 you
@art_eric

Folgen   ⌄

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

Which emotions are expressed?

Anger   Anticipation   Disgust   Fear   Joy   Sadness   Surprise   Trust

Motivation

Which emotions are expressed?

Anger   Anticipation   Disgust   Fear   Joy   Sadness   Surprise   Trust

What is Emotion Analysis?

Sentiment analysis

positive vs. negative (neutral, mixed)

Subjectivity analysis

subjective vs. objective

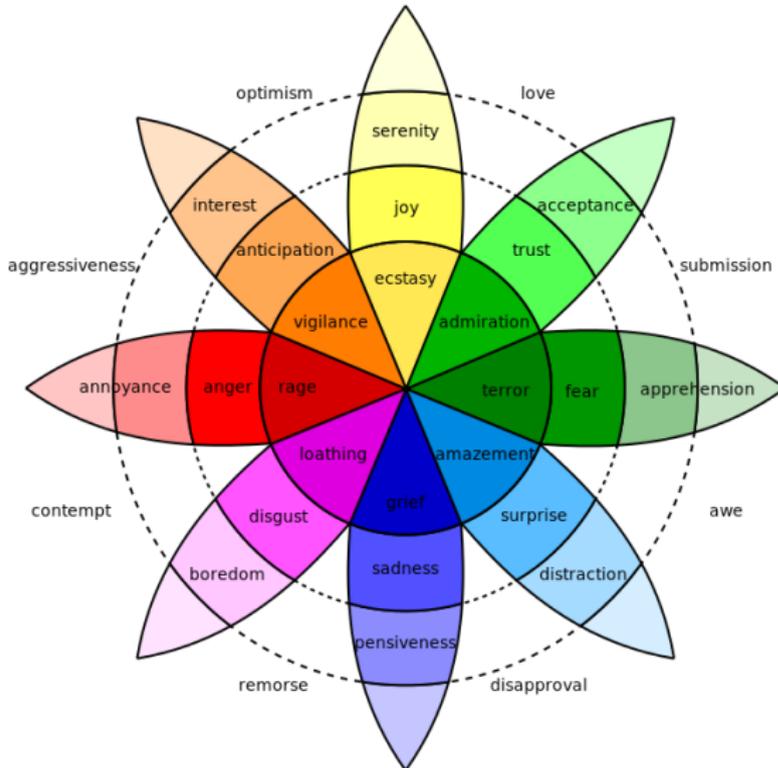## Emotion analysis discrete (Ekman/Plutchik)

discrete emotion classes

Emotion analysis cont. (Posner/Russell/Peterson)
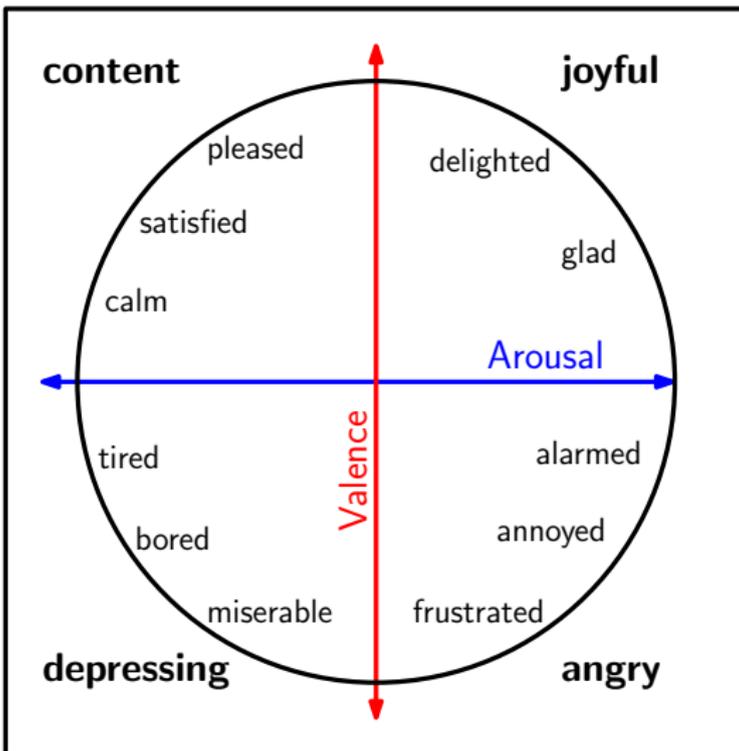
valence and arousal

Emotion Models: Ekman

Emotion Models: Plutchik's Wheel

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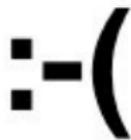- Surprise
- Trust

Models opposing emotions and intensity!

Emotion Models: Continuous

Ekman in Social Media

Corpora

Dataset	Type	Annotation	Size	Source	Avail.
AffectiveText	📄	🔳 + {valence}	1,250	Strapparava (2007)	D-U
Blogs	🔲	🔳 + {mixed, noemo}	5,025	Aman (2007)	R
CrowdFlower	🐦	🔳 + {fun, love, …}	40,000	Crowdflower (2016)	D-U
DailyDialogs	💬	🔳	13,118	Li et al. (2017)	D-RO
Electoral-Tweets	🐦	✳	4,058	Mohammad (2015)	D-RO
EmoBank	📕📄🔲		10,548	Buechel (2017)	CC-by4
EmoInt	🐦	🔳 - {disgust, surprise}	7,097	Mohammad (2017)	D-RO
Emotion-Stimulus	📄	🔳 + {shame}	2,414	Ghazi et al. (2015)	D-U
fb-valence-arousal	f		2,895	Preoţiuc (2016)	D-U
Grounded-Emotions	🐦	☺☹	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	🐦	✳	4,868	Schuff et al. (2017)	D-RO
TEC	🐦	🔳 + {±surprise}	21,051	Mohammad (2012)	D-RO

Bostan/Klinger, COLING 2018

Task Description and Research Question
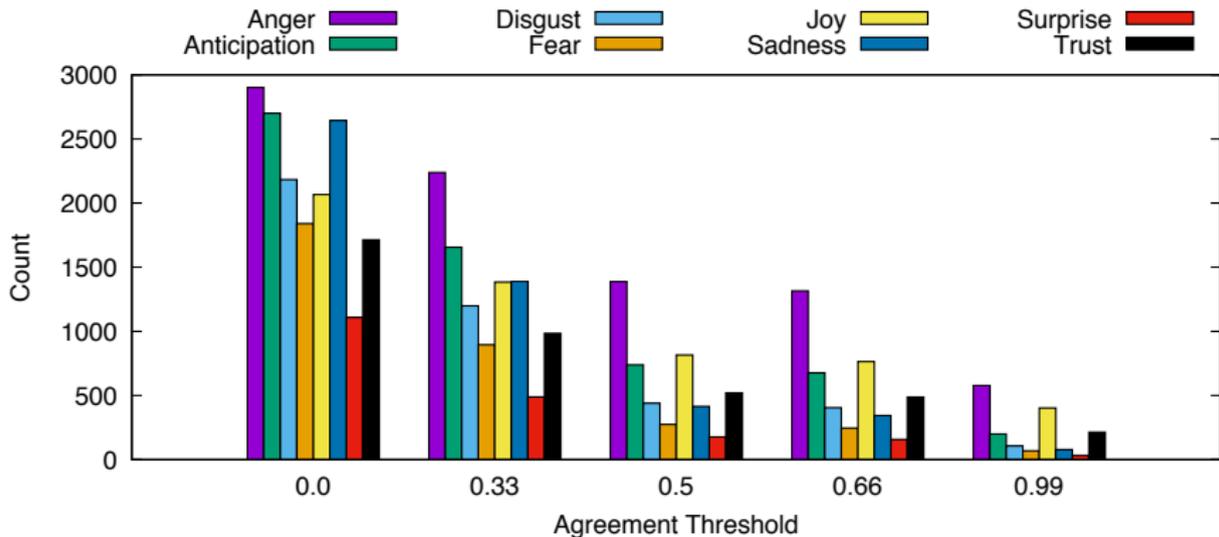
Corpus Generation Task

- 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

Label Counts

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

Difficult Examples (1)

Amanda
@Euringer

Folgen

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

Original (Englisch) übersetzen

17:59 - 7. Juli 2015

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
> 0.33					> 0.33	> 0.33	

Difficult Examples (2)

"2 pretty sisters are dancing with cancered kid"

Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust
			> 0.0	> 0.0	> 0.0		> 0.0

Cooccurrences of Labels

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Positive	Negative	Neutral	In Favor	Against	None
	Emotions								**Sentiment**			**Stance**		
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										**3032**	0	622	1665	745
Neutral											**312**	97	71	144
In Favor												**1204**	0	0
Against													**2409**	0
None														**1255**

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

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."
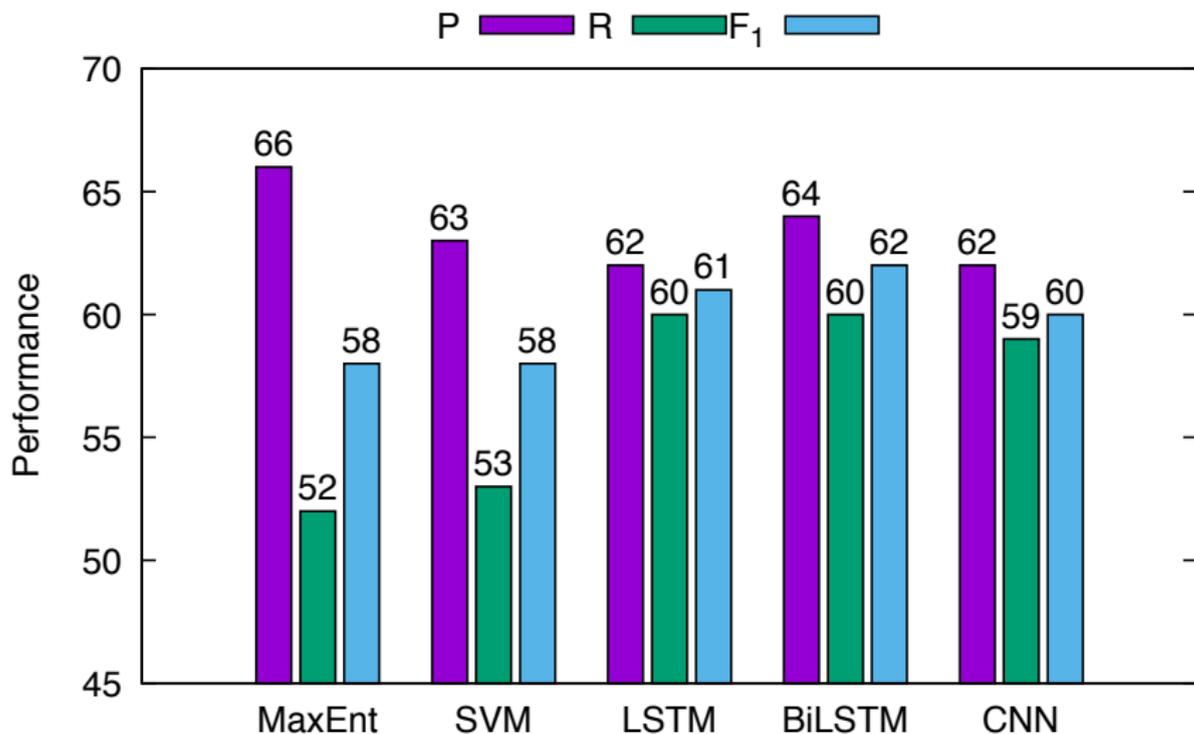
Negative Joy

"Global Warming! Global Warming! Global Warming! Oh wait, it's summer."
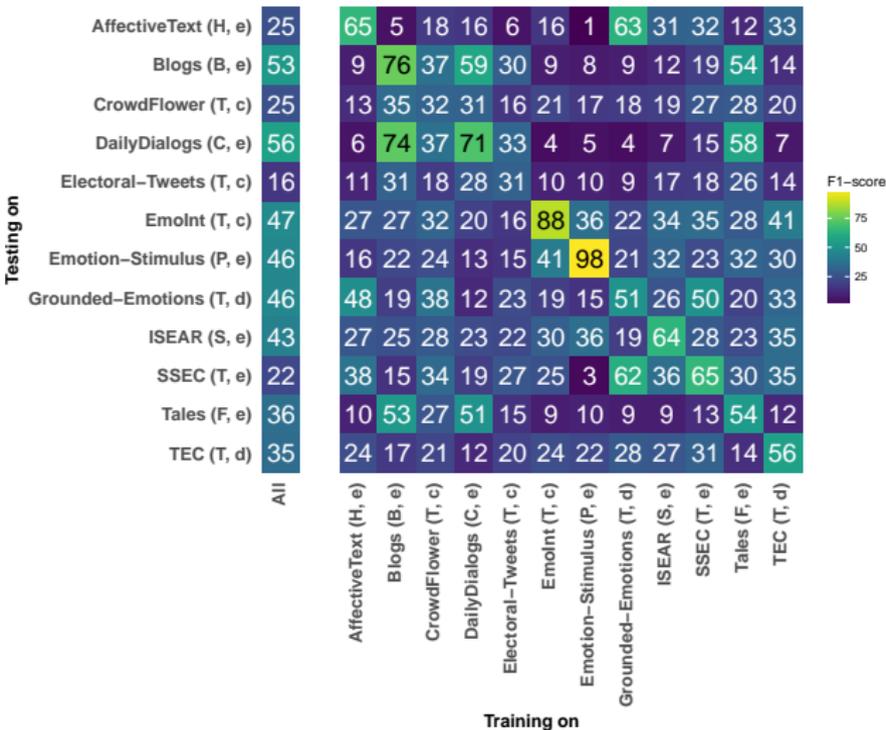"I love the smell of Hillary in the morning. It smells like Republican Victory."

Positive Disgust

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

Models

Transfer learning between corpora

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

Previous Work: Mohammad, 2011

Hamlet

Joy(discs)
Trust(- -)
Fear(—)

As You Like It

Joy(discs)
Trust(- -)
Fear(—)

Previous Work: Reagan, 2016
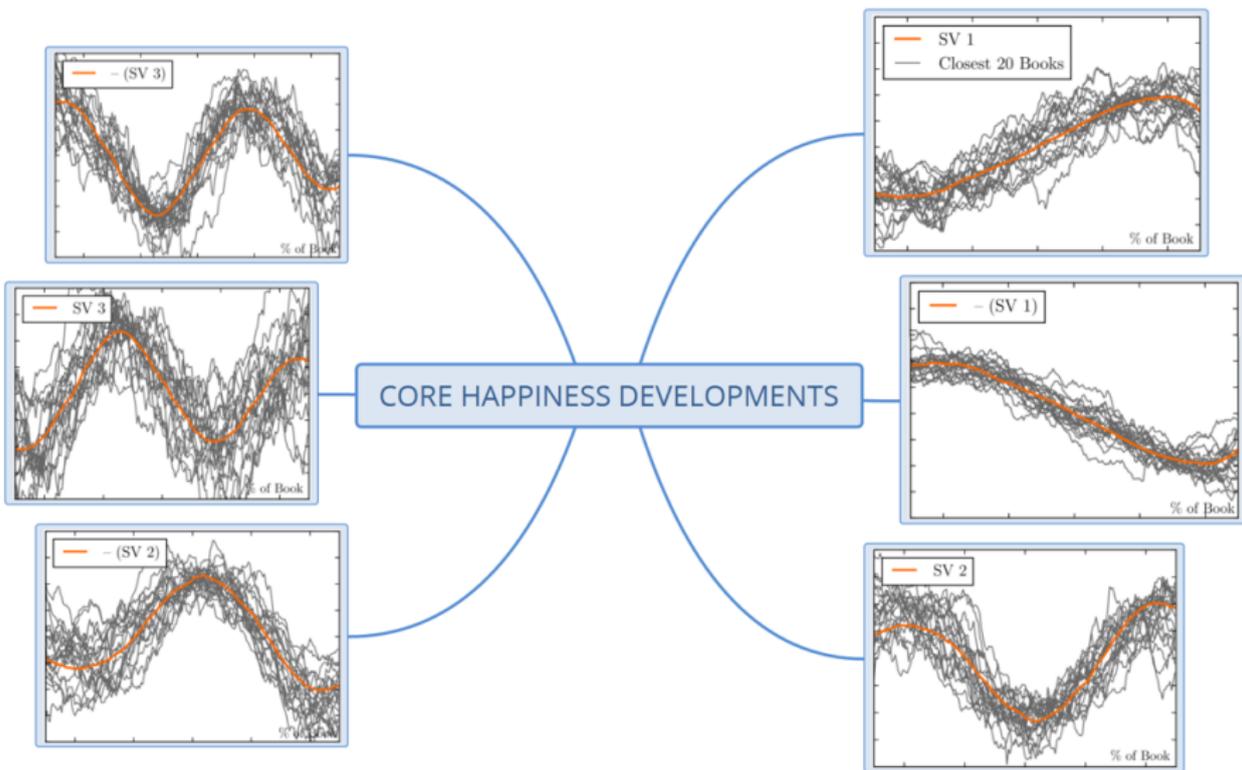
Can we use this information to predict genres?

Setting

Corpus

Project Gutenberg

adventure	romance	mystery	humor	sci-fi
569	327	379	202	542

2019 books

Kim et al, LaTeCH-CLfL 2017

Genres and Emotion
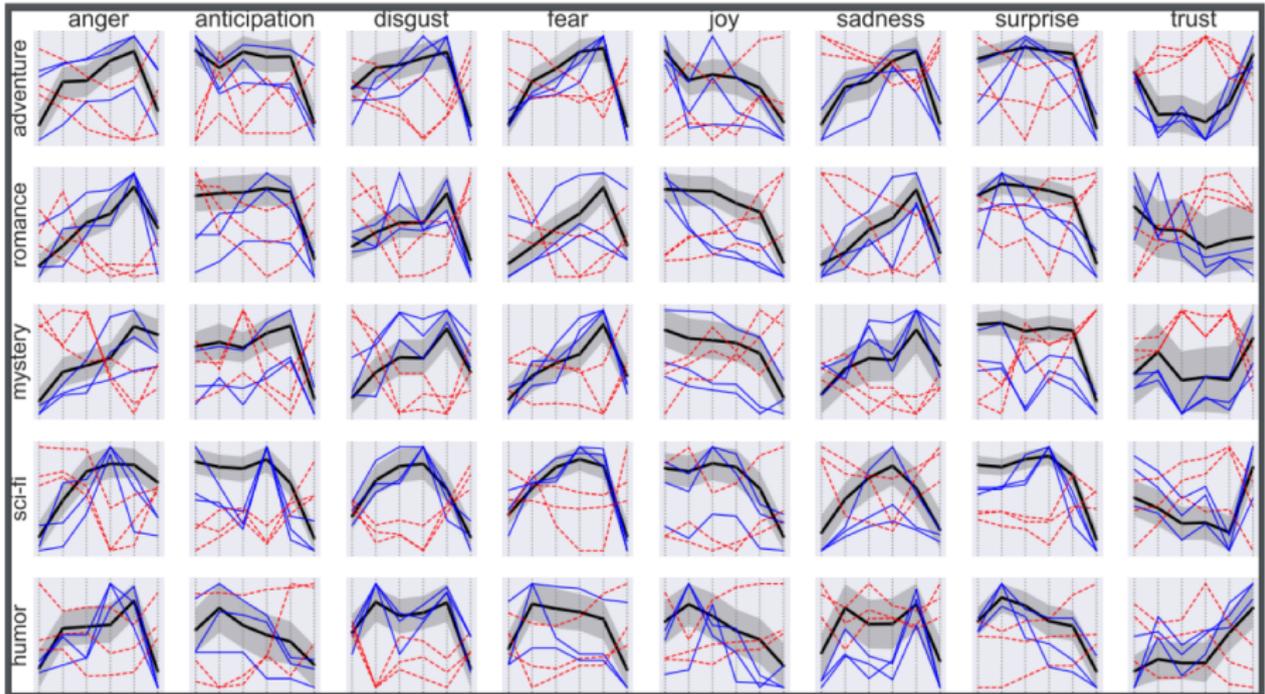
Results in Short

- Emotion development curve enables classification ($F_1 \approx 0.6$)
- Word-based classification much better ($F_1 \approx 0.8$)
- Only with Emotion-words: even slighly better ($F_1 \approx 0.81$)
- Information is complementary

Summary and Future

- Emotion curves and words predict genres clearly better than random

Challenge

Approach ignores differences in characters and interactions
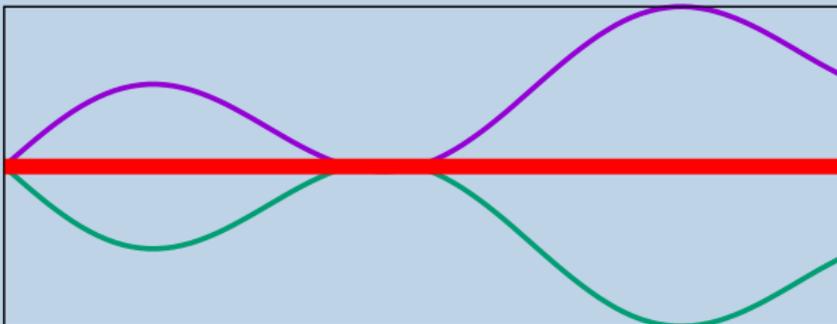
Current Work: Structured Emotion Prediction

If [character] I catch [character] you in there again, I won't stop to talk.
— experiencer / target — anger

When [event] I mentioned the house, [character] he seemed [surprise] surprised
— cause / experiencer

That makes me think [character] you don't really [trust | negated / joy | negated] love [target] [character] me
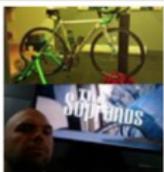— experiencer / target
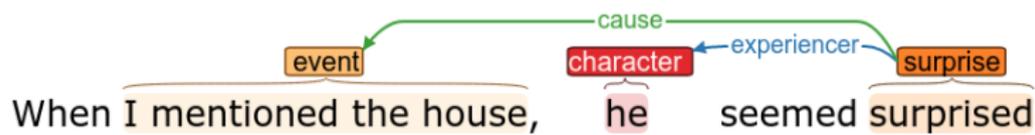
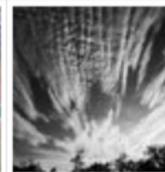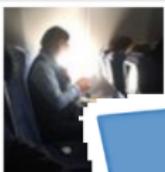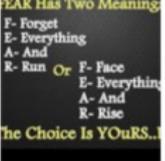REMAN Corpus (Kim, COLING 2018)

Emotion Character Networks
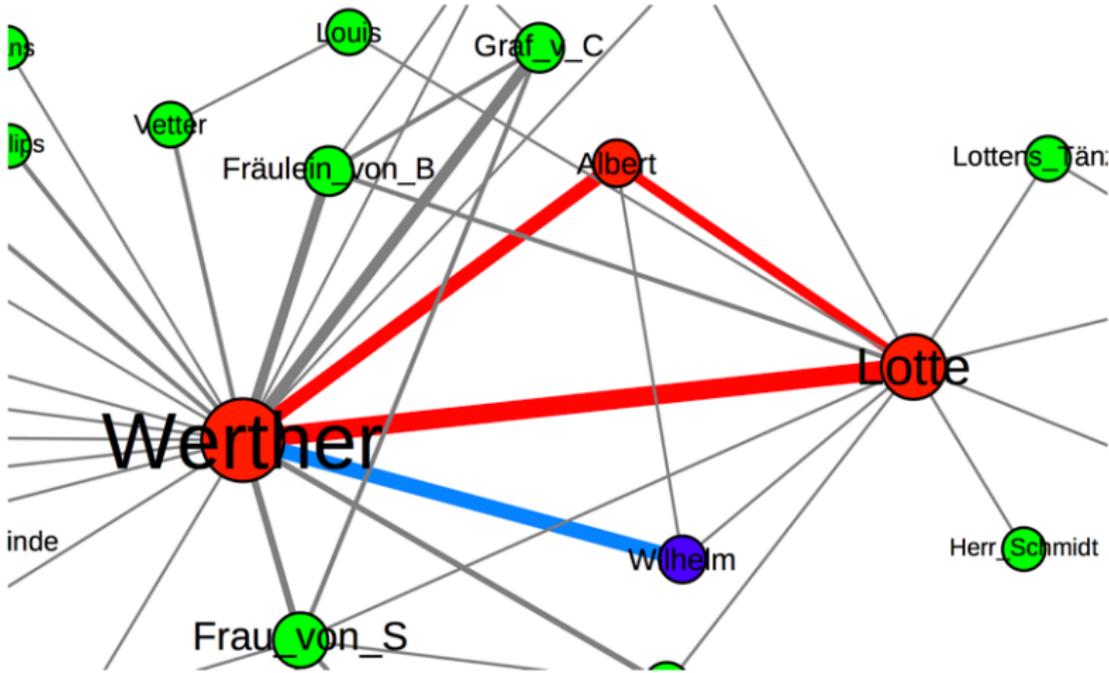
(Barth, Kim, Murr, Klinger. DHd 2018)

Emotion Character Networks
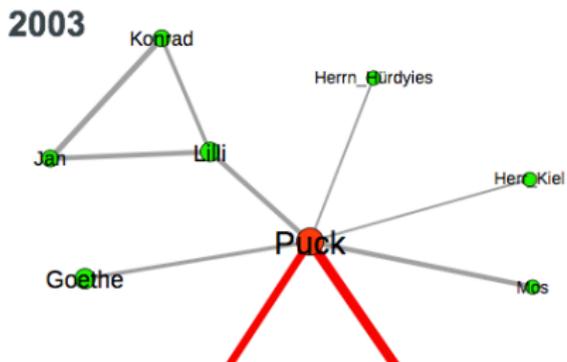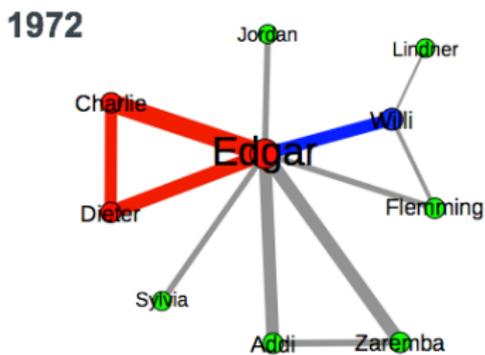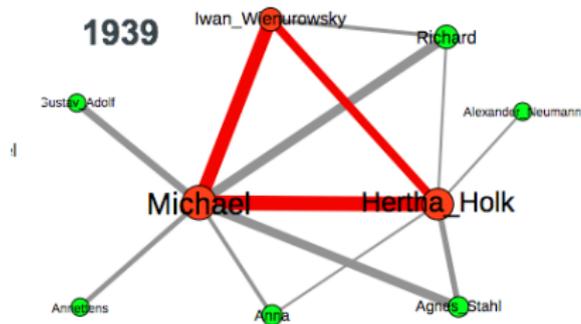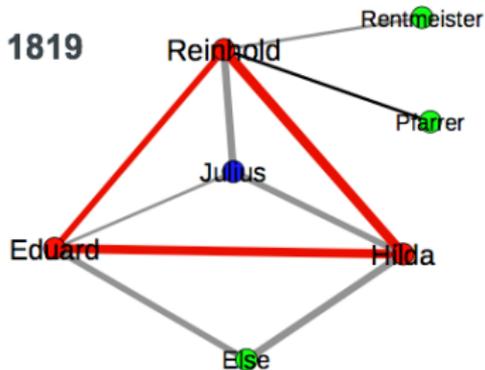
Conclusion

- 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
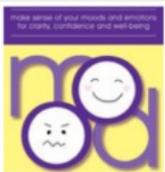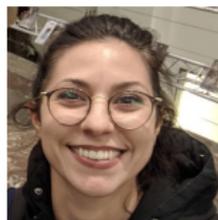
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