Linguistic Temporal Trajectory Analysis on Video Transcripts

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Workshop on Linguistic Temporal Trajectory Analysis

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Kleinberg, B., Mozes, M. and van der Vegt, I., 2018. **Identifying the sentiment styles of YouTube's vloggers.**

In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing* (pp. 3581 - 3590).

Video blogs

- Blogs in video format
- People filming their (daily) activities
- Can be domain-specific, e.g.
  - Technical product reviews
  - Beauty vlogs
  - „How-to“ vlogs

Continuous sentiment

- Vloggers try to arouse viewer‘s interest
- Sentiment as a means to achieve that?
- We measure continuous sentiment in videos
- Clustering approach to group similar sentiment styles

Why video transcripts?

- Large amounts of data
- „Implicit annotations“
- Use of language in videos

Why vlogs?

Many **samples** from single source

Many **sources** for the same domain

Many **domains**

Daily life vlogs,
technical reviews,
beauty vlogs, ...

Data

- **27,333** vlog transcripts (24 users (13 male, 3 female))
- Each transcript consists of „textual chunks“, e.g.

1	*there are so many boogers in my nose*
2	*right now*
3	*forgot my memory card of my blog camera*
4	*in my room so now we're starting the*
5	*vlog on my phone what's going on I am so*
6	*not awake right now my makeup is*
7	*actually a hot and disaster*

Problem: no punctuations!

Dealing with non-punctuated data

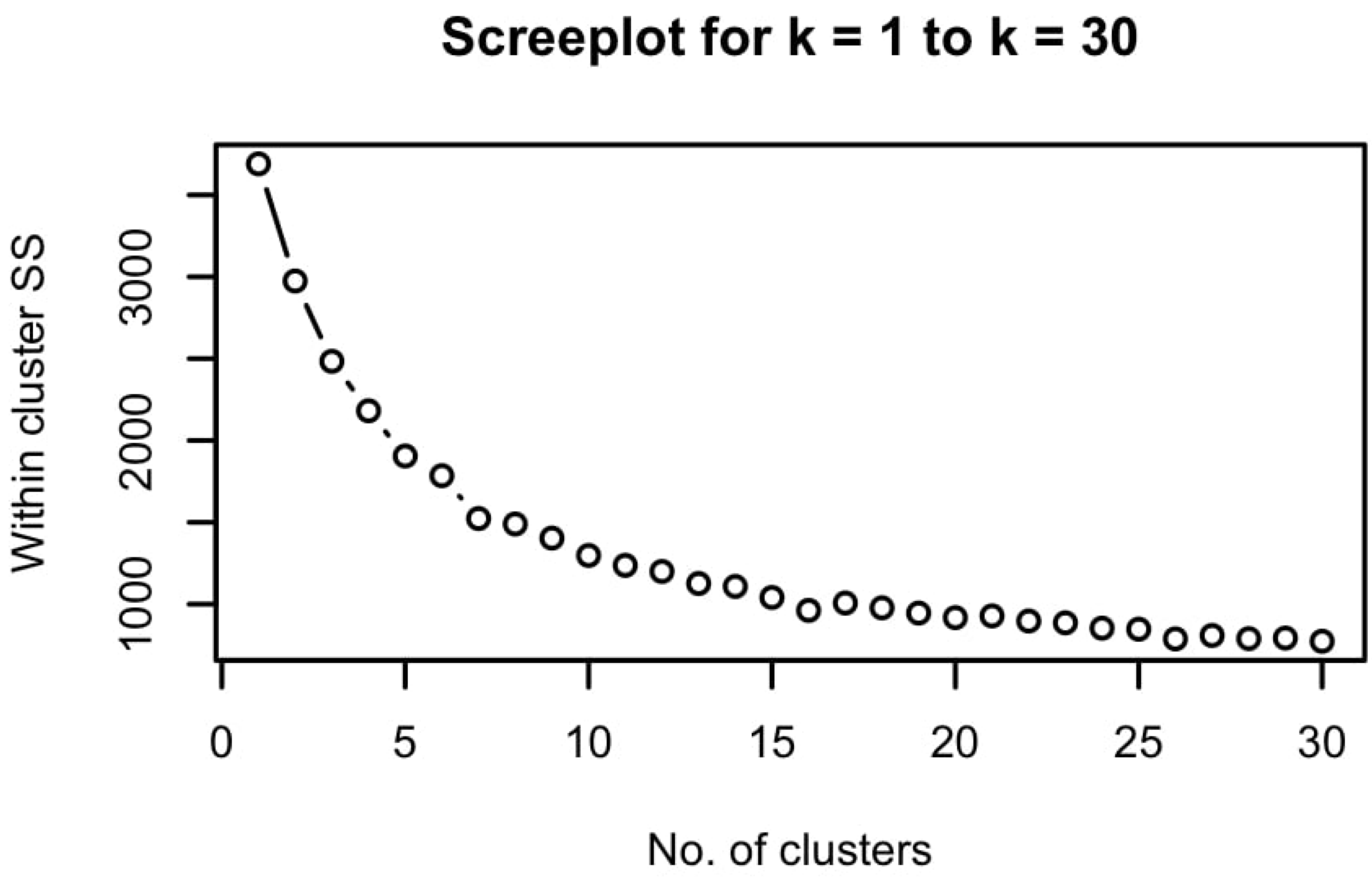
- Sentiment analysis and non-punctuated data do not work well together
- Solution: analyze sentiment‘s neighborhood and check for
  - **negators** („not“, „never“)
  - **(de-)amplifiers** („really“, „hardly“)
  - **adversative conjunctions** („but“, „yet“)

$$\text{„...this } \underbrace{\text{was not a}}_{-3} \textbf{ bad } \underbrace{\text{day at all}}_{+3} \text{ ...“}$$

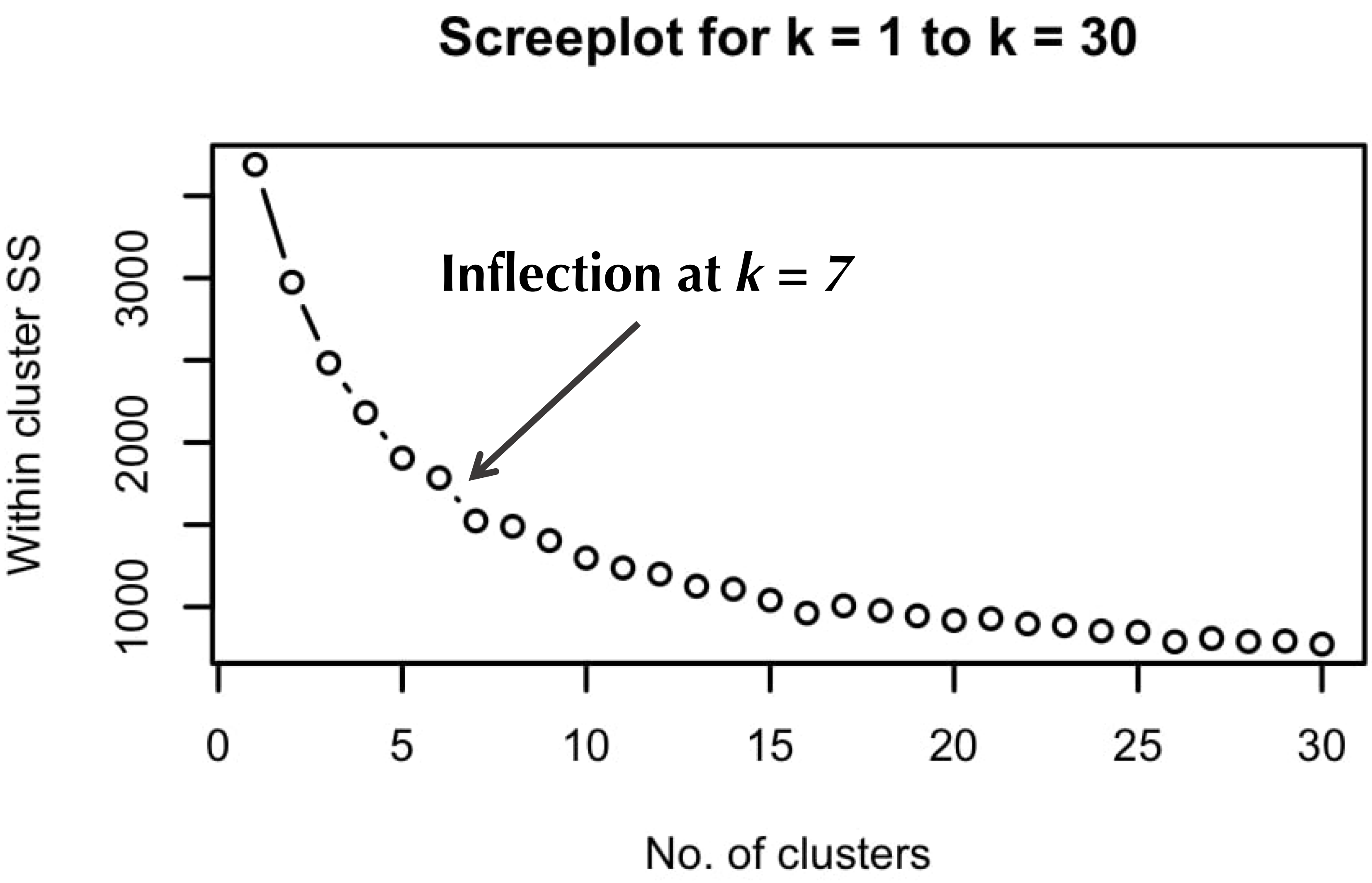
Pipeline

1. **Identify sentiment values** for each transcript (Jockers & Rinker Polarity Lookup Table (Rinker, 2018))
2. **Normalize** sentiment values to 100-dimensional vector
3. ***k*-means clustering** to identify groups of sentiment styles

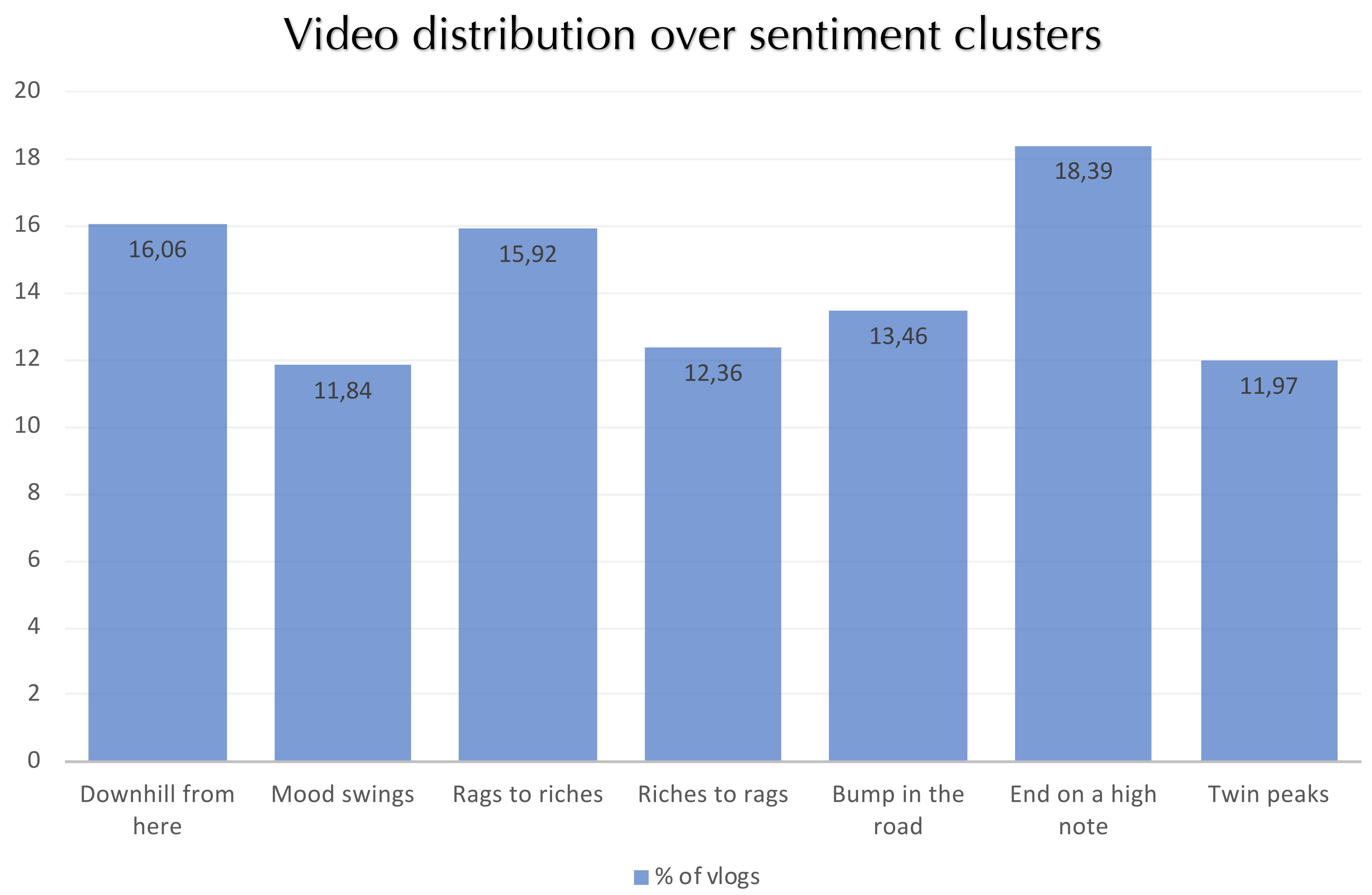
Results (finding *k*)



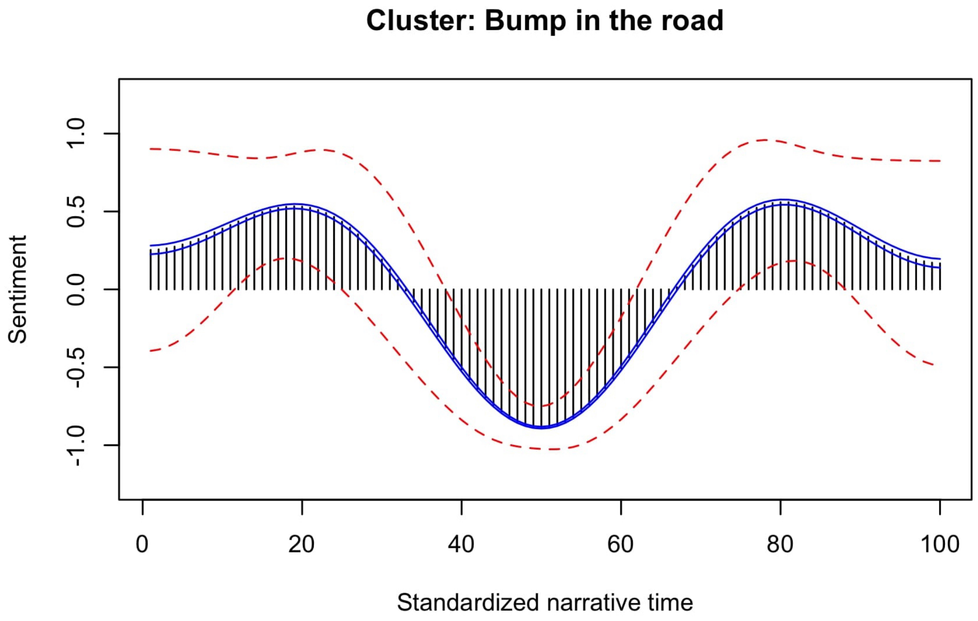
Results (finding *k*)

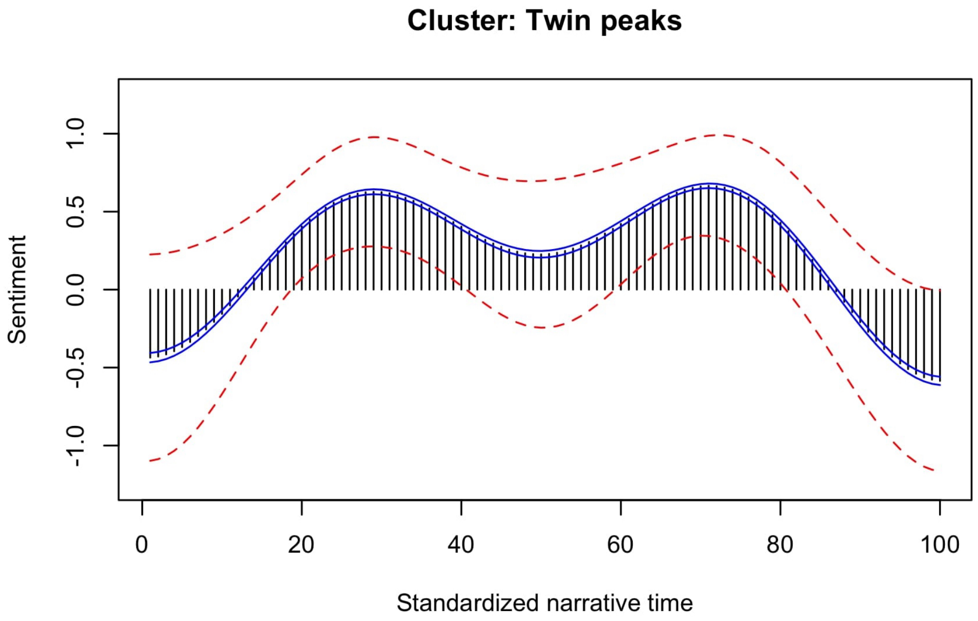


Clusters (k = 7)


Video distribution over sentiment clusters
20
18
16
14
12
10
8
6
4
2
0
16,06
11,84
15,92
12,36
13,46
18,39
11,97
Downhill from here
Mood swings
Rags to riches
Riches to rags
Bump in the road
End on a high note
Twin peaks
% of vlogs

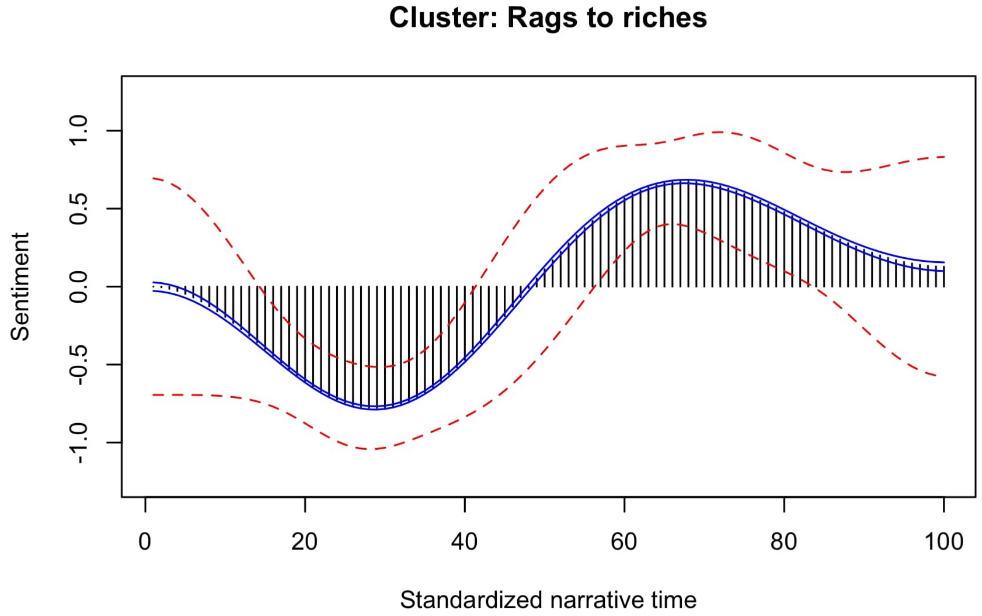
Bump in the road vs. twin peaks

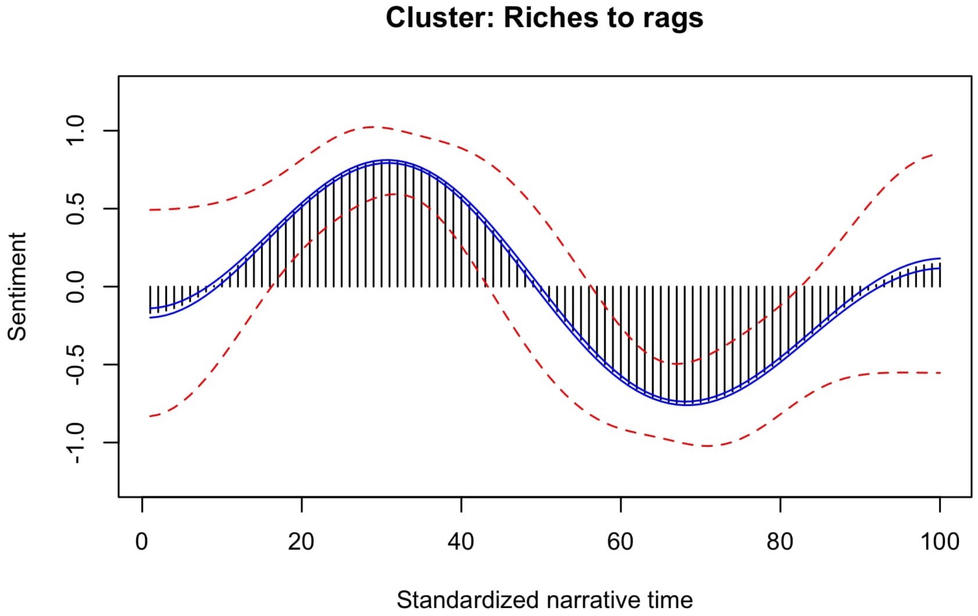




Figures: Average sentiment style shapes. Dotted red lines = +/- 1 SD; blue lines = 99% CI.

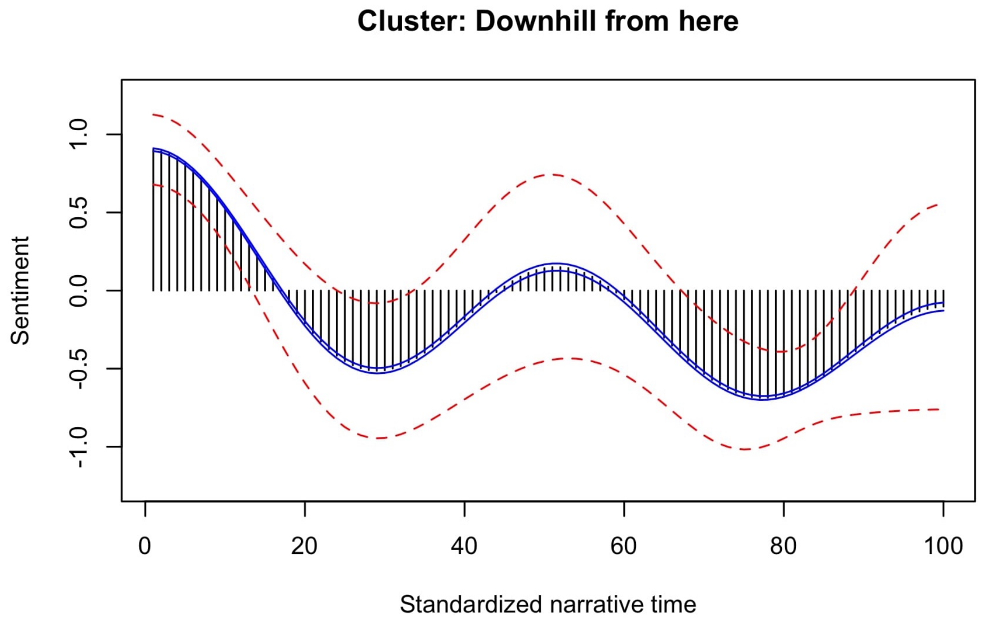
Rags to riches vs. riches to rags

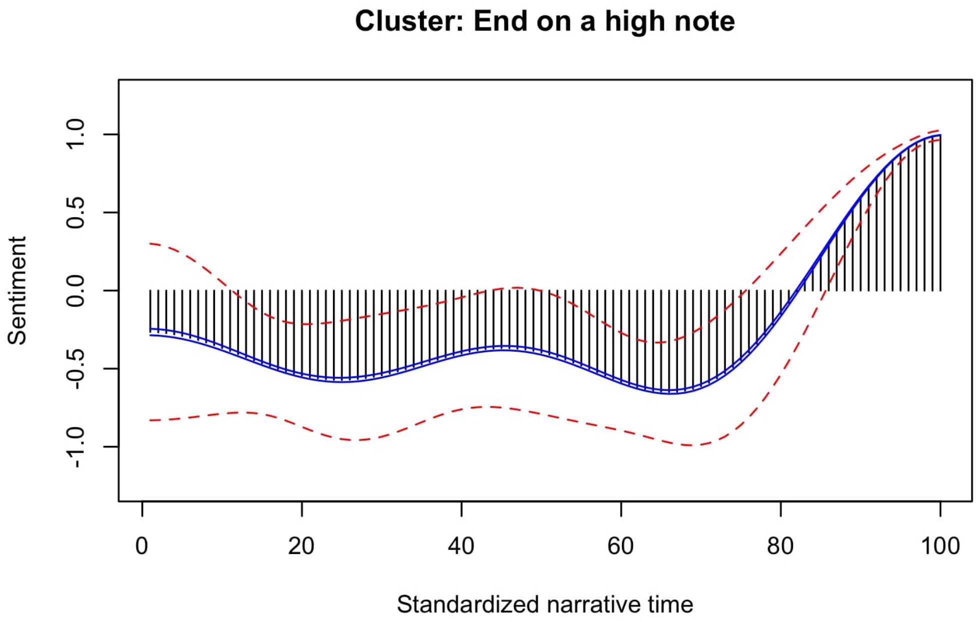




Figures: Average sentiment style shapes. Dotted red lines = +/- 1 SD; blue lines = 99% CI.

Downhill from here vs. end on a high note





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Mood swings

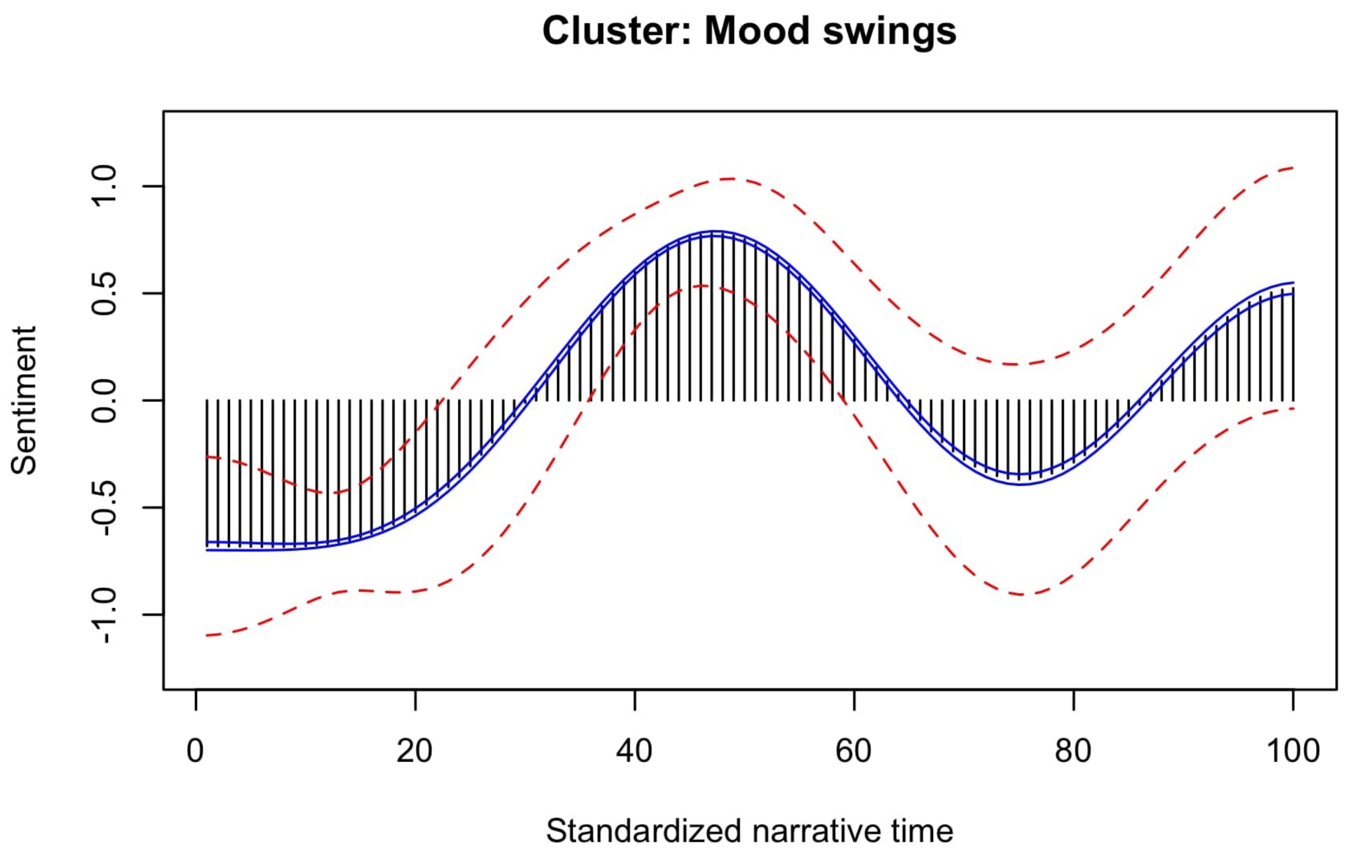

Figure: Average sentiment style shapes. Dotted red lines = +/- 1 SD; blue lines = 99% CI.

Sentiment styles and gender

	+	-
Families	twin peaks*	end on a high note*
Female	riches to rags*	end on a high note*
Male	end-on-a-high-note*	twin peaks*, downhill from here*

* = significant at $p < .01$

Limitations

- Automatic transcripts
- Only successful vloggers
- No visual and audio features

References

- Tyler Rinker. 2018a. lexicon: Lexicon Data. http://github.com/trinker/lexicon

Resources

- GitHub: https://github.com/ben-aaron188/narrative_structures
- EMNLP publication: https://aclweb.org/anthology/D18-1394

Thank You