Using machine learning and clinical AI to improve patient care

UNIVERSITY OF OXFORD

Prof. David A. Clifton

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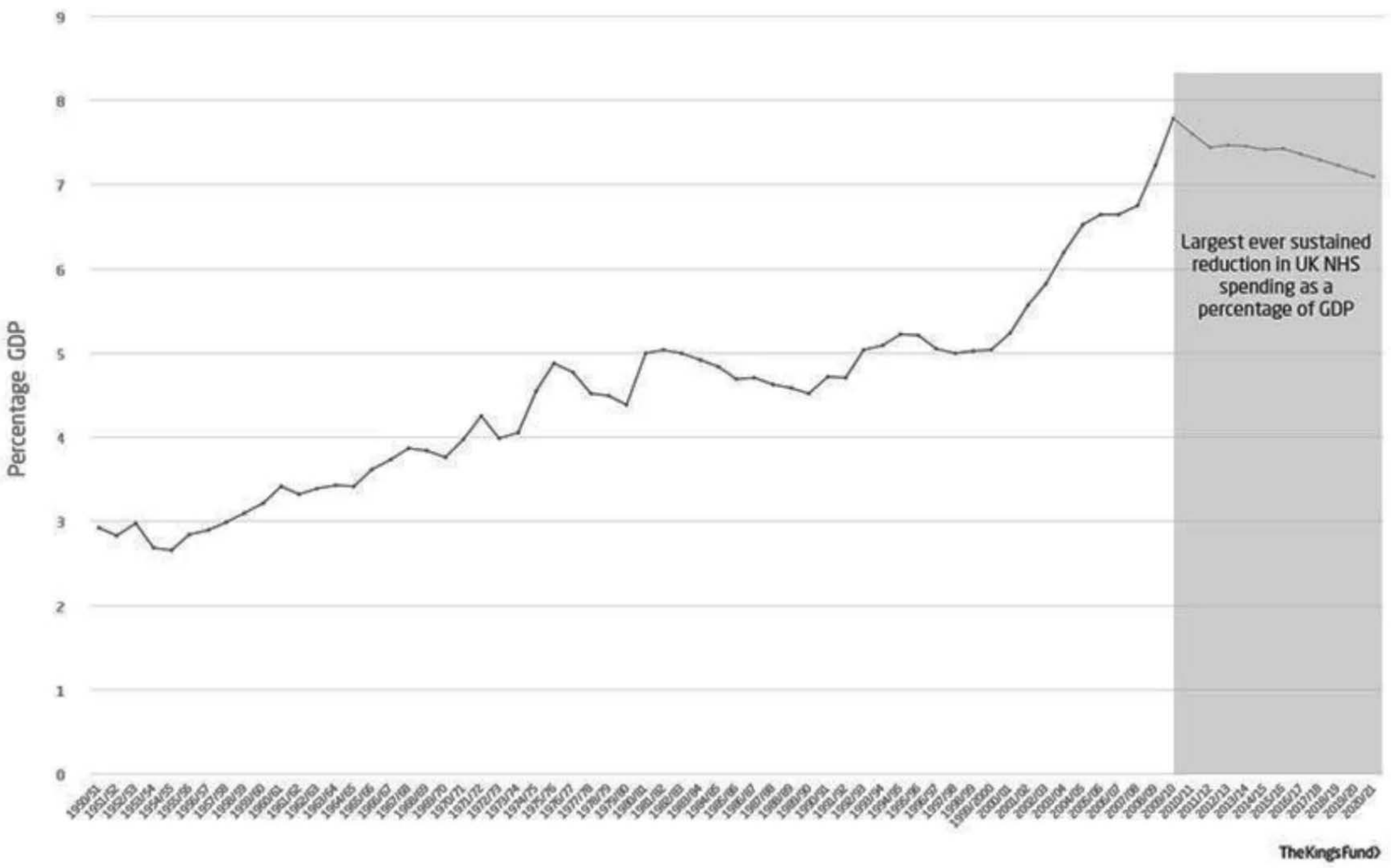
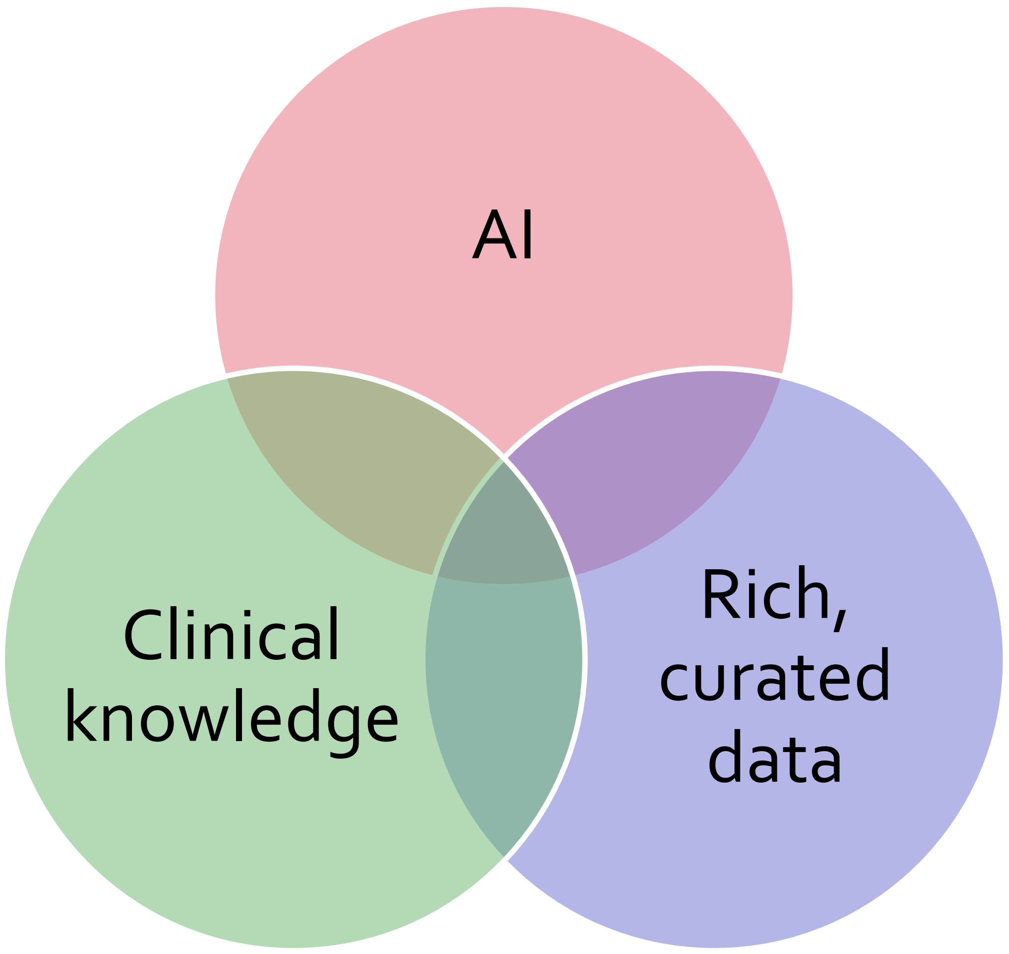
Oxford, UK

Suzhou, China



Source: Kings Fund. – The grey area starts in 2010 and shows forecasts for 2020.


AI
Clinical knowledge
Rich, curated data

Pioneering the IntelligentEngine


BioSign

A healthcare technology company accelerating medical research and improving patient care

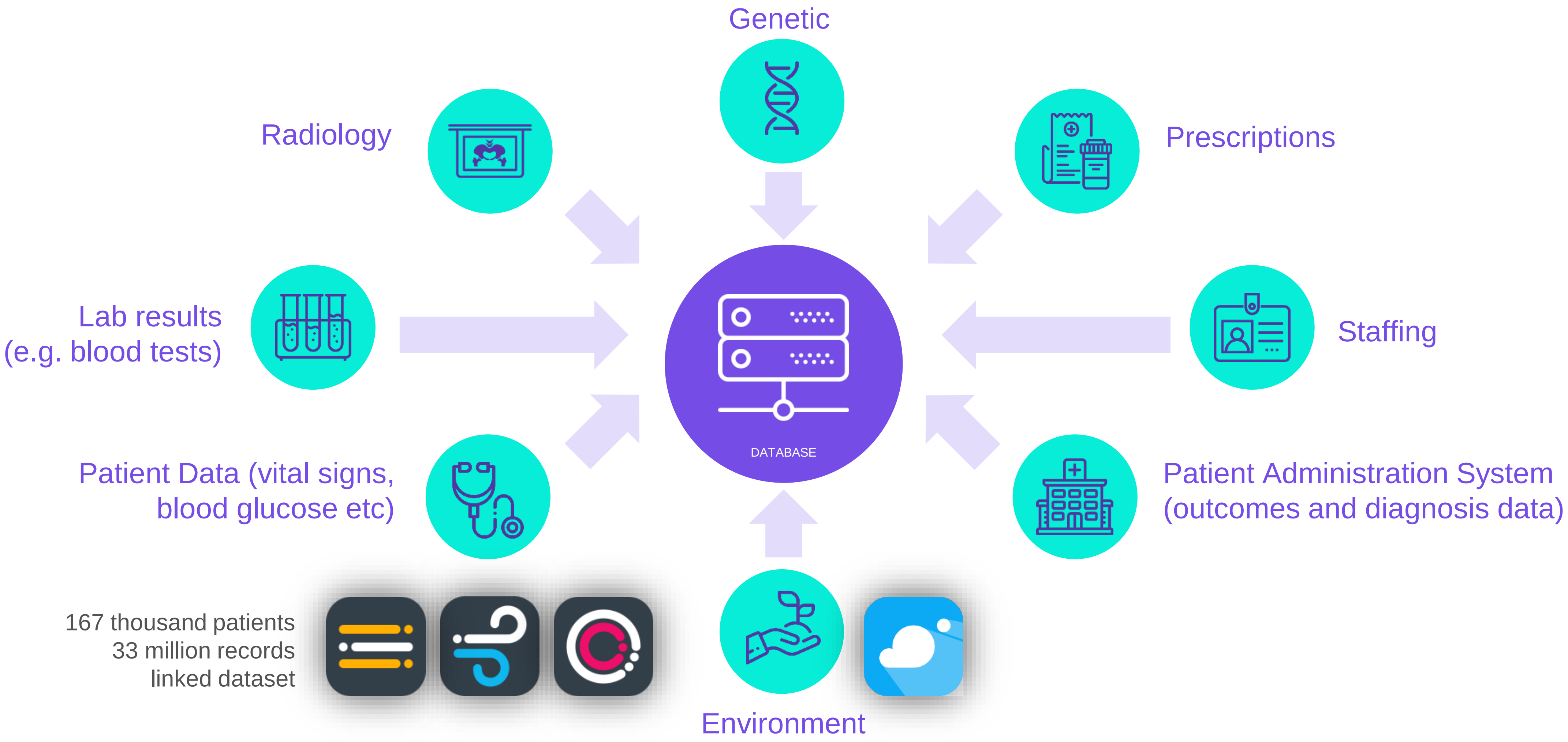
Designed by clinicians, focused on patients, powered by AI.

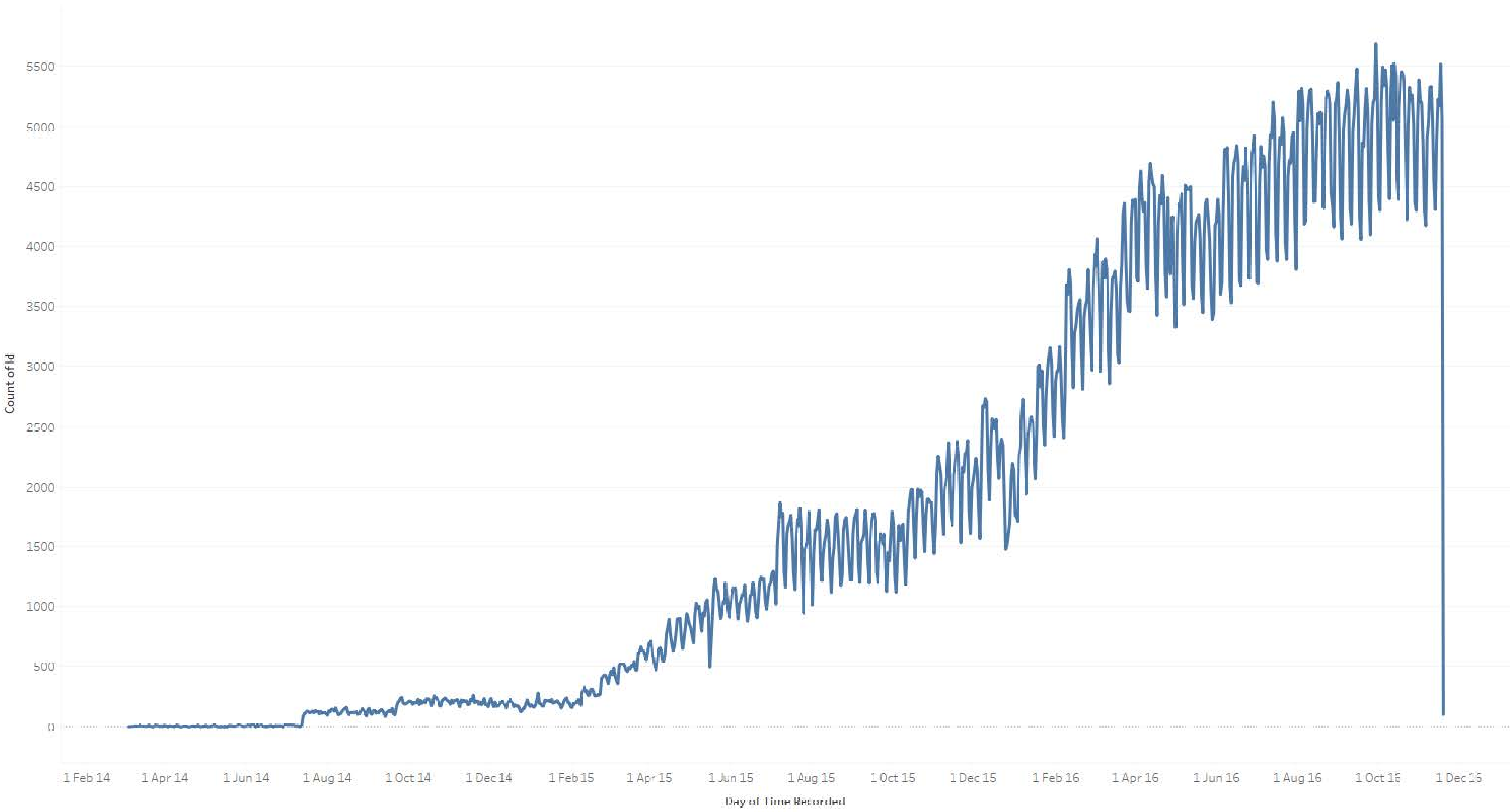
Sensyne Health

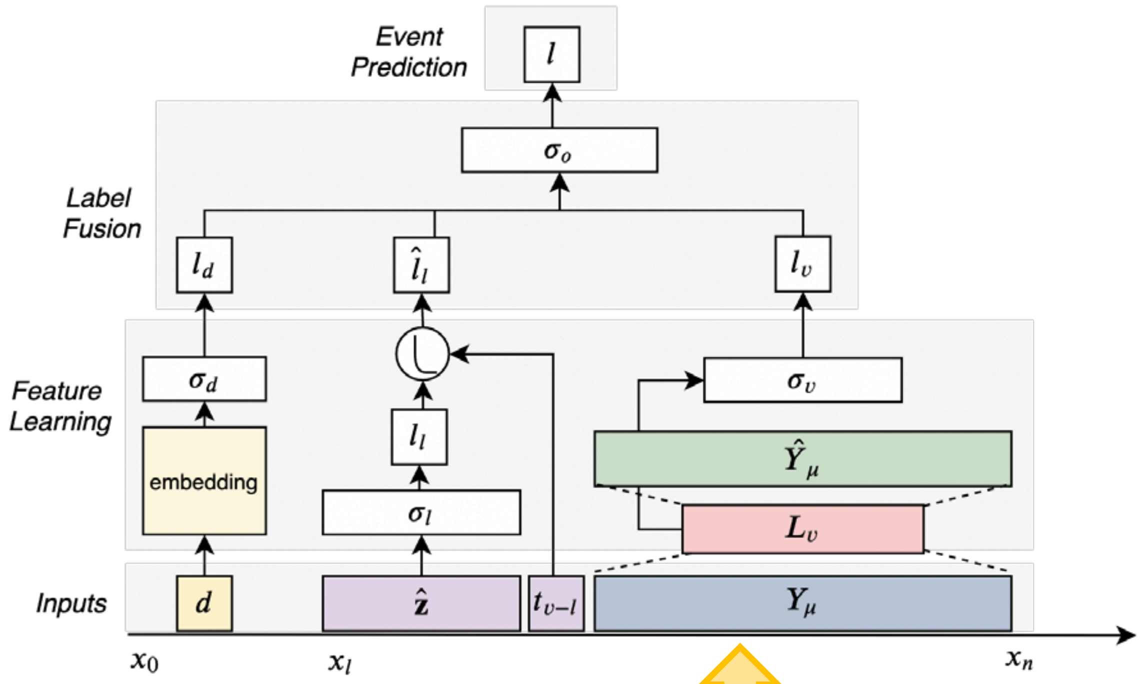
UNIVERSITY OF OXFORD

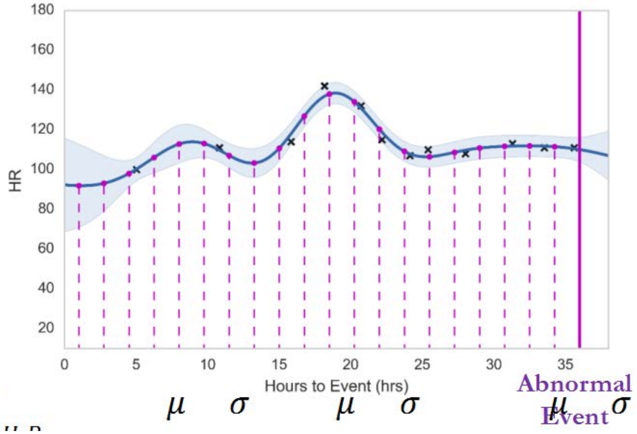
Oxford University Hospitals NHS Foundation Trust

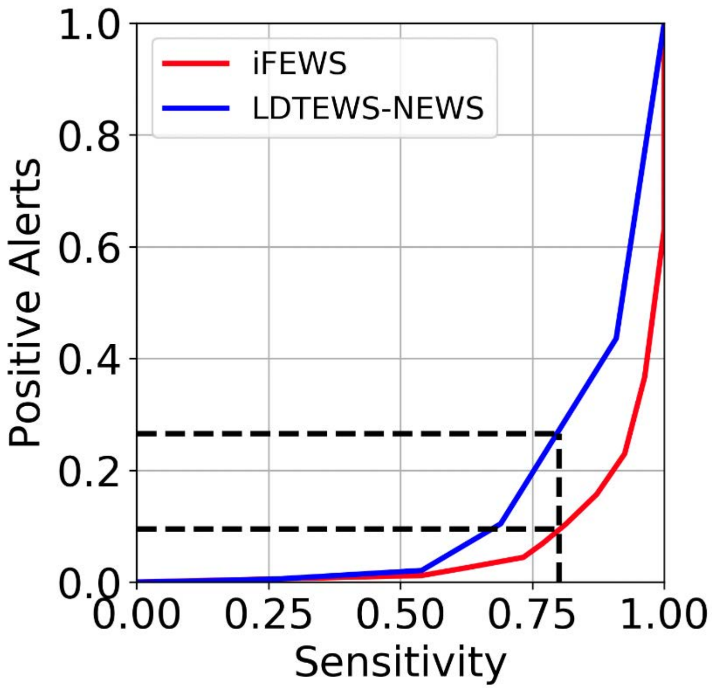
NHS


Genetic
Radiology
Prescriptions
Lab results
(e.g. blood tests)
DATABASE
Staffing
Patient Data (vital signs,
blood glucose etc)
Patient Administration System
(outcomes and diagnosis data)
167 thousand patients
33 million records
linked dataset
Environment


5500
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
Count of Id
1 Feb 14
1 Apr 14
1 Jun 14
1 Aug 14
1 Oct 14
1 Dec 14
1 Feb 15
1 Apr 15
1 Jun 15
1 Aug 15
1 Oct 15
1 Dec 15
1 Feb 16
1 Apr 16
1 Jun 16
1 Aug 16
1 Oct 16
1 Dec 16
Day of Time Recorded








Farah Shamout


Dr. Tingting Zhu

lab

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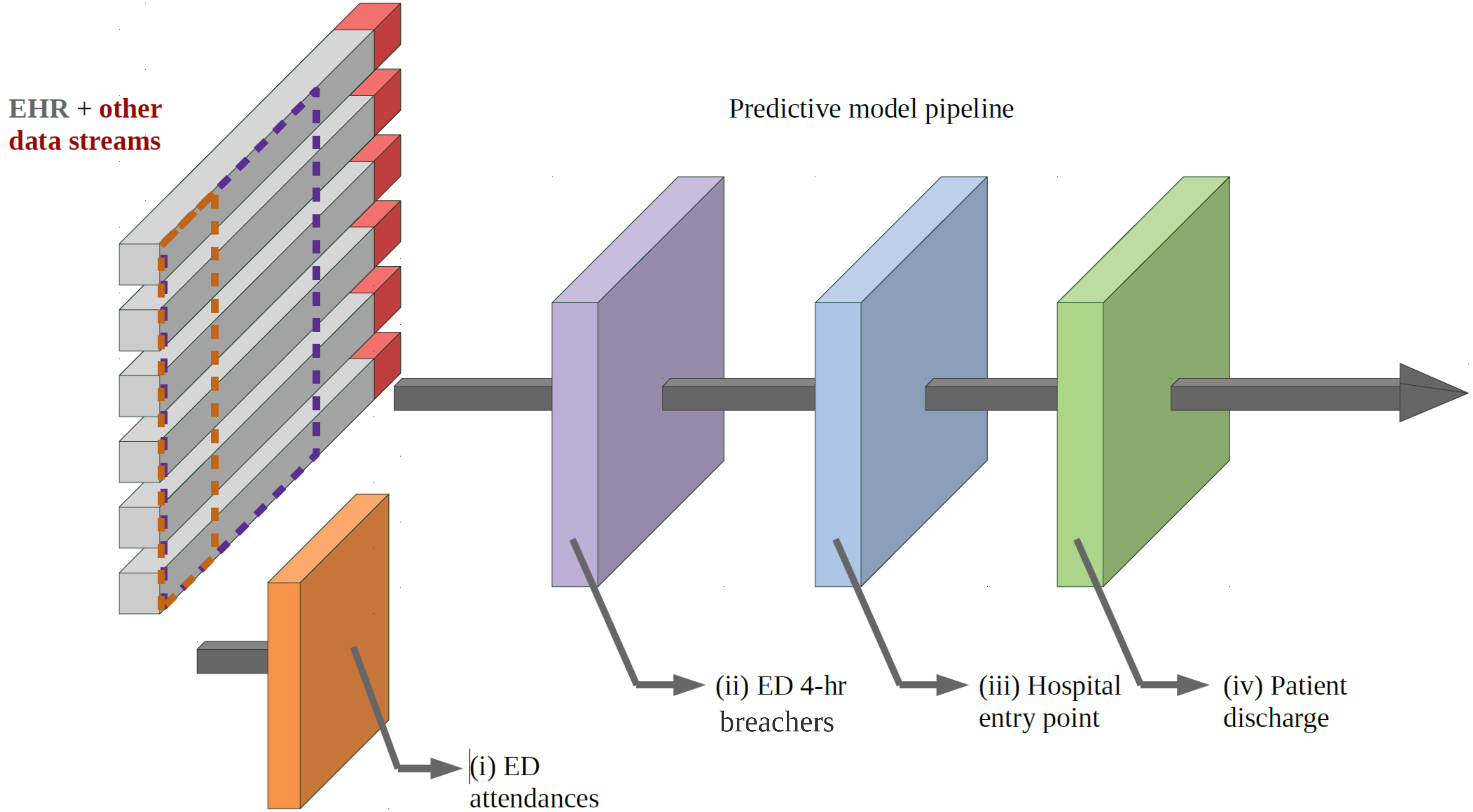
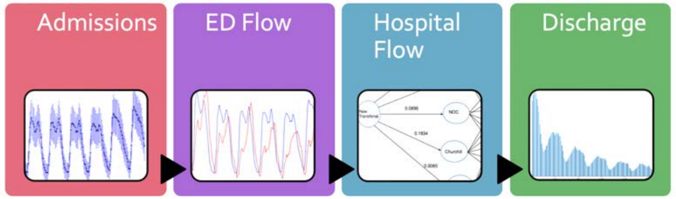
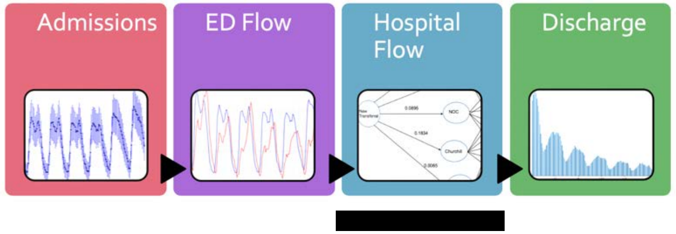
HAVEN


EHR + other
data streams
Predictive model pipeline
(i) ED
attendances
(ii) ED 4-hr
breachers
(iii) Hospital
entry point
(iv) Patient
discharge



Dr. Hamza Javed

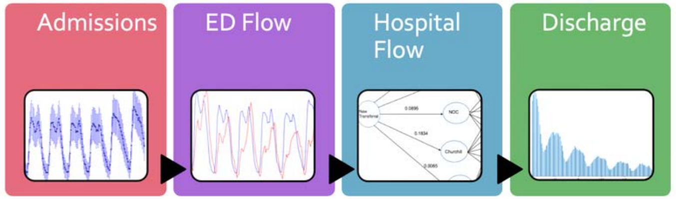
- Approx. 19% of OUH ED patients not seen within 4 hrs (2016-2017)
- Our analysis shows 1 in 5 of breaches potentially avoidable (i.e., discharged home)
- Using ML, we can predict who will be one of these “avoidable breachers” with > 85% accuracy

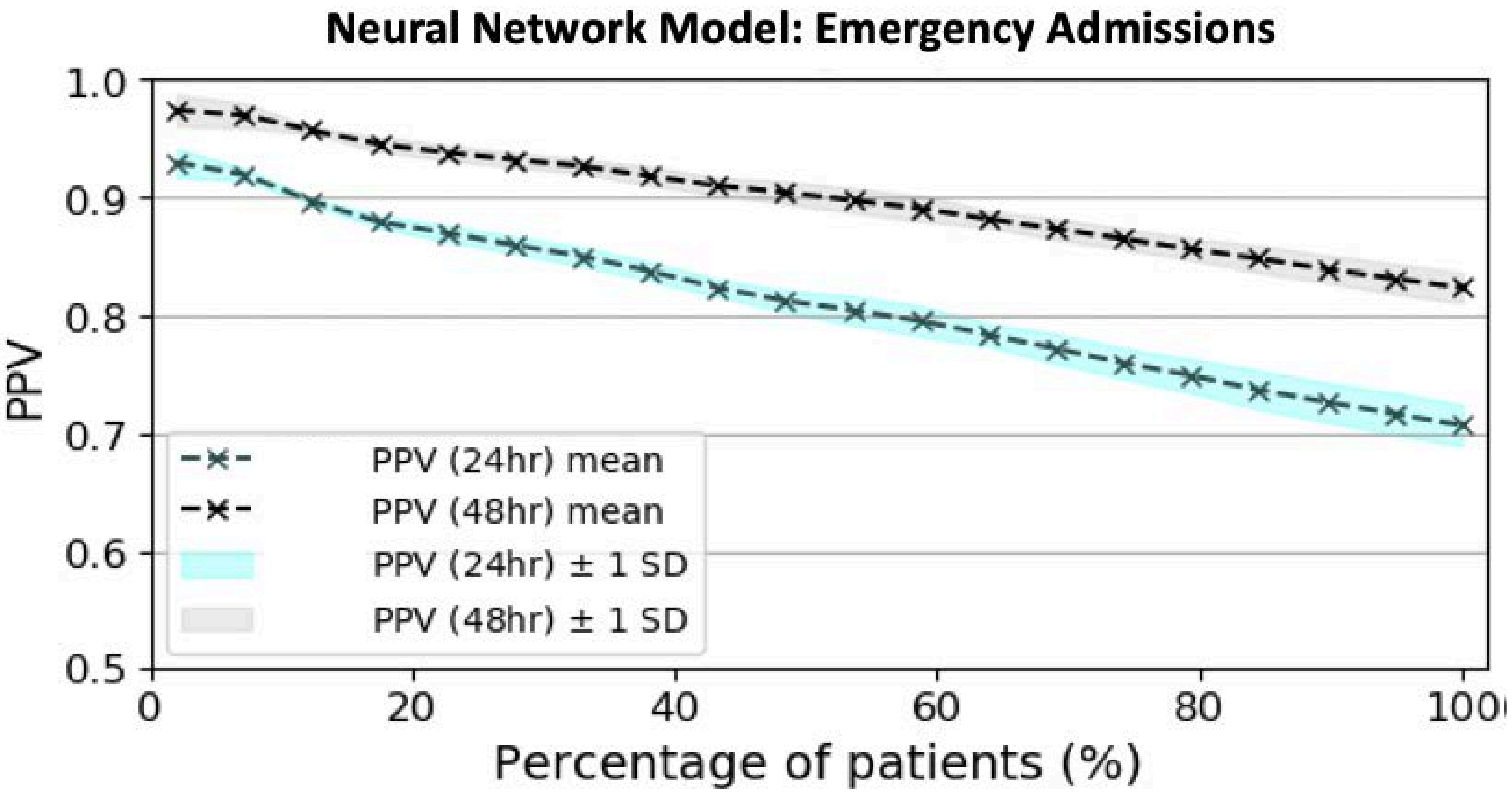


Rasheed El-Bouri

- There are (very) many wards in the OUH
- Hospital managers define 7 main ward types
- Can we predict to which ward a patient will be moved after ED?
- The goal is pre-emptive allocation of beds…

Test Data	Model			
	SVM	ff-NN	CL	CL-MAB
Avg. Acc.	0.14	0.39	0.46	**0.52**
AUC0	0.50	**0.67**	**0.67**	**0.67**
AUC1	0.55	**0.78**	**0.78**	**0.78**
AUC2	0.56	0.51	0.56	**0.60**
AUC3	0.66	**0.75**	**0.75**	**0.75**
AUC4	0.65	**0.71**	**0.71**	**0.71**
AUC5	0.50	0.59	**0.63**	**0.63**
AUC6	0.54	0.64	0.66	**0.68**





Jennifer Bishop

lab

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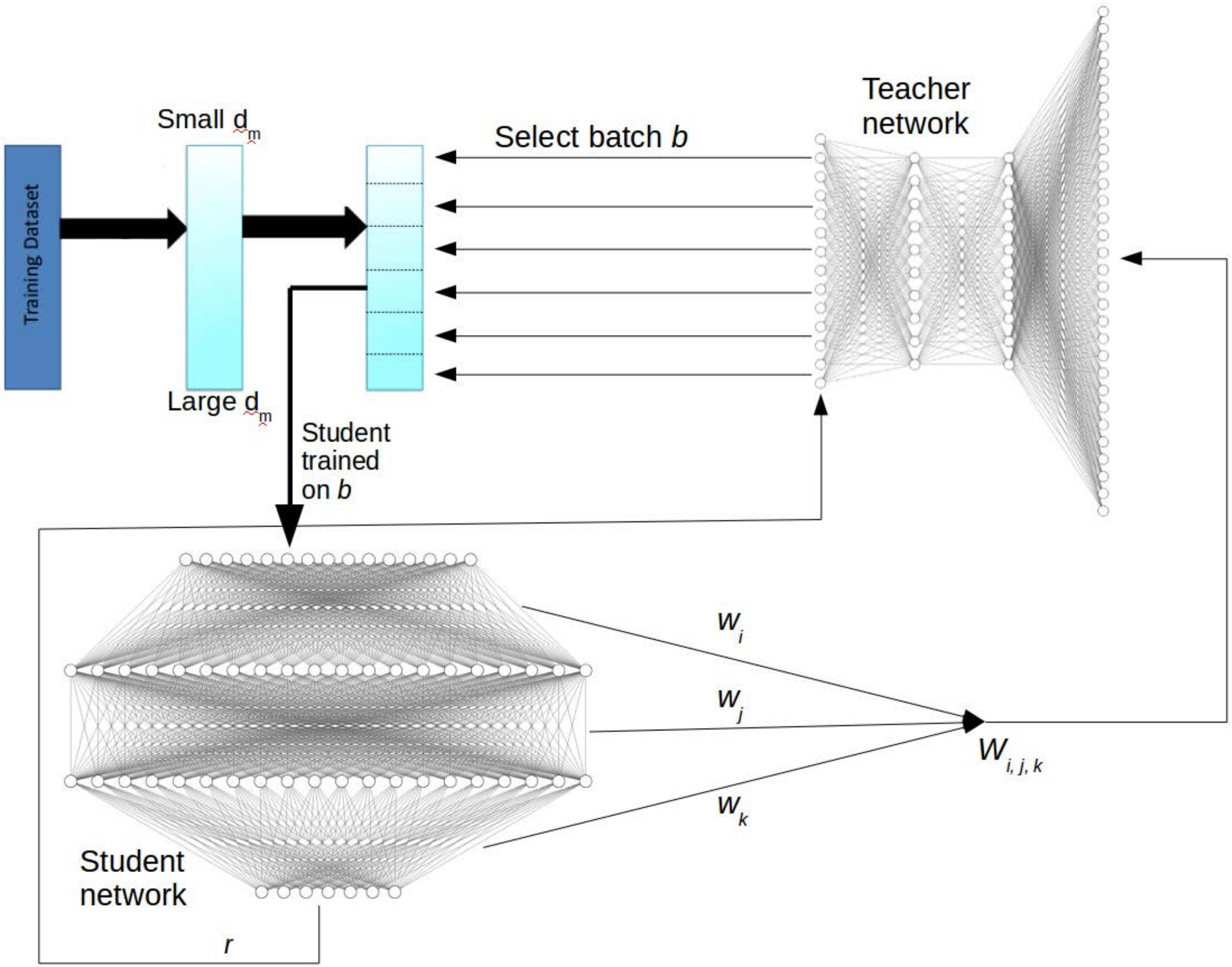
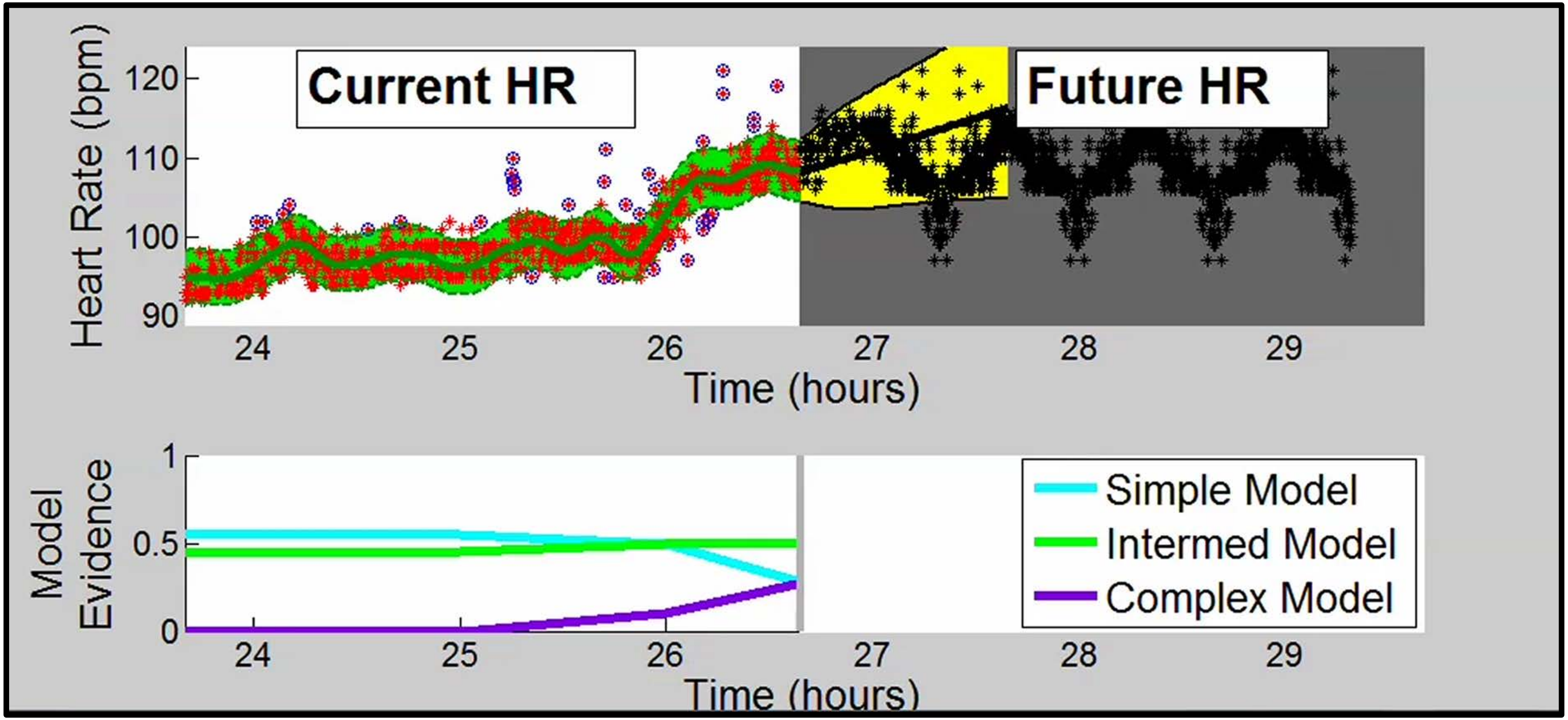
Predicting discharge

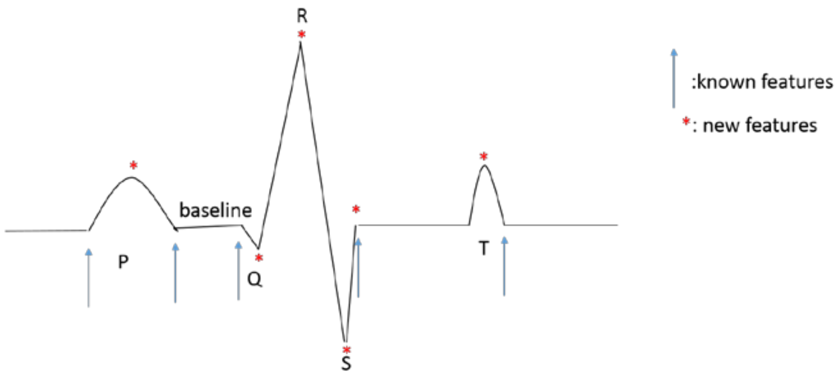

Training Dataset
Small d
m
Large d
m
Select batch *b*
Teacher
network
Student
trained
on *b*
w_i
w_j
w_k
$W_{i, j, k}$
Student
network
r

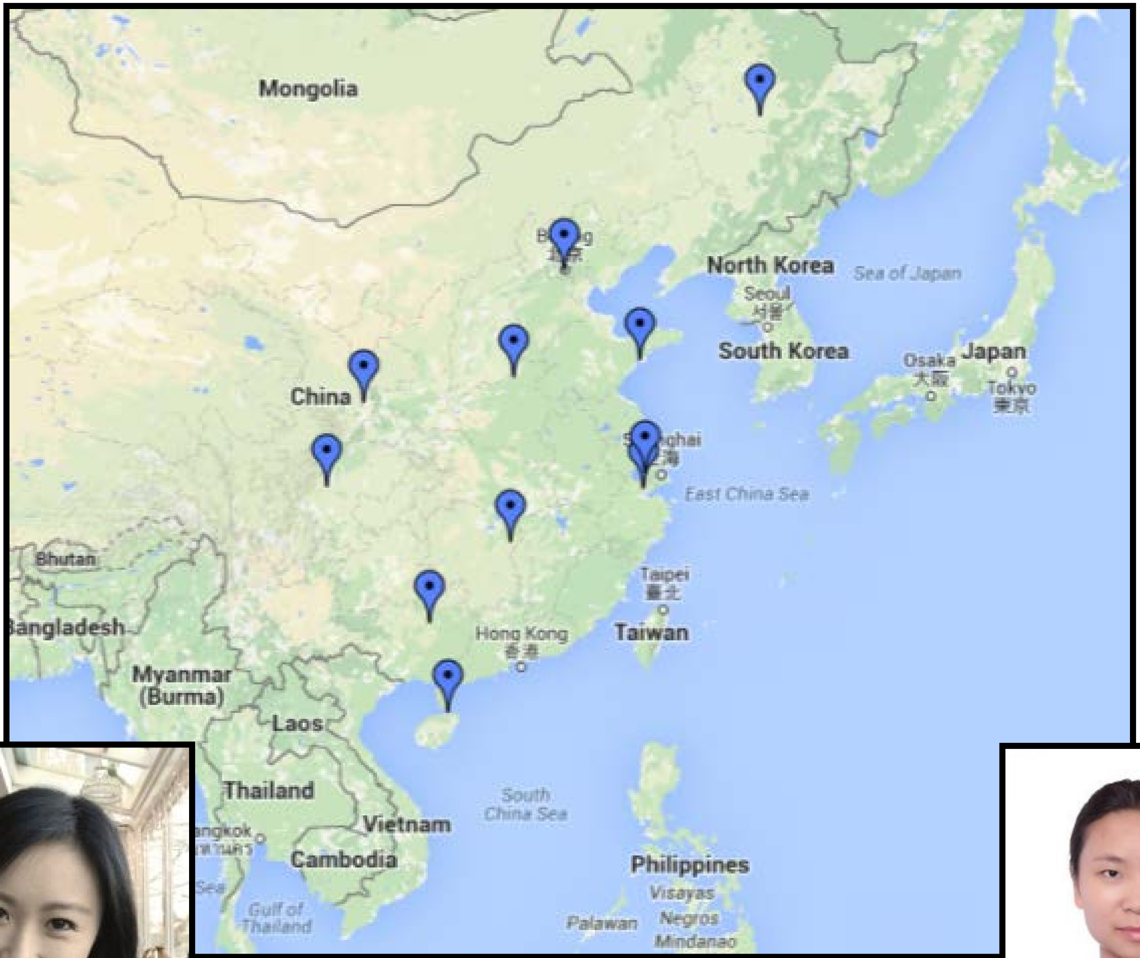

Class 6
Class 2
Class 5
Class 3
Class 1
Class 0
Class 4



Current HR
Future HR
Heart Rate (bpm)
120
110
100
90
24
25
26
27
28
29
Time (hours)
Model Evidence
1
0.5
0
Simple Model
Intermed Model
Complex Model

- 500,000 adults,
  from 10 regions across China:
- 6m health records (in Chinese)
- + genetic data
- + pollution data
- **Machine learning is being used to estimate risk of cardiovascular and respiratory disease**






Dr. Tingting Zhu


Yanting Shen

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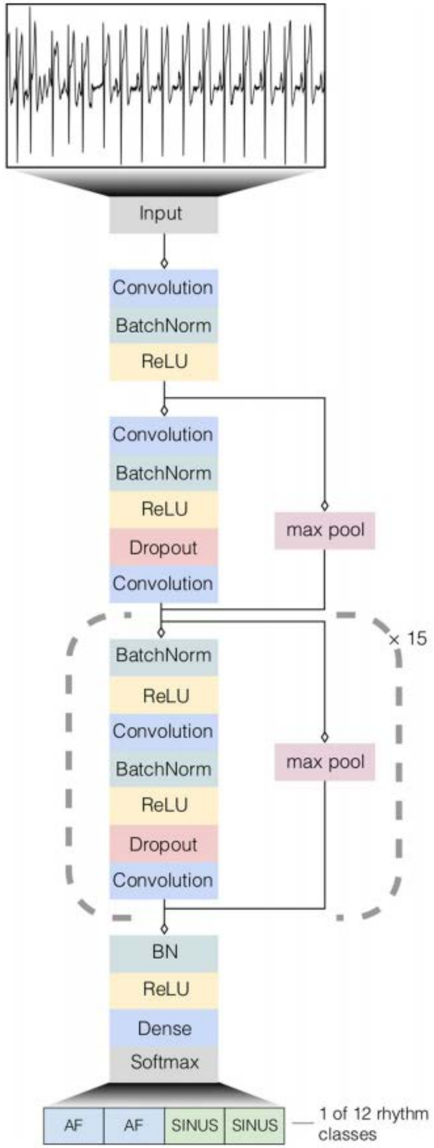
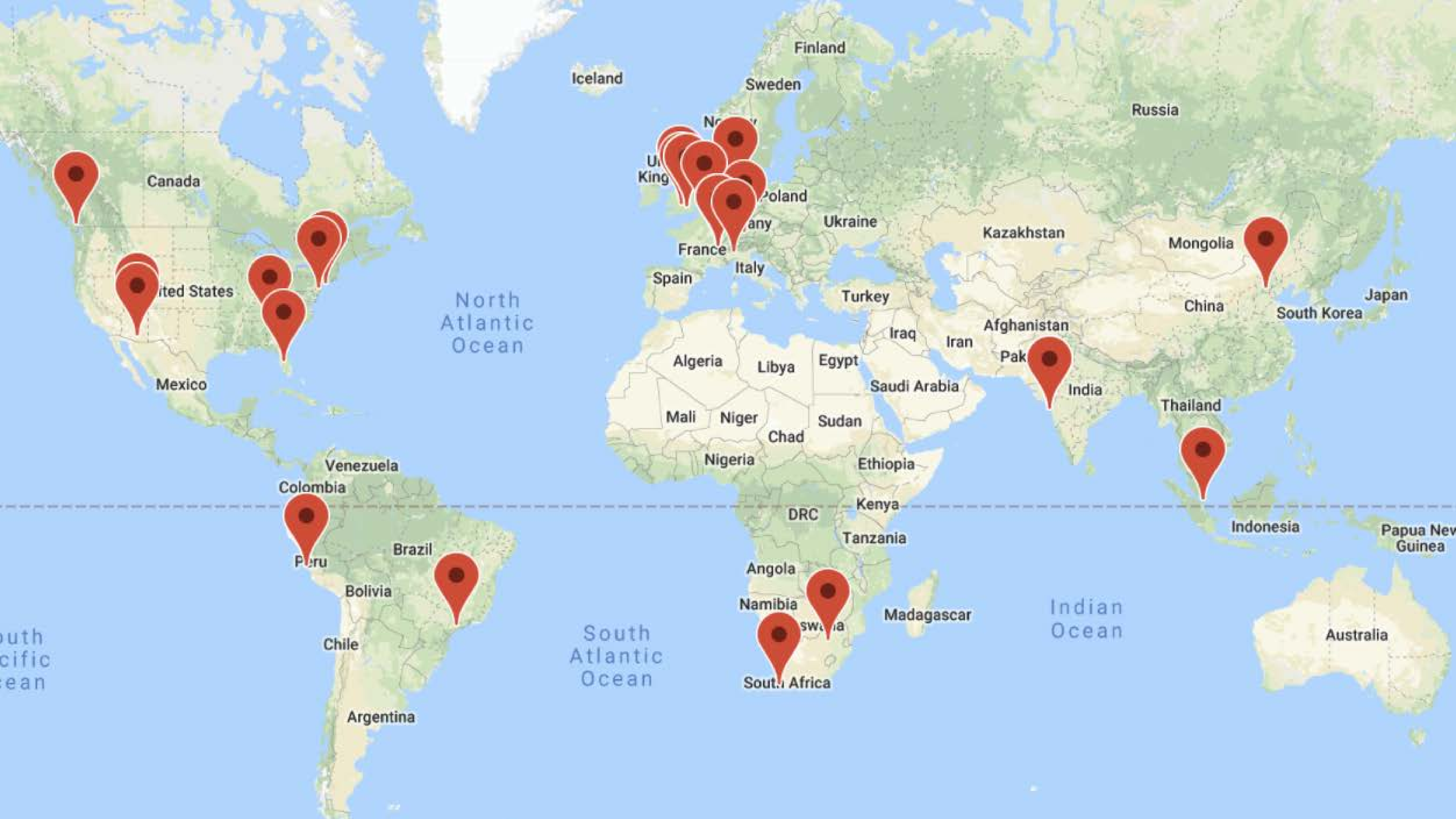
China Kadoorie Biobank

Yanting Shen

Dr. Tingting Zhu

Class	Proposed model	Andreotti et al.[26]
Normal	0.76±0.02	0.69±0.04
AF	0.82±0.01	0.81±0.04
I-AVB	0.80±0.01	0.79±0.03
LBBB	0.76±0.06	0.80±0.04
RBBB	0.87±0.01	0.85±0.02
PAC	0.52 ±0.04	0.41±0.01
PVC	0.75±0.03	0.69±0.06
STD	0.74±0.02	0.69±0.06
STE	0.44±0.05	0.42±0.06
overall	0.72±0.01	0.68±0.05



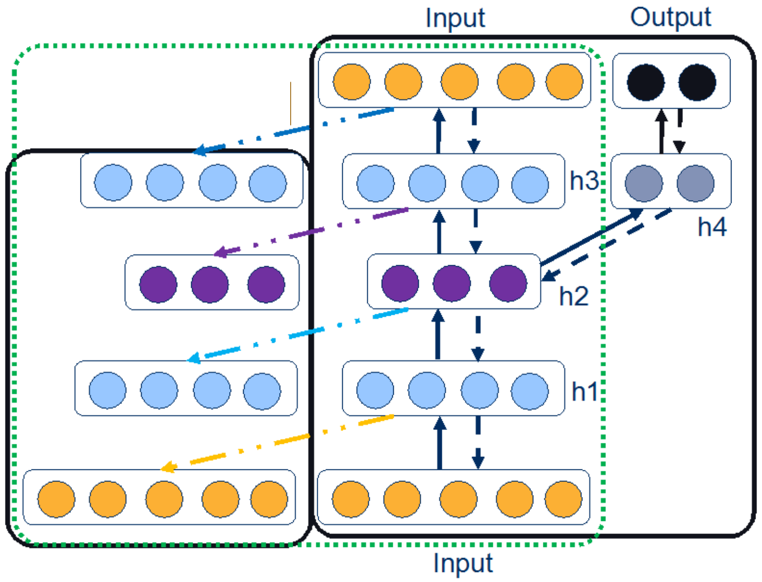

Iceland
Finland
Sweden
Russia
Canada
Poland
Ukraine
Kazakhstan
Mongolia
France
Italy
Spain
Turkey
United States
North Atlantic Ocean
China
Japan
South Korea
Afghanistan
Iraq
Iran
Algeria
Libya
Egypt
Saudi Arabia
India
Mexico
Thailand
Mali
Niger
Sudan
Chad
Nigeria
Ethiopia
Venezuela
Colombia
Kenya
DRC
Indonesia
Tanzania
Papua New Guinea
Brazil
Angola
Bolivia
Namibia
Madagascar
Indian Ocean
South Atlantic Ocean
Chile
Australia
Argentina

1000s mutations

100,000 isolates

[0 0 0 0 0 1 0 0 0 1 … 0 0 1 0]
[0 0 0 0 0 0 0 0 1 1 … 0 0 0 0]
[0 0 1 0 0 0 0 1 0 0 … 0 0 1 0]
…
[1 0 0 0 0 0 0 0 0 0 … 0 0 0 0]

Affected by drug A?	Affected by drug B?	…
[0]	[0]	
[1]	[0]	
[1]	[1]	…
…	…	
[0]	[0]	




Dr. Yang Yang

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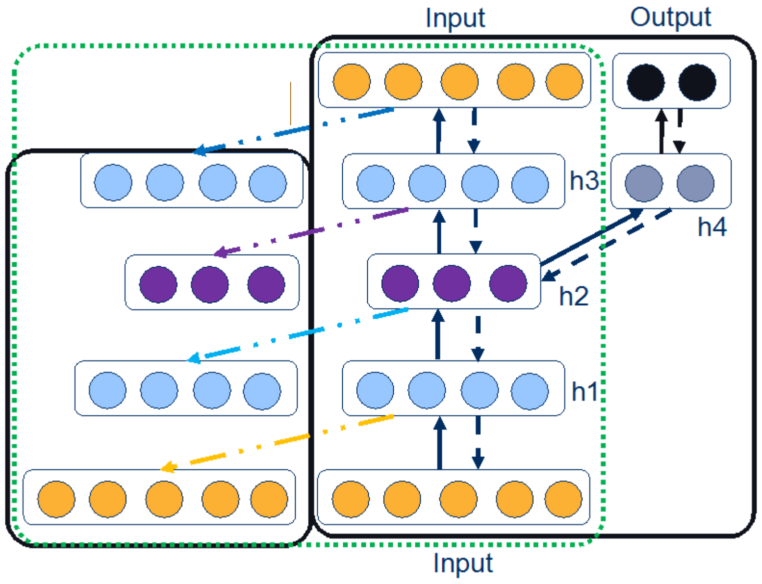
SNPs2risk

```
CTGCATCGAGTGGTCGGCGGTGTGGGCCTCA 120
ATCCGATCGCATGAGCCGGGAAGGCTATGAA 191
CGTCCAGACGCAGCAGGACCTCGGGTCCGCC 131
AGGCGGGCCGTCAGGCATGGTATTTCAACTC 91
GTCAGAAAAAATGTCGTACTGGCCCACGATA 152
ATGCGCAGAAACGCCGAGCGCCAGTTCGCGG 162
AGCGTTCCAAGATTGGCGAGAAGTCTATGGG 156
ACTTGCAGATCGGGCTGTTCGGCGGCAATCT 145
AGCCCGGCGGCGATATTTCCAATCCCCTGGC 127
```

[0]	[0]	
[1]	[0]	
[1]	[1]	...
...	...	
[0]	[0]	
Affected by drug A?	Affected by drug B?	...



Alexander Lachapelle


Dr. Tingting Zhu


Dr. Yang Yang


Dr. Marco Pimentel


Dr. Achut Manandhar


Dr. Nazli Farajidavar


Dr. Samaneh Kouchaki


Dr. Hamza Javed


Dr. Xiaorong Ding

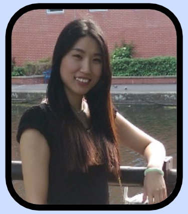

Dr. Huiqi Lu


Dr. Girmaw Abebe Tadesse


Dr. Pulkit Sharma


Thomas Taylor


Dr. Gert Mertes


Dr. Jun Qi


Mauro Santos


Farah Colchester


Glen Wright Colopy


Drew Birrenkott


Yangting Shen

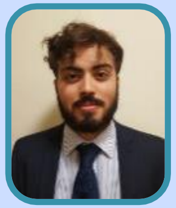

John Prince


Heloise Greeff


Peter Gyring


Farah Shamout


Sarah-Jane Rodgers

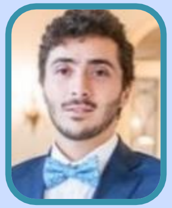

Rasheed El-Bouri


David Morelli


Matthew Chun


Kumeren Govender


Alexander Lachapelle


Dani Kiyasseh

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