Translational Data Science & AI

A case of Natural Language Processing for Violence Risk Assessment using CRISP-DM

Speaker: *Prof. dr. Marco Spruit (LUMC/LIACS)*

Mission: *"Translating novel AI technologies to practically usable solutions in population health & wellbeing"*

ZyLAB

1993 1995 1997 2003 2007

2020

Health Campus Den Haag

LUMC

LEIDEN BIO SCIENCE PARK

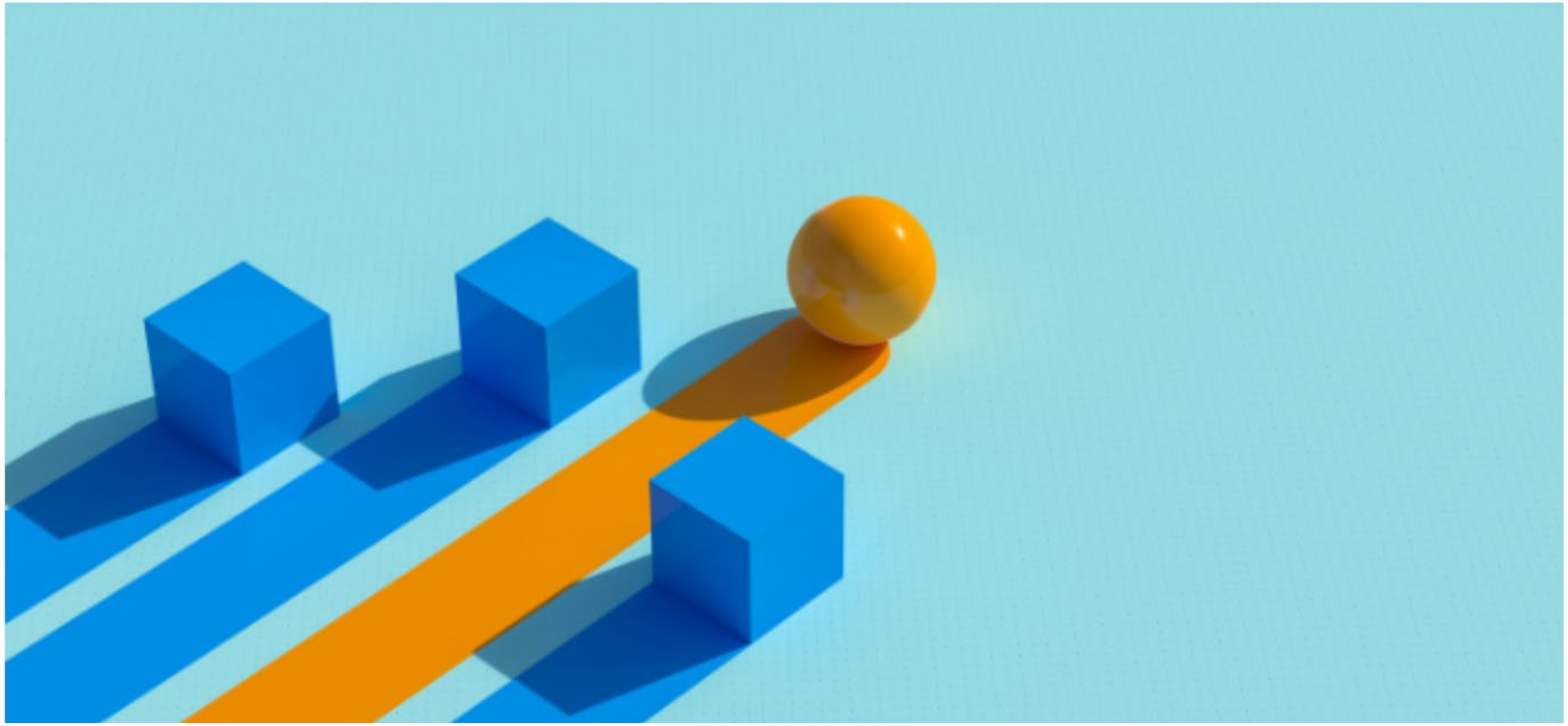
liacs

WHY ME??

https://patientengagementhit.com/features/understanding-crime-violence-as-a-social-determinant-of-health

Understanding Crime, Violence as a Social Determinant of Health

Violence is a key social determinant of health that can have both physical and psychological well-being impacts.



April 12, 2023 - As the US healthcare system comes to understand the numerous non-clinical factors that influence health and well-being, it can begin to acknowledge exposure to crime and violence as a social determinant of health.

What is… Health Campus The Hague?

1. Reduce health **inequalities**
2. Pursue a **sustainable** approach
3. Utilise **positive** health perspective

1) *Trans-disciplinary,*
2) *Cross-domain,*
3) *Regional* data infra:

ELAN

→ 1.1M records!

Leids Universitair Medisch Centrum

Population health/data research

De Haagse Hogeschool

Population health/data research

HagaZiekenhuis

Hospital data

Reinier de Graaf

Hospital data

parnassia groep
Specialist in geestelijke gezondheid

Mental health data

HMC

Hospital data

hadoks

GP data

Universiteit Leiden

Data science & AI

Vrede en Recht
Den Haag

Social Support Act data (ao)

GGD Haaglanden

Vaccination data (ao)

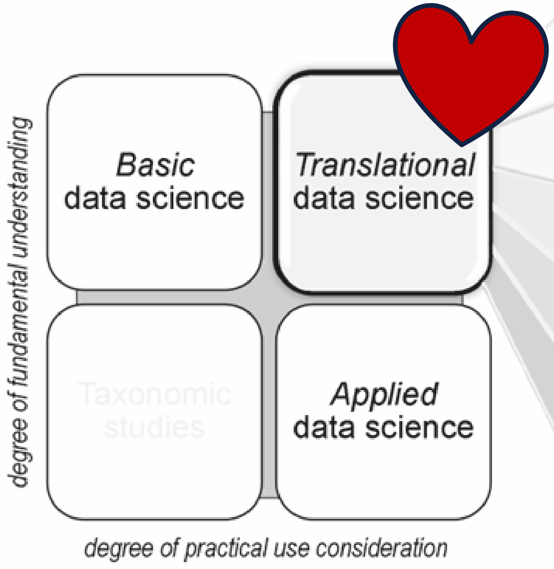
\+ cbs

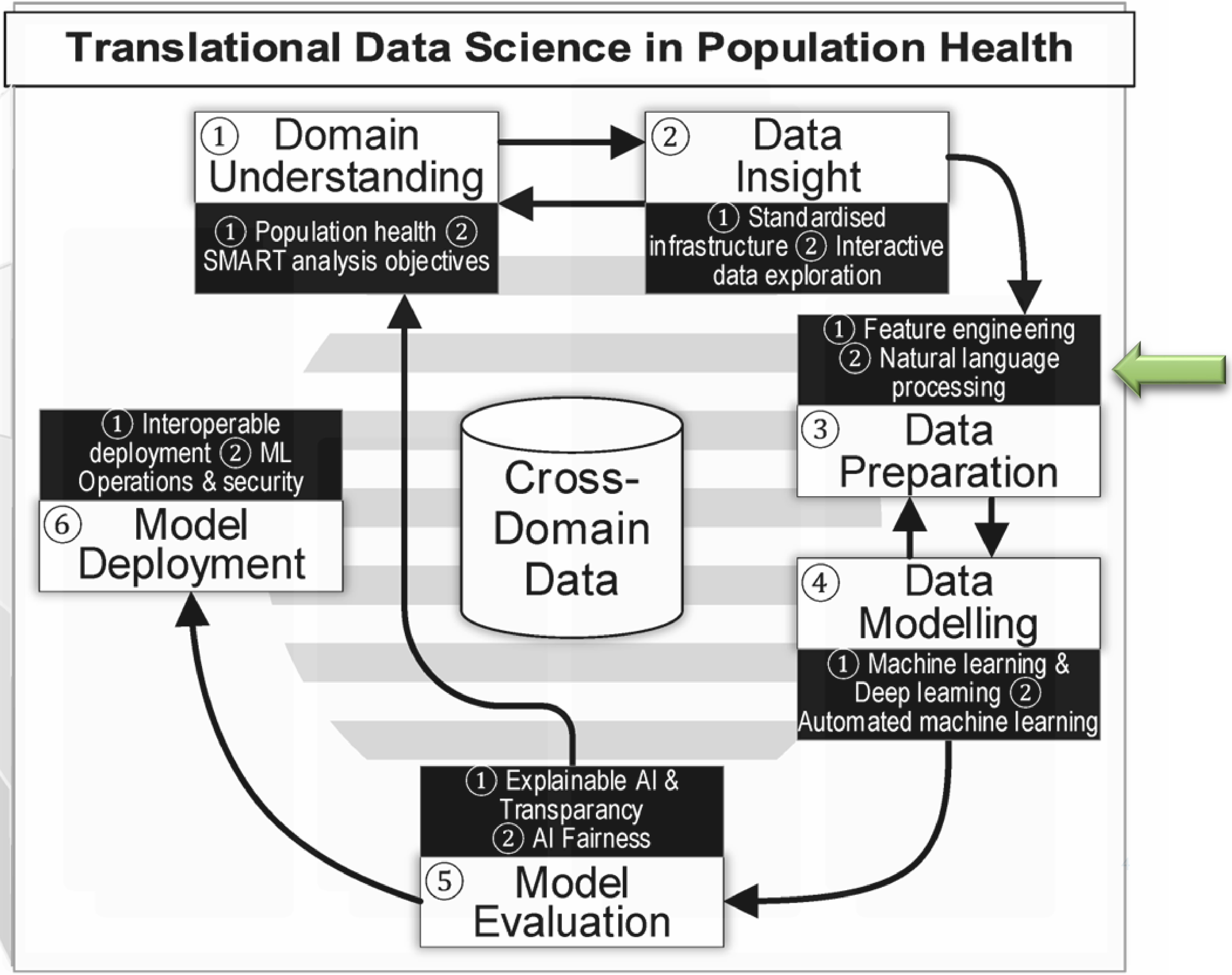
Health Campus Den Haag

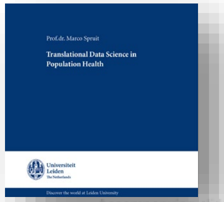
healthcampusdenhaag.nl

TRANSLATIONAL DATA SCIENCE LAB

https://tdslab.nl







Spruit, Marco. (2022). Translational Data Science in Population Health (20 pages). Leiden University. https://doi.org/10.5281/zenodo.7665858

Accompanying text to inaugural lecture of Prof. Dr. Marco Spruit on 1 April 2022 at Leiden University

[0.341, -0.359, 0.7, 0.926, -0.004, …, -0.129]

[Positive, Negative]

Predicting Inpatient Violence Risk with Clinical Notes in Electronic Health Records

CASE STUDY 2

Menger,V., Spruit,M., Est,R. van, Nap,E., & Scheepers,F. (2019). Machine Learning Approach to Inpatient Violence Risk Assessment Using Routinely Collected Clinical Notes in Electronic Health Records. *JAMA Network Open*, 2(7), e196709. https://doi.org/10.1001/jamanetworkopen.2019.6709

[1/6]
Domain Understanding: Objective

- "Predict for which admissions a violence incident will occur in the first 30 days, based on clinical texts that are written up to and including the first day of admission"
  - Prediction task excludes incidents on Day 1 of admission
    - insufficient data available to make a prediction
  - 30 days interval chosen for sufficient specificity
    - majority of incidents included
    - mean duration of admission is 40.3 days
    - 81.9% of incidents happen during the first 30 days
- Area Under Curve (AUC) to report performance

[2/6]
Data Understanding

- Site 1: UMC Utrecht
- Site 2: Antes, Parnassia Group, Rotterdam

Table 1. Descriptive Statistics of the Data Sets Obtained From the 2 Sites

	No. (%)	
Characteristic	Site 1	Site 2
Demographic characteristics		
Age, mean (SD), y	34.0 (16.6)	45.9 (16.6)
Men	1536 (48.2)	2097 (64.5)
Data set		
Admissions, No.	3189	3253
Unique patients, No.	2209	1919
Length of stay, median (IQR), d	16.0 (6.0-41.0)	15.0 (5.0-40.5)
No. of words in notes, median (IQR)	2091 (1541-2981)	1961 (1160-3060)
Admissions with violent incidents	290 (9.1)	247 (7.7)
Incidents		
During admission, No.	962	652
During first 4 wk	658 (68.4)	318 (48.8)
During first 24 h	90 (9.4)	42 (6.4)
Staff Observation Aggression Scale-Revised score, median (IQR) [range]	12.0 (8.0-16.0) [2-21]	11.0 (7.0-14.0) [2-19]
Diagnostic and Statistical Manual		

[2/6]
DATA UNDERSTANDING

(2012-07-29) "Ms slept moderately, slept from 1am to 4am. Then came out of bed, ate biscuits and drank tea. Still advised to take medication and expressed my concerns about possibly slipping into mania. Mw was unresponsive and reacted agitatedly. Mw was talkative but indicated that when she feels well she also talks a lot. Mw is going to <PERSON-1> with her son today, is not looking forward to it now because the symptoms she experienced on her feet yesterday have disappeared. Mw went back to bed after 4am and did not come out of her room until morning."

(2012-07-29)
"Mw heeft matig geslapen, sliep van 1.00 uur tot 4.00 uur. Kwam toen uit bed, at koekjes en dronk thee. Nog geadviseerd medicatie te nemen en mijn zorgen geuit over evt. doorschieten in een manie. Mw was er niet gevoelig voor en reageerde geagiteerd. Mw had spreekdrang maar gaf aan dat wanneer zij zich goed voelt ook veel praat. Mw gaat vandaag naar <PERSOON-1> met haar zoon, ziet daar nu niet meer tegenop omdat de klachten die zij gisteren aan haar voeten ervaarde verdwenen zijn. Mw ging na 4.00 uur weer naar bed en kwam niet meer uit haar kamer tot de ochtend."

?

[2/6]
DATA UNDERSTANDING

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(2012-08-05)[...] "In defiance, Ms kicked me against the side of my leg" [...].

[3/6]
Data Preparation

Text representation

- Represent all clinical notes related to 1 admission as 1 vector (not words)

- *paragraph2vec*
- *SVM classifier*

[3/6]
Data Preparation: Alternative ML Models

Menger,V., Scheepers,F., & Spruit,M. (2018). Comparing Deep Learning and Classical Machine Learning Approaches for Predicting Inpatient Violence Incidents from Clinical Text. *Applied Sciences, 8*(6), Data Analytics in Smart Healthcare, 981. [JIF: 2.679].
https://doi.org/10.3390/app8060981

- In previous work, we determined SVM as an appropriate classifier for VRA, based on literature and experiments

Table 4. The performance for optimal hyperparameter values for each of the representations combined with the models, based on a 5-fold stratified cross validation. The performance is measured in AUC, along with its standard deviation. The best performance over different models is marked with an [a], the best performance over representations with a [b].

Model	Bag-of-Words Binary	Bag-of-Words tf-idf	Word Embeddings	Document Embeddings
RNN [1]	0.771 ± 0.018 [b]	0.753 ± 0.031	0.654 ± 0.043	0.788 ± 0.018 [a,b]
CNN [2]	0.729 ± 0.030	0.716 ± 0.038	0.684 ± 0.038	0.763 ± 0.024 [a]
NN [3]	0.727 ± 0.033	0.717 ± 0.038	0.751 ± 0.036 [a]	0.745 ± 0.022
NB [4]	0.686 ± 0.026	0.704 ± 0.034 [a]	0.700 ± 0.051	0.692 ± 0.046
SVM [5]	0.759 ± 0.040	0.756 ± 0.036 [b]	0.764 ± 0.024 [b]	0.770 ± 0.029 [a]
DT [6]	0.727 ± 0.018 [a]	0.719 ± 0.041	0.685 ± 0.041	0.665 ± 0.035

[1] Recurrent Neural Network; [2] Convolutional Neural Network; [3] Neural Network; [4] Naive Bayes; [5] Support Vector Machine; [6] Decision Tree.

[4/6] *Modelling:* Prediction performance

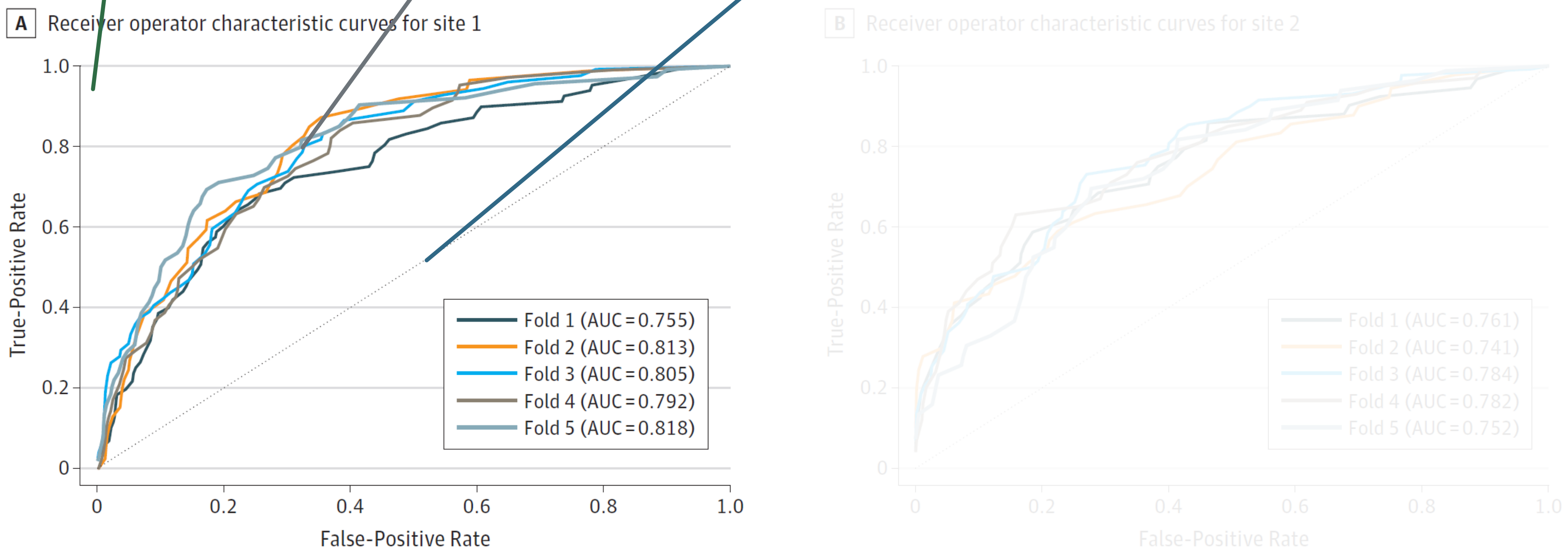
(SVM CLASSIFIER)

Perfect Score

Actual Score

Random Score

Figure. Receiver Operator Characteristic Curves for Internal Cross-validations



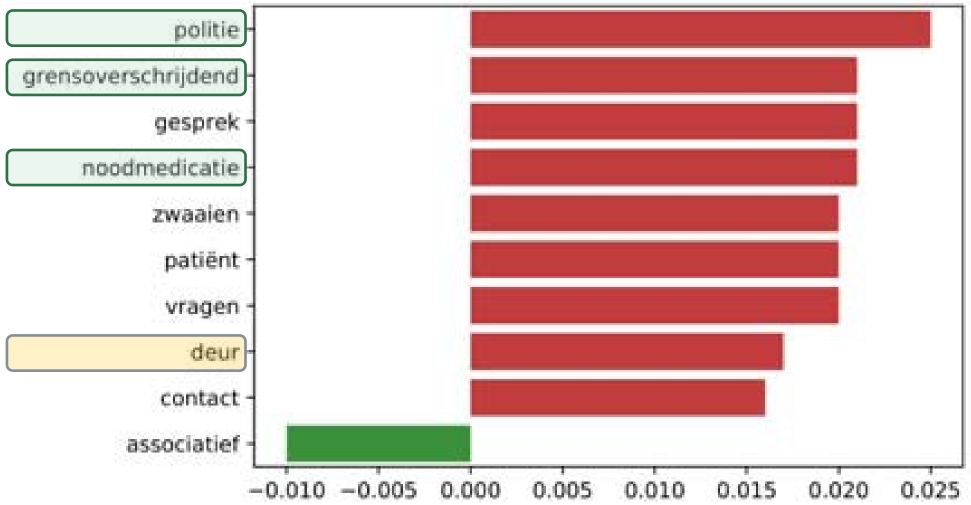
Receiver operator characteristic curves are shown for each fold, according to internal cross-validation in site 1 (A) and site 2 (B). Dashed diagonal lines denote an area under the curve (AUC) of 0.5, ie, predictive validity equivalent to chance. AUC indicates area under the curve.

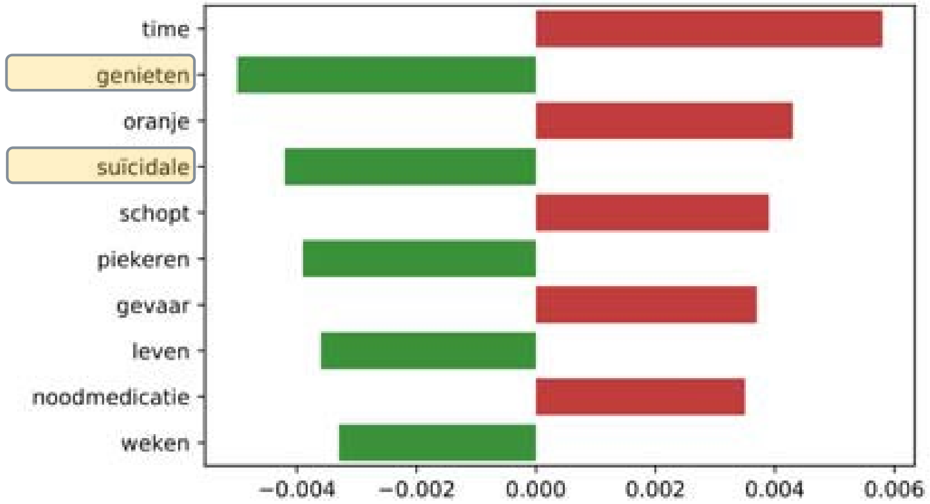
[5/6]
Evaluation: Exploratory Analysis

Table 3. Results of Exploratory Analysis

	Site 1				Site 2			
Rank[a]	Term (English Translation)[b]	Ratio	MCC (95% CI)[c]	*P* Value[d]	Term (English Translation)[b]	Ratio	MCC (95% CI)[c]	*P* Value[d]
1	Agressief (aggressive)	1.00	0.17 (0.13 to 0.21)	<.001	Verbaal (verbal)	1.00	0.14 (0.10 to 0.18)	<.001
2	Reageert (reacts)	1.00	0.15 (0.11 to 0.19)	<.001	Dreigend (threatening)	1.00	0.13 (0.08 to 0.16)	<.001
3	Aangeboden (offered)	1.00	0.14 (0.11 to 0.18)	<.001	Agressie (aggression)	1.00	0.15 (0.11 to 0.17)	<.001
4	Boos (angry)	1.00	0.16 (0.12 to 0.19)	<.001	Hierop ([up]on this)	1.00	0.13 (0.09 to 0.16)	<.001
5	Deur (door)	1.00	0.14 (0.10 to 0.18)	<.001	Kantoor (office)	1.00	0.12 (0.08 to 0.16)	<.001
6	Loopt (walks)	1.00	0.15 (0.11 to 0.18)	<.001	Personeel (staff)	1.00	0.12 (0.07 to 0.16)	<.001
7	Ibs (arrest)	1.00	0.14 (0.10 to 0.17)	<.001	Aangesproken (spoke to)	1.00	0.11 (0.08 to 0.15)	<.001
8	Aanbieden (offer)	1.00	0.12 (0.08 to 0.15)	<.001	Agressief (aggressive)	0.99	0.11 (0.08 to 0.15)	<.001
9	Noodmedicatie (emergency medication)	0.99	0.14 (0.10 to 0.17)	<.001	Gevaar agressie (danger aggression)	0.99	0.11 (0.07 to 0.15)	<.001
10	Liep (walked)	0.99	0.12 (0.08 to 0.16)	<.001	Agitatie (agitation)	0.99	0.11 (0.07 to 0.14)	<.001
11	Agressie (aggression)	0.99	0.13 (0.09 to 0.18)	<.001	Geirriteerd (irritated)	0.99	0.10 (0.06 to 0.14)	.001
12	Vraagt (asks)	0.99	0.13 (0.10 to 0.17)	<.001	Separeer (seclusion room)	0.99	0.10 (0.06 to 0.15)	<.001
13	Status vrijwillig (status voluntary)	0.99	−0.12 (−0.14 to −0.09)	<.001	Loopt (walks)	0.99	0.11 (0.08 to 0.14)	.02
14	Psychotisch (psychotic)	0.98	0.12 (0.09 to 0.16)	<.001	Grond (ground)	0.98	0.10 (0.06 to 0.14)	<.001
15	Collega (colleague)	0.98	0.11 (0.07 to 0.15)	<.001	Aanvang (commencement)	0.98	0.11 (0.08 to 0.14)	.01
16	Spreekt (speaks)	0.97	0.12 (0.08 to 0.15)	<.001	Mede (also)	0.98	0.10 (0.07 to 0.14)	.001
17	Gehouden (obliged)	0.97	0.11 (0.07 to 0.15)	<.001	Dhr wilde (Mr wanted)	0.98	0.10 (0.06 to 0.14)	.001
18	Beoordelen (judge), verb	0.96	0.11 (0.07 to 0.15)	<.001	Liep (walked)	0.98	0.10 (0.06 to 0.14)	.006
19	Momenten (moments)	0.96	0.12 (0.08 to 0.15)	<.001	Geagiteerd (agitated)	0.96	0.10 (0.06 to 0.14)	.01
20	Somber (dejected)	0.95	−0.14 (−0.17 to −0.11)	<.001	cvd (not available)	0.96	0.10 (0.06 to 0.14)	.004

[5/6]
EVALUATION: MODEL EXPLAINABILITY





- Sample of Local Explanation predicting high risk of aggression

The *"Linear Model-Agnostic Explanations"* (LIME) method

- Sample of Local Explanation predicing low risk of aggression

[6/6]
Deployment

- Mosteiro,P., Rijcken,E., Zervanou,K., Kaymak,U., Scheepers,F., & Spruit,M. (2021). Machine Learning for Violence Risk Assessment Using Dutch Clinical Notes. *Journal of Artificial Intelligence for Medical Sciences, 2*(1–2), 44–54. https://doi.org/10.2991/jaims.d.210225.001
- Rijcken,E., Kaymak,U., Scheepers,F., Mosteiro,P., Zervanou,K., & Spruit,M. (2022). Topic Modeling for Interpretable Text Classification from EHRs. *Frontiers in Big Data, 5*, Section Data Mining and Management, 846930. https://doi.org/10.3389/fdata.2022.846930
- Rijcken, E., Zervanou, K., Spruit, M., Mosteiro, P., Scheepers, F., & Kaymak, U. (2022, October). Exploring embedding spaces for more coherent topic modeling in electronic health records. In *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. 9-12 Oct 2022, Prague, Czech Republic (pp. 2669-2674). https://doi.org/10.1109/SMC53654.2022.9945594
- Rijcken, E., Scheepers, F., Zervanou, K., **Spruit, M.**, Mosteiro, P., & Kaymak, U. (2023). Towards Interpreting Topic Models with ChatGPT. In *The 20th World Congress of the International Fuzzy Systems Association (IFSA)*. 20-24 August 2023, Daegu, South Korea. https://research.tue.nl/files/300364784/IFSA_InterpretingTopicModelsWithChatGPT.pdf

Thanks for your attention 👍

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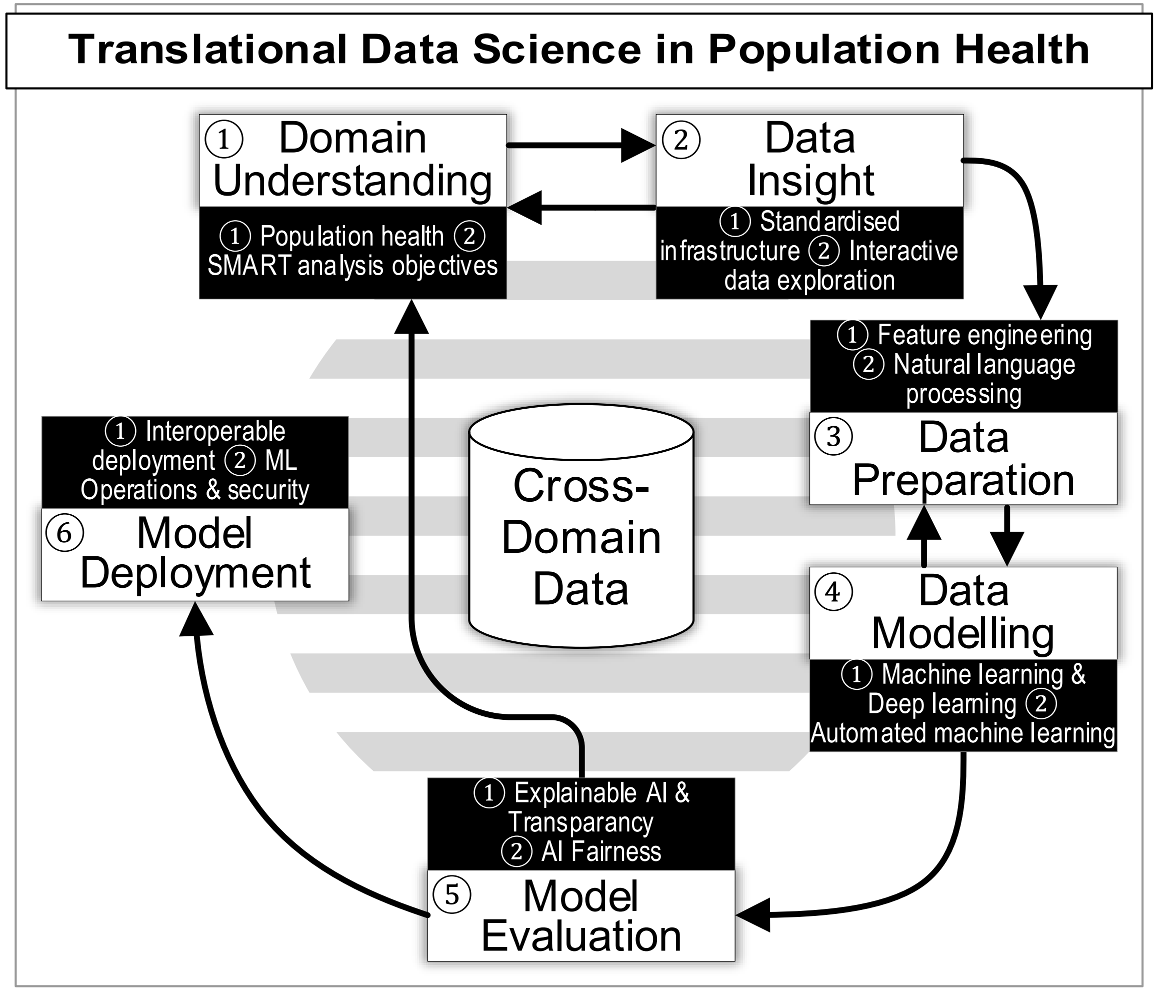
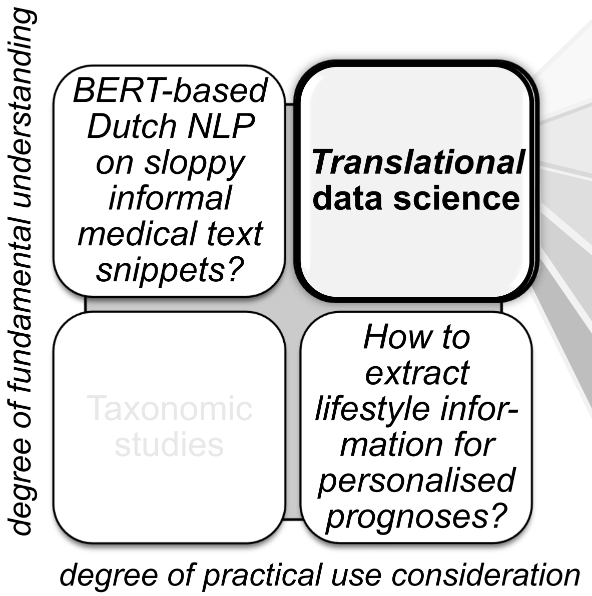


[NEXT CYCLE]
LLMs



Extracting Lifestyle Characteristics with NLP

Muizelaar,H., Haas,M., Putten,P. v.d., & Spruit,M. (submitted). [preprint]

Example text data	Smoking	Alcohol	Drugs
Patient smokes, does not drink or use drugs	Current user	Non-user	Non-user
Patient used to smoke, drinks 1 beer a day	Former user	Current user	Unknown
Patient used to smoke, uses marihuana daily	Former user	Unknown	Current user

Model	***Smoking***	***Alcohol***	***Drugs***
String Matching	0.84	0.74	0.68
Machine Learning (SGD)	0.85	0.71	0.60
HAGALBERT	0.66	0.54	0.43
RobBERT-HAGA	0.87	0.71	0.63
belabBERT-HAGA	0.48	0.64	0.57
MedRoBERTa.nl-HAGA	0.93	0.79	0.77
BioBERT (translated)	0.91	0.72	0.52
ClinicalBERT (translated)	0.92	0.80	0.61

RECENTLY LAUNCHED PET PROJECT: LLMS FOR WELLBEING AI

TOP-3 functionele kenmerken

1. Vrijwillig en altijd beschikbaar maatje
   - *Minder eenzaamheid*
2. Gesprekken mét *Fun* factor, niet enkel functioneel
   - *Minder depressie*
3. 24/7 inzicht voor behandelend arts
   - *Meer preventie*

TOP-3 technische kenmerken

1. Taalherkenning afgestemd op laagdrempelig taalgebruik (“inclusief” begrip niet-standaard-NL)
2. Automatisch detecteren van iemand’s mentale gezondheidstoestand door spraak en teksten te analyseren op taalmarkeringen (‘biomarkers’)
   - Bijv. overmatig gebruik van de 3e persoon meervoud in het taalgebruik als indicatie voor schizofrenie
3. Gesprekken worden aangestuurd door gestandaardiseerde vragenlijst(en) ROM/PROM/PREM
   - Veiligere AI én beter medisch inzicht/therapietrouw

➔ WelZijn.AI verbindt kwetsbare ouderen met de eerstelijnszorg op speelse wijze door korte vragenlijstjes te combineren met gezellige gesprekjes die met menselijke maat geborgd zijn.