Technical University of Munich

Clustering-Based Sentiment Analysis for Media Agenda Setting

Opinion Lab Group 2.3

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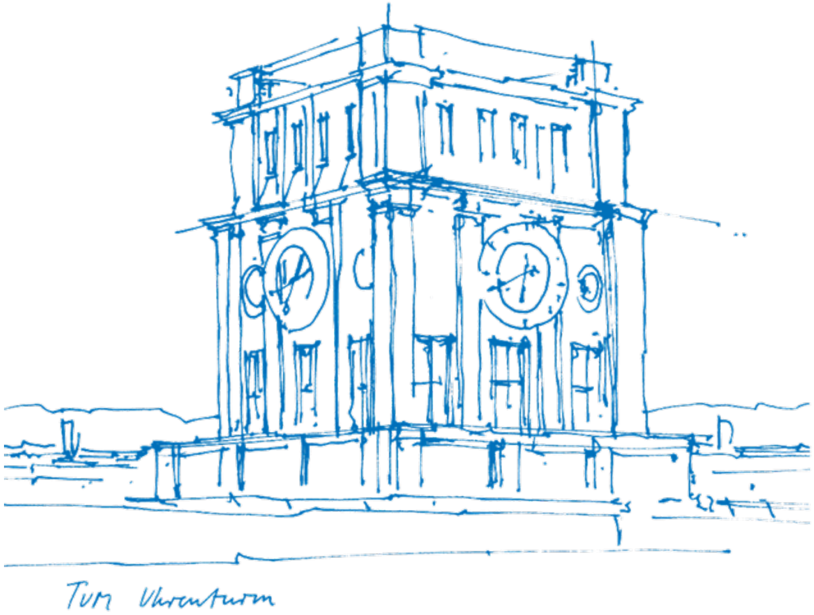

Outline

- Aims
- Dataset
- Expected outputs
- Todo
  - Stage 1
    - Generate word / token / sentence embeddings with our corpus
    - Build a k-mean clustering model for identifying sub-topics in organic dataset
    - Select a sentiment pre-trained model
  - Stage 2
    - Visualize distribution of samples among clusters and corresponding sentiment frequency
  - Stage 3
    - Investigate Media Agenda Setting
- Milestones

Aims

Measure the influence of two online newspapers onto the social media according to Agenda setting theory

Agenda setting theory:

Suggest the news item which is covered more frequently and prominently indicates that the audience will regard the issue as more important.

Dataset

Articles and respective comments on the domain of organic food with search terms *organic food* and *organic farming*

- Articles from two online newspapers, *New York Times* (English) and *Der Spiegel* (German)
- Direct response (bilingual): comments right under those articles
- Indirect response: posts in unrelated discussion forums, *Quora*

	Start	End	No. of articles
New York Times			
With comments	2006	2017	99
Without comments	1970	2017	228
Der Spiegel			
With comments	2007	2017	61
Without comments	2007	2017	91
Quora			
With comments	2009	2017	1304
Without comments	2010	2017	193

Table: Statistics for data crawled from New York Times, Der Spiegel and Quora with 'relevant' labelled as 1.0

Expected outputs (Processes)

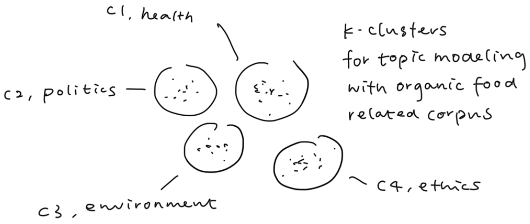

Figure: Stage 1: Cluster, tuple(aspect,sentiment)

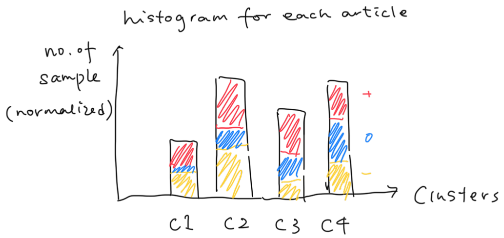

Figure: Stage 2: Distribution of clusters per articles

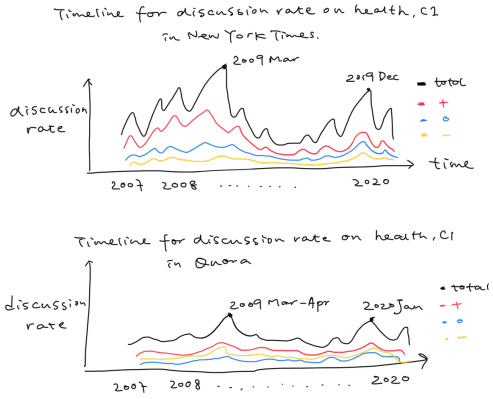

Figure: Stage 3: Timeline analysis, influence on social media

Todo Stage 1.1

Generate embeddings

text $\rightarrow$ *lines split* $\rightarrow$ list of sentences $\rightarrow$ *sentence embedding* $\rightarrow$ **vectors**

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[2] dalequark 2019.

Todo Stage 1.1

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Example: *sentence* ="You are what you eat."

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Possible embedding models (on TensorFlow Hub) to apply:

- Universal sentence encoder[1]
- Bert[2]

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```
embed = hub.Module("https://tfhub.dev/google/universal-sentence-encoder-xling/en-de/1")
with tf.Session() as session:
  session.run()
  print(session.run(embed(sentence)))
```

$\rightarrow [0.02, 0.01, ..., -0.12]$

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Todo Stage 1.2

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Now, let's start working with **vectors**!

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nclusters= 3
km = KMeans(nclusters)
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$\rightarrow$ interpret/extract $clusters[0]$ to an aspect (like environment).

$\rightarrow$ sentences s_0, s_4, s_5 are assigned to environment.

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analyzer = SentimentIntensityAnalyzer()
print(analyzer.polarity_scores(arr))
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$\rightarrow$ **(Environment, pos)**

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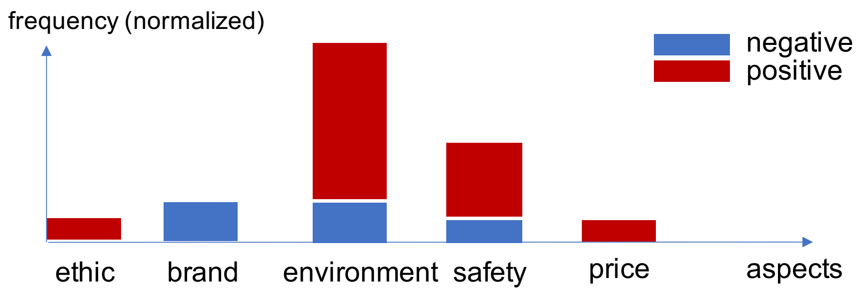

Figure: Aspects distribution on one text

Todo Stage 3

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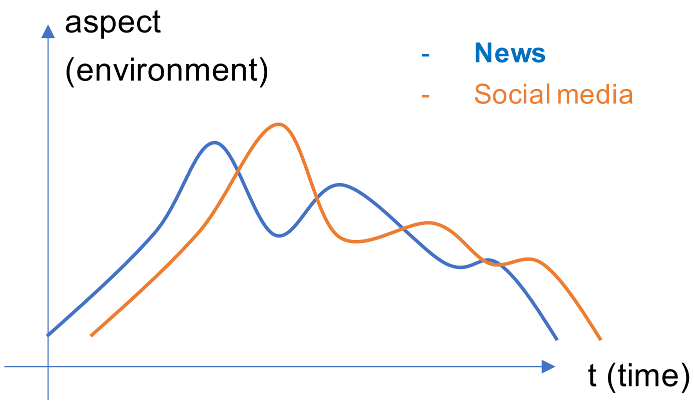

Milestones

- **now**
- **18.05**
  - Stage 1.1 - 1.2
  - Finish embedding
- **02.06**
  - Stage 1.2 -1.3
  - result of clustering and aspect-labels
- **15.06**
  - **Stage 1.3-2**
  - **result of stage 1**
- **29.06**
  - Stage 2-3
  - distributions on articles
- **13.07**
  - Stage 3
  - Start influence analysis
- **20.07**
  - Finish stage 3

Pre-processing and Stage 1 (now – 15.06)

Stage 2

Stage 3

References

- Chidambaram, M. et al. (2018). "Learning cross-lingual sentence representations via a multi-task dual-encoder model". In: *arXiv preprint arXiv:1810.12836*.
- dalequark (2019). *predicting movie reviews with bert on tf hub*. URL: https://github.com/google-research/bert/blob/master/predicting_movie_reviews_with_bert_on_tf_hub.ipynb (visited on 2019).
- Hutto, C. J. and E. Gilbert (2014). "Vader: A parsimonious rule-based model for sentiment analysis of social media text". In: *Eighth international AAAI conference on weblogs and social media*.