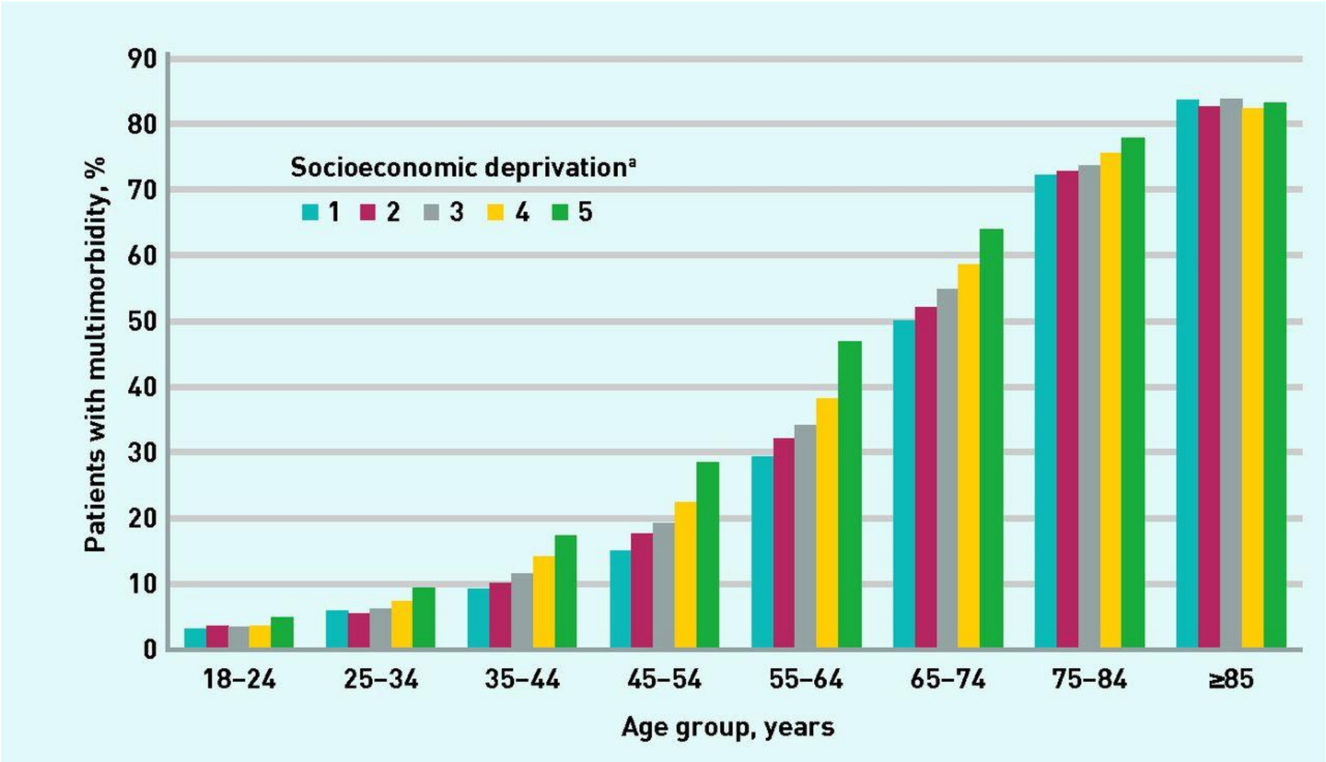
Disease-Atlas:
Navigating Disease Trajectories with Deep Learning

Bryan Lim & Mihaela van der Schaar

University of Oxford

Background: Chronic Disease Management

- Patients with long-term conditions have complex medical needs
- Requires long-term monitoring and complicated treatment regimens
- Strong correlation between multimorbidity and age
- **Effective decision support tools required!**



% of Cohort of Patients with Multimorbidity by Age Group[(1)]

(1) Cassell et al. Br J Gen Pract 12 March 2018. -"The epidemiology of multimorbidity in primary care: a retrospective cohort study".

Beyond Simple Prognostic Questions

What is the expected rate of lung function deterioration?

Is the patient likely to develop any infections or comorbidities?

What is the expected survival time of the patient?

How do expected outcomes change over time?

Beyond Simple Prognostic Questions

What is the expected rate of lung function deterioration?

Is the patient likely to develop any infections or comorbidities?

What is the expected survival time of the patient?

How do expected outcomes change over time?

Beyond Simple Prognostic Questions

What is the expected rate of lung function deterioration?

Is the patient likely to develop any infections or comorbidities?

What is the expected survival time of the patient?

How do expected outcomes change over time?

Beyond Simple Prognostic Questions

What is the expected rate of lung function deterioration?

Is the patient likely to develop any infections or comorbidities?

What is the expected survival time of the patient?

How do expected outcomes change over time?

Beyond Simple Prognostic Questions

How long will the patient survive?

Not enough!

Clinical biomarkers

What will happen to the patient in the future?

Model the Entire Health Trajectory

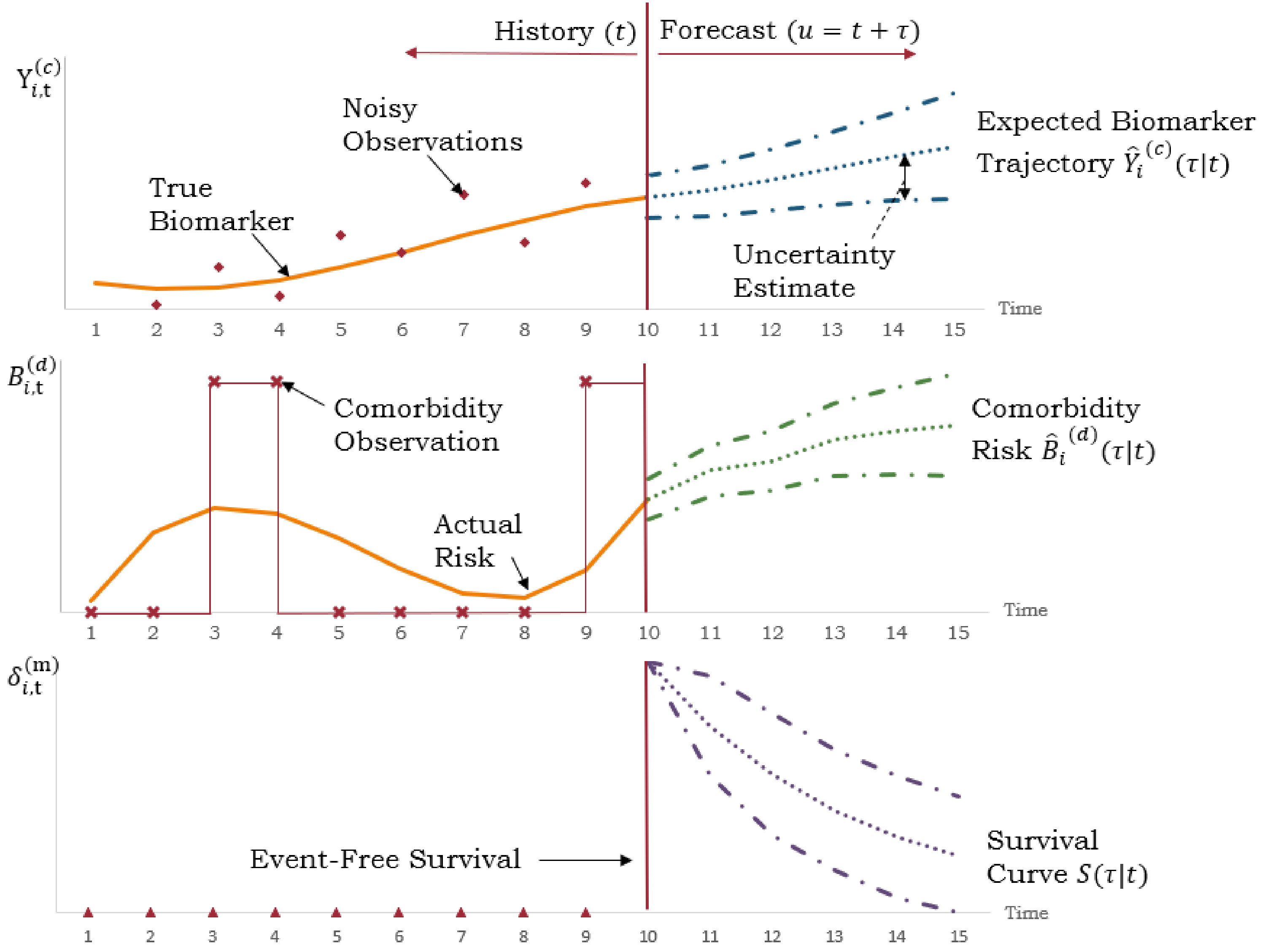
Predict patterns of decline

=

Patterns of interactions with healthcare system

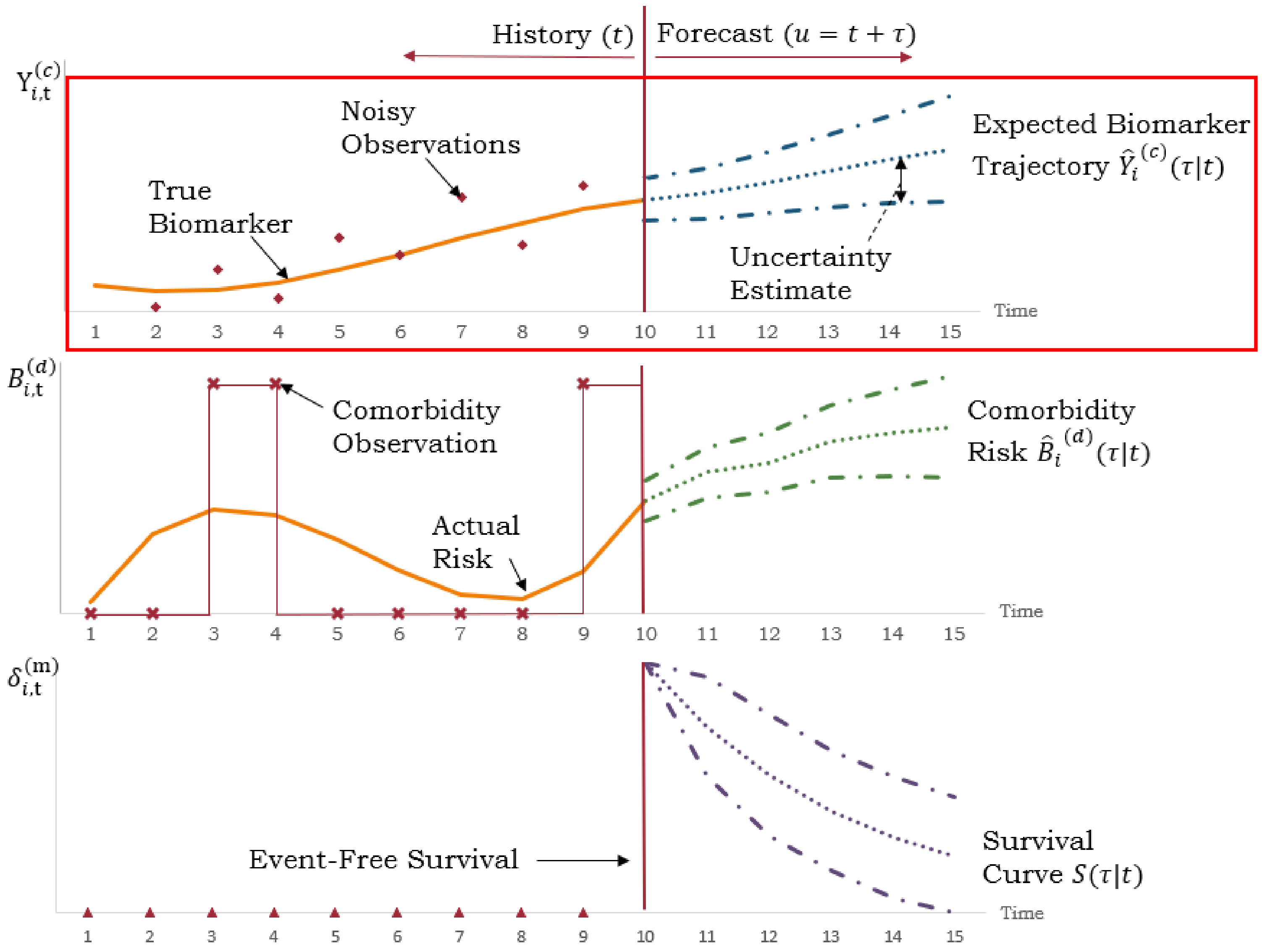
Disease-Atlas

- **Predicting biomarkers.**
- **Predicting complications.**
- **Predicting infections.**
- **Predicting survival.**



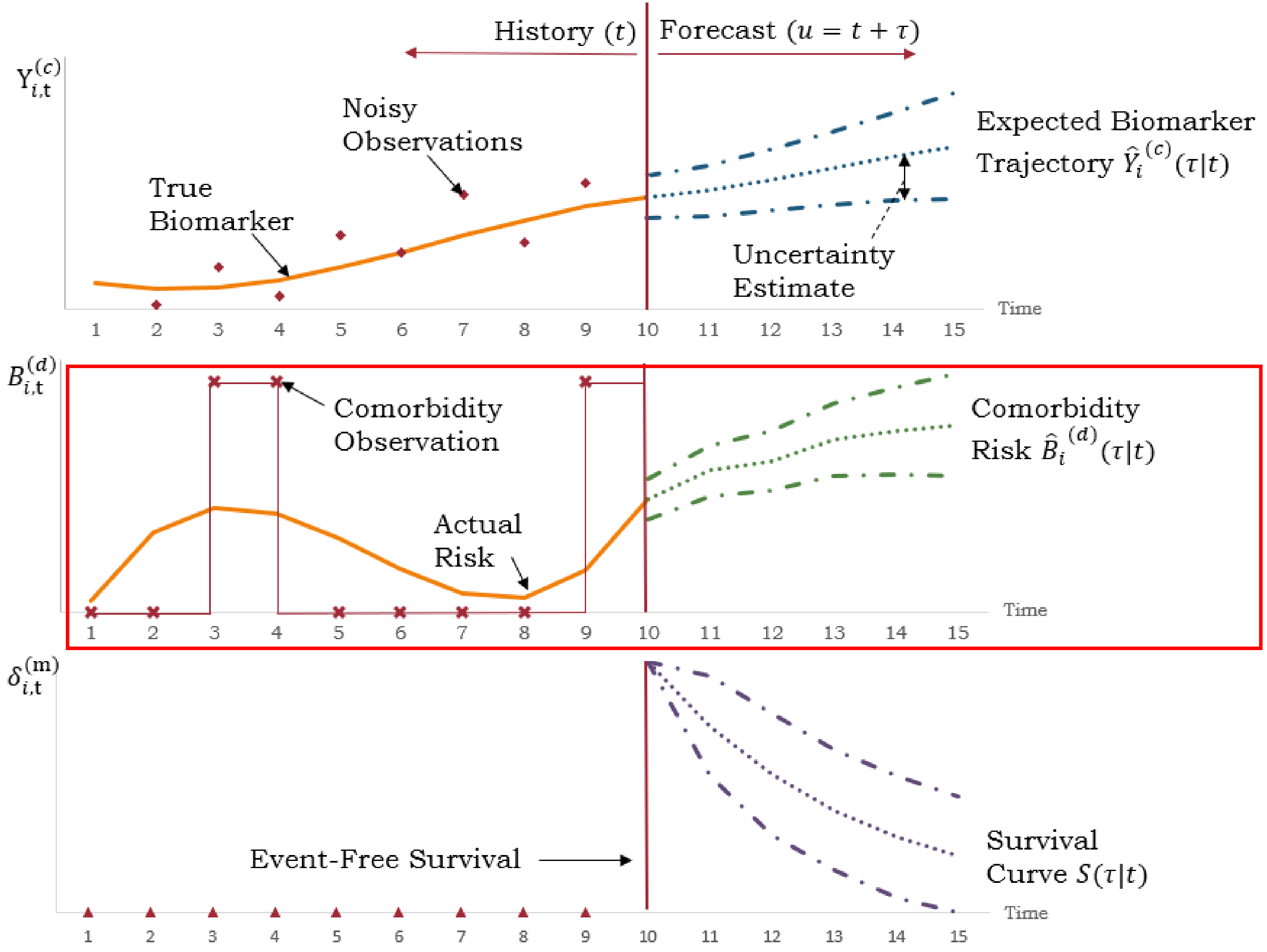
Disease-Atlas

- **Predicting biomarkers.**
- **Predicting complications.**
- **Predicting infections.**
- **Predicting survival.**



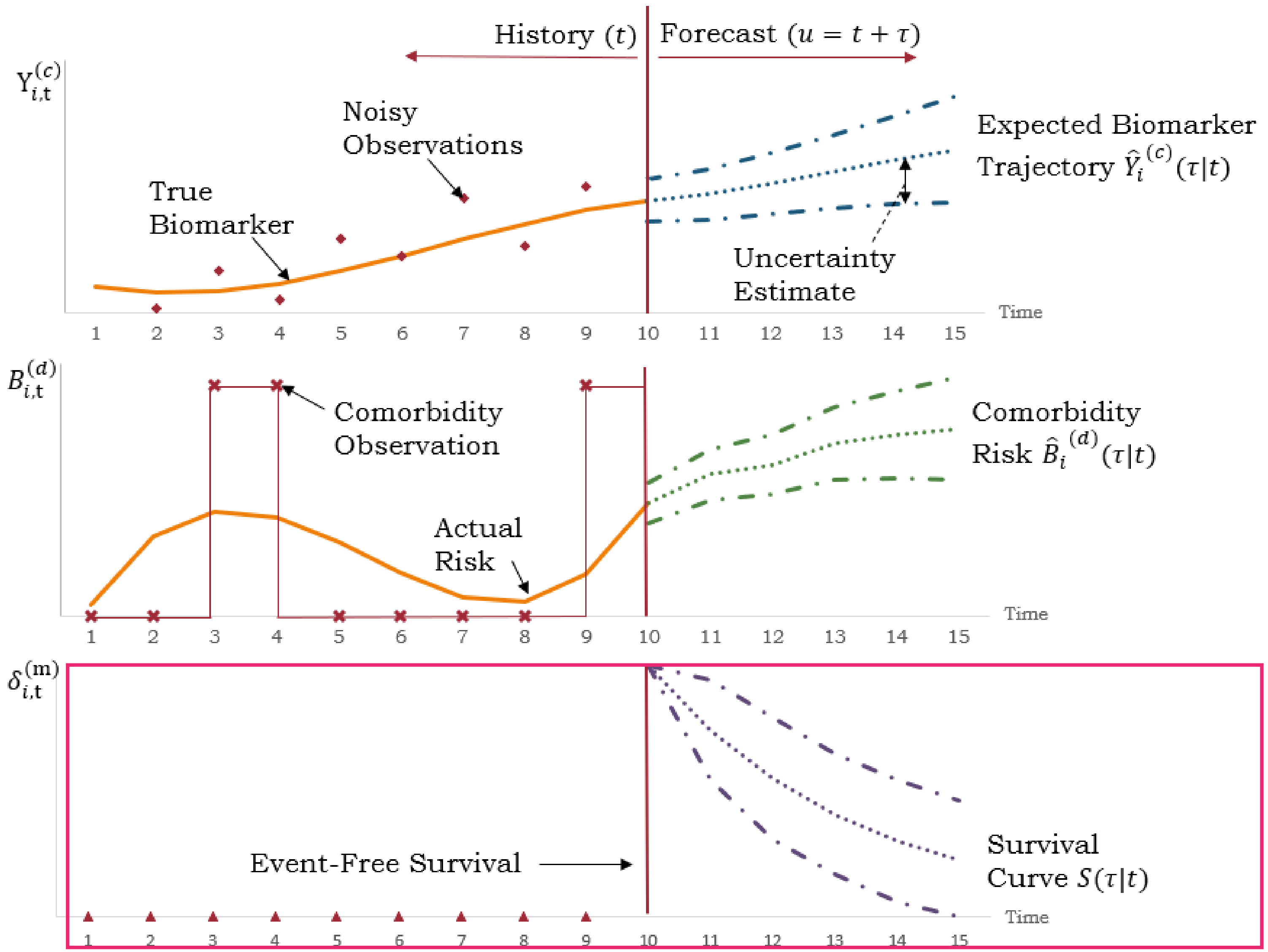
Disease-Atlas

- **Predicting biomarkers.**
- **Predicting complications.**
- **Predicting infections.**
- **Predicting survival.**



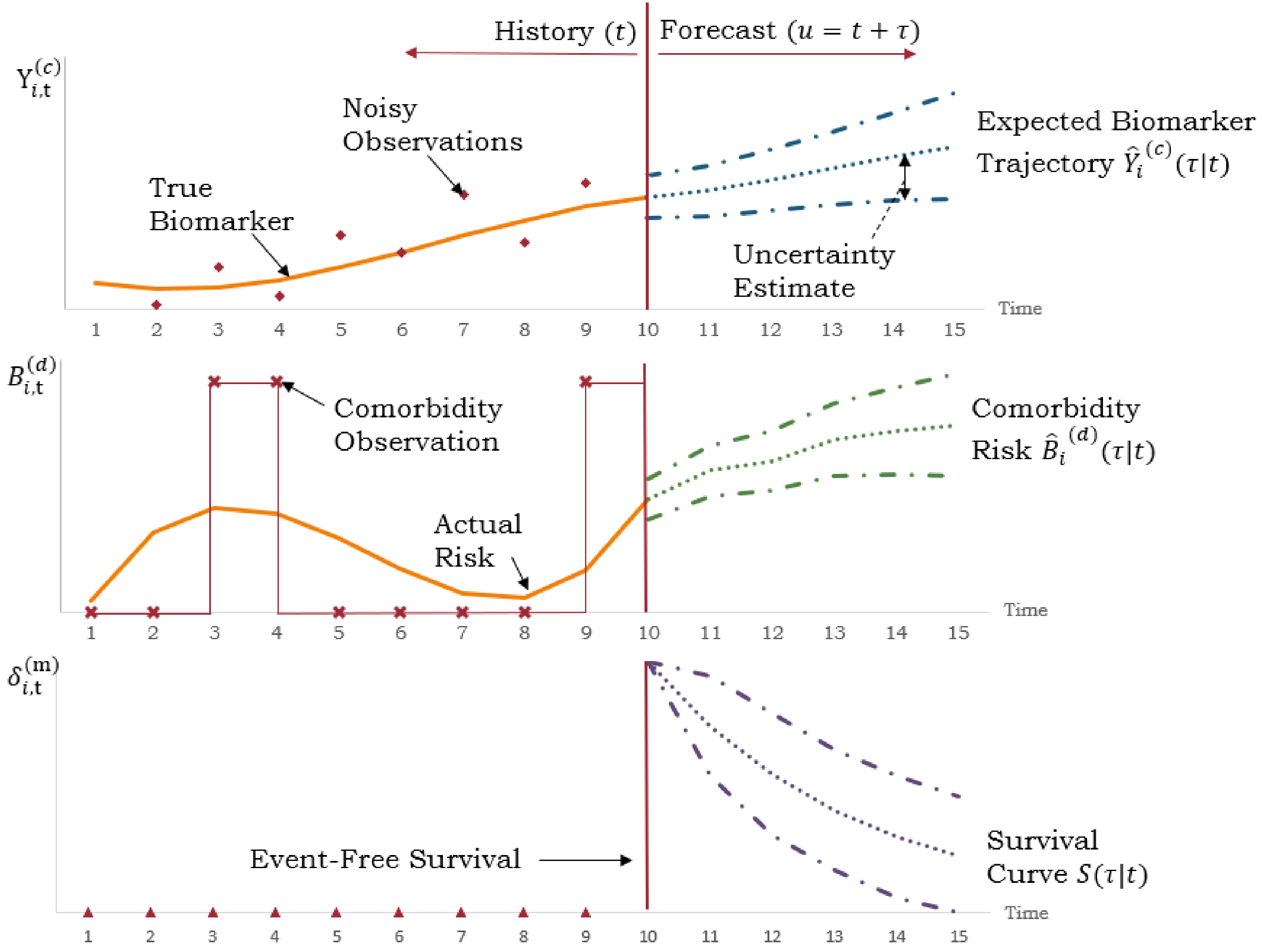
Disease-Atlas

- **Predicting biomarkers.**
- **Predicting complications.**
- **Predicting infections.**
- **Predicting survival.**

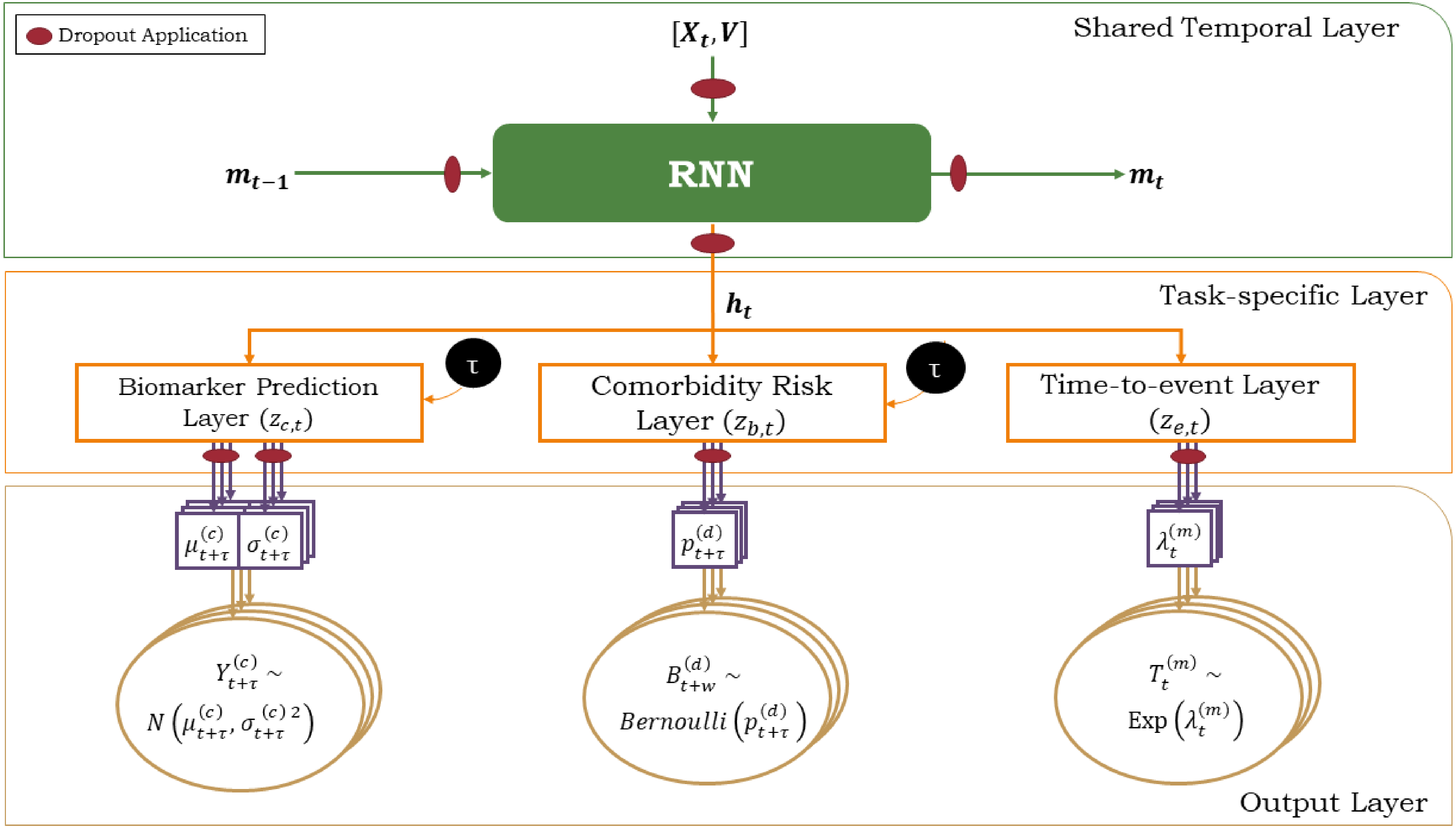


Additional Characteristics

- ***Personalised*** based on a patient's unique characteristics and history
- Predictions over multiple horizons
- Quantifies uncertainty of forecasts



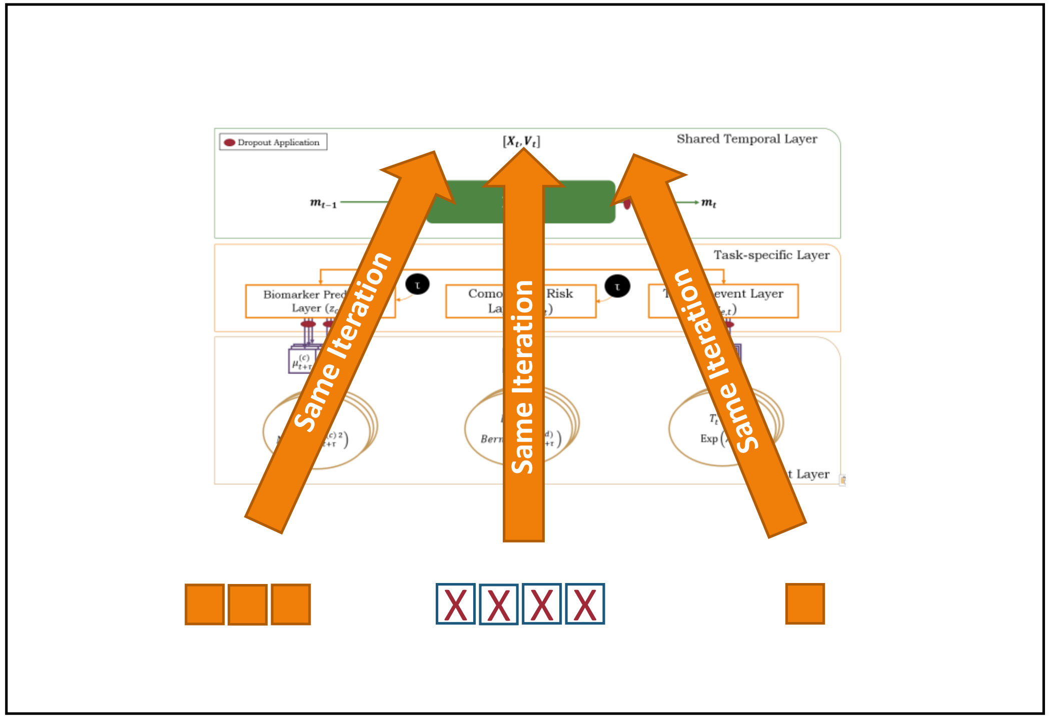
Disease-Atlas Architecture



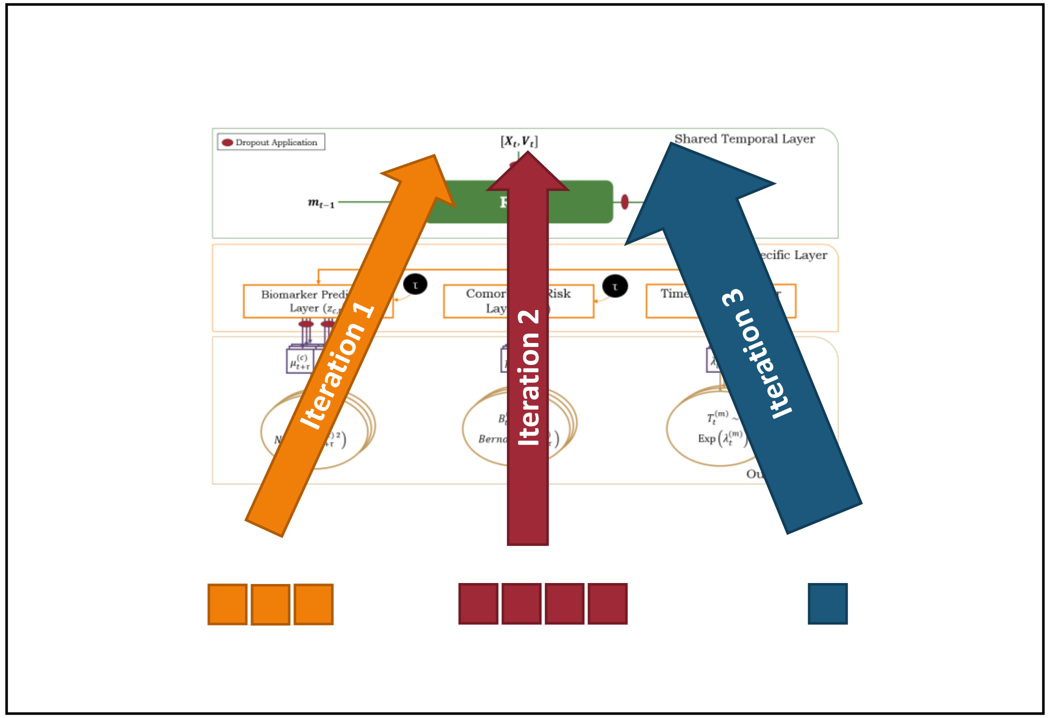
Multitask Learning

$$L(\mathbf{W}) = \underbrace{-\alpha_c \sum^{i,t,w,c} \log f_c\left(Y^{(c)}_{t+\tau}|\mathbf{W}\right)}_{\text{Continuous Longitudinal Loss } l_c} \underbrace{-\alpha_b \sum^{i,t,w,d} \log f_b\left(B^{(d)}_{t+\tau}|\mathbf{W}\right)}_{\text{Binary Longitudinal Loss } l_b} \underbrace{-\alpha_T \sum^{i,t,m} \log f_T\left(T^{(m)}_{t}|\mathbf{W}\right)}_{\text{Time-to-event Loss } l_T}$$

Standard (Multivariate) Training

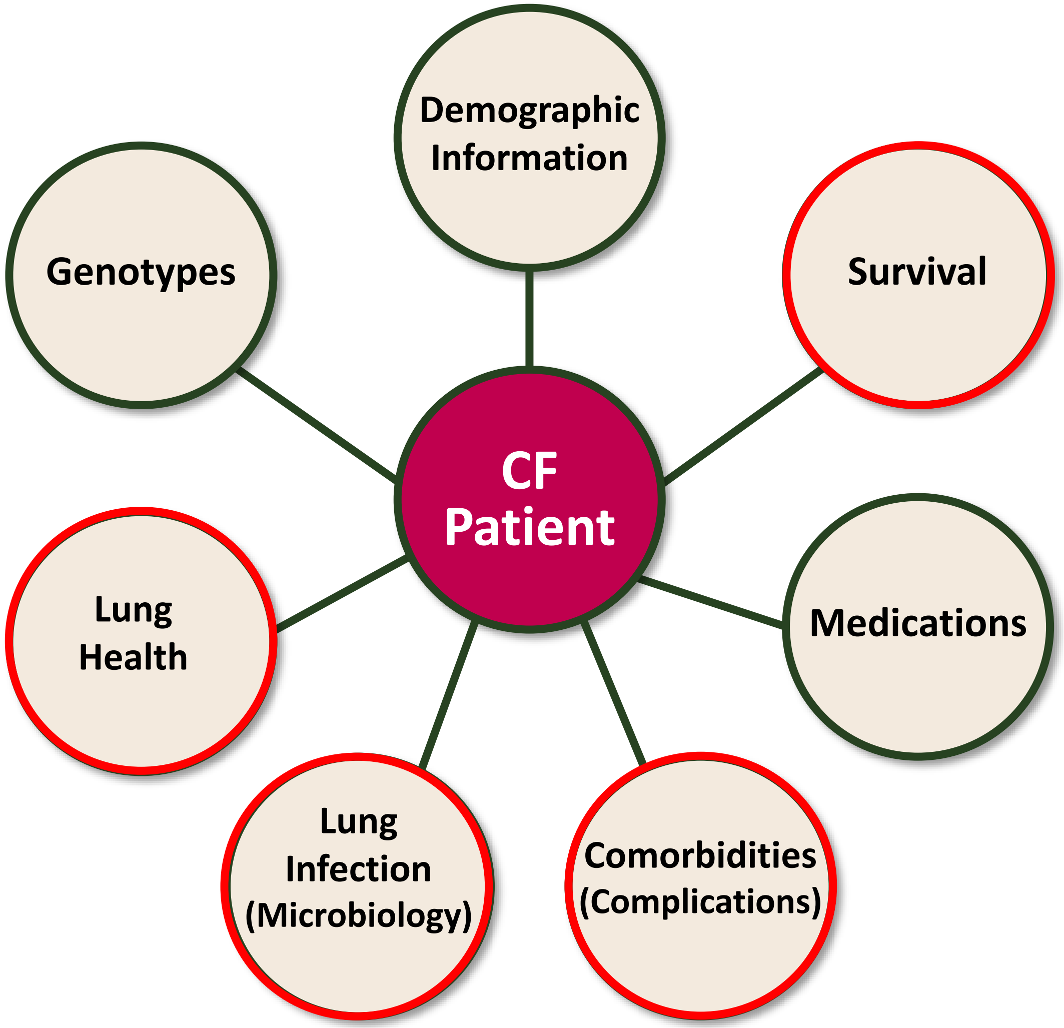


Multitask Learning



Case Study: Cystic Fibrosis

Annual review data for 10,000+ patients over the period from <u>2008</u> to <u>2015</u>



Each patient is associated with 87 variables!

Dynamic Prediction Results

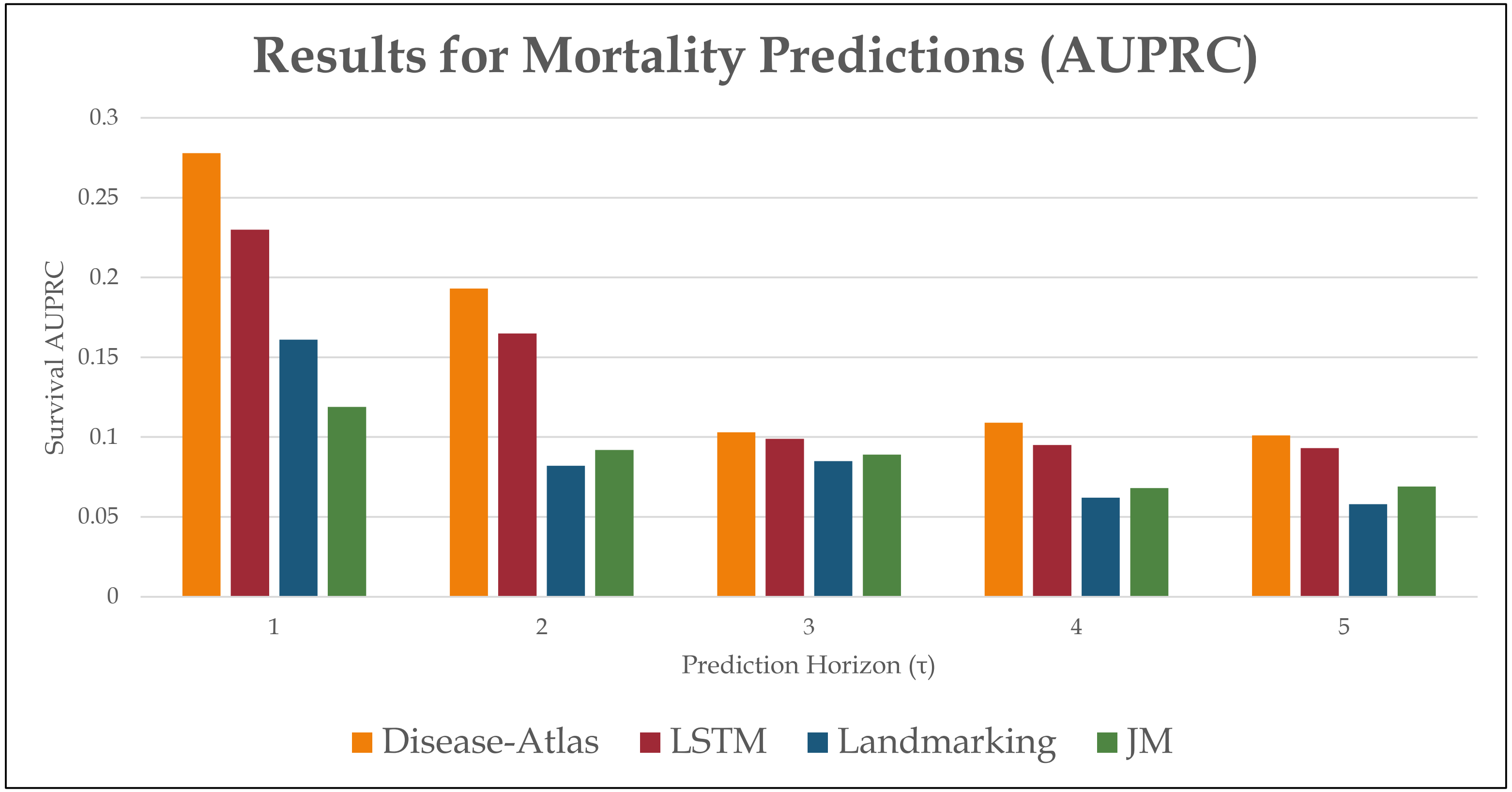
Jointly Predicting…

- **Mortality** as the event-of-interest

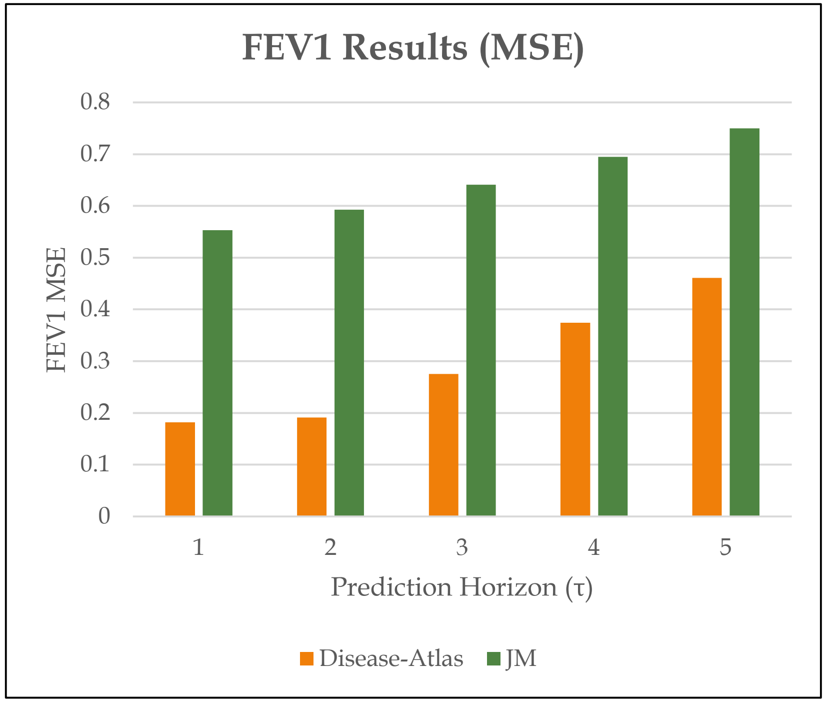
- **Lung Function Scores** – *FEV1, Predicted FEV1*

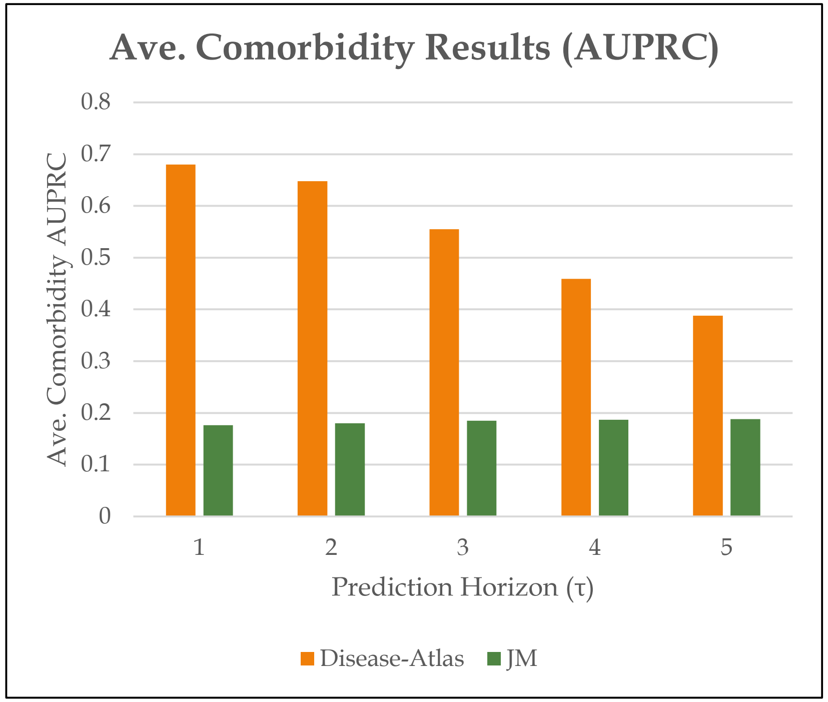
- **9 Comorbidities** – *Liver Disease, Asthma, Arthropathy, Bone fracture, Raised Liver Enzymes, Osteopenia, Osteoporosis*

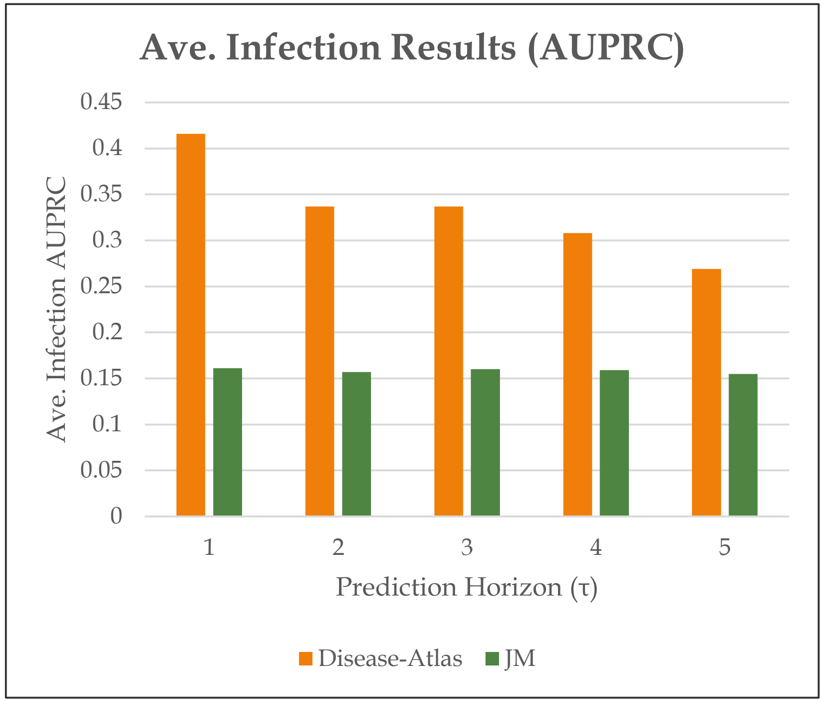
- **11 Infections** – *Burkholderia Cepacia, Pseudomonas Aeruginosa, Haemophilus Influenza, Aspergillus, NTM, Ecoli, Klebsiella Pneumoniae, Gram-Negative, Xanthomonas, Staphylococcus Aureus, ALCA*



Dynamic Prediction Results







Web Demo: Use Cases for Clinicians

Thank you

See you at the poster session!