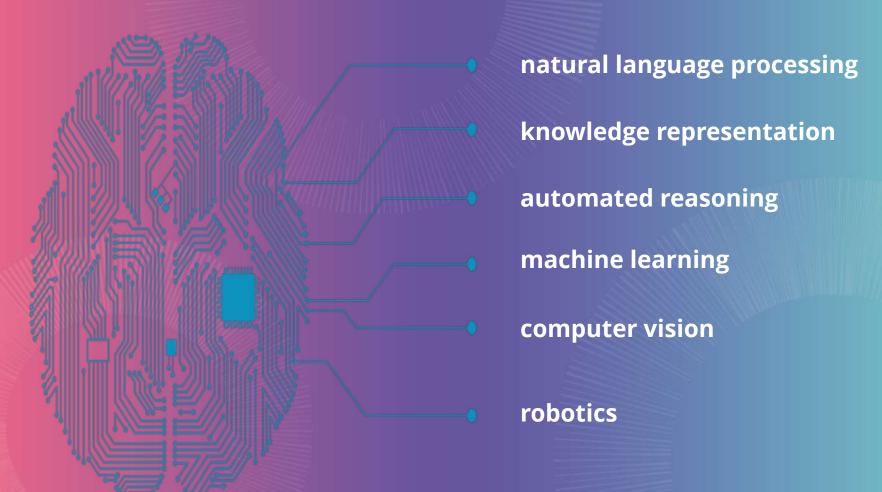
Data warehousing and analytics for healthcare

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TU/e Data Science Center

Eindhoven, 29 May 2019

The promise of AI: will computers be able to do all this?



Real life is less sexy, and more hard work

Level 8	Personalized Medicine & Prescriptive Analytics	Tailoring patient care based on population outcomes and genetic data. Fee-for-quality rewards health maintenance.
Level 7	Clinical Risk Intervention & Predictive Analytics	Organizational processes for intervention are supported with predictive risk models. Fee- for-quality includes fixed per capita payment.
Level 6	Population Health Management L Suggestive Analytics	Tailoring patient care based upon population metrics. Fee-for-quality includes bundled per case payment.
Level 5	Waste & Care Variability Reduction	Reducing variability in care processes. Focusing on internal optimization and waste reduction.
Level 4	Automated External Reporting	Efficient, consistent production of reports and adaptability to changing requirements.
Level 3	Automated Internal Reporting	Efficient, consistent production of reports and widespread availability in the organization.
Level 2	Standardized Vocabulary & Patient Registries	Relating and organizing the core data content.
Level 1	Enterprise Data Warehouse	Collecting and integrating the core data content.
Level 0	Fragmented Point Solutions	Inefficient, inconsistent versions of the truth. Cumbersome internal and external reporting.



Today's agenda

Level 8	Personalized Medicine & Prescriptive Analytics
Level 7	Clinical Risk Intervention & Predictive Analytics
Level 6	Population Health Management L Suggestive Analytics
Level 5	Waste & Care Variability Reduction
Level 4	Automated External Reporting
Level 3	Automated Internal Reporting
Level 2	Standardized Vocabulary & Patient Registries
Level 1	Enterprise Data Warehouse
Level 0	Fragmented Point Solutions

5 – 8: Healthcare analytics

Case study: predicting outcomes of surgery

1 – 4: Laying the foundation

- Data warehousing
- Data integration
- Semantic modelling
- Business intelligence

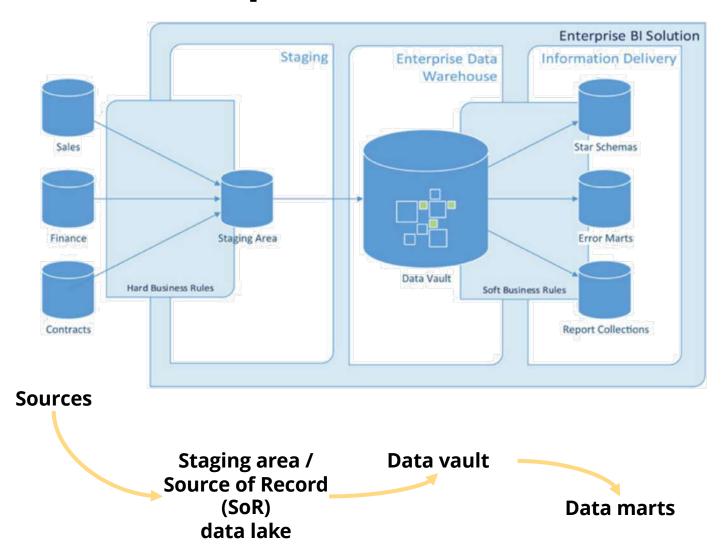


Part I: Laying the Foundation

DATA WAREHOUSING IN HEALTHCARE



The main components of a data warehouse





The 'Supplier Landscape': choices, choices ...



- How many layers: decoupling vs. simplicity?
- Storage platform:
 RDBMS, NoSQL, cloud ...?
- **Data integration:**Semantic modelling,
 dimensional modeling ...?
- Way of working: hand-coded vs. graphical tools?
- Dashboarding & data viz: Yellowfin, Tableau, PowerBl ...



Choosing the storage engine

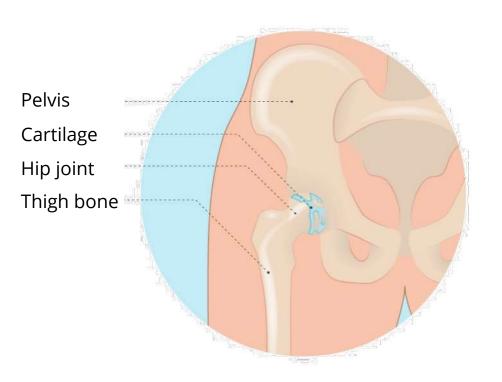






		•	
Daily use (from a data scientist's perspective)	 good CSV handling Unicode support Regular expressions ANSI SQL compliance 	 native Excel Nice GUI IDE for querying, maintenance and workflow 	 Cloud-native, low maintenance Easy to use with API
Platform	All major OS-es	 Windows, Linux added recently 	Cloud (lock-in)
Extensibility	 Many languages built- in (Python, Javascript, R) 	R built-in (acquisition RStudio).NET framework	 Javascript Tight integration GCP
Specific for data analytics	 Best-in-class for GIS jsonb format for unstructured data storage MADlib for built-in machine learning 	 Integrates well with Power BI stack Hybrid solution cloud – on-premise possible with Azure SQL 	 StandardSQL performs well even on petabytes BigQuery ML
TCO	 Forever free with community version Enterprise DB for paid support (same pricing as MS SQL) 	 Value for money with Standard Edition Gets expensive when Enterprise features are needed 	Pay only for queried volume

Data integration with semantic dimensional modelling

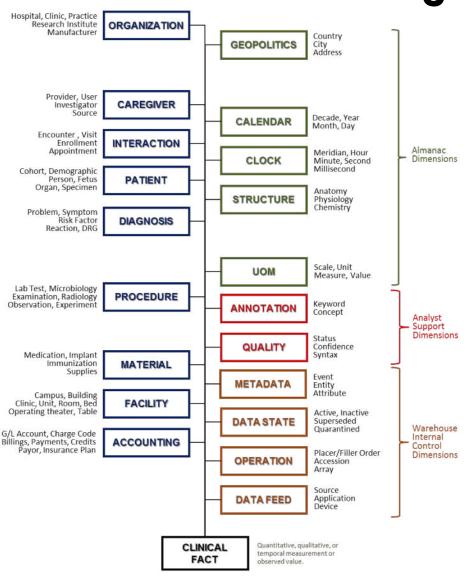


- Open a webbrowser and go to: <u>https://zibs.nl/wiki/HCIM_Mainpage</u>
- Assignment: design a data model for a orthopedic clinics
- Each data element should be captured/mapped to a 'zorginformatiebouwsteen'

Think about all the data you need to integrate so you can do funky machine learning on it



Data integration with semantic dimensional modelling



- Concept of star schema:
 - Typically 5 to 10 fact-tables
 - 20 to 30 dimension tables
- Modelling challenges:
 - Uniformity of dimensions (using same codes)
 - Uniformity of business keys (how to uniquely identify a hip implant)
 - Privacy-sensitive data (SSN, identifiable data)
- Engineering challenges:
 - Dealing with changes in data
 - Speed of batch processing

Biehl (2015), Data Warehousing for Biomedical Informatics

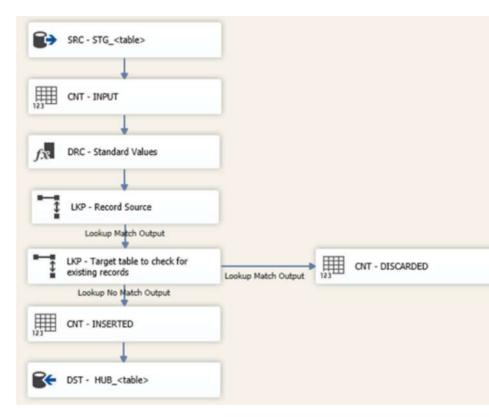


Choose your way of working

Hard/hand-coded scripts

```
def init_sor_persoon_hstage_to_patient_mappings(sor):
    mappings = []
    mapping = SorToEntityMapping('persoon_hstage', Patient, sor)
    mapping.map_bk(["'timeff'", 'ifct_relationr'])
    # SAT Patient. Identificatie
    mapping.map_field("extern_patientnummer", Patient.Identificatie.extern_nummer)
    mapping.map_field("ifct_relationr", Patient.Identificatie.nummer)
    mapping.map_field("ifct_id", Patient.Identificatie.bron_id)
    # SAT Patient.Default
    mapping.map_field("ifct_geboortedtm::date", Patient.Default.geboortedatum)
    mapping.map_field("ifct_geslacht", Patient.Default.geslacht_code)
    mapping.map_field("", Patient.Default.meerling_indicator)
    mapping.map_field("", Patient.Default.overlijdens_indicator)
    mapping.map_field("", Patient.Default.datum_overlijden)
    # SAT Patient.IdentificatieBewijs
    mapping.map_field("ifct_bsn", Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewij
    mapping.map_field("", Patient.IdentificatieBewijs.geldig_tot, type=Patient.IdentificatieBewijs.T
    mapping.map_field("ifct_legitimatieid", Patient.IdentificatieBewijs.nummer, type=Patient.Identif
    mapping.map_field("", Patient.IdentificatieBewijs.geldig_tot, type=Patient.IdentificatieBewijs.Type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer, type=Patient.IdentificatieBewijs.nummer
    mapping.map_field("", Patient.IdentificatieBewijs.geldig_tot, type=Patient.IdentificatieBewijs.Ty
    mapping.map_field("ifct_straat_b", Patient.Adres.straat, type=Patient.Adres.Types.woonadres)
    mapping.map_field('(sor_timeff.split_huisnummer(ifct_huisnr_b)).huisnummer', Patient.Adres.huisnummer'
    mapping.map_field("", Patient.Adres.huisnummerletter, type=Patient.Adres.Types.woonadres)
    mapping.map_field('(sor_timeff.split_huisnummer(ifct_huisnr_b)).huisnummer_toevoeging', Patient.
    mapping.map_field("", Patient.Adres.aanduiding_bij_nummer_code, type=Patient.Adres.Types.woonadre
    mapping.map_field("ifct_plaats_b", Patient.Adres.woonplaats, type=Patient.Adres.Types.woonadres)
    mapping.map_field("", Patient.Adres.gemeente, type=Patient.Adres.Types.woonadres)
    mapping.map_field("", Patient.Adres.land_code, type=Patient.Adres.Types.woonadres)
    mapping.map_field("ifct_postcode_b", Patient.Adres.postcode, type=Patient.Adres.Types.woonadres)
    mapping.map_field("", Patient.Adres.additionele_informatie, type=Patient.Adres.Types.woonadres)
```

Graphical user interface





Design data marts for flexibility and human-readability



subtraject_zorgactiviteit_link



Let end-users choose their own tool

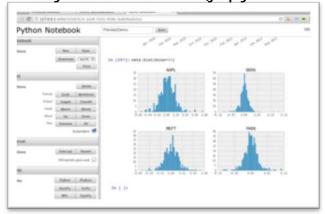
Dedicated BI tool (Tableau, PowerBI, Yellowfin)



Spreadsheets (Excel, Google Sheets, Libre Office)



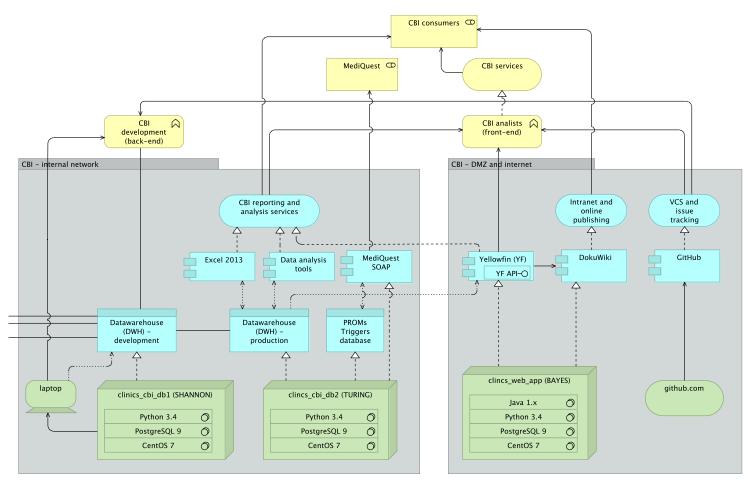
Analytical software (jupyter notebooks, SAS, SPSS)



(... and many more)



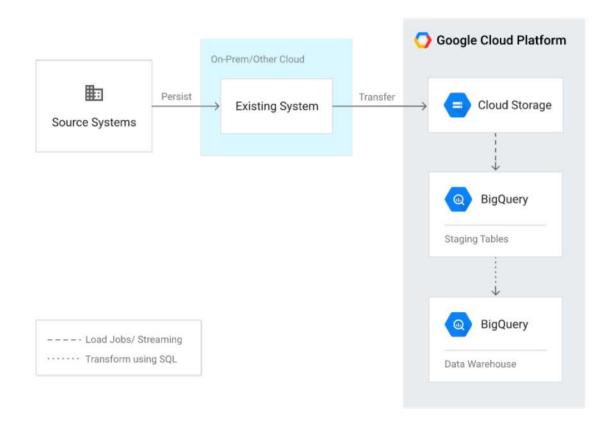
End-result: with own hardware



- Python as the core language for building datavault and analytics
- PostgreSQL database as storage engine
- Infrastructure: virtualized CentOS with SSD SAN



End-result: on Google Cloud Platform



- Python and Clojure as the core languages
- BigQuery and Cloud storage as storage engines
- see https://cloud.google.com/solutions/bigquery-data-warehouse
 for more details

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Part II: Healthcare Analytics

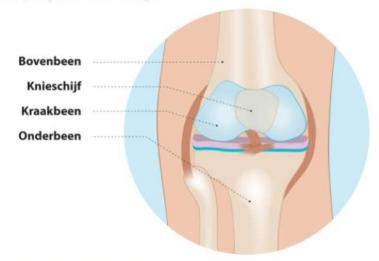
PREDICTING OUTCOMES



Imagine you are consulting an orthopedic surgeon because of knee osteoarthritis

Kniegewricht

Het kniegewricht bestaat uit het bot in het bovenbeen, het grote bot in het onderbeen en de knieschrijf. Tussen de botten zit kraakbeen (afbeelding). Het zachtere kraakbeen zorgt ervoor dat de botten makkelijk langs elkaar kunnen bewegen.



Afbeelding: een gezond kniegewricht.

bron: https://www.keuzehulp.info/

Een versleten knie

Als je ouder wordt, verslijt je kraakbeen. Dit wordt een versleten knie genoemd, of knie-artrose. Bij een versleten knie is het kraakbeen bijna helemaal verdwenen (afbeelding). De botten kunnen niet makkelijk meer langs elkaar bewegen. Dit zorgt voor een pijnlijke en stijve knie. Een versleten knie komt veel voor.



Afbeelding: een versleten kniegewricht.



You have a choice: operate (new knee) or conservative treatment

Operation:

90 out of 100 patient have less pain. They are also more active.



Conservative treatment:

Half of all patient have less pain after physiotherapy and taking painkillers.



bron: https://www.keuzehulp.info/



What if an algorithm says that in your case, chance of succesful operation is also 50%

Operation:

Chance of success of 50%



Conservative treatment:

Half of all patient have less pain after physiotherapy and taking painkillers.





So, what are outcomes in healthcare?

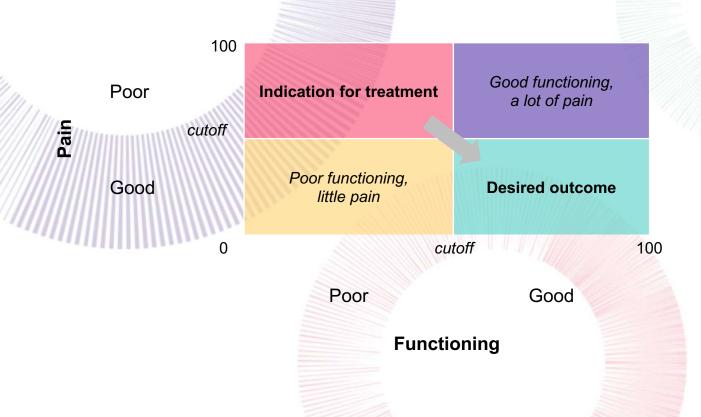
	Condition				
	Cataract	Macular Degeneration	Low Back Pain	Hip & Knee Osteoarthiritis	
Outcome category					
PACs*	Re-operationEndopthalmitisCorneal oedema	Endopthalmitis	 Mortality Readmissions Postop infections	 Mortality Readmissions Postop infections	
Patient-reported	• Catquest-9SF	Brief IVI	EQ-5DOswestry Disability IndexNRS painscoreWork status	EQ-5DKOOS/HOOSNRS painnscoreSatisfactionWork status	
Clinical reported	Best corrected visual acuityRefraction	Best corrected visual acuityRefraction		Timed-Up and Go	
*Potentially avoidable com	olications			mediquest	

^{*}Potentially avoidable complications

Project Nightingale.

- 1. Compounded outcome measures relevant for shared-decision making, using existing data dictionairies (ICHOM, national registries)
- 2. Supervised learning for e.g. identifying highrisk patients prior to an intervention
- 3. 'Unboxing the black box' by relating results of machine learning to existing epidemiological research

A simple idea: choose the two most relevant indicators and determine cutoff values for each





Outcome total knee replacement in the UK

(data NHS Digital | n=140.000 | period 2011 – 2017 | 284 providers)

Prior to operation

Pre-operative (T0)		Functioning		
		Poor	Good	
Pain	Poor	83%	9%	11111
ı aiii	Good	3%	5%	N. W. W. W. W.

After operation

Б. 1		Functioning	
Post-operative (T1)		Poor	Good
Pain	Poor	18%	1%
	Good	20%	61%

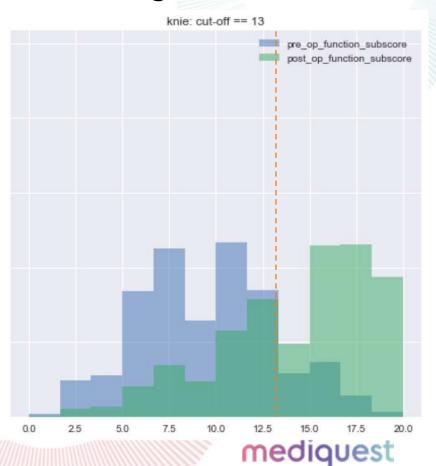


Measuring outcomes is not always straightforward

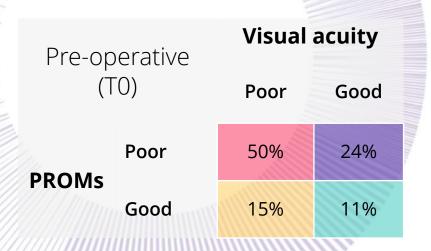
Pain

knie: cut-off pain == 16 pre_op_pain_subscore post op pain subscore 10 20

Functioning



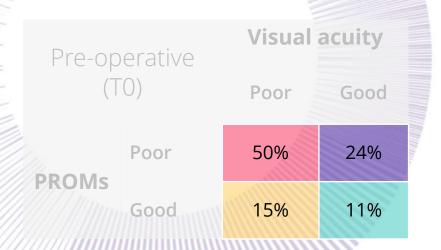
Prior to cataract surgery.



- 50% of patients have consistent indication (poor-poor)
- ... but how about the other half?



After cataract surgery.



Post-operative Visual acuity			acuity
(T1)		Poor	Good
PROMs	Poor	3%	12%
	Good	4%	81%

- 50% of patients have consistent indication (poor-poor)
- ... but how about the other half?

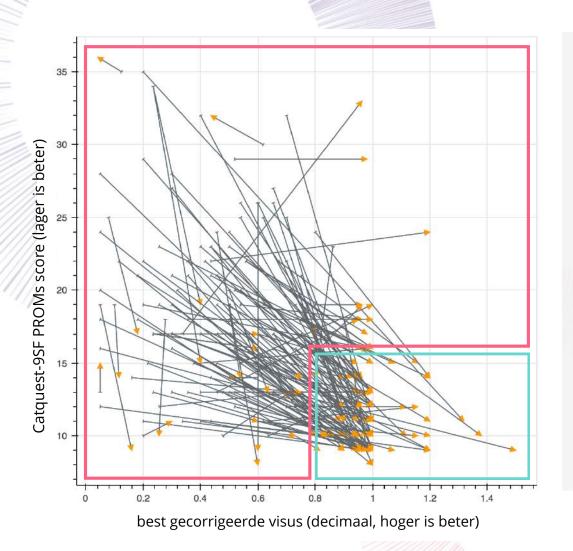
- Good outcome for 81% of all patients
- Remaining 'outliers' of 19% require more detailed inspection



No simple, linear mapping between pre to post



Can we predict the outcome prior to surgery?



Sensitivity 0.5
 Half of the arrows that end up in the red quadrants kan be identified prior to surgery; 9% of all patient receive correct warning

signal

Positive predictive value 0.58
I.e. 42% of warning signals is false-positive. Good enough?

Do we understand what the algorithm does?

Risk factors known from literature

Post-operative complications

Best corrected visual acuity

Target refraction

Capsule complications

Ocular co-morbidities

PROMs sumscore

Gender

Age

- Lundström, M. and Stenevi, U., Analyzing Patient-Reported Outcomes to Improve Cataract Care, Optometry and Vision Science 2013: vol. 90 no. 8: 754-759
- Grimfors et al., Ocular comorbidity and selfassessed visual function after cataract surgery, J. Cataract Refract Surg 2014; 40:1163-1169
- Lundström et al., Visual outcome of cataract surgery, J. Cataract Refract Surg 2013: 39:673-679
- Mollazadegan, K. and Lundström, M., A study of the correlation between patient-reported outcomes and clinical outcome after cataract surgery in ophthalmic clinics, Acta Ophthalmol. 2015: 93: 293-298

Relative feature importance in random forest

Target refraction

Age

Best gecorrected visual acuity

PROMs sumscore

PROMs sub-score near-vision

PROMs sub-score far-vision

PROMs sub-score general satisfaction

Individual PROMs items

Gender

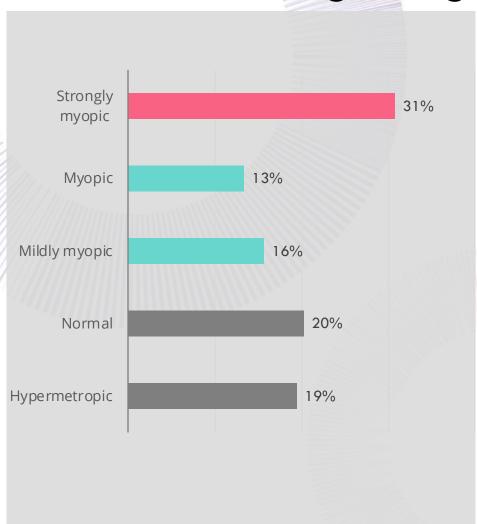
Previous surgery other eye

Macular degeneration

Other ocular co-morbidities



Significant effect size in outcome by target refraction (strength of glasses)



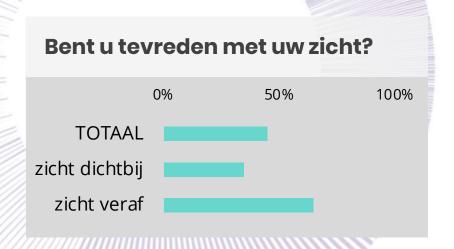
Percentage poor outcome by target refraction, i.e. chosen strength of glasses post-surgery

Target refraction group in diopters (n observations)

- Strongly myopic: < -4.0 (n=13)
- Myopic: between -4.0 and -2.0 (n=771)
- Mildly myopic: between -2.0 and -0.5 (n=319)
- Normal: between -0.5 and 0.5 (n=3993)
- Hypermetropic:> 0.5 (n=36)



Staaroperatie keuzehulp



Wat vindt u belangrijk? Activiteiten en hobbies met: zicht dichtbij zicht veraf Ik wil dit met/zonder bril kunnen

Uw ogen op dit moment

		L	R
zicht met bril:		0.6	0.4
brilsterkte:		-1.5	-2.0
andere aandoeningen:	macula degeneratie		eneratie

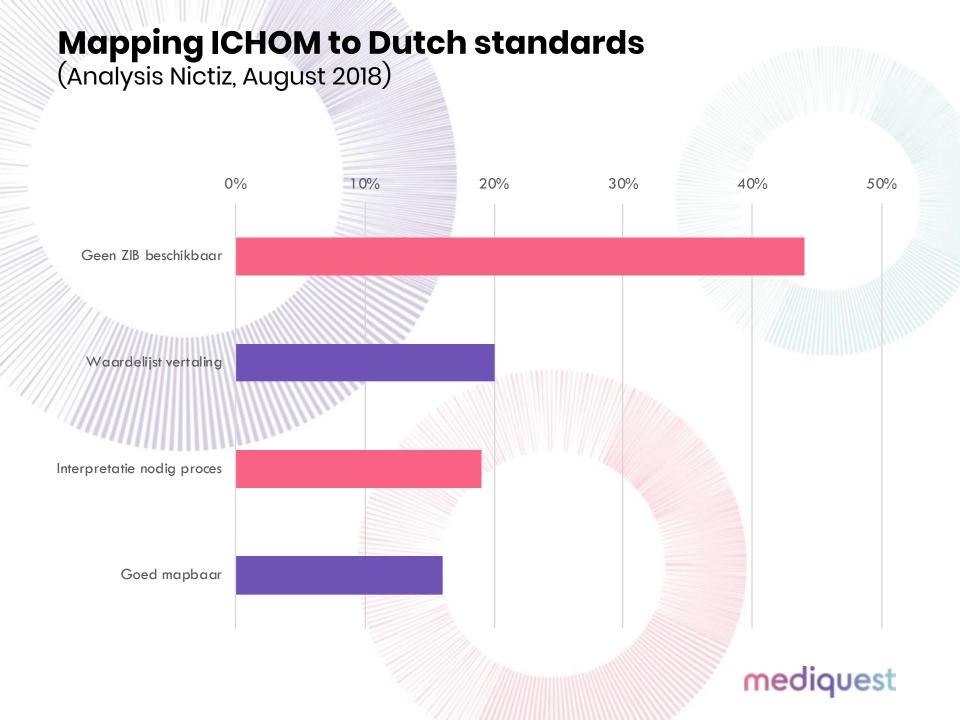
Verwachte uitkomst operatie

L R
zicht met bril: 0.6 1.0
brilsterkte: -1.5 -0.5
aandachtspunt: 1 risico eindresultaat



Lessons learned from applying machine learning in daily operations

- 1. Data quality (registratie aan de bron)
- 2. Harmonisation and semantic integration of different registries (e.g. recent analysis Nictiz)
- 3. Open sourcing trained models for clinical decision support



More info?

- Drop me an email at <u>dkapitan@mediquest.nl</u>
- Connect on LinkedIn
 https://www.linkedin.com/in/dkapitan/

