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Using wearables and machine learning to predict cardiovascular disease

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Shing Chen, Rosemary Walmsley, Khizr Nawab, Alaina Cockerell, Matthew Willetts, Sven Hollowell

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Martin Landray, Gil McVean, and many others…

Aiden Doherty (Oxford) - Statistical machine learning of wearable sensor data for the prediction of atherosclerotic cardiovascular disease

Most people with heart disease are identified too late

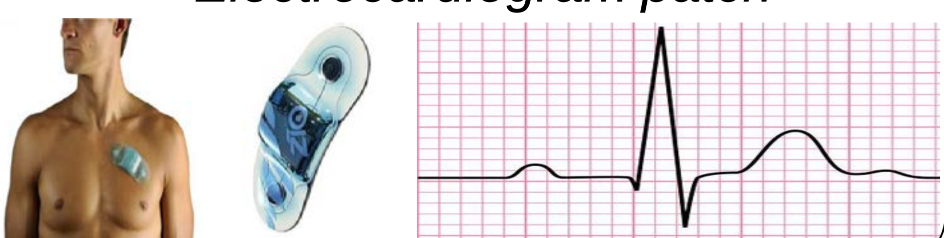
Many cardiac events not predicted by current models

6.8 million regular wearable users in the UK

Accelerometer

Potential to identify new powerful signals of disease risk from sensors

Electrocardiogram patch



Could these signals help improve current models used in clinical practice?


nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
UK BIOBANK
Genetic and health data from half a million people in the United Kingdom
PAGES 194, 203 & 210
TECHNOLOGY
TIME TO THINK SMALL
Fleets of tiny satellites could change space exploration
PAGE 185
OPTOELECTRONICS
TURNING UP THE LIGHT
Boost in performance for perovskite LEDs
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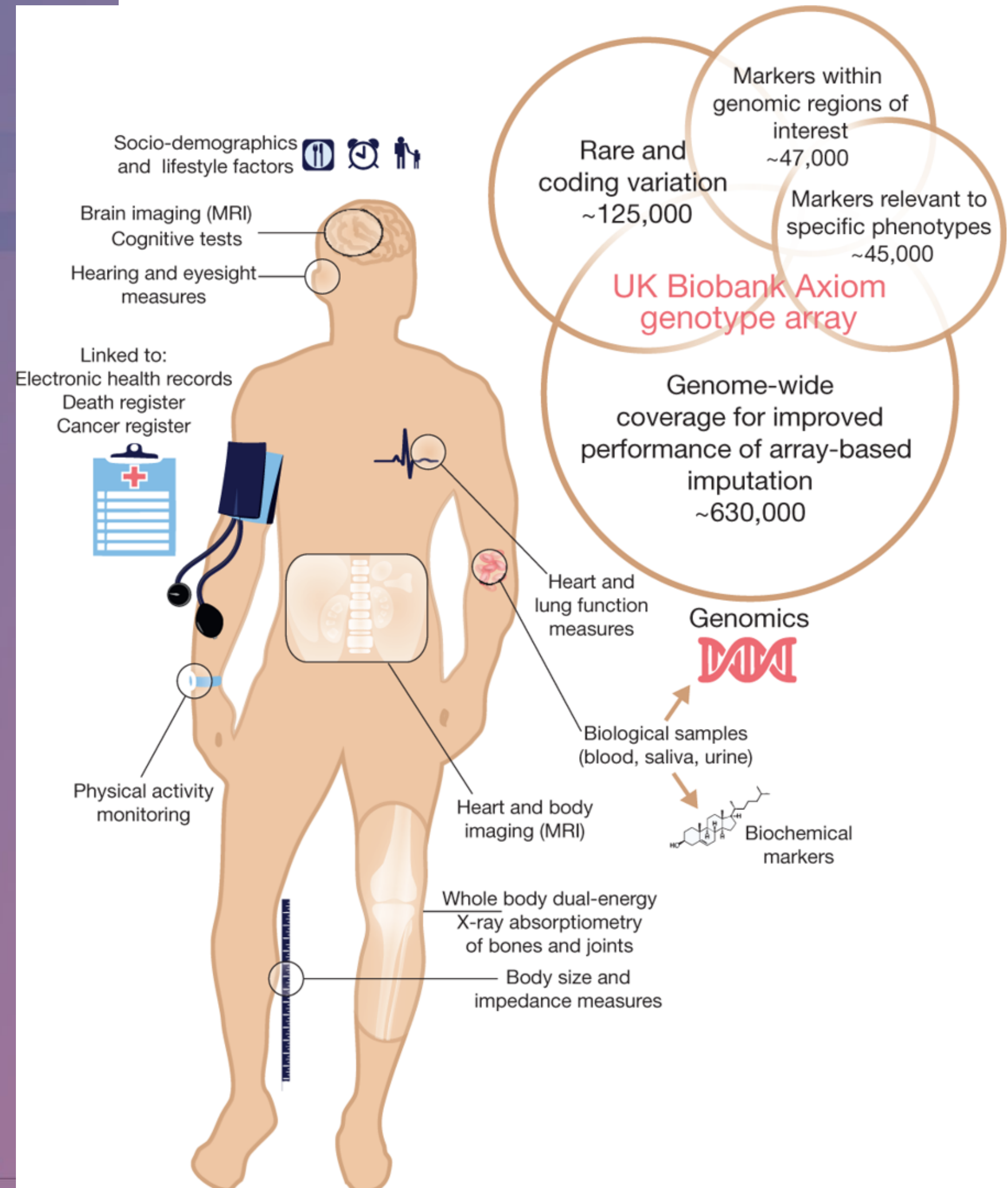
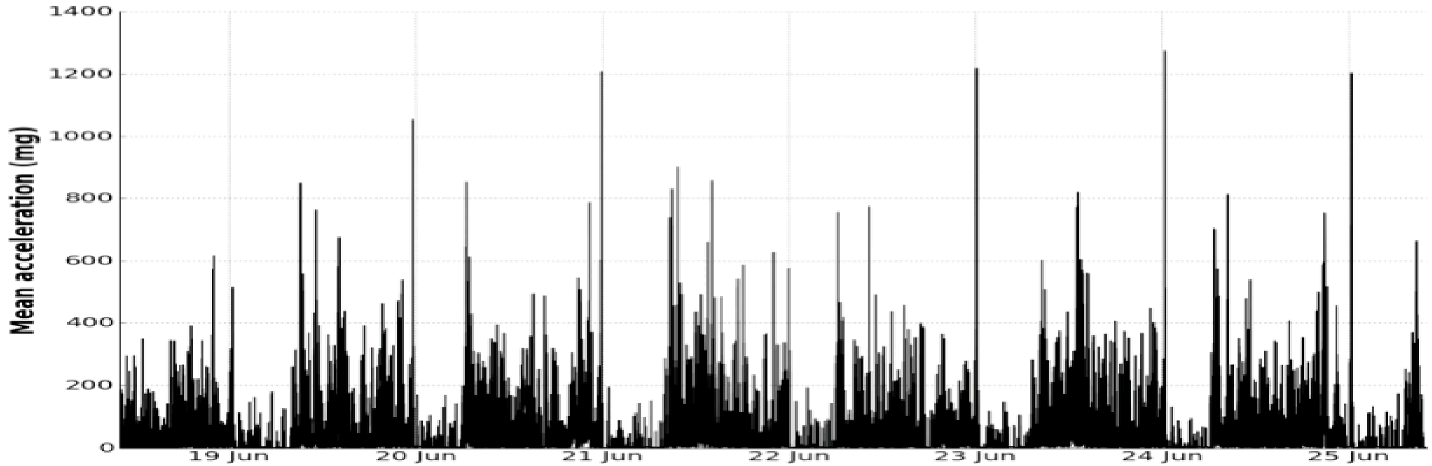
DEVELOPMENTAL BIOLOGY
TWO WAYS TO GROW
A second source for the cells that line blood vessels
PAGES 195 & 223
NATURE.COM
11 October 2018
Vol. 562, No. 7726


Socio-demographics and lifestyle factors
Brain imaging (MRI)
Cognitive tests
Hearing and eyesight measures
Linked to:
Electronic health records
Death register
Cancer register
Physical activity monitoring
Heart and lung function measures
Heart and body imaging (MRI)
Biological samples (blood, saliva, urine)
Biochemical markers
Whole body dual-energy X-ray absorptiometry of bones and joints
Body size and impedance measures
Genomics
Rare and coding variation ~125,000
Markers within genomic regions of interest ~47,000
Markers relevant to specific phenotypes ~45,000
UK Biobank Axiom genotype array
Genome-wide coverage for improved performance of array-based imputation ~630,000

Careful phenotyping is very important



Resample x/y/z to 100Hz → Calibration to local gravity → Vector magnitude → Remove noise & gravity → 5-sec epoch analysis → Non-wear detection → Activity volume & intensity summary

n = 103,712

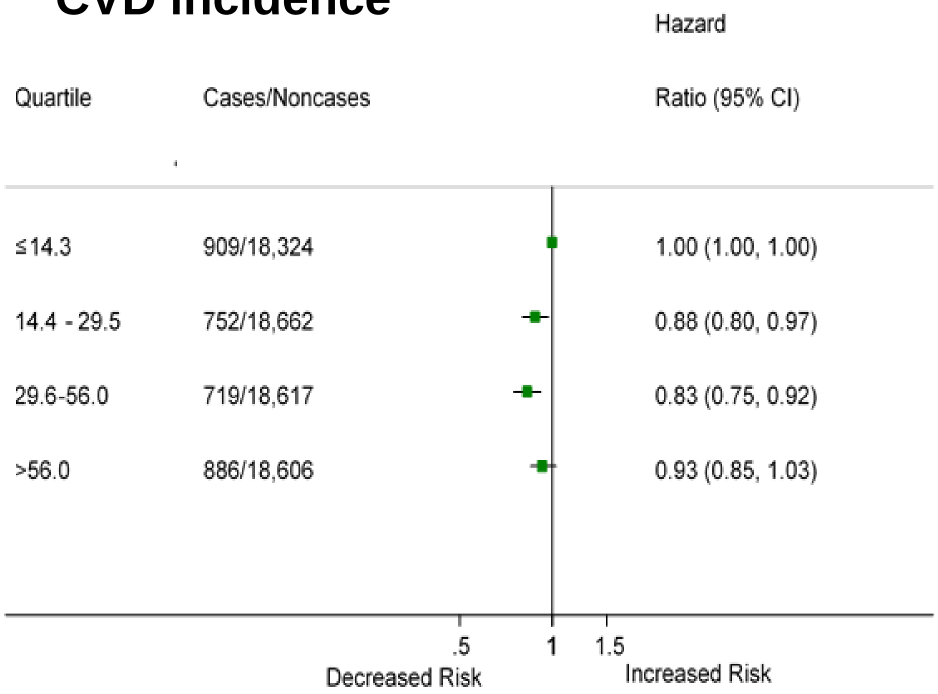
Asked to wear for 7 days

~180 million data points per person per week

Doherty et al. ***PLoS One*** 12, (2017). 12(2):e0169649
van Hees; J App Physiol 2014; 117(7): 738-744

Physical activity & incident CVD

Self-report - 17% reduction in CVD incidence



Hazard ratios[a] for incident cardiovascular disease (CVD) by equal fourths of measured physical activity.

[a] Stratified by age-at-risk and adjusted for ethnicity, education, Townsend Deprivation Index, smoking, and alcohol consumption

Ramakrishnan, Doherty … Dwyer *(under review)*

Physical activity & incident CVD

Self-report - 17% reduction in CVD incidence

Quartile	Cases/Noncases	Hazard Ratio (95% CI)
≤14.3	909/18,324	1.00 (1.00, 1.00)
14.4 - 29.5	752/18,662	0.88 (0.80, 0.97)
29.6-56.0	719/18,617	0.83 (0.75, 0.92)
>56.0	886/18,606	0.93 (0.85, 1.03)

.5 1 1.5
Decreased Risk Increased Risk

Device - 52% reduction in CVD incidence

	Cases/Noncases	Hazard Ratio (95% CI)
≤22.7	568/22,166	1.00 (1.00, 1.00)
22.8 – 27.3	397/22,330	0.81 (0.71, 0.92)
27.4-32.7	309/22,409	0.67 (0.58, 0.78)
>32.7	204/22,528	0.48 (0.41, 0.56)

.5 1 1.5
Decreased Risk Increased Risk

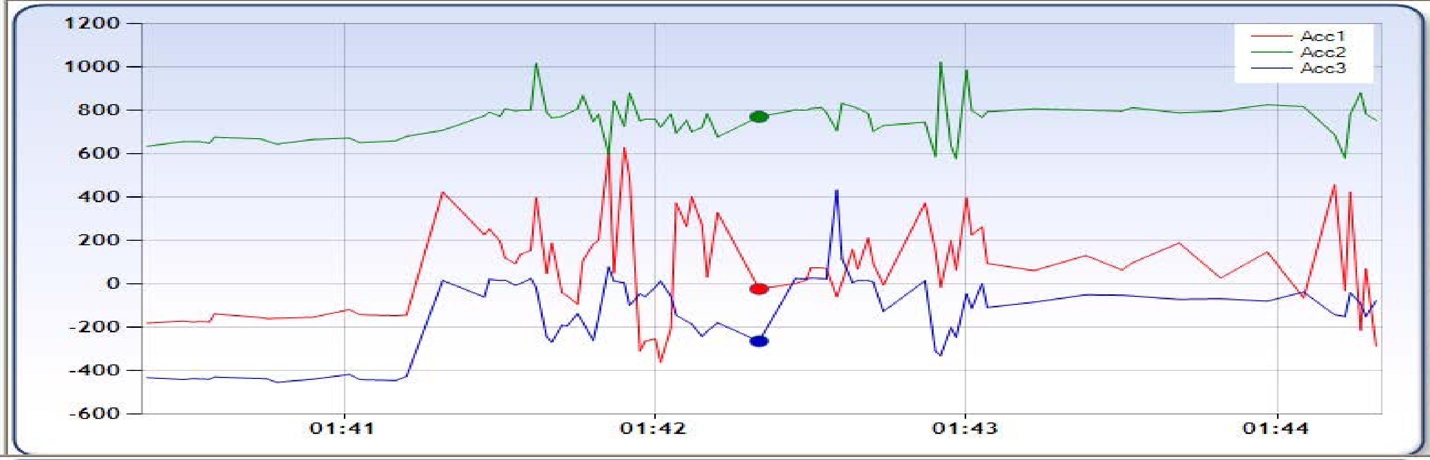
Hazard ratios[a] for incident cardiovascular disease (CVD) by equal fourths of measured physical activity.

[a] Stratified by age-at-risk and adjusted for ethnicity, education, Townsend Deprivation Index, smoking, and alcohol consumption

Ramakrishnan, Doherty … Dwyer *(under review)*

AI to learn functional activities from wearables

Sitting



Walking

Driving

Bao L., Intille S.S**. Pervasive 2004**, LNCS
Staudenmayer et al **J Appl Physiol** 107: 1300–1307, 2009

Machine learning of behaviours from acc data

150 people – activity monitors + cameras

Behaviour classification – free living groundtruth

- 188,355 mins annotated behaviour from 153 people
- 230 different behaviours types
- Kappa = 0.74 (accuracy = 83%)

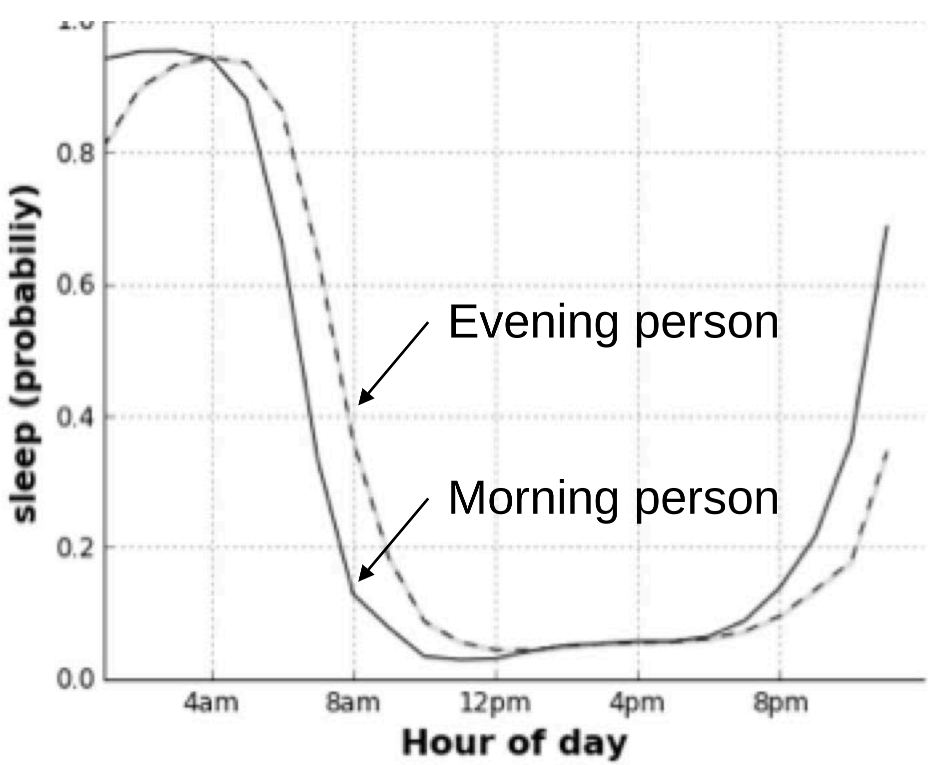
Prediction→ Ground truth↓	Sleep	Sedentary	Tasks-light	Walking	Moderate activity
Sleep	91%	8%	<1%	<1%	<1%
Sedentary	6%	81%	5%	3%	6%
Tasks-light	<1%	29%	25%	20%	26%
Walking	<1%	11%	15%	58%	16%
Moderate	<1%	12%	14%	15%	58%

Willetts, M., Hollowell, S., Aslett, L., Holmes, C. & Doherty, A. ***Sci. Rep.*** 8, 7961 (2018).
Doherty, Smith-Bryne, Ferreira, MV Holmes, C Holmes, Pulit, Lindgren ***Nature Communications*** 9:5257 (2018)

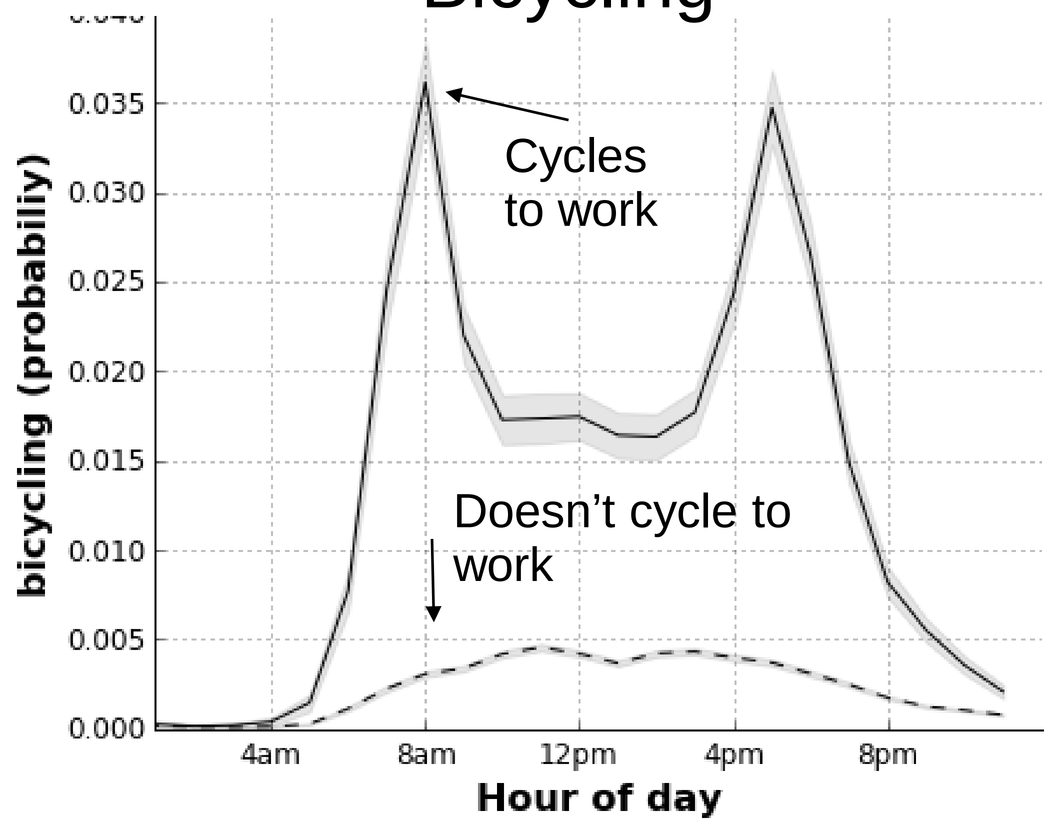
Behaviour classification – face validity

Variation in accelerometer-measured behaviour types (2013–2015) across the day by participant characteristics (measured 2007–2010): the UK Biobank study.

Sleep

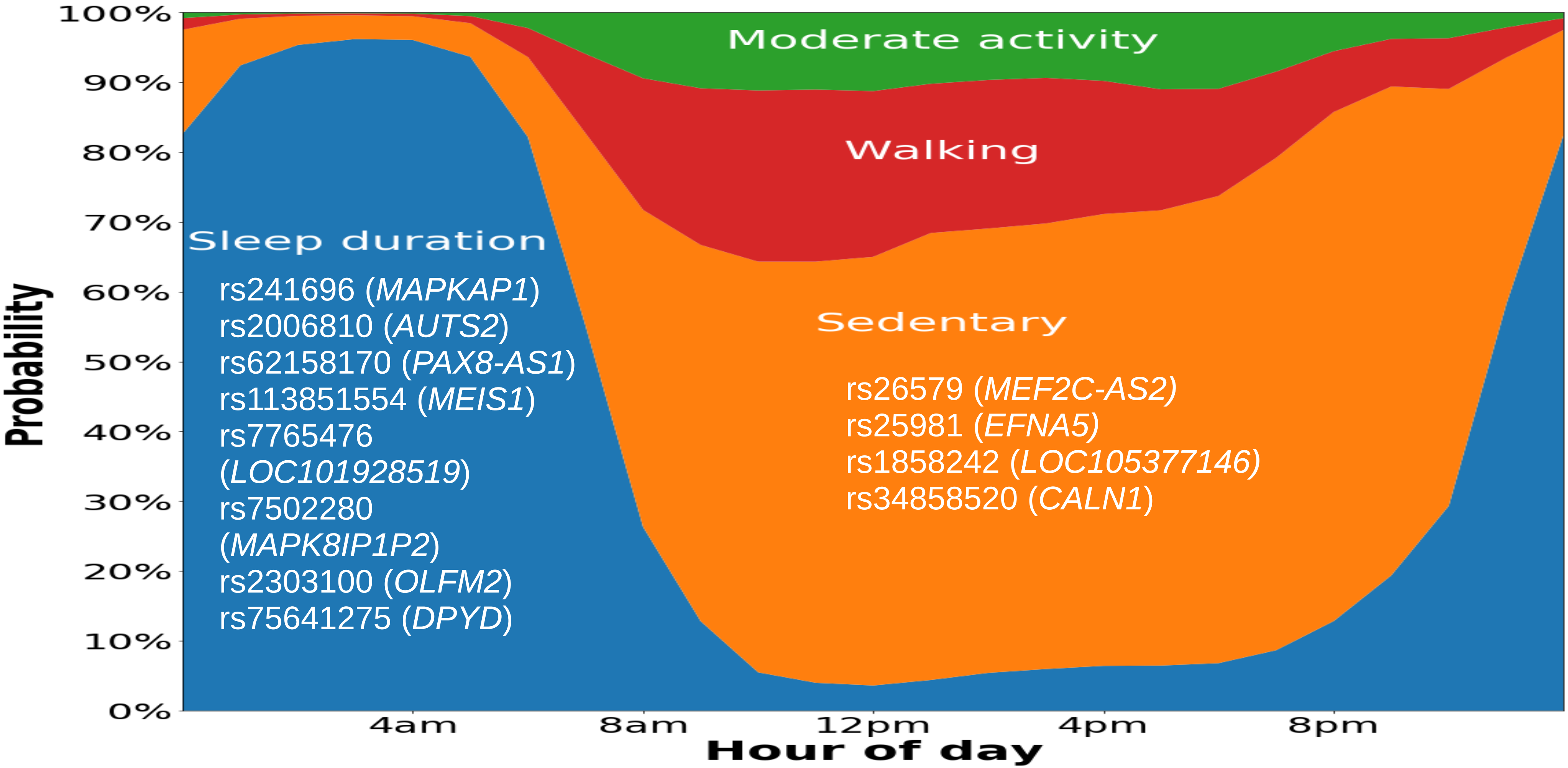


Bicycling



Willetts, M., Hollowell, S., Aslett, L., Holmes, C. & Doherty, A. ***Sci. Rep.*** 8, 7961 (2018).

Objectively measured activity behaviours in UK Biobank (n=91,105)



Mendelian randomization (MR) suggests that increased overall activity reduces:

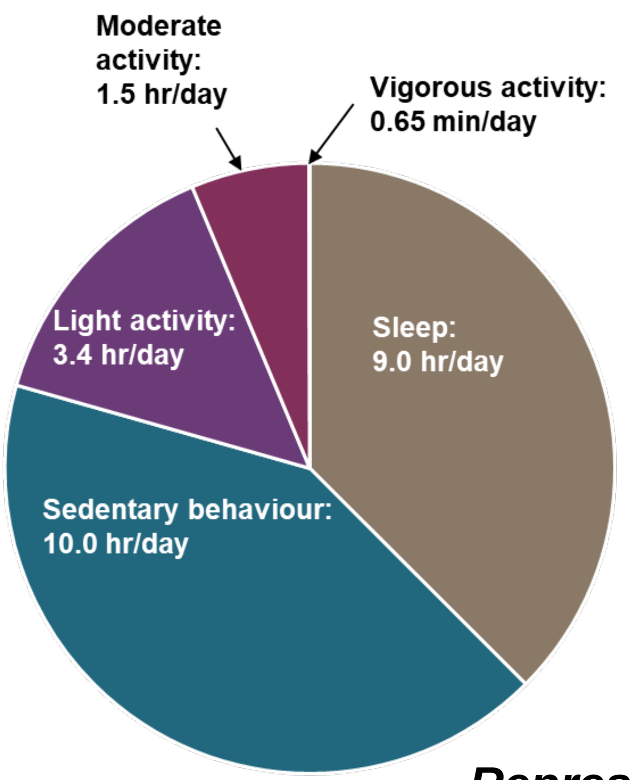
- odds of depression *(β/SD: -0.95, SE=0.19, p=9.5x10^{-7})*
- odds of hypertension *(OR/SD: 0.85, SE=0.03, p=4.5x10^{-7})*

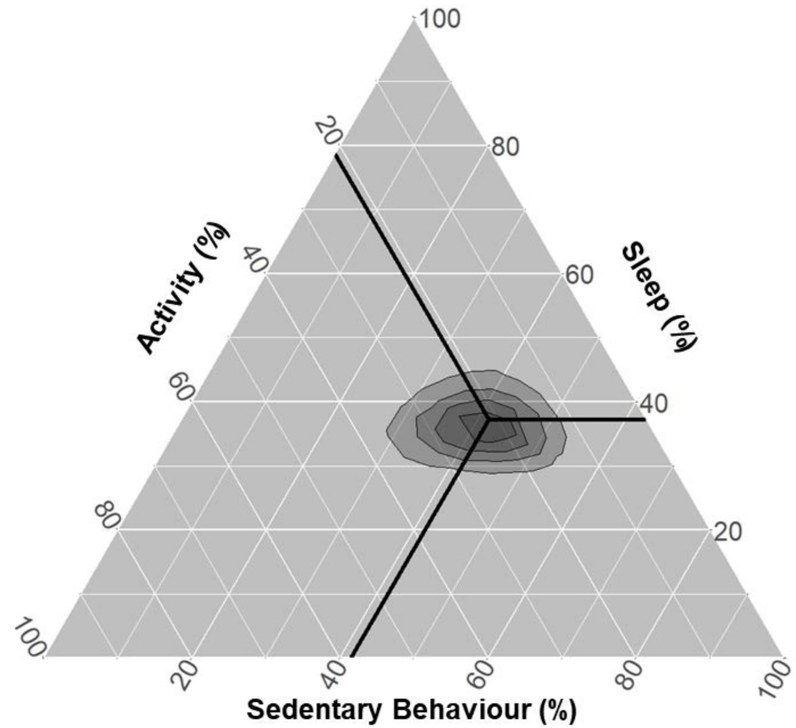
Doherty, Smith-Bryne, Ferreira, MV Holmes, C Holmes, Pulit, Lindgren ***Nature Communications*** 9:5257 (2018))
Choi, K. W. et al. ***JAMA Psychiatry*** doi:10.1001/JAMAPSYCHIATRY.2018.4175 (2019)

Time use association with future disease

Time use can be considered as compositional data.

We use a compositional data analysis approach, based on isometric log ratio transformation

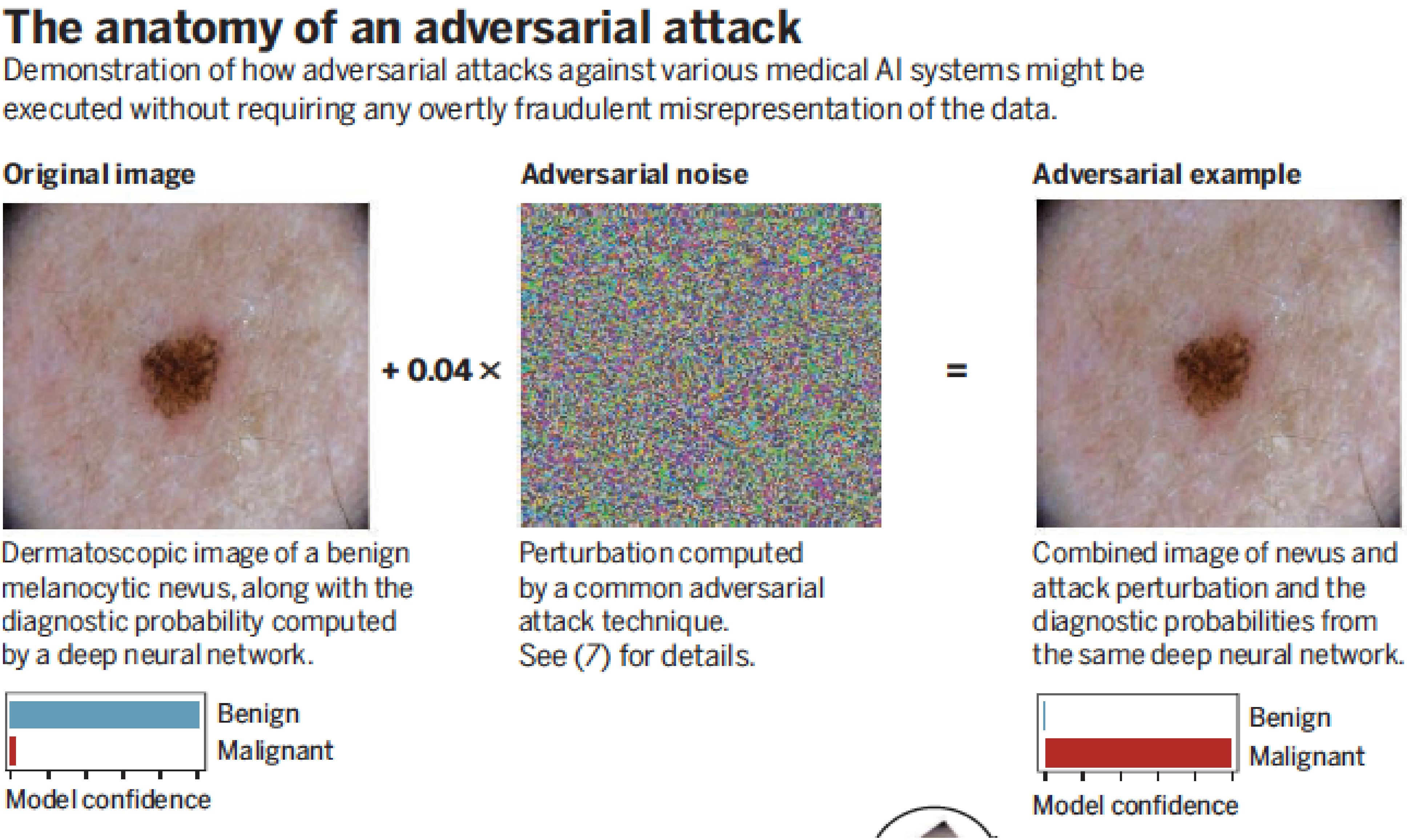




Representations of time use compositions of 89,957 UKB participants

Robustness of machine learning methods

A small change to the input causes a large, highly confident, change to the prediction



Reproducibility of machine learning in health care

There is a broad concern around the lack of reproducibility, replicability and robustness in science

		Data: Same	Data: Different
Analysis	Same	Reproducible	Replicable
Analysis	Different	Robust	Generalisable

'The Turing Way' - A handbook for reproducible data science | The Alan Turing Institute.

MIMIC data challenge - large deviation in reported sample sizes

Neuroimaging - similarity coefficients between tools range from 0 - 0.74 while completing the same task.

Health data science - data often only accessed in restricted safe-havens

Viewpoint

ONLINE FIRST FREE

January 6, 2020

Challenges to the Reproducibility of Machine Learning Models in Health Care

Andrew L. Beam, PhD[1,2]; Arjun K. Manrai, PhD[2,3]; Marzyeh Ghassemi, PhD[4,5]

» Author Affiliations | Article Information

JAMA. Published online January 6, 2020. doi:https://doi.org/10.1001/jama.2019.20866

Reproducibility has been an important and intensely debated topic in science and medicine for the past few decades.[1] As the scientific enterprise has grown in scope and complexity, concerns regarding how well new findings can be reproduced and validated across different scientific teams and study populations have emerged. In some instances,[2] the failure to replicate numerous previous studies has added to the grow-

Johnson, A. E. W., Pollard, T. J. & Mark, R. G. In ***Machine Learning for Healthcare Conference***, 2017.
Bowring, A., Maumet, C. & Nichols, T. E. Exploring the Impact of Analysis Software on Task fMRI Results. ***Hum Brain Mapp*** 2019;40:3362-3384

Next steps:

Deep learning of sensor data for disease prediction

Reproducible machine learning

Replication in other cohorts

Can we collaborate with Japanese cohorts?
wearable sensor, genomic, & outcome data

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