

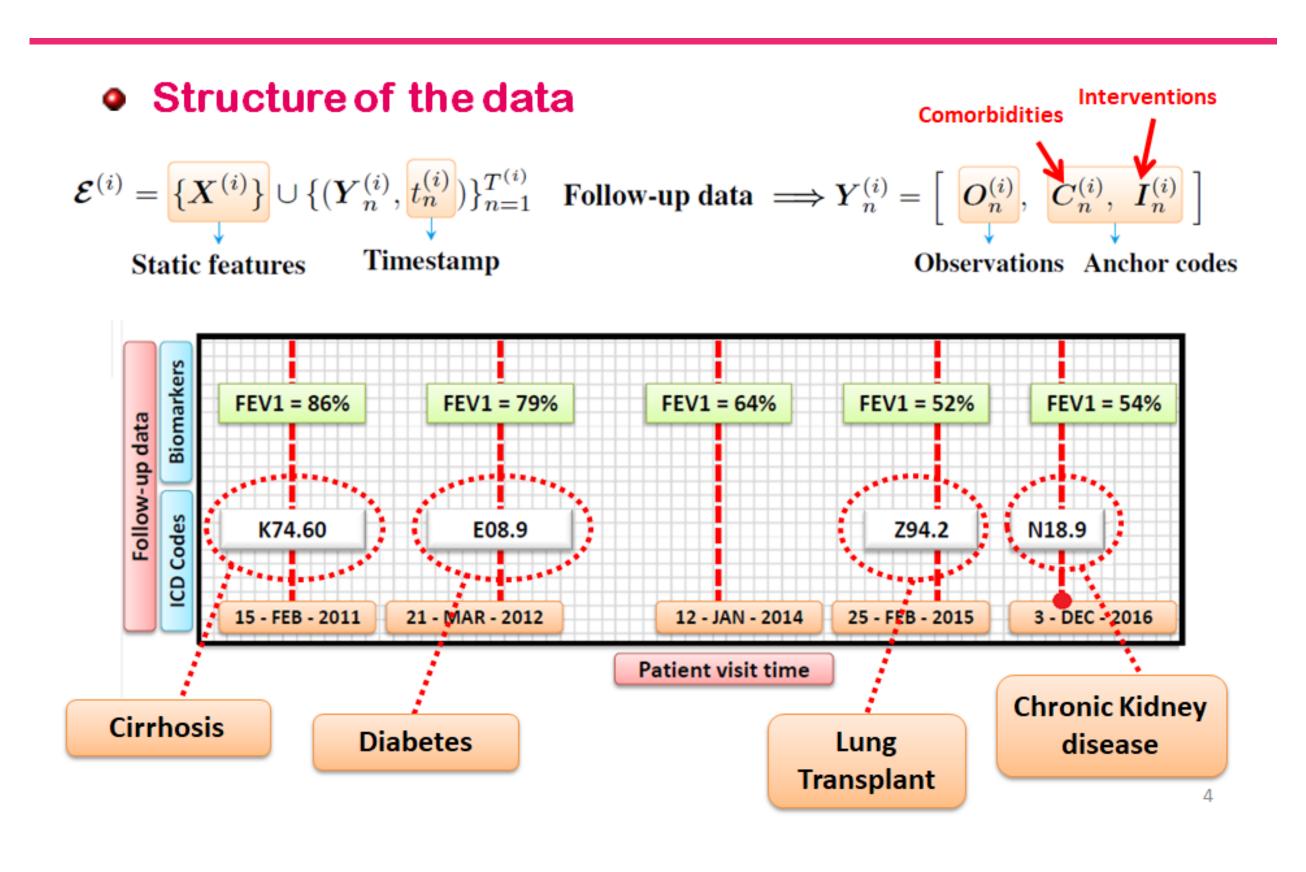
## MOTIVATIONS

**Chronic disease management is challenging!** 

• Managing chronic diseases requires balancing multiple clinical out**comes of interests** – taking into account both quality of life and treatment considerations.

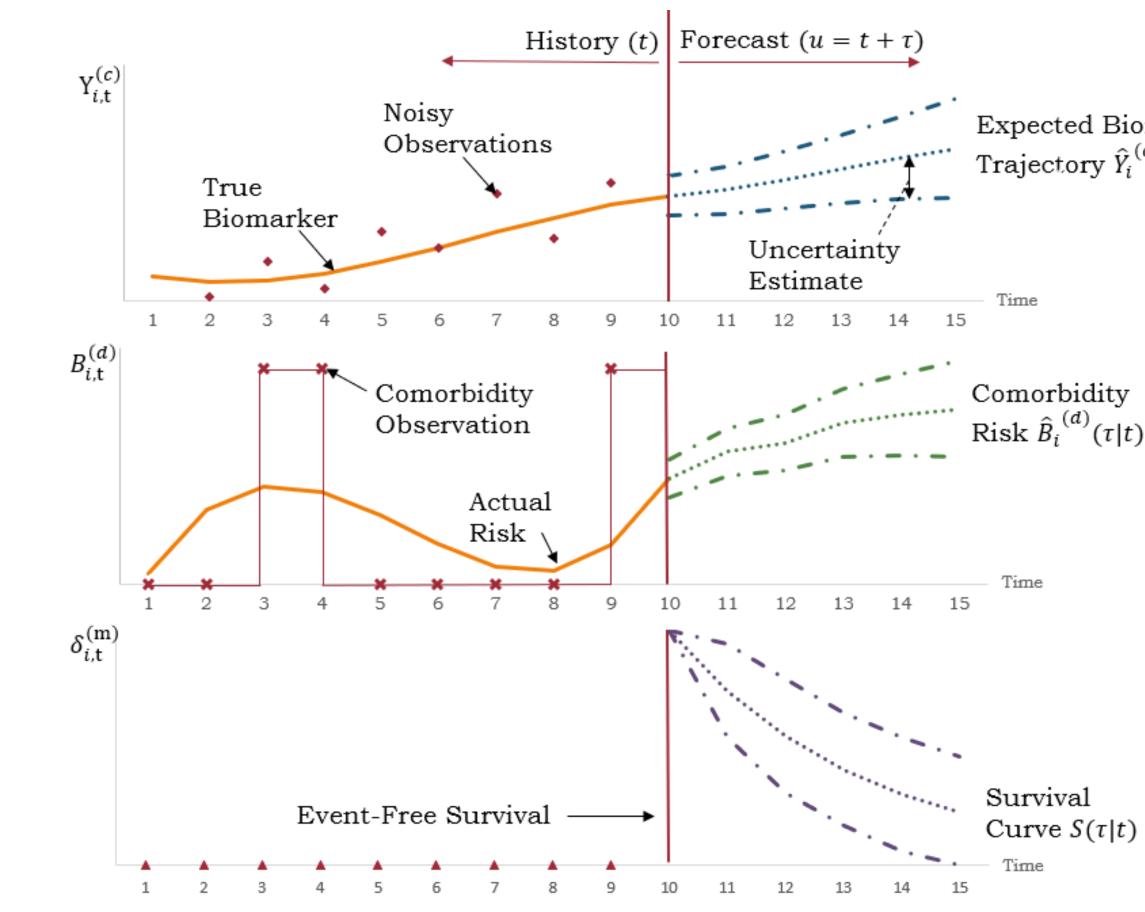
• Multiple factors need to be considered during the decision making process to help inform decisions around **frequency of testing**, intensity of treatment, and treatment burden.

• Patients require monitoring at **infrequent intervals** but **over a very long duration** – e.g. annual follow ups over **multi-year** horizons.



**Solution – Disease-Atlas:** New deep learning model to **simultaneously forecast** multiple outcomes over time, incorporating uncertainty estimates to reflect model confidence.

# DISEASE-ALTAS OUTPUT TYPES



# **Forecasting Disease Trajectories in Cystic Fibrosis with Deep Learning**

BRYAN LIM<sup>1</sup>, THOMAS DANIELS<sup>2</sup>, ANDRES FLOTO<sup>3,4</sup>AND MIHAELA VAN DER SCHAAR<sup>1,5</sup> <sup>1</sup> DEPT. OF ENGINEERING, UNIVERSITY OF OXFORD, <sup>2</sup> UNIVERSITY HOSPITAL SOUTHAMPTON, <sup>3</sup> Dept. of Medicine, University of Cambridge, <sup>4</sup> Royal Papworth Hospital, Cambridge, <sup>5</sup>Alan Turing Institute

Expected Biomarker Trajectory  $\hat{Y}_i^{(c)}(\tau|t)$ 

# PATIENT DATA

#### **Data Description**

• Data obtained from UK Cystic Fibrosis Trust for a cohort of **10980** patients with annual follow ups between 2008 – 2015. • Each patient associated with **87 variables**.

- Joint predictions of death, 2 lung function scores, 9 comorbidities
- and **11** infections.

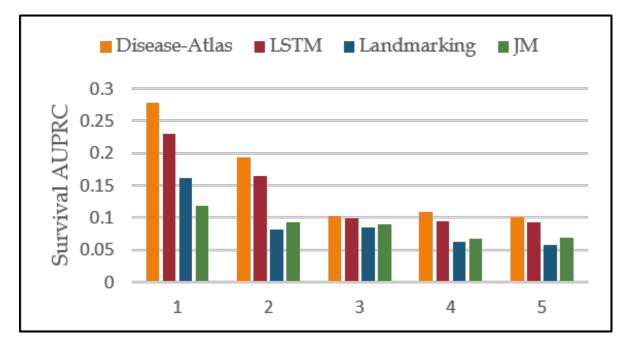
# **ACCURACY OF FORECASTS**

#### **Performance Metrics**

• **FEV** forecasts evaluated in terms of mean squared error (MSE). • Mortality, comorbidity and infection prediction accuracy measured by the area under the precision-recall curve (AUPRC).

• Benchmarks used - deep neural networks (i.e. Long Short Term Memory Networks (LSTM)) and traditional statistical methods (i.e. landmarking & joint models (JM))

### **Mortality & FEV1 Predictions**



#### **Figure 1:** Mortality AUPRC

### **Comorbidity Predictions (AUPRC)**

	Disease-Atlas					Joint Models					
Prediction Horizon (Yrs)	1	2	3	4	5	1	2	3	4	5	
Liver Disease	0.862	0.825	0.709	0.616	0.513	0.181	0.186	0.197	0.2	0.207	
Asthma	0.904	0.845	0.773	0.642	0.544	0.272	0.261	0.258	0.245	0.24	
Arthropathy	0.799	0.76	0.621	0.5	0.347	0.134	0.142	0.148	0.155	0.154	
Bone Fracture	0.064	0.043	0.052	0.032	0.031	0.006	0.007	0.007	0.009	0.01	
Raise Liver Enzymes	0.784	0.726	0.536	0.409	0.338	0.163	0.16	0.156	0.157	0.172	
Osteopenia	0.758	0.742	0.648	0.577	0.526	0.245	0.255	0.266	0.278	0.28	
Osteoporosis	0.658	0.644	0.507	0.406	0.322	0.144	0.149	0.151	0.146	0.134	
Hypertension	0.308	0.34	0.309	0.277	0.227	0.123	0.13	0.141	0.142	0.142	
Diabetes	0.85	0.798	0.774	0.663	0.64	0.319	0.334	0.342	0.348	0.356	
Average	0.665	0.636	0.548	0.458	0.388	0.176	0.180	0.185	0.187	0.188	
Standard Deviation	0.287	0.269	0.237	0.205	0.189	0.093	0.094	0.096	0.097	0.099	

## **Infection Predictions (AUPRC)**

	Disease-Atlas					Joint Models					
Prediction Horizon (Years)	1	2	3	4	5	1	2	3	4	5	
Burkholderia Cepacia	0.692	0.672	0.639	0.576	0.471	0.054	0.058	0.056	0.056	0.062	
Pseudomonas Aeruginosa	0.84	0.828	0.815	0.8	0.794	0.636	0.641	0.65	0.655	0.649	
Haemophilus Influenza	0.369	0.332	0.265	0.243	0.278	0.181	0.204	0.233	0.231	0.202	
Aspergillus	0.38	0.315	0.337	0.27	0.293	0.22	0.22	0.218	0.212	0.216	
NTM	0.237	0.073	0.181	0.133	0.138	0.076	0.068	0.072	0.062	0.041	
Ecoli	0.506	0.242	0.089	0.036	0.008	0.098	0.037	0.025	0.011	0.005	
Klebsiella Pneumoniae	0.299	0.146	0.06	0.01	0.015	0.051	0.037	0.026	0.025	0.027	
Gram-Negative	0.028	0.038	0.022	0.027	0.022	0.009	0.01	0.012	0.012	0.015	
Xanthomonas	0.298	0.202	0.218	0.18	0.128	0.079	0.079	0.087	0.092	0.098	
Staphylococcus Aureus	0.771	0.706	0.612	0.537	0.497	0.336	0.337	0.344	0.347	0.345	
ALCA	0.153	0.148	0.155	0.144	0.175	0.037	0.04	0.037	0.04	0.047	
Average	0.416	0.337	0.308	0.269	0.256	0.162	0.157	0.160	0.158	0.155	
Standard Deviation	0.259	0.274	0.265	0.259	0.246	0.184	0.190	0.195	0.197	0.195	

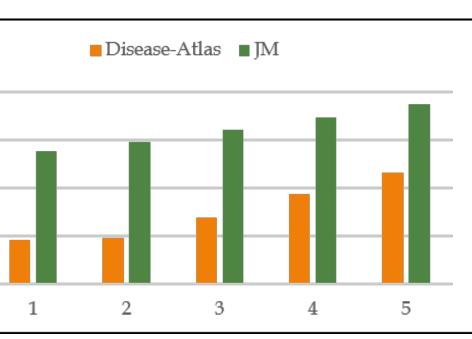


Figure 2: FEV1 MSE

## **DECISION SUPPORT WITH DISEASE-ATLAS**

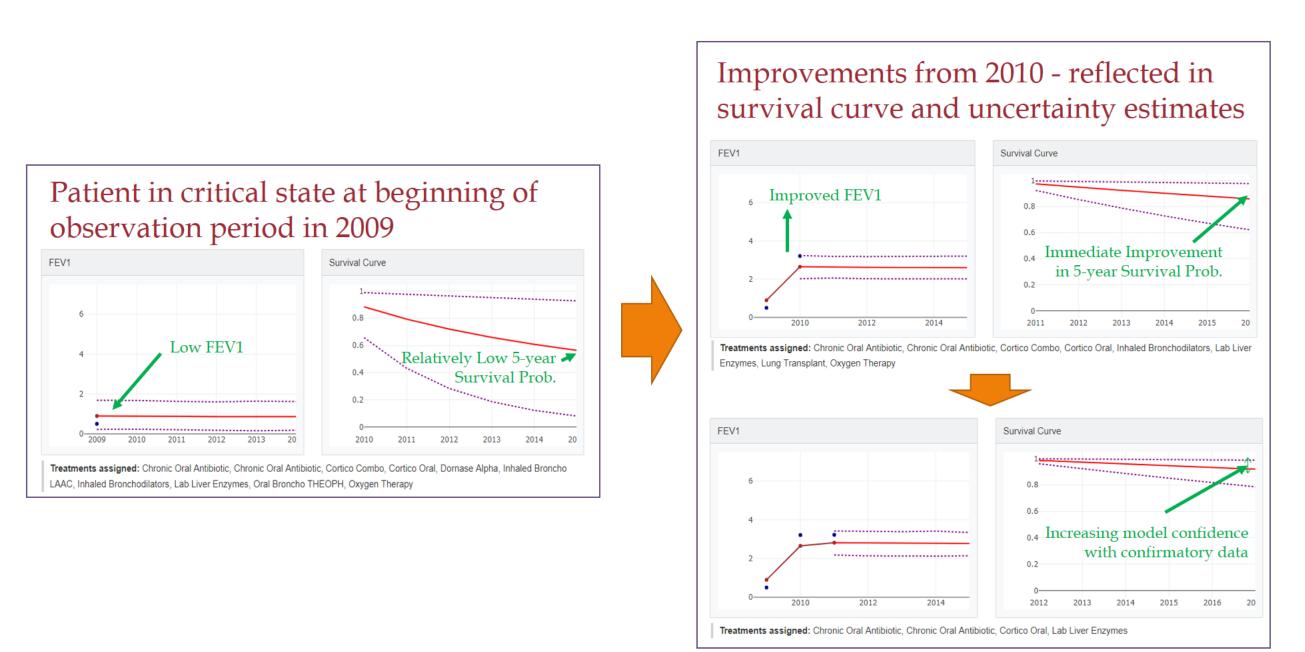
Web App Available!

### https://disease-atlas-online.herokuapp.com

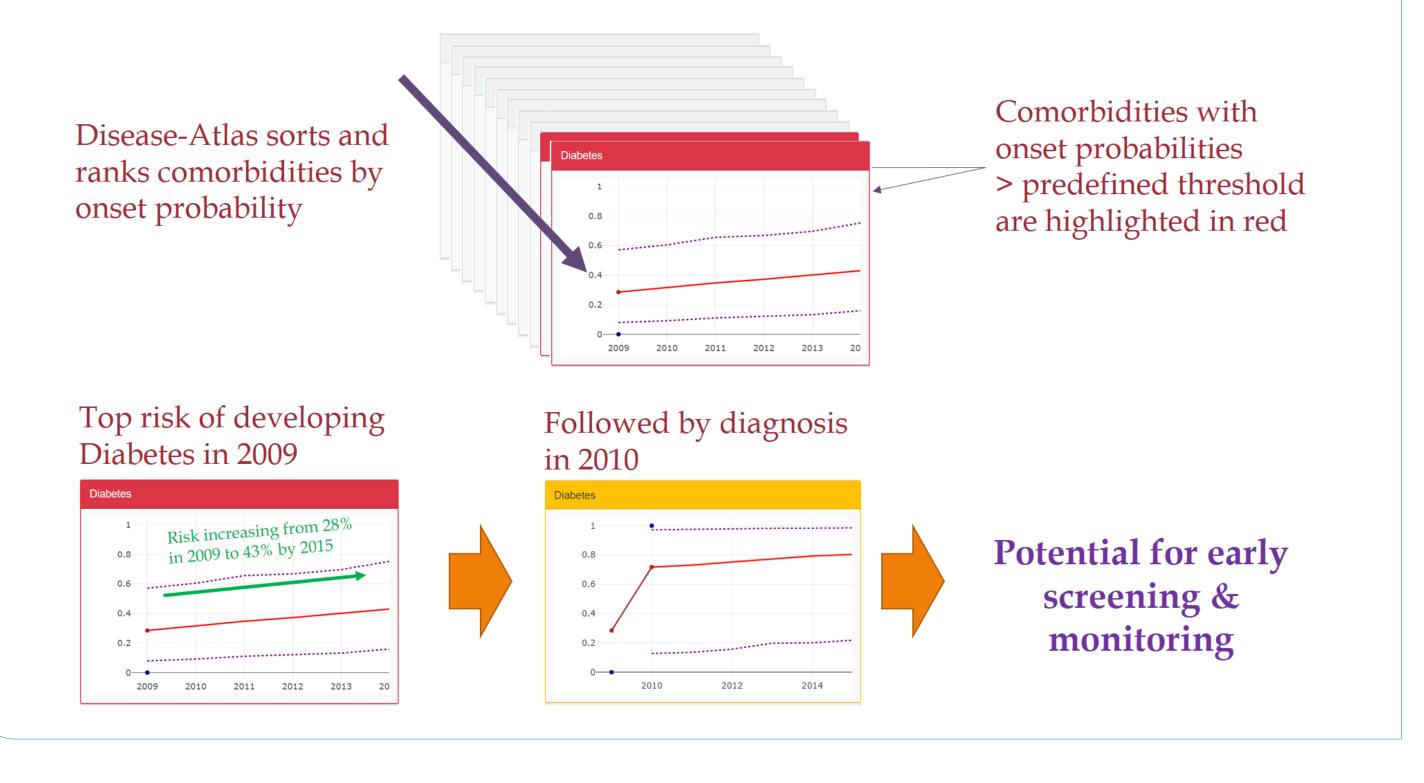
### **Test Patient**

In the following use cases, we consider the Disease-Atlas forecasts for a **27-year old male patient** with follow ups between **2009 - 2015**.

# **Use Case 1 – Patient Monitoring**



# **Use Case 2 – Prioritising Screening**



# CONCLUSIONS

• Translating predictive analytics into real-time decision support tools can facilitate personalised data-driven decision making in CF clinics – leveraging the individuals' own data and associated risks.

• Large, high quality datasets provide opportunities for machine learning methods to predict future health events for people with CF.

• The methodology should also be validated on a different cohort.