Caplena

Open-End Analysis Masterclass

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Presenters

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Open-Ends aus Analysesicht

Fully open

Phrases or sentences. Sub-types:

- Sentiment-directional “What did you like about the TV spot?”
- Sentiment-bidirectional “Why did you give this score?”
- Sentiment-agnostic “What does company need to do to address this?”

Semi open

Brand-awareness or List-Type: “Bei welchem Geldinstitut oder welchen Geldinstituten sind Sie ?”

Survey of methods & tools

Exploring different natural language processing problems

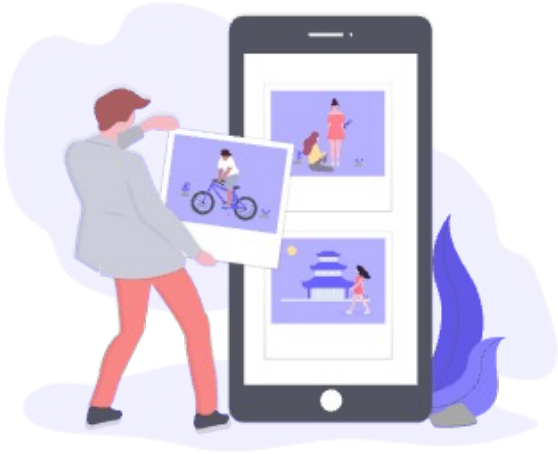
ML applications (non-exhaustive)

Written Language

- Translation
- Sentiment Analysis
- Content Categorization

Spoken language

- Speech to text
- Text to speech
- Emotion recognition



Vision

- Image classification
- Object recognition
- Photo tagging

METHODS

Sentiment analysis

- Assigning categorical (“negative”, “neutral”, “positive”) or continuous (between -1 and 1) sentiment score
- Global or entity level
- Optional emotion recognition
- Might need tuning towards specific domain

MR: Open-ended responses, social media data, voice transcripts, reviews

https://monkeylearn.com/sentiment-analysis-online/
https://cloud.google.com/natural-language/#natural-language-api-demo

Commercial sentiment analysis: Almost every text analysis suite
Emotion analysis: canvs.ai
Aspect level sentiment: Caplena

METHODS

Categorization

- Assigning one or more categories to each element of text
- Off the shelf algorithms trained on specific categories (e.g. “news”)
- Some applications allow customization

MR: Open-ended responses, social media data, voice transcripts, “coding”

https://monkeylearn.com/blog/text-classification-apis/
https://demo.caplena.com
Commercial: Caplena, MAXQDA, Ascribe, Qualtrics TextIQ

METHODS

Entity extraction

- Identifying people, organizations, dates, events etc. from a text
- Applications include parsing unstructured text into a structured form or anonymization

MR: Anonymization, Social media data, voice transcripts, blog posts, news articles, Qual data

https://dandelion.eu/semantic-text/entity-extraction-demo/
https://cloud.google.com/natural-language/#natural-language-api-demo
Commercial: Aircloak (Anonymization)

METHODS

Summarization

- Creating summaries of longer texts
- Two different methods exist:
  - Removing “unimportant” sentences
  - Rewriting entire text

MR: Social media posts, news articles, blog posts, voice transcripts, Reviews, qual data

https://deepai.org/machine-learning-model/summarization
https://huggingface.co/google/pegasus-large
https://resoomer.com/en/
Commercial: Unknown

METHODS

Text generation

- Input text -> Output text
- Generalized problem solving
  - Few shot learning an objective

Applications in MR: Inspiration, quick prototyping

https://chat.openai.com (login required)
https://transformer.huggingface.co/doc/distil-gpt2 (remove text first)

METHODS

Keyword extraction

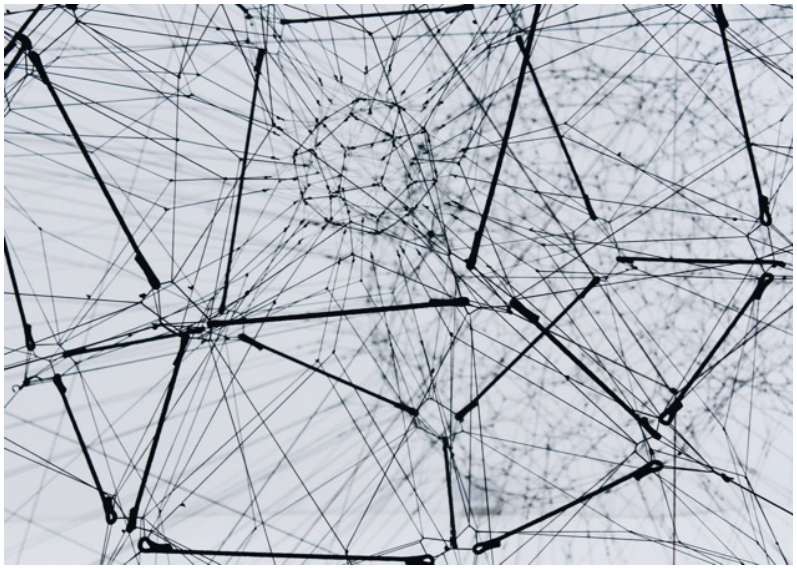
- Extracting the most relevant / important words from a paragraph of text
- Often done by comparing occurrence frequency of words to *reference corpus*
- Resulting words are not aggregated

MR: Open-ended responses, social media data, voice transcripts, reviews, news articles, blog posts, qual data

https://natural-language-understanding-demo.ng.bluemix.net/
https://monkeylearn.com/keyword-extractor-online/
Commercial: Gavagai, Smartcoder.at

METHODS

Clustering



- Grouping together related / similar words
- Often displayed in a graph-like structure

MR: Social media posts, news articles, blog posts, qual data

http://textexture.com/
https://demo.caplena.com/embeddings/#projector&run=. (Chrome / Firefox only, search for words on the right)
Commercial: Unknown

METHODS

Translation

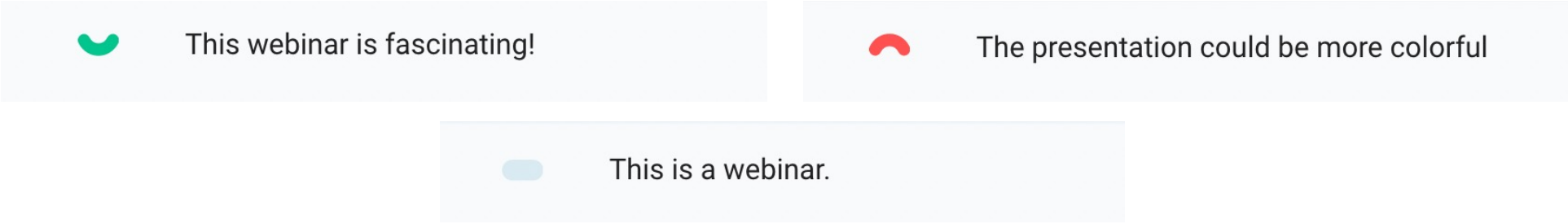
- Google Translate
- DeepL

Sentiment analysis in depth

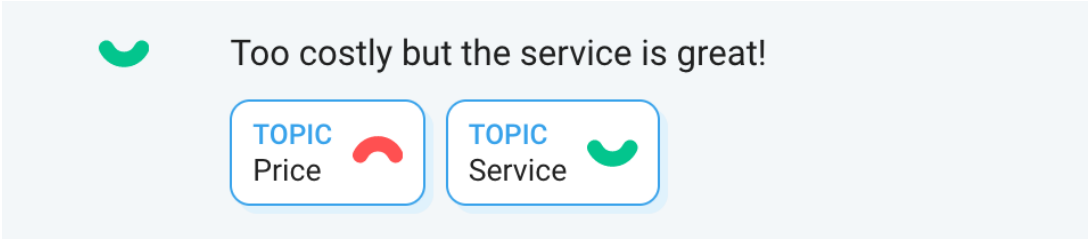
The most common AI method in CX, marketing and MR

Kinds of sentiment analysis

Verbatim-level → Aggregated evaluation



Topic-Level → Aggregated evaluation and topic-level actions



TYPES & EVALUATION

Automation vs quality: Walking a thin line

A healthy mix: (Semi-) automated analysis

Photo by @SensoryArtHouse [Unsplash]

Effort vs quality: Results

	5 min	30 min	90 min	Fully manual (~ 480min, Excel)

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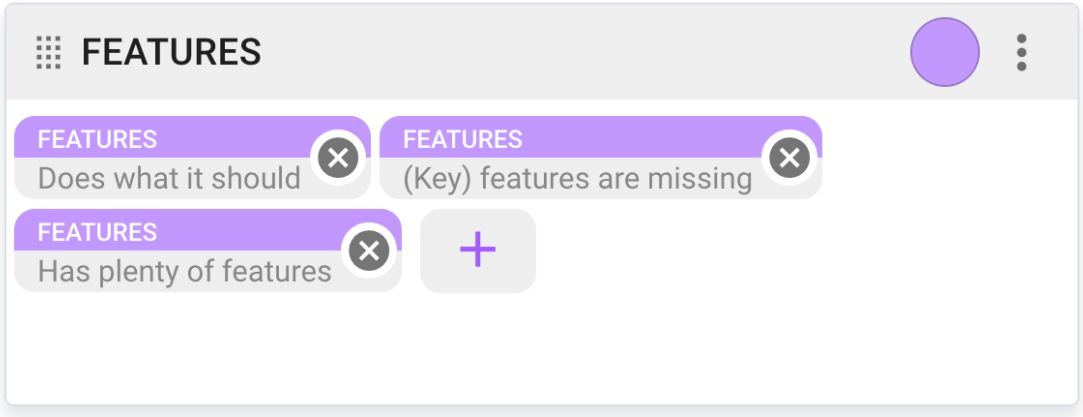
# Topics	29	36	44	50



Effort vs quality: Results

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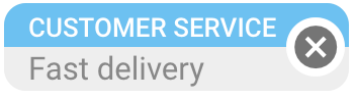
# Topics	29	36	44	50
Topic quality	★★☆	★★★	★★★	★★☆



Effort vs quality: Results

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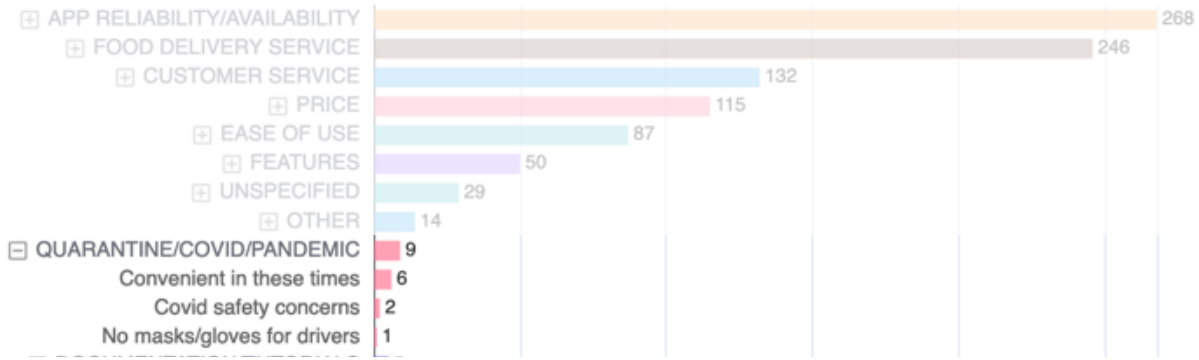
# Topics	29	36	44	50
Topic quality	★★☆	★★★	★★★	★★☆
Topic depth	★★☆	★★☆	★★★	★★★



Effort vs quality: Results

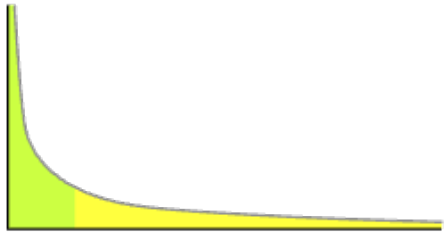
	5 min	**30 min**	**90 min**	**Fully manual** (~ 480min)
# Topics	29	36	44	50
Topic quality	★★☆	★★★	★★★	★★☆
Topic depth	★★☆	★★☆	★★★	★★★
Verbatims with code	75%	93%	96%	100%
Coding Quality	★★☆	★★★	★★★	★★★

Effort vs quality: Results

	5 min	30 min	90 min	Fully manual (~ 480min)
# Topics	29	36	44	50
Topic quality	★★☆	★★★	★★★	★★☆
Topic depth	★★☆	★★☆	★★★	★★★
Verbatims coded	75%	93%	96%	100%
Coding Quality	★★☆	★★★	★★★	★★★
Analysis Quality	★★★	★★★	★★★	★★☆

KI-Analyse: Unterschiede zu manuell

Umgang mit “Long Tail”
KI arbeitet grundsätzlich assoziativ



- Weist passende Themen zu Nennungen zu
- Wenn nichts passt, dann wird auch nichts zugewiesen (nicht Code “Anderes”)

Context
Umfrage-Kontext muss irgenwie in die KI gebracht werden

Codebook
- Codebook sollte möglichst verständlich sein mit wenig Überlappung
- Extrem viele Codes sind möglich

Visualisierungen

1. Wordclouds

2. Contextuelle Visualisierungen