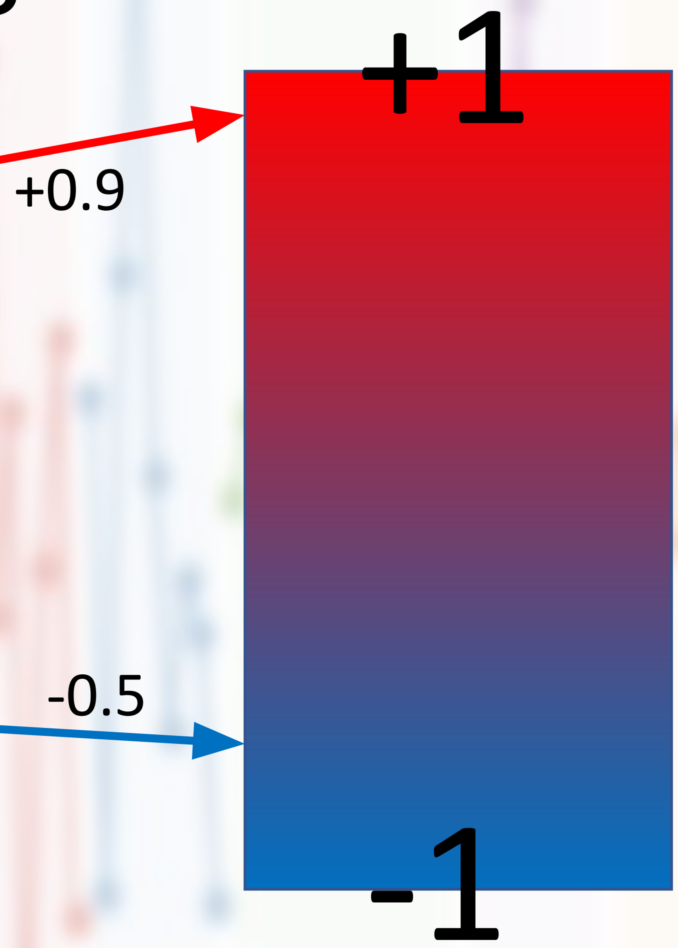
Sentiment analysis

Sentiment Analysis

"This book is fantastic!
It tells wonderful and beautiful things…"

"In those days, sadness
shadowed my heart"



Sentiment Analysis

“[…] is the field of study that analyzes people’s opinions, sentiments, appraisals, attitudes, and emotions towards entities and their attributes expressed in written text. The entities can be products, services, organizations, individuals, events, issues, or topics”

(Liu, 2015)

Sentiment Analysis

ABOUT ARTICLES BOOKS COURSES LECTURES/EVENTS PAPERS WORKSHOPS NOTED

Matthew L. Jockers

Search... Go

05
Thursday
JUN 2014

A Novel Method for Detecting Plot

POSTED BY MATTHEW JOCKERS IN COMMENTARY, TEXT-MINING ≈ COMMENTS OFF

While studying anthropology at the University of Chicago, Kurt Vonnegut proposed writing a master's thesis on the shape of narratives. He argued that "the fundamental idea is that stories have shapes which can be drawn on graph paper, and that the shape of a given society's stories is at least as interesting as the shape of its pots or spearheads." The idea was rejected.

In 2011, Open Culture featured a video in which Vonnegut expanded on this idea and suggested that computers might someday be able to model the shape of stories, that is, the movement of the narratives, the plots. The video is about four minutes long; it's worth watching.

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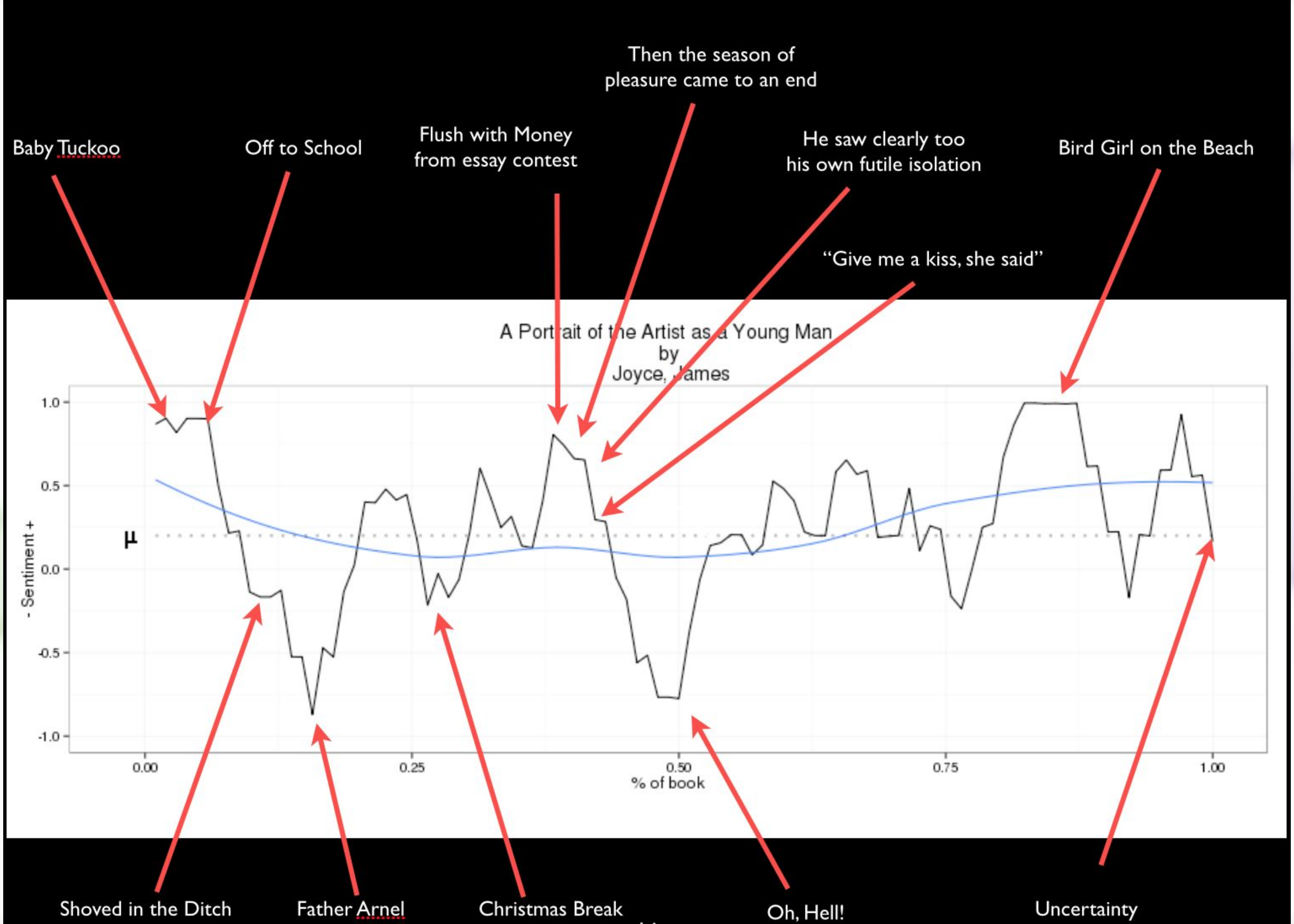
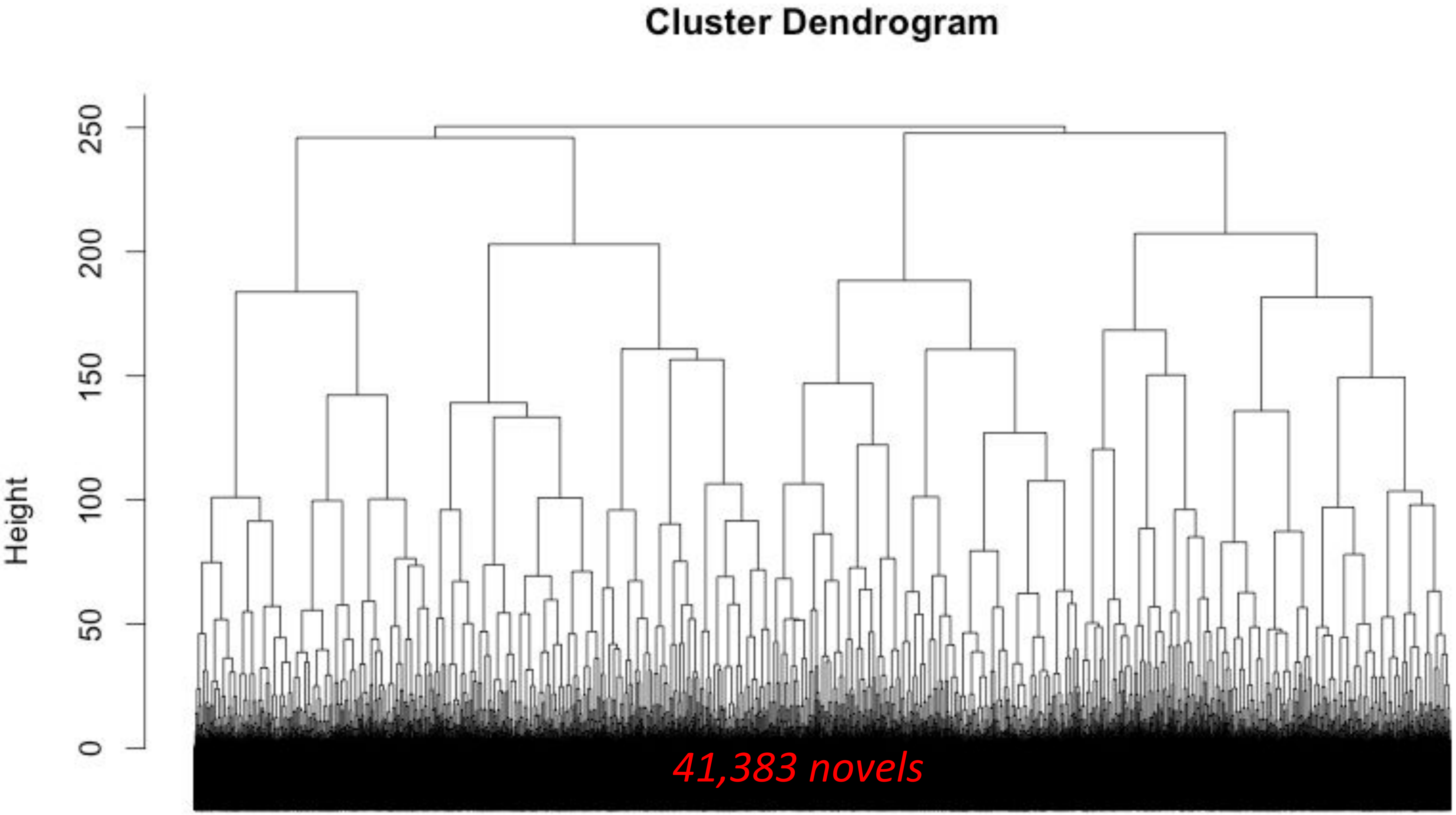
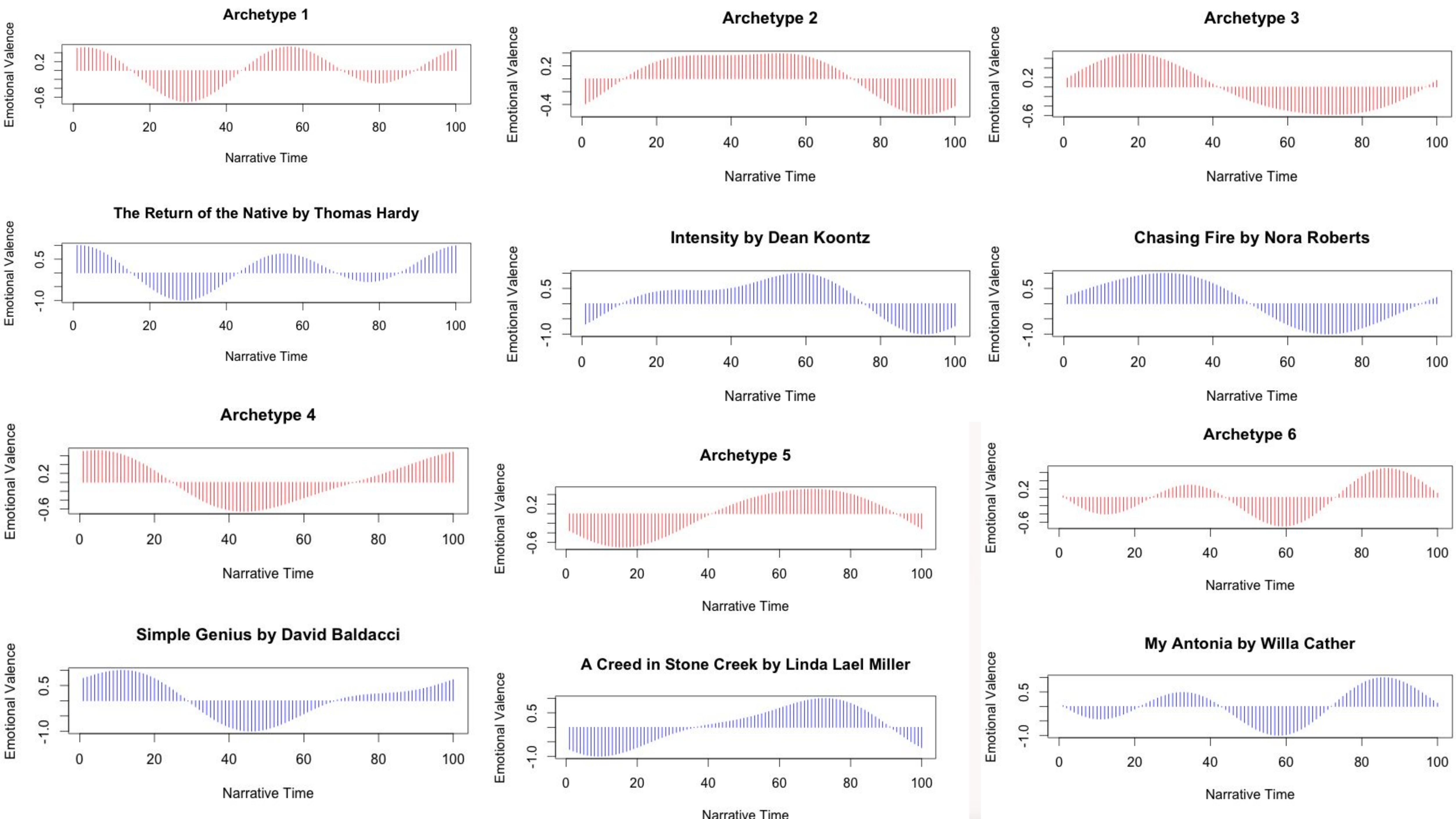
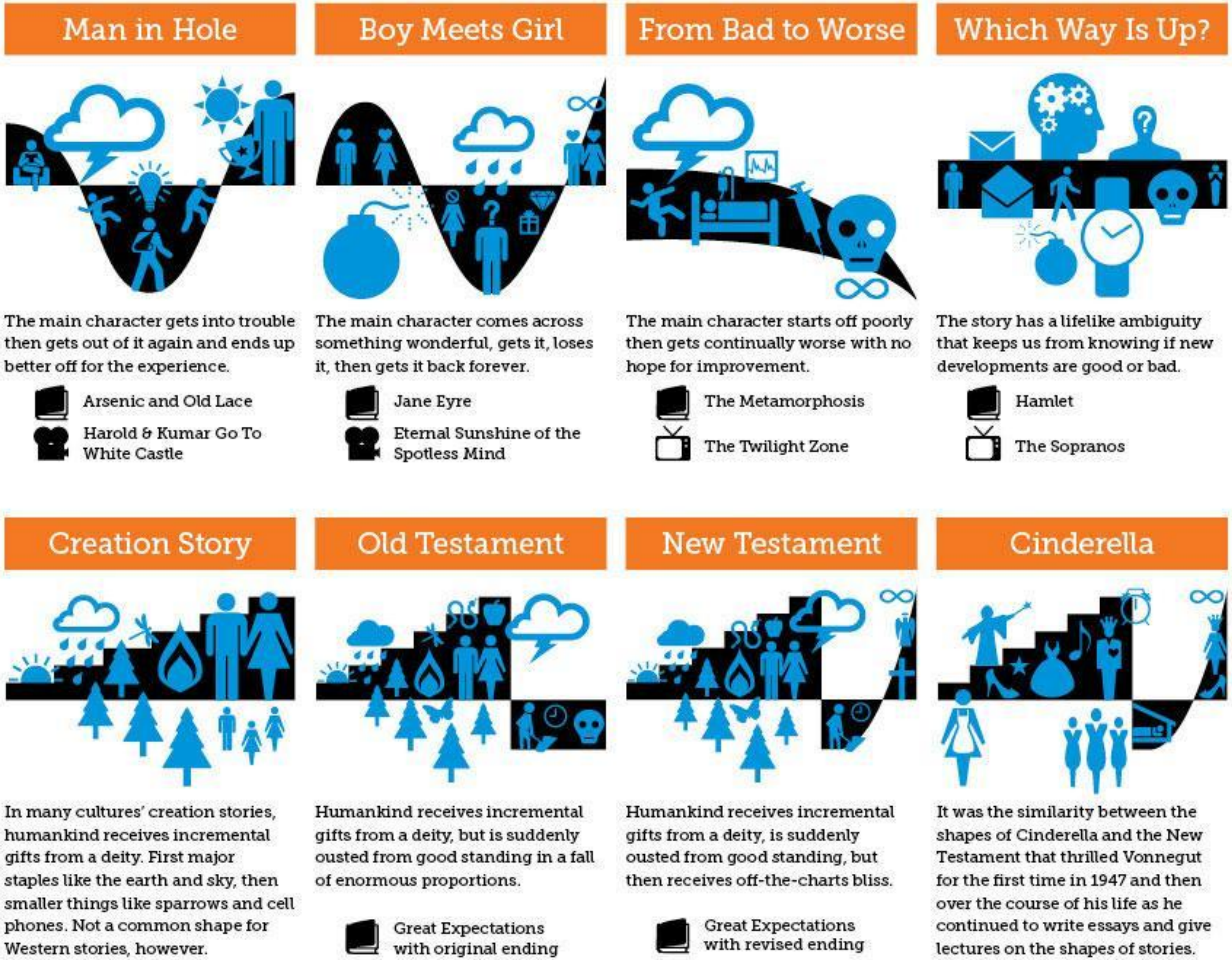


Then the season of pleasure came to an end
Baby Tuckoo
Off to School
Flush with Money from essay contest
He saw clearly too his own futile isolation
Bird Girl on the Beach
"Give me a kiss, she said"
A Portrait of the Artist as a Young Man
by
Joyce, James
1.0
0.5
0.0
-0.5
-1.0
μ
- Sentiment +
0.00
0.25
0.50
0.75
1.00
% of book
Shoved in the Ditch
Father Arnel
Christmas Break
Oh, Hell!
Uncertainty


Cluster Dendrogram
Height
250
200
150
100
50
0
41,383 novels


Archetype 1
Archetype 2
Archetype 3
The Return of the Native by Thomas Hardy
Intensity by Dean Koontz
Chasing Fire by Nora Roberts
Archetype 4
Archetype 5
Archetype 6
Simple Genius by David Baldacci
A Creed in Stone Creek by Linda Lael Miller
My Antonia by Willa Cather
Emotional Valence
Narrative Time

The Shapes of Stories
by Kurt Vonnegut



Sentiment Analysis - Critical Aspects

From a **theoretical point of view:**

- Jockers called his software «syuzhet», referring to Russian formalism (see Vladimir Propp) and narratology (the “science of narration”)
- However, traditional narratological studies (see Gérard Genette, Mieke Bal, et al.) do not consider emotions at all
- Only Patrick Colm Hogan wrote a book on *Affective Narratology* (2012), but looking at much more complex phenomena than “plot arcs”

From a **practical point of view:**

- Emotions are subjective (of course!), so their measurement can be unreliable
- SA software are generally unstable: you modify a few parameters, and you get completely different results

Sentiment Analysis

SA and cognitive literary studies

Jacobs, A. M., Schuster, S., Xue, S., and Lüdtke, J. (2017). What's in the brain that ink may character… A quantitative narrative analysis of Shakespeare's 154 sonnets for use in (Neuro-)cognitive poetics. *Scientific Study of Literature*, *7*(1): 4-51.

SA for the study of secondary literature

Mellmann, K. and Du, K. (2018). "Sentimentanalyse in Unstrukturierten Texten (Am Bsp. Literaturgeschichtlicher Rezeptionsanalyse)." In DHd 2018 Konferenzabstracts, 305–8. Cologne: Universität zu Köln.

SA for the study of social reading

Rebora, S. and Pianzola F. (2018). A New Research Programme for Reading Research: Analysing Comments in the Margins on Wattpad. DigitCult - Scientific Journal on Digital Cultures, 3(2): 19–36

SA for Italian language

Sprugnoli, R., Tonelli, S., Marchetti, A., and Moretti, G. (2016). Towards sentiment analysis for historical texts. *Digital Scholarship in the Humanities*, *31*(4): 762-772.

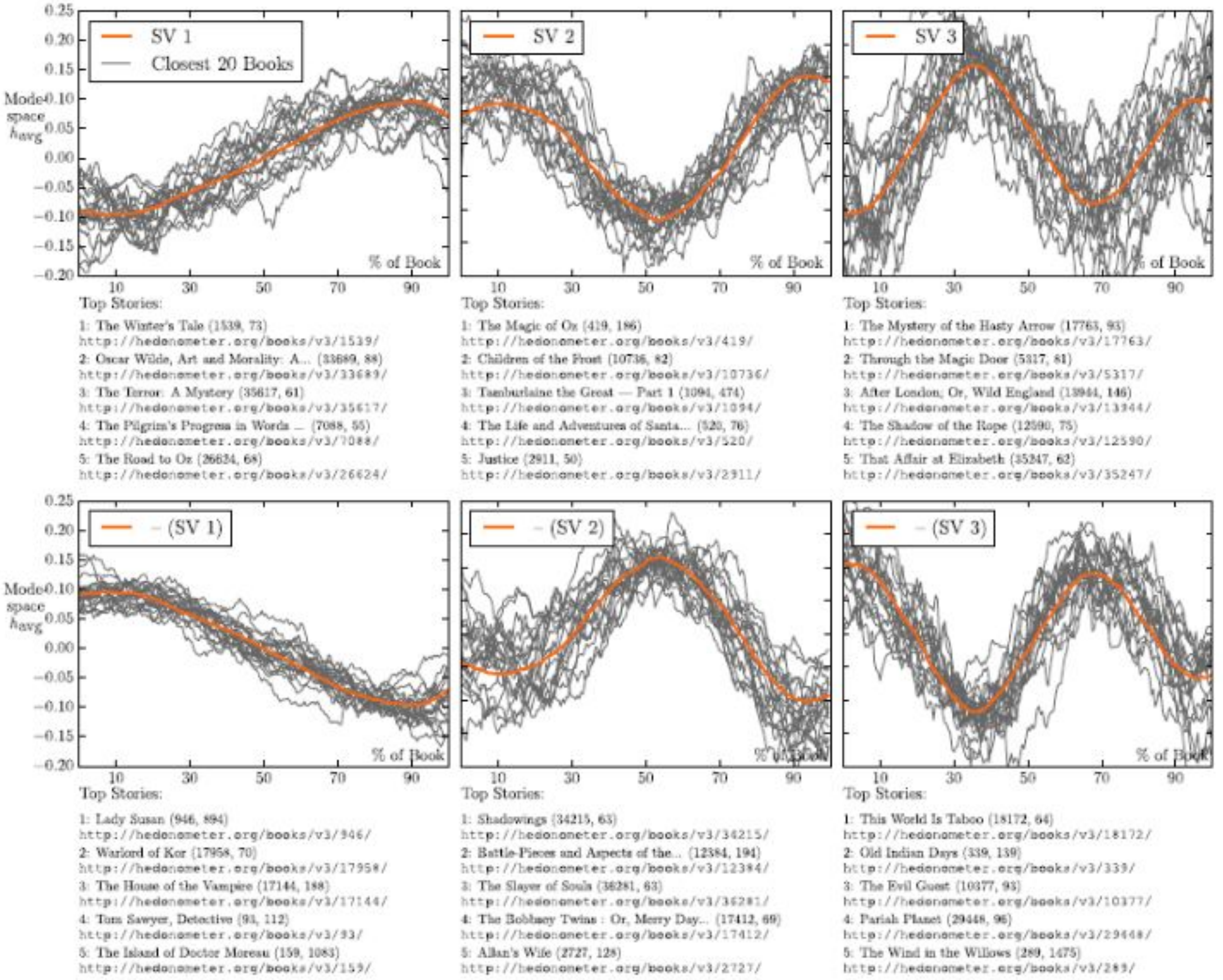
SA for German language

Zehe, A., Becker, M., Jannidis, F., and Hotho, A. (2017). Towards Sentiment Analysis on German Literature. In *Joint German/Austrian Conference on Artificial Intelligence (Künstliche Intelligenz)*. Cham: Springer, pp. 387-394.

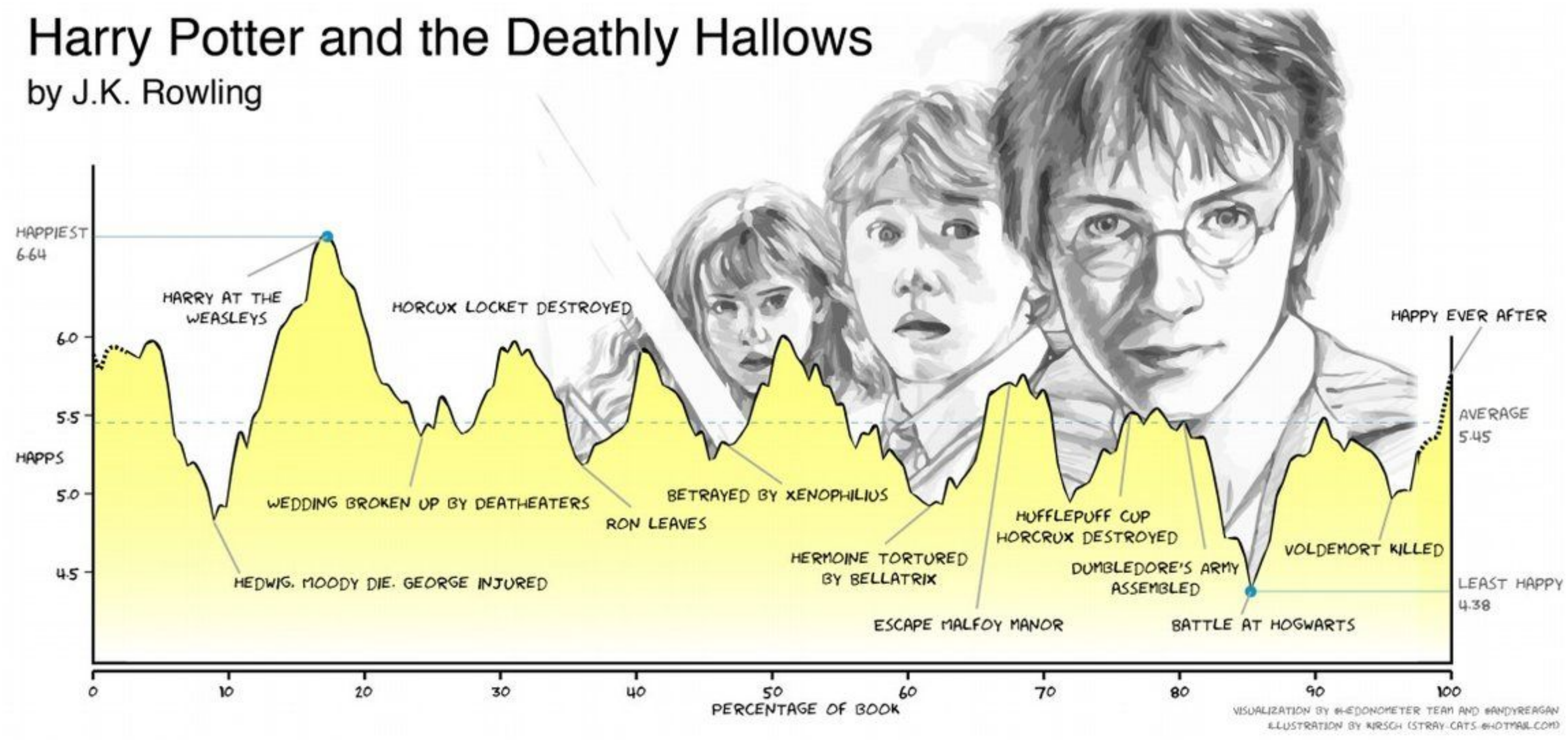
SA for emotional arcs (again)

Reagan, A. J., Mitchell, L., Kiley, D., Danforth, C. M., and Dodds, P. S. (2016). The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Science*, *5*(1): 31.

Andrew J Reagan et al. 2016. “The emotional arcs of stories are dominated by six basic shapes.” *EPJ Data Science*



http://hedonometer.org/



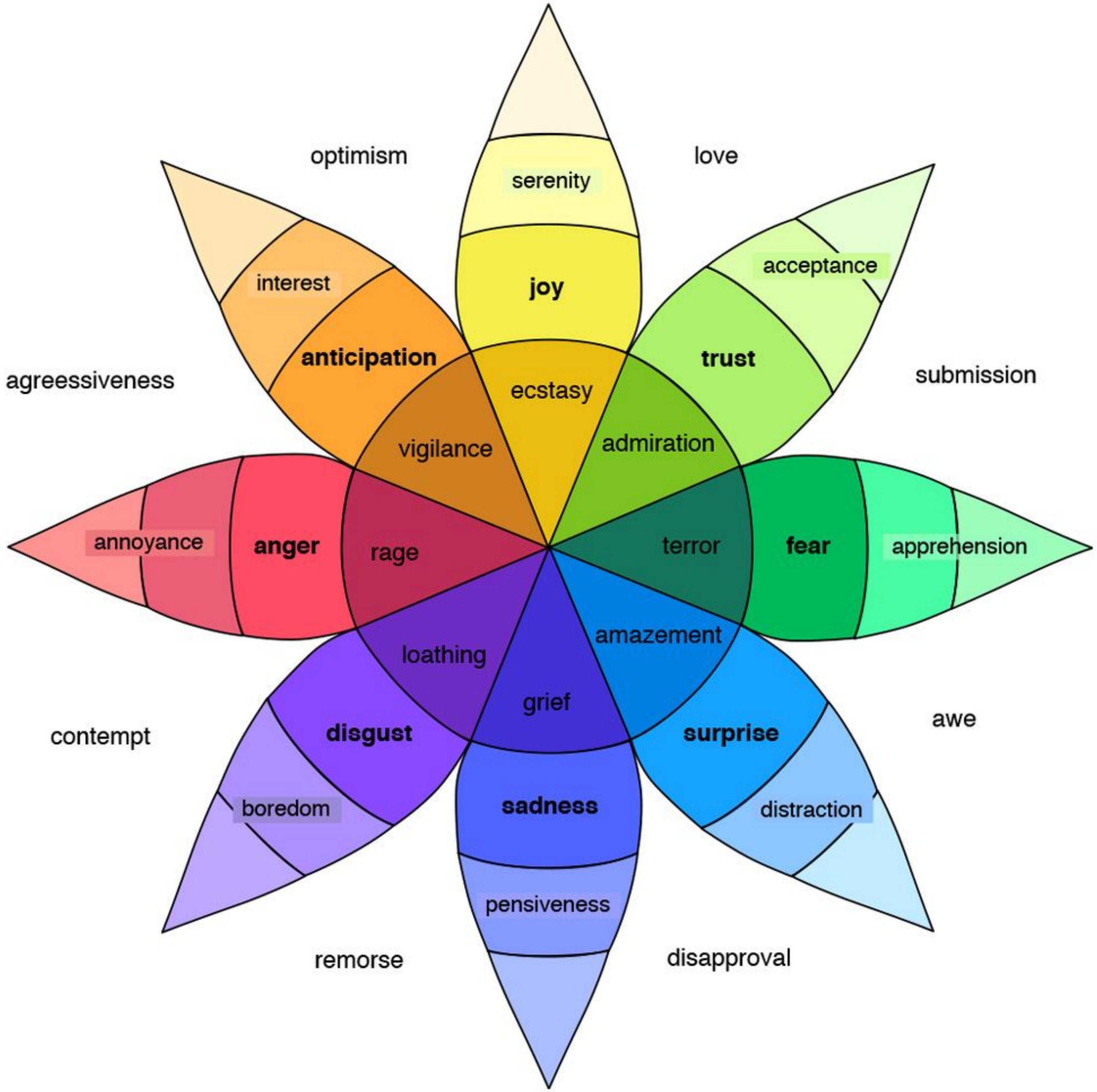
Sentiment Analysis Tools - A (Simple) Taxonomy

Two **defining elements:**

- the emotion theory adopted by the tool
- the technique to accomplish the analysis

Emotion Theories

1. Plutchik's eight basic emotions



Emotion Theories

2. Ekman's Theory of (Six) Basic Emotions

Emotion Theories

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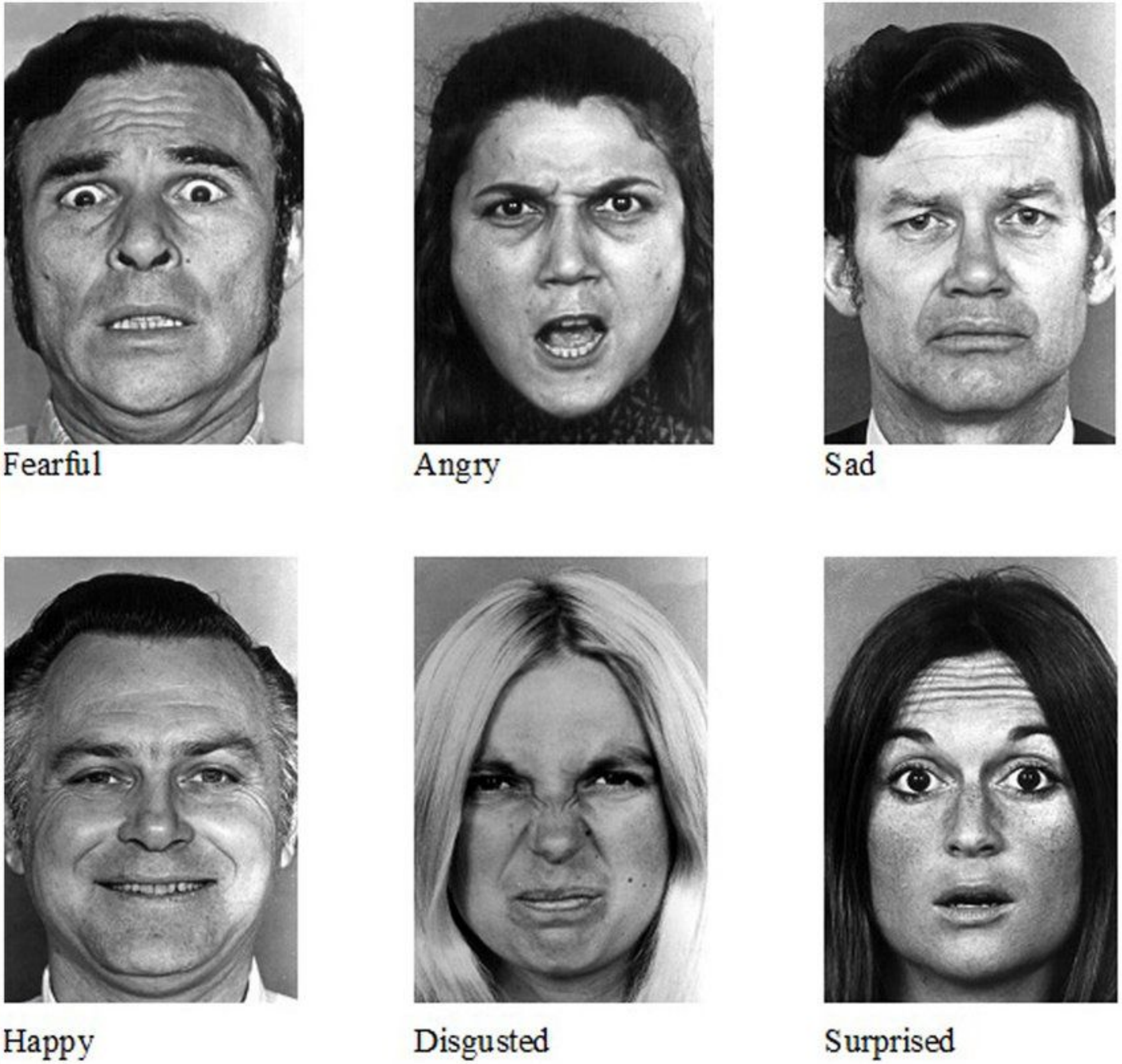
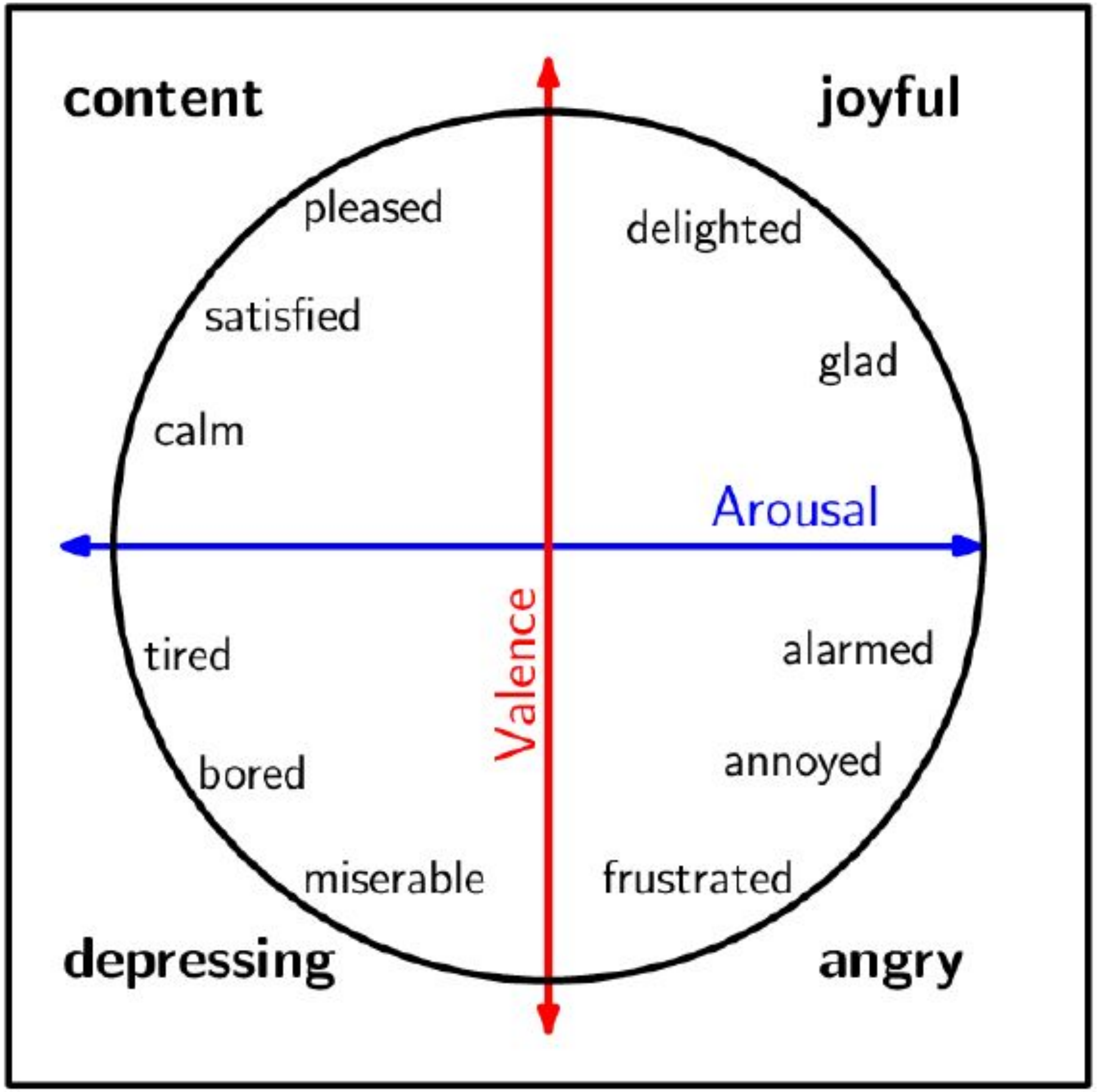


Emotion Theories

3. Russel's Circumplex Model



SA – How it works

Approach_1: Syuzhet **(Jockers, 2015)**

Sentiment Dictionary

English Word	Arabic Translation (Google Translate)	Basque Translation (Google Translate)	Positive (Valence)	Negative (Valence)
aback	الى الوراء	aback	0	0
abacus	طبلية تاج	abako	0	0
abandon	تخلى	alde batera utzi	0	1
abandoned	مهجور	abandonatu	0	1
abandonment	هجر	abandono	0	1
abate	انحسر	abate	0	0
abatement	انحسار	murrizteko	0	0
abba	أبا	abba	1	0
abbot	رئيس الدير	abade	0	0
abbreviate	اختصر	laburtu	0	0
abbreviation	الاختصار	laburdura	0	0
abdomen	بطن	abdominalak	[illegible]	0
abdominal	البطن	sabeleko	[illegible]	0
abduction	اختطاف	urrunketa	[illegible]	1
aberrant	شاذ	aberranteari	0	1
aberration	انحراف	aberrazio	0	1
abeyance	abeyance	etena	0	0
abhor	مقت	gaitzesten	0	1
abhorrent	مشمئز	nazkagarria	0	1

NRC-Emotion-Lexicon-v0.92

(Mohammad and Turney, 2013)

SA – How it works

Approach_1: Syuzhet **(Jockers, 2015)**

Sentiment Dictionary

Text

He was a happy man

Sentiment

+1

SA – How it works

Approach_1: Syuzhet **(Jockers, 2015)**

Sentiment Dictionary

Text

He was a sad and boring man

Sentiment

-2

SA – How it works

Approach_1: Syuzhet **(Jockers, 2015)**

Sentiment Dictionary

Text

He was neither sad nor boring

Sentiment

-2

SA – How it works

Approach_1: Syuzhet **(Jockers, 2015)**

Sentiment Dictionary	**Text**	**Sentiment**
	Well, he was like a potato	**+2**

SA – How it works

Approach_2: SEANCE **(Crossley et al., 2017)**

Sentiment Dictionary

Negation Detector

Text

He was neither sad nor boring

Sentiment

+2

…and many other values!

Number	Index	Variable description	POS	Negation Filtered	examples (not POS specific)
1	filename	name of source file	NA	NA	NA
2	nwords	number of words in source file	NA	NA	NA
3	Admiration/Awe_GALC	Admiration/Awe	All	No	admir*, ador*, awe*, dazed, dazzl*
4	Amusement_GALC	Amusement	All	No	amus*, fun*, humor*, laugh*, play*
5	Anger_GALC	Anger	All	No	anger, angr*, cross*, enrag*, furious
6	Anxiety_GALC	Anxiety	All	No	anguish*, anxi*, apprehens*, diffiden*, jitter*
7	Beingtouched_GALC	Beingtouched	All	No	affect*, mov*, touch*
8	Boredom_GALC	Boredom	All	No	bor*, ennui, indifferen*, languor*, tedi*
9	Compassion_GALC	Compassion	All	No	commiser*, compass*, empath*, pit*,
10	Contempt_GALC	Contempt	All	No	contempt*, denigr*, deprec*, deris*, despi*
11	Contentment_GALC	Contentment	All	No	comfortabl*, content*, satisf*
12	Desperation_GALC	Desperation	All	No	deject*, desolat*, despair*, desperat*, despond*
13	Disappointment_GALC	Disappointment	All	No	comedown, disappoint*, discontent*, disenchant*, disgruntl*
14	Disgust_GALC	Disgust	All	No	abhor*, avers*, detest*, disgust*, dislik*
15	Dissatisfaction_GALC	Dissatisfaction	All	No	dissatisf*, unhapp*
16	Envy_GALC	Envy	All	No	envious*, envy*
17	Fear_GALC	Fear	All	No	afraid*, aghast*, alarm*, dread*, fear*
18	Feelinglove_GALC	Feelinglove	All	No	affection*, fond*, love*, friend*, tender*
19	Gratitude_GALC	Gratitude	All	No	grat*, thank*
20	Guilt_GALC	Guilt	All	No	blame*, contriti*, guilt*, remorse*, repent*
21	Happiness_GALC	Happiness	All	No	cheer*, bliss*, delect*, delight*, enchant*
22	Hatred_GALC	Hatred	All	No	acrimon*, hat*, rancor*

SA – How it works

Approach_2: SEANCE **(Crossley et al., 2017)**

Sentiment Dictionary

Negation Detector

Text

He was neither sad nor boring

Admiration/Awe_GALC	1
Amusement_GALC	0
Anger_GALC	1
Anxiety_GALC	2
Beingtouched_GALC	-1
Boredom_GALC	0
Compassion_GALC	1
Contempt_GALC	1
Contentment_GALC	1
Desperation_GALC	0
Disappointment_GALC	0
Disgust_GALC	0
Dissatisfaction_GALC	1
Envy_GALC	0
Fear_GALC	1
Feelinglove_GALC	2
Gratitude_GALC	-1
Guilt_GALC	0
Happiness_GALC	1
Hatred_GALC	1
Hope_GALC	1
Humility_GALC	0
Interest/Enthusiasm_GALC	0
Irritation_GALC	0
Jealousy_GALC	1
[illegible]	0
[illegible]	1
Lust_GALC	2
Pleasure/Enjoyment_GALC	-1
Pride_GALC	0
Relaxation/Serenity_GALC	1
Relief_GALC	1
Sadness_GALC	1
Shame_GALC	0
Surprise_GALC	0
Tension/Stress_GALC	0

SA – How it works

Approach_3: BERT **(Devlin et al., 2019)**

(Big) Language Model	Manual Annotation	Machine Learning	New Sentences	Sentiment
	"He was happy" + 1 "He was sad" -1 "What a headache" -0.7 [...]		"He was good" "He was mad" "It's a pleasure" [...]	+1 -0.9 +0.8 [...]

SA Evaluation

TABLE 3 Results on the Sentiment Treebank for binary and fine-grained classification

Model	Accuracy	
	Fine-grained	Binary
RNN (Li et al., 2015)	42.0	80.7
RsNN (Socher et al., 2013)	43.2	82.4
Bi-RNN (Li et al., 2015) (+)	43.5	81.6
MV-RsNN (Socher et al., 2013)(*)	44.4	82.9
RsNTN(Socher et al., 2013)(*)	45.7	85.4
LSTM (Tai et al., 2015)	46.4	84.9
CNN-multichannel (Kim, 2014)	47.4	88.1
CNN-non-static (Kim, 2014)	48	87.2
DTree-LSTM (Tai et al., 2015)	48.4	85.7
DCNN(Kalchbrenner et al., 2014)	48.5	86.8
2-layer Bi-LSTM (Tai et al., 2015) (+)	48.5	87.5
Paragraph-Vec (Le & Mikolov, 2014)	48.7	87.8
DRsNN (Irsoy & Cardie, 2014)	49.8	86.6
CTree-LSTM(Tai et al., 2015)	51.0	88.0

(Rojas-Barahona, 2016)

SA Evaluation

TABLE 3 Results on the Sentiment Treebank for binary and fine-grained classification

- Even the most advanced SA tools hardly reach 90% accuracy in distinguishing positive from negative emotions
- Accuracy drops to below 50%, when distinguishing more fine-grained emotions (Ekman, Plutchick, etc.)

(Rojas-Barahona, 2016)