Getting to know people by automatic text analysis of talks and tweets

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Outline

- Automatic text analysis and opinion mining
- Two case studies:
    - Detecting Corona-related opinions on Twitter
    - BLISS: talking with a conversational agent about well-being
- Reflections on pricacy and personalisaton

Mining different kinds of knowledge from data

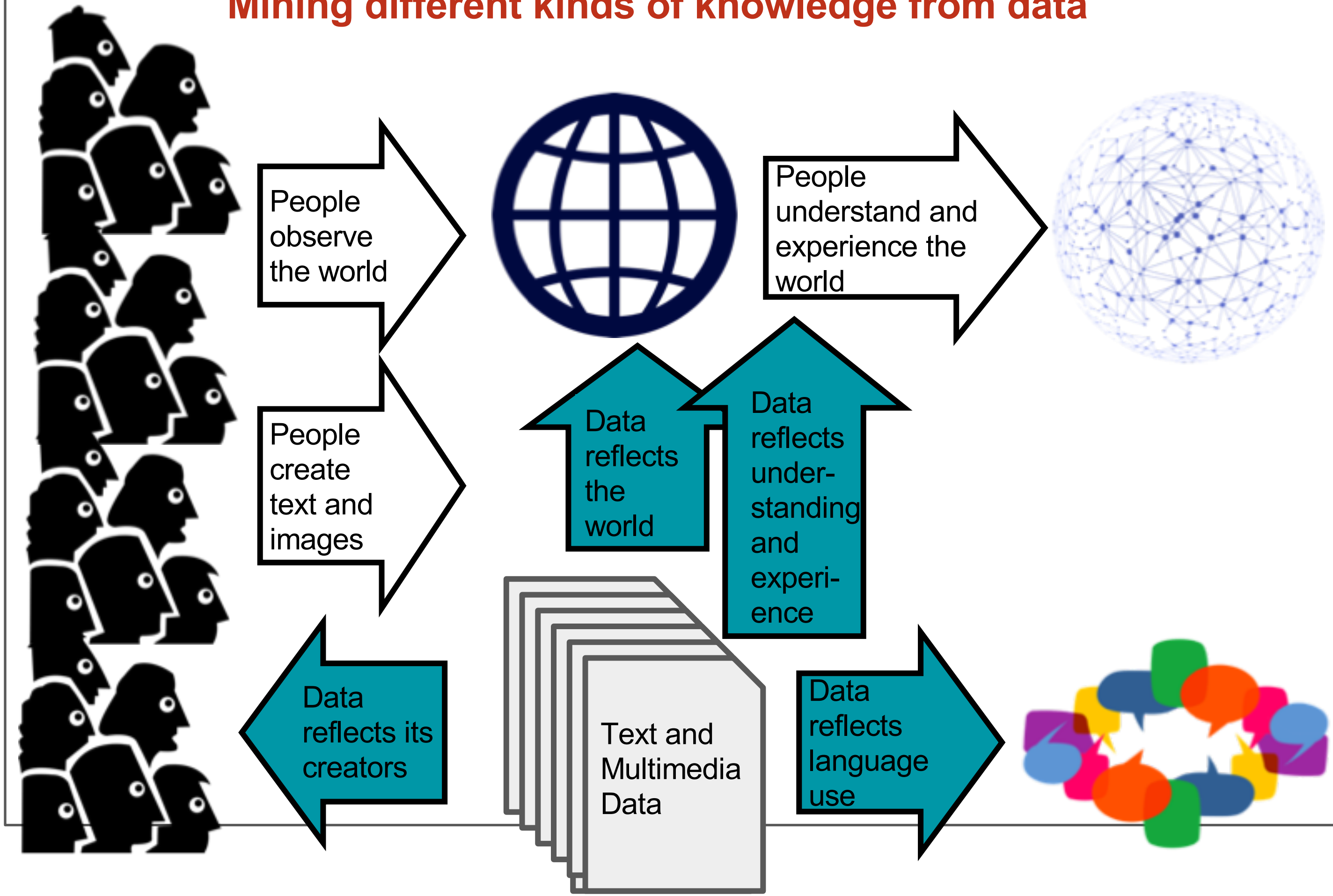


Image credit https://pixabay.com/, Zhai and Massung, 2016

Data reflects its creators

We can learn about authors and speakers by automatically analysing their text and speech:

Subjective information: opinions and sentiments

Objective infomation: facts

Implicit information: origin, education level, health ..

Subtleties: Subjective/Objective/Personal

Subjective language use: person expresses its internal private state (not always sentiment)

I think he went home

He broke my heart

vs Objective: verifiable via an external reference (facts can be personal)

Her name was Jannis

Social media monitoring for RIVM

April-May-June 2020

Goal: Social media monitoring

- Monitoring the general public’s attitude, stance, and trust in the government measures during the Corona crisis in the Netherlands

- Focus is mainly on Twitter

- https://www.rivm.nl/coronavirus-covid-19/onderzoek/gedrag

Team

- Nijmegen: Erkan Başar, Nelleke Oostdijk, Ali Hurriyetoğlu, Iris Hendrickx and Stergios Morakis
- Together with **Leiden University** (Suzan Verberne) and the **Meertens Institute** (Antal van den Bosch), the Netherlands
- Collaboration with the PuReGoMe project (**Utrecht University & E-Science Centre**)

  PuReGoMe = Dutch Public Reaction on Governmental COVID-19 Measures and Announcements

Project structure: Two-week sprints

- Every two weeks RIVM wanted an update on particular questions; for example
  - What is general public's opinion on current government measures?
  - Is there support among the Dutch public for the use of face masks?
  - What do people think of the testing facilities offered?
- Reporting: fact sheet + more detailed report

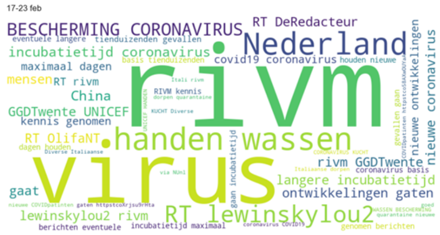
Various types of analyses

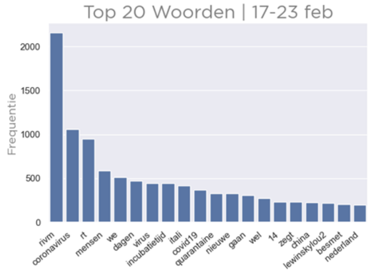
- Community network analysis
- User analysis
- Sentiment analysis (LIWC, BERTje)
  – overall & topic-specific (e.g. face masks)
- Topic modeling
- Clustering
- In-depth analysis using linguistic patterns (topic, stance, arguments)

“Time dimension”:

state of affairs at a given point In time & development over a period of time

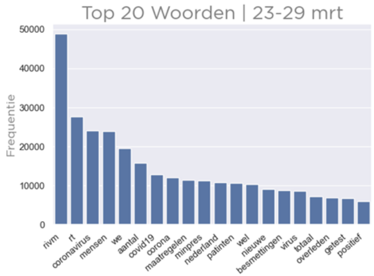
Note: a variety of datasets was used





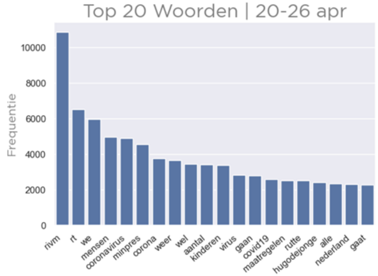
Week 8: 17-23 February

- situation in other countries
- hygiene (washing hands)



Week 13: 23-29 March

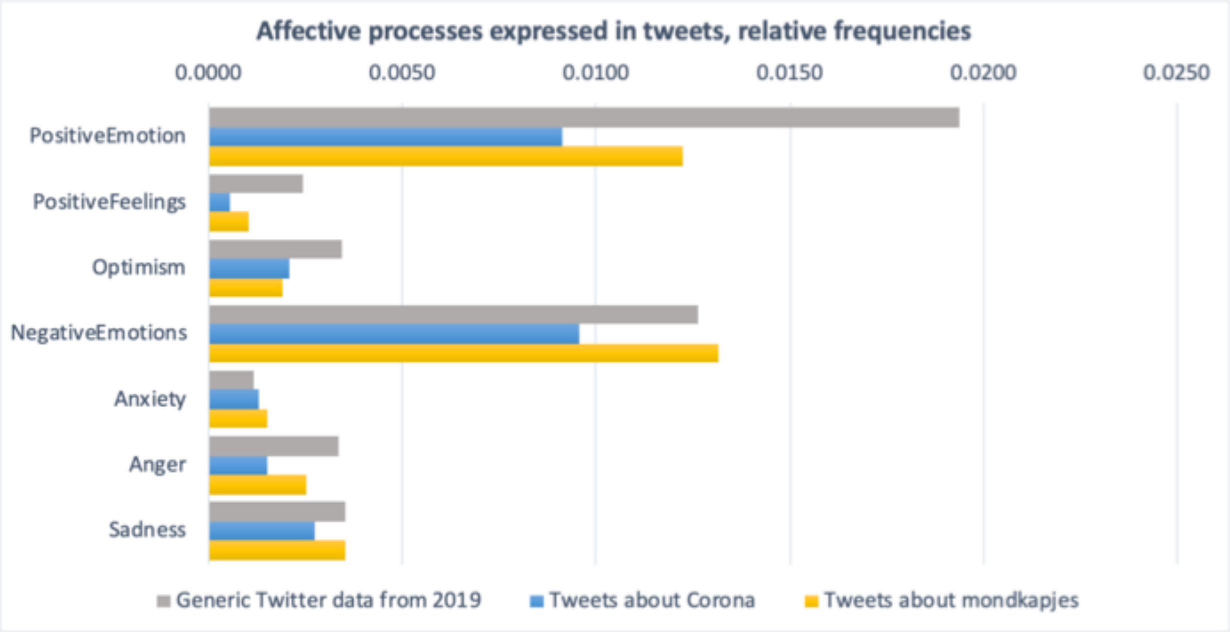
- situation in the Netherlands
- stay home
- tested positively
- hospital admissions



Week 17: 20-26 April

- government actions in corona crisis
- hospital admissions
- deaths

Leiden univ: Sentiment analysis



CLST: In-depth analysis using linguistic patterns

Pinto (Oostdijk et al. 2019): Search engine with task-specific filters

- **filters** are used to extract information; a filter is based on a lexicon and a set of rules; the rules define what lexical items can co-occur (specification of n-grams, where n is in principle not limited)
- each filter assigns a label to a tweet representing a topic, a type of argument, semantic class, etc.

Case study: Face masks

Investigated:

- Stance (pro, neut, or con) and arguments used as regards the use of face masks
- Types of argument, e.g.

Availability
- pos: *zijn overal te koop, ruim beschikbaar*
- neg: *onvoldoende, niet genoeg, veel te weinig*

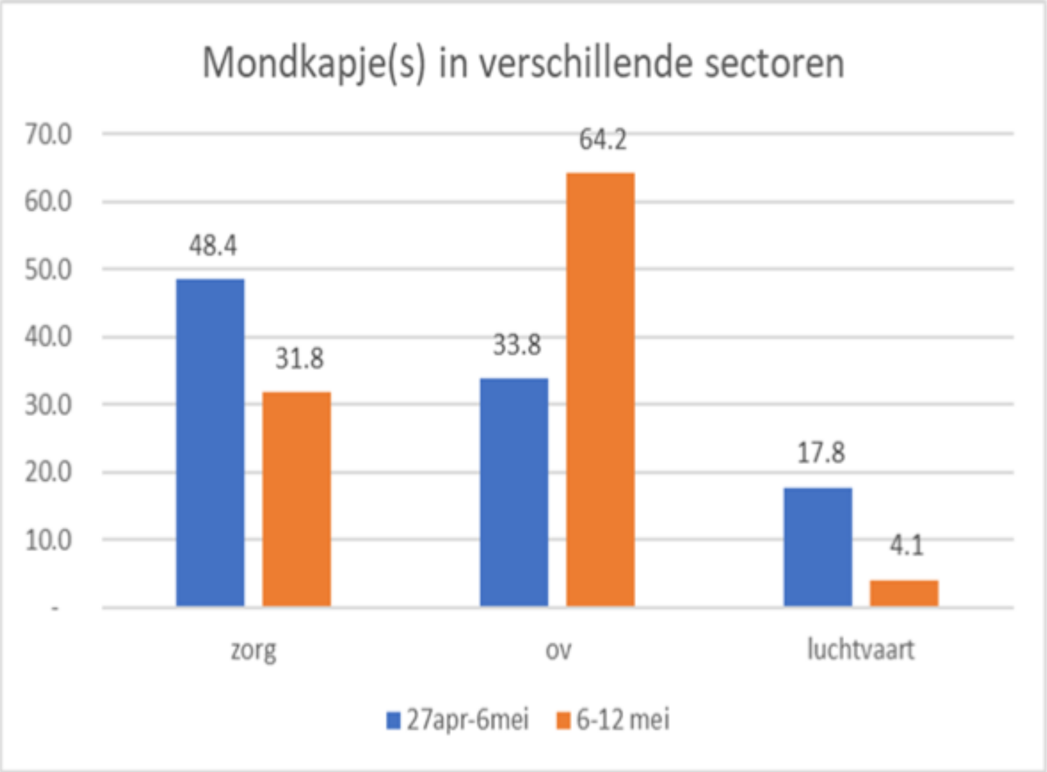
Protection

Suitability

2 datasets: before and after press conference with the announcement that face masks became obigatory in public transport: 27 Apr – 6 May (18:59), 6 May (19:00)-12 May

Hypothesis

Shift in stance is an effect of press conference (6 May) during which it was announced that the general public should wear face masks in public transport



Stance before and after 6 May

Before 6 May:

- Stance mostly negative; exceptions: ‘protection’ and ‘suitability’

After 6 May:

- ‘Spreading’ and ‘availability’: similar to before (negative)
- ‘Usefulness/necessity’ and ‘opinion’: still negative, but less so than before
- ‘Protection’ remains positive, but less so than before
- ‘Risk’ shifts from negative to positive

Relevancer

- Tool that can cluster related tweets https://relevancer.science.ru.nl/about
- Can be used for first exploration and initial annotation:
  manual inspection and labeling of (parts of) clusters presented by the system
  => interactive development of annotation
- Labeled data can be used to train a classifier for further annotation
- Topic exploration on tweets about Corona

B

relevancer.science.ru.nl/datasets/RIVM_20200524_Relevancer_dump_clusters_Mondkapjes-6May-1900_12May-KeyValue/labeled:True

Apps Stats Work News Me Maps Money Google Calendar Dropbox - Files -... Google Docs Overleaf #LST Talky Other Bookmarks

Relevancer

HOME HOW DOES IT WORK? CLUSTERS ANALYSIS FILTER ABOUT

All Tweets

Bij elke reis heb je een nieuw mondkapje nodig

Zeg eens eerlijk, je reist 2 x per dag met de trein. Neem je elke rit een nieuw mondkapje a €1,- of ga je hergebruiken? #mondkapje

nieuw mondkapje een nadeel bril beslaat

Wat zullen die mensen doen met de #mondkapjes in het ov. Zal dat helpen? Ik denk niet dat iedereen elke rit een nieuw mondkapje neemt

Als ik het goed begrijp moet je voor elke reis met het OV (heenreis, terugreis, etc) een nieuw/schoon #mondkapje opdoen en daar mag je tijdens de reis niet aanzitten. Wanneer je maar één mondkapje hebt; kan je wel ergens heen en mag je niet terug naar huis? #durftevragen

Mondkapjes. Jaaaa roept t kabinet, werking twijfelachtig zegt t RIVM een nieuw verdienmodel?

The labels used before in this collection (and how many times they are used)
Click labels to use them again:

relevant,mondkapje,critical,boetes_mondkapje_ov (1)

Outcomes Relevancer
In the week before 6 May

,

- 8 clusters expressed disagreement with government measures and acts of the government;
- Most clusters represented negative sentiments and a critical stance towards the government and RIVM.

After the May 6 split point, in 24 coherent clusters

- 9 clusters were neutral in stance and opinion, and discussed the announced measures (mostly related to public transport);
- A smaller set of 5 clusters discussed the inconsistencies in the logic used over time by the government offering arguments to wear face masks;
- a new topic emerged around the availability of face masks (where to buy them, how to make them) in 4 clusters.

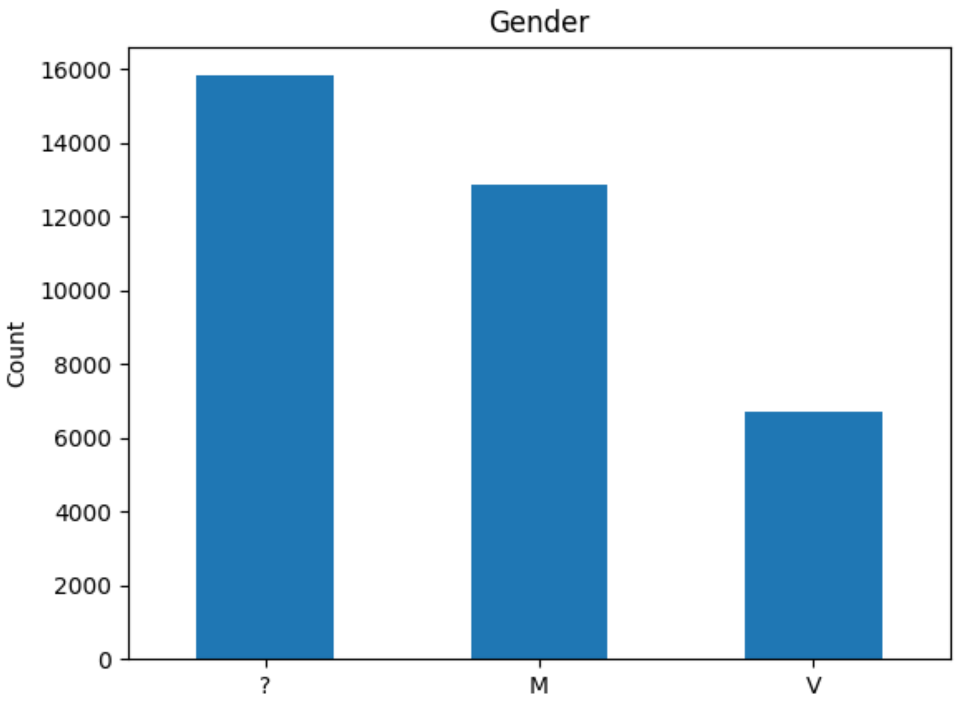
Representativeness of tweets

Q: Who is tweeting about face masks?

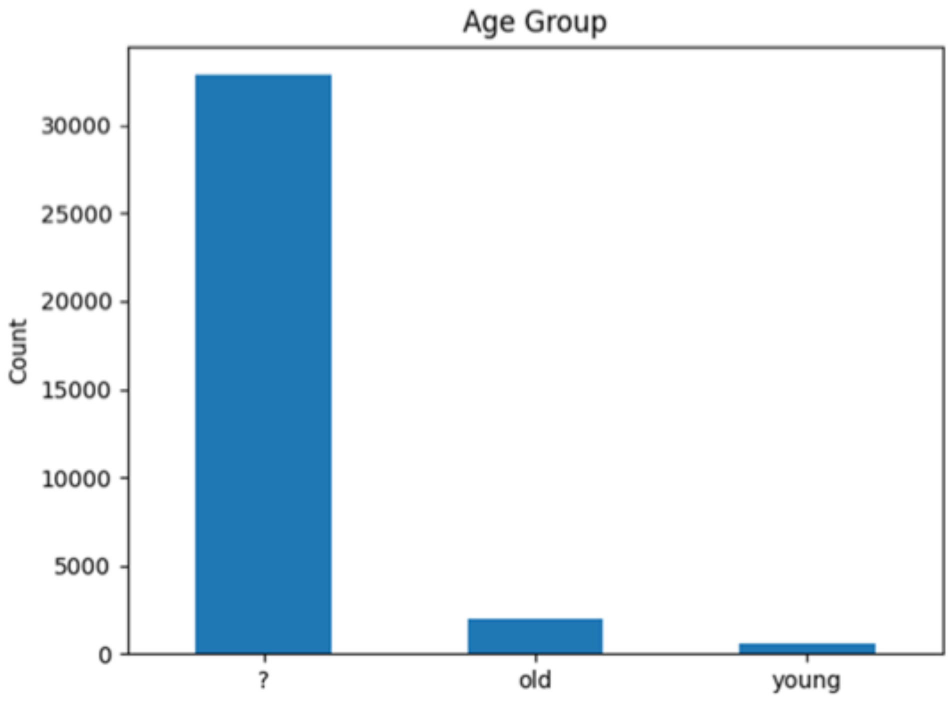
- age
- gender
- locations
- friends and followers

A: Overall, older males tweet about face masks

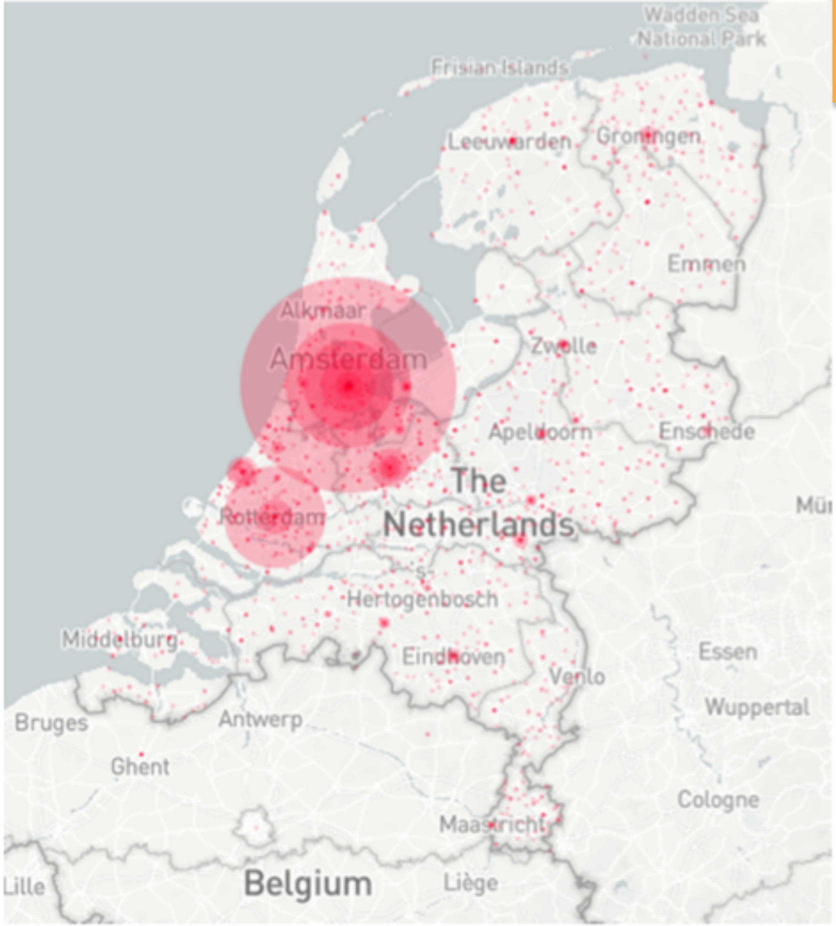
Gender classification



Age classification



Location


Wadden Sea National Park
Frisian Islands
Leeuwarden
Groningen
Emmen
Alkmaar
Amsterdam
Zwolle
Apeldoorn
Enschede
The Netherlands
Rotterdam
's-Hertogenbosch
Middelburg
Eindhoven
Venlo
Essen
Wuppertal
Bruges
Antwerp
Ghent
Cologne
Maastricht
Lille
Belgium
Liège

Overall conclusion

We applied several methods to gain insights in what stances and topics were discussed on Twitter during the corona crisis

We successfully showed that stances change over time, e.g. before and after a press conference

Due to a clear demographic bias in the Twitter population, we cannot say anything about the general public's opinion

Behaviour-based Language-Interactive Speaking Systems

BLISS

an NWO Data2Person project, duration 03/2019 - 09/2022

bliss.ruhosting.nl

Team

- Helmer Strik, Catia Cucchiarini, Louis ten Bosch, Iris Hendrickx
- Jelte van Waterschoot, Mariët Theune
- Rob Tieben, Werner Rutten, Jurriaan van Rijswijk
- Marcel de Korte, Esther Klabbers, Staffan Meij

Conversational agents (CA)

- trending & popular
- voice assistants in our homes and daily life: : Amazon alexa, Apple Siri, Google home assistant
- company helpdesks & costumer service: chatbots (mostly text-based)

chatbots /CAs Advantages

- 24/7 available
- immediate respons
- patient
- consistent
- non-judgemental

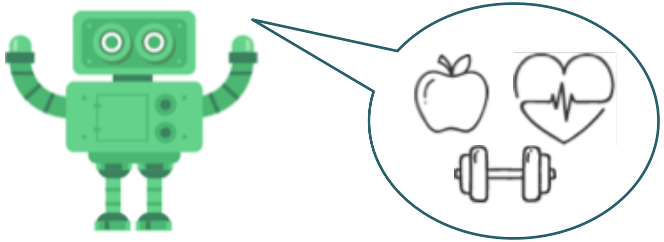
chatbots /CAs

- repetitive /boring
- unemotional
- lack of personalization
- hardly any long-term interactions (single turn bots)
- lack of memory

Context

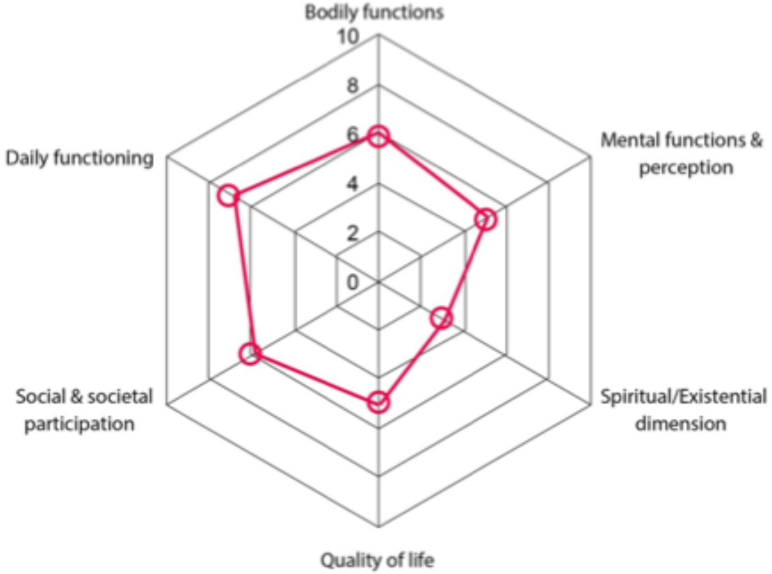
- increase in health care at home: need for self-management and empowerment
- technological developments in big data analysis and (spoken) language technology

Can we develop intelligent, personalized systems that talk to clients in Dutch to facilitate their self/joint-management of health and well-being?



Happiness model

Health & wellbeing is conceptualized in a happiness model based on theory of positive health (Huber et al., 2016)



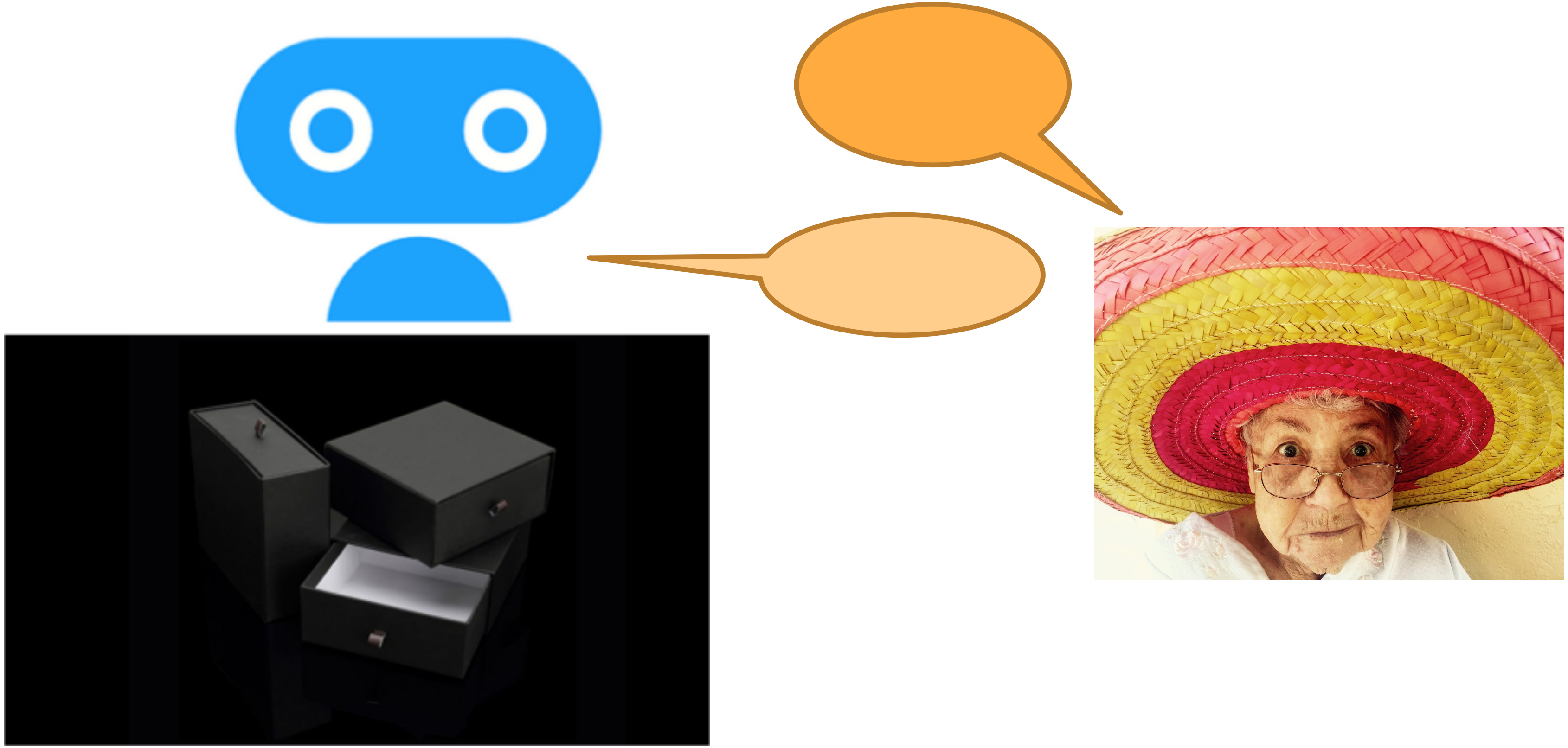
Huber M, van Vliet M, Giezenberg M, et al. Towards a 'patient-centred' operationalisation of the new dynamic concept of health: a mixed methods study *BMJ Open* 2016;6:e010091. doi: 10.1136/bmjopen-2015-010091

spoken dialogue systems(SDS)

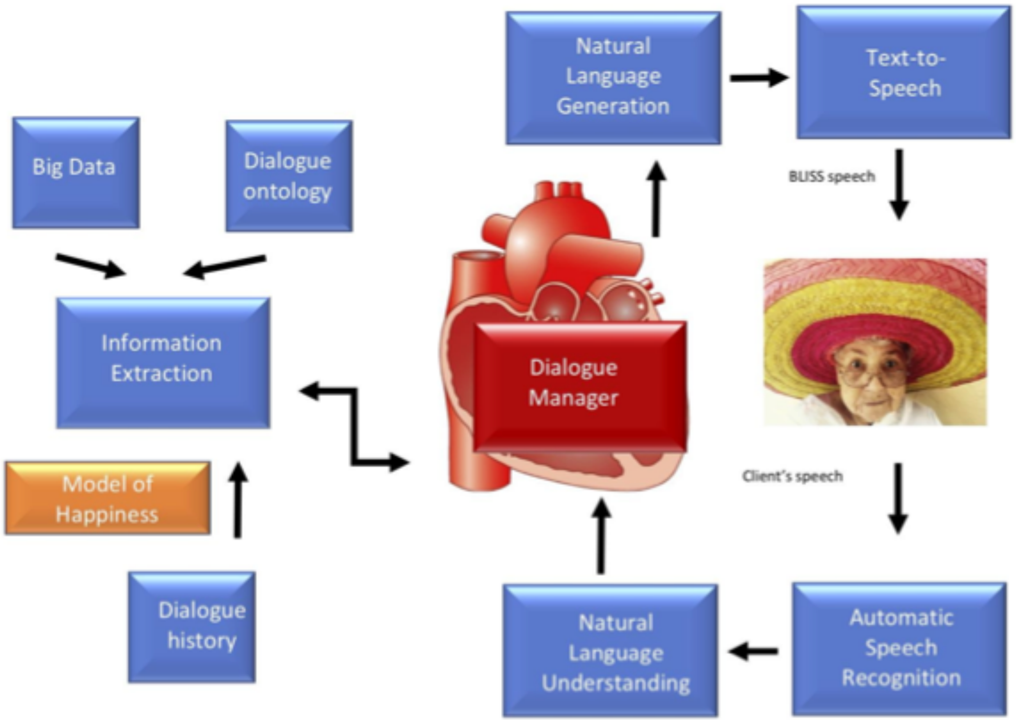
dialogue example

9	Agent	If you could choose one thing you want to do this weekend, what would it be?
10	User	Reading a bit.
11	Agent	Sounds good. Why do you like that?
12	User	It's very relaxing.
13	Agent	And if you could choose a second activity, what would that be?
14	User	I think that would be cycling.
15	Agent	What would you miss most if you wouldn't do cycling?
16	User	The physical activity, but then I would resort to walking.
17	Agent	Looking back at last week, which activity did you enjoy most?
18	User	Visiting my friends.
19	Agent	Great! What kind of feeling did it give you?
20	User	A lot of fun

how does a dialog system work?



BLISS architecture



modules BLISS

- *IE: information extraction*
- *DM: dialogue manager*
- *NLG: natural language generation*
- *NLU: natural language understanding:*
- *TTS: text-to-speech*
- *ASR: automatische spraak herkenning*

What is exactly the information about social participation and activities that we aim to extract and which questions should we ask to get this information?

Activities

Tijdsbestedings onderzoeken in Nederland

https://www.scp.nl/over-scp/data-en-methoden/onderzoeksbeschrijvingen/tijdsbestedingsonderzoek-tbo

3611 Dagelijkse boodschappen
Winkelen
 kopen van kleren
 kado's
 huishoudelijke goederen
 planten kopen.
3613 Meubelboulevard etc

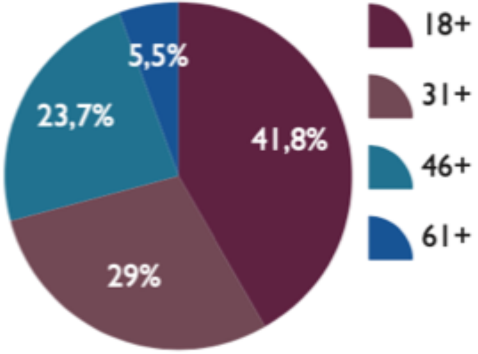
bliss v1

BLISS v1 system

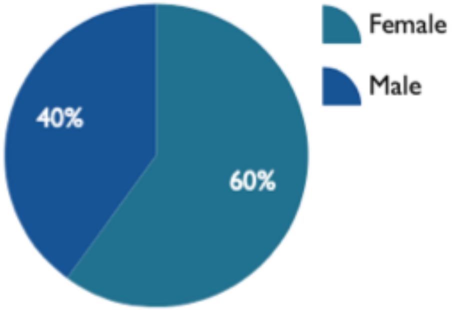
- Detect sentiment when chatting with the agent to measure user expectations.
- Ask three questions about activities and three follow-up questions about motivations based on IPH questionnaire (Huber et al., 2011).
- Extract verb phrases from users utterances for input for a more personalized follow-up question.

Dialogue data set

- 55 dialogues
- ~ 2:30 minutes
- Full dialogues in Dutch
- Audio of user speech
- Automated transcripts of user speech
- Demographic information
- Available for reseach for others



Age



Gender

dialogue example

#	Speaker	Turn (translated transcript)
1	Agent	Sounds good. Why do you like that?
2	User	he faltered already with the question.**
3	Agent	And if you could choose a second activity, what would that be?
4	User	uhm then I would go have a drink with my friends in the city
5		yes*
6		yes I do still have a little bit of patience**
7		because he took my text also this time**
8	Agent	What would you miss most if you wouldn't do take?
9	User	if you take, what do you mean with take?**
10	Agent	Looking back at last week, which activity did you enjoy most?
11	User	uh last week i found too active, i liked the best to uh on Sunday go to hockey with the kids
12		mmm.*
13		are we getting any other questions?**
14	Agent	Great! What kind of feeling did it give you?
15	User	uh yes*
16		that makes me happy

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Dialog errors

- speech recognition error
- `dat is mijn google sissend.    (Google Assistant)`
- speech recognition: cannot recognize unknown words

`een aflevering kijkt van <unk> favoriete serie op de <unk>`

- too slow processing

crucial for fluent dialogs

- recognition of backchannels “mmm”, ‘yeah”
- recognition of stalling : uh”, “uhm” and “mmm
- find correct end-of-turn pauze
  (huge problem for SDS)

future version;
- recognize explicit problem signals (‘user: i dont understand ’)

Reflections on privacy and personalisation

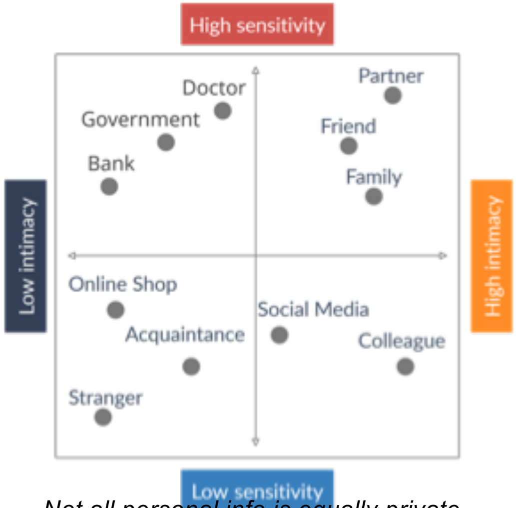
privacy, personalization and ethics

Twitter analysis: detecting location, gender, age
Bliss: extract personal profile about persons' well being

personalisation in conversational agents

Personalization can take place at many levels:

- Conversation style (informal or formal, level of language complexity)
- Choice of agent voice (accent, age and gender)
- Content of conversations



Not all personal info is equally private

In our project a personal profile for every user is created storing information from previous dialogs

Transparency

Control and access of the user on how their personal information is stored by the agent

Current situation: informed consent before experiments

After giving consent, the user no longer has control on what is stored from the conversations.

We argue that **this insufficient!**

We need methods to improve transparency and control by the user

Photo by Igor Tudoran on Unsplash

Potential Solutions

We plan to investigate two approaches:

- **Conversational abstractive summarization:** present the user a summary at the end of the conversation

- **Editable online webform** with user profile in a table format

Thanks for listening!

Questions?

Our Dutch online speech recognition demo:
https://cls.ru.nl/online-asr/

Current BLISS Demo (Dutch):
https://accept.whappbot.com/chat/bliss_demo

CLST: https://www.ru.nl/clst/

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