



Prediction of ADHD using Natural Language Processing

Toegepaste data science

1. Zorg verbeteren

Het inzetten van **data** van ①patiënt, ②behandeling en ③uitkomsten van de behandeling om d.m.v. (complexe) **algoritmen** verborgen **verbanden zichtbaar te maken** ter ondersteuning van de patiënt en de behandelaar bij het inzetten van de 'beste' behandeling.



Roel van Est



Eline Nap



Rosa Meijer

2. Kennis, infrastructuur en methoden centraal beschikbaar maken binnen PG

Algoritmes, modellen, data en methoden binnen de groep delen
→ verhogen effectiviteit, efficiëntie en inzetbaarheid.

Samenwerking met externe partijen; kennisoverdracht aan de PG

Vraag

ADHD komt voor bij 3-5% van de kinderen, volwassenen en ouderen. **In de psychiatrie is de prevalentie veel hoger:** ADHD komt voor bij 25% van de verslaafden (van Emmerik-van Oortmerssen 2012), 35% van de borderline patiënten (van Dijk 2012)), 20% van de bipolaire en chronisch depressieve patiënten (Bron 2016; Pinna 2019), en bij 25% van de patiënten met paniekstoornis (Fones 2000). De aantallen zijn opvallend consistent in de range van **20-30%**.

Het is belangrijk ADHD te herkennen omdat met **behandeling** niet alleen de ADHD verbetert, maar ook de **kans op chroniciteit van de andere stoornissen afneemt**. Bijvoorbeeld iemand met ADHD en bipolaire stoornis zal minder therapietrouw zijn en eerder ontregelen wat betreft de stemming. Dit blijkt ook al uit de Scandinavische registratie studies: er zijn minder hypomane episoden als patiënten met bipolaire stoornis en ADHD medicamenteus behandeld worden voor de ADHD. Ditzelfde geldt voor de behandeling van depressie, of het zich houden aan een dieet voor diabetes, of chronisch medicatie gebruik voor astma of elke andere aandoening: dit verloopt minder goed als ADHD niet is behandeld.

Sandra Kooij, specialismeleider ADHD Parnassia Groep

Question

Find patients, using existing data, that have ADHD without it having been diagnosed in the EHR

Goal

- Prevent under treatment of ADHD
- Proof of concept of methodology
 - Usability for other diagnoses
 - More focussed methodology to find additional diagnoses

Inspiration



Screening for posttraumatic stress disorder using verbal features in self narratives: A text mining approach

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ABSTRACT

Much evidence has shown that people's physical and mental health can be predicted by the words they use. However, such verbal information is seldom used in the screening and diagnosis process probably because the procedure to handle these words is rather difficult with traditional quantitative methods. The first challenge would be to extract robust information from diversified expression patterns, the second to transform unstructured text into a structured dataset. The present study developed a new textual assessment method to screen the posttraumatic stress disorder (PTSD) patients using local features in the self narratives with text mining techniques. Using 300 self narratives collected online, we extracted highly discriminative keywords with the Chi-square algorithm and constructed a textual assessment model to classify individuals with the presence or absence of PTSD. This resulted in a high agreement between computer and psychiatrists' diagnoses for PTSD and revealed some expressive characteristics in the writings of PTSD patients. Although the results of text analysis are not completely analogous to the results of structured interviews in PTSD diagnosis, the application of text mining is a promising addition to assessing PTSD in clinical and research settings.

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ORIGINAL RESEARCH ARTICLE

Front. Psychiatry, 11 April 2019 | <https://doi.org/10.3389/psyt.2019.00189>



Text Analysis of Electronic Medical Records to Predict Seclusion in Psychiatric Wards: Proof of Concept

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Aim: With the introduction of "Electronic Medical Record" (EMR) a wealth of digital data has become available. This provides a unique opportunity for exploring precedents for seclusion. This study explored the feasibility of text mining analysis in the EMR to eventually help reduce the use of seclusion in psychiatry.

Methods: The texts in notes and reports of the EMR during 5 years on an acute and non-acute psychiatric ward were analyzed using a text mining application. A period of 14 days was selected before seclusion or for non-secluded patients, before discharge. The resulting concepts were analyzed using chi-square tests to assess which concepts had a significant higher or lower frequency than expected in the "seclusion" and "non-seclusion" categories.

Results: Text mining led to an overview of 1,500 meaningful concepts. In the 14 day period prior to the event, 115 of these concepts had a significantly higher frequency in the seclusion category and 49 in the non-seclusion category. Analysis of the concepts from days 14 to 7 resulted in 54 concepts with a significantly higher frequency in the seclusion-category and 14 in the non-seclusion category.

JAMA Network **Open**



Original Investigation | Psychiatry

Machine Learning Approach to Inpatient Violence Risk Assessment Using Routinely Collected Clinical Notes in Electronic Health Records

Vincent Menger, MSc, Marco Spruit, PhD, Roel van Est, MSc, Eline Nap, MSc, Floor Scheepers, MD, PhD

Abstract

IMPORTANCE Inpatient violence remains a significant problem despite existing risk assessment methods. The lack of robustness and the high degree of effort needed to use current methods might be mitigated by using routinely registered clinical notes.

OBJECTIVE To develop and validate a multivariable prediction model for assessing inpatient violence risk based on machine learning techniques applied to clinical notes written in patients' electronic health records.

DESIGN, SETTING, AND PARTICIPANTS This prognostic study used retrospective clinical notes registered in electronic health records during admission at 2 independent psychiatric health care institutions. No exclusion criteria for individual patients were defined. At site 1, all adults admitted between January 2013 and August 2018 were included, and at site 2 all adults admitted to general psychiatric wards between June 2016 and August 2018 were included. Data were analyzed between September 2018 and February 2019.

MAIN OUTCOMES AND MEASURES Predictive validity and generalizability of prognostic models measured using area under the curve (AUC).

RESULTS Clinical notes recorded during a total of 3189 admissions of 2209 unique individuals at site 1 (mean [SD] age, 34.0 [16.6] years; 1536 [48.2%] male) and 3253 admissions of 1919 unique individuals at site 2 (mean [SD] age, 45.9 [16.6] years; 2097 [65.8%] male) were analyzed. Violent outcome was determined using the Staff Observation Aggression Scale-Revised. We used nested cross-validation to train and evaluate models that assess violence risk during the first 4 weeks of admission, based on clinical notes available after 24 hours. The predictive validity of models was measured at site 1 (AUC = 0.797; 95% CI, 0.771-0.822) and site 2 (AUC = 0.764; 95% CI, 0.732-0.797). Applying trained models to data from other sites resulted in a significantly lower AUC at site 1 (AUC difference = 0.075; 95% CI, 0.045-0.105; $P < .001$) and site 2 (AUC difference = 0.121; 95% CI, 0.085-0.156; $P < .001$).

CONCLUSIONS AND RELEVANCE Internally validated predictions result in AUC values with good predictive validity, showing that automatic violence risk assessment using routinely registered clinical notes is possible. The validation of trained models using data from other sites corroborates previous findings that violence risk assessment generalizes modestly to different populations.

JAMA Network Open. 2019;2(7):e196709. doi:10.1001/jamanetworkopen.2019.6709

Key Points

Question To what extent can inpatient violence risk assessment be performed by applying machine learning techniques to clinical notes in patients' electronic health records?

Findings In this prognostic study, machine learning was used to analyze clinical notes recorded in electronic health records of 2 independent psychiatric health care institutions to predict inpatient violence. Internal predictive validity was measured using areas under the curve, which were 0.797 for site 1 and 0.764 for site 2; however, applying pretrained models to data from other sites resulted in significantly lower areas under the curve.

Meaning Inpatient violence risk assessment can be performed automatically using already available clinical notes without sacrificing predictive validity compared with existing violence risk assessment methods.

+ Supplemental content

Author affiliations and article information are listed at the end of this article.

Aanpak

Preprocessing

ADHD → diagnose = ADHD
Niet-ADHD → diagnose != ADHD EN
→ screener != ADHD

Analyseset

1.042 patiënten ADHD, met rapp-tekst
1.712 patiënten niet-ADHD, met
rapportage tekst

Preprocessing

Stammen, stopwoorden, lengte >1,
<deduce> eruit

Onderscheidende woorden

- Chi2
- # 2.148

Model- / Feature selectie

- 3 Repres.: BOW, TF-IDF, W2V
- 5 modellen: DT, RF, SVM, LR, ET
- 10 aantallen woorden:
alle, 2000, 1500, ..., 100, 50

150 modellen

- Representatie: TF-IDF
- Model: Random Forest
- Aantal woorden: 150
- 5x crossvalidatie

Recall / Sens : 0,69
Precision : 0,86
Specifiteit : 0,93

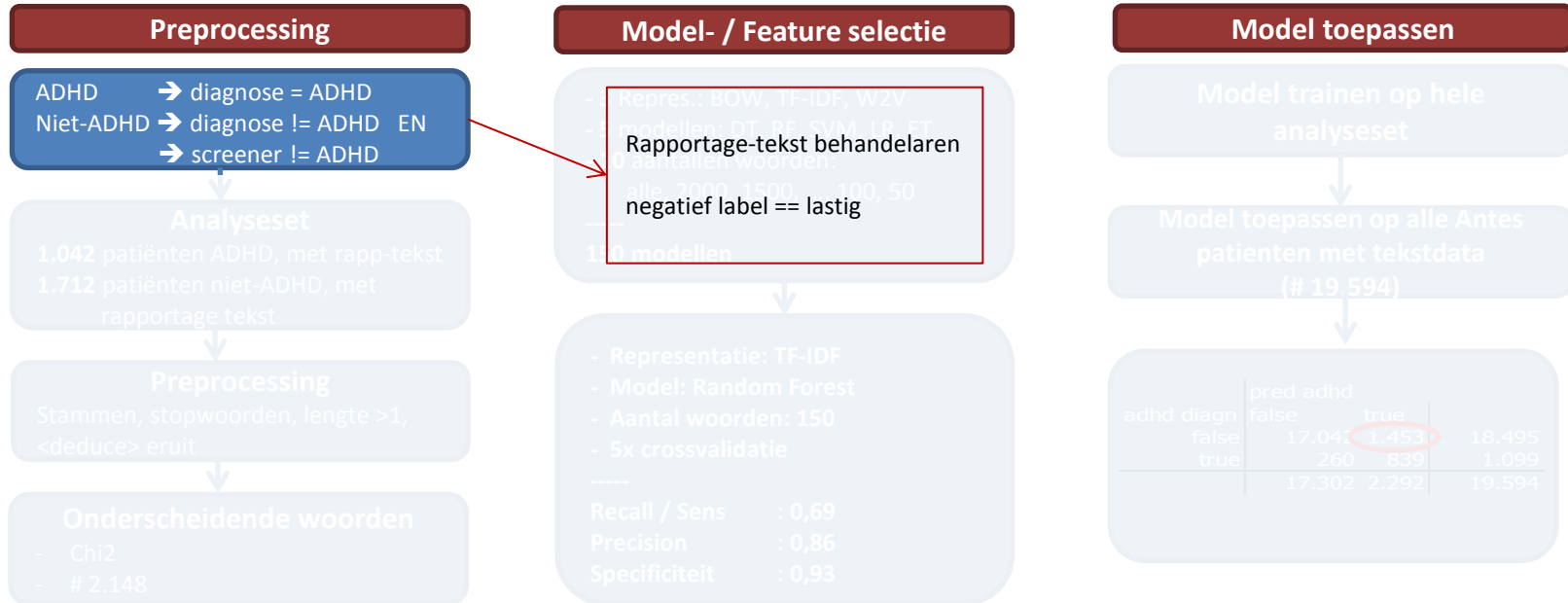
Model toepassen

Model trainen op hele
analyseset

Model toepassen op alle Antes
patienten met tekstdata
(# 19.594)

		pred adhd		
adhd diagn	false	true		
false	17.041	1.453		18.495
true	260	839		1.099
	17.302	2.292		19.594

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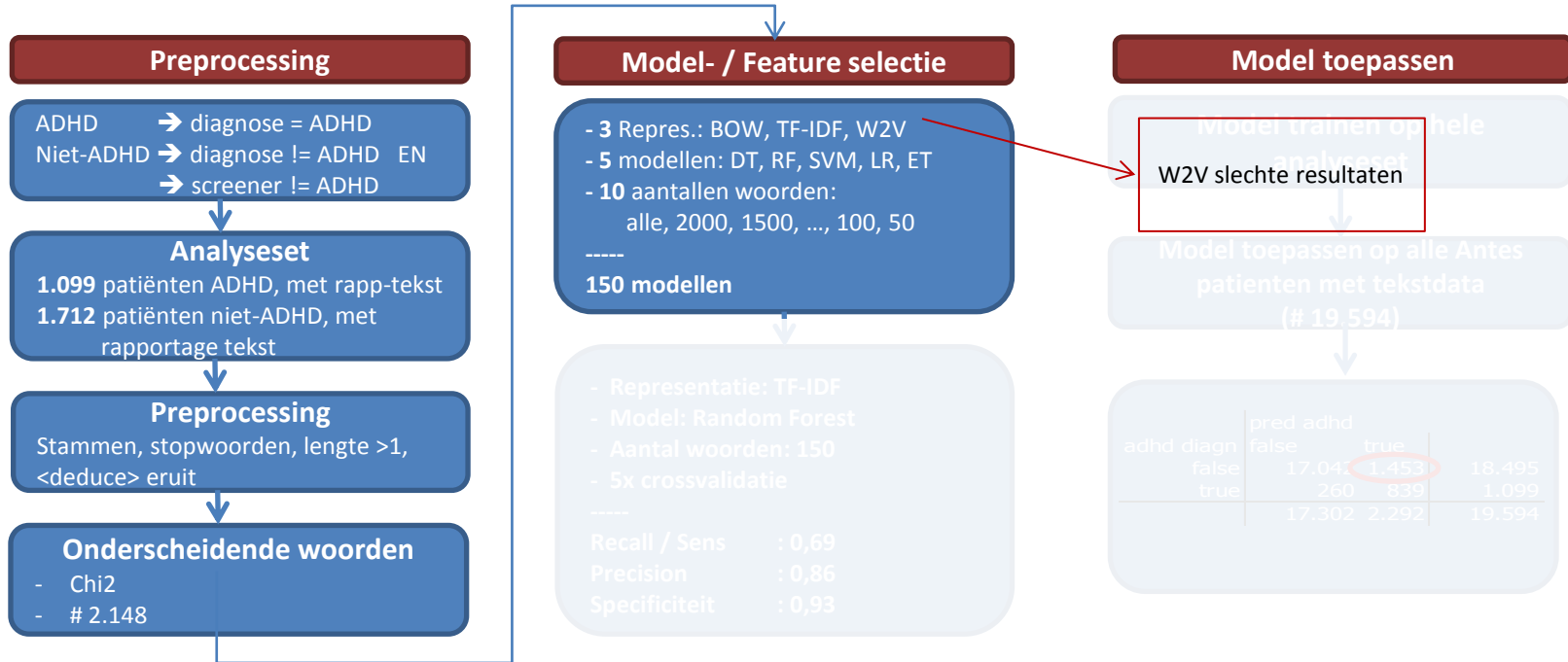
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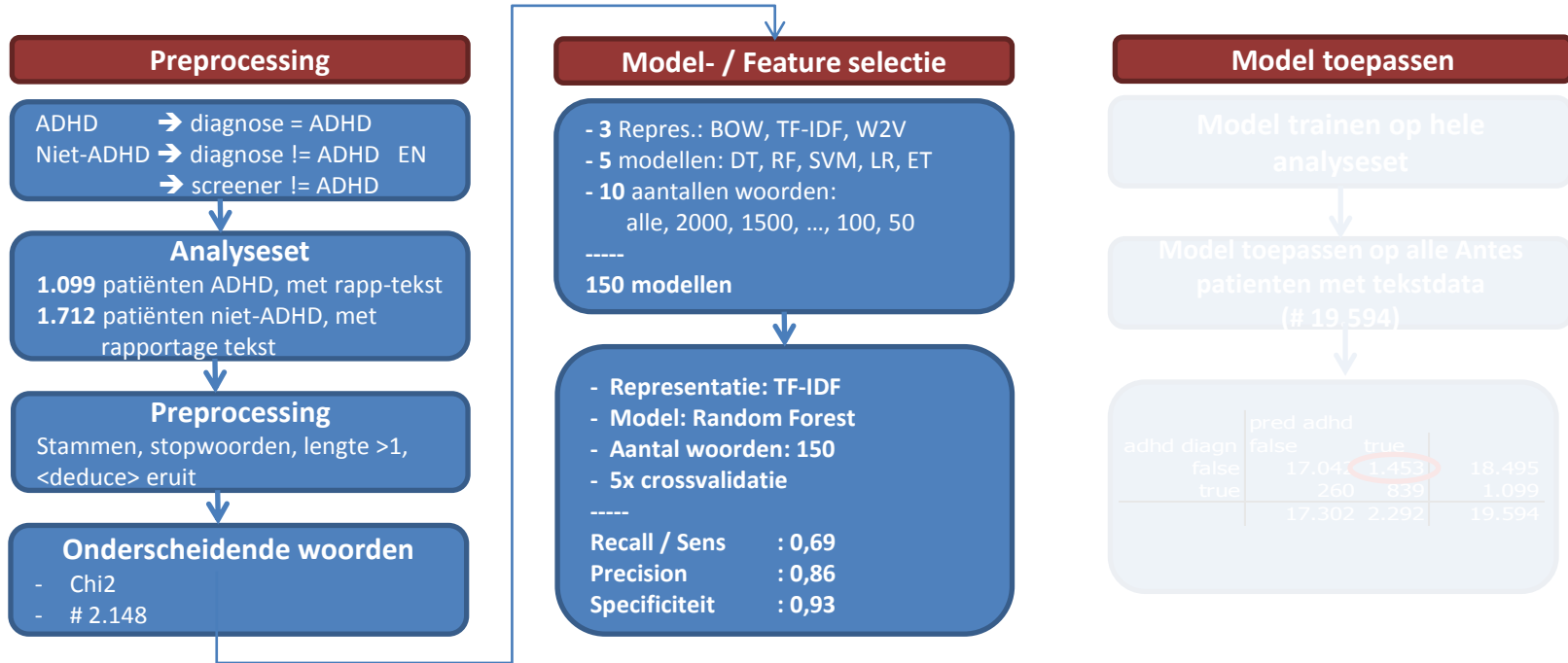
Chi2 woorden

1 huisbezoek	41 amfetamin	81 ambulat	121 psychiatrie	161 sapelli
2 ritalin	42 kliniek	82 toepass	122 gebeld	162 aansprak
3 alcoholgebruik	43 add	83 overdracht	123 structur	163 art
4 boszom	44 doel	84 her	124 welbutrin	164 veldzicht
5 separer	45 observaties	85 vpk	125 gebruikt	165 woonsituatie
6 methyfenidat	46 sliep	86 abtinent	126 psychisch	166 blaz
7 drink	47 gge	87 chaotisch	127 gemobiliseerd	167 drug
8 alcohol	48 gevar	88 pakhuis	128 rustiger	168 afroep
9 adhd	49 monitor	89 wmo	129 diagnos	169 ggen
10 patient	50 contact	90 programma	130 huis	170 verslav
11 ingenom	51 vrouw	91 otz	131 uur	171 longfunctie
12 medicatie	52 groepscontact	92 to	132 zelfverzorg	172 handel
13 gg	53 moeder	93 sep	133 nachtcontrol	173 verhal
14 drinkt	54 bac	94 familie	134 blaast	174 decompensatie
15 pt	55 pdh	95 feedback	135 bier	175 seroquel
16 mener	56 thiamin	96 middel	136 kamer	176 dr
17 dhr	57 npo	97 kwam	137 coll	177 medebewoner
18 concerta	58 opgenom	98 zoontj	138 msc	178 aanmeld
19 mw	59 voorwaard	99 innam	139 middelenmisbruik	179 hoofd
20 fvk	60 afsprak	100 verbal	140 gpt	180 thuiszorg
21 nachtrit	61 gesepareerd	101 detox	141 campral	181 huishoud
22 rm	62 ouder	102 therapieprogramma	142 waargenom	182 fles
23 fac	63 control	103 motorisch	143 digibord	183 beeldvorm
24 dexamfetamin	64 wek	104 vriendin	144 wac	184 geldzak
25 fitheid	65 mild	105 tm	145 oef	185 clozapin
26 automutilatie	66 truxal	106 gok	146 diacetylmorfin	186 ander
27 bvc	67 staf	107 groep	147 og	187 spanning
28 onrust	68 opnam	108 schol	148 vrijwilligerswerk	188 uitgift
29 refusal	69 gedrag	109 cl	149 ontslag	189 separatie
30 druk	70 ftf	110 awb	150 dagsluit	190 dreigement
31 verstrekt	71 behandelar	111 zus	151 gewekt	191 amb
32 wijn	72 nacht	112 volgend	152 huisart	192 dienst
33 gedronk	73 pi	113 uds	153 gat	193 zorginzet
34 ongewijzigd	74 psychotisch	114 behandelcontact	154 verstrekt	194 bijeenkomst
35 telefonisch	75 agressie	115 bupropion	155 alcoholafhank	195 eig
36 sped	76 toezicht	116 ctb	156 thuis	196 archad
37 partner	77 broer	117 betrok	157 later	197 arbeidsmat
38 dgt	78 wellbutrin	118 zelfzorg	158 geagiteerd	198 gedur
39 individueel	79 blok	119 echtgenot	159 pte	199 ciz
40 vader	80 labo	120 fjord	160 toestandsbeeld	200 policontract

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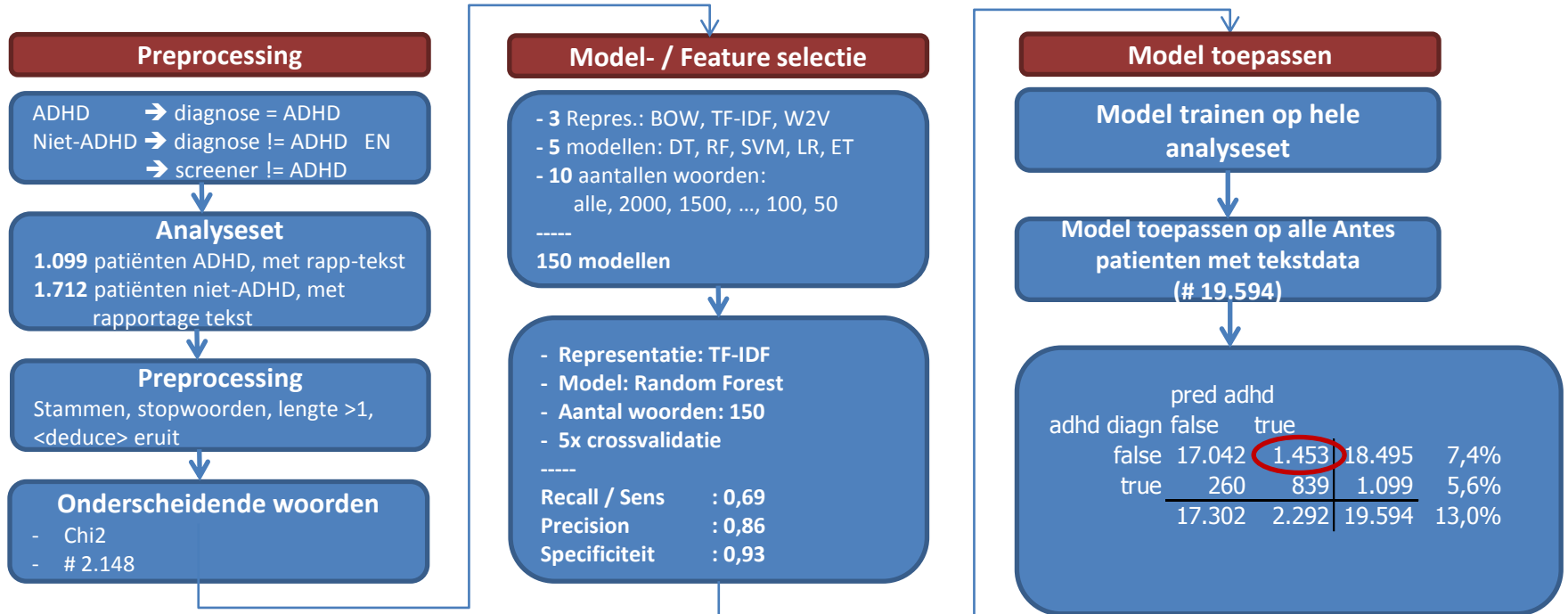
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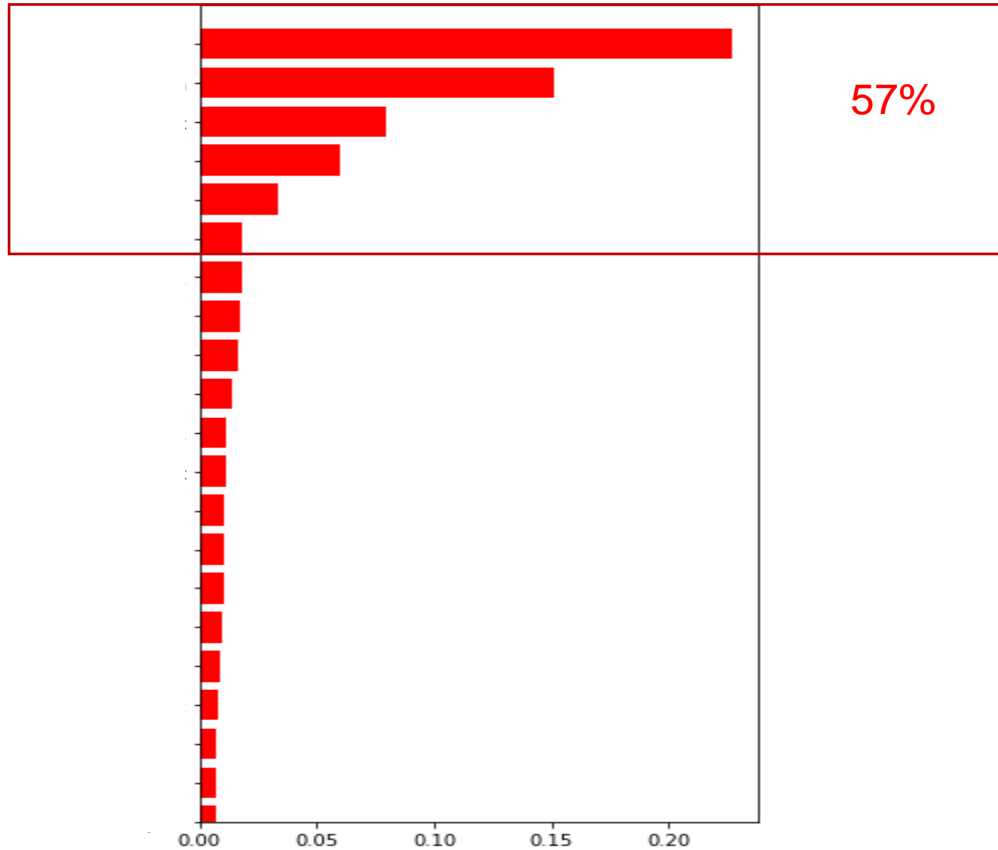
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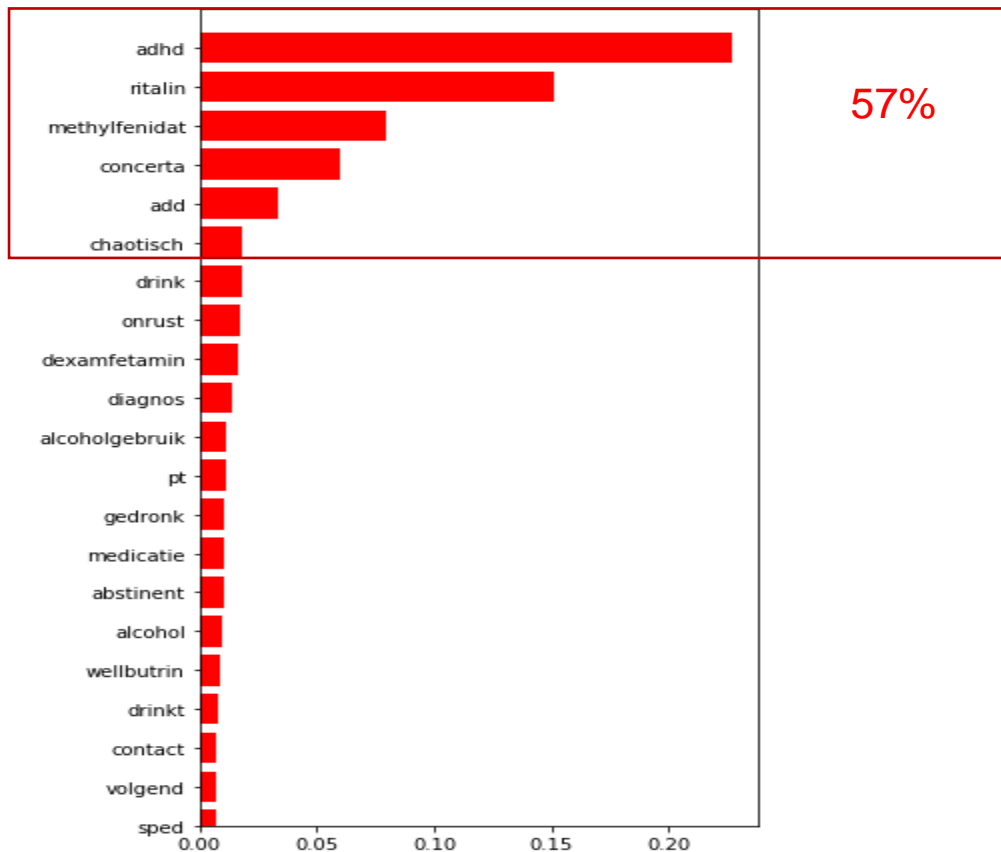
Feature importance



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Next steps

ADHD

- Train model on larger (Parnassia Group) data set
- Add structured, tabular data to increase accuracy (recall)
- Verify the results with medical practitioners

NLP

- Build prediction model for PTSD diagnosis
- Improve, test, implement violence risk assessment
- Prediction for involuntary admission

- EHR summarisation
- Compare patient (groups) based on topic modelling
- Speech-to-text

Questions / discussion

Questions

- ?

Discussion

- Best practices for NLP model / feature selection?
- How to cope with missing labels? Semi-supervised methods?
- Importance of explainability for end-users?