AI & healthcare

Key figures

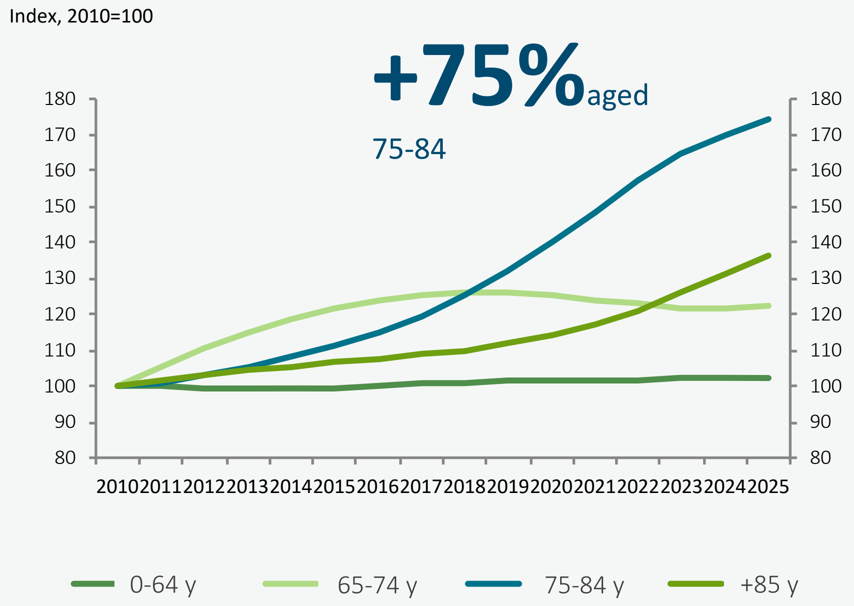
A change in our demography

The population is getting older

In 2025 the number of citizens aged 0-64 will be the same as in 2010.

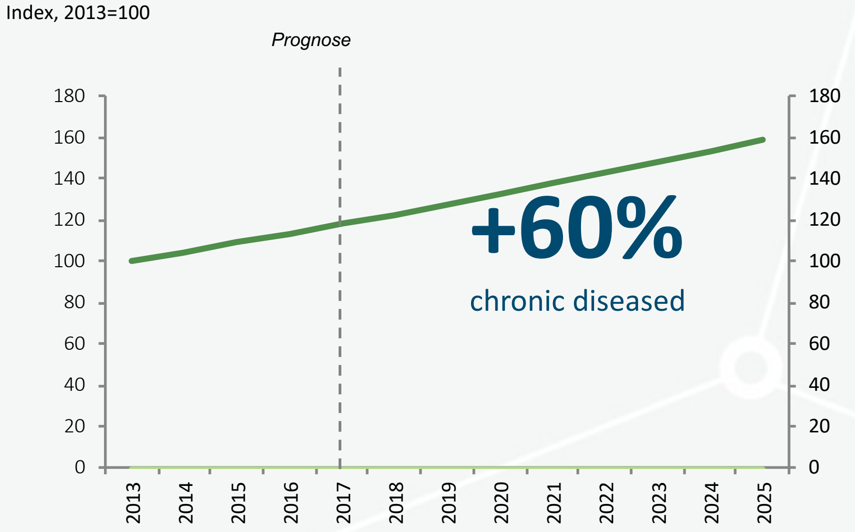
- but the number of citizens aged 75-84 will have increased by 75 percent.

→ Less tax payers and fewer health care workers



- and more people will suffer from chronic diseases

From 2013 to 2025 the number of citizens living with the most common chronic diseases is expected to increase by 60 pct.



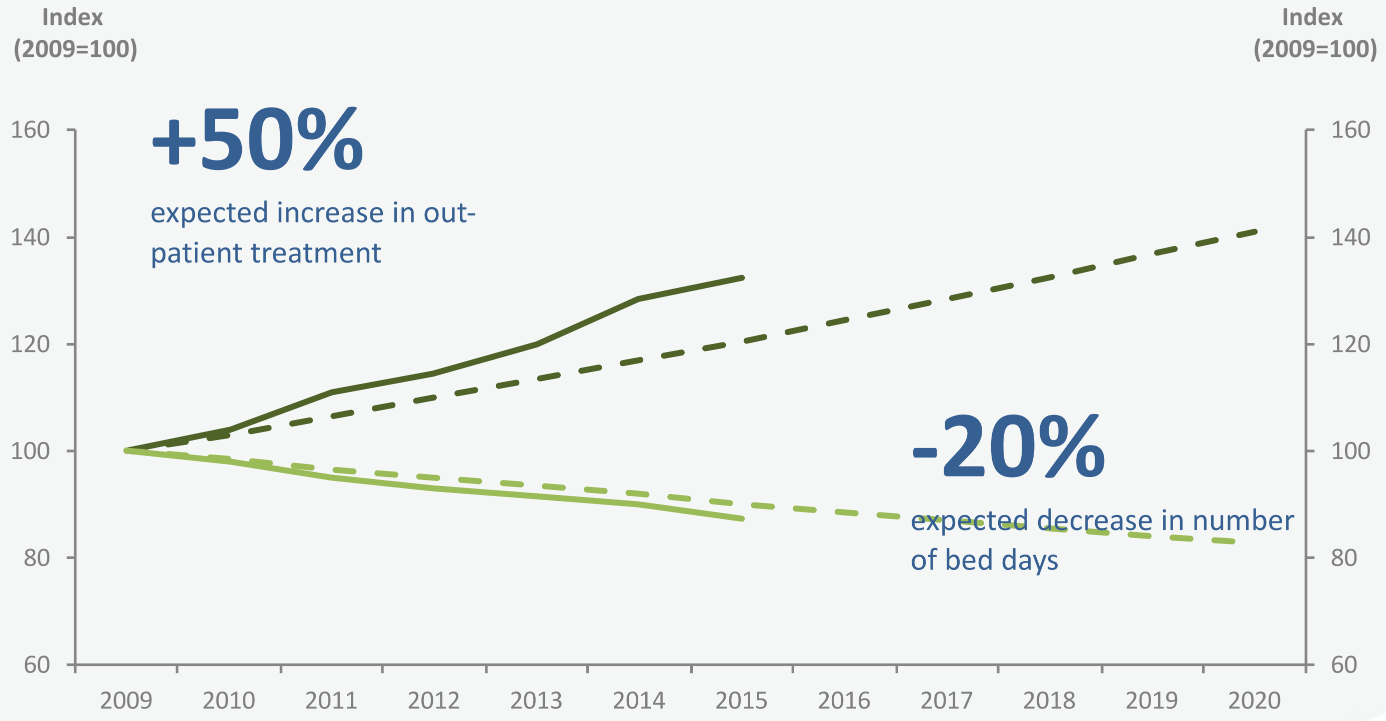
Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

A change in our structuring of hospitals

Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

Key numbers

A change in hospitalisation and technology



Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

There is no real alternative to increased digital cooperation

- The percentage of elderly people will increase
- More people will live with a chronic disease
- Fewer, larger and more specialised hospitals
- Patient pathways will be faster
- More treatment will take place in the patient’s home

Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

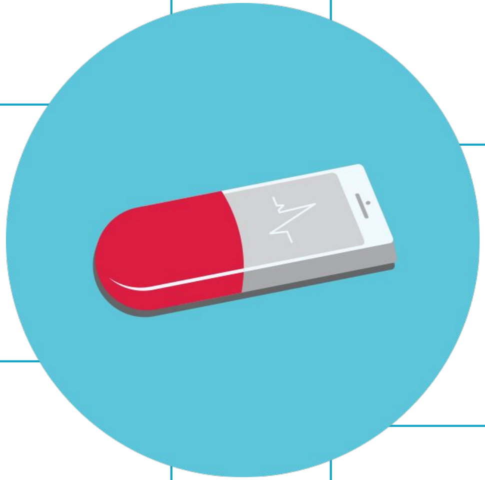
Healthcare Challenges

Chronic diseases management
Accounting for 2/3 of all healthcare spend worldwide – and increasing – chronic disease management is and will be the main focus of health.

Preventive and predictive health
Obesity, lack of physical activity and unhealthy lifestyle are the major factors for health problems and needs to be addressed early

Regulatory
Legal and regulatory demands for protecting patient privacy, data, and safety will be enforced heavily as digital and personalized health emerge

Evidence & outcome-based health
New business models both for suppliers and vendors will be tied to clinical evidence and real-world patient outcome (efficiency)



Technology Opportunities

Personalized technology
Engaging, patient-centric, and participatory technology can deliver interventions tailored to the individual and sustain engagement “beyond-the-pill” outside traditional care settings.

Digitalization
The ubiquity of digital health and communication technology drive new models for virtual and semi-automated doctor-patient contact.

Health IoT
Pervasive, mobile and wearable technology for sensing and engaging with patients create a unique platform for personalized health delivery

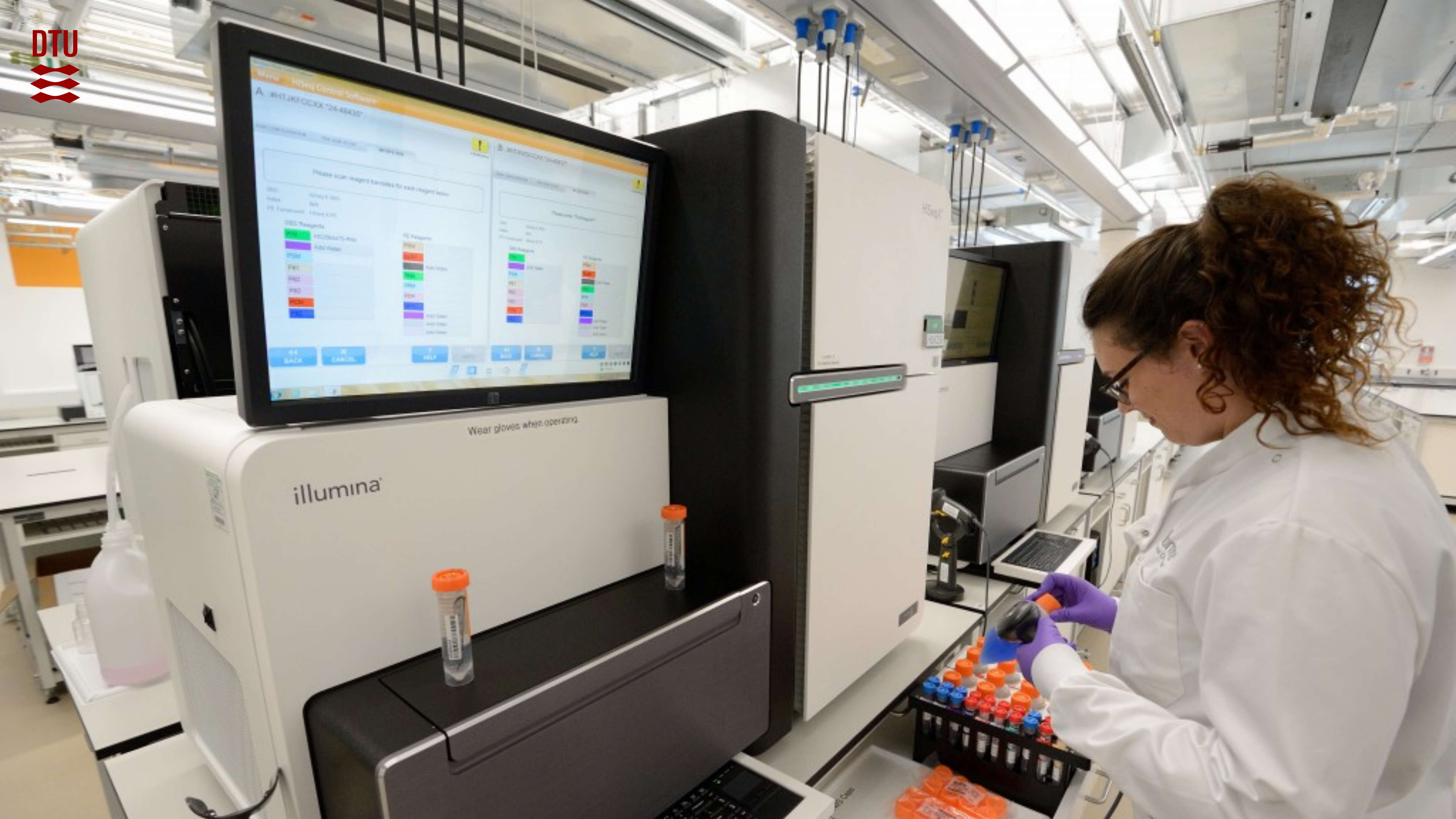
Big data analytics
Computing power and advanced analytics and learning algorithms drive insight and prediction of patient behavior, treatment, and care costs

cachet | Copenhagen Center for Health Technology


DTU


SIEMENS
191.0
-88.5
MEDRAD Stellant


102


DTU
Wear gloves when operating.
illumina

Machine learning provides predictions and prescriptions

Types of analytics (in order of increasing complexity)

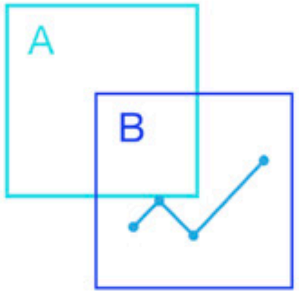
Descriptive

- Describe **what happened**
- Employed heavily across all industries

Predictive

- Anticipate **what will happen** (inherently probabilistic)
- Employed in data-driven organizations as a key source of insight

Prescriptive

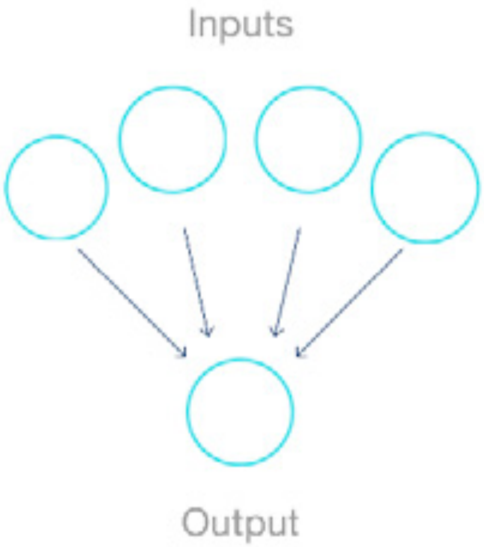


- Provide recommendations on **what to do** to achieve goals
- Employed heavily by leading data and Internet companies

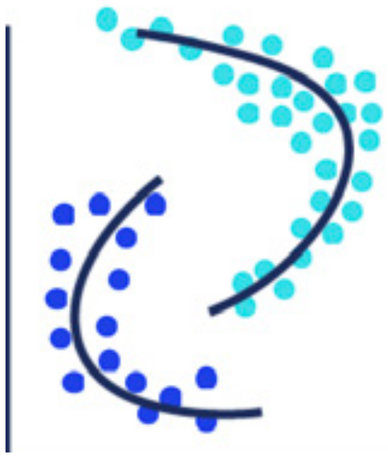
Focus of machine learning (Predictive and Prescriptive)

Source: An executive's guide to AI. McKinsey & Co., 2019

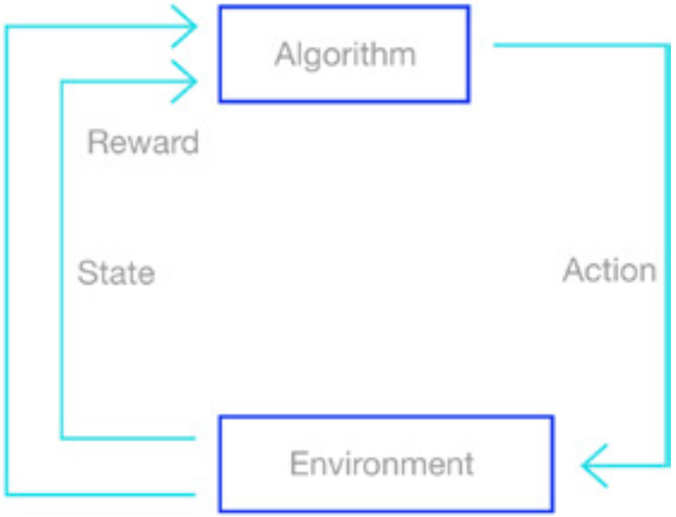
Supervised learning



Unsupervised learning



Reinforcement learning



Source: An executive's guide to AI. McKinsey & Co., 2019

AI in Healthcare

- Screening / Prevention
  - early detection / classification / prediction of disease progression (e.g. mental health)
  - image screening (e.g. breast cancer)
- Diagnosis
  - clinical decision support systems (e.g. diabetes)
  - image analysis (e.g. radiology, MR, PET, CT)
- Treatment & Care
  - treatment / medication prescription (e.g. oncology)
  - robot surgery
  - speech interfaces @home

Mobility & Depression

- "…significant **correlation** between mobility trace characteristics and depressive moods"
- "…possible to develop **inference** algorithms for unobtrusive monitoring and prediction of depressive mood disorders"

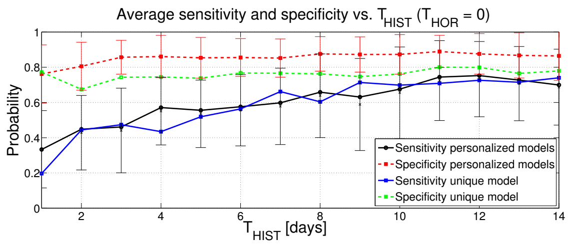


Figure 8: Average sensitivity and specificity values vs. T_{HIST}, for $T_{HOR} = 0$ days.

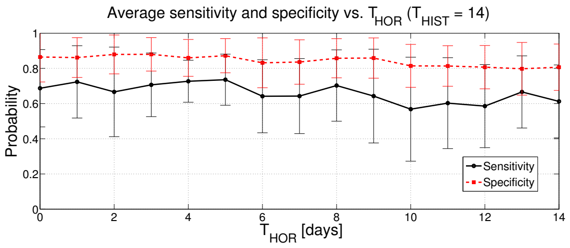
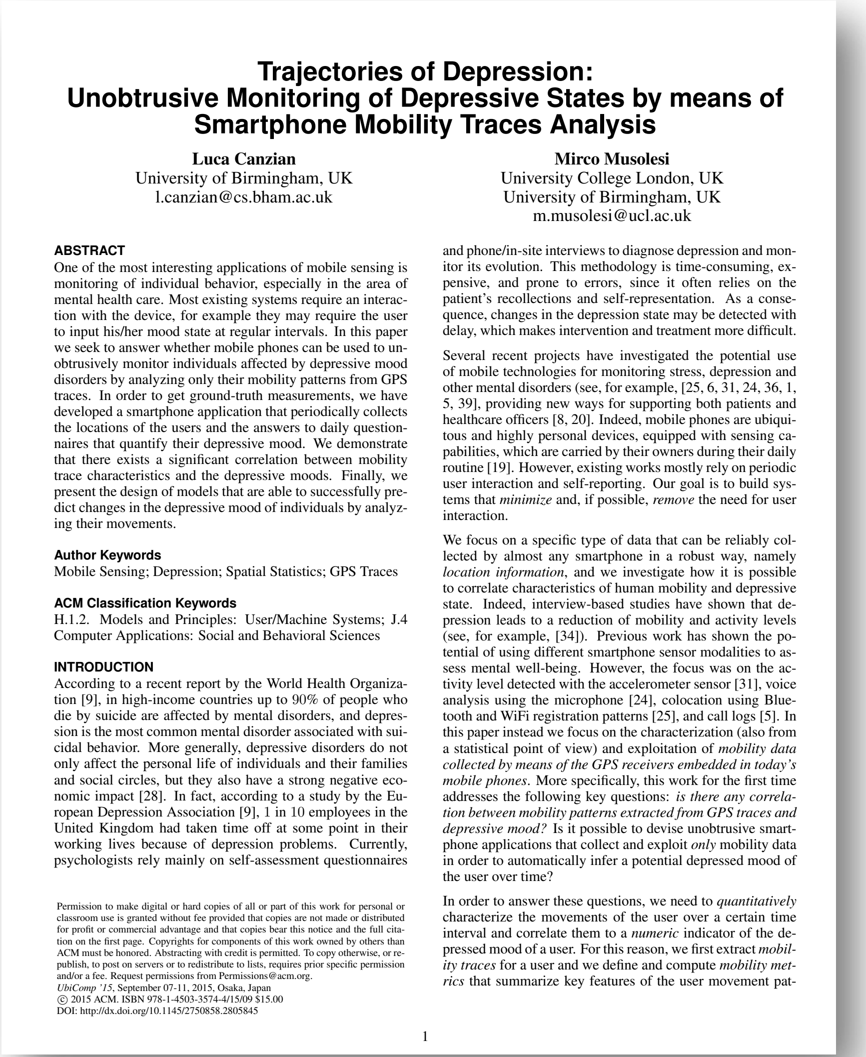


Figure 9: Average sensitivity and specificity values vs. T_{HOR}, for $T_{HIST} = 14$ days.



Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis

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University of Birmingham, UK
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ABSTRACT

One of the most interesting applications of mobile sensing is monitoring of individual behavior, especially in the area of mental health care. Most existing systems require an interaction with the device, for example they may require the user to input his/her mood state at regular intervals. In this paper we seek to answer whether mobile phones can be used to unobtrusively monitor individuals affected by depressive mood disorders by analyzing only their mobility patterns from GPS traces. In order to get ground-truth measurements, we have developed a smartphone application that periodically collects the locations of the users and the answers to daily questionnaires that quantify their depressive mood. We demonstrate that there exists a significant correlation between mobility trace characteristics and the depressive moods. Finally, we present the design of models that are able to successfully predict changes in the depressive mood of individuals by analyzing their movements.

Author Keywords

Mobile Sensing; Depression; Spatial Statistics; GPS Traces

ACM Classification Keywords

H.1.2. Models and Principles: User/Machine Systems; J.4 Computer Applications: Social and Behavioral Sciences

INTRODUCTION

According to a recent report by the World Health Organization [9], in high-income countries up to 90% of people who die by suicide are affected by mental disorders, and depression is the most common mental disorder associated with suicidal behavior. More generally, depressive disorders do not only affect the personal life of individuals and their families and social circles, but they also have a strong negative economic impact [28]. In fact, according to a study by the European Depression Association [9], 1 in 10 employees in the United Kingdom had taken time off at some point in their working lives because of depression problems. Currently, psychologists rely mainly on self-assessment questionnaires and phone/in-site interviews to diagnose depression and monitor its evolution. This methodology is time-consuming, expensive, and prone to errors, since it often relies on the patient's recollections and self-representation. As a consequence, changes in the depression state may be detected with delay, which makes intervention and treatment more difficult.

Several recent projects have investigated the potential use of mobile technologies for monitoring stress, depression and other mental disorders (see, for example, [25, 6, 31, 24, 36, 1, 5, 39], providing new ways for supporting both patients and healthcare officers [8, 20]. Indeed, mobile phones are ubiquitous and highly personal devices, equipped with sensing capabilities, which are carried by their owners during their daily routine [19]. However, existing works mostly rely on periodic user interaction and self-reporting. Our goal is to build systems that *minimize* and, if possible, *remove* the need for user interaction.

We focus on a specific type of data that can be reliably collected by almost any smartphone in a robust way, namely *location information*, and we investigate how it is possible to correlate characteristics of human mobility and depressive state. Indeed, interview-based studies have shown that depression leads to a reduction of mobility and activity levels (see, for example, [34]). Previous work has shown the potential of using different smartphone sensor modalities to assess mental well-being. However, the focus was on the activity level detected with the accelerometer sensor [31], voice analysis using the microphone [24], colocation using Bluetooth and WiFi registration patterns [25], and call logs [5]. In this paper instead we focus on the characterization (also from a statistical point of view) and exploitation of *mobility data collected by means of the GPS receivers embedded in today's mobile phones*. More specifically, this work for the first time addresses the following key questions: *is there any correlation between mobility patterns extracted from GPS traces and depressive mood?* Is it possible to devise unobtrusive smartphone applications that collect and exploit *only* mobility data in order to automatically infer a potential depressed mood of the user over time?

In order to answer these questions, we need to *quantitatively* characterize the movements of the user over a certain time interval and correlate them to a *numeric* indicator of the depressed mood of a user. For this reason, we first extract *mobility traces* for a user and we define and compute *mobility metrics* that summarize key features of the user movement pat-

UbiComp '15, September 07-11, 2015, Osaka, Japan

DOI: http://dx.doi.org/10.1145/2750858.2805845

Canzian L, Musolesi M. Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis. In: *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (ACM UbiComp'15)*. ACM; 2015.

Voice & Mood

Collection of voice features in naturalistic setting

- N=28 | 12 weeks
- HDRS-17 (depres
- 179 clinical rating
- openSMILE (emo

Classification resul

- depressive state
- manic state : 61% (0.04)

Classification accuracy were not significantly increased when combining voice features with automatically generated objective data

"Voice features collected in naturalistic settings using smartphones may be used as objective state markers in patients with bipolar disorder. "


OPEN

Citation: Transl Psychiatry (2016) **6**, e856; doi:10.1038/tp.2016.123
www.nature.com/tp

ORIGINAL ARTICLE

Voice analysis as an objective state marker in bipolar disorder

M Faurholt-Jepsen[1], J Busk[2], M Frost[3], M Vinberg[1], EM Christensen[1], O Winther[2], JE Bardram[2] and LV Kessing[1]

Changes in speech have been suggested as sensitive and valid measures of depression and mania in bipolar disorder. The present study aimed at investigating (1) voice features collected during phone calls as objective markers of affective states in bipolar disorder and (2) if combining voice features with automatically generated objective smartphone data on behavioral activities (for example, number of text messages and phone calls per day) and electronic self-monitored data (mood) on illness activity would increase the accuracy as a marker of affective states. Using smartphones, voice features, automatically generated objective
...ities and electronic self-monitored data were collected from 28 outpatients with bipolar
...daily basis during a period of 12 weeks. Depressive and manic symptoms were assessed
...g Scale 17-item and the Young Mania Rating Scale, respectively, by a researcher blinded
...zed using random forest algorithms. Affective states were classified using voice features
...calls. Voice features were found to be more accurate, sensitive and specific in the classification
...under the curve (AUC) = 0.89 compared with an AUC = 0.78 for the classification of depressive
...n automatically generated objective smartphone data on behavioral activities and electronic
...curacy, sensitivity and specificity of classification of affective states slightly. Voice features
...g smartphones may be used as objective state markers in patients with bipolar disorder.

...6; doi:10.1038/tp.2016.123; published online 19 July 2016

...such as the Hamilton
...)[1] and the Young Mania
...n standards to assess the
...mptoms when treating
...using these clinical rating
...er. Further, the severity of
...termined by a subjective
...interview with the risk of
...bjective and continuous
...st the clinical assessment
...ods using continuous and
...servable data on illness
...be able to discriminate
...linicians to improve the
...ions for early intervention
...or close and continuous
monitoring and collection of real-time data on depressive and manic symptoms outside clinical settings between outpatient visits.

Studies analyzing the spoken language in affective disorders date back as early as 1938.[5] A number of clinical observations suggest that reduced speech activity and changes in voice features such as pitch may be sensitive and valid measures of prodromal symptoms of depression and effect of treatment.[6–12] Conversely, it has been suggested that increased speech activity may predict a switch to hypomania.[13] Item number eight on the HAMD (psychomotor retardation) and item number six on the YMRS (speech amount and rate) are both related to changes in speech, illustrating that factors related to speech activity are important aspects to evaluate in the assessment of symptoms' severity in bipolar disorder. Based on these clinical observations there is an increasing interest in electronic systems for speech emotion recognition that can be used to extract useful semantics from speech and thereby provide information on the emotional state of the speaker (for example, information on pitch of the voice).[14]

Software for ecologically extracting data on multiple voice features during phone calls made in naturalistic settings over prolonged time-periods has been developed[15] and a few preliminary studies have been published.[16–20] One study extracted voice features in six patients with bipolar disorder type I using software on smartphones and demonstrated that changes in speech data were able to detect the presence of depressive and hypomanic symptoms assessed with weekly phone-based clinicians administrated ratings using the HAMD and the YMRS, respectively.[17] However, none of the patients in the study presented with manic symptoms during the study period, and the clinical assessments were phone-based. Another study on six patients with bipolar disorder showed that combining statistics on objectively collected duration of phone calls per day and extracted voice features on variance of pitch increased the accuracy of classification of affective states compared with solely using variance of pitch for classification.[18,19] The study did not state if and how the affective states were assessed during the monitoring period.

In addition to voice features, changes in behavioral activities such as physical activity/psychomotor activity[21–24] and the level of engagement in social activities[25] represent central aspects of

[1]Psychiatric Center Copenhagen, Rigshospitalet, Copenhagen, Denmark; [2]DTU Compute, Technical University of Denmark (DTU), Lyngby, Denmark and [3]The Pervasive Interaction Laboratory, IT University of Copenhagen, Copenhagen, Denmark. Correspondence: Dr M Faurholt-Jepsen, Psychiatric Center Copenhagen, Rigshospitalet, Blegdamsvej 9, DK-2100 Copenhagen, Denmark.
E-mail: maria@faurholt-jepsen.dk
Received 25 January 2016; revised 4 April 2016; accepted 5 May 2016

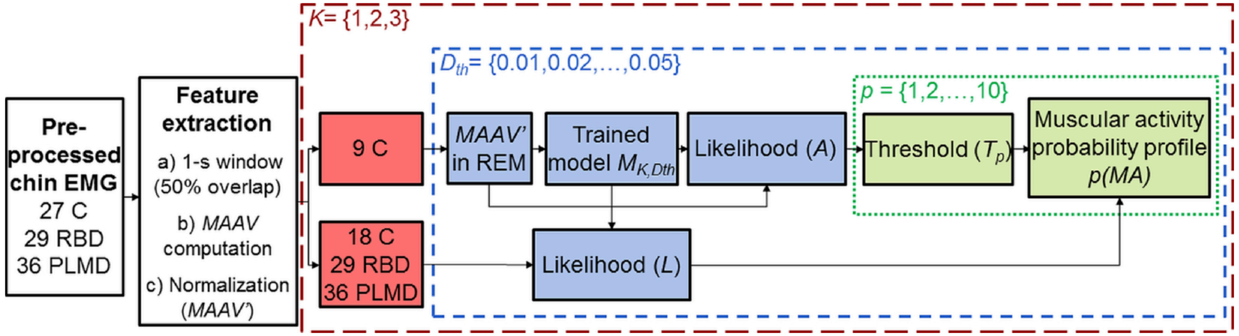
M Faurholt-Jepsen, J Busk, M Frost, M Vinberg, EM Christensen, O Winther, JE Bardram, LV Kessing (2016,). Voice analysis as an objective state marker in bipolar disorder. *Transl Psychiatry.* Macmillan Publishers Limited.

Diagnosis in Sleep Disorders

- REM sleep behavior disorder (RBD)
  – an early biomarker for many neurological diseases (e.g. Parkinson)
- Today a very tedious maual labeling process
  – one clinician one week for one patient

- Novel ML approach for automatic detection / labeling

- 71% accuracy shown



Journal of Neuroscience Methods 312 (2019) 53–64

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journal homepage: www.elsevier.com/locate/jneumeth

Validation of a new data-driven automated algorithm for muscular activity detection in REM sleep behavior disorder

Matteo Cesari[a,*], Julie A.E. Christensen[a,b], Friederike Sixel-Döring[c,d], Claudia Trenkwalder[c], Geert Mayer[d], Wolfgang H. Oertel[d], Poul Jennum[b], Helge B.D. Sorensen[a]

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[b] *Danish Center for Sleep Medicine, Department of Clinical Neurophysiology, Rigshospitalet Glostrup, Denmark*
[c] *Paracelsus-Elena Klinik, Kassel, Germany*
[d] *Department of Neurology, Philipps University, Marburg, Germany*

A R T I C L E I N F O

Keywords:
Data-driven method
Electromyography
Muscular activity
Periodic limb movement disorder
Polysomnography
REM sleep behavior disorder
REM sleep without atonia

A B S T R A C T

Background: Documentation of REM sleep without atonia is fundamental for REM sleep behavior disorder (RBD) diagnosis. The automated REM atonia index (RAI), Frandsen index (FRI) and Kempfner index (KEI) were proposed for this, but achieved moderate performances.
New method: Using sleep data from 27 healthy controls (C), 29 RBD patients and 36 patients with periodic limb movement disorder (PLMD), we developed and validated a new automated data-driven method for identifying movements in chin and tibialis electromyographic (EMG) signals. A probabilistic model of atonia from REM sleep of controls was defined and movements identified as EMG areas having low likelihood of being atonia. The percentages of movements and the median inter-movement distance during REM and non-REM (NREM) sleep were used for distinguishing C, RBD and PLMD by combining three optimized classifiers in a 5-fold cross-validation scheme.
Results: The proposed method achieved average overall validation accuracies of 70.8% and 61.9% when REM and NREM, and only REM features were used, respectively. After removing apnea and arousal-related movements, they were 64.2% and 59.8%, respectively.
Comparison with existing method(s): The proposed method outperformed RAI, FRI and KEI in identifying RBD patients and in particular achieved higher accuracy and specificity for classifying RBD.
Conclusions: The results show that i) the proposed method has higher performances than the previous ones in distinguishing C, RBD and PLMD patients, ii) removal of apnea and arousal-related movements is not required, and iii) RBD patients can be better identified when both REM and NREM muscular activities are considered.

1. Introduction

Rapid eye movement (REM) sleep behavior disorder (RBD) is a parasomnia characterized by loss of muscle atonia during REM sleep and a clinical history of dream enactment (American Academy of Sleep Medicine, 2014; Schenck et al., 1986; Schenck and Mahowald, 2002). Follow-up studies (Postuma et al., 2015; Schenck et al., 2013) and neurophysiological investigations (Boeve et al., 2013) support the hypothesis that RBD is an early stage of alpha-synucleinopathies, including Parkinson's disease (PD), PD dementia, dementia with Lewy bodies and multiple system atrophy (Högl et al., 2018). Therefore, a correct diagnosis of RBD becomes of critical importance in order to identify alpha-synucleinophathies in their early stages, and RBD patients may become the target of neuroprotective treatments when they will become available.

In the diagnosis of RBD, the documentation of REM sleep without atonia (RSWA) in electromyographic (EMG) signals during polysomnography (PSG) is essential. Currently, the gold standard for RSWA scoring is the application of one of the following visual methods: i) The American Academy for Sleep Medicine (AASM) recommends RSWA identification when either tonic and phasic activity in the chin or phasic activity in the limbs is seen in more than 27% of 30-s REM sleep epochs (Berry et al., 2016); ii) RSWA is identified by the Montréal method when either in the chin signal more than 30% of 20-s REM sleep epochs show tonic activity, or when in the same signal more than 15% of these epochs contain phasic activity (Lapierre and Montplaisir, 1992;

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E-mail address: maces@elektro.dtu.dk (M. Cesari).

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Received 14 August 2018; Received in revised form 7 November 2018; Accepted 19 November 2018
Available online 20 November 2018

Cesari, Matteo, et al. "Validation of a new data-driven automated algorithm for muscular activity detection in REM sleep behavior disorder." *Journal of neuroscience methods* 312 (2019): 53-64.

Detection of Atrial Fibrillation

- ECG monitoring is core to most cardio-vascular diseases
- Today
  - – a constrained Holter Monitoring setup w. manual data upload
  - – a manual labeling and detection process

- Novel deep learning model for real-time detection of atrial fibrillation (AFIB)
  - – 98% accuracy
  - – both seen and unseen (benchmark) data
  - – analyze 24 hours of data in less than one second

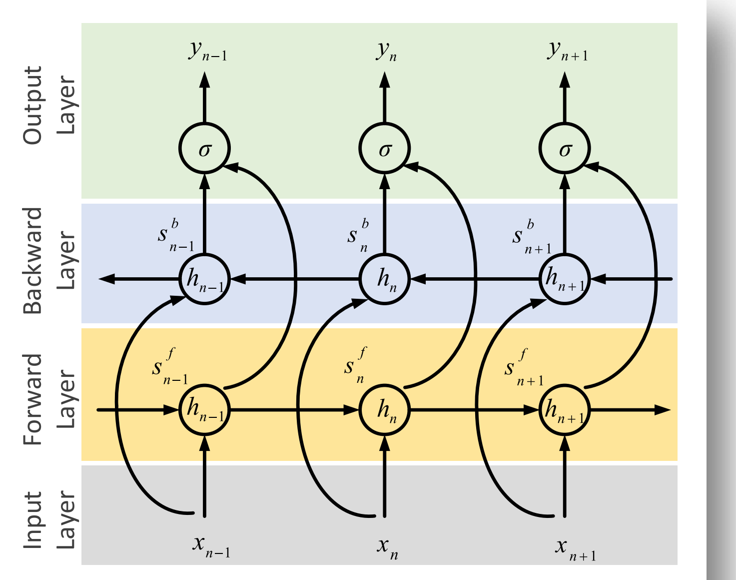


Fig. 4. Illustration of an unfolded bidirectional LSTM. The input sequence is fed into two separate hidden layers and processed in both directions before combining the two outputs in the output layer.

Andersen, Rasmus S., Abdolrahman Peimankar, and Sadasivan Puthusserypady. "A deep learning approach for real-time detection of atrial fibrillation." *Expert Systems with Applications*115 (2019): 465-473.

AI in Healthcare

Patient-Facing

AI Chatbots
buoy, Your.MD, med what, GYANT, Dr.AI

Wearables & Devices
physIQ, QARDIO, sano, QUANTUS, DietSensor, kiwi.ai, BIOSERENITY, Bodytrak, Magnea, kinsa, aira, SCANADU, AliveCor, 19 Labs, CliniCloud

Personalized Genetics
iCarbonX 碳云智能, rthm, CG, DAY TWO, Positive Bioscience, LIFENOME, MEDICUS, 23andMe, VITAGENE, Arivale, habit, Suggestic, VIOME

Mental Health
Woebot, TOUCHKIN, BIOBEATS, Ginger.io, AURA, koko, NeuroLex

Women's Health
CYRCADIA HEALTH, bloomlife, celmatix, flutter, eva, Clue, elyse, Natural Cycles

Skin
SkinVision, skinIO, skin analytics, SCANZ, skin, DOCTOR HAZEL, FIRST DERM

Telehealth

Telemedicine
ada, SENSELY (how are you feeling today?), babylon, anamnèse, Remedy, pager, MDLIVE, spruce, Z

Lifestyle Management
AiCure, MedAware, ovia health, next IT, Catalia Health, Healthcare lucina, Health Next Gen, Doctella, NarrativeDx, cardiogram, Wellframe, Welltok, CareAngel

Disease Management
prognos, INFOBIONIC, HealthReveal, HEALTH FIDELITY, DIABNEXT, SENTRIAN, TEMPUS, dreamed, Healint, WIKAYA, FLASHBACK TECHNOLOGIES, RxPREDiCT, BELONG

Doctor-Facing

Medical Records
APIXIO, AUGMEDIX, clinithink, MODERNIZING MEDICINE, saykara, nimblr, emr.ai, WellSheet, hCue, patientory, SANSORO HEALTH, PROTENUS, BloomAPI

Data Analytics
ZEPHYR HEALTH, burstIQ, MD.ai, Infermedica, jvion, CareSkore, CLOUDMEDX, flatiron, PROFILITY, lumiata, ROAM, Hindsait, Oncora MEDICAL, GRAIL, MEDALOGIX, ensodata, pulseData, healthcare.ai, KenSci, COMBINOSTICS, impacthealth, LYTICS

Medical Imaging
VIZ, AMARA HEALTH ANALYTICS, enlitic, zebra MEDICAL VISION, 推想科技 infervision, CureMetrix, BAYLABS, VUNO, ADVENIO, koios, BUTTERFLY Network, Inc., ARTERYS, SIG TUPLE, Behold.ai, imagia, IMAGEN, Mindshare MEDICAL, aidence, aidoc, Lunit, Cardiologs, Genetesis, HubMedX, DIA, SemanticMD, Blackford analysis

Hospital
FORWARD, Qventus, MedyMatch, gauss, orgo.ai, MEDASENSE, P3d, AURIS, VERB SURGICAL, Qualaris

Research

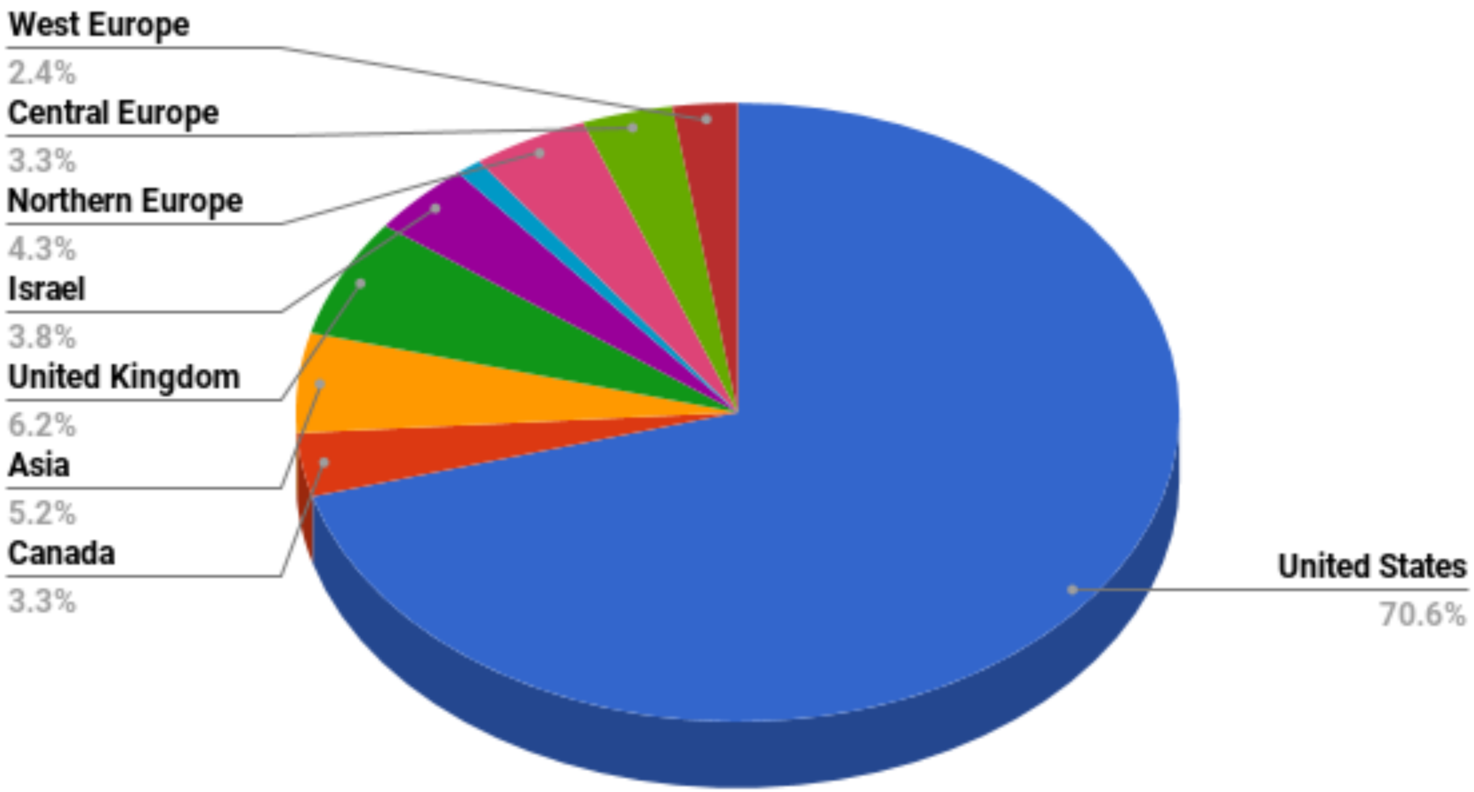
Drug Discovery
Mind the Byte, SagS, DATAVANT, QUANTITATIVE MEDICINE, Standigm, BERG, RECURSION, ENVISAGENICS, BenevolentAI, Athelas, Exscientia, NuMedii, healx, transcriptic, Numerate, twoXAR, Atomwise (Better medicines faster.), INSILICO MEDICINE, CloudPharmaceuticals, Globavir

Information & Clinical Trials
trials.ai, PathAI, BenchSci, CYCLICA, Mendel.ai, rativ, peptone, Brite Health, iPLEXUS, antidote, Plex Research, nference, RESULTCARE

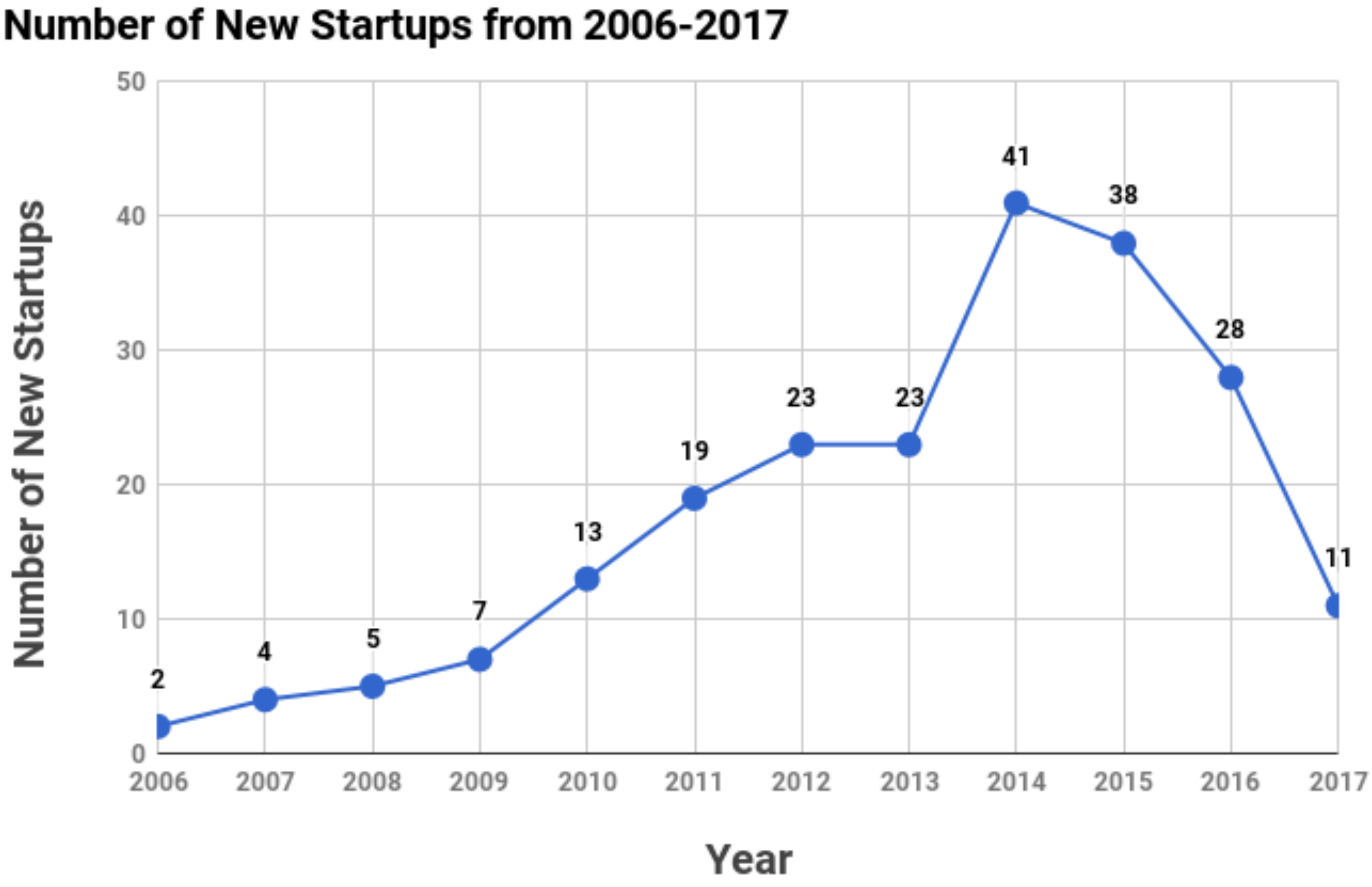
Genetic Research
MolecularMatch, Blueprint Genetics, VERGE GENOMICS, NURITAS, diploid, HUMAN LONGEVITY, INC., SOPHIA GENETICS, freenome, FDNA, PATHWAY GENOMICS, deep genomics, DESKTOP GENETICS

Source: Emily Kuo. AI in Healthcare: Industry Landscape, Medium 2017

Percentage of Startups by International Region



Source: Emily Kuo. AI in Healthcare: Industry Landscape, Medium 2017



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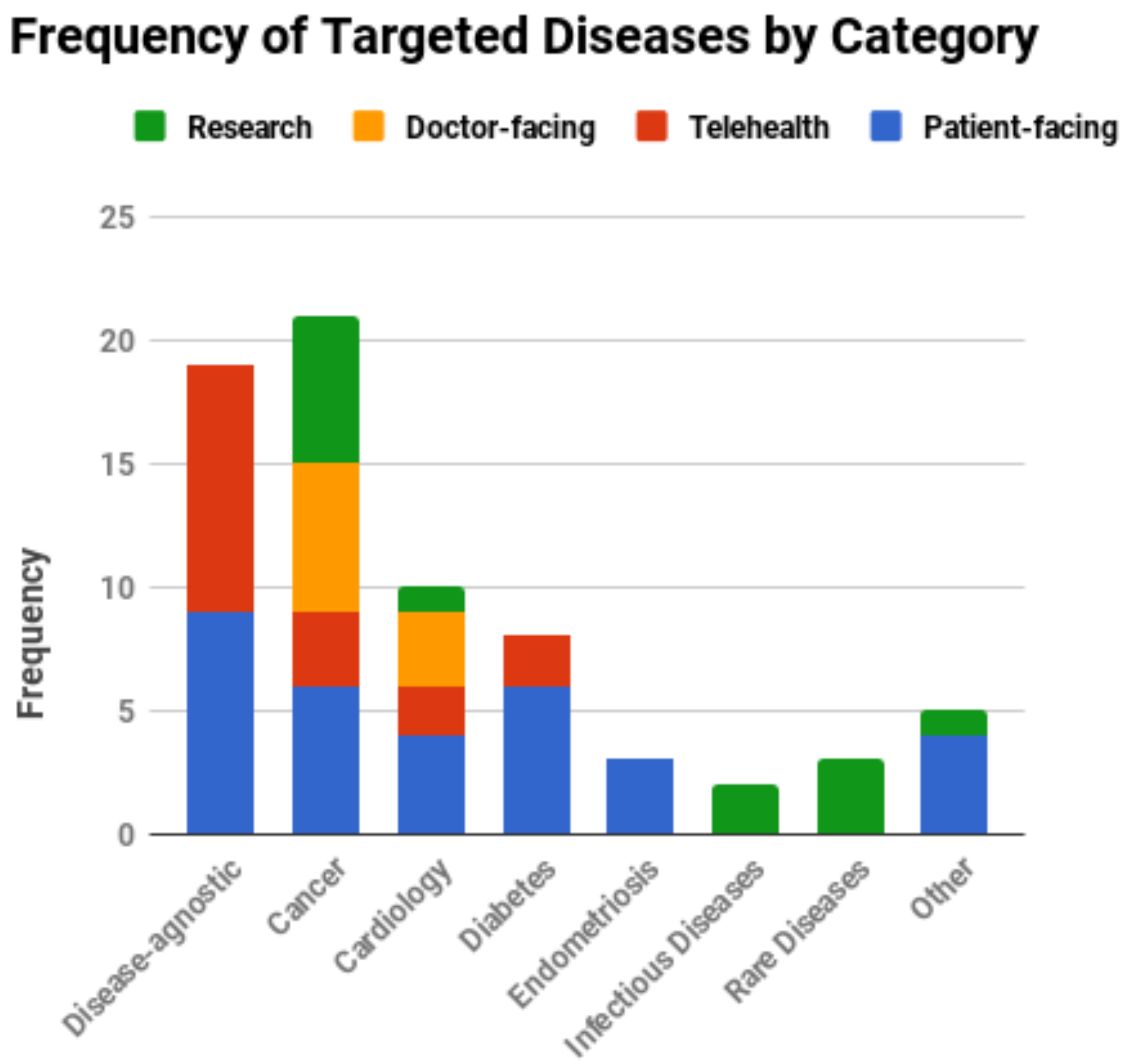

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